Conservation In Cambodia: Linking Forests, Wildlife, And People In Dynamic Landscapes

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SUMMARY ABSTRACT

Cambodia is a country rich in biodiversity and cultural heritage, yet between 1970 and 1993 the country experienced civil war and genocide, with long-lasting implications for the country's environment, politics, and people. Cambodia's post-conflict economic recovery has been remarkably successful; reducing poverty rates, expanding agriculture, and improving the socioeconomic status of many in the country, making it an excellent case study for other countries that have experienced rapid political, socioeconomic, and environmental change. Yet, there has been little research into the effects of Cambodia's economic recovery on forests, nor into the effects of current policies and funding regimes on the country's protected area network. In this thesis, I address these research gaps by focussing on two themes: 1) economic development and forest loss; 2) protected area, wildlife, and landscape management.

First, I reveal that metrics of economic development and agricultural commodities do not predict forest loss but do predict the expansion of commercial agriculture. I then demonstrate that there are complex relationships between socioeconomic, human, and geographical predictors of forest cover at different scales across the country.

Second, I present evidence that in contrast to arboreal species, anthropogenic threats are having serious negative effects on ground-based wildlife within a flagship protected area. I then identify the potential consequences of different funding regimes for conservation management within a social-ecological landscape. I demonstrate that short-term grant cycles, which are the dominant conservation funding mechanisms around the world, are not optimal for maximising long-term conservation outcomes.

My thesis provides novel and policy-relevant research into the effects of Cambodia's post-conflict recovery on forest conservation and landscape management. I reveal the implications of policies that prioritise economic development and agricultural expansion over natural resource management and biodiversity conservation, and I recommend the development of agricultural policies and schemes that embrace modern innovation and promote socioeconomic development yet embody environmental sustainability. Finally, I recommend the urgent reduction in wildlife hunting, action to reduce reliance on wild meat, and the prioritisation of sustainable long-term funding for protected areas.

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This thesis is dedicated to you. We'll take you to Cambodia one day little man, and we'll walk with you through the forests.

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Chapter 1

General introduction

1.1 A rapidly changing world

Humans have exerted pressure on the natural world for millennia, yet the last 500 years have seen dramatic increases in the use of natural resources for human development (Steffen et al., 2015; Williams, 2003). Increases in human populations, agricultural expansion and intensification, and the liberalisation and expansion of the global free market economy have all driven increases in the exploitation of natural resources, with profound implications for nature (Alston and Pardey, 2014; Behrens et al., 2007; Conca, 2001; Everett et al., 2010; Wiedmann and Lenzen, 2018). Continued economic growth and development via natural resource exploitation is particularly prevalent in the developing world where governments strive to reduce poverty rates, natural resources are more abundant, and the globalisation of the commodity market has allowed resource-rich countries to capitalise on international trade (Adams et al., 2019; Hoang and Kanemoto, 2021; Pendrill et al., 2019; Sachs and Warner, 2001).

There is little debate that human exploitation of natural systems can have negative effects on biodiversity; changes in anthropogenic pressure can directly predict changes in species extinction risk (Di Marco et al., 2018) and can lead to species extinctions both directly via the destruction of habitats and overexploitation of wildlife populations, and indirectly by triggering amplifying feedback loops which typify the collapse of natural systems (Brook et al., 2008). The dynamic nature of global economics and human society means that human pressure on the environment changes over space and time, operates across multiple scales, and interacts with an immeasurable number of social-ecological subsystems (Berkes et al., 2000; Venter et al., 2016). This complexity makes predicting the effects of human pressure on biodiversity and natural systems difficult, which in turn makes sustainable land management and the design of effective economic and environmental policies aimed at reducing environmental degradation challenging.

1.1.1 Forests

Throughout human history deforestation has likely affected more of the earth’s surface than any other human activity (Williams, 2003). Today, millions of people around the world, often the poorest and most marginalised, still rely on forests and the natural resources within them for their livelihoods (Wunder et al., 2014). Forests are a source of medicine, protein, fibre, timber, and are often places of spiritual and cultural importance (Clark, 2011; Djoudi et al., 2015; Humphreys, 2009; Sunderlin et al., 2005). Furthermore, forests are critical for biodiversity (Estoque et al., 2019), water and soil regulation (Millennium Ecosystem Assessment, 2005), ecosystem functions, processes, and services (Ceccherini et al., 2020; de Groot et al., 2002), and climate regulation (Jiao et al., 2017). The loss of forests due to human activities, particularly in the tropics, is a major source of biodiversity loss and carbon emissions (IPCC, 2019), and can have negative effects on local people through the loss of land and livelihoods (Caravaggio, 2020a; Dressler et al., 2017). The primary driver of global deforestation is the expansion of commodity production which causes permanent land use change, with other contributing drivers including wildfires, forestry, and shifting agriculture (Curtis et al., 2018).

Modern consumption patterns, in combination with globalised trade and increasing human populations, have increased the global demand for agricultural commodities (Hoang and Kanemoto, 2021; Pendrill et al., 2019). Between 1960 and 2019 the global area under harvest for primary crops increased by over 13 million km^2 (FAO, 2021). Agricultural sector growth is an important goal for improving food security in many developing nations with increasing human populations, and can also contribute towards economic development via lucrative exports of commodities (Caravaggio, 2020b; Eliste and Zorya, 2015). Large-scale commercial agriculture has emerged in many parts of the world in response to the global demands for commodities and the opportunities for commercial gain via global markets, often replacing smallholder agriculture or reducing forest cover via permanent land use change (Broegaard et al., 2017; van Vliet et al., 2012).

In contrast to global and regional drivers such as demand for commodities and market fluctuations, there are a multitude of local conditions that can influence forest loss, both directly as local drivers, and indirectly through interactions with broader drivers (Geist and Lambin, 2002). Proximate causes of deforestation at the local scale can include agricultural expansion, infrastructure development, and urbanisation, all of which are driven by complex interactions between socioeconomic conditions, land tenure, migration, increasing human populations, and local economies (Ceddia, 2019; Culas, 2012; Gatto et al., 2015; Geist and Lambin, 2002; Khuc et al., 2018; Mena et al., 2006). At the smallest scale, decision-making by agents of change, for example smallholders and individual households, is influenced by a range of multifaceted drivers and conditions as they respond to changes in economic opportunities and attempt to meet their economic, social, and cultural objectives (Rowcroft, 2008).

Disentangling the interactions and feedback loops between drivers of deforestation at different scales is complex, which makes the design of effective policy frameworks and conservation interventions challenging. Advanced modelling frameworks have developed which are allowing greater understanding of the processes underlying land use change (LUC), and subsequently more accurate predictions into the future (Basse et al., 2014; Bonilla-Bedoya et al., 2018). Methodological approaches fall broadly into two groups governed largely by the aims of the study. First, modelling the spatial processes of LUC is a common goal, as this allows researchers to use patterns of past LUC to predict which areas are at higher risk of land conversion in the future, with the potential to explore a number of plausible future scenarios (Basse et al., 2014). There are several spatially explicit cell-based modelling frameworks that can achieve these aims, including maximum entropy (Bonilla-Bedoya et al., 2018; de Souza and De Marco, 2014), and cellular automata (Stevens and Dragićević, 2007; Yang et al., 2012), which rely on discrete spatial units that have associated variable values and tend to be spatially correlated.

Second, researchers may want to focus their models on the relationships between LUC and trends in predictor variables over time, with less emphasis on spatial processes. These approaches are generally less deterministic than the spatial process modelling above, and are often at much larger scales (e.g., Bhattarai and Hammig, 2004; Ceddia, 2019; Ewers, 2006). These analyses are often targeting broader economic, socioeconomic, cultural, political, and institutional drivers of LUC, which are less amenable to spatial sampling. Generalised linear mixed models (GLMMs, also known as multilevel or hierarchical models) are often employed in such analyses, as GLMMs can account for temporal autocorrelation and hierarchical data structures (Zuur et al., 2009). Studies have used these, and other regression-type models, to investigate the relationships between LUC and national income and forest policies (Bhattarai and Hammig, 2004), income, land, and wealth inequalities (Ceddia, 2019), indigenous land tenure (Ceddia et al., 2015), macroeconomics and economic development (Culas, 2007; Ewers, 2006), and urban socioeconomics (Gong et al., 2013). Studies that use GLMMs to investigate LUC almost exclusively use data from multiple countries, taking advantage of the ability of these models to harness large longitudinal data sets with few “subjects” without succumbing to pseudoreplication (Gelman and Hill, 2006). Another advantage of GLMMs is the ability to quantify between-group variance, which not only offers crucial insight about the differences between groups (e.g., countries) from which inference can be drawn (Zuur et al., 2009), but can also highlight potential problems with ‘global’ predictions (i.e., predictions that are made with all random effect terms set at their mean).

1.1.2 Wildlife

Wildlife populations are declining across the globe as species are overexploited and natural habitats are degraded and lost through human activities including agricultural expansion and urbanisation (Johnson et al., 2017; Leung et al., 2020; Mokany et al., 2020). Extirpation of individual populations are causing the collapse of entire species as human activities, particularly over the last century, place unsustainable pressure on the biosphere (Ceballos et al., 2020). Species extinctions can have negative effects on key environmental processes, with severe implications for Earth’s ecosystems (Hooper et al., 2012, 2005; Wardle et al., 2011). Estimates have suggested that up to one-fifth of all vertebrates are threatened with extinction, and that drivers of biodiversity loss are still far greater than conservation efforts to mitigate them (Hoffmann et al., 2010; Tittensor et al., 2014).

As with deforestation, the drivers of wildlife declines are multifaceted and operate across a range of scales. At the largest scale, climate change is already negatively affecting wildlife populations by rapidly changing habitat conditions which can facilitate the influx of invasive species, force rapid range shifts, and render existing habitat unsuitable (Ayebare et al., 2018; Hamilton et al., 2018; Malakoutikhah et al., 2018; Walls et al., 2019). Habitat degradation and loss is one of the most important direct causes of species declines, and is driven by landscape change resulting predominantly from deforestation, agricultural expansion, urbanisation, and land use intensification (Fuller et al., 2017; Hearn et al., 2018; Lendrum et al., 2018; Pellissier et al., 2017; Wilcove et al., 2013; Wilkinson et al., 2018). At the smallest scale, hunting and live capture of wildlife occurs for subsistence (in terms of food and livelihoods, Coad et al., 2013; Ferreguetti et al., 2018), medicine (Alves et al., 2010; Chassagne et al., 2016), and the wildlife trade (Fukushima et al., 2020; Scheffers et al., 2019).

One of humanity's primary tools for species and landscape conservation has been the protected area (PA), whereby important natural areas are designated and protected by law. International treaties, predominantly the United Nations Convention on Biological Diversity (CBD, https://www.cbd.int), require the continuing expansion of the global PA estate both on land and at sea. Although the emphasis has moved towards a broader range of area-based conservation tools in recent years (e.g., 'Other area-based conservation measures', (IUCN, 2019), PAs remain an important tool for conservation. Protected areas require adequate resourcing and effective management if they are to fulfil their role in halting species declines (Armsworth et al., 2018; Coad et al., 2019b; Geldmann et al., 2018). A fundamental component of effective PA management is biodiversity monitoring, which allows managers to assess conservation action and track progress against targets (Dixon et al., 2019). For monitoring within PAs to be effective, efforts must provide reliable measures of appropriate metrics over time (White, 2019). Monitoring key species is a common approach within PAs, because 1) it can deliver information on important trends, for example changes in populations of threatened species (Lindenmayer et al., 2012), 2) carefully selected species can act as indicators for broader changes in biodiversity (Bal et al., 2018), and 3) species can be specifically selected for factors such as size or behaviour to maximise detectability and thus improve monitoring efficiency (Einoder et al., 2018).

The methodological approach selected for monitoring wildlife in PAs depends on a range of factors including the species of interest, available resources, and the habitat and other environmental conditions. Arguably the most important factor however, is the desired output metric, which in turn is dictated by the desired outcome from the area (Lindenmayer et al., 2012), as this will dictate the monitoring approach. Wildlife monitoring is a well-established field with a range of robust methods and tools including occupancy modelling for species distributions, colonisation and extinction (MacKenzie et al., 2003, 2002), density and abundance estimation using capture-recapture (CMR, Otis, 1978; Pollock et al., 1990), including more recent spatially-explicit approaches (Efford and Fewster, 2013), and distance sampling (Buckland et al., 2004, 2001). Despite the wealth of robust methods, count-based methods that only provide relative indices of the population metric of choice are common, particularly in monitoring programmes that cover large spatial scales (Pollock et al., 2002). Indices can be useful approaches to monitoring wildlife (e.g., Siddig et al., 2015), but often suffer from calibration issues between the index and the true abundance (DeCesare et al., 2016). Within PAs, absolute density and abundance estimates for target species that account for imperfect detection and quantify uncertainty provide the highest quality data for decision-making (Buckland et al., 2015; Kellner and Swihart, 2014; Moore and Kendall, 2004; Woinarski, 2018). Furthermore, reliable population estimates and trends are critically important for broader species threat assessments, such as for the IUCN Red List (Woinarski, 2018).

1.1.3 Dynamic social-ecological landscapes

The Earth's biosphere is inherently complex, being comprised of countless systems which are characterised by open, non-linear, and interactive relationships (Dawson et al., 2010). In his seminal paper, Holling (1973) proposed a new way of viewing the dynamics of ecosystems and identified the impact that a growing human population, and our subsequent increasing demand for natural resources, has on equilibrium states within natural systems. The term "social-ecological system" (SES) was later coined to recognise that humans are fundamentally involved in shaping the dynamics and processes of natural systems (Berkes et al., 2000). It had become clear that the paradigm that assumed social systems and ecological systems were separate entities no longer reflected reality (Folke et al., 2005). As the scale of human influence and modification of the natural world grows, the more integrated the social and ecological sub-systems within and across landscapes become (Backstrom et al., 2018). Human modified landscapes are therefore complex, dynamic systems in which natural and human sub-systems interact and influence each other at various scales via myriad mechanisms. This complexity makes the management of such landscapes challenging, as the dynamics of the natural systems interact in non-linear feedback loops with the behaviour and decision-making of the human stakeholders within the social systems (Bunnefeld et al., 2011).

Social-ecological systems research recognises the complexity of the non-linear relationships and feedbacks between the multiple social and ecological sub-systems within land- and seascapes. Earlier advances in SES research centred around fisheries (Little et al., 2004; Smith et al., 2007) and rangelands (Galvin et al., 2006; Holdo et al., 2009), but since then significant progress has been made in methodological and conceptual approaches to modelling SESs, for example using agent-based models (Duthie et al., 2018a; Filatova et al., 2013), identifying social-ecological variables affecting ecosystem services (Meacham et al., 2016), understanding governance through social networks (Bodin et al., 2016), and how social learning impacts resource use (Barfuss et al., 2017). Frameworks such as management strategy evaluation, for modelling SESs in the context of resource exploitation and management decisions, were developed for fisheries science (Smith et al., 1993), and hold huge potential for terrestrial landscape conservation as management decisions and interventions, stakeholder decision-making, and resource use can be modelled whilst accounting for uncertainty and error (Bunnefeld et al., 2011; Milner-Gulland, 2011; Nuno et al., 2014).

1.2 Introduction to Cambodia

Cambodia is a country with a rich natural and cultural history, yet its modern character is built upon a foundation that has been largely defined by colonialism, genocide, war, and foreign occupation (Brickell and Springer, 2016; Chandler, 2008). Cambodia's recent history has meant that the country's society and environment have been rapidly changing over the last 60 years (Hughes and Un, 2011; Loucks et al., 2008), with profound implications for biodiversity conservation. Most of the research in this thesis is focussed on Cambodia (except Chapter Five, which uses a simulated 'generic' conservation landscape), as it provides an excellent case study for assessing the effects on biodiversity of rapid changes within a society from an economic, socioeconomic, and policy perspective.

1.2.1 Biophysical characteristics

Cambodia is in mainland Southeast Asia (SEA) and is bordered by Laos (NE), Thailand (NW), Vietnam (E), and the Gulf of Thailand (SW) (Figure 1.1 A). The country has a surface area of 176,520 km^2 (UNCTAD, 2020) and is located at latitudes 10-14° north of the equator and thus has a tropical monsoon climate where average temperatures vary little throughout the year, ranging from 25°C – 30°C (McSweeney et al., 2010a, 2010b). The latest government statistics state that 76,950 km^2 of the country is covered in natural forest (excluding plantations and forest regrowth) which equates to 42.4% of the total land area of the country (MoE, 2020). The dominant natural forest habitats are deciduous (~18%), evergreen (~15%), and semi-evergreen (~6%) (MoE, 2020, Figure 1.1 C). Topographically, Cambodia can be divided into two broad areas: 1) the low lying central plains and coastal areas, and 2) the mountainous regions and plateaus that, reaching elevations of 1,800 masl, surround the central plains (Figure 1.1 B, MoE and UNEP, 2009). The Tonle Sap Lake and the Bassac and Mekong rivers are the most important hydrological features in the country (Figure 1.1 C). As of 2019, the total human population of Cambodia was 15.6 million, approximately 60% of which were rural (CNIS, 2019).

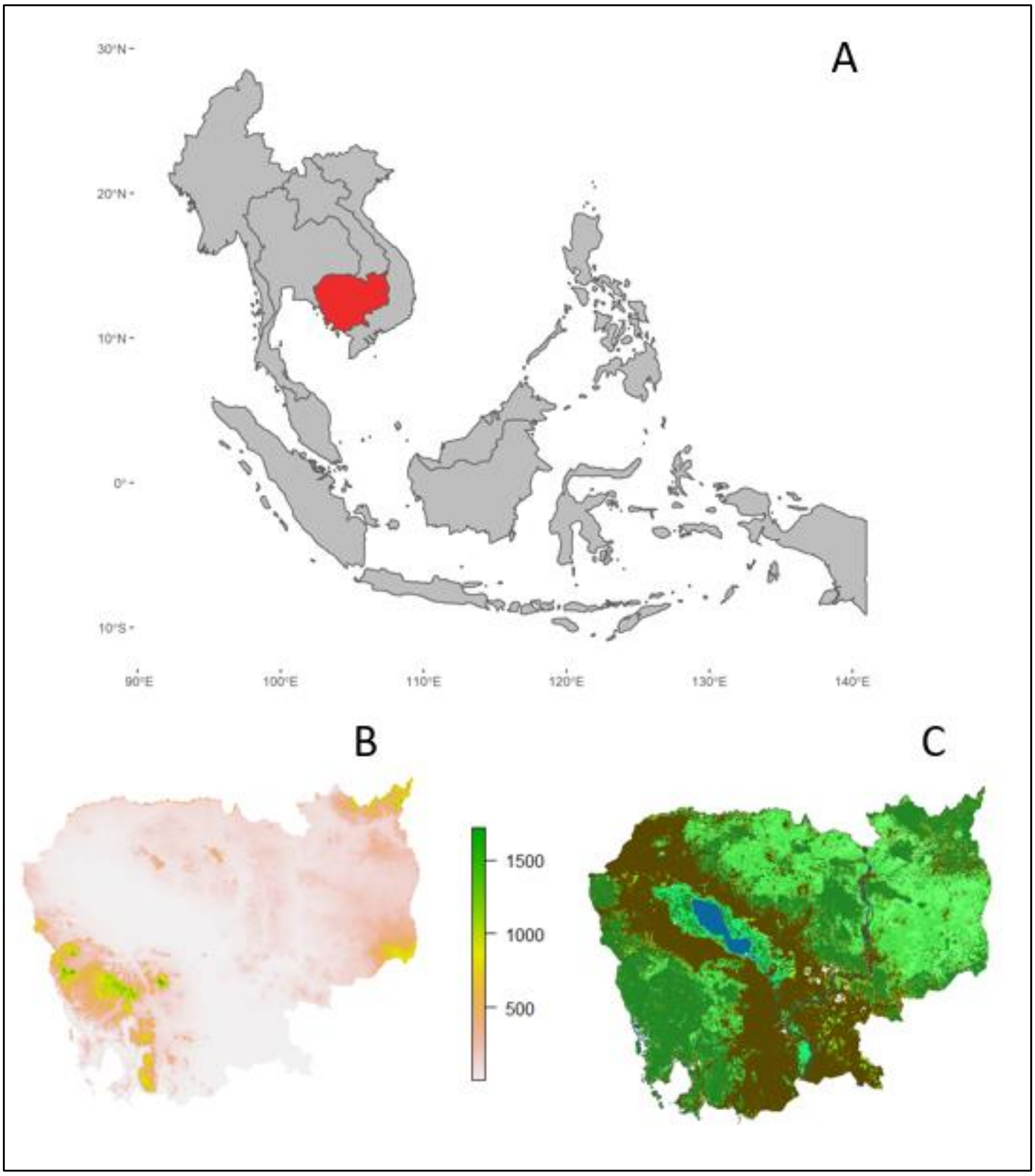

Figure 1.1. Maps of Cambodia. A = Cambodia within Southeast Asia. B = Elevation across Cambodia in metres above sea level. C = Broad habitat from the European Space Agency Climate Change Initiative land cover product. Dark green areas are evergreen and semi-evergreen forest, light green areas are open/deciduous forest, brown areas are agricultural and other non-forest habitat. Blue areas are water.

1.2.2 A recent history: war and post-conflict recovery

Since the decline of the Khmer Empire, which began around the 15th century, the country that is now the Kingdom of Cambodia has experienced tumultuous times. In 1863 Cambodia became a

Protectorate of France and remained so until 1953 (Chandler, 2008). Following a coup in 1970, the country was closely allied to the USA and drawn into the American-Vietnam war until 1975, when the Communist Party of Kampuchea (widely known as the Khmer Rouge), led by Pol Pot, captured the capital of Phnom Penh and overthrew the government (Chandler, 2008). In the four years that followed, the Khmer Rouge, following largely Maoist principles, forcibly evicted all of the country's cities and enacted an extreme form of agricultural reform based on collectivisation and which led to widespread famine (Bergin, 2009). A failing agricultural sector, in combination with state-sponsored genocide, led to the deaths of approximately a quarter of the Cambodian population by 1979 (Kiernan, 2003). While the Khmer Rouge were in power, they dismantled virtually all aspects of the former society including government institutions, religion, education, health care, private property, and all non-agricultural parts of the economy (Chandler, 2008). The Khmer Rouge was overthrown by the Vietnamese Army in 1979, and the country remained at war and under Vietnamese occupation until the 1991 Paris Peace Accords, which ended the war and transferred governance responsibility to the United Nations under the Transitional Authority in Cambodia (Widyono, 2015). The first democratic elections took place in Cambodia in 1993, and the Cambodian People's Party, led by Hun Sen, have remained in power from 1993 to the present day.

Once the economic powerhouse of Indochina, Cambodia was the world's third largest exporter of milled rice during the 1960s, behind only Thailand and the United States (Hughes and Un, 2011). Therefore, the recognition that political leaders are given for bringing the economy from complete collapse during the civil war, to a growth rate in 2006 that was larger than any other Asian economy apart from China, is in many ways justified (Solcomb, 2010). Much of this growth has been driven by large increases in foreign direct investment into agro-industry, mining, hydro-electricity, pharmaceuticals, and the garment industry, particularly from China, Vietnam, Thailand, and Malaysia (Sullivan, 2011). Furthermore, international development aid has been a feature of Cambodia's socioeconomic recovery and development since the end of the civil war (Ear, 2007). By 2004, one-third of the government's budget was from international aid (Sodhy, 2004). Rapid growth in both the garment sector and the tourism sector have also played major roles in driving post-conflict economic development (Ear, 2011).

Agriculture, particularly rice, is a fundamental part of Cambodia in terms of socioeconomic development, but also from a cultural perspective (Chhun et al., 2020). Memories of famine and starvation during the Khmer Rouge period are still present in those alive today (personal observation). The agricultural sector has been a large component of the national economy in the post-war recovery period and has played a major role in reducing poverty and increasing food security, particularly for the rural poor (Eliste and Zorya, 2015). Between 2004 and 2012 agricultural production increased by an average of 8.7% per year - one of the highest rates in the world - with much of the growth coming from increases in the production of paddy rice, maize, cassava, and sugar cane (Eliste and Zorya, 2015). Much of the agricultural expansion in the years immediately following the end of the civil war came from small-holder expansion, as families moved back to their homelands after the forced migration under the Khmer Rouge and refugees and former soldiers were resettled (Eliste and Zorya, 2015; Hought et al., 2012; Kong et al., 2019). A growing agricultural sector, in combination with legal provisions for leasing of public land outlined in the 2001 Land Law (RGC, 2001), drove the growth of the commercial agricultural sector (Solcomb, 2010). For example, the rubber industry, a feature of the Cambodian economy since its colonial days, saw significant growth in the post-conflict years thanks to strong commodity price performance on international markets and the privatisation of the industry (Solcomb, 2011).

The economic recovery over the last two decades has driven significant improvements in access to services, poverty, and inequality, thanks to pro-poor growth in consumption, which together pushed Cambodia's poverty reduction well beyond the Millennium Development Goal targets (World Bank, 2014). However, relative metrics of inequality (e.g., Gini Index) mask the actual gap between the rich and the poor in absolute terms, which has been increasing dramatically (World Bank, 2014). There exists a very large wealth gap between urban and rural populations, and between the urban rich and urban poor, and the gaps are growing (Solcomb, 2010). The healthcare available to the general population remains expensive and of poor quality (Gryseels et al., 2019; WHO, 2019), and although the provision of education has increased dramatically since the 1990's, rural areas still lack sufficient facilities and the general quality of education across the country remains low (Kitamura et al., 2016). The unequal economic development between urban and rural areas has resulted in a polarised society; on one hand there are the wealthy urban elites who have benefited greatly from rapid economic development, whilst on the other hand the rural population, particularly those in remote provinces, remain poor and almost entirely reliant on natural resources for their subsistence (Hammer, 2008; Ironside, 2008; Nguyen et al., 2015; Phillips and Davy, 2021).

The post-war years saw dramatic changes in Cambodia's economy and society, some of which have had negative consequences for the environment. The repatriation of people to their former homelands, the resettlement of refugees, increasing access to remote provinces, a lack of formal land ownership, and increased access to markets all combined with an increasing human population to drive the expansion of smallholder agriculture into forested land (Eliste and Zorya, 2015; Evans et al., 2013; Hought et al., 2012; Kong et al., 2019; Lonn et al., 2018; Top et al., 2009). Furthermore, the lucrative international commodity market and the privatisation of state land (Neef et al., 2013) drove increases in selective logging of high value timber and commercial agriculture in the form of economic land concessions (ELCs), which have not only had negative effects on forest cover and structure (Coad et al., 2019a; Davis et al., 2015; Toyama et al., 2015), but have also degraded protected areas and caused land conflicts with local people (Magliocca et al., 2019; Neef et al., 2013; Oldenburg and Neef, 2014; Watson et al., 2014). Between 2000 and 2020 Cambodia lost approximately 10.5% of its total forest cover (Hansen et al., 2013).

The social and economic changes that have occurred since the cessation of civil conflict have also had implications for Cambodia's wildlife. As recently as sixty years ago Cambodia was described as "a Serengeti of Asia" (Wharton, 1957), with an abundant and diverse assemblage of species. The country sits within the Indo-Burma Biodiversity Hotspot (CEPF, 2020), and is known to be of global and regional importance for a variety of rare and threatened species including banteng (*Bos javanicus*, Gray et al., 2012), three vulture species (*Gyps bengalensis*, *Sarcogyps calvus*, *Gyps tenuirostris*, Loveridge et al., 2018), and at least three primates (Moody, 2018; Chapter 4). Although robust, long-term biodiversity monitoring is rare in Cambodia (and Southeast Asia more generally), what evidence there is suggests that wildlife populations are declining (Groenenberg et al., 2020; Loveridge et al., 2018, Chapter 4). Cambodia's emergence out of civil war and into the global market opened the door to the international trade in wildlife (Heinrich et al., 2020) and agricultural expansion eroded critical habitats (Davis et al., 2015; Kong et al., 2019). Additionally, as human populations increased, slow socioeconomic development in rural areas and a lack of diversity in livelihood options has meant that rural people have continued to rely on wildlife and other natural resources for subsistence and additional income (Coad et al., 2019a; Ibbett et al., 2020).

1.2.3 Conservation management, funding, and policy

After the first election in 1993, the legacy of the Khmer Rouge meant that the newly formed Cambodian government had to develop and enact an entirely new constitution, including those to govern natural resources, which included laws on land (RGC, 2001), and forestry (RGC, 2002). The land law in particular had important implications for conservation in the country as it paved the way for the privatisation of state land via long-term leases, which allowed for the rapid proliferation of land acquisitions for commercial agriculture (Neef et al., 2013). In 1925, Cambodia was the first country in SEA to gazette a PA, and this ambition continued after the period of conflict with a further designation of 23 PAs in 1993 (Edwards, 1998). By 2012, approximately 24% of Cambodia's land was designated as a PA (O'Kelly et al., 2012), and all of the major international conservation non-governmental organisations (NGOs) had established programmes of activity within the country, bringing with them donor funding, relatively high salaries, and technical expertise.

As stability and safety increased in Cambodia, work began to assess the state of the country's wildlife and forests. Researchers began conducting the first biodiversity surveys in Cambodia for over 20 years, revealing a country that still held important biodiversity (e.g., Duckworth and Hedges, 1998; Mundkur et al., 1995; Phipps, 1994; Walston et al., 2001). These surveys guided the NGOs (including the World Wide Fund for Nature, Wildlife Conservation Society, Fauna & Flora International, Birdlife International, and Conservation International) to the PAs with high biodiversity value, where they each established close working relationships with the government in separate portfolios within the national PA estate. The working relationships between the government and the NGOs varied between the 'co-management' and 'financial and technical support' models of Baghai et al (2018), with the NGOs providing technical advice, training, and equipment, as well as considerable financial support for PA management and operations. Government investment into PA management was, and remains, low, with funding for all activities including many staff salaries coming from NGOs and their ability to leverage external funding via limited-term grants (Milne and Mahanty, 2015).

Despite large investments into the PA network by a range of donors, development organisations, and NGOs, Cambodia's forests and wildlife remain under extreme pressure from human activities (Groenenberg et al., 2020; Heinrich et al., 2020; Loveridge et al., 2018). Smallholder and commercial agriculture continues to drive deforestation even within PAs (Appendix; Davis et al., 2015; Grogan et al., 2019, 2015; Watson et al., 2014), selective logging (both legal and illegal) of high value timber has driven forest degradation (Milne, 2015; Toyama et al., 2015), and the hunting of wildlife for meat, medicine, and the wildlife trade are having negative effects on wildlife populations (Alves et al., 2010; Coad et al., 2019a; Heinrich et al., 2020; Ibbett et al., 2020; Nuttall et al., 2017). Protected area management policies have, in the past, focussed resources heavily on illegal logging because of the high value and high-profile nature of the trade (e.g., Amnesty International, 2021; Global Witness, 2013; Vrieze and Kuch, 2012), particularly in 'Siamese Rosewood', which can fetch up to $6,000 per cubic metre on the international market (EIA, 2012). This policy has drawn PA resources away from land clearance and hunting to the detriment of forest cover and wildlife populations (Chapter 4).

The governance structure and lines of authority between the Cambodian government and PA management teams are complex (Figure 1.2) and can make effective PA management challenging. The Ministry of Environment, which since 2016 has been responsible for all PAs in the country, has offices, staff, policies, and projects both at the national level and the provincial level. Although ultimate authority lies at the national level, politics, poor communication, and differing priorities between national and provincial levels often results in fragmented policy implementation. This is true also of the Military Police, who provide staff to bolster law enforcement within PAs. The policies and strategy from the national level are often poorly executed at the local level. Additional complexity is added by provincial governors, who are politically influential and often have policies and priorities that are not aligned with the Ministry of Environment, NGOs, or indeed PA management teams. Finally, local administrative officials, for example district governors, commune chiefs, and village chiefs, all play a role in influencing the implementation of laws and policies and can have both positive and negative effects on local politics and the management of PAs.

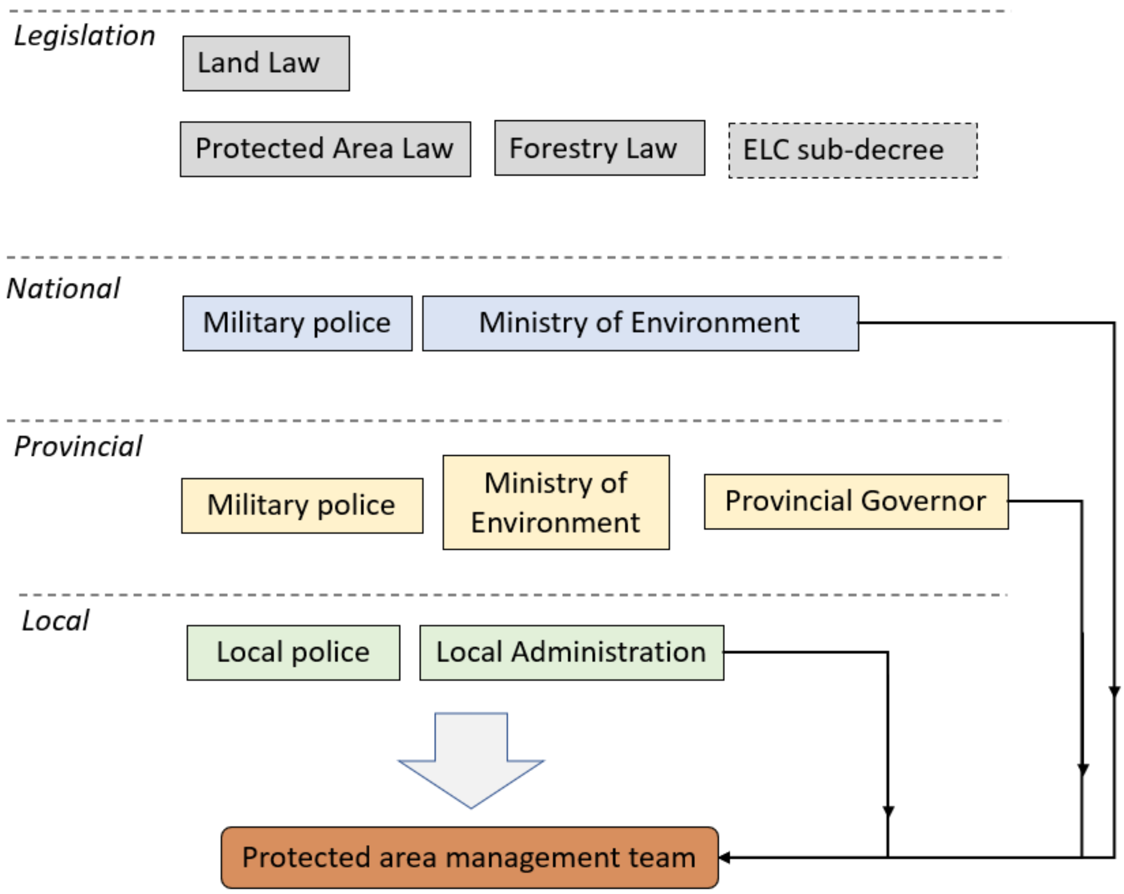

Figure 1.2. The governance structure that influences protected area management teams in Cambodia. Authority and governance flow from the top down; from the national level through the provincial level, to the local level. However, each administrative level also influences protected area management directly, through provincial and local departments and administrations.

1.2.4 A case study for conservation

Southeast Asia is an important region for global biodiversity, yet has one of the highest rates of deforestation in the world, and the rate of increase in extinction risk is the highest globally (Hoffmann et al., 2010; Hughes, 2017). Deforestation and biodiversity loss are affecting all SEA countries (Gray et al., 2017; Harrison et al., 2016; Hughes, 2018, 2017), but Cambodia presents a unique case study due to the relatively recent status as a post-conflict nation and the rapid economic recovery. Economic growth in Cambodia over the last two decades has been greater than any other SEA country (Solcomb, 2010), and this has brought with it profound social change (Kong et al., 2019; Milne, 2013a; Milne and Mahanty, 2015; World Bank, 2014). The environmental laws, policies, and protected area estate are the youngest in the region, having been developed in their entirety since the end of the civil war in the 1990s. Furthermore, the reliance on NGOs to finance much of the PA estate poses questions about long-term management strategies and the sustainability of conservation investments. Therefore, there are many important questions to be asked of Cambodia's performance on environmental stewardship, particularly regarding the effects of economic growth and the expansion of the agricultural sector, social change, and conservation policy on biodiversity. Existing evidence in the literature suggests that environmental policies and governance are not adequately addressing deforestation (Davis et al., 2015; Eliste and Zorya, 2015; Hought et al., 2012; Kong et al., 2019; Lonn et al., 2018; Riggs et al., 2018) nor biodiversity loss (Coad et al., 2019a; Groenenberg et al., 2020; Ibbett et al., 2020; Loveridge et al., 2018; O'Kelly et al., 2012; Packman et al., 2014). This evidence suggests that existing environmental policies are insufficient to mitigate the primary drivers of forest and biodiversity loss, either because of inadequate formulation or ineffective implementation.

To support environmental protection in Cambodia through improved policy frameworks and effective governance it is necessary to 1) understand the economic and social drivers of forest loss and how these interact with agricultural expansion, 2) to evaluate the performance of PAs, as these are likely to be the last refuges for wildlife, and 3) understand the implications of unsustainable financing of PAs and the trade-offs between managers and local people in dynamic conservation landscapes. Answering these questions will not only improve our understanding of environmental governance and conservation management in Cambodia but will also provide insights into these factors across SEA where many of the same pressures are driving deforestation and biodiversity loss. Commercial agriculture has driven extensive forest loss in other parts of SEA (Shevade and Loboda, 2019), and the interactions between forest policies, socioeconomics, and commercial agricultural commodities have been shown to be important factors in understanding land use change in Indonesia (Gatto et al., 2015). Thailand has some of the most effective PAs in SEA, yet still struggles with wildlife declines and conflicts with local people (Phromma et al., 2019), and economic growth is negatively affecting wildlife across Asia (Linkie et al., 2018). Therefore, increasing our understanding of Cambodia's environmental governance and conservation management will help to place the country within the broader SEA context, and will fill regional knowledge gaps.

1.3 Aims and objectives of this thesis

My overarching goal for this thesis was to contribute to the conservation of Cambodia by providing some of the fundamental science that links economic activity and government policy to forest loss, wildlife status, and PA management. More specifically, my aims were to examine the drivers of deforestation across Cambodia, to evaluate the performance of PAs for wildlife protection, and to assess the implications of unsustainable financing in dynamic conservation landscapes where there are trade-offs between managers, local people, and nature. My specific objectives for each chapter were:

Chapter 2 - Quantify the relationships between changes in metrics of economic development and a) deforestation, and b) commercial agricultural expansion, both at a national scale;

Chapter 3 - Evaluate the relationships between socioeconomics and forest cover at a national scale but at multiple spatial resolutions;

Chapter 4 - Assess the performance of a flagship PA through the analysis of temporal and spatial population trends for a suite of wildlife species;

Chapter 5 - Identify the potential consequences of different conservation funding patterns on forest loss in a dynamic landscape with an increasing human population

1.4 Thesis outline

In Chapters 2 and 3, I explore the implications of Cambodia's economic and socioeconomic recovery, changing agricultural sector, and entry into the global commodity market, as discussed in section 1.2.2, on forest cover at a national scale. In Chapter 2, I look specifically at whether Cambodia's economic development and changes in the agricultural sector have driven forest loss and the expansion of commercial agricultural land acquisitions. I demonstrate that economic development has not been a primary driver of forest loss, but it has had a tangible effect on the expansion of commercial agriculture. I propose potential reasons for the lack of effects between economic development and forest loss and discuss the significance of the expansion of commercial agriculture for forest cover and local people.

In Chapter 3, I further explore how Cambodia's post-war recovery, specifically socioeconomic development, has influenced forest cover. I harness a spatially explicit socioeconomic dataset and demonstrate how socioeconomic development and additional human and environmental factors have varying effects on forest cover at different scales across Cambodia. I reveal important methodological challenges with large scale, fine resolution analyses, and discuss the implications of these challenges for future researchers. I further provide a socioeconomic typology of Cambodia at the provincial level, which reveals that the large, rural, least-developed provinces are the most forested, and I discuss these policy-relevant insights.

In Chapters 4 and 5 I focus on landscape level conservation management, assessing the management and performance of a protected area and a social-ecological landscape considering the post-war recovery covered in Chapters 1 through 3, and in the context of the conservation funding, management, and policy discussed in section 1.2.3. In Chapter 4, I use a long-term wildlife monitoring dataset from the Keo Seima Wildlife Sanctuary - one of Cambodia's flagship PAs – and provide evidence that although the populations of arboreal species are generally stable, ground-based threats and inappropriately targeted management have resulted in serious population declines for all monitored ungulates and ground-dwelling primates. I provide management recommendations and highlight the importance of long-term monitoring for PA management in southeast Asia.

In Chapter 5, I use agent-based simulation modelling to assess the implications of different conservation funding models on forest cover within dynamic social-ecological landscapes. I construct a generic conservation landscape which contains an increasing population of local people and a conservation management authority, all of whom have competing interests on the landscape. I test the effects on forest cover of five different funding situations for the conservation manager, all of which reflect real-world financial situations. I provide evidence that short-term grants, which are the dominant form of conservation funding across Cambodia and much of the world, are not the optimal way to fund landscape conservation. I discuss the implications of this, and other findings, for conservation in Cambodia and beyond.

I conclude this thesis with Chapter 6, synthesising the results from Chapters 2 to 5 within the themes of economic development and forests, and protected area and landscape management (Figure 1.2.). I discuss the implications of Cambodia's rapid economic development on forests, wildlife, and local people, and highlight the need for government policy that enables and promotes environmentally sustainable agricultural development. I further discuss the urgent need for shifts in protected area management strategies to halt the decline of wildlife populations, and for funding mechanisms that can provide stable, long-term funding for landscape managers.

There is a single appendix to this thesis, where I present a manuscript that has been prepared as a 'practitioners' perspective' for the journal Conservation Science and Practice. This manuscript has been prepared in parallel to my thesis, and although I did not feel it was sufficient to form a full chapter, I believe it is relevant to many of the subjects discussed throughout this thesis. I have therefore included it as an appendix, for the interest of the reader. The appendix is a case study that describes events that lead to the downgrading, downsizing, or degazettement of two adjacent PAs in Cambodia. I describe the economic, social, and political context within which these events occur, and provide some explanation as to why one PA was affected more than the other.

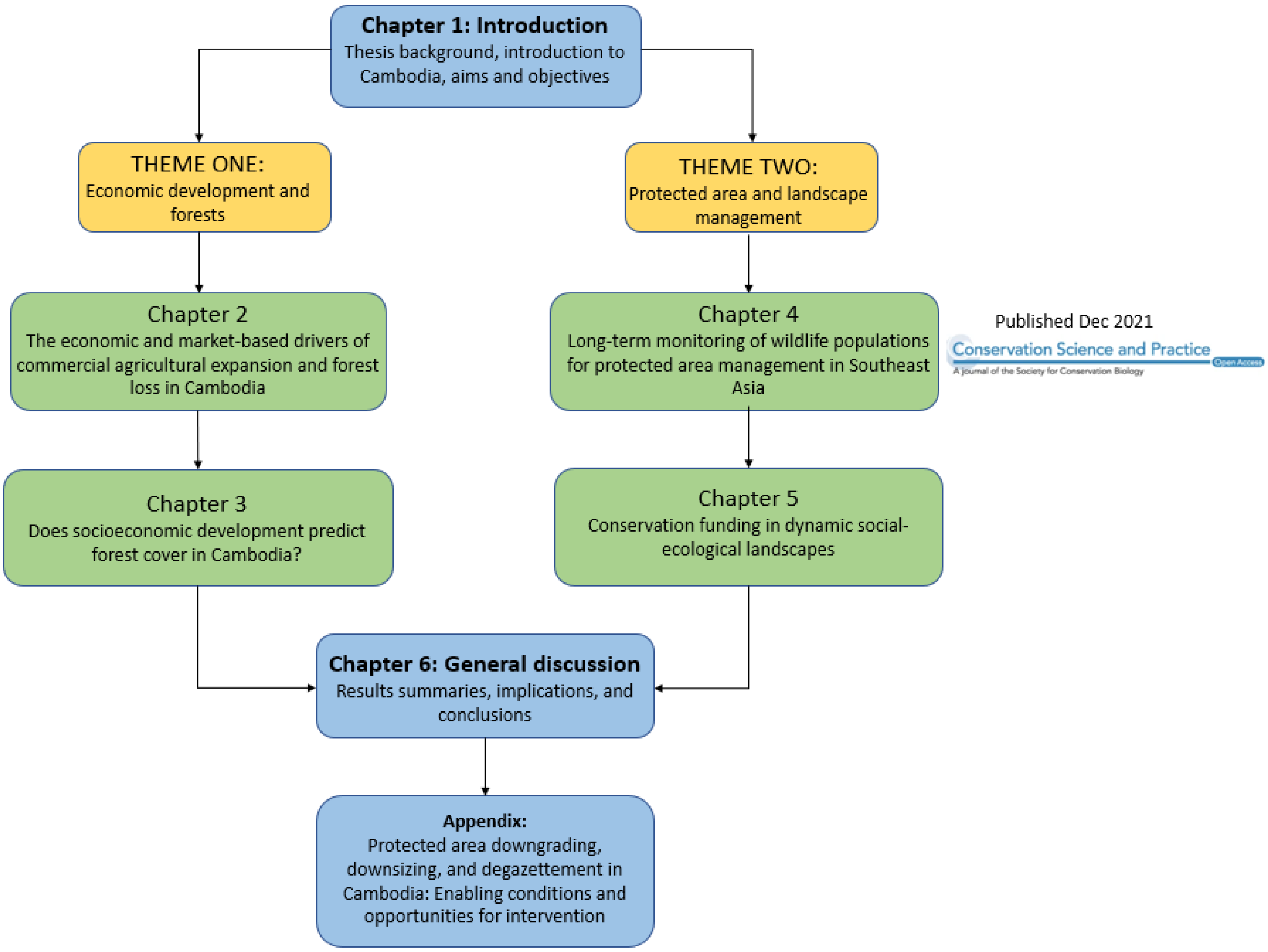

Figure 1.3. Diagram of the structure of the thesis

Chapter 2

The economic and market-based drivers of commercial agricultural expansion and forest loss in Cambodia

2.0 ABSTRACT

Economic development is closely linked to the loss of forests, particularly in developing countries. Appropriate policies and legal frameworks, operationalised through effective governance, can guide a country towards a forest transition whereby net forest loss is eliminated. Cambodia's economic recovery after the end of civil conflict in 1991 has been remarkably swift, with significant growth in the agricultural sector contributing to economic development. Much of this growth has been driven by investment into agro-industrial land concessions for commercial agricultural (economic land concessions, 'ELCs'), which have led to widespread forest loss. The development of sustainable agriculture and forest policies requires knowledge of the relationships between economic development, commodity production, and forest loss. Therefore, this chapter models the relationships between Cambodia's economic development, rates of forest loss, and the expansion of ELCs at a national scale between 1993 and 2015. My analysis showed that measures of economic development were unable to directly predict rates of forest loss but were effective at predicting the expansion of new ELCs, which in turn increase forest loss. Increases in the agricultural sector's proportion of national GDP and increases in foreign investment both had positive effects on the number of new ELCs. Increases in the market price of corn and sugar, and increases in the non-food agricultural index, all had positive effects on the number of new ELCs, as did increases in the producer price of rubber, corn, and sugar. My results demonstrate strong links between Cambodia's recent economic development and external market forces on the expansion of ELCs, which has been responsible for widespread forest loss. My results highlight the need for improved governance and strengthened agricultural policies that together can eliminate the expansion of commodity production into forested areas and stabilise the agricultural sector against external market fluctuations.

2.1 INTRODUCTION

Deforestation from human activities is one of the greatest threats to biodiversity around the world (Estoque et al., 2019; Hoang and Kanemoto, 2021), and the scale of land use change is such that the global climate is being affected through changes to the radiative forcing caused by land cover and land use (Jiao et al., 2017). The production and trade in agricultural commodities driven by modern consumption patterns is responsible for the majority of forest loss around the world (Curtis et al., 2018; Hoang and Kanemoto, 2021; Pendrill et al., 2019). This is because agricultural production is a fundamental component of many national economies, both for improving food security within countries and for national income generation via international export markets (Eliste and Zorya, 2015). Growth within agricultural sectors, and other natural resource-based industries, is therefore an important approach for lower income nations where economic development is a priority (Caravaggio, 2020b; Eliste and Zorya, 2015). Forests have been used to sustain economic growth throughout much of human history (Williams, 2003), and this trend continues today; between 2005-2013 the expansion of commercial agriculture, plantations, and pastures were responsible for 62% of forest loss across the tropics and subtropics (Pendrill et al., 2019). As developing nations strive for economic development, forests and other natural resources are exploited, often with negative consequences for biodiversity, climate change, local livelihoods, and environmental processes and services (Caravaggio, 2020a).

2.1.1 Economic development and deforestation

There are several environmental economic theories that link economic development to forest loss, with the environmental Kuznets curve for deforestation (EKCd, Cropper & Griffiths 1994) and Forest Transitions (FT, Mather 1992) being the most studied and debated (Caravaggio, 2020a). The ECkd predicts increasing rates of deforestation with increasing economic development until a tipping point is reached, after which further economic development (and associated shifts in the structure of economies) results in decreasing rates of deforestation until net forest loss changes to net forest gain (Bhattarai and Hammig, 2004). Similarly, the FT theory predicts decreasing forest cover with increasing economic development, with the rate of forest cover loss accelerating until the tipping point, as described above, is reached, after which loss of forest cover slows. The point at which forest cover begins to increase is termed a forest transition (Lambin and Meyfroidt, 2010). Thus, the EKCd and the FT curves are correlated but inverse. Despite rampant deforestation in much of the tropics (Estoque et al., 2019; Sodhi et al., 2010), global deforestation rates (of natural forests) are decreasing (FAO, 2020). Recent studies provide evidence to support the EKCd theory, and suggest a possible move towards a global forest transition (Caravaggio, 2020b). Indeed, there are multiple case studies demonstrating how individual countries have undergone forest transitions and are increasing national forest cover, including India (Bhattacharya et al., 2010), Vietnam (Meyfroidt and Lambin, 2008), China (He et al., 2014), and South Korea (Youn et al., 2017), although it is worth noting that these increases can include planted forests. Nevertheless, there are still many countries where economic development and global demand for commodities are driving high rates of forest loss, often in some of the most biodiverse regions (Hoang and Kanemoto, 2021). In addition to meeting the required economic conditions that precede forest transitions, for example integration into global markets for capital, commodities, and labour, effective governance relating to land use, forest protection, and agriculture is critical to ensure that forest transitions occur (Riggs et al., 2018). Therefore, understanding the relationships between both economic development and the agricultural sector on direct and indirect drivers of forest loss is crucial to develop appropriate policies, identify leverage points, and support effective governance. No previous studies have modelled the relationships between economic factors, agriculture, and forest loss in Cambodia, and this chapter aims to fill this knowledge gap.

2.1.2 Deforestation in Southeast Asia

Southeast Asia (SEA) is characterised by complex biogeography and extensive tropical forest cover resulting in exceptional biological diversity, but has one of the highest deforestation rates in the world (Hughes, 2017). As with deforestation around the world, the loss of SEA's forests has potentially severe consequences for climate change (Ceddia et al., 2015), ecosystem-based adaptation (Estoque et al., 2019), local people (Culas, 2007; Frewer and Chan, 2014; Gaughan et al., 2009; Poffenberger, 2006), and biodiversity (Chapman et al., 2018; Hearn et al., 2018). The drivers of tropical deforestation vary both by location and by scale, ranging from broader drivers such as population pressure and weak institutions (Geist and Lambin, 2002), to proximate causes at a local level such as the expansion of cash crops, agriculture and other food production (Estoque et al., 2019; Imai et al., 2018; Stibig et al., 2014; Wilcove et al., 2013; Zeng et al., 2018), the associated development of roads and infrastructure that facilitate such expansion (Hughes, 2018), and civil unrest and war (Kaimowitz and Fauné, 2003; Price, 2020). Despite the pressure on SEA's forests, some countries within the region have undergone forest transitions and are seeing net increases in forest cover (Youn et al., 2017). There are legitimate criticisms of the simplicity of traditional metrics of forest transitions; primarily that using the broadest interpretation of 'forest cover' ignores forest type or quality resulting in, for example, non-native plantations counting towards net forest gains (Kull, 2017).

In all Asian case studies of successful forest transition, state intervention has played a role; government policies and legal frameworks that disincentivise forest clearance and promote sustainable land use are critical factors in facilitating behaviour change at all levels (Youn et al., 2017). Understanding the direct and indirect drivers of forest loss can be challenging as the processes are complex, operate at a variety of scales, and consist of multiple feedback loops and dependencies (Geist and Lambin, 2002; X. Xu et al., 2019). Nevertheless, for effective government policies to be developed, researchers must strive to disentangle some of these relationships (Redo et al., 2012). As commercial agriculture is one of the most important drivers of forest loss around the world (Curtis et al., 2018; Pendrill et al., 2019), and because it is a fundamental part of developing economies (Hoang and Kanemoto, 2021), it is critical to understand the links between economic development and commodity production, as this will reveal important implications for forest loss in developing countries.

2.1.3 Economic land concessions

Land acquisitions for commercial agriculture have become widespread in recent years, particularly in developing countries that have large areas of undeveloped land and that are striving for private investment to boost economic development (Kugelman and Levenstein, 2012). Such enterprises can improve agricultural productivity, stimulate local economies, and support rural development (Deininger and Byerlee, 2011), yet face substantial criticisms for lacking transparent processes, abusing local land rights, and negatively affecting local livelihoods and biodiversity (Davis et al., 2015; De Schutter, 2011; Deininger and Byerlee, 2011). Cambodia saw an unprecedented surge in private land acquisitions via long-term leases for commercial agriculture, or 'economic land concessions' (ELCs), between 2000 and 2012, resulting in over 2 million hectares being leased by 2015 (Davis et al., 2015). Economic land concessions in Cambodia have faced criticism due to widespread accusations of land rights abuses, corruption in the awarding of contracts, and extensive deforestation, even within protected areas (Beauchamp et al., 2018; Davis et al., 2015; Global Witness, 2013; Magliocca et al., 2019; Neef et al., 2013; Oldenburg and Neef, 2014; Tsujino et al., 2019; Vrieze and Kuch, 2012).

2.1.4 Cambodia

Compared to most other countries in the world, Cambodia has seen swift economic growth since the end of civil conflict in in the 1990s (Solcomb, 2010), with much of the economic development built upon the growth of the agricultural sector (Eliste and Zorya, 2015; Kong et al., 2019). This economic development has brought many benefits, including poverty reduction and food security (World Bank, 2014), yet the expansion of the agricultural sector has caused deforestation (Beauchamp et al., 2018). Forest loss, even within protected areas, has increased as a result of the boom in ELCs (Davis et al., 2015; Watson et al., 2014). To minimise future forest loss and the associated loss of biodiversity, ecosystem services, and local livelihoods, Cambodia needs to reduce deforestation rates and move towards a forest transition by establishing appropriate policies, legal frameworks, and importantly, the governance to effectively implement such mechanisms (Riggs et al., 2018). Identifying which development pathway Cambodia is on, and the measures that are required to move towards a forest transition, will require a greater understanding of the relationships between economic development, forest loss, and agriculture. There has been some research on drivers of forest loss in Cambodia, for example the direct effect of ELCs on forest cover (Davis et al., 2015), drivers of deforestation in the north western uplands of the country (Kong et al., 2019), social and political factors influencing forest transition (Riggs et al., 2018). Yet there have been no studies that investigate the relationships between economic development, agriculture, and forest loss at the country scale. These are the relationships I aim to investigate in this chapter.

In this study, I aim to address this research gap and provide quantitative evidence of relationships between measures of economic development, agricultural commodities, ELCs, and forest loss. For the period 1993 to 2015, I use generalised linear models to 1) model the relationships between the rate of forest loss and variables that describe, or are proxies for, economic development and agricultural commodity prices and 2) model the relationships between the allocation of new ELCs and variables that describe, or are proxies for, economic development and agricultural commodity prices. My results will provide important data to identify direct and indirect drivers of forest loss in Cambodia, aiding in the identification of leverage points, supporting the development of agricultural and forest policies, and contributing more widely to the forest transition literature.

2.2 METHODS

2.2.1 Study area

This study area for this chapter is the whole of Cambodia. See Chapter 1 section 1.2 for a detailed background to the country, and Chapter 1 section 1.2.1 for detailed biophysical characteristics of the country.

2.2.2 Data sources

National economic variables were acquired from publicly available sources (Table 2.1) for the period 1993 – 2015. Data on economic land concessions and shapefiles for the country were provided by the Royal Government of Cambodia (via the Wildlife Conservation Society). Forest cover layers were taken from the publicly available European Space Agency Climate Change Initiative (ESACCI) satellite data for the years 1993 – 2015.

2.2.3 Variable selection

The response variables were 1) change in forest cover (forest loss) from time t to time t_{+1} and 2) the number of new ELC allocations in year t. Predictor and control variables were selected based on a combination of previous studies, data availability, and my knowledge of Cambodia. Variables were selected to create three sets of predictors, each targeting a different driver: economic development (n=8), agricultural commodity prices (external market forces, n=8), and producer (or farm gate) prices (internal market forces, n=5) (Table S2.1, Nelson et al. 2006; Ewers 2006; Gong et al. 2013; Kuang et al. 2016; Fan & Ding 2016; Bonilla-Bedoya et al. 2018). Each predictor was hypothesised to be a driver of forest loss (Table S2.2). Human population density was included as a control variable for the economic set and total forest remaining was included as control variable across all sets, as both were expected to influence forest loss. Both per capita Gross Domestic Product (GDP) and amount of forest remaining were included to reflect the economic development path and the forest scarcity path respectively (Lambin and Meyfroidt, 2010; Rudel et al., 2005). After pre-analysis checks for errors the resulting variable set contained 20 variables (Table 2.1).

2.2.4 Data processing

The forest cover response variable was extracted from the ESACCI product by totalling the number of pixels (1 Pixel = 0.09km^2) in each year classified as bands 50, 60, 61, 62, 70, 71, 72, 80, 81, 82, 90, and 100 (Table S2.3). Forest cover data processing was done in QGIS (QGIS Geographic Information System v3.16). The ELC response variable was created by summing the number of new ELC contracts that were dated in each year of the study period, resulting in a count of new ELCs per year.

Predictor variables were checked for collinearity, and if two variables in the same set had a correlation coefficient of >0.6 then generally one was removed (Table S2.4). Forest cover was converted to change in forest cover using $\textit{forest cover}_{t+1} - \textit{forest cover}_{t}$, where t represents year t. There were no periods of forest gain during the study period, and so the response can be considered as rate of forest loss. All predictors were converted from raw values to change in values using $X_{t+1} – X_t$, where t represents year t (Barrett et al., 2006). The variable *forest remaining* was left as raw values (km^2). Cambodia's first general election and subsequent adoption of a free market economy occurred in 1993, resulting in unreliable GDP-related values for 1993 (Chhair and Ung, 2013) and subsequent change values in 1994, and so these years were removed. Predictor variables were not centred or scaled prior to analysis because in this case the value of the intercept, in other words the value of the response y when the value of a given predictor x is 0 (i.e., there is no change in the predictor from time t_{-1} to time t) is more meaningful than the value of y when the value of x is at its mean.

Table 2.1. Variables selected for the final analysis. Variables range from 1993 – 2015. GDP = Gross Domestic Product, USD = US Dollars, UNCTAD = United Nations Conference on Trade and Development, CNIS = Cambodian National Institute of Statistics, FAO = Food and Agricultural Organisation, RASCE = Rubber Association Singapore Commodity Exchange, ESACCI = European Space Agency Climate Change Initiative

Predictor variable	Units	Resolution	Source	Details
Economy				
GDP per capita	Billions USD	National	World Bank	Constant 2010 rates
GDP growth	%	National	World Bank	Annual percentage growth rate of GDP at market prices based on constant local currency
Foreign Direct Investment	Millions USD	National	UNCTAD	Inward and outward flows and stock
Agricultural sector proportion of GDP	%	National	CNIS	Proportion of national GDP
Development flows to agriculture	Millions USD	National	FAO	Donor development investment flows, other official flows, and private donor flows at constant 2016 prices to all agriculture and forestry sub-sectors
Development flows to environment	Millions USD	National	FAO	Donor development investment flows, other official flows, and private donor flows at constant 2016 prices to general environment protection
Commodity prices				
Crop Production	Index	National	FAO	Relative level of the aggregate volume of agricultural production for each year in comparison with the base period 2004-2006
Non-food agricultural production	Index	National	FAO	Relative level of the aggregate volume of non-food agricultural production for each year in comparison with the base period 2004-2006
Forestry production	m^3	National	FAO	Total production values for industrial roundwood, non-coniferous tropical wood, other industrial roundwood, sawlogs and veneer logs (coniferous and non-coniferous), and sawnwood (coniferous and non-coniferous
Price of rice	USD/ton	Global	World Bank	Median annual global market price of rice

Price of corn	USD/ton	Global	World Bank	Annual global market price of corn
Price of rubber	USD/ton	Regional	RASCE	Monthly regional market value of rubber on the Singapore Exchange
Price of sugar	USD/ton	Global	World Bank	Annual global market price of sugar
Producer prices				
Producer price of Rice	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of rubber	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of cassava	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of corn	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of sugar	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Control				
Population density	pax/km^2	National	FAO	People per km^2
Forest remaining	Km^2	National	ESACCI	Raw value of forest remaining

2.2.5 Modelling

This analysis aimed to model the relationships between changes in predictors that described economic development or agricultural commodity value and 1) the change in forest cover at a national level and 2) the allocation of new ELCs. I ran models for both response variables with each of the three variable sets: economic development, commodity prices, and producer prices. To account for the effect of time, a linear model of the response as a function of time (year) was run and the model residuals were extracted and used as a control predictor in all subsequent models (Crawley, 2007). This process minimises the effect of time on changes in the response and reduces temporal autocorrelation. The amount of forest remaining (km^2) was also included as a control variable in all models. Modelling was done using Generalised linear models (GLM) and followed an information theoretic approach (Burnham and Anderson, 2007). For the models with rate of forest loss as the response I tested both gaussian and gamma distributions, and for the models with ELC allocation I used a Poisson distribution. Resulting models were compared using Akaike's Information Criterion (AIC). Final rate of forest loss models used gaussian distributions. All predictors in each model set had been selected because of a priori hypotheses (Table S2.2), and so within each set all combinations of possible models were run and compared using AIC. Models with $\Delta AIC < 6$ were considered to have sufficient support and retained in the final model set. Model averaging was implemented for the final model set, resulting in model-averaged coefficients for all model terms (Burnham and Anderson, 2007). Models were run and averaged using the MuMIn package in R (Version 1.43.17, Bartoń 2020). This modelling procedure was repeated for a one-year time lag and two-year time lag as follows (using the ELC response models as an example):

No time lag:

$$\log(E(y_t)) = \beta_0 + \beta_1 x_{1t} + \cdots + \beta_p x_{pt}$$

Where γ is the response at time t, and $x_j, j = 1, \dots, p$ is predictor variable j at time t.

One year time lag:

$$\log(E(y_{t+1})) = \beta_0 + \beta_1 x_{1t} + \cdots + \beta_p x_{pt}$$

Where γ is the response at time $t + 1$, and $x_j, j = 1, \dots, p$ is predictor variable j at time t.

Two year time lag:

$$\log(E(y_{t+2})) = \beta_0 + \beta_1 x_{1t} + \cdots + \beta_p x_{pt}$$

Where γ is the response at time $t + 2$, and $x_j, j = 1, \dots, p$ is predictor variable j at time t.

2.3 RESULTS

2.3.1 Forest loss

During the study period (1993-2015) 167,477 km^2 of forest was lost which represented nearly 16% of the total forest cover. The models for changes in the rate of forest loss as a function of changes in economic and agricultural commodity predictors produced no strong effects (Figures S2.1 to S2.4). For each predictor set there were between 5 and 28 models in the top model set and final coefficients were calculated using full averages (Tables S2.5 – S2.13). The largest effect was from the control variable population density with a one-year time lag (full averaged coefficient = -632.9, SE = 64.8, Table S2.6). The largest effect excluding control variables was for agricultural proportion of GDP with a one-year time lag (full averaged coefficient = -14.9, SE = 7.9) suggesting, counterintuitively, that there is a small reduction in the rate of forest loss as the contribution of agriculture to national GDP increases, although this effect is weak (Figure S2.3, Table S2.9) and therefore inference is limited.

2.3.2 New economic land concessions

There were 287 new ELCs allocated within the study period, with the majority (51%) being designated for rubber production (Table S2.14). The largest effect overall was for the economic control variable population density, where there were very strong negative effects across all time lags (rate ratios for one-year lag = 0.012, two-year lag = 0.002, three-year lag = 0.0005, Table 2.2), indicating that new ELCs are not allocated in areas of high human population density. The largest overall effect excluding control variables was for changes in agricultural proportion of GDP with no time lag and a one-year time lag (no time lag rate ratio = 1.310, and one-year time lag rate ratio = 1.284, Table 2.2, Figure 2.1).

From an economic perspective there were positive relationships between the allocation of new ELCs and increases in the agricultural proportion of GDP and increases in foreign direct investment (one-year time lag rate ratio = 1.004, Table 2.2, Figure 2.1). There was also a positive relationship between new ELC allocation and increases in development flows to the environment sector (no time lag rate ratio = 1.031). There was a negative relationship between new ELC allocation and positive changes in per capita GDP (one-year time lag rate ratio = 0.985 and two-year time lag rate ratio = 0.974, Table 2.2, Figure 2.1).

The largest effect within the commodity set was for the change in the market price of corn in the same year as the response (no time lag) with a rate ratio of 1.03 (Table 2.2). There were further positive relationships between the changes in the non-food production index (one-year time lag rate ratio = 1.007, and two-year time lag rate ratio = 1.007), and changes in the market price of sugar (rate ratio for all three time steps = 1.01). There were negative relationships between ELC allocation and the change in the market price of rice, rubber, corn, and the crop production index, at various time lags (Table 2.2).

The producer price variable set, which reflects the farmgate prices of the commodities, had both positive and negative relationships with ELC allocation (Figure 2.3, Table 2.2). The strongest positive relationship was with changes in the producer price of rubber (no time lag rate ratio = 1.035). The effect of positive changes (i.e., net increases) in the price a farmer will get for rubber production can be seen in the predictions of new ELCs (Figure 2.3). There were also positive relationships between ELC allocation and changes in the producer price of corn (one-year time lag rate ratio = 1.011) and the producer price of rice (two-year time lag rate ratio = 1.013, Figure 2.3, Table 2.2).

There were four negative relationships between producer price variables and new ELC allocations (Figure 2.3). Increases in the producer prices of rice and cassava resulted in fewer predicted ELCs in the same year (no time lag rate ratio = 0.976) and two years later (two-year time lag rate ratio = 0.982), respectively. The difference in the direction of the effect of rice producer prices in year *t* and year *t+2* (Figure 2.3) suggests that there is a complex relationship between rice production and new ELC allocation. The negative relationship between the producer price of cassava and new ELC allocation was strong (two-year time lag rate ratio = 0.982, Figure 2.3).

Table 2.2. Parameter coefficients, standard errors, and rate ratios from the top model(s) in the analysis with rate of economic land concession allocation response. Missing values denote predictor variables that were not selected in the top model(s) for that lag period. Coefficients are on the log scale. SE = Standard Error

Variable	*No time lag*			*1 year time lag*			*2 year time lag*		
	Coefficient	**SE**	**Rate ratio[a]**	**Coefficient**	**SE**	**Rate ratio[a]**	**Coefficient**	**SE**	**Rate ratio[a]**
Economy									
GDP	-	-	-	-0.01500	0.00340	0.985	-0.02600*	0.00390	0.974
Agricultural proportion of GDP	0.27000	0.07000	1.310	0.25000	0.06600	1.284	-0.03400*	0.07600	0.967
Development flows – agriculture	-	-	-	-	-	-	-0.00005*	0.00020	1.000
Development flows – environment	0.03100	0.00400	1.031	-	-	-	-0.00260*	0.00450	0.997
Foreign direct investment	-	-	-	0.00360	0.00050	1.004	0.00040*	0.00060	1.000
Population density	-4.43000	0.85000	0.012	-6.09000	0.81000	0.002	-7.68000*	0.95000	0.000
Forest remaining	-0.00030	0.00004	0.999	-0.00004	0.00004	0.999	0.00004*	0.00005	1.000
Commodity / production									
Change in median market price – corn	0.03	0.005697	1.03	0.00704*	0.00647	1.007	-0.00365*	0.00329	0.996
Change in median market price – rice	-0.007	0.00198	0.99	-0.00429*	0.00272	0.996	0.00004*	0.00058	1.000
Change in median market price – rubber	-0.0009	0.00024	0.99	0.00019*	0.00022	1.000	-0.00004*	0.00009	0.999
Change in median market price – sugar	0.013	0.001931	1.01	0.00708*	0.00127	1.007	0.00877*	0.00124	1.009
Non-food agricultural production index	0.007	0.00175	1.01	0.00672*	0.00264	1.007	-0.00149*	0.00203	0.999

Crop production index	-	-	-	0.00042*	0.00144	1.000	-0.00328*	0.00427	0.997
Total production from forestry	-	-	-	0.00000*	0.00000	1.000	0.00000*	0.00000	1.000
Forest remaining	-0.0002	0.00002	0.999	-0.00017*	0.00003	0.999	-0.00013*	0.00003	0.999
Producer prices									
Producer price of corn	0.00415	0.00355	1.004	0.01093*	0.00240	1.011	0.00014*	0.00081	1.000
Producer price of rice	-0.02465	0.00436	0.976	0.00452*	0.00564	1.005	0.01258*	0.00474	1.013
Producer price of rubber	0.03424	0.00401	1.035	-0.00075*	0.00228	0.999	-0.00431*	0.00467	0.996
Producer price of sugar	0.00004	0.00010	1.000	0.00016*	0.00018	1.000	0.00000*	0.00006	1.000
Producer price of cassava	0.00032	0.00123	1.000	0.00006*	0.00076	1.000	-0.01791*	0.00214	0.982
Forest remaining	-0.00023	0.00002	0.999	-0.00015*	0.00002	0.999	-0.00013*	0.00002	0.999

* Coefficients derived from full averaging of models within dAIC < 6. In some cases, there was a single top model and therefore model averaging was not necessary.

[A] Rate ratio = exp(coefficient)

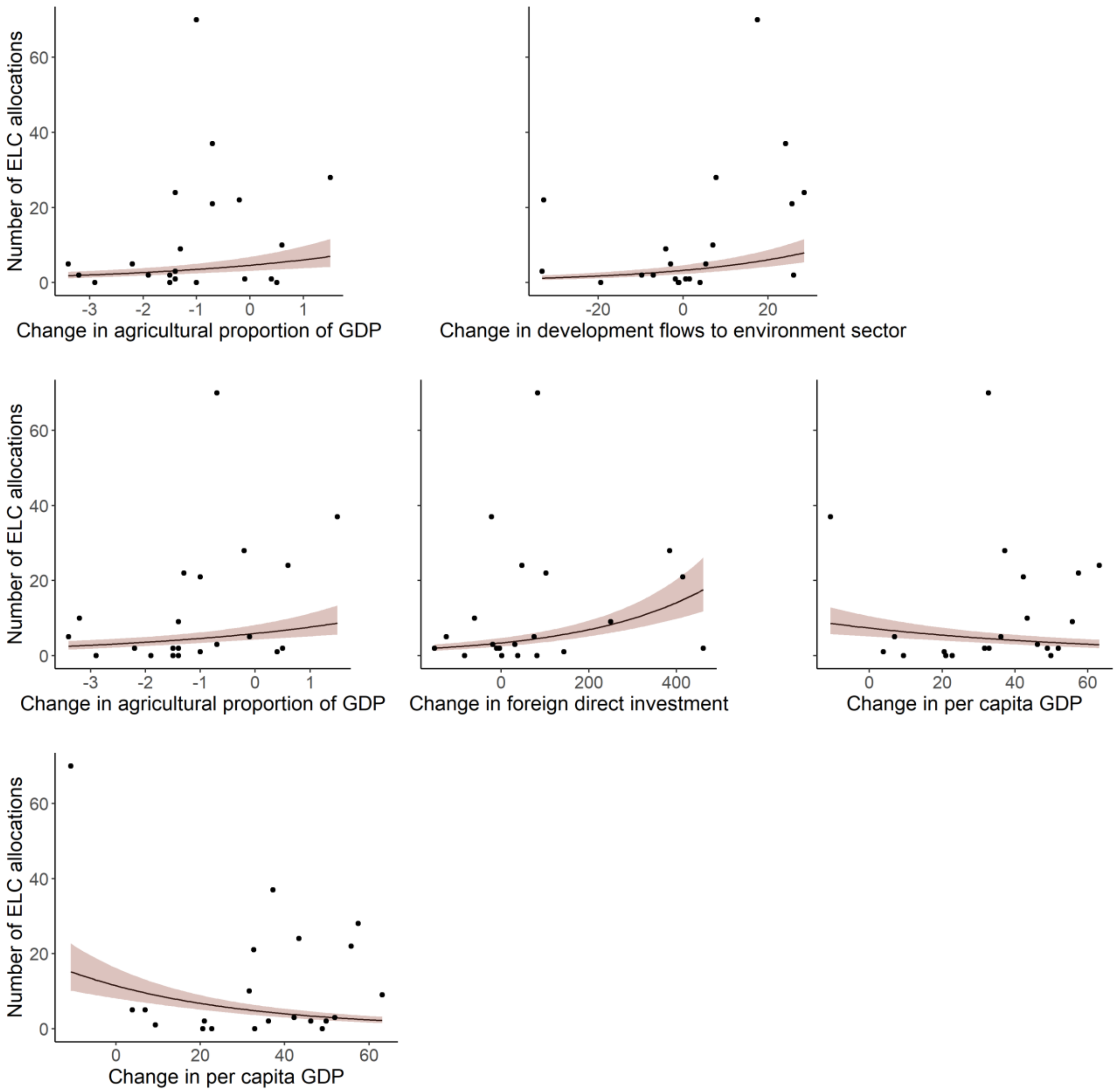

Figure 2.1. Modelled relationships between economic predictors and the allocation of new economic land concessions in Cambodia between 1993 – 2015. Points are the observed data, black lines are model predictions, and coloured ribbons are 95% confidence intervals. Top row: no time lag between predictor and response; middle row: 1-year time lag between predictor and response; bottom row: 2-year time lag between predictor and response. Models had Poisson error structures with a log link; points and predictions were back-transformed to the original scale for plotting above.

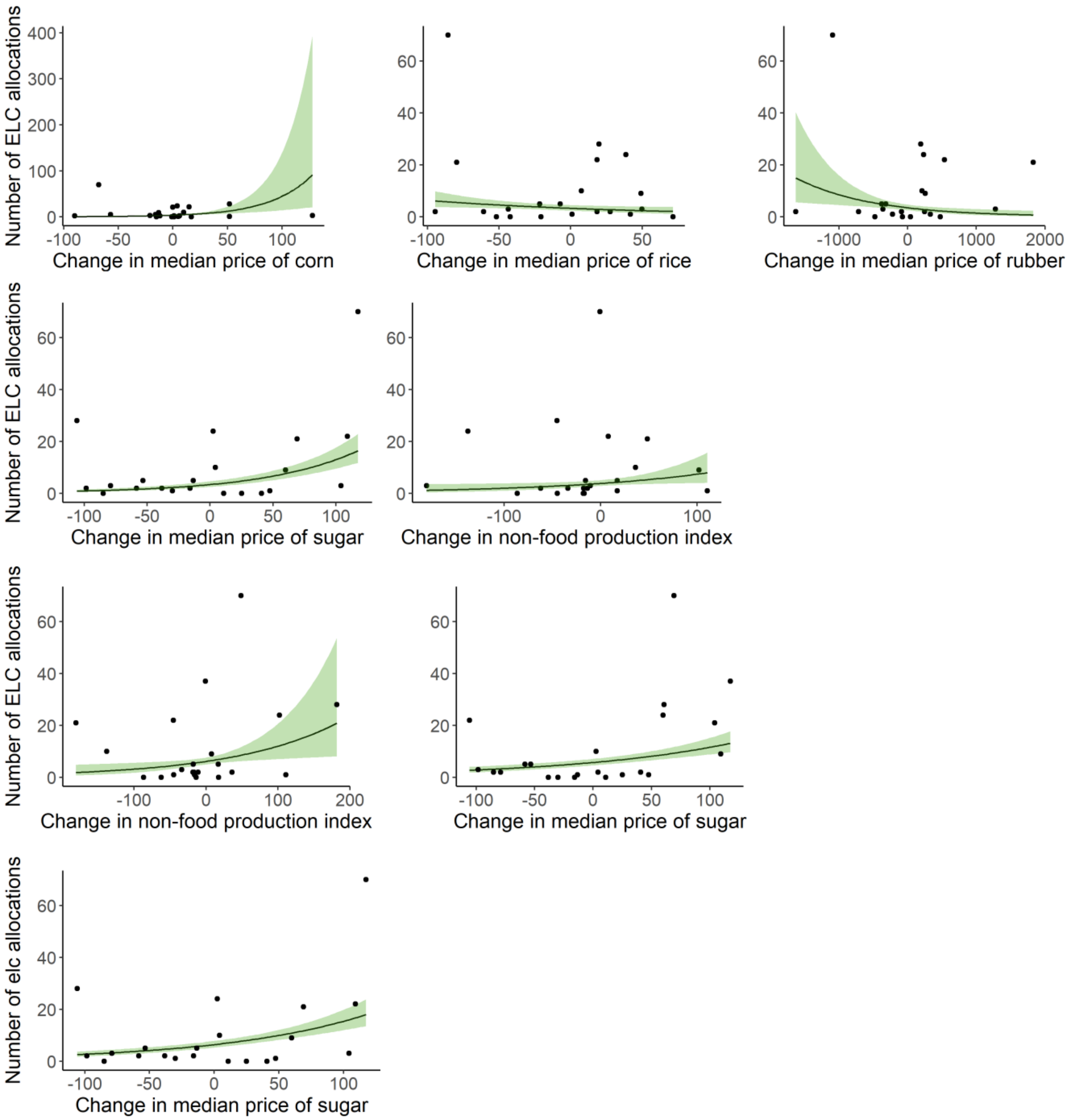

Figure 2.2. Modelled relationships between commodity price predictors and the allocation of new economic land concessions in Cambodia between 1993 – 2015. All x axis values are in US dollars/ton. Points are the observed data, black lines are model predictions, and coloured ribbons are 95% confidence intervals. Top two rows: no time lag between predictor and response; third row: 1-year time lag between predictor and response; bottom row: 2-year time lag between predictor and response. Models had Poisson error structures with a log link; points and predictions were back-transformed to the original scale for plotting above.

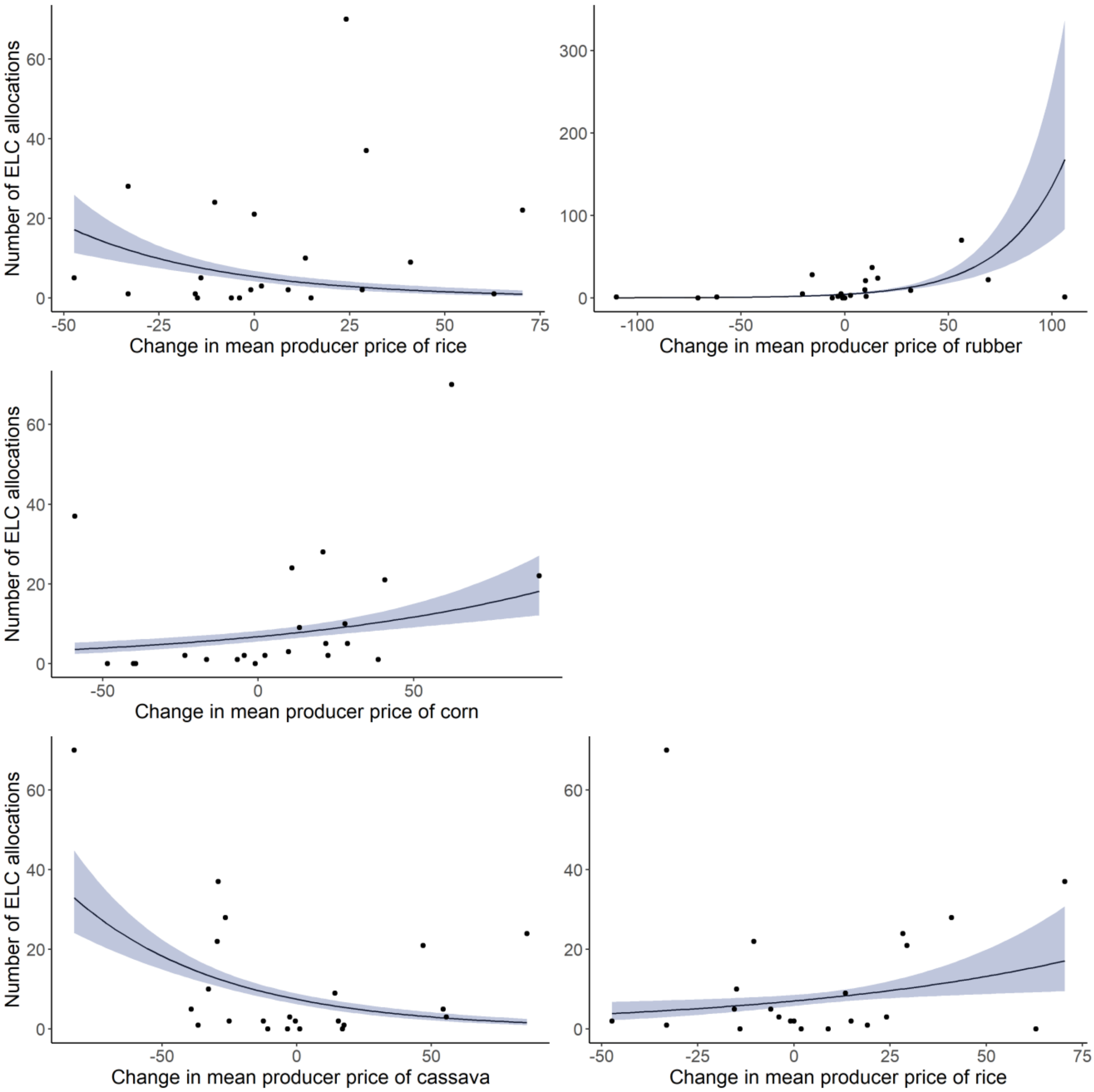

Figure 2.3. Modelled relationships between producer price predictors and the allocation of new economic land concessions Cambodia between 1993 – 2015. All x axis values are in US dollars/ton. Points are the observed data, black lines are model predictions, and coloured ribbons are 95% confidence intervals. Top row: no time lag between predictor and response; middle row: 1-year time lag between predictor and response; bottom row: 2-year time lag between predictor and response. Models had Poisson error structures with a log link; points and predictions were back-transformed to the original scale for plotting above.

2.4 DISCUSSION

In this study, I have modelled the relationships between metrics of economic development and the agricultural sector, and forest loss and the development of industrial-scale agriculture. My analysis has revealed some important relationships between changes in the national economy and the growth of the commercial agriculture sector, from which I can make inferences regarding drivers of forest loss. Understanding the relationships between economic development and deforestation is critical in countries that are undergoing rapid economic and social development such as Cambodia (Hughes and Un, 2011), as it is within these conditions of socioeconomic transition that forest loss is often accelerated (Imai et al., 2018). Knowledge of these relationships can be used to develop land use policies that can guide a country through forest transition periods towards sustainable forestry (Culas, 2012).

2.4.1 New Economic Land Concessions

The economic and agricultural commodity variables were effective at predicting the allocation of new ELCs. Although ELCs do not guarantee deforestation (indeed not all ELCs are awarded on forested land), the deforestation rates within ELCs are up to 105% higher than comparable areas with no ELCs (Davis et al., 2015). There has also been widespread allocation of ELCs within forested community land and protected areas, resulting in the loss of important forest habitat, rural livelihoods, and indigenous land rights (Beauchamp et al., 2018; Davis et al., 2015; Magliocca et al., 2019; Neef et al., 2013; Oldenburg and Neef, 2014; Watson et al., 2014). Therefore, ELCs themselves can be considered direct drivers of forest loss in some contexts, which may mean that the economic and agricultural commodity predictors are indeed indirect drivers. My results have demonstrated that during the study period, the national economy and economic development of the country, including increases in foreign investment, changes in the structure of national GDP, and fluctuations in agricultural commodity prices, were closely linked to the increase in ELCs, which in turn have been shown to drive forest loss. These effects suggest ties between both the development of new ELCs and the growth of the agricultural sector, and the injection of foreign wealth into the sector via the purchasing of concessions by international companies.

2.4.1.1 Economics

There were clear relationships between the size of the agricultural sector, the rates of foreign investment, and the number of new ELCs. When the agricultural sector's contribution to national GDP increased, so did the predicted number of new ELCs. For example, when the agricultural sector's GDP proportion decreased by 3% in a given year relative to the previous year, the number of new ELCs allocated that year is predicted to be approximately two, whereas when the sector's GDP proportion increased in a given year by 1% relative to the previous year, the number of new ELCs is predicted to be six. Likewise, when foreign investment into the country increased, so did the predicted number of new ELCs. For example, when the amount of foreign investment decreased by approximately $10 million relative to the previous year, the number of new ELCs one year later is predicted to be three. Conversely, when foreign investment in a given year increased by approximately $300 million relative to the previous year, then one year later the number of new ELCs is predicted to be 10. Although my results do not describe causation, there are important relationships between foreign investment, agriculture, and the development of new ELCs. Interestingly, increases in development flows to the environment sector did not reduce the number of new ELCs within the same year as the investment, however, after two years this relationship becomes negative. This suggests that in the short-term (i.e., over periods less than two years), investments into the environment sector via development funding (predominantly from international donors) do not reduce the number of new ELC allocations, but that perhaps over the longer term they do.

Cambodia is likely to continue prioritising growth within the agricultural sector (Eliste and Zorya, 2015), and neoliberal economic policies will continue to encourage foreign investment (Green, 2020; Hughes and Un, 2011; Phillips and Davy, 2021). Therefore, it is likely that the development of industrial-scale commercial agriculture will continue, despite a visible effort to decrease them since 2012 (Neef et al., 2013). The process of awarding ELC contracts in Cambodia has been criticised for lacking transparency and for corruption (Neef et al., 2013; Vrieze and Kuch, 2012), and so it is not always possible to identify who owns a particular concession. Nevertheless, of those identified (80% are identifiable), 48% were foreign owned (Licadho, 2019). Despite real and perceived benefits of attracting foreign investment and promoting the expansion of cash crops (Li et al., 2018; Taylor et al., 2019), there are numerous negative effects on local people and the environment (Curtis et al., 2018; Magliocca et al., 2019; Neef et al., 2013; Oldenburg and Neef, 2014; Zaehringer et al., 2020). Development of potential agricultural land by investors comes with opportunity costs for local people, who otherwise may have had access to the land, water, and other resources, and could have developed agriculture themselves that would have alleviated poverty more effectively than an externally owned commercial agricultural enterprise (De Schutter, 2011).

2.4.1.2 Agricultural commodity and producer prices

Changes in new ELC allocation can be predicted from my models by several key agricultural commodity prices, both on the international market and internally at the scale of the individual producer. Rubber, sugar, corn, and rice were all important variables in the models, and over certain time scales increases in the market prices and producer prices of these commodities predicted increases in the allocation of ELCs. Economic land concessions in Cambodia are predominantly agro-industrial concessions, and therefore the positive relationships between the price of agricultural commodities and new ELC allocations is not surprising. Rubber and rice are the most valuable market commodities within the variable set (Table S2.14), and this is reflected in the model; when the producer price of rubber decreased in value, very few new ELCs were predicted in the following year, but when prices increased by, for example, $30/ton, in the following year 12 new ELCs were predicted. This suggests that producers are highly influenced by sale prices of commodities, particularly of high value products such as rubber, and that they will act quickly when there is the potential for financial gain.

The differences in the effects of commodity and producer prices on ELC allocation at different time lags is interesting, as it suggests that either investors will delay investing in a new crop for up to two years after the prices increase, or that the process of purchasing land and establishing an ELC venture can, in some cases, be a slow process. International market forces are known to drive land use change (LUC) in Cambodia (Grogan et al., 2019), and globally, land conversion for commodity production is the single largest driver of deforestation (Curtis et al., 2018). Grogan et al (2015) provide an empirical example of how the international market price of rubber can drive deforestation in frontier areas of Cambodia and Vietnam. My study reinforces this link between commodity and producer prices of key agricultural products and development activities that reduce forest cover.

2.4.2 Direct forest loss

Apart from population density and agricultural proportion of GDP, there were no significant effects from the models with forest loss as the response variable. Some of the predictor variables that were non-significant have been shown to correlate with LUC in other studies, such as GDP (Ewers, 2006; Fan and Ding, 2016; Gong et al., 2013; Kuang et al., 2016), the contribution of economic sectors to national GDP (Gong et al., 2013), human population growth and density (Bonilla-Bedoya et al., 2018; Fan and Ding, 2016), and agricultural output (Fan and Ding, 2016). There are several possible explanations for the lack of effects in this study. First, previous studies have been at different scales to this study, such as global (e.g., Ewers, 2006), or sub-national (e.g., Gong et al., 2013), and therefore the drivers which are operating at those scales may be different to the drivers operating at the national scale in Cambodia. Second, Cambodia's economy is a rare example of civil unrest and war resulting in economic collapse, followed by subsequent rapid economic revival (other Asian examples include Japan and Vietnam, see Hamada & Kasuya 1992 and Riedel & Turley 1999). This may render comparison of economic or agricultural drivers of forest loss and LUC with other Asian countries uninformative. For example, Cambodia's economy is in its infancy relative to many other countries in the region, and therefore forest loss during the study period may have been driven more by local drivers such as poverty, insecure land tenure, and land speculation by migrants, rather than national-level economics. Third, I did not include predictor variables covering institutional factors, land rights or tenure, or environmental policies, which have been shown to be important (Culas, 2007). Finally, I only investigated up to two years of time lag between changes in predictor variables and changes in forest cover. It is possible that changes in certain economic factors take longer than two years to have a significant effect on forest cover. For example, the “trickle down” effect of foreign investment, whereby the local economies of the host nation see increased productivity and profitability which in turn may drive land use change and forest loss at the local scale, is smaller and more fragile than usually assumed (Jensen, 2006). Therefore, if there is an indirect effect of foreign investment on forest loss, it may take several years for this effect to trickle down to forests at local levels.

2.4.3 Conclusions

Cambodia’s post-war economic recovery has been remarkably swift, boasting GDP growth rates greater than any other Asian country excluding China (Solcomb, 2010). On one hand this has benefited the Cambodian people through poverty reduction and improved access to services (World Bank, 2014), yet on the other hand much of this economic growth has been built upon natural resource exploitation (Davis et al., 2015; Eliste and Zorya, 2015), which has had negative effects on protected areas, forests, and local people (Beauchamp et al., 2018; Magliocca et al., 2019; Oldenburg and Neef, 2014; Vrieze and Kuch, 2012; Watson et al., 2014). Economic land concessions have been used by the Cambodian government as a mechanism with which to direct foreign investment, expand industrial-scale commercial agriculture, and boost economic activity, yet have also been a key driver in deforestation (Tsujino et al., 2019). High rates of deforestation, in the context of Cambodia’s economic status and the rural population’s reliance on natural resources (Nguyen et al., 2015), suggests that the country is on the increasing deforestation trajectory of the EKCd (Bhattarai & Hammig 2004), whereby national economic development is improved at the expense of natural forest cover (Stern, 2004).

The most relevant case study to compare with Cambodia is that of its neighbour Vietnam, which underwent a forest transition in the 1990s, and over the next two decades national forest cover increased (Meyfroidt and Lambin, 2008). Vietnam’s forest transition was driven by a combination of factors including land scarcity due to increasing human populations, reductions in hillside cultivation owing to land degradation and land use policies, increased productivity in existing agricultural lands, government policies that promoted smallholder forestry, increased demand for timber, and a scarcity of forest products that provided incentives for reforestation (Meyfroidt and Lambin, 2008). Recent studies have highlighted Cambodia’s readiness for a forest transition; all of the necessary econometric milestones have been reached including robust government policies and legal frameworks, the promotion and expansion of tourism, integration into global markets for capital, commodities, and labour, and prevalent international conservation ideologies, yet deforestation rates between 1990 and 2015 remained above 1% (Ota et al., 2020). Case studies of other Asian countries that have gone through forest transitions, including Vietnam, have highlighted the need for at least one element of effective governance (Bhattacharya et al., 2010; Clement et al., 2009; He et al., 2014). Governance failures in Cambodia are likely hindering progress towards more sustainable forest management and ultimately a forest transition (Milne and Mahanty, 2015; Riggs et al., 2018).

Understanding which economic factors and agricultural commodities are driving land conversion via ELCs, the strength of the effects, the time lags, and the legal and institutional mechanisms that facilitate the link between prices and forest loss, is critical for both predicting future forest loss and identifying the appropriate institutional levels to target policy interventions. The opaque legal mechanisms and weak institutional frameworks that govern ELCs, natural resource management, and forest governance in Cambodia are likely to continue to hinder the development of sustainable forest and agricultural policies in the short term (Milne and Mahanty, 2015). Industrial-scale agriculture in low income countries such as Cambodia are often criticised for failing to alleviate poverty or contribute to rural development, and often come with huge opportunity costs for local people, who would likely benefit more if they were given access to the land (De Schutter, 2011). Furthermore, agro-industrial production of cash crops for international markets leaves the country open to price shocks and other suboptimal market fluctuations. Nevertheless, the agricultural sector is still a fundamental part of the national economy and labour force, and further agricultural development that embodies sustainability, increased productivity through improved technology, and value-addition via further processing rather than land expansion, can continue to contribute to national development and poverty alleviation without the need for further deforestation (Eliste and Zorya, 2015).

2.5. ACKNOWLEDGEMENTS

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2.6. SUPPORTING INFORMATION

Table S2.1. Full list of predictor variables. Some variables were removed from the analysis prior to modelling due to collinearity. Variables cover the time period 1993 – 2015. GDP = Gross Domestic Product, USD = US Dollars, UNCTAD = United Nations Conference on Trade and Development, CNIS = Cambodian National Institute of Statistics, FAO = Food and Agricultural Organisation, RASCE = Rubber Association Singapore Commodity Exchange, ESACCI = European Space Agency Climate Change Initiative

Predictor variable	Units	Resolution	Source	Details
Economy				
GDP per capita	Billions USD	National	World Bank	Constant 2010 rates
GPD growth	%	National	World Bank	Constant 2010 rates
GNI per capita	USD	National	World Bank	Gross National Income per capita. Calculated as gross national income divded by the mid-year population at current USD rates
Foreign Direct Investment	Millions USD	National	UNCTAD	Inward and outward flows and stock
Agricultural sector value of GDP	%	National	CNIS	Proportion of national GDP
Industrial sector value of GDP	%	National	CNIS	Proportion of national GDP
Development flows to agriculture	Millions USD	National	FAO	Donor development investment flows, other official flows, and private donor flows at constant 2016 prices to all agriculture and forestry sub-sectors
Development flows to environment	Millions USD	National	FAO	Donor development investment flows, other official flows, and private donor flows at constant 2016 prices to general environment protection
Commodity prices				

Agricultural Raw Materials	Index	Global	IMF	Price index for global agricultural raw materials including timber, cotton, wool, rubber, and hides
Crop Production	Index	National	FAO	Relative level of the aggregate volume of agricultural production for each year in comparison with the base period 2004-2006
Non-food agricultural production	Index	National	FAO	Relative level of the aggregate volume of non-food agricultural production for each year in comparison with the base period 2004-2006
Forestry production	m3	National	FAO	Total production values for industrial roundwood, non-coniferous tropical wood, other industrial roundwood, sawlogs and veneer logs (coniferous and non-coniferous), and sawnwood (coniferous and non-coniferous
Price of rice	USD/ton	Global	World Bank	Median annual global market price of rice
Price of corn	USD/ton	Global	World Bank	Annual global market price of corn
Price of rubber	USD/ton	Regional	RASCE	Monthly regional market value of rubber on the Singapore Exchange
Price of sugar	USD/ton	Global	World Bank	Annual global market price of sugar
Producer prices				
Producer price of Rice	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of rubber	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of cassava	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of corn	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Producer price of sugar	USD/ton	National	FAO	Farmgate prices for Cambodian producers
Control				
Forest remaining	km2	National	ESACCI	Total forested area
Population density	pax/km2	National	FAO	

Table S2.2. Hypothesised relationships between predictor variables and forest loss

Variable	Hypothesis
Economic development	
GDP	Increases in national economic development and wealth will increase forest loss
GDP growth	The rate of GDP growth will affect the rate of forest loss
FDI	Increased foreign investment will increase forest loss (e.g. through economic land concessions)
Agricultural sector proportion of GDP	As the agricultural sector's contribution to GDP increases, so will forest loss (reflecting increases in agro-industrial concessions).
	Alternative hypothesis: as the agricultural sector's contribution to GDP decreases forest loss will increase (reflecting urbanisation and urban expansion)
Development flows to agriculture	Increased investment into the agricultural sector will increase forest loss (agricultural expansion)
	Alternative hypothesis: Increased investment into the agricultural sector will decrease forest loss (increased productivity and intensification of existing agricultural land)
Development flows to the environment	Increased investment into the environment sector will decrease forest loss
Commodities	
Crop production index	Increases in crop production will increase forest loss
Non-food production index	Increases in non-food agricultural production will increase forest loss
Median rice price	Increases in the price of rice will increase forest loss
Median rubber price	Increases in the price of rubber will increase forest loss
Median corn price	Increases in the price of corn will increase forest loss
Median sugar price	Increases in the price of sugar will increase forest loss
Production value from forestry	Increases in the production of forestry products will increase forest loss
Producer prices	
Producer price, rubber	Increases in the producer price of rubber will increase forest loss
Producer price, cassava	Increases in the producer price of cassava will increase forest loss
Producer price, corn	Increases in the producer price of corn will increase forest loss
Producer price, sugar	Increases in the producer price of sugar will increase forest loss
Producer price, rice	Increases in the producer price of rice will increase forest loss
Control	

Population density	Human population density will affect forest loss
Forest remaining	Forest loss will be affected by the raw quantity of forest remaining – i.e., forest loss will decrease as the total amount of forest remaining decreases

Table S2.3. European Space Agency Climate Change Initiative satellite bands. Bands highlighted in green were grouped to represent "forest cover".

Value	Label
0	No data
10	Cropland, rainfed
11	Herbaceous cover
12	Tree or shrub cover
20	Cropland, irrigated or post-flooding
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)
50	Tree cover, broadleaved, evergreen, cosed to open (>15%)
60	Tree cover, broadleaved, deciduous, closed to open (>15%)
61	Tree cover, broadleaves, decisuous, closed (>40%)
62	Tree cover, broadleaves, deciduous, open (15 - 40%)
70	Tree cover, needleleaved, evergreen, closed to open (>15%)
71	Tree cover, needleleaved, evergreen, closed (>40%)
72	Tree cover, needleleaved, evergreen, open (15 - 40%)
80	Tree cover, needleleaved, deciduous, closed to open (>15%)
81	Tree cover, needleleaved, deciduous, closed (>40%)
82	Tree cover, needleleaved, deciduous, open (15 - 40%)
90	Tree cover, mixed leaf type (broadleaved and needleleaved)
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
120	Shrubland
121	Evergreen shrubland
122	Deciduous shrubland
130	Grassland
140	Lichens and mosses
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)
152	Sparse shrub (<15%)
153	Sparse herbaceous cover (<15%)
160	Tree cover, flooded, fresh or brakish water

Table S2.4. Correlation matrix for predictor variables. Values over 0.6 are highlighted in red, and values below -0.6 are highlighted in yellow. For_cov = forest cover, for_cov_perc = percent forest cover, gdp = Gross Dometic Product, gdp_gr = percent growth in GDP, gni = Gross National Income, fdi = Foreign Direct Investment, ind_gdp = industrial sector value of GDP, agr_gdp = agricultural sector value of GDP, dev_agri = development flows to the agricultural sector, dev_env = development flows to the environment sector, pop_den = population density, armi = agricultural raw materials index, cpi = crop production index, nfi = non-food agricultural production, rice_med = median price of rice, rub_med = median price of rubber, corn_med = median price of corn, sug_med = median price of sugar, for_prod = forestry production, prod_rice = producer price of rice, prod_rub = producer price of rubber, prod_cass = producer price of cassava, prod_corn = producer price of corn, prod_sug = producer price of sugar, for_rem = forest remaining.

	for_cov	for_cov_perc	gdp	gdp_gr	gni	fdi	ind_gdp	agr_gdp	dev_agri	dev_env	pop_den	armi	cpi	nfi	rice_med	rub_med	corn_med	sug_med	for_prod	prod_rice	prod_rub	prod_cass	prod_corn	prod_sug	for_rem
for_cov			-0.30	0.30	-0.30	-0.31	0.47	-0.53	0.16	-0.05	0.39	0.00	-0.23	-0.21	-0.06	0.11	0.00	-0.02	-0.58	-0.25	-0.28	0.28	-0.19	-0.33	0.65
for_cov_perc			-0.30	0.30	-0.30	-0.31	0.47	-0.53	0.16	-0.05	0.39	0.00	-0.23	-0.21	-0.06	0.11	0.00	-0.02	-0.58	-0.25	-0.28	0.28	-0.19	-0.33	0.65
gdp	-0.30	-0.30		0.40	0.99	0.25	0.12	-0.22	-0.01	-0.01	-0.51	0.30	0.35	0.00	0.19	0.22	0.23	-0.15	0.14	0.41	0.63	0.26	0.57	0.19	-0.60
gdp_gr	0.30	0.30	0.40		0.39	0.20	0.12	-0.30	0.27	0.14	0.00	0.30	0.28	-0.06	-0.20	0.37	0.02	-0.22	0.12	-0.02	0.11	0.52	0.60	-0.09	-0.03
gni	-0.30	-0.30	0.99	0.39		0.24	0.13	-0.21	0.01	0.03	-0.51	0.34	0.35	-0.02	0.16	0.24	0.22	-0.14	0.14	0.41	0.60	0.23	0.62	0.15	-0.55
fdi	-0.31	-0.31	0.25	0.20	0.24		-0.48	0.23	0.01	0.41	-0.31	0.03	0.30	0.09	0.03	0.09	0.24	-0.12	0.26	0.24	0.19	0.06	0.46	0.54	-0.26
ind_gdp	0.47	0.47	0.12	0.12	0.13	-0.48		-0.61	-0.16	0.02	0.21	0.07	-0.30	-0.50	-0.25	0.08	-0.01	-0.01	-0.48	-0.21	-0.07	0.23	-0.20	-0.33	0.16
agr_gdp	-0.53	-0.53	-0.22	-0.30	-0.21	0.23	-0.61		-0.04	0.15	-0.24	-0.08	0.55	0.51	0.14	-0.11	-0.09	0.37	0.19	0.02	-0.06	-0.38	-0.01	0.20	-0.20
dev_agri	0.16	0.16	-0.01	0.27	0.01	0.01	-0.16	-0.04		-0.12	0.01	0.26	0.15	-0.08	-0.06	0.02	0.02	0.12	-0.06	-0.08	0.16	0.05	0.13	0.06	0.02
dev_env	-0.05	-0.05	-0.01	0.14	0.03	0.41	0.02	0.15	-0.12		-0.03	0.05	0.30	-0.24	-0.35	0.11	0.03	0.32	-0.01	-0.28	-0.04	0.03	0.08	0.16	0.01
pop_den	0.39	0.39	-0.51	0.00	-0.51	-0.31	0.21	-0.24	0.01	-0.03		-0.43	-0.45	-0.06	-0.31	-0.31	-0.19	-0.38	-0.26	-0.58	-0.79	-0.06	-0.35	-0.48	0.79
armi	0.00	0.00	0.30	0.30	0.34	0.03	0.07	-0.08	0.26	0.05	-0.43		0.54	-0.01	0.26	0.89	0.57	0.56	0.03	0.41	0.59	0.23	0.48	-0.27	-0.20
cpi	-0.23	-0.23	0.35	0.28	0.35	0.30	-0.30	0.55	0.15	0.30	-0.45	0.54		0.33	0.33	0.43	0.41	0.48	0.09	0.22	0.50	-0.06	0.42	0.08	-0.32
nfi	-0.21	-0.21	0.00	-0.06	-0.02	0.09	-0.50	0.51	-0.08	-0.24	-0.06	-0.01	0.33		0.39	0.02	-0.15	0.13	-0.01	0.10	-0.02	-0.41	0.02	0.21	0.03
rice_med	-0.06	-0.06	0.19	-0.20	0.16	0.03	-0.25	0.14	-0.06	-0.35	-0.31	0.26	0.33	0.39		0.24	0.60	0.16	0.00	0.67	0.47	0.01	0.20	0.13	-0.09
rub_med	0.11	0.11	0.22	0.37	0.24	0.09	0.08	-0.11	0.02	0.11	-0.31	0.89	0.43	0.02	0.24		0.56	0.48	0.05	0.48	0.40	0.48	0.49	-0.39	-0.07
corn_med	0.00	0.00	0.23	0.02	0.22	0.24	-0.01	-0.09	0.02	0.03	-0.19	0.57	0.41	-0.15	0.60	0.56		0.15	-0.10	0.46	0.48	0.23	0.40	-0.15	-0.04
sug_med	-0.02	-0.02	-0.15	-0.22	-0.14	-0.12	-0.01	0.37	0.12	0.32	-0.38	0.56	0.48	0.13	0.16	0.48	0.15		-0.19	0.11	0.28	-0.01	-0.12	-0.07	-0.14
for_prod	-0.58	-0.58	0.14	0.12	0.14	0.26	-0.48	0.19	-0.06	-0.01	-0.26	0.03	0.09	-0.01	0.00	0.05	-0.10	-0.19		0.27	0.15	0.11	0.25	0.11	-0.41

prod_rice	-0.25	-0.25	0.41	-0.02	0.41	0.24	-0.21	0.02	-0.08	-0.28	-0.58	0.41	0.22	0.10	0.67	0.48	0.46	0.11	0.27		0.63	0.36	0.47	0.15	-0.46
prod_rub	-0.28	-0.28	0.63	0.11	0.60	0.19	-0.07	-0.06	0.16	-0.04	-0.79	0.59	0.50	-0.02	0.47	0.40	0.48	0.28	0.15	0.63		0.05	0.39	0.41	-0.73
prod_cass	0.28	0.28	0.26	0.52	0.23	0.06	0.23	-0.38	0.05	0.03	-0.06	0.23	-0.06	-0.41	0.01	0.48	0.23	-0.01	0.11	0.36	0.05		0.36	-0.37	-0.07
prod_corn	-0.19	-0.19	0.57	0.60	0.62	0.46	-0.20	-0.01	0.13	0.08	-0.35	0.48	0.42	0.02	0.20	0.49	0.40	-0.12	0.25	0.47	0.39	0.36		0.01	-0.29
prod_sug	-0.33	-0.33	0.19	-0.09	0.15	0.54	-0.33	0.20	0.06	0.16	-0.48	-0.27	0.08	0.21	0.13	-0.39	-0.15	-0.07	0.11	0.15	0.41	-0.37	0.01		-0.51
for_rem	0.65	0.65	-0.60	-0.03	-0.55	-0.26	0.16	-0.20	0.02	0.01	0.79	-0.20	-0.32	0.03	-0.09	-0.07	-0.04	-0.14	-0.41	-0.46	-0.73	-0.07	-0.29	-0.51	

The following decisions were made based on high correlation (Table S2.4):

- GNI variable dropped due to very high correlation with GDP. Competing theories about drivers of forest loss – national economy (GDP) or socioeconomic status of population (GNI). Because Chapter 3 was focusing on socioeconomics, I decided that GDP was more interesting in this case.
- Neither population density (pop_den) or producer price for rubber (prod_rub) were dropped despite correlation. There is no plausible relationship between these two variables, and they were included to explain different drivers of forest loss. The two variables were in different variable sets, and so both were retained.
- Population density and amount of forest remaining (for_rem) were positively correlated, which was counterintuitive. Previous studies have highlighted remaining forest as an important control variable, and so both variables were retained (O'Brien, 2017).
- Producer price for rubber (prod_rub) and forest remaining were negatively correlated. Previous studies have highlighted remaining forest as an important control variable, and so both variables were retained (O'Brien, 2017).
- Agricultural Raw Materials Index (armi) was correlated with median price for rubber (rub_med). This was likely to be a genuine correlation. The index was slightly correlated with more than one of the commodity price variables, and I was interested in the individual commodities, and so armi was dropped.
- Agricultural sector proportion of GDP (agr_gdp) and industrial sector proportion of GDP (ind_gdp) were correlated, and conceptually I was more interested in the impact of the agricultural sector (as it is more likely to affect forest cover), and so ind_gdp was dropped.
- Median price of rice (rice_med) and producer price of rice (prod_rice) were correlated. These two variables were in different sets, and so were retained for the initial modelling.
- The producer price for rubber (prod_rub) and the producer price for rice (prod_rice) were correlated. A large number of the economic land concessions allocated in Cambodia were for rubber, and so my hypothesis was that rubber prices would be more important for predicting forest loss than rice. Therefore prod_rice was dropped

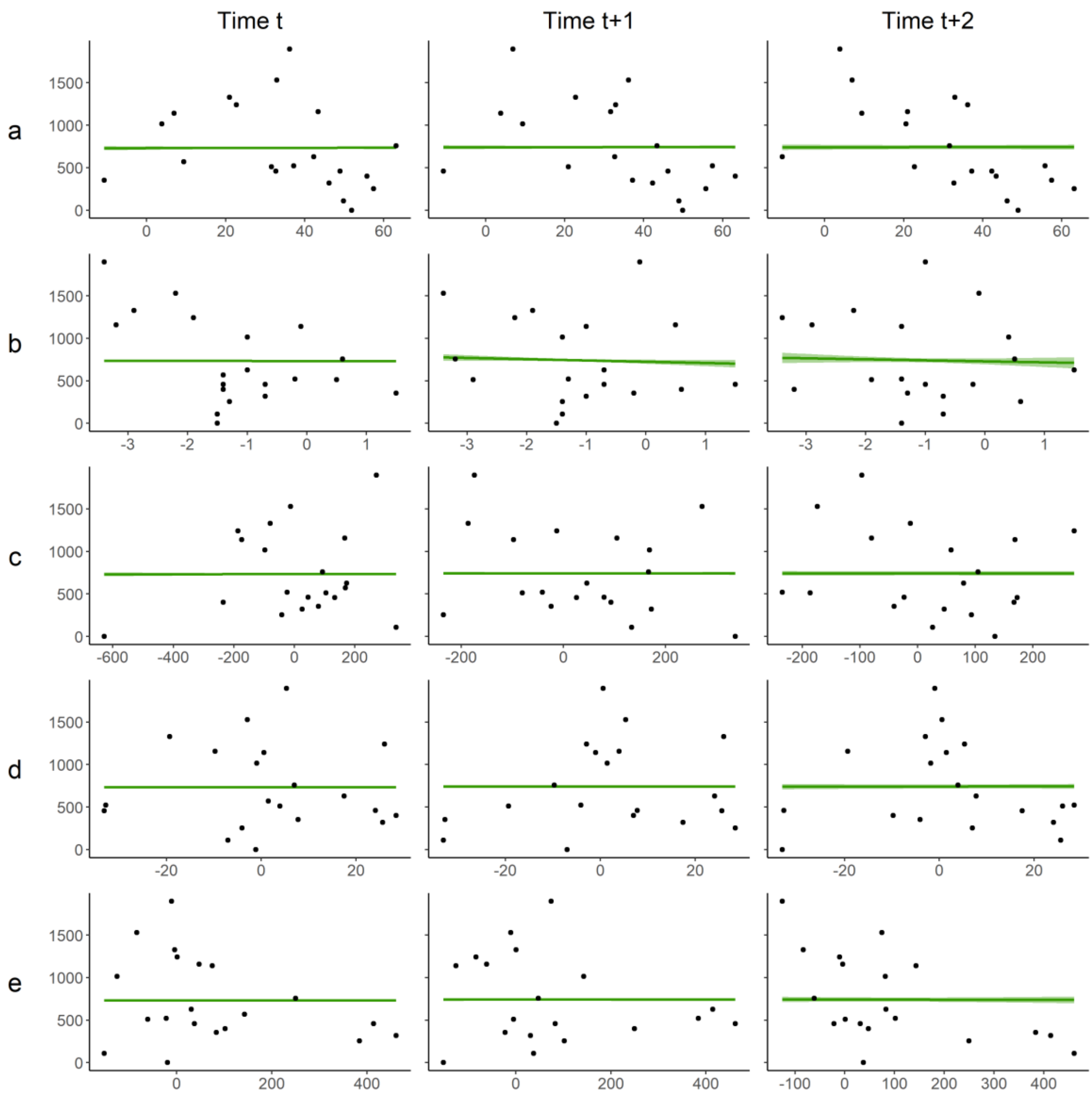

Figure S2.1 Predicted relationship between rate of forest loss for Cambodia and variables that measure economic development. All y-axes are the amount of forest lost in km². Points are the observed data, thick lines are model predictions, and faded ribbons are 95% confidence intervals. Row a: Gross Domestic Product (GDP), row b: agricultural sectors contribution (%) to GDP, row c: development flows to the agricultural sector (USD millions), row d: development flows to the environment sector (USD millions), row e: Foreign Direct Investment (USD millions).The left column of plots are the effects on forest cover at time t (i.e. the variable values and forest loss values from the same year), the middle column of plots are the effects at time t+1 (i.e. the effects on forest loss in the subsequent year), and the right column of plots are the effects at time t+2 (i.e. the effects on forest loss two years after the variable values).

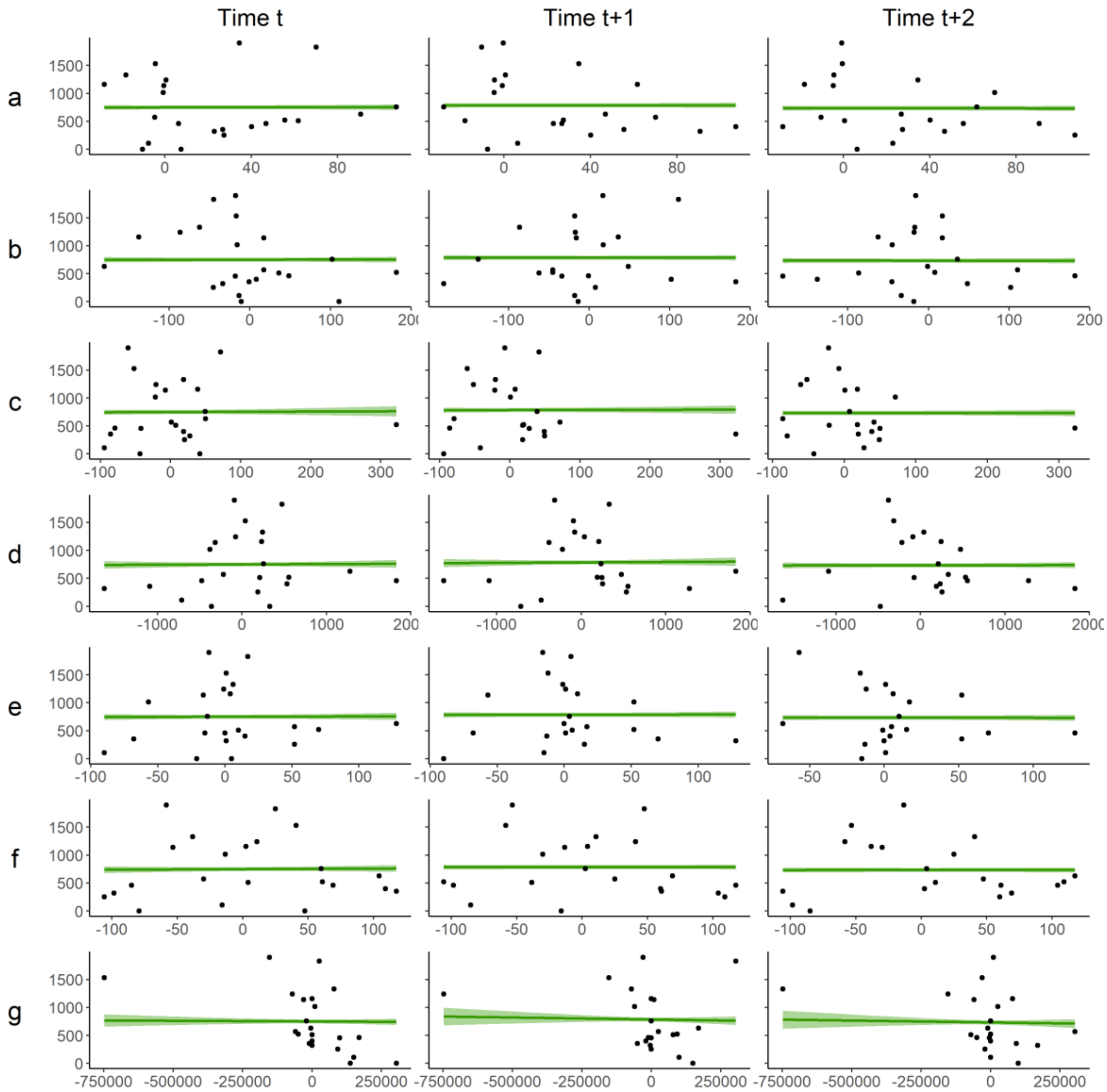

Figure S2.2. Predicted relationship between forest loss and variables that measure agricultural commodity production and price. All y-axes are the amount of forest lost in km². Points are the observed data, thick lines are model predictions, and faded ribbons are 95% confidence intervals. Row a: Crop Production Index, row b: Non-food Production Index, row c: median annual market price for rice (USD/t), row d: median annual market price for rubber (USD/t), row e: median annual market price for corn (USD/t), row f: median annual market price for sugar (USD/t), row g: total production from forestry (m³). The left column of plots are the effects on forest cover at time t (i.e. the variable values and forest loss values from the same year), the middle column of plots are the effects at time t+1 (i.e. the effects on forest loss in the subsequent year), and the right column of plots are the effects at time t+2 (i.e. the effects on forest loss two years after the variable values).

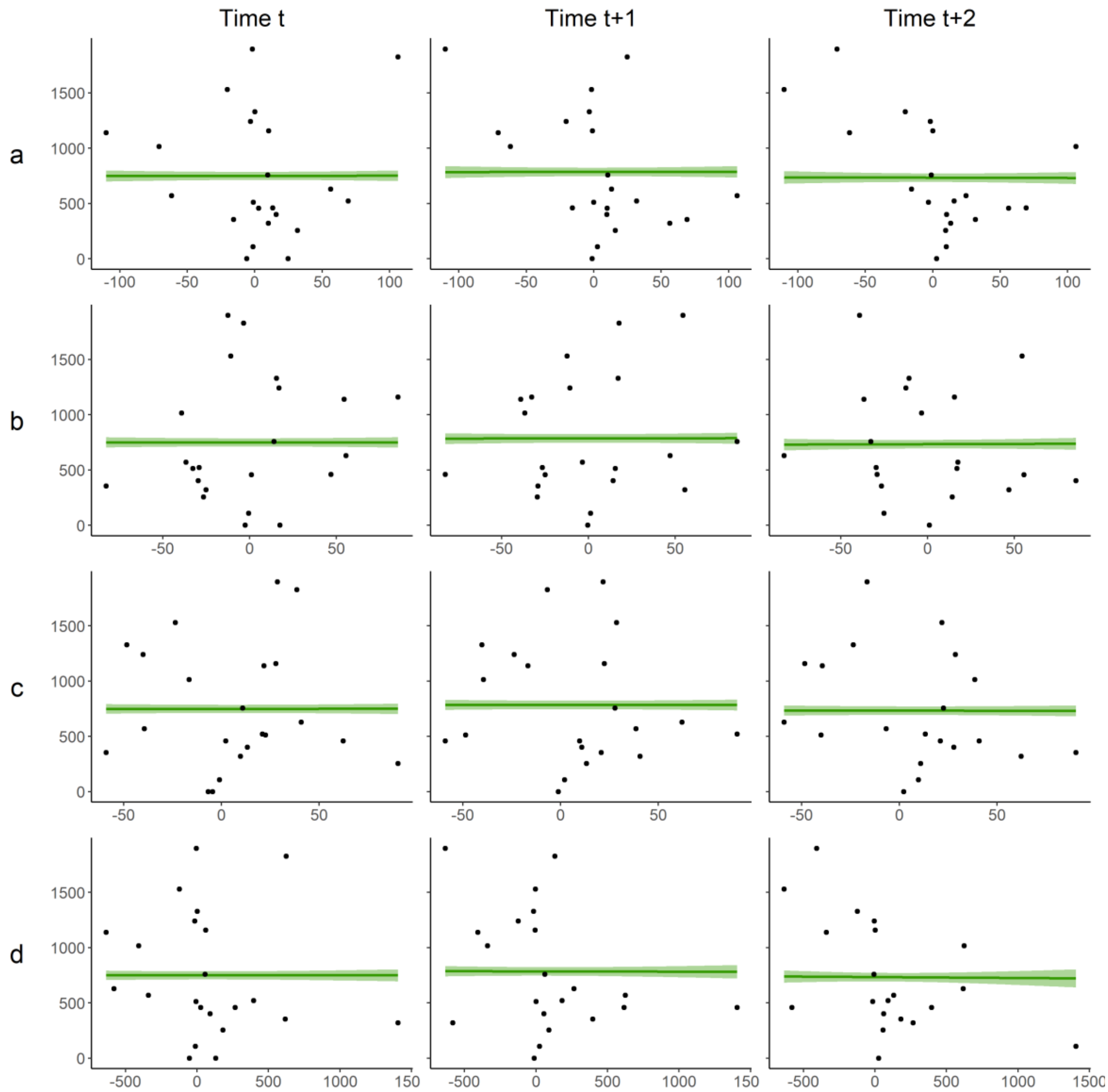

Figure S2.3. Predicted relationship between forest loss and variables that measure the producer prices of agricultural commodities. All y-axes are the amount of forest lost in km^2. Points are the observed data, thick lines are model predictions, and faded ribbons are 95% confidence intervals. Row a: producer price for rubber (USD/t) row b: producer price for cassava (USD/t), row c: producer price for corn (USD/t), row d: producer price for sugar (USD/t). Left column of plots are the effects on forest cover at time t (i.e. the variable values and forest loss values from the same year), the middle column of plots are the effects at time t+1 (i.e. the effects on forest loss in the subsequent year), and the right column of plots are the effects at time t+2 (i.e. the effects on forest loss two years after the variable values).

Table S2.5. Raw model coefficients and full averaged coefficients from the top economic models (dAIC < 6) where change in forest cover is the response. No time lag. Agric GDP = agricultural sector proportion of GDP, Dev agri = development flows to the agriculture, Dev env = development flows to the environment, For rem = forest remaining, GDP = gross domestic product, GDP gr = GDP growth, Pop den = population density.

	(Intercept)	SE	Agric GDP	SE	Dev agri	SE	Dev env	SE	FDI	SE	For rem	SE	GDP	SE	GDP gr	SE	Pop den	SE	Time	SE	Model weight
Model																					
401	-6308.3		NA		NA		NA		NA		0.08		NA		NA		-599.4		1.1		0.3832
403	-6309.3		NA		0.03		NA		NA		0.08		NA		NA		-599.6		1.1		0.1053
433	-6415.7		NA		NA		NA		NA		0.09		0.4		NA		-595.9		1.1		0.1007
402	-6312.0		-3.8		NA		NA		NA		0.08		NA		NA		-605.3		1.1		0.0607
405	-6302.8		NA		NA		0.2		NA		0.08		NA		NA		-597.5		1.1		0.0569
465	-6299.4		NA		NA		NA		NA		0.08		NA		-1.04		-597.9		1.1		0.0558
409	-6313.1		NA		NA		NA		0.01		0.08		NA		NA		-596.8		1.1		0.0502
497	-6456.3		NA		NA		NA		NA		0.09		0.6		-2.7		-589.7		1.1		0.0231
435	-6418.9		NA		0.03		NA		NA		0.09		0.4		NA		-595.9		1.1		0.0216
Model averaged coefficients	-6327.0	167.5	-0.3	1.9	0.005	0.02	0.01	0.10	6.5	0.01	0.08	0.002	0.08	0.23	-0.1	0.82	-598.7	46.15	1.1	0.02	

Table S2.6. Raw model coefficients and full averaged coefficients from the top economic models (dAIC < 6) where change in forest cover is the response. One year time lag. Agric GDP = agricultural sector proportion of GDP, Dev_agr = development flows to the environment sector, FDI = foreign direct investment, For_rem = forest remaining, GDP = gross domestic product, GDP_gr = GDP growth, Pop den = population density

	(Intercept)	SE	Agric GDP	SE	Dev_agr	SE	Dev_env	SE	FDI	SE	For_rem	SE	GDP	SE	GDP_gr	SE	Pop den	SE	Time	SE	Model weight
Model																					
402	-6743.74		-16.97		NA		NA		NA		0.089		NA		NA		-635.97		1.10		0.56
401	-6806.15		NA		NA		NA		NA		0.090		NA		NA		-616.65		1.09		0.07
410	-6714.42		-16.39		NA		NA		-0.028		0.089		NA		NA		-639.33		1.10		0.05
434	-6804.80		-15.58		NA		NA		NA		0.090		0.243		NA		-631.50		1.10		0.04
406	-6747.27		-17.25		NA		0.160		NA		0.089		NA		NA		-634.30		1.10		0.04
404	-6708.95		-17.23		-0.016		NA		NA		0.089		NA		NA		-627.77		1.10		0.04
466	-6750.66		-16.67		NA		NA		NA		0.089		NA		0.3026		-635.79		1.10		0.04
433	-6983.52		NA		NA		NA		NA		0.091		0.7718		NA		-607.51		1.10		0.02
Model averaged coefficients	-6757.0	259.2	-14.94	7.94	-0.0008	0.01	0.0082	0.11	-0.0017	0.01	0.09	0.003	0.038	0.22	0.014	0.6	-632.9	64.8	1.103	0.03	

Table S2.7. Raw model coefficients and full averaged coefficients from the top economic models (dAIC < 6) where change in forest cover is the response. Two year time lag. Agr_gdp = agricultural sector proportion of GDP, Dev agr = development flows to the agricultural sector, Dev env = development flows to the environment sector, FDI = foreign direct investment, For_rem = forest remaining, GDP = gross domestic product, Pop den = population density.

	(Intercept)	SE	Agr_gdp	SE	Dev agr	SE	Dev env	SE	FDI	SE	For_rem	SE	GDP	SE	Pop den	SE	Time	SE	Model weight
Model																			
210	-7292.91		-19.61		NA		NA		NA		0.095		NA		-602.51		1.11		0.40
209	-7309.82		NA		NA		NA		NA		0.096		NA		-604.68		1.11		0.22
214	-7313.49		-20.63		NA		0.67		NA		0.096		NA		-606.74		1.11		0.06
217	-7114.83		NA		NA		NA		-0.11		0.093		NA		-572.66		1.08		0.06
218	-7155.86		-18.14		NA		NA		-0.08		0.094		NA		-579.96		1.09		0.05
213	-7325.70		NA		NA		0.5		NA		0.096		NA		-607.90		1.11		0.03
241	-7390.57		NA		NA		NA		NA		0.096		0.6		-597.90		1.12		0.03
212	-7263.13		-19.85		-0.025		NA		NA		0.095		NA		-593.45		1.10		0.03
242	-7270.04		-20.35		NA		NA		NA		0.095		-0.16		-604.29		1.10		0.03
211	-7304.68		NA		-0.0043		NA		NA		0.096		NA		-603.11		1.11		0.03
Model averaged coefficients	-7283	508.6	-11.94	11.93	-0.0009	0.03	0.060	0.29	-0.011	0.04	0.095	0.01	0.015	0.27	-600	117.4	1.105	0.05	

Table S2.8. Raw model coefficients and full averaged coefficients from the top commodity models (dAIC < 6) where change in forest cover is the response. No time lag. Med corn = median corn price, CPI = crop production index, For prod = forest production, For rem = forest remaining, NFI = non-food production index, Med rice = median rice price, Med rub = median rubber price, Med sug = median sugar price.

	(Intercept)	SE	Med corn	SE	CPI	SE	For prod	SE	For rem	SE	NFI	SE	Med rice	SE	Med rub	SE	Med sug	SE	Time	SE	Model weight
Model																					
265	-4816.38		NA		NA		NA		0.06		NA		NA		NA		NA		1.07		0.16
393	-4828.96		NA		NA		NA		0.06		NA		NA		NA		0.40		1.08		0.11
329	-4797.76		NA		NA		NA		0.06		NA		NA		0.03		NA		1.07		0.07
297	-4806.01		NA		NA		NA		0.06		NA		0.26		NA		NA		1.08		0.07
269	-4738.73		NA		NA		-0.0001		0.06		NA		NA		NA		NA		1.04		0.06
266	-4817.37		0.414		NA		NA		0.06		NA		NA		NA		NA		1.07		0.05
267	-4877.51		NA		0.37		NA		0.06		NA		NA		NA		NA		1.07		0.04
281	-4799.42		NA		NA		NA		0.06		0.13		NA		NA		NA		1.08		0.03
333	-4701.74		NA		NA		-0.0001		0.06		NA		NA		0.04		NA		1.03		0.03
425	-4819.19		NA		NA		NA		0.06		NA		0.21		NA		0.36		1.08		0.03
397	-4768.10		NA		NA		-0.0001		0.06		NA		NA		NA		0.36		1.05		0.02
394	-4828.66		0.33		NA		NA		0.06		NA		NA		NA		0.37		1.08		0.02
301	-4727.53		NA		NA		-0.0001		0.06		NA		0.26		NA		NA		1.05		0.02
457	-4815.93		NA		NA		NA		0.06		NA		NA		0.02		0.31		1.07		0.02
361	-4793.48		NA		NA		NA		0.06		NA		0.20		0.03		NA		1.07		0.02
409	-4819.38		NA		NA		NA		0.06		0.07		NA		NA		0.39		1.08		0.02
395	-4833.18		NA		0.03		NA		0.06		NA		NA		NA		0.40		1.08		0.02
270	-4746.51		0.37		NA		-0.0001		0.06		NA		NA		NA		NA		1.05		0.01
271	-4801.88		NA		0.40		-0.0001		0.06		NA		NA		NA		NA		1.04		0.01
330	-4802.21		0.19		NA		NA		0.06		NA		NA		0.03		NA		1.07		0.01
345	-4784.40		NA		NA		NA		0.06		0.10		NA		0.03		NA		1.08		0.01

331	-4816.57		NA		0.20		NA		0.06		NA		NA		0.03		NA		1.07		0.01
298	-4809.09		0.20		NA		NA		0.06		NA		0.19		NA		NA		1.07		0.01
299	-4834.33		NA		0.20		NA		0.06		NA		0.23		NA		NA		1.07		0.01
282	-4793.78		0.46		NA		NA		0.06		0.18		NA		NA		NA		1.09		0.01
313	-4805.31		NA		NA		NA		0.06		0.01		0.26		NA		NA		1.08		0.01
285	-4730.61		NA		NA		-0.0001		0.06		0.10		NA		NA		NA		1.05		0.01
268	-4846.23		0.36		0.18		NA		0.06		NA		NA		NA		NA		1.07		0.01
Model averaged coefficients	-4803	330.9	0.05	0.21	0.03	0.21	0.00	0.00	0.06	0.003	0.01	0.09	0.04	0.13	0.01	0.02	0.10	0.22	1.07	0.04	

Table S2.9. Raw model coefficients and full averaged coefficients from the top commodity models (dAIC < 6) where change in forest cover is the response. One year time lag. Med corn = median corn price, CPI = crop production index, For prod = forest production, For rem = forest remaining, NFI non-food production index, Med rice = median rice price, Med rub = median rubber price, Med sug = median sugar price.

	(Intercept)	SE	Med corn	SE	CPI	SE	For prod	SE	For rem	SE	NFI	SE	Med rice	SE	Med rub	SE	Med sug	SE	Time	SE	Model weight
Model																					
265	-4862.09		NA		NA		NA		0.0601		NA		NA		NA		NA		1.06		0.17
269	-4836.39		NA		NA		-0.0002		0.0598		NA		NA		NA		NA		1.05		0.15
333	-4815.99		NA		NA		-0.0002		0.0596		NA		NA		0.04		NA		1.06		0.07
329	-4845.84		NA		NA		NA		0.0599		NA		NA		0.03		NA		1.07		0.07
297	-4834.65		NA		NA		NA		0.0598		NA		0.20		NA		NA		1.08		0.05
266	-4861.48		0.33		NA		NA		0.0601		NA		NA		NA		NA		1.07		0.04
393	-4873.57		NA		NA		NA		0.0602		NA		NA		NA		0.22		1.07		0.04
301	-4807.10		NA		NA		-0.0002		0.0595		NA		0.21		NA		NA		1.06		0.04
267	-4907.83		NA		0.2912		NA		0.0605		NA		NA		NA		NA		1.07		0.03
281	-4877.63		NA		NA		NA		0.0603		-0.08		NA		NA		NA		1.06		0.03
270	-4836.75		0.27		NA		-0.0002		0.0598		NA		NA		NA		NA		1.05		0.03
397	-4846.20		NA		NA		-0.0002		0.0599		NA		NA		NA		0.17		1.06		0.03
271	-4879.54		NA		0.2738		-0.0002		0.0602		NA		NA		NA		NA		1.06		0.02
285	-4841.58		NA		NA		-0.0002		0.0599		-0.03		NA		NA		NA		1.05		0.02
361	-4828.26		NA		NA		NA		0.0597		NA		0.14		0.03		NA		1.08		0.01
345	-4863.45		NA		NA		NA		0.0601		-0.09		NA		0.03		NA		1.07		0.01
457	-4851.32		NA		NA		NA		0.0600		NA		NA		0.03		0.07		1.07		0.01
365	-4798.02		NA		NA		-0.0002		0.0594		NA		0.14		0.03		NA		1.07		0.01
330	-4847.16		0.08		NA		NA		0.0599		NA		NA		0.03		NA		1.07		0.01
331	-4849.63		NA		0.0226		NA		0.0600		NA		NA		0.03		NA		1.07		0.01

Model averaged coefficients	-4849	379.2	0.026	0.16	0.02	0.18	-0.0001	0.0001	0.06	0.004	-0.005	0.07	0.023	0.1	0.007	0.02	0.017	0.11	1.06	0.06

Table S2.10. Raw model coefficients and full averaged coefficients from the top commodity models (dAIC < 6) where change in forest cover is the response. Two year time lag. Med corn = median corn price, CPI = crop production index, For prod = forest production, For rem = forest remaining, NFI = non-food production index, Med rice = median rice price, Med rub = median rubber price, Med sug = median sugar price.

	(Intercept)	SE	Med corn	SE	CPI	SE	For prod	SE	For rem	SE	NFI	SE	Med rice	SE	Med rub	SE	Med sug	SE	Time	SE	Model weight
Model																					
265	-5052.38		NA		NA		NA		0.06		NA		NA		NA		NA		1.08		0.25
269	-5093.28		NA		NA		-0.0002		0.06		NA		NA		NA		NA		1.04		0.18
329	-5059.43		NA		NA		NA		0.06		NA		NA		0.02		NA		1.09		0.05
266	-5029.09		-0.21		NA		NA		0.06		NA		NA		NA		NA		1.08		0.05
267	-4995.22		NA		-0.24		NA		0.06		NA		NA		NA		NA		1.08		0.05
393	-5066.24		NA		NA		NA		0.06		NA		NA		NA		0.11		1.08		0.04
281	-5065.00		NA		NA		NA		0.06		-0.04		NA		NA		NA		1.08		0.04
297	-5052.17		NA		NA		NA		0.06		NA		-0.01		NA		NA		1.08		0.04
333	-5104.49		NA		NA		-0.0002		0.06		NA		NA		0.02		NA		1.04		0.03
270	-5064.63		-0.27		NA		-0.0002		0.06		NA		NA		NA		NA		1.03		0.03
271	-5039.57		NA		-0.22		-0.0002		0.06		NA		NA		NA		NA		1.04		0.02
397	-5100.33		NA		NA		-0.0002		0.06		NA		NA		NA		0.06		1.04		0.02
285	-5099.98		NA		NA		-0.0002		0.06		-0.02		NA		NA		NA		1.04		0.02
301	-5093.26		NA		NA		-0.0002		0.06		NA		-0.001		NA		NA		1.04		0.02
Model averaged coefficients	-5064	410.5	-0.02	0.16	-0.02	0.18	-0.0001	1.07e-4	0.06	0.004	-0.003	0.07	-0.0005	0.07	0.002	0.01	0.007	0.09	1.06	0.06	

Table S2.11. Raw model coefficients and full averaged coefficients from the top producer price models (dAIC < 6) where change in forest cover is the response. No time lag. For rem = forest remaining, Prod cass = producer price for cassava, prod corn = producer price of corn, Prod rub = producer price of rubber, Prod sug = producer price of sugar

	(Intercept)	SE	For rem	SE	Prod cass	SE	Prod corn	SE	Prod rub	SE	Prod sug	SE	Time	SE	Model weight
Model															
34	-4816.38		0.06		NA		NA		NA		NA		1.07		0.5223
42	-4836.13		0.06		NA		NA		0.10		NA		1.07		0.0988
36	-4816.61		0.06		-0.03		NA		NA		NA		1.07		0.0957
38	-4818.89		0.06		NA		0.02		NA		NA		1.07		0.0956
50	-4813.07		0.06		NA		NA		NA		-0.002		1.07		0.0956
Model averaged coefficients	-4818	335.5	0.06	0.004	-0.003	0.17	0.002	0.18	0.01	0.15	-0.0002	0.02	1.07	0.04	

Table S2.12. Raw model coefficients and full averaged coefficients from the top producer price models (dAIC < 6) where change in forest cover is the response. One year time lag. For rem = forest remaining, Prod cass = producer price of cassava, Prod corn = producer price of corn, Prod rub = producer price of rubber, Prod sug = producer price of sugar

	(Intercept)	SE	For rem	SE	Prod cass	SE	Prod corn	SE	Prod rub	SE	Prod sug	SE	Time	SE	Model weight
Model															
34	-4862.09		0.06		NA		NA		NA		NA		1.06		0.5219
50	-4817.18		0.06		NA		NA		NA		-0.02		1.06		0.1029
36	-4875.06		0.06		0.19		NA		NA		NA		1.06		0.0980
42	-4873.20		0.06		NA		NA		0.10		NA		1.07		0.0930
38	-4843.97		0.06		NA		-0.12		NA		NA		1.06		0.0928
Model averaged coefficients	-4858	391.1	0.06	0.004	0.02	0.18	-0.012	0.18	0.012	0.17	-0.003	0.02	1.06	0.06	

Table S2.13. Raw model coefficients and full averaged coefficients from the top producer price models (dAIC < 6) where change in forest cover is the response. Two year time lag. For rem = forest remaining, Prod cass = producer price of cassava, Prod corn = producer price of corn, Prod rub = producer price of rubber, Prod sug = producer price of sugar

	(Intercept)	SE	Forest rem	SE	Prod cass	SE	Prod corn	SE	Prod rub	SE	Prod sug	SE	Time	SE	Model weight
Model															
34	-5052.38		0.06		NA		NA		NA		NA		1.08		0.47
50	-4941.11		0.06		NA		NA		NA		-0.05		1.06		0.14
36	-5051.34		0.06		0.37		NA		NA		NA		1.09		0.11
42	-5013.60		0.06		NA		NA		-0.27		NA		1.06		0.09
38	-5018.31		0.06		NA		-0.21		NA		NA		1.08		0.08
Model averaged coefficients	-5027	416.4	0.06	0.01	0.04	0.21	-0.02	0.18	-0.03	0.18	-0.01	0.03	1.08	0.06	

Table S2.14. Summary of new ELCs allocated during the study period, the stated primary crop, and the commodity and producer prices for the different crops.

			Commodity prices ($/ton)			Producer prices ($/ton)		
ELC primary crop	**Number of new ELCs**	**% of total**	**Max value**	**Min value**	**Mean value**	**Max value**	**Min value**	**Mean value**
Rubber	147	51.2	4830	585	1743	477	208	317
Sugar	23	8.0	573	138	282	3714	1193	2115
Rice	5	1.7	647	172	348	270	96	182
Cassava	14	4.9	-	-	-	263	96	185
Corn	2	0.7	295	90	151	316	74	197
Other	96	33.4						
Total	287	100.0						

Chapter 3

Does socioeconomic development predict forest cover in Cambodia?

3.0 ABSTRACT

Deforestation is caused by complex interactions between landscape actors, proximate drivers that influence decision making, and underlying causes that shape the proximate drivers. Local socioeconomic conditions are important factors contributing to these interactions, as they both shape the social and economic environment within which actors make decisions and influence the effects of broader underlying causes on local people. Previous studies have demonstrated that socioeconomic variables are important in describing and predicting deforestation both within Cambodia and the wider region, yet no study has attempted to formalise the relationships between forest cover and socioeconomic variables at the national scale for Cambodia. This is an important research gap, given the rapid social and economic change and the high rates of forest loss in the country. Therefore, this chapter models the relationships between socioeconomic predictors and forest cover at two spatial resolutions, and further describes these relationships via a cluster analysis. My analysis revealed very few socioeconomic variables that were effective predictors of forest cover at the resolution of either the commune or province. The biophysical and infrastructure control variables were more effective predictors of forest cover, and the analysis revealed important methodological challenges associated with modelling fine resolution data at a large scale. The cluster analysis produced five clusters from which a socioeconomic typology could be described, revealing that regions with large, rural, remote, poor provinces generally have much higher forest cover, and that there are a few examples of provinces that have seen economic development without significant forest loss. My results demonstrate the importance of scale when modelling social-ecological systems and highlight important associated challenges for future researchers. The cluster analysis demonstrates spatial and geopolitical patterns in socioeconomic development across Cambodia and relates these patterns to forest cover. Importantly for policy makers, the cluster analysis suggests that economic development within provinces need not rely on deforestation.

3.1 INTRODUCTION

Tropical deforestation is a significant threat to biodiversity, ecosystem processes, and local people (Estoque et al., 2019; Frewer and Chan, 2014), and is particularly insidious in its complexity (Kong et al., 2019; Mena et al., 2006; Rowcroft, 2008). The drivers of forest loss in the tropics are not only numerous and multifaceted, but they operate at multiple scales and are comprised of complex feedback loops between ecological, biophysical, social, cultural, political, and economic factors (Geist and Lambin, 2003, 2002; Mannan et al., 2019; Shrestha et al., 2018; X. Xu et al., 2019). This complexity means that underlying drivers operating at national, regional, or even global scales manifest themselves in a variety of proximate causes, which themselves are governed and shaped by local conditions (Fox and Vogler, 2005; Geist and Lambin, 2002; Van Den Hoek et al., 2014). The dynamics between drivers that operate at different scales makes disentangling the causes of deforestation highly contextual, making generalisations difficult to draw and increasing the value of local studies.

3.1.1 Socioeconomics and deforestation

Local socioeconomic conditions are important factors in understanding the link between broader drivers of land use change (LUC) and deforestation, and can be effective predictors of forest loss (Bonilla-Bedoya et al., 2018; Liu et al., 2016; Redo et al., 2012). Proximate causes of deforestation such as agricultural expansion and infrastructure development are often closely linked via feedback loops and dependencies to socioeconomic conditions including poverty, migration, local economies, and land and wealth inequality (Geist and Lambin, 2002; Khuc et al., 2018). Therefore, understanding the link between socioeconomics and forest cover at different scales is a crucial step in the development of effective economic and environmental policies that have positive effects on both people and forests.

Socioeconomics can encompass a huge variety of conditions that describe the social, demographic, and economic state of local people, and can affect which drivers of LUC are most influential in causing forest loss (Mena et al., 2006). The complexity of social-ecological systems means that it is challenging for researchers to identify and model the appropriate socioeconomic predictors of forest loss, but there is a wealth of research that has helped to disentangle relationships in specific locations and at specific scales. At the local scale, socioeconomic drivers and economics that affect decision-making processes within households, coupled with institutional factors, are often the most relevant for influencing LUC (Gatto et al., 2015; Van Den Hoek et al., 2014). Poverty was once believed to be the single most important socioeconomic driver of deforestation (e.g., Lomborg 2001), although further research has added significant nuance to this argument (Geist and Lambin, 2003), while other studies have demonstrated that poverty played very little role at all in deforestation (Onojeghuo and Blackburn, 2011).

Poverty itself is a complex metric encompassing a multitude of factors such as income, wealth, land, agriculture, migration, education, and healthcare, all of which interact to influence deforestation (Khuc et al., 2018). Inequalities in land, income, and wealth, and insecure land tenure and forest rights for local people are all common factors in driving deforestation (Ceddia, 2019). Such inequalities, in combination with debt and overpopulation, drive the expansion of agriculture and other natural resource-based activities, to the detriment of forests, as local people strive for subsistence and economic development (Ceddia et al., 2015; Culas, 2012).

3.1.2 Socioeconomics and deforestation in Asia

Studies from Asia have highlighted the importance of socioeconomics in influencing the effects of economic and other underlying drivers on deforestation. The differences in population density between urban and rural locations and the choice of agricultural crop had an interaction effect on deforestation in Indonesia (Gatto et al., 2015), and changes in urban structure and local economic development boosted in-migration in Shenzhen, China, which drove urban forest fragmentation (Gong et al., 2013). Population density has been shown to drive forest loss in India (Krishnadas et al., 2018), and in Pakistan, Mannan et al (2019) found that a combination of geographic, socioeconomic, and environmental factors were effective predictors of deforestation and other LUC, whereas Zeb et al (2019) found that household demographics and poverty were underlying factors of forest clearance for livestock and agricultural expansion. In Thailand and Vietnam livelihoods and local economics were highly influential in farmer's decision-making related to LUC (Nguyen et al., 2017), and in the mountainous regions of Southeast Asia it has been national policies in combination with local economics that governed LUC (Fox and Vogler, 2005).

The extensive literature on the socioeconomic predictors of deforestation emphasises the breadth and complexity of relationships between local socioeconomic conditions, broader economic factors, the environmental context, and government policy. The scale at which studies are undertaken is revealed to be important, as is local context. For example, the two case studies from Pakistan (Mannan et al., 2019; Zeb et al., 2019) are from very similar areas within the country, yet their analyses were carried out at different spatial resolutions, and they identify different socioeconomic predictors of forest loss. Therefore, environmental and economic policies that improve socioeconomic conditions for local people without forest loss and environmental degradation will require an understanding of the relationships between socioeconomics and forest cover at different scales.

3.1.3 Cambodia

Since the early 1990s, after more than two decades of war and unrest, Cambodia has experienced extraordinary economic development and social change (Milne and Mahanty, 2015; Solcomb, 2010). There have been significant improvements in rates of poverty reduction, access to services, and education, yet inequality between the rich and the poor has increased (World Bank, 2014). There has been dramatic socioeconomic development in Cambodia's major urban centres, yet rural, marginalised groups and ethnic minorities, particularly in the remote provinces, largely remain poor with minimal access to services, and where insecure land tenure leaves them exposed to land grabbing and conflict (Hammer, 2008; Ironside, 2008; Neef and Touch, 2012; Phillips and Davy, 2021). Such rapid social and economic changes make identifying the drivers of deforestation particularly challenging, as broad-scale drivers and their effect on local landscape actors, and the subsequent proximate causes of deforestation, are likely to fluctuate rapidly over time and space.

There are several studies from Cambodia that have focussed on socioeconomic predictors of deforestation, which provide some important context. At the national scale, human population pressure has been identified as an important driver of deforestation (Dasgupta et al., 2005), and in Northwest Cambodia there have been many direct and indirect drivers of deforestation since 1975, including repatriation of Khmer Rouge soldiers and in-migration following the end of the civil conflict, refugee repatriation, the subsequent clearance for subsistence agriculture, and the expansion of cash crops such as cassava (Hought et al., 2012; Kong et al., 2019). In the Angkor Basin, home to the Angkor temples, a complex mix of global, regional, and local drivers including tourism, climate change, government policies, economic development, and environmental management caused over 23% of the existing forest cover to be lost to agricultural expansion and charcoal production between 1989 and 2005 (Gaughan et al., 2009).

Integrated conservation and development projects (ICDPs) that aim to tackle both forest loss and socioeconomic development at the same time have had mixed results (e.g., Geist & Lambin 2003; Chambers et al. 2020; Bernhard et al. 2021). These projects can have unintended consequences for a number of reasons, including poor management of incentives or weak enforcement of protective laws, misinterpretation of stakeholder motivations, or failure to account for underlying economic drivers operating at a broader scale (Chambers et al., 2020). National economic and environmental policies, and interventions such as ICDPs, will be likely to fail if the relationships between forest cover and loss and: 1) broad economic drivers; and 2) local socioeconomic conditions are not understood and accounted for. In Chapter 1, I addressed the relationships between macroeconomic drivers and forest loss at the national scale. Previous studies have evaluated the relationships between forest cover and socioeconomics in small, discrete locations in Cambodia (Dasgupta et al., 2005; Gaughan et al., 2009; Hought et al., 2012; Kong et al., 2019), but to my knowledge, no study has attempted this at a national scale.

Therefore, in this chapter I aim to fill this research gap by exploring whether high resolution spatially explicit socioeconomic data from across Cambodia can be used to predict forest cover. This will reveal whether certain features of socioeconomic development, or indeed lack of development, can be considered proximate causes of deforestation, and whether there is spatial heterogeneity in the effects. These insights will contribute to the development of future conservation and development interventions, and to policy development. I will: 1) model the relationship between socioeconomic variables and the proportion of forest cover for the whole country at two spatial resolutions (Province, Commune) using generalised liner mixed models; and 2) use a cluster analysis to create a provincial-level socioeconomic typology which further describes the relationships between socioeconomic development and forest cover.

3.2 METHODS

3.2.1 Study area

This study area for this chapter is the whole of Cambodia. See Chapter 1 section 1.2 for a detailed background to the country, and Chapter 1 section 1.2.1 for detailed biophysical characteristics of the country. There are 24 provinces in Cambodia, each of which is made up of several further administrative layers (Figure 3.1). Districts are the administrative level below province, and each district is comprised of multiple communes, with each commune containing multiple villages. The number of communes is not static, with changes in the number of communes between years reflecting shifting administrative boundaries. Between 2007 and 2012 the number of communes ranged from 1,317 (2007) to 1,512 (2012).

3.2.2 Data sources

Socioeconomic variables were extracted from the Cambodian Commune Database for the years 2007 – 2012 (Table 3.1) which are available from Open Development Cambodia (www.opendevelopmentcambodia.net). Data on economic land concessions, protected areas, and elevation (digital elevation model), and shapefiles for the country, provinces, and communes were provided by the Royal Government of Cambodia (via the Wildlife Conservation Society). Forest cover layers were taken from the publicly available European Space Agency Climate Change Initiative (ESACCI) satellite data.

3.2.3 Variable selection

The response variable was the proportion of forest cover (in either a Commune or a Province) and was calculated using the ESACCI data product (see 'data processing' below). Socioeconomic and control variables were selected based on a combination of previous studies, data availability, and the authors' knowledge of Cambodia. Socioeconomic variables were selected to create 8 variable sets reflecting different aspects of socioeconomic status and development, each of which was hypothesised to be either a driver or predictor of forest cover (Table S3.1, Dasgupta et al. 2005; Mena et al. 2006; Rowcroft 2008; Luck et al. 2009; Ty et al. 2012; Kristensen et al. 2016; Bonilla-Bedoya et al. 2018). The variable sets were population demographics (n=8), education (n=4), employment (n=5), economic security (n=2), access to services (n=4), crime and legal disputes (n=2), migration (n=2), and control variables (n=6). Control variables were included to account for the effects of environmental and other human factors including presence of economic land concessions (Abdullah and Nakagoshi, 2007; Davis et al., 2015; X. Xu et al., 2019), presence of protected areas (Bonilla-Bedoya et al., 2018), elevation (Ty et al., 2012), and distance to human infrastructure (Ty et al., 2012). A habitat control variable was excluded because the response variable (proportion of forest cover) was extracted from a land cover layer and represented a specific type of habitat, resulting in non-independence between the response and habitat.

3.2.4 Data processing

The proportion of forest cover response variable was extracted from the ESACCI product by totalling the number of pixels (1 Pixel = 0.09km^2) in each year and in each commune and province classified as bands 50, 60, 61, 62, 70, 71, 72, 80, 81, 82, 90, and 100 (Table S3.2). The number of pixels were converted into km^2, and this was divided by the total area (km^2) of the unit (commune, province). Forest cover data processing was done in QGIS (QGIS Geographic Information System v3.16). Predictor variables were checked for collinearity, and if two variables in the same set had a correlation coefficient of >0.6 then generally one was removed (Supporting Information).

Data from the Commune Database were at the resolution of individual village, and so the selected variables (Table 3.1) were aggregated (averaged using either mean or median, or summed) to the commune and province level after error checking and cleaning (see Supporting Information for details on aggregation and error checking). This resulted in between 1,317 and 1,512 communes, and 23 Provinces (excluding Phnom Penh). The number of communes changed between years due to administrative changes. Some variables were converted from raw values to proportional data to account for large differences in commune and province size and human population (Table 3.1). Data were checked for errors in R (Supporting Information, R Core Team, version 4.0).

3.2.5 Modelling

This analysis aimed to model the relationships between forest cover and socioeconomic variables within communes between 2007 – 2012. The results of initial commune-level modelling prompted further aggregation of the data to the province-level and models were built to investigate the relationships between forest cover and socioeconomic variables within provinces for the same time period.

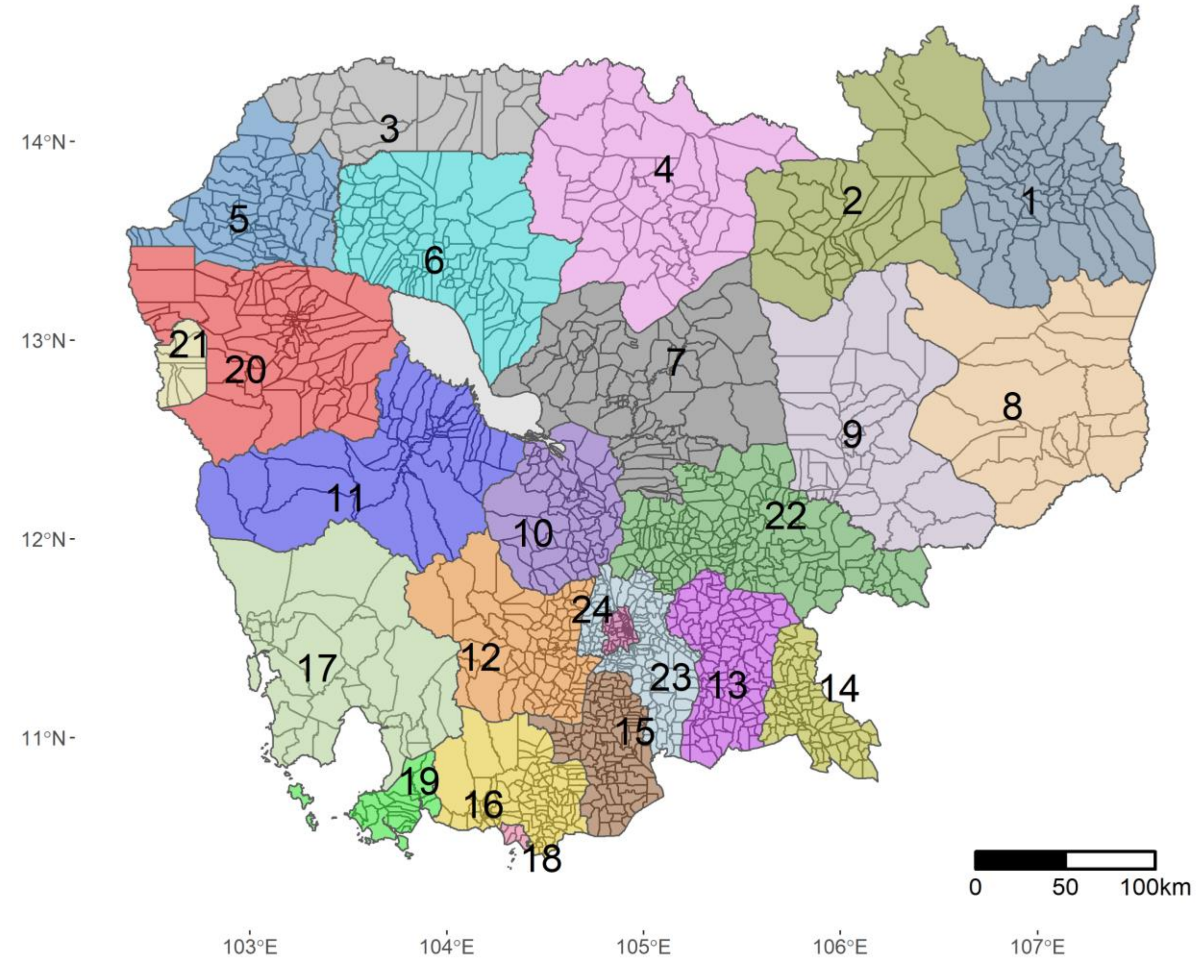

Figure 3.1. A map of Cambodia with the 24 provinces coloured and numbered, with the smaller communes shown with black lines within each province. The provinces are 1 – Ratanak Kiri, 2 – Stung Treng, 3 – Otdar Meanchey, 4 – Preah Vihear, 5 – Banteay Meanchey, 6 – Siem Reap, 7 – Kampong Thom, 8 – Mondul Kiri, 9 – Kracheh, 10 – Kampong Chhnang, 11 – Pursat, 12 - Kampong Speu, 13 – Prey Veng, 14 – Svay Rieng, 15 – Takeo, 16 – Kampot, 17 – Koh Kong, 18 – Kep, 19 – Preah Sihanouk, 20 – Battambang, 21 – Pailin, 22 – Kampong Cham, 23 – Kandal, 24 – Phnom Penh (capital city).

3.2.5.1 Commune-level models

Generalised linear mixed models (GLMM) with beta errors were built with commune nested within province as random intercept terms to account for repeat measurements and the hierarchical data structure, and year as a random slope term to account for temporal autocorrelation (Zuur et al., 2009). The natural logarithm of commune area (km^2) was used as an offset term in all models to account for large variation in commune size. A beta error distribution was used due to the response being a proportion (i.e., continuous and bounded by 0 and 1, Ferrari and Cribari-Neto, 2004), and the models were parameterised for zero-inflation using the 'glmmTMB' package in R (Brooks et al., 2017). Due to the large number of available predictor variables, maximal within-set models were run first for each of the 8 variable sets (Table S3.5), and variables with no effect were dropped. Simplified models were compared with maximal models using likelihood ratio tests and analysis of variance tests. If a variable set had only one variable, this was automatically taken forward. Because assessment of term significance in GLMMs is complex, predictions and plots were made for all terms before being dropped to ensure noteworthy effects were not being missed. This process resulted in a final set of 13 variables which were used to create a candidate set of 10 models (Table S3.6). Prior to running the 10 pre-defined models, a global model containing all 13 predictor variables was run, and diagnostics assessed to ensure acceptable model fit (tests were conducted for overdispersion, residuals versus fitted, and quantile-quantile of random effects, Supporting Information, Harrison et al (2018)). Following an information theoretic approach (Burnham and Anderson, 2007) models were compared via AIC to select the top model or models.). Marginal (fixed effects only) and conditional (fixed and random effects) pseudo-R^2 values were calculated based on Nakagawa & Schielzeth (2017) using the R package 'MuMIn' (Bartoń, 2020). To investigate the variation in effects between provinces, predictions were made for each variable within each commune and the 50% quantile from all commune-level predictions within each province was extracted as the provincial median prediction. Confidence intervals for all prediction plots were calculated as 2 × SE (Zuur et al., 2009).

3.2.5.2 Province-level models

The same GLMM model formulation was used for the province-level models except that commune was removed from the random effects structure. Based on provincial-level histograms of predictor variables, which revealed two distinct 'peaks' in 14 of the variables, these predictors were converted to categorical variables by splitting the data by the mean, resulting in "high" and "low" values (Table 3.1). Following an information theoretic approach, a candidate set of models was created (Table S3.7) and model comparison was done using AIC. Confidence intervals for all prediction plots were calculated as 2 × SE (Zuur et al., 2009).

3.2.6 Cluster analysis

Agglomerative clustering was conducted to create a typology for provinces based on the socioeconomic variables in Table 3.1 (excluding control variables). Several agglomerative clustering approaches were assessed. These were single linkage, complete linkage, unweighted pair-group using arithmetic averages (UPGMA), unweighted pair-group using centroids (UPGMC), Ward's minimum variance, and flexible clustering. The methods were compared using cophenetic correlation and Gower distance metrics, and the appropriate number of clusters (k) was selected using the matrix correlation statistics (Borcard et al., 2018). The capital city of Phnom Penh, which is technically a province in itself, was removed prior to clustering because it has extreme values for many of the variables and is thus an outlier that affects the clustering.

Table 3.1. Variables selected for the socioeconomic models and the transformations done for the modelling. Variables with a * indicate they were included in the cluster analysis. Variables range from 2007 – 2012.

Set	Variable	Transformation for analysis	Province-level class	Details
Demographics	Total population*		NA	Includes women, men, and children of all ages
	Population density*			
	Number indigenous*	Proportion of total population	Categorical	Total number of people who are indigenous/ethnic minority (non-Khmer, as defined by the RGC)
Education	Males aged 6 – 24 in school*	Proportion of total number of males aged 6 - 24		Number of males aged 6 - 24 in full time education
Employment	Number of adults employed in primary sector*	Proportion of total adult population	Categorical	The primary sector includes agriculture (rice and other crop farming), fishing, livestock farming, forestry, and non-timber forest product collection (Kenessey 1987)
	Number of adults employed in secondary sector*	Proportion of total adult population	Categorical	The secondary sector includes wood-based production (e.g. furniture), metal- and glass-based production, foodstuff production, plastic- and rubber-based production, textiles production (Kenessey 1987)
Economic security	Number of families with <1ha rice land (including no rice land)*	Proportion of total number of families	Categorical	
	Number of families who keep pigs*	Proportion of total number of families	Categorical	
Access to services	Distance to nearest school*		Categorical	Median distance from any village in the commune to the nearest school (primary or secondary)
	Number of families with access to waste collection*	Proportion of total number of families		

	Distance to the Commune Office*			Median distance from any village in the commune to the Commune Office (government administration office)
Crime and legal disputes	Number of criminal cases*	Criminal cases per capita	Categorical	Includes murder, theft, and other criminal cases
	Number of land conflict cases*		Categorical	In the previous 12 months
Migration	Number of in-migrants*		Categorical	Migration into the commune
	Number of out-migrants*		Categorical	Migration out of the commune
Control	Mean elevation (masl)		Categorical	Mean elevation for the commune
	Distance to international border (km)		Categorical	Distance from the centre of the commune to the nearest international border
	Distance to Provincial Capital (km)		Categorical	Distance from the centre of the commune to the centre of the provincial capital (town or city)
	Presence of economic land concessions			Binary. 1 = part or all of an economic land concession falls within the boundary of the commune, 0 = no economic land concession falls within the commune boundary
	Presence of protected area			Binary. 1 = part or all of an protected area falls within the boundary of the commune, 0 = no protected area falls within the commune boundary. "Protected area" includes Wildlife Sanctuary, National Park, Protected Landscapes, Multiple-use areas, RAMSAR sites
	Protected area category			None = no protected area falls within commune, MULTI = more than one category of protected area falls within commune, WS = wildlife

sanctuary, NP = national park, PL = protected landscape, MUA = multiple-use area, RMS = RAMSAR

3.3 RESULTS

3.3.1 Socioeconomic predictors of forest cover at the Commune level

Initial within-set model selection resulted in a final candidate set with 10 models and 14 unique variables (Table S3.6). All models except model 8 and model 10 had some support (delta AIC < 4), and so models 1 to 7 and model 9, were model averaged to obtain full averaged coefficients. The socioeconomic variables that were retained in the final averaged model set were population density, the proportion of males (aged 6 to 24 years old) in school, the proportion of families with pigs, the median distance to the nearest school, the proportion of families with access to waste collection, the number of criminal cases per capita, the proportion of adults employed in the primary sector, and the number of out-migrants (Table S3.6). The random effects term with the highest variance was province (the range across all averaged models was 2.14 – 2.15 [SD range = 1.46 – 1.47]) followed by commune (the range across all averaged models was 1.92 – 1.93 [SD range = 1.388 – 1.389], Table 3.2). The variance explained by year at both the commune and province level was low (the ranges across all averaged models were 0.001 – 0.002 [SD range = 0.038 – 0.039] for province, and 0.009 – 0.01 [SD range = 0.09 – 0.1] for commune).

The largest positive effect was from mean elevation (rate ratio = 1.63, Table 3.2) which relates to a predicted forest cover proportion of 0.02 within an average commune (i.e., all other fixed and random effects set to their mean) when mean elevation is at the minimum within the country. When the mean elevation is at the maximum found within the country (and all other terms are set to their mean), the proportion of forest cover is predicted to be 0.4. This highlights that higher elevation areas of Cambodia are much more likely to be forested than lower elevation areas. The strongest negative effect was from population density (rate ratio = 0.97, Table 3.2) which relates to a predicted proportion of forest cover of 0.030 at the minimum value of population density found within the country, contrasting with a predicted proportion of forest cover of 0.028 at the highest value of population density within the country. In addition to population density, the proportion of adults employed in the primary sector, the proportion of families with access to waste collection, and the presence of ELCs in a commune all had negative effects on the proportion of forest cover in a commune. All the remaining socioeconomic and control variables had a positive effect on the proportion of forest cover (Table 3.2). All other model terms, excluding the presence of ELCs, had positive effects on forest cover (Table 3.2). These effects suggest that remote communes (large distances to provincial capitals) that are centrally located within the country (far away from international borders), and those that have PAs and higher levels of out-migration are predicted to have high forest cover.

The results from the final commune-level model must, however, be viewed with caution because model validation revealed some serious underlying issues. As is suggested by the variance associated with the commune-level random effect term, there was large variation between communes for all variables (predictors and response, Figure 3.2). This between-group variance results in the model being unsuitable for generalised (i.e., 'global') predictions (Figure 3.2). Intercept and slope estimates between communes, even within the same province, varied hugely (Figure 3.3), and this issue was highlighted in diagnostic plots where we see that the assumption of normality of deviations of the conditional means of the random effects (for commune) from the global intercept is violated (Figure S3.3). Furthermore, the model residuals displayed heteroskedasticity, with the model predicting particularly poorly for lower values of the response (Figure S3.4). Therefore, drawing general inferences about the relationships between forest cover and socioeconomics at the country level using this model is inappropriate.

3.3.2 Socioeconomic predictors of forest cover at the Province level

The province-level models were run to eliminate the commune-level variation and to identify any broader relationships between forest cover and socioeconomics. A candidate set of 19 models was built and an evaluation of AIC showed that two models had sufficient support (delta AIC <4, model 3 and model 8 Table S3.7). The random effects term with the highest variance was Province (the range across models was 3.03 – 3.05 [SD range = 1.741 – 1.747]), followed by year (0.0075 [SD = 0.09]). Presence of ELCs and presence of PAs had the largest two positive effects relative to their refences levels (no ELCs, no PAs), suggesting that provinces that have those two features are predicted to also have a higher proportion of forest cover (Table 3.2, rate ratios = 7.35 and 19.49 respectively). Provinces with lower proportions of males aged 6 to 24 in school and lower proportions of adults employed in the primary sector are predicted to have a higher proportion of forest cover than those with lower proportions of the same variables (Table 3.2). Provinces with higher median distances to the nearest school, higher mean elevation, and higher median distances to the provincial capital are predicted to have a higher proportion of forest cover than provinces where the opposite is true (Table 3.2). Three socioeconomic variables were retained in the final models, but the effects were weak. For example, the difference in the prediction proportion of forest cover between a province with a low proportion of males in school and a province with a high proportion (with all other variables set to "low"), is 0.014. The difference in the predicted proportion of forest cover between a province with low median distances to schools and a province with high median distances is 0.01.

Presence of PAs had the largest effect on predicted proportion of forest cover. The proportion of forest cover predicted for a province with PA presence is 0.5 higher than for a province with no PA presence. This emphasises the relationship between forested land and protected areas in Cambodia. The size of the effects for the three socioeconomic predictors (proportion of males in school, the proportion of adults in the primary sector, and distance to school) in the top models suggest that these variables have little power to predict forest cover at the provincial level in Cambodia, but that the presence of protected areas and economic land concessions do.

Table 3.2. Model outputs and odds ratios from the averaged models from the commune-level analysis and the province-level analysis. Reported coefficients are on the link (log) scale. Reported variance is the mean across the individual models that were included in model averaging.

Variable	Variance	Std.Dev	Coefficient	SE	Odds ratio[a]
Commune-level final model					
Random effects					
Commune (intercept)	1.93	1.39	-	-	
Year/Commune (slope)	0.01	1.39	-	-	
Province (intercept)	2.14	1.46	-	-	
Year/Province (slope)	0.002	0.04	-	-	
Fixed effects					
Intercept	-	-	-6.49	0.37	
Population density	-	-	-0.03	0.21	0.971
Proportion primary sector	-	-	-0.003	0.01	0.99
Number of out-migrants	-	-	0.0008	0.002	1.001
Proportion with access to waste collection	-	-	-0.002	0.005	0.99
Proportion males in school	-	-	4.9×10^{-5}	0.001	1
Proportion families with pigs	-	-	1.0×10^{-5}	0.001	1
Criminal cases per capita	-	-	5.3×10^{-5}	0.0004	1
Median distance to nearest school (km)	-	-	1.4×10^{-4}	0.001	1
Mean elevation	-	-	0.49	0.05	1.63
Distance to In'tl border	-	-	0.43	0.1	1.54
Distance to Provincial capital	-	-	0.22	0.05	1.25
ELC presence	-	-	-0.01	0.007	0.99
PA presence	-	-	0.02	0.02	1.02
Province-level final model					
Random effects					
Province (intercept)	3.04	1.74	-	-	
Year/Province (slope)	0.008	009	-	-	
Fixed effects			-	-	
Intercept	-	-	-13.4	0.74	
Males in school (low)	-	-	0.06	0.03	1.06
Distance to school (low)	-	-	-0.04	0.03	0.97
Proportion primary sector	-	-	0.005	0.02	1.01
Mean elevation (low)	-	-	-0.07	0.02	0.93
Distance to border (low)	-	-	0.01	0.02	1.01
Distance to Prov capital (low)	-	-	-0.07	0.02	0.94
Presence of economic concessions (1)	-	-	1.99	0.64	7.35
Presence of PAs (1)	-	-	2.97	0.76	19.5

[a] Odds ratio = exp(coefficient)

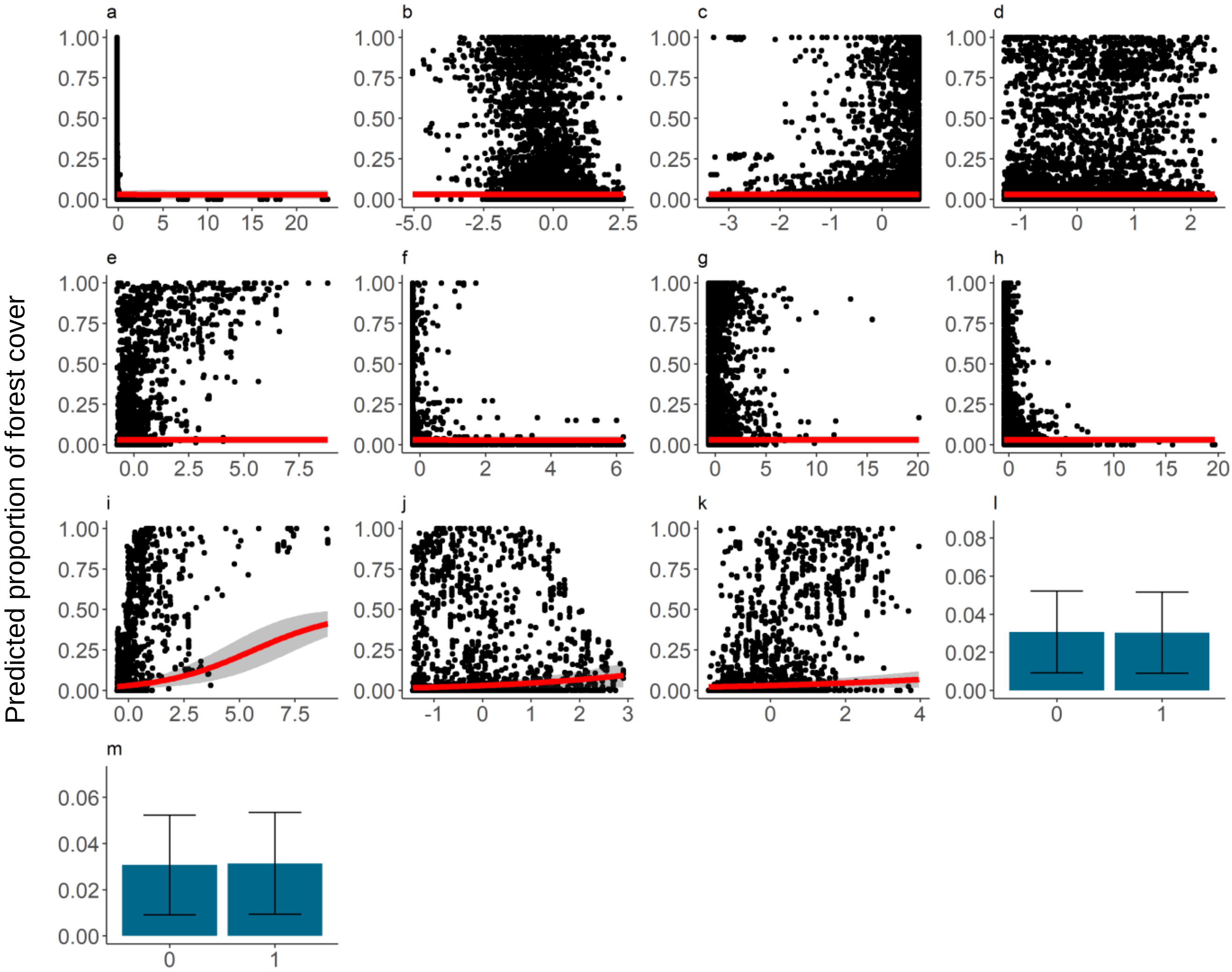

Figure 3.2. Predicted relationships (red lines, blue bars) between socioeconomic variables and the proportion of forest cover in Cambodia between 2007 – 2012 from the top averaged, zero-inflated, commune-level model. Predictions are 'global' i.e., all random effects were set to their mean values, and thus predictions are not for any specific commune. Black points are the raw data points. a = population density, b = proportion of males in school, c = proportion of adults employed in the primary sector, d = proportion of families with pigs, e = median distance to the nearest school, f = proportion of families with access to waste collection, g = number of criminal cases per capita, h = number of out-migrants, i = mean elevation (masl), j = distance to international border (KM), k = distance to provincial capital (KM), l = presence of economic land concessions, m = presence of protected areas. All predictor variables, excluding presence of ELCs and PAs were centred and scaled.

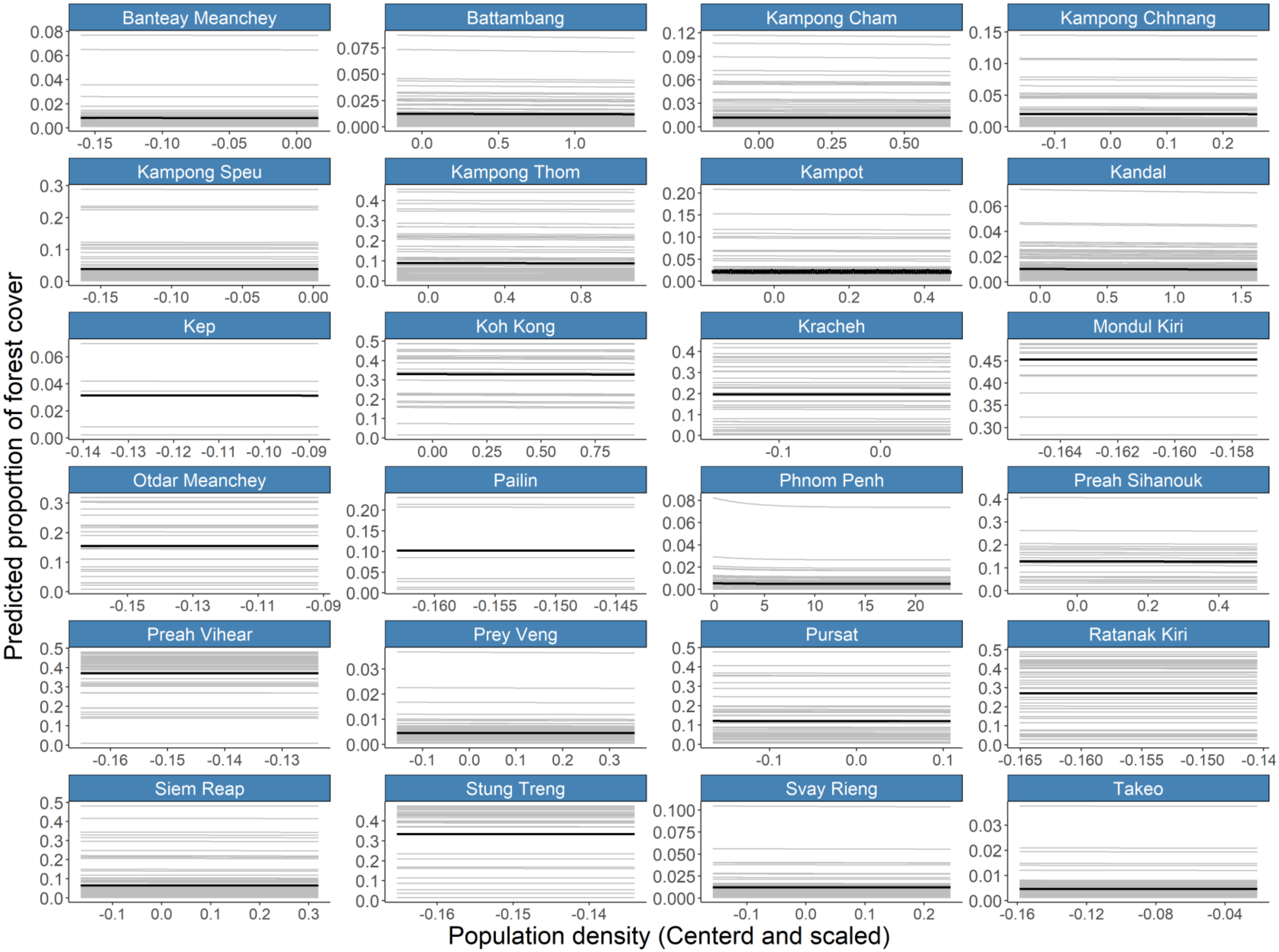

Figure 3.3. Predicted relationships between population density and the proportion of forest cover within Cambodian provinces between 2007 – 2012 using the top averaged commune-level model. Faded grey lines are the predictions for each individual commune within each province. Black lines are the mean provincial predictions, which were computed using the 50% quantile from all commune predictions. Plot panels have non-standard y axis ranges.

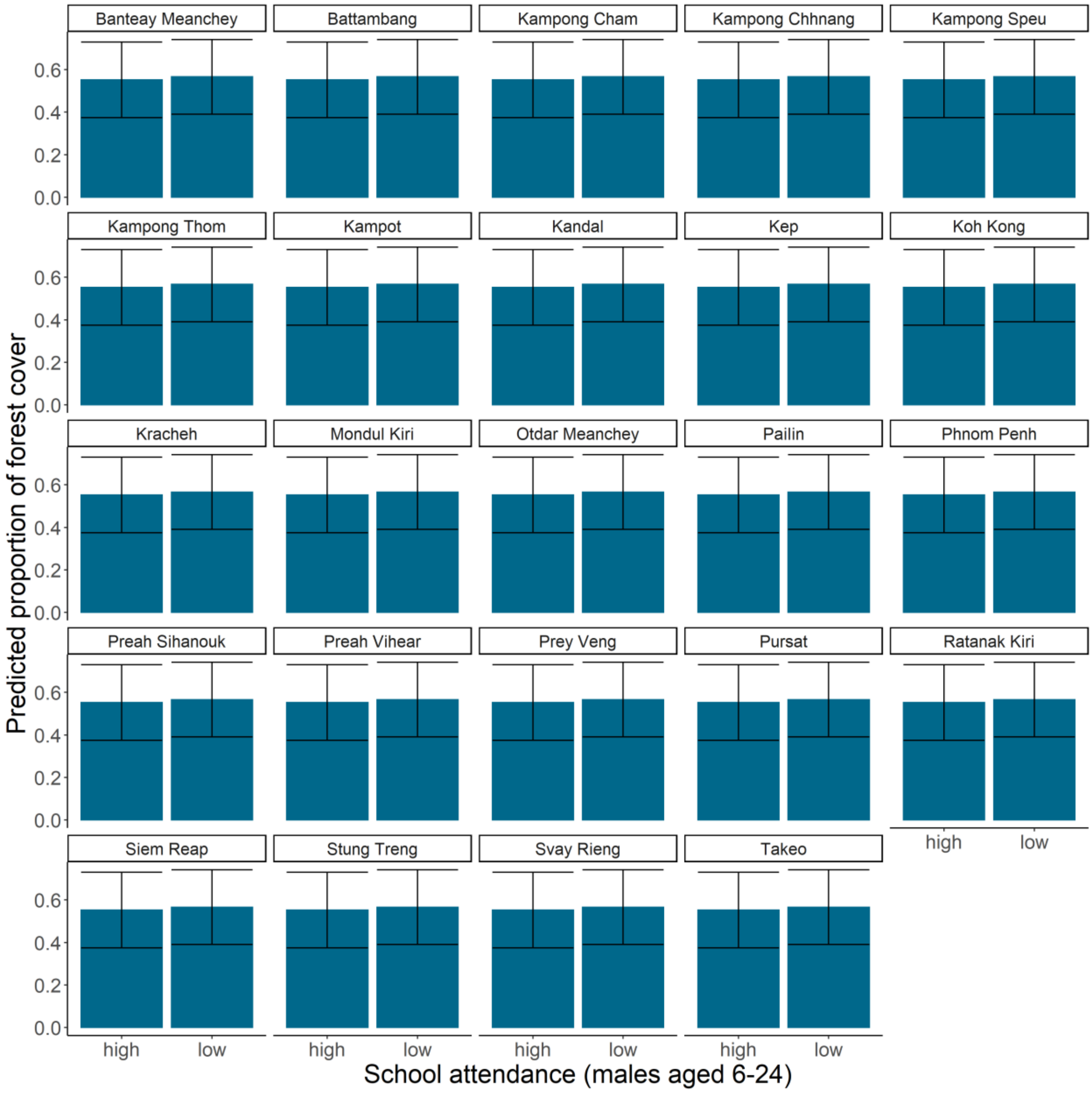

Figure 3.4. Predicted proportion of forest cover within each Cambodian province given high and low levels of school attendance (males aged 6 – 24 in school) from the top averaged province-level model. All other variables in the model were set to their reference level (distance to school = low, proportion of adults in the primary sector = low, elevation = low, distance to international border = low, distance to provincial capital = low, economic land concession = yes, protected area = yes). Error bars are equal to 2 × standard error.

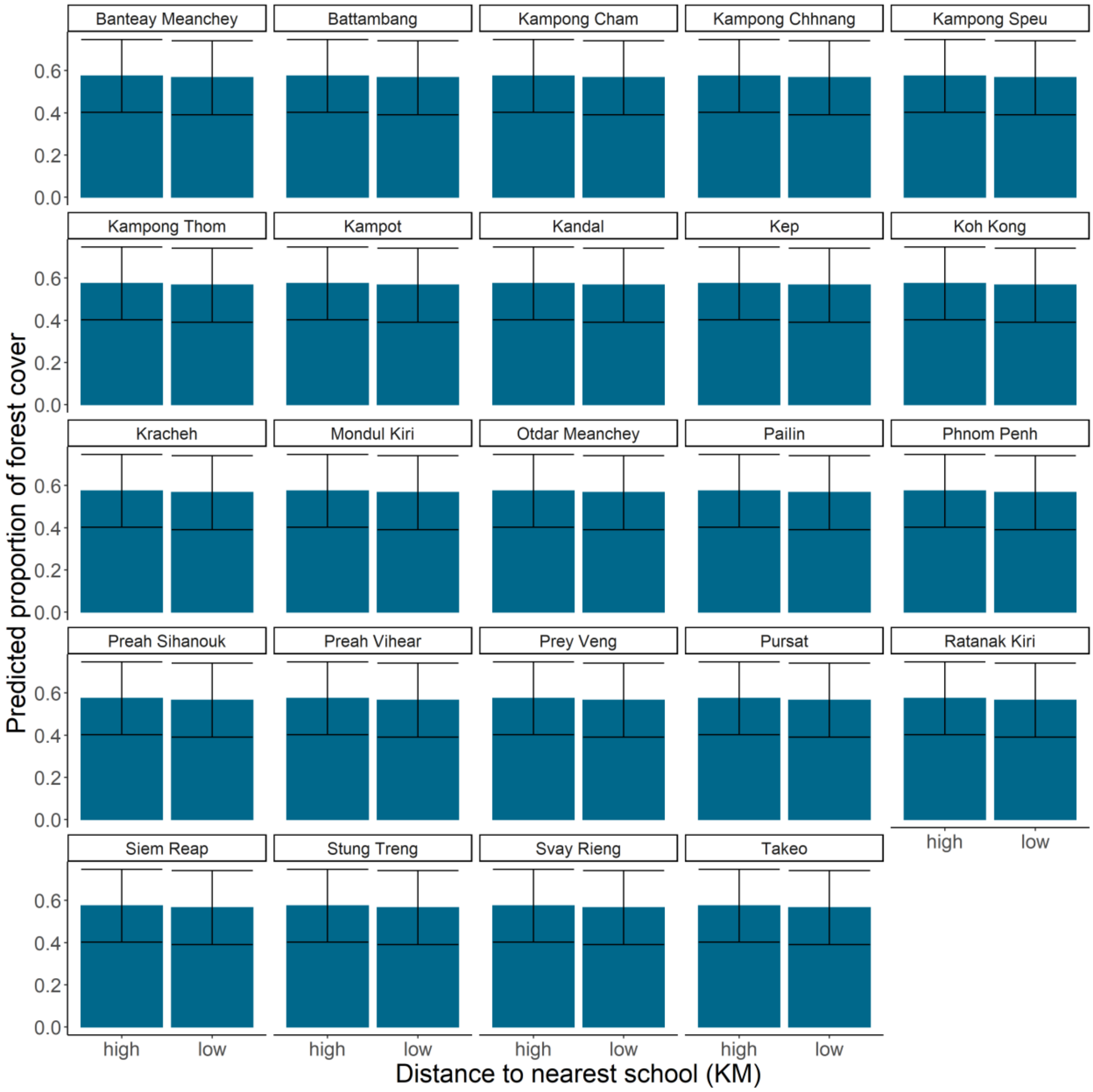

Figure 3.5. Predicted proportion of forest cover within each Cambodian province given high and low distances to the nearest school from the top averaged province-level model. All other variables in the model were set to their reference level (school attendance = low, proportion of adults in the primary sector = low, elevation = low, distance to international border = low, distance to provincial capital = low, economic land concession = yes, protected area = yes). Error bars are present, but very small (error bars are equal to 2 × standard error).

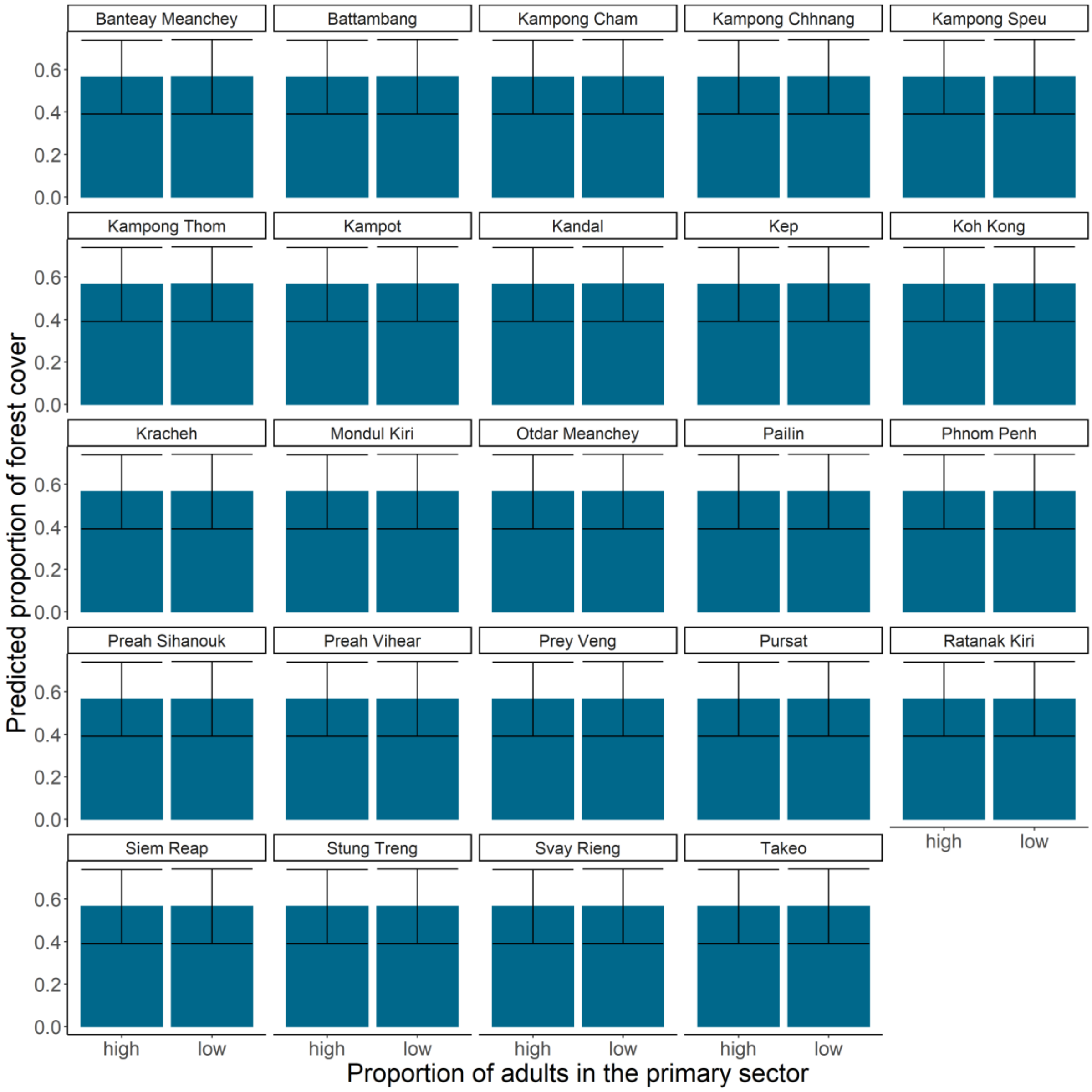

Figure 3.6. Predicted proportion of forest cover within each Cambodian province given high and low proportions of adults employed in the primary sector from the top averaged province-level model. All other variables in the model were set to their reference level (school attendance = low, distance to the nearest school = low, elevation = low, distance to international border = low, distance to provincial capital = low, economic land concession = yes, protected area = yes). Error bars are present, but very small (error bars are equal to 2 × standard error).

3.3.3 Cluster analysis

The UPGMA clustering had the highest cophenetic correlation (0.79) and the lowest Gower distance (254.14) and was therefore selected. The matrix correlation statistic suggested that 4 clusters were optimal, but that between 3 and 7 clusters had very similar support. When divided by 4 clusters, there was a large group (n = 16) of provinces that fell into a single cluster, and so I chose 5 clusters to add further nuance (Figure S3.5). The provinces within clusters were geographically contiguous (Figure

3.7), although clusters that had smaller cophenetic distances (i.e., were closer on the dendrogram, Figure S3.5) were not necessarily geographically contiguous. The largest cluster (cluster 5) dominated a central strip of the country, separating the smaller, and more similar clusters (Figure 3.7). These results suggest that provinces often have similar socioeconomic conditions to that of their neighbours, but that there are also distinct regions within the country that can be characterised by their socioeconomics rather than their geography. A heatmap of the socioeconomic variable values for each cluster revealed some distinguishing patterns (Figure 3.8). The largest cluster (cluster 5) was categorised by high or very high values of all variables, which translates to provinces with high population density, high education levels, high proportions of primary and secondary sector workers, and high migration (Table 3.3). This contrasts with cluster 2, which has predominantly low values for the socioeconomic variables which translates to provinces with low population density, low levels of education, low levels of primary sector employment (higher secondary sector employment), and low levels of migration (Table 3.3). Clusters 3 and 4 had the highest levels of migration (and interestingly the highest levels of land conflict), education, and population density, reflecting the presence of two of the three largest cities and significant urban development. Cluster 1 had the lowest population density, education, proportion of secondary sector workers, and migration, reflecting the clusters remote geography and rural character. Provinces within cluster 1 were also the most forested but had also lost the most forest during the study period (Figure 3.9). Provinces within cluster 5 were generally the next most forested after cluster 1 and had also lost large areas of forest during the study period (Figure 3.9). Cluster 3 had the least amount of forest, which was expected due to high levels of urbanisation and agriculture. Clusters 1 and 2 had the highest elevation, and clusters 1 and 5 had the highest mean distance to a provincial capital (Figure 3.9).

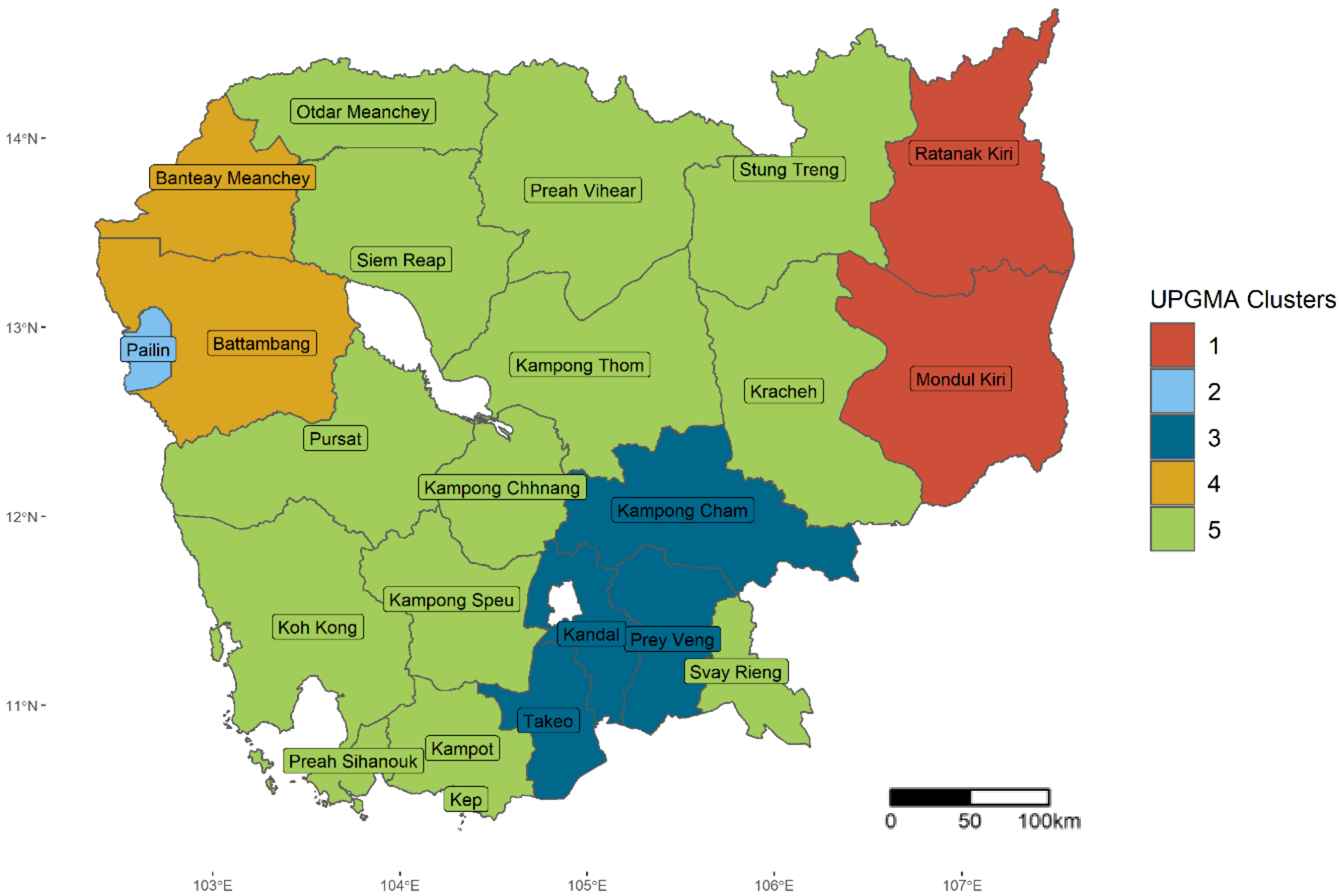

Figure 3.7. Map of Cambodia showing the clusters resulting from the unweighted pair-group using arithmetic averages (UPGMA) method. Province s are labelled. The upper white polygon is the Tonle Sap lake, and the lower white polygon is the city of Phnom Penh, both of which were excluded from the analysis.

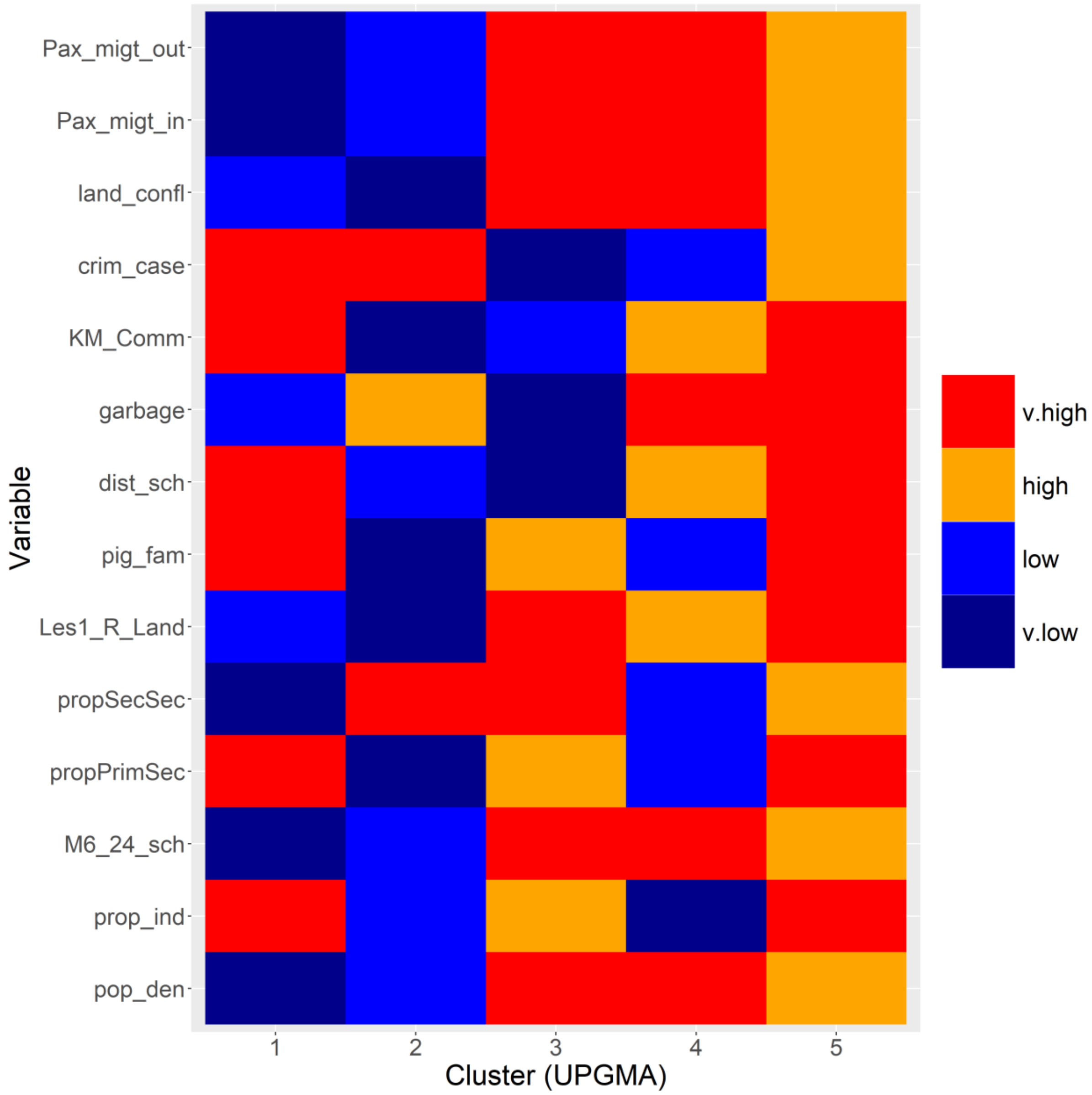

Figure 3.8. Heatmap showing variable value categories for each cluster resulting from the unweighted pair-group using arithmetic averages (UPGMA) method. Variables were categorised as "v.low" if the mean (across provinces within that cluster) was below the 25% quantile for that variable across the whole country, "low" if the mean was above 25 and below 50%, "high" if the mean was above 50% but below 75%, and "v.high" if the mean was above the 75% quantile. Pax_migt_out = numbers of out-migrants, Pax_migt_in = numbers of in-migrants, land_confl = number of land conflicts, crim_case = criminal cases per capita, KM_Comm = distance to commune office, garbage = proportion of families with access to waste collection, dist_school = distance to nearest school, pig_fam = proportion of families who keep pigs, Les1_R_Land = proportion of families with no rice land, propSecSec = proportion of adults employed in the secondary sector, propPrimSec = proportion of adults employed in the primary sector, M6_24_sch = proportion of males aged 6-24 in education, prop_ind = proportion of the population that is indigenous, pop_den = population density.

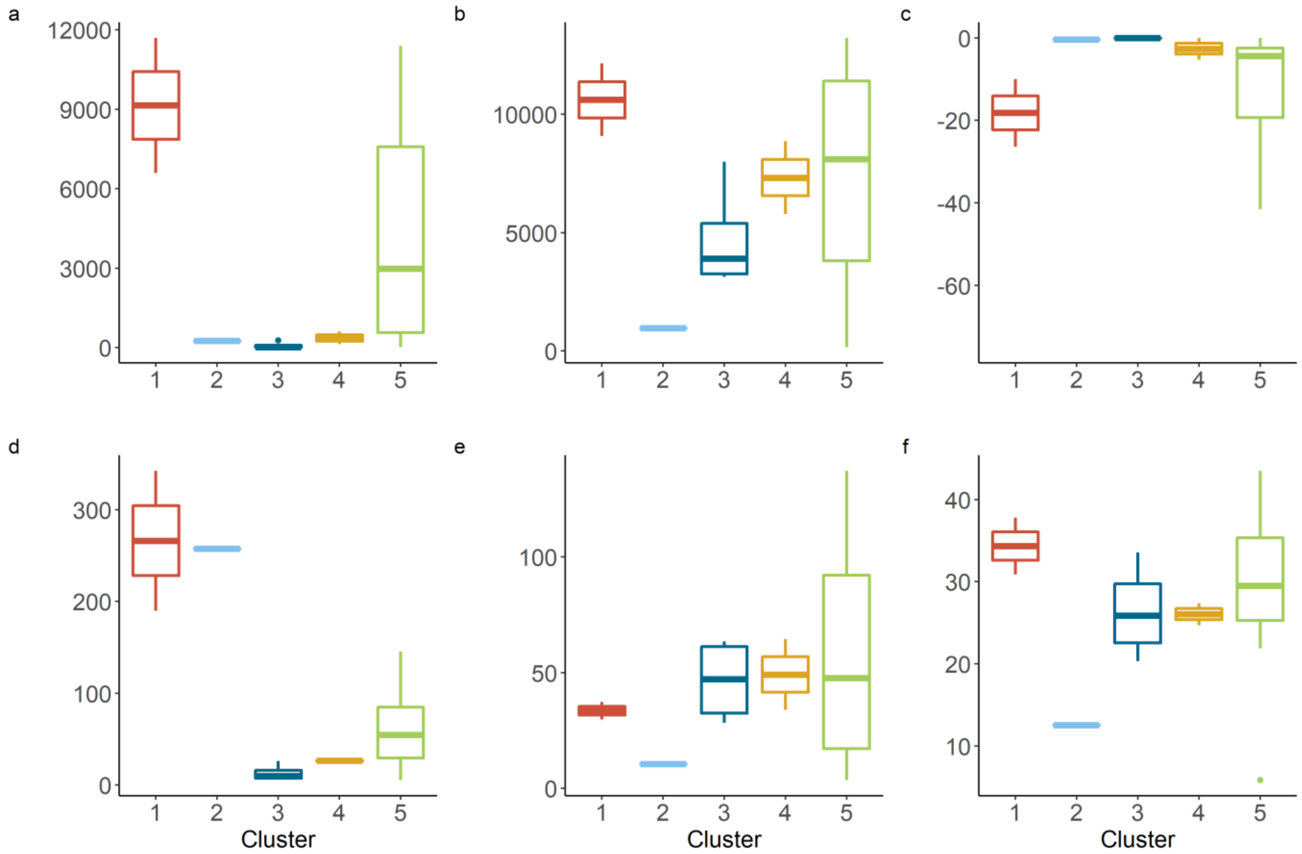

Figure 3.9. Boxplots showing the distribution of environmental variables for each cluster: a = mean forest area (km^2), b = mean province area (km^2), c = change in forest cover between 2007-2012 (km^2), d = mean elevation (masl), e = mean distance to international border (Km), f = mean distance to a provincial capital (Km). Boxplots show the median (centre line within boxes), 25 and 75% percentiles (box edges), and minimum and maximum values (upper and lower whiskers, not exceeding 1.5 × interquartile range). 5 UPGMA clusters.

Table 3.3. Descriptive typology of the provinces and clusters within Cambodia, clustered using socioeconomic variables and the unweighted pair group using arithmetic mean (UPGMA)

UPGMA cluster	Provinces	Description
1	Mondulkiri, Ratanikiri	Very large provinces with very high elevations. Very low population density, and very high proportion of indigenous people. Very low education levels, very high proportion of primary sector workers and very low proportion of secondary sector workers. Economic security provided by rural livelihoods - few people have no farmland and livestock ownership is common. Very low access to services, high crime per capita, low land conflict, and very low migration levels.
2	Pailin	Very small province with very high elevations. Low population density and low proportion of indigenous people. Low levels of education, low proportion of people in the primary sector but higher proportion of people in the secondary sector. Very few people with no farmland, but very little livestock ownership. High access to services and high crime per capita. Low land conflict and low migration.
3	Kampong Cham, Kandal, Prey Veng, Takeo	Small provinces with very low elevations. Very high population density and high proportion of indigenous people. Very high levels of education, high proportion of people in the primary sector, but very high proportion of people in the secondary sector. High proportion of people with no farmland, but high levels of livestock ownership. High access to services and low crime per capita. But very high migration levels and very high rates of land conflict.
4	Banteay Meanchey, Battambang	Large provinces with low elevations. Very high population density and very low proportion of indigenous people. Very high levels of education, and relatively low proportion of workers in the primary and secondary sectors (suggesting higher proportions in the other sectors e.g., tertiary). High proportion of people with no farmland, and low levels of livestock ownership (suggesting very urban). Low access to services, but this may be explained by the mean size of the provinces in this cluster (there is high access to garbage collection). Low crime per capita, but very high migration and very high rates of land conflict
5	Kampong Chhnang, Kampong Speu, Kampong Thom, Kampot, Kep, Koh Kong, Kracheh, Otdar Meanchey, Preah Sihanouk, Preah Vihear, Pursat, Siem Reap, Stung Treng, Svay Rieng	Large provinces with high elevations. High population density and very high proportion of indigenous people. High levels of education, and a high proportion of workers in both primary and secondary sectors. Very high proportion of people with no farmland, but also very high proportion of people with livestock. Low access to services (although very high access to garbage collection) - this may be an artefact of the very large mean area of the provinces in this cluster. Very high crime rates, very high migration, and very high rates of land conflict.

3.4 DISCUSSION

Understanding the drivers and proximate causes of deforestation is critical for the development of sustainable environmental policies and forest conservation initiatives. In this study, I have modelled the relationships between variables describing socioeconomic development and forest cover at multiple scales and have investigated these relationships using two different approaches. This study has revealed some important relationships from which we can make inferences regarding the socioeconomic, geographical, and biophysical predictors of forest cover across Cambodia. Furthermore, I have revealed key methodological issues, particularly around scale and model variance, that are likely to be common in analyses such as this, which focus on large spatial scales and fine resolutions, but which often remain unexplored or unreported in the literature. Studies investigating the socioeconomic drivers of deforestation need to target multiple scales to build a cohesive picture of the social-ecological systems within which deforestation occurs, so that policy development targets the appropriate drivers at each scale (e.g., at different administrative levels).

3.4.1 The effect of scale on predicting forest cover

This analysis highlights the importance of scale when modelling complex social-ecological systems; researchers must not only select the scale of the analysis carefully but must also be aware of underlying variation which may be affecting estimates, requiring cautious interpretation of results. The results from the GLMMs have highlighted the effect of scale on predictors of forest cover. The direction of the effect of distance to an international border changes depending on whether you are looking at the commune-level or the province-level; it was positive within communes and negative within provinces. This reversal of effect direction between scales also occurs for the proportion of males in school (positive within communes and negative within provinces), and the presence of ELCs (negative within communes and positive within provinces). Taken together, the two models can add important nuance to the interpretation of results. Provinces that are close to international borders have higher forest cover, but within those provinces, the communes that are furthest away from the border are predicted to have the highest forest cover. Provinces furthest away from the major the urban centres of Phnom Penh, Siem Reap, and Battambang tend to be the large, rural provinces that have an international border (e.g., Mondul Kiri, Ratanak Kiri, Stung Treng, Koh Kong) and have high forest cover. Increases in human population density over time, including from in-migration, often result in agricultural expansion, exploitation of forest resources (e.g., timber), and increased urbanisation, all of which could be reducing forest cover. International borders promote the movement of people, commodities, economic activity, and all the associated infrastructure that is required to maintain such activity. When combined with illegal cross-border activities such as logging, land clearance, and the wildlife trade (see Evans et al. 2013), it is plausible that communes closer to the international borders are more likely to have reduced forest cover (Grogan et al., 2015). The reversal of effect direction for the presence of ELCs at different scales is also plausible. The placement of ELCs in remote, highly forested provinces has been common, and there has been much speculation surrounding the drivers of this strategy, with some arguing that the clearance of forest and subsequent timber sales from new ELCs is the primary source of income for concession companies (Davis et al., 2015; Vrieze and Kuch, 2012). This will, however, drive a loss of forest cover at a finer scale (i.e., the commune), resulting in a negative effect of ELC presence on forest cover.

3.4.2 Socioeconomic typography of provinces in Cambodia

The cluster analysis revealed an interesting pattern of distinct socioeconomic regions across Cambodia, suggesting that in many cases provinces that are adjacent to each other tend to have similar socioeconomic characteristics, resulting in clusters that are comprised of spatially contiguous provinces. The two cluster that generally display the largest differences are clusters 1 and 3. Cluster 1 contains the provinces of Mondul Kiri and Rattanak Kiri which are large, remote, and some of the least developed provinces in the country. They are home to the Eastern Plains Landscape which is one of the most important areas in SEA for biodiversity (Chapter 4; Gray et al., 2012; Nuttall et al., 2017, 2021). Mondul Kiri and Rattanak Kiri (cluster 1) have the highest forest cover, low population density, low access to services, and low migration. Economic development in the first two decades after the civil war was focused almost entirely on the major cities: Phnom Penh (cluster 3), Sihanoukville (cluster 5), and Battambang (cluster 4), with rural provinces remaining underdeveloped, inaccessible, and poor (Hughes and Un, 2011). The lack of infrastructure and access, coupled with low population density and few employment opportunities that limited in-migration, have all likely contributed to forest cover remaining high (Evans et al., 2013).

Conversely, Kampong Cham, Kandal, Prey Veng, Takeo (cluster 3) have the lowest levels of forest cover and the cluster contains the capital city of Phnom Penh and the surrounding provinces which are the hubs for industry and economic activity (such as the garment sector). Cluster 5, which contains the provinces of Kampong Chhnang, Kampong Speu, Kampong Thom, Kampot, Kep, Koh Kong, Kracheh, Otdar Meanchey, Preah Sihanouk, Preah Vihear, Pursat, Siem Reap, Stung Treng, Svay Rieng, is interesting because it contains the largest number of provinces. The expectation was that the provinces that most closely resembled cluster 1 (i.e., large, rural provinces with high forest cover) such as Stung Treng, Preah Vihear, and Koh Kong, would have been clustered either with cluster 1, or within a separate cluster. However, they were clustered with the central belt of provinces (e.g., Kampong Speu, Kampong Chhnang, Kampong Thom) which are almost exclusively low elevation agricultural provinces that are geared towards rice production. The inclusion of Stung Treng, Preah Vihear, and Koh Kong within this cluster and the resulting cluster typologies, suggest that there has been some success in increasing the socioeconomic status of rural, highly forested provinces without excessive loss of forest cover.

3.4.3 Methodological approach

3.4.3.1 Mixed models

The commune-level model revealed despite 8 non-control variables being selected in the final model set, the effects were very weak. I was limited in the socioeconomic variables that were available, and it is possible that the variables selected were simply poor predictors of forest cover. However, the modelling process revealed very large between-commune variation in both predictor and response variables, in addition to many random effect levels (between 1,317 and 1,512). Model predictions from the final averaged model, and from preliminary models, showed that the parameter estimates (intercepts and slopes) for a given socioeconomic variable (see Figure 3.3 for an example from population density) varied widely from commune to commune, even within the same province. Therefore, it is possible that the difficulty in estimating a single parameter from the surrounding "noise" resulted in the detection of weak, or no effects, rather than a genuine lack of effects. The province-level model was built to counter the issue of excessive between-commune variance by approaching the analysis from a different scale. Three socioeconomic variables remained in the final province-level model set but again, the effects were relatively weak. It is still possible that the weak effects represented a genuine lack of correlation between socioeconomics and forest cover, however, modelling the effects at a larger scale will simply mask the large variation that exists at the finer scale, rather than eliminating it. An advantage of GLMMs is the ability to quantify between-group variance, which not only offers crucial insight about the differences between groups (e.g., countries) from which inference can be drawn (Zuur et al., 2009), but can also highlight potential problems with 'global' predictions (i.e., predictions that are made with all random effect terms set at their mean). Yet very few studies that use these models for LUC report any values for variance associated with the random (group-level) effects. For example, Bhattari and Hammig (2004) use data from 63 countries to produce a single effect for GDP per capita on deforestation, yet do not report any value for country-level variance. The effect size is relatively small, and therefore if there was large between-country variance then the country-level effects could be vastly different, rendering the single global effect misleading.

The inherent complexity within social-ecological systems results in significant challenges when researchers attempt to model them (Basse et al., 2014). Taking this study as an example, a researcher has a choice between modelling at a large scale (e.g., national, regional) where effects may be weak or unrepresentative of much of the country or region, or modelling at a fine scale where effects may be swamped by variation resulting in the loss of the true signal. By reframing analytical goals and aiming for description of the data, for example using cluster analyses, over statistical hypothesis testing and attempts at explanation, researchers can reduce the need for increasingly complex data and models.

3.4.3.2 Cluster analysis

The purpose of the cluster analysis was to explore an approach that was different to the traditional statistical modelling I had done using GLMMs, and to remove the above issues of variance. I was interested to see what patterns would emerge when the underlying goal of statistical hypothesis testing (i.e., the effect of the predictor x on response y is significantly different from 0) was removed. The cluster analysis revealed patterns beyond those produced using the GLMMs and was therefore a worthwhile addition to the study. The advantage of clustering techniques such as UPGMA is that although there are metrics that can suggest optimal numbers of clusters, the researcher can select the number of clusters that is most useful for their particular investigation (Borcard et al., 2018). Unlike statistical models, cluster analysis does not produce estimates of effect sizes, nor can predictions be made. Nevertheless, by altering the number of clusters, investigating different clustering approaches, followed by considered exploratory analysis and plotting, a comprehensive picture of the study system can be produced. This may be a sensible first step in a larger analysis which can increase understanding of the system before modelling approaches are decided upon. Furthermore, methods such as cluster analysis are in some cases, conceptually simpler than advanced statistical and mechanistic modelling, making interpretation and explanation simpler.

3.4.4 Policy implications

The results of this study have highlighted that the regions of Cambodia that have the highest forest cover also tend to be the rural, remote, poor provinces with high proportions of indigenous people. It is people living within these areas that will be reliant on natural resources and forest products for their subsistence and livelihoods. In these circumstances, the efforts of an individual actor to increase their socioeconomic status is likely to include agricultural expansion, resulting in forest loss. Therefore, to avoid forests being the price of socioeconomic development, national and sub-national government need to develop economic policy frameworks that deliver economic benefits whilst encouraging forest protection, such as payments for ecosystem services schemes, and support for agricultural improvement technologies and diversification (Eliste and Zorya, 2015). The Cambodian government, however, has shown enthusiasm in the past for economic development via private land leases for industrial-scale commercial agriculture (Chapter 2), many of which have been awarded in rural, remote, forested land. These economic land concessions (ELCs) have frequently been placed on traditional lands of indigenous people, on the lands of the rural poor who had yet to be awarded legal land titles, and in areas of high forest cover, including protected areas (Beauchamp et al., 2018; Davis et al., 2015; Magliocca et al., 2019; Neef et al., 2013; Oldenburg and Neef, 2014; Vrieze and Kuch, 2012). Remote provinces with a low density of relatively poor inhabitants, low levels of land tenure security, and plentiful forests, are particularly vulnerable to the allocation of new ELCs, particularly if the economic policies of the last decade are pursued. Despite legal requirements to the contrary, ELCs often contribute very little to local economies, and are sources of land conflict, illegal settlement, and extensive, unregulated, and often illegal deforestation (Beauchamp et al., 2018; Davis et al., 2015; Global Witness, 2013; Milne and Mahanty, 2015; Neef et al., 2013; Oldenburg and Neef, 2014; Vrieze and Kuch, 2012; Watson et al., 2014). There has been a reduction in new ELC allocations in recent years (www.opendevelopmentcambodia.net), which may suggest that new avenues for economic development and growth in the agriculture sector are being developed.

Since the end of civil conflict in the early 1990s, there has been significant migration and resettlement into rural provinces as people move back into traditional homelands or move in search of new land to settle (Milne and Mahanty, 2015). This post-war migration has come at a cost to forest cover, as families look to establish and expand their agricultural land (Hought et al., 2012; Kong et al., 2019). The rural provinces with high forest cover are still vulnerable to in-migration and land speculation, as access to the provinces has improved significantly over the last decade and poor, landless families seek to establish themselves in frontier areas (Evans et al., 2013). This, and other studies, have demonstrated that increases in human population density can predict forest loss (Dasgupta et al., 2005; Krishnadas et al., 2018). In the context of poor environmental governance and weak institutions, as in Cambodia (Milne and Mahanty, 2015; Riggs et al., 2018), rural in-migration could continue to drive forest loss. Government policies for rural settlement and land titling need to pre-empt increased migration into rural areas, particularly those with protected areas, and ensure forest loss is minimised. The two most prominent settlement initiatives – social land concessions and Directive 01 – have been widely criticised for poor management and implementation, and both have resulted in the loss of forests inside protected areas (Milne 2013; Oldenburg & Neef 2014; Grimsditch & Schoenberger 2015, also see Appendix).

The cluster analysis placed the provinces Preah Vihear, Stung Treng, and Koh Kong into cluster 5, suggesting that these provinces have socioeconomic conditions similar to the wealthier, more developed provinces such as Siem Reap, and to provinces with extensive agriculture such as Kampong Chhnang. This placement was despite many similarities with the provinces in cluster 1 (Mondul Kiri, Rattanak Kiri), including being large, rural, and with high forest cover. This clustering suggests that Preah Vihear, Stung Treng, and Koh Kong have made progress in increasing the socioeconomic conditions of the population, without extensive forest loss (median forest loss within cluster 5 is less than for cluster 1). These improvements may have been driven by the expansion of economic sectors that do not rely on natural resource extraction or agricultural expansion, or indeed by the growth of nature-friendly sectors, such as ecotourism. These results warrant further investigation to identify whether there are specific policies, initiatives, economic conditions, or social movements that have improved socioeconomic conditions with minimal deforestation, and which could be replicated in other poor, forested provinces.

3.5. ACKNOWLEDGEMENTS

I am grateful to Nils Bunnefeld and Luc Bussière for support in designing this study, to Nils Bunnefeld and Jeroen Minderman for support with the analysis, and to Nils Bunnefeld, Phil McGowan, Kate Abernethy, and Jeroen Minderman for commenting on the chapter.

3.6. SUPPORTING INFORMATION

Each of the eight model sets were selected because they were hypothesised to be potential drivers or effective predictors of forest cover (Table S3.1). The predictors within each of the sets were selected as proxies for the set because of their relevance, or because they were the best quality data that related to the set.

Table S3.1. Hypothesised relationships between socioeconomic variables and the proportion of forest cover.

Set	Hypotheses	Variable(s)
Demographics	Communes/provinces with higher human populations and higher human population density will have lower forest cover due to urbanisation and agricultural expansion. Communes/provinces with higher indigenous populations will have higher forest cover because areas with high indigenous populations are more remote, and indigenous communities rely more on forests for traditional livelihoods.	Total population Population density Proportion indigenous
Education	Communes/provinces with lower levels of education will have lower forest cover because logging and forest clearance is conducted predominantly by young males of school age. Alternative hypothesis: communes/provinces with higher levels of education will have lower forest cover because education levels are likely to be higher in urban areas.	Proportion of males aged 6 – 24 in full time education
Employment	Communes/provinces with higher proportions of adults in the primary sector will have higher forest cover because these areas are likely to be more remote and have more natural resources such as forests. Communes/provinces with higher proportions of adults in the secondary sector will have lower forest cover as the secondary sector will be more prominent in urban/developed areas.	Proportion of adults employed in the primary sector Proportion of adults employed in the secondary sector
Economic security	Communes/provinces with higher proportions of families with poor economic security (farmland, livestock) will have lower forest cover because rural populations in areas with high forest cover have access to land and livestock, whereas poor families in urban/developed areas do not.	Proportion of families with <1ha of rice land Proportion of families who keep pigs
		Distance to nearest school

Access to services	Communes/provinces with large distances to schools are likely to be large, remote communes/provinces with high forest cover. Alternative hypothesis: areas with large distances to schools will lead to higher proportions of males out of education and engaging in forest clearing activities. Communes/provinces with higher proportions of families with access to waste collection will be in developed, urban areas and will have lower forest cover. Communes/provinces with larger distances to commune offices will be larger, more remote areas with higher forest cover. Alternative hypothesis: communes/provinces with larger distances to commune offices will have weaker governance and less law enforcement, resulting in lower forest cover.	Proportion of families with access to waste collection Distance to the Commune office
Crime and legal disputes	Communes/provinces with a higher number of criminal cases will be more urbanised area and therefore will have lower forest cover. Communes/provinces with a higher number of land conflicts will be in areas of high forest cover where land speculation and land disputes are high. Alternative hypothesis: communes/provinces with a higher number of land conflicts will be in areas with a high number of economic land concessions where forest clearance has occurred, and so will have lower forest cover.	Number of criminal cases Number of land conflicts
Migration	Communes/provinces with a high number of in-migrants will be urban areas with large industry (i.e., high job availability) and therefore low forest cover. Alternative hypothesis: communes/provinces with a high number of in-migrants will be areas with new economic land concessions which are often in areas of high forest cover. Communes/provinces with a high number of out-migrants will have higher forest cover because they are rural, remote areas with fewer job opportunities.	Number of in-migrants Number of out-migrants
Control	All of these variables have potential to influence forest cover within communes/provinces, yet were not specific targets for investigation. Therefore they were included as control variables.	Mean elevation Distance to international border Distance to provincial capital Presence of economic land concessions Presence of protected areas Protected area category

Table S3.2. European Space Agency Climate Change Initiative satellite bands. Bands highlighted in green were grouped to represent "forest cover" in both the macroeconomic and socioeconomic analyses.

Value	Label
0	No data
10	Cropland, rainfed
11	Herbaceous cover
12	Tree or shrub cover
20	Cropland, irrigated or post-flooding
30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)
50	Tree cover, broadleaved, evergreen, cosed to open (>15%)
60	Tree cover, broadleaved, deciduous, closed to open (>15%)
61	Tree cover, broadleaves, decisuous, closed (>40%)
62	Tree cover, broadleaves, deciduous, open (15 - 40%)
70	Tree cover, needleleaved, evergreen, closed to open (>15%)
71	Tree cover, needleleaved, evergreen, closed (>40%)
72	Tree cover, needleleaved, evergreen, open (15 - 40%)
80	Tree cover, needleleaved, deciduous, closed to open (>15%)
81	Tree cover, needleleaved, deciduous, closed (>40%)
82	Tree cover, needleleaved, deciduous, open (15 - 40%)
90	Tree cover, mixed leaf type (broadleaved and needleleaved)
100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)
110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
120	Shrubland
121	Evergreen shrubland
122	Deciduous shrubland
130	Grassland
140	Lichens and mosses
150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)
152	Sparse shrub (<15%)
153	Sparse herbaceous cover (<15%)
160	Tree cover, flooded, fresh or brakish water

3.6.1 Socioeconomic data cleaning

Prior to aggregation to the commune level, village data were checked for missing values. In some cases, villages had data for a subset of years but were missing data for other years. If the missing data were at the start of the study period or the end of the study period, it was assumed that the village was either an old or a new village. Villages can be merged with larger villages, or two sub-villages, or "*Kroms*", can be split into two distinct villages over time for administrative purposes. In these cases, the rows (years) with missing data were deleted, but the years with data were retained as these represent villages that existed in that year. If the missing data were in the middle of the study period (for more than one year), or if data for that village only exists for one or several years in the middle of the study period, then the data were assumed to be incomplete, and the village was deleted. If the village had data for all years except one, then the missing values were estimated using linear interpolation. If the village existed in all years, but was missing data from multiple years, the village was deleted. If an entire commune was missing in some years, the commune was deleted. The above cleaning process removed 312 villages (total number of villages = 84,195), or 0.37% of the data. Data were then split into individual years, and the final village-level data were aggregated to the commune- and province level using the operations defined below in Table S5.

After aggregation, each variable was checked for obvious errors or unlikely outliers via plotting of histograms and trends. Plots were done at the province level first, to identify any communes within a province that had particularly unusual values or trends. If unusual values or trends were identified the commune was investigated in more detail. Outlier values that appeared inconsistent or implausible were removed and replaced with a value estimated via linear interpolation (Figure S1). In some cases, where data had been converted from raw values to a proportion of the total population, errors in the raw data were discovered. This became clear when the resulting proportion was >1. In these cases, the proportion was changed to 1.

Table S3.3. Mathematical operations used to aggregate socioeconomic variables from the village to the commune and province level.

Variable	Operation
Total population	Sum
Number of families	Sum
Number of males aged 18-64	Sum
Number of females aged 18-64	Sum
Number of people aged over 61	Sum
Total number of indigenous people	Sum
Number of families whose main occupation is farming	Sum
Number of land conflict cases	Sum
Number of in-migrants	Sum
Number of out-migrants	Sum
Number of criminal cases	Sum
Proportion of population that is indigenous	Mean
Proportion of females aged 6-24 in full time education	Mean
Proportion of males aged 6-24 in full time education	Mean
Proportion of females aged 15-45 who are illiterate	Mean
Proportion of males aged 15-45 who are illiterate	Mean
Proportion of families whose main occupation is farming	Mean
Proportion of people who are primarily employed in the primary sector	Mean
Proportion of people who are primarily employed in the secondary sector	Mean
Proportion of people who are primarily employed in the tertiary sector	Mean
Proportion of people who are primarily employed in the quaternary sector	Mean
Proportion of families who have less than 1ha of farmland	Mean
Proportion of families who have buffalo	Mean
Proportion of families who have pigs	Mean
Proportion of families who have access to waste collection	Mean
Number of infant (<6mo) mortality cases	Mean
Number of child (<5 years old) mortality cases	Mean
Distance to the nearest school	Median
Distance to the Commune Office	Median
Distance to the nearest health centre	Median

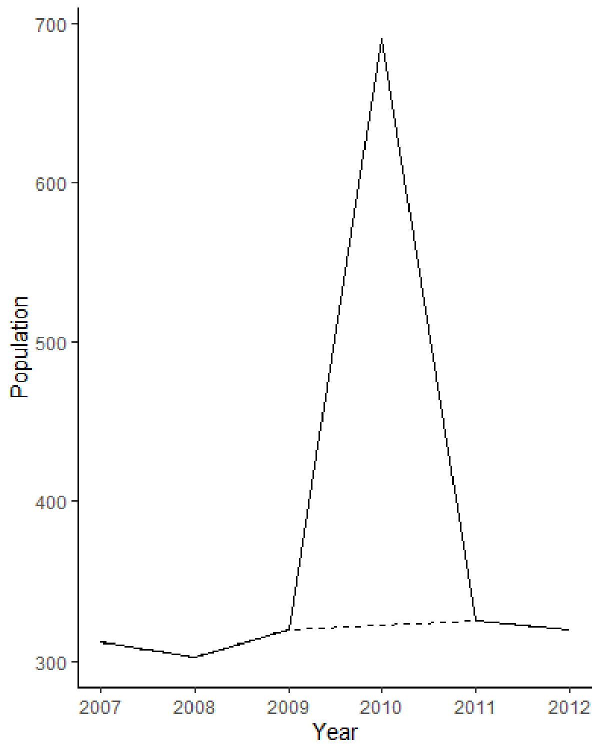

Figure S3.1. An example of linear interpolation for a commune with an implausible outlier. The example shows a value for the population of a commune in 2010 which is likely to be an error (solid line), and the resulting correction (dashed line).

3.6.2. Correlation

For both analyses, correlation of predictors was assessed.

For the socioeconomic variables, correlation was assessed within each variable set. If there were incidents of high correlation, a principal component analysis (PCA) was conducted to see which variables explained the most variance. Based on these analyses, the following decisions were made:

- Total population, number of families, number of males, number of females, and population over 61 were all correlated. Following a PCA, total population was selected.
- As expected, all education variables were highly correlated. In this case, the proportion of males aged 6-24 was selected (without a PCA) because in this cultural context, males are far more likely to be engaged in activities that contribute to forest loss.
- As expected, there was a negative correlation between the proportion of people employed in the primary sector and the proportion of people employed in the tertiary and quaternary sectors, and a correlation between the proportion of people employed in the primary sector and the proportion of people whose main occupation was farming. The PCA results suggested that the proportion of people employed in the primary sector (propPrimSec) and secondary sector (propSecSec) were the most valuable predictors.

- Proportion of people with less than 1 hectare of farmland, and proportion of families who keep buffalos, were dropped due to inconsistencies in the data which suggested changes in the data collection or questions over time.
- Distance to the nearest school (dist_sch) and distance to the nearest health centre (KM_Heal_cen) were correlated, and the PCA analysis was inconclusive about which variable to retain. Distance to school was retained based on the theory that forest clearance activities are more likely to be conducted by young males. An absence of accessible education is likely to be more of a driving factor in these activities than an absence of accessible health care.
- Both healthcare variables (infant mortality and child mortality) were dropped due to poor data quality.

A final assessment of correlation between predictor variables (after removal of the above) revealed no major correlations (Table S3.4).

Table S3.4. Correlation matrix for the socioeconomic variables. There were no coefficients greater than 0.6 or less than -0.6. tot_pop = total population, prop_ind = proportion indigenous, pop_den = population density, M6_24_sch = proportion males (aged 6-24) in education, propPrimSec = proportion in primary sector, propSecSec = proportion in secondary sector, Les1_R_Land = proportion with <1ha rice land, pig_fam = proportion families with pigs, dist_sch = median distance to nearest school, garbage = proportion households with waste collection, KM_Comm = median distance to commune office, land_confl = number of land conflicts, crim_case = criminal cases per capita, Pax_migt_in = number of in-migrants, Pax_migt out = number of out-migrants, mean_elev = mean elevation, dist_border = distance to international border, dist_provCap = distance to provincial captial

	tot_pop	prop_ind	pop_den	M6_24_sch	propPrimSec	propSecSec	Les1_R_Land	pig_fam	dist_sch	garbage	KM_Comm	land_confl	crim_case	Pax_migt_in	Pax_migt_out	mean_elev	dist_border	dist_provCap
tot_pop		-0.33	0.42	0.19	-0.31	0.04	0.15	-0.28	-0.36	0.10	0.00	0.32	-0.10	0.39	0.35	-0.34	0.14	-0.10
prop_ind	-0.33		-0.22	-0.36	0.15	-0.04	-0.16	0.20	0.43	-0.04	0.21	-0.08	0.13	-0.12	-0.14	0.47	-0.18	0.06
pop_den	0.42	-0.22		0.30	-0.46	0.16	0.20	-0.26	-0.35	0.35	-0.21	-0.03	-0.12	0.11	0.05	-0.31	0.01	-0.39
M6_24_sch	0.19	-0.36	0.30		-0.09	0.01	0.11	0.07	-0.37	0.03	-0.21	0.04	-0.09	-0.04	-0.06	-0.20	0.07	-0.21
propPrimSec	-0.31	0.15	-0.46	-0.09		-0.26	0.09	0.50	0.24	-0.32	0.14	0.05	0.01	-0.18	-0.21	0.02	0.08	0.27
propSecSec	0.04	-0.04	0.16	0.01	-0.26		0.02	-0.14	-0.08	0.05	-0.05	-0.02	-0.02	0.04	0.03	-0.02	0.04	-0.09
Les1_R_Land	0.15	-0.16	0.20	0.11	0.09	0.02		0.01	-0.23	-0.08	-0.11	-0.01	-0.09	0.07	0.01	-0.21	0.20	-0.14
pig_fam	-0.28	0.20	-0.26	0.07	0.50	-0.14	0.01		0.19	-0.14	0.06	-0.02	-0.03	-0.21	-0.21	0.02	-0.10	0.15
dist_sch	-0.36	0.43	-0.35	-0.37	0.24	-0.08	-0.23	0.19		-0.07	0.36	-0.06	0.07	-0.12	-0.15	0.36	-0.14	0.38
garbage	0.10	-0.04	0.35	0.03	-0.32	0.05	-0.08	-0.14	-0.07		-0.06	-0.03	0.04	0.05	0.02	0.00	-0.05	-0.13
KM_Comm	0.00	0.21	-0.21	-0.21	0.14	-0.05	-0.11	0.06	0.36	-0.06		0.09	0.03	0.04	0.00	0.11	-0.05	0.24
land_confl	0.32	-0.08	-0.03	0.04	0.05	-0.02	-0.01	-0.02	-0.06	-0.03	0.09		0.27	0.13	0.05	-0.06	0.04	0.07
crim_case	-0.10	0.13	-0.12	-0.09	0.01	-0.02	-0.09	-0.03	0.07	0.04	0.03	0.27		-0.03	-0.05	0.16	-0.13	0.02
Pax_migt_in	0.39	-0.12	0.11	-0.04	-0.18	0.04	0.07	-0.21	-0.12	0.05	0.04	0.13	-0.03		0.42	-0.10	0.01	0.01
Pax_migt_out	0.35	-0.14	0.05	-0.06	-0.21	0.03	0.01	-0.21	-0.15	0.02	0.00	0.05	-0.05	0.42		-0.12	0.02	-0.03
mean_elev	-0.34	0.47	-0.31	-0.20	0.02	-0.02	-0.21	0.02	0.36	0.00	0.11	-0.06	0.16	-0.10	-0.12		-0.26	0.15
dist_border	0.14	-0.18	0.01	0.07	0.08	0.04	0.20	-0.10	-0.14	-0.05	-0.05	0.04	-0.13	0.01	0.02	-0.26		-0.05
dist_provCap	-0.10	0.06	-0.39	-0.21	0.27	-0.09	-0.14	0.15	0.38	-0.13	0.24	0.07	0.02	0.01	-0.03	0.15	-0.05	

3.6.3. Modelling

Table S3.5. Within-set models for the commune-level socioeconomic analysis. Maximal within-set models were run followed by subsequent, less complex models, to identify the most important variables within each set. The variables with the largest effects were taken forward to the final candidate set. Only variables with negligible effects were dropped. If a variable set only had one variable it was automatically taken forward. All models included an offset term which was the logged commune area (km²), and a random effects structure of the form ~(year|Province/Commune).

Model set / model	Variables				
Population demographics					
popdem.m1	Population density	Proportion indigenous			
popdem.m2	Population density				
Education					
edu.m1	Proportion males in school				
Employment					
emp.m1	Proportion primary sector	Proportion secondary sector			
emp.m2	Proportion primary sector				
Economic security					
econ.m1	Proportion no farmland	Proportion with pigs			
econ.m2	Proportion with pigs				
Access to services					
acc.m1	Distance to school	Access to waste collection	Distance to commune office		
acc.m2	Distance to school	Access to waste collection			
acc.m3	Access to waste collection				
Crime and legal disputes					
jus.m1	Criminal cases	Land conflicts			
jus.m2	Criminal cases				
Migration					
mig.m1	In-migration *	Out-migration			
mig.m2	In-migration	Out-migration			
mig.m3	Out-migration				
mig.m4	In-migration				
Control					
env.m1	Elevation				

hum.m1	Distance to International border	Distance to provincial capital	Presence of ELC	Presence of PA	PA category
hum.m2	Distance to International border	Distance to provincial capital	Presence of ELC	Presence of PA	

* Indicates interaction

Table S3.6. Final candidate model set for the commune-level socioeconomic analysis. Variables were selected based on the results of the within-set models (see table S3.5). All models included an offset term of the logged commune area (km^2), and a random effects structure of the form ~(year|Province/Commune). Model selection was done using an Information Theoretic approach. Shaded models all had dAIC <4 and were included in model averaging and used for predictions and inference.

Model	Delta AIC	Population density	Prop males in school	Prop adults in primary sector	Prop families with pigs	Distance to school	Prop families with waste collection	Criminal cases per capita	Number out-migrants	Mean elevation	Dist I'ntl border	Dist prov capital	Presence ELC	Presence PA
m1	2.4	X								X	X	X	X	X
m2	2.5		X							X	X	X	X	X
m3	0.0			X						X	X	X	X	X
m4	2.6				X					X	X	X	X	X
m5	3.1					X	X			X	X	X	X	X
m6	3.1						X	X		X	X	X	X	X
m7	2.4						X		X	X	X	X	X	X
m8	4.07		X			X				X	X	X	X	X
m9	1.2			X					X	X	X	X	X	X
m10	10.2	X	X	X	X	X	X	X	X	X	X	X	X	X

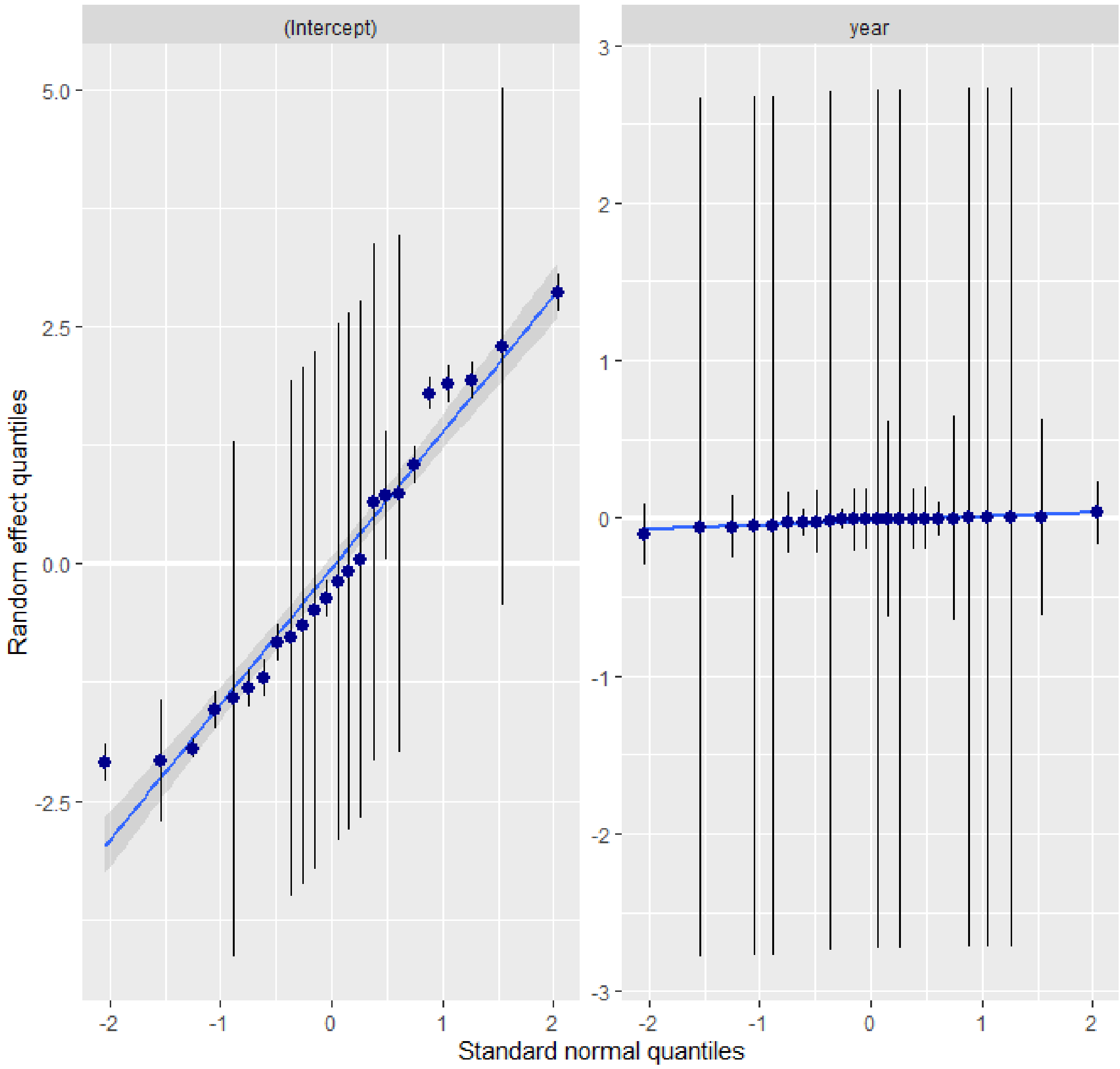

Figure S3.2. Quantile-quantile plots for the random effect "Province" of the final averaged socioeconomic model.

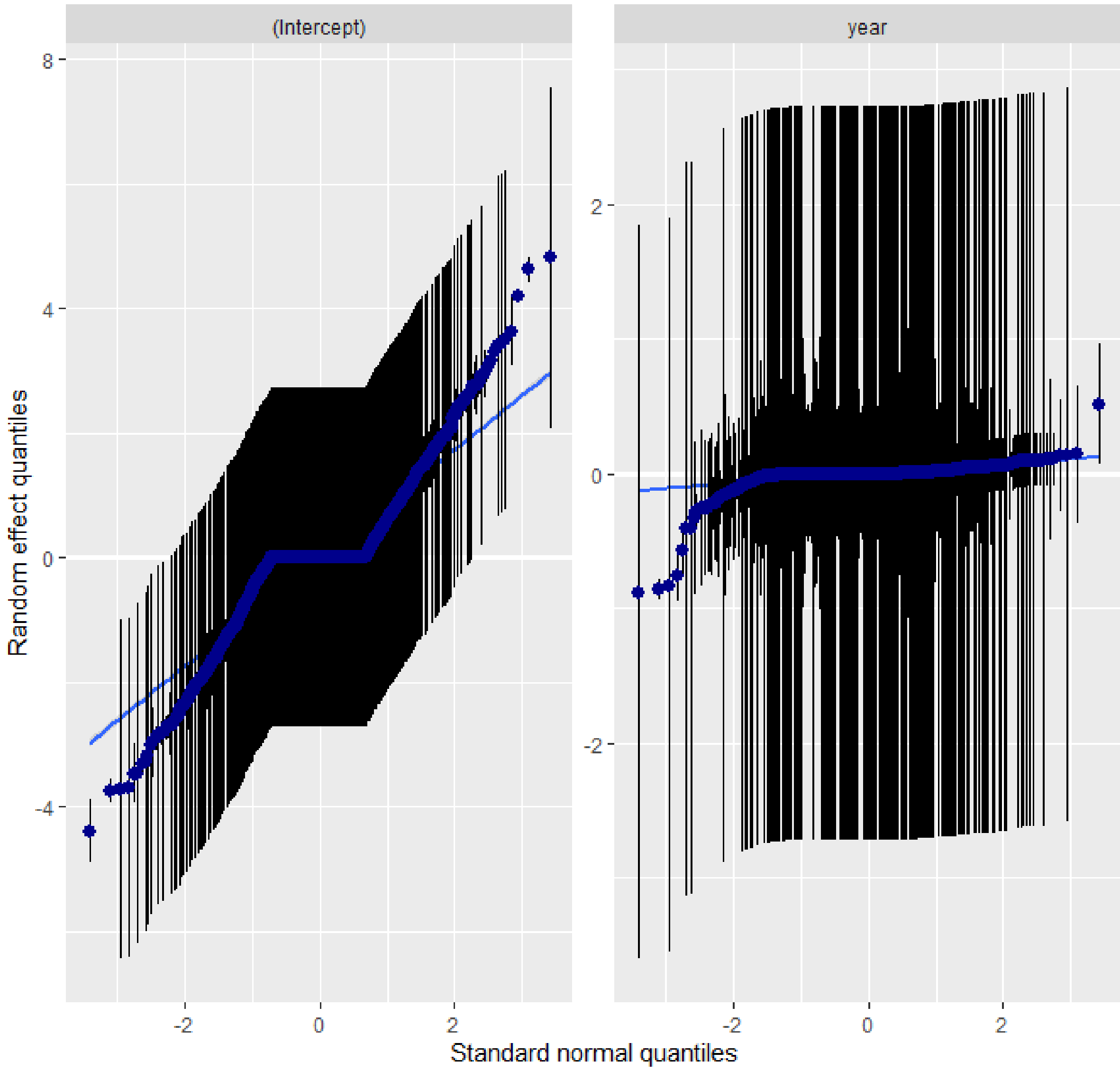

Figure S3.3. Quantile-quantile plots for the random effect "Commune" of the final averaged socioeconomic model. Plots suggest the assumption of normality of deviations of the conditional means of the random effects from the global intercept is violated.

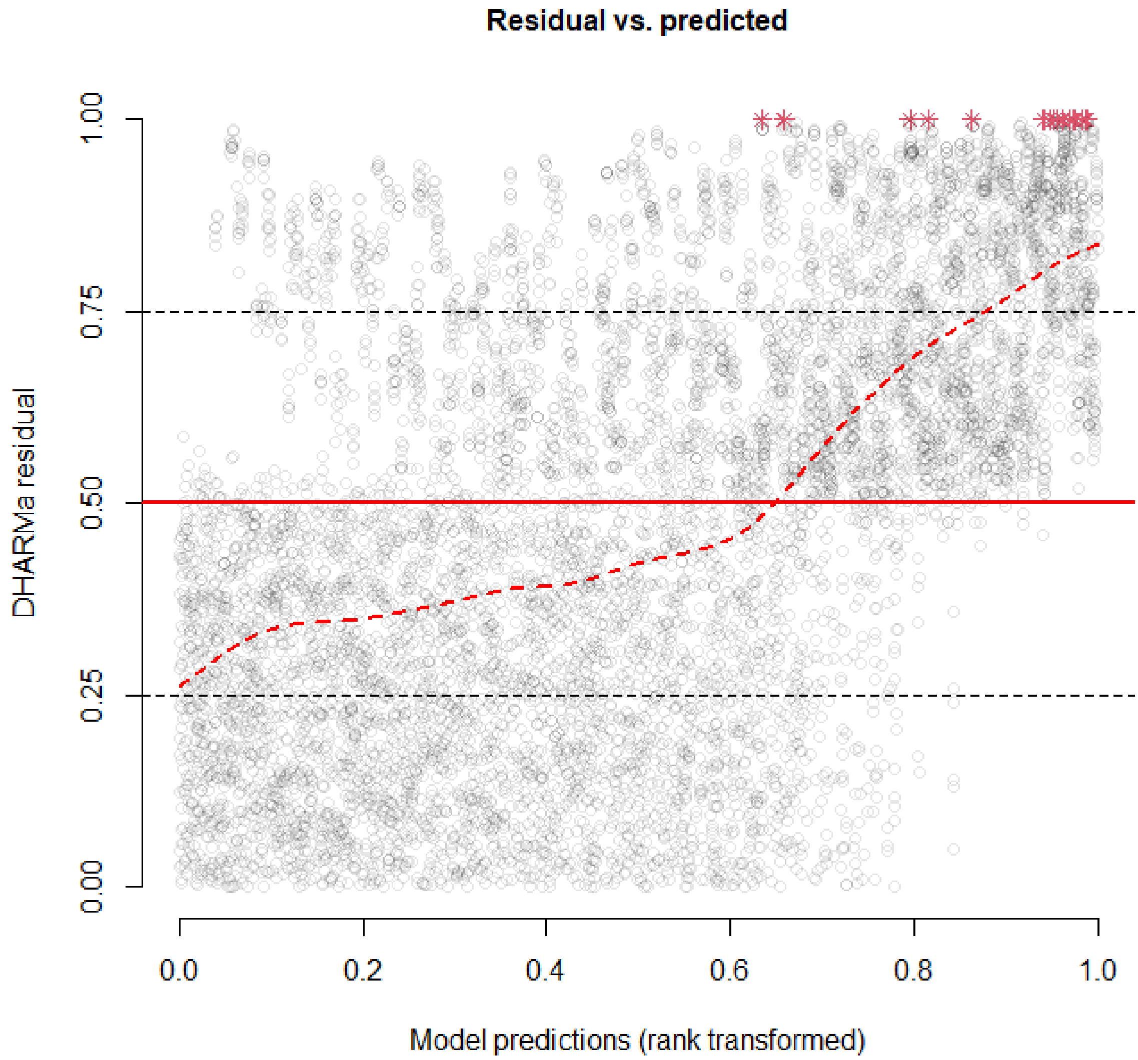

Figure S3.4. Plot of residuals versus fitted values for the final averaged socioeconomic model.

Table S3.7. Final candidate model set for the province-level socioeconomic analysis. Variables were selected based on the results of the within-set models (see table S3.5). All models included a random effects structure of the form ~(year|Province). Model selection was done using an Information Theoretic approach. Shaded models were the top model and was used for predictions and inference.

Model	Delta AIC	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
m1	2.4	X												X	X	X	X	X
m2	2.5		X											X	X	X	X	X
m3	0.0			X										X	X	X	X	X
m4	2.6					X								X	X	X	X	X
m5	3.1						X	X						X	X	X	X	X
m6	3.1								X					X	X	X	X	X
m7	2.4										X			X	X	X	X	X
m8	4.07		X				X							X	X	X	X	X
m9	1.2			X							X			X	X	X	X	X
m10	10.2	X																
m11	60.7								X			X						
m12	70.6									X	X							
m13	53.7		X															
m14	59.9			X	X													
m15	60.8					X							X					
m16	65.9						X											
m17	39.3													X				
m18	35.8														X	X		
m19	54.7																X	X

A – population density, B – proportion of males in school, C – proportion of adults employed in the primary sector, D – proportion of adults employed in the secondary sector, E – proportion of families with pigs, F – median distance to nearest school (km), G – proportion of families with access to waste collection, H – criminal cases per capita, I – number of in-migrants, J – number of out-migrants, K – number of land conflicts, L – proportion of families with no farmland, M – mean elevation (masl), N – distance to nearest international border, O – distance to the provincial capital, P – presence of economic land concessions, Q – presence of PAs

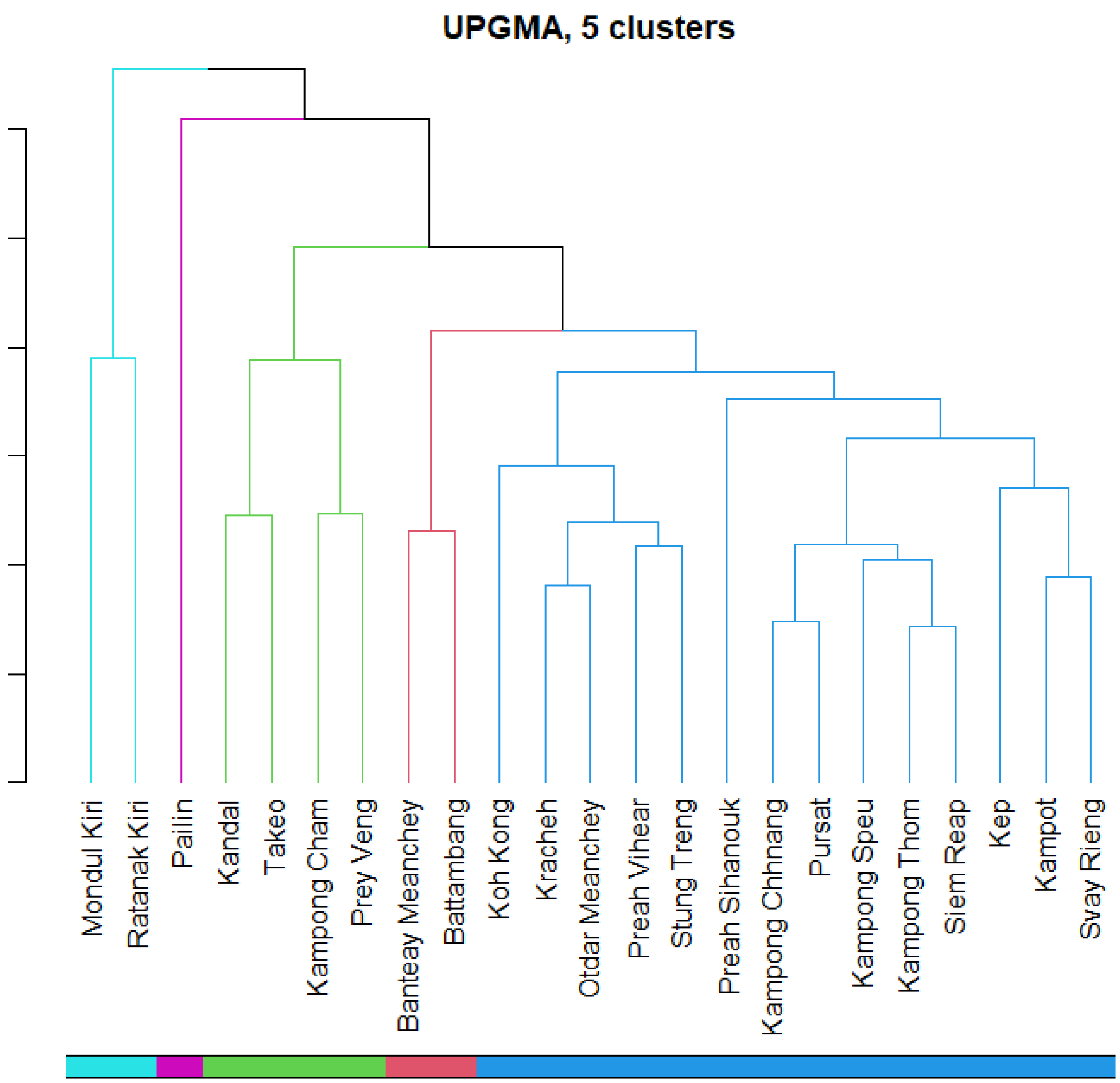

Figure S3.5. Cambodian provinces clustered using unweighted pair-group using arithmetic averages (UPGMA). Clustering was based on a selection of the socioeconomic variables used during the modelling. Data were averaged across the study period 2007 – 2012. Variables included were total population, population density, number of land conflict cases, number of criminal cases per capita, number of in- and out-migrants, the proportion of the population classified as indigenous, proportion of males aged 6 – 24 in school, proportion of the population employed in the primary and secondary sectors, proportion of families with no access to agricultural land, proportion of families who kept pigs, distance to the nearest school, proportion of families with access to waste collection, and distance to the commune (administrative) centre.

Chapter 4

Long-term monitoring of wildlife populations for protected area management in Southeast Asia

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HOK designed the survey, HOK, MN, MNN, VS, OG conducted the fieldwork, MNN conducted the analysis with support from OG and RF and advice from NB. MNN wrote the paper with significant contributions from NB, KA, PJKM, OG and RF.

4.0. ABSTRACT

Long-term monitoring of biodiversity in protected areas (PAs) is critical to assess threats, link conservation action to species outcomes, allow informed decision-making, and facilitate improved management. Yet rigorous longitudinal monitoring within PAs is rare. In Southeast Asia there is a paucity of long-term wildlife monitoring within PAs, and many threatened species lack population estimates from anywhere in their range, making global assessments difficult. Here, we present abundance estimates and population trends for 11 species between 2010 and 2020, and spatial distributions for 7 species, derived from line transect-based distance sampling data collected in Keo Seima Wildlife Sanctuary (KSWS) in Cambodia. These represent the first robust population estimates for 4 threatened species from anywhere in their range and are among the first long-term wildlife population trend analyses from the entire Southeast Asia region. Our study revealed that arboreal primates and Green Peafowl (*Pavo muticus*) generally had either stable or increasing population trends, whereas ungulates and semi-arboreal primates generally had declining trends. This suggests that ground-based threats, such as snares and domestic dogs, are having serious negative effects on terrestrial species. Our estimates confirm that KSWS holds the largest population of the endangered yellow-cheeked crested gibbon (*Nomascus gabriellae*) (abundance in 2020: 1,432 [95% CI = 750 - 2,735]) from anywhere in its range, and a large and globally significant population of the critically endangered black-shanked douc (*Pygathrix nigripes*) (abundance in 2020: 24,929 [95% CI = 16,241 - 38,266]). Our results provide PA managers with rigorous information to assess past management action and support decision-making and strategic allocation of resources. These findings have important conservation implications for PAs across Southeast Asia that face similar threats yet lack reliable monitoring data. They also highlight the critical need for effective long-term monitoring in PAs to ensure effective protection of biodiversity.

4.1. INTRODUCTION

Biodiversity is declining worldwide as unsustainable human activities drive the degradation and loss of natural habitats and overexploitation of species (Johnson et al. 2017; Leung et al. 2020; Mokany et al. 2020). Global efforts to protect habitats and slow biodiversity decline are structured within the Convention on Biological Diversity (CBD, https://www.cbd.int). The Aichi Biodiversity Targets within the Strategic Plan for Biodiversity 2011-2020 identify protected areas (PAs) as key tools for improving the status of biodiversity; Target 11 outlines explicit targets for PA coverage (CBD 2010). Historically seen as critical tools for conservation (Margules & Pressey 2000), PAs provide the most likely refuges for biodiversity in increasingly human-dominated landscapes (Bruner et al. 2001). However, increasing PA size and coverage does not guarantee improved conservation outcomes (Bruner et al. 2004; Armsworth et al. 2018), and in some cases can have perverse consequences such as reduced management capacity across a PA network (Barnes et al. 2018). Protected areas must be adequately resourced and managed in order to fulfil their potential to maintain viable biological populations in the context of increasing human pressure (Geldmann et al. 2018; Coad et al. 2019b).

Effective monitoring using appropriate biodiversity indicators is critical for PA managers to make informed decisions and assess conservation actions, thus allowing improved management over time (Dixon et al. 2019). Yet rigorous longitudinal monitoring within PAs is often lacking (Hughes et al. 2017), hampering informed decision-making and effective deployment of resources. A lack of monitoring systems and frameworks to assess management effectiveness are common challenges facing PAs; only 9.4% of CBD signatories have assessed half or more of their PAs for effectiveness (Secretariat of the CBD 2020). Assessing PA performance requires well designed monitoring regimes that provide reliable, informative, and appropriate metrics of biodiversity over time (White 2019). The critical role PAs play in halting biodiversity decline is emphasized in the Post-2020 Global Biodiversity Framework, which is currently being negotiated to replace the 2011-2020 Strategic Plan and includes quantitative biodiversity targets (CBD 2020a). Therefore, the ability to assess PA efficacy and link conservation action to species outcomes, for which effective long-term monitoring is essential, will become increasingly important.

Southeast Asia (SEA) is characterized by exceptional faunal diversity and endemism (Hughes 2017) yet has the highest rate of increase in extinction risk globally (Hoffmann et al. 2010). This region has the highest percentage of the world's threatened plants, reptiles, birds, and mammals (Sodhi et al. 2010), and one of the highest rates of deforestation globally (Hughes 2017). Hunting in particular is an urgent threat (Gray et al. 2017). Increasing demand for wild meat and wildlife products, both domestically and for international trade, is driving unsustainable levels of hunting within SEA's forests (Harrison et al. 2016; Gray et al. 2018; Heinrich et al. 2020). Despite the urgency, there is a paucity of long-term quantitative data on wildlife populations in SEA. In many cases, species of conservation interest lack even a single estimate of population size (Table 4.1), making it hard to assess the performance of individual PAs and national and regional conservation programs. Empirical data are needed to make evidence-based decisions on PA management, evaluate the impact of past action (Geldmann et al. 2018), and increase the accuracy and utility of global assessments of status and trends. Understanding how wildlife populations respond to anthropogenic pressure is of particular importance in PAs, given their role in safeguarding species' persistence (Watson et al. 2014).

Table 4.1. Existing population estimates that account for imperfect detection and quantify uncertainty from peer-reviewed literature[a], and the global status of the 11 species monitored in Keo Seima Wildlife Sanctuary (KSWS)

Common name	Scientific name	In-text abbreviation	IUCN Red List status and global trend[b]	Known threats (entire range)[c]	Locations of population estimates[d]	Density (unit/km^{-2}) [e]	Source
Southern yellow-cheeked crested gibbon	*Nomascus gabriellae*	Gibbon	EN ↓	Hunting (trade) Habitat loss and degradation	KSWS, Cambodia Chu Yang Sin NP, Vietnam Cat Tien NP, Vietnam	0.6 – 0.9 ind 0.3 – 0.4 grp 0.5 – 1.0 grp	Rawson et al., 2009 Thinh et al., 2016 Thinh et al., 2018
Black-shanked douc	*Pygathrix nigripes*	Douc	CR ↓	Hunting (traditional medicine, consumption) Habitat loss and degradation	-	-	-
Germain's silver langur	*Trachypithecus germaini*	Langur	EN ↓	Hunting (trade, traditional medicine) Habitat loss and degradation Dam construction	-	-	-
Long-tailed macaque	*Macaca fascicularis*	LT macaque	VU ↓	Hunting (trade, biomedical, consumption, sport) Habitat loss and degradation	Baluran NP, Java, Indonesia	23.0 – 74.4 ind	Hansen et al., 2019
Northern pig-tailed macaque	*Macaca leonina*	PT macaque	VU ↓	Habitat loss and degradation Hunting (trade, consumption, traditional medicine)	-	-	-
Stump-tailed macaque	*Macaca arctoides*	ST macaque	VU ↓	Habitat loss and degradation Hunting (trade, consumption, traditional medicine, sport)	-	-	-
Banteng	*Bos javanicus*	Banteng	EN ↓	Hunting (consumption, trade, trophy) Habitat loss and degradation Genetic diversity	Phnom Prich WS & Srepok WS, Cambodia	0.7 – 1.2 ind 0.1 – 0.8 ind	Gray et al., 2012 O'Kelly et al., 2012

					KSWS, Cambodia (wild cattle combined)	0.002 – 0.02 ind	Gardner et al., 2019
					Malua Forest, Borneo	0.005 – 0.02 ind	Gardner et al., 2019
					Tabin Forest, Borneo		
Gaur	*Bos gaurus*	Gaur	VU ↓	Hunting (consumption, trade, traditional medicine, trophy) Habitat loss and degradation Competition with livestock Disease	Nagarahole NP (Nalkeri), India	3.5 – 8.2 ind	Madhusudan and Karanth, 2000
					Nagarahole NP (Arkeri), India	0.7 – 2.7 ind	Madhusudan and Karanth, 2000
					Bahdra TR, India	0.5 – 4.3 ind	Jathanna et al., 2003
					Trishna WS, India	3.2 – 8.6 ind	Dasgupta et al., 2008
					KSWS, Cambodia (wild cattle combined)	0.1 – 0.8 ind	O'Kelly et al., 2012
Northern red muntjac	*Muntiacus vaginalis*	Muntjac	LC ↓	Hunting (consumption, trade)	Bahdra TR, India	2.3 – 5.9 ind	Jathanna et al., 2003
					KSWS, Cambodia	1.2 – 2.5 ind	O'Kelly et al., 2012
					Srepok WS & Phnom Prich WS, Cambodia	1.8 – 2.6 ind	Gray et al., 2012
					Murree-Kotli Sattian-Kahuta NP, Pakistan	0.2 – 0.9 ind	Habiba et al., 2020
Wild pig[f]	*Sus scrofa*	Pig	LC ?	Hunting (consumption, sport, trade, reprisals for crop damage) Habitat loss and degradation	Pasoh FR, Malaysia	16.2 – 44.7 ind	Ickes, 2001
					KSWS, Cambodia	1.2 – 3.5 ind	O'Kelly et al., 2012
					Srepok WS & Phnom Prich WS, Cambodia	0.6 – 2.2 ind	Gray et al., 2012
Green Peafowl	*Pavo muticus*	Peafowl	EN ↓	Hunting (consumption, trade) Collection of chicks and eggs Habitat loss and degradation	Yok Don NP, Vietnam	0.1 – 0.6 calling birds	Sukumal et al., 2015
						1.4 – 10.3 calling birds	Sukumal et al., 2015
					Cat Tien NP, Vietnam	0.1 – 0.6 ind	Nuttall et al., 2017
					KSWS, Cambodia	Riverine: 1.1 – 2.7, Non-riverine: 0.2 – 0.6	Loveridge et al., 2017
					Siem Pang WS, Cambodia	0.3 – 30.0 calling birds	Sukumal et al., 2017
					Huai Kha Khaeng WS, Thailand		

[a] See Supporting Information for additional references that do not meet the criteria of this table.
[b] LC = least concern, VU = vulnerable, EN = endangered, CR = critically endangered, ? = unknown (www.iucnredlist.org). ↓ = decreasing global trend
[c] Threats taken from the species assessment page on the IUCN Red List of Threatened species (www.iucnredlist.org)
[d] Only estimates derived from methods that account for imperfect detection and estimate some form of error or variance are included. Minimum counts and relative abundance/density are not included. Publications with limited details on methods that prevented an assessment of the type of estimate were not included. Abbreviations: WS = Wildlife Sanctuary, NP = National Park, TR = Tiger Reserve, FR = Forest Reserve
[e] Where available, the 95% confidence range is reported. Where 95% confidence intervals were not available, the range shown is the reported estimate ± (1.96 × SE). Where available, the density of individuals is reported, otherwise density of groups is reported. ind = individual density, grp = group density
[f] List of reported population estimates is not exhaustive

In this paper, we present 10 years of wildlife population monitoring from Keo Seima Wildlife Sanctuary (KSWS) in Cambodia, a globally important site for several species (Nuttall et al. 2017), to help address the knowledge gap created by the lack of empirical data on wildlife populations in SEA. Many of the species in our study lack a single reliable population estimate from anywhere else in their range (Table 4.1). We provide abundance estimates for 11 species within KSWS between 2010 and 2020 and model their population trends over time. We also provide spatial distributions for 7 of the species, for which adequate data were obtained. Our study is among the first in the literature to report long-term wildlife population trends with absolute estimates from SEA. We highlight the importance of these results for SEA and International Union for the Conservation of Nature (IUCN) Red List status assessments, and for evaluating conservation action and future conservation decision-making in KSWS. Finally, we discuss the need for long-term monitoring in PAs and the implications of our results for conservation programs across SEA.

4.2. METHODS

4.2.1 Study site

Keo Seima Wildlife Sanctuary (*12.3346, 106.8418,* formerly Seima Biodiversity Conservation Area and Seima Protection Forest) falls within Mondulkiri and Kratie provinces in eastern Cambodia. It has an area of 2,927 km^2, sharing its southeastern edge with Vietnam (Figure 4.1). Our 1,880 km^2 study area is the former core zone (Figure 4.1). KSWS is characterized by a diverse mosaic of habitats; the southeastern area extends into the Southern Annamite Mountain Range with higher altitudinal mountainous topography and dense evergreen and semi-evergreen forest (Evans et al. 2013). The central and western areas form the edge of the Eastern Plains Landscape, dominated by low altitudes and dry deciduous dipterocarp forests (O'Kelly et al. 2012; Evans et al. 2013). Complementing the altitudinal and habitat gradients are semi-natural grasslands and seasonal and permanent water bodies that together support rich biodiversity (Nuttall et al. 2017, Griffin & Nuttall 2019).

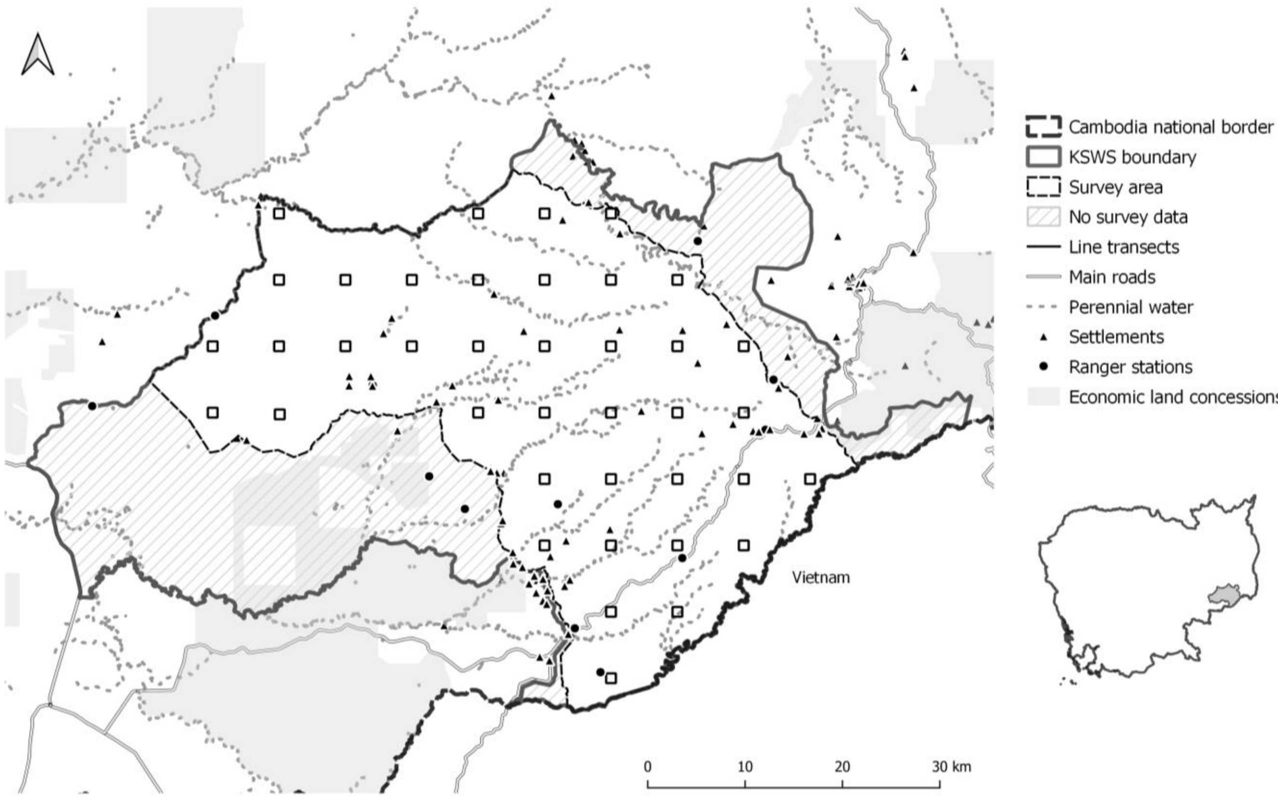

Figure 4.1. Keo Seima Wildlife Sanctuary in eastern Cambodia

4.2.2. Data collection

Data were collected jointly by the Wildlife Conservation Society (WCS) and the Forestry Administration of the Royal Government of Cambodia (RGC) between 2010 and 2016, and by WCS and the Ministry of Environment of the RGC in 2018 and 2020. Forty square line transects of 4 km length were arranged throughout KSWS in a systematic grid with a random start point. Field teams conducted distance sampling surveys along these line transects in 2010, 2011, 2013, 2014, 2016, 2018, and 2020. Teams recorded visual observations of a pre-defined set of 11 species: those listed as Threatened on the IUCN Red List, easily detected on line transects, or both. The target species were southern yellow-cheeked crested gibbon (*Nomascus gabriellae*, hereafter "gibbon"), black-shanked douc (*Pygathrix nigripes*, hereafter "douc"), Germain's silver langur (*Trachypithecus germaini*, hereafter "langur"), long-tailed macaque (*Macaca fascicularis*, hereafter "LT macaque"), northern pig-tailed macaque (*Macaca leonina*, hereafter "PT macaque"), stump-tailed macaque (*Macaca arctoides*, hereafter "ST macaque"), banteng (*Bos javanicus*), gaur (*Bos gaurus*), northern red muntjac (*Muntiacus vaginalis*, hereafter "muntjac"), wild pig (*Sus scrofa*, hereafter "pig"), and green peafowl (*Pavo muticus*, hereafter "peafowl"). See Table 4.1 for the target species' global status, threats, and existing population estimates.

Surveys were conducted during the dryer months of December – June. Temporal replication was achieved through multiple visits to each transect within each year. Field teams visited transects for between one and eight days at a time and conducted surveys twice a day, at dawn and dusk. Teams would record only direct visual observations of target species. Laser rangefinders and compasses were used to measure distances and angles from the line transect to detected objects, which constituted either isolated individuals or spatially aggregated individuals (clusters), and cluster sizes were recorded. Distances were measured to the geometric center of clusters. Perpendicular distances from detected objects to the line transect were calculated prior to analysis. Additional data collected for quality assurance and covariate modelling included date, time, observer name, location of observer, and habitat type (2013 onwards). Field protocols followed standard line transect methodology outlined in Buckland et al. (2001) and were consistent between years. For further details of field protocols, including testing for bias associated with transect corners, see Supporting Information, O'Kelly et al. (2012), and Nuttall et al. (2017).

4.2.3. Annual abundance estimates

We used the conventional distance sampling framework (Buckland et al. 2001) to obtain point estimates of individual density and abundance for each species in each survey year. Only douc had sufficient within-year observations to allow for annual detection functions to be estimated. For the remaining species distance data from all years were pooled in order to improve the model fit for detection function estimation (Buckland et al., 2001). To account for potential heterogeneity in detection between years, a scaled continuous Year variable was tested for all species except douc. We fitted detection function models using the R package distance (R Core Team 2017; Miller et al. 2019a, version 0.9.8). Distance data for all species were truncated to improve model fitting and reduce bias (Buckland et al. 2001). We explored models with uniform, half-normal, and hazard rate key functions and cosine, simple polynomial, and hermite polynomial adjustments, both with and without observation-level covariates. Only the following key functions and adjustment combinations were tested: Uniform-cosine, Uniform-simple polynomial; Half normal-cosine, Half normal-hermite polynomial; Hazard rate-cosine, Hazard rate-simple polynomial. Models were compared, assessed, and selected using a combination of diagnostic plots, goodness-of-fit tests, Akaike's Information Criterion (AIC), and the authors' knowledge about the ecology and observation process of each species. Generally, models within a set were discarded if a) the Cramer-von Mises test statistic was significant ($p < 0.05$), or b) the delta AIC value was greater than 3. Remaining models were considered to have some support and were assessed and selected via visual inspection of the model fit, taking both AIC and the species ecology and detection process into account.

For further details on density, abundance, and variance estimation in distance sampling see Buckland et al. (2001, 2004, 2015); Fewster et al. (2009); and Miller et al. (2019a).

4.2.4. Temporal population trends

We used generalized additive models (GAMs) combined with bootstrapping (Hamilton et al. 2018) to estimate long-term population trends. The original systematic sampling design ensured representative coverage of habitat types, so we employed a bootstrap scheme that would preserve this property (Supporting Information). Each transect was categorized by habitat as either dense or open forest. Transects were sampled with replacement within each category until total within-category effort across all years equalled that of the original data. We fitted detection functions to each set of replicate data and fitted a GAM to the resulting annual abundance estimates to generate a temporal trend curve for each replicate. This process was repeated 2,000 times per species. The 50%, 2.5%, and 97.5% quantiles from the replicate GAM curves were extracted pointwise to generate overall population trends and 95% confidence intervals (Fewster et al. 2000). The trend from a single bootstrap replicate was considered positive if the predicted estimate from 2020 was higher than that from 2010, and negative if the opposite was true. The overall trend for a given species was reported as significant if at least 95% of replicates agreed on trend direction, otherwise the species was classified as stable. Banteng had insufficient observations to support the bootstrap procedure, precluding computation of confidence intervals and trend significance, so a single GAM was fitted to the annual abundance estimates produced from distance sampling analysis.

4.2.5. Spatial analysis

We conducted spatial analyses to examine the distribution of each species across KSWS and link relative abundance to spatial covariates. The number of within-year observations for each species was generally low (Table S4.2), and so to support the spatial modelling we combined data from all years into a single analysis, creating a map of relative abundance spanning the whole study period for each species. If a species had fewer than 50 observations from the whole study period they were excluded from the spatial analysis.

Line transects were partitioned into equally sized, discrete spatial segments and wildlife observations were allocated to the segment within which they fell. We inspected distance data for all species to identify an appropriate single truncation distance which was used to establish an effective strip width W and subsequent segment size (Buckland et al., 2004). We chose a truncation distance of 50 m which resulted in segments of size 100m × 100m, and between 0 and 27% of observations furthest from the line being discarded. The per-segment abundance was estimated using a Horvitz-Thomson-like estimator (Buckland et al., 2004) and adjusted for imperfect detection using the species-specific detection function selected in the abundance estimation process above. GAMs were then used to quantify the relationship between the estimated abundance in each segment and the supplied covariates (Buckland et al., 2004; Wood, 2006). For covariate data, we acquired spatial datasets for several environmental and anthropogenic variables which were hypothesized to relate to animal abundance in KSWS. These were within-segment habitat, elevation, distance to water bodies, distance to human settlements, distance to ranger stations, distance to the Vietnamese border, and latitude and longitude (Supporting Information). The distance to the Vietnam border covariate was included to capture factors such as cross-border wildlife trade and hunting (Harrison et al. 2016).

We ran three groups of models for each species, with each model group assuming a different response distribution (response = number of groups or individuals in a segment): quasi-Poisson, Tweedie, or negative binomial. We conducted model selection using a combination of diagnostic plot assessment and AIC for Tweedie and negative binomial distributions, and analysis of variance for the quasi-Poisson distribution. We retained the habitat variable in all models, based on our knowledge of the importance of habitat for the species in this study. Each final model was tested for autocorrelation (see Supporting Information for further details on modelling approach). The selected GAM for each species and a prediction grid with 200m × 200m cells were used to predict relative abundance for each species over the study area. Spatial analyses were conducted in the R package dsm (Miller et al. 2019b).

4.3 RESULTS

4.3.1. Annual abundance estimates

Effort across all transects and years was 9,460 km, resulting in 5,056 observations across the study period. The minimum and maximum annual effort was 1,260 km (2013) and 1,600 km (2010), resulting in 588 and 729 observations, respectively (Table S4.2). In 2020, the most abundant species among those with increasing populations was PT macaque (estimated abundance 3,929 individuals [95% CI = 2,457 - 6,284; Table 4.2], encounter rate 0.18 km^{-1} [Table S4.3]), while the least abundant species among those with declining populations was banteng, which was not observed in 2020 (Table 4.2). The most abundant species overall was douc (estimated abundance 24,929 individuals [95% CI = 16,241 - 38,266; Table 4.2], encounter rate 1.08 km^{-1} in 2020 [Table S4.3]). Cluster size and year were the most frequently retained covariates in the detection function models (6 species). Observer and habitat were retained for douc only (Table S4.3).

4.3.2 Temporal population trends

Significant trends were detected for 6 species: 2 positive (PT macaque, peafowl) and 4 negative (ST macaque, gaur, muntjac, wild pig, Table 4.2, Figure 4.2). Trends for 4 species that did not reach 95% directional agreement among replicates were recorded as stable (Table 4.2). Trend agreement among replicates for ST macaque and muntjac (both negative) was 100% (Table 4.2).

4.3.3. Spatial analysis

Results for banteng, gaur, and ST macaque were excluded because of too few observations. Pig results were excluded because of poor model fit (<5% deviance explained). Final models for the remaining 7 species ranged in deviance explained from 16.3% (muntjac) to 66.1% (langur, Table S4.5). The median coefficient of variation (CV) for the spatial predictions for each species ranged from 19% (muntjac) to 125% (langur). Coefficients of variation were high in areas with few or no observations but were generally low (<40%) in areas with high predicted relative abundance (Figure S4.8).

Distribution and relative abundance were heterogeneous among species (Figure 4.3). Species with known preference for evergreen and semi-evergreen forest (gibbon, douc, PT macaque) had higher predicted relative abundance in the central and southeastern sections of KSWS where this habitat is dominant (Figure 4.3). Peafowl, muntjac, and langur had highest predicted relative abundance in mosaic habitat and open deciduous forest (peafowl and muntjac: central, north, and northwest; langur: northwest, southwest). Long-tailed macaque had highest predicted relative abundance in areas of KSWS that range from mosaic to open deciduous forest (central, northeast). Distance to the Vietnamese border was the most commonly retained spatial covariate (6 species), followed by distance to water and distance to ranger station (5), elevation (4) and distance to settlement (2, Table S4.5).

Table 4.2. Temporal trends and density and abundance estimates derived from line transect surveys between 2010 and 2020 for 11 species in Keo Seima Wildlife Sanctuary.

Species	Replicate agreement (% and direction)[a]	Trend[b]	Density[c] [ind/km^2] (LCI,UCI)[d]		Abundance[c] (LCI, UCI)[d]	
			2010	2020	2010	2020
Yellow-cheeked crested gibbon	89 positive	Stable	0.507 (*0.235*,*1.093*)	0.762 (*0.399*,*1.455*)	952 (*441*,*2055*)	1432 (*750*,*2735*)
Black-shanked douc	88 positive	Stable	12.920 (*8.476*,*19.692*)	13.260 (*8.639*,*20.354*)	24289 (*15936*,*37021*)	24929 (*16241*,*38266*)
Germain's silver langur	54 positive	Stable	1.549 (*0.518*,*4.634*)	0.791 (*0.313*,*1.999*)	2912 (*974*,*8712*)	1487 (*588*,*3758*)
Long-tailed macaque	71 negative	Stable	1.662 (*0.733*,*3.766*)	0.833 (*0.421*,*1.647*)	3125 (*1379*,*7080*)	1566 (*792*,*3097*)
Pig-tailed macaque	97 positive	Increasing	1.068 (*0.486*,*2.349*)	2.090 (*1.307*,*3.342*)	2008 (*913*,*4417*)	3929 (*2457*,*6284*)
Stump-tailed macaque	100 negative	Decreasing	0.281 (*0.085*,*0.935*)	0.122 (*0.023*,*0.663*)	529 (*159*,*1758*)	230 (*42*,*1246*)
Banteng[e]	-	-	0.203 (*0.040*,*1.040*)	-	382 (*75*,*1956*)	-
Gaur	96 negative	Decreasing	0.264 (*0.074*,*0.946*)	0.017 (*0.003*,*0.095*)	497 (*139*,*1778*)	33 (*6*,*17*9)
Northern red muntjac	100 negative	Decreasing	1.800 (*1.295*,*2.502*)	0.439 (*0.279*,*0.692*)	3383 (*2434*,*4703*)	825 (*524*,*1300*)
Wild pig	97 negative	Decreasing	1.796 (*0.982*,*3.286*)	0.585 (*0.312*,*1.097*)	3377 (*1846*,*6176*)	1100 (*587*,*2063*)
Green Peafowl	99 positive	Increasing	0.164 (*0.082*,*0.328*)	0.396 (*0.199*,*0.788*)	309 (*154*,*617*)	745 (*375*,*1481*)

[a] The trend from a single bootstrap replicate was reported as positive if the predicted estimate for 2020 was higher than that for 2010, and negative if the predicted estimate for 2020 was lower than that for 2010.

[b] Overall trend was reported as positive if >95% of the bootstrap replicates were positive, and negative if >95% of bootstrap replicates were negative. All trends that did not reach the 95% level were reported as stable.

[c] Density and abundance were estimated using conventional distance sampling and the analysis was conducted separately from the bootstrapped trend analyses. Abundance refers to the estimated number of individuals in the study area.

[d] LCI = lower 95% confidence interval, UCI = upper 95% confidence interval

[e] There were insufficient observations of banteng in 2020 to produce density and abundance estimates.

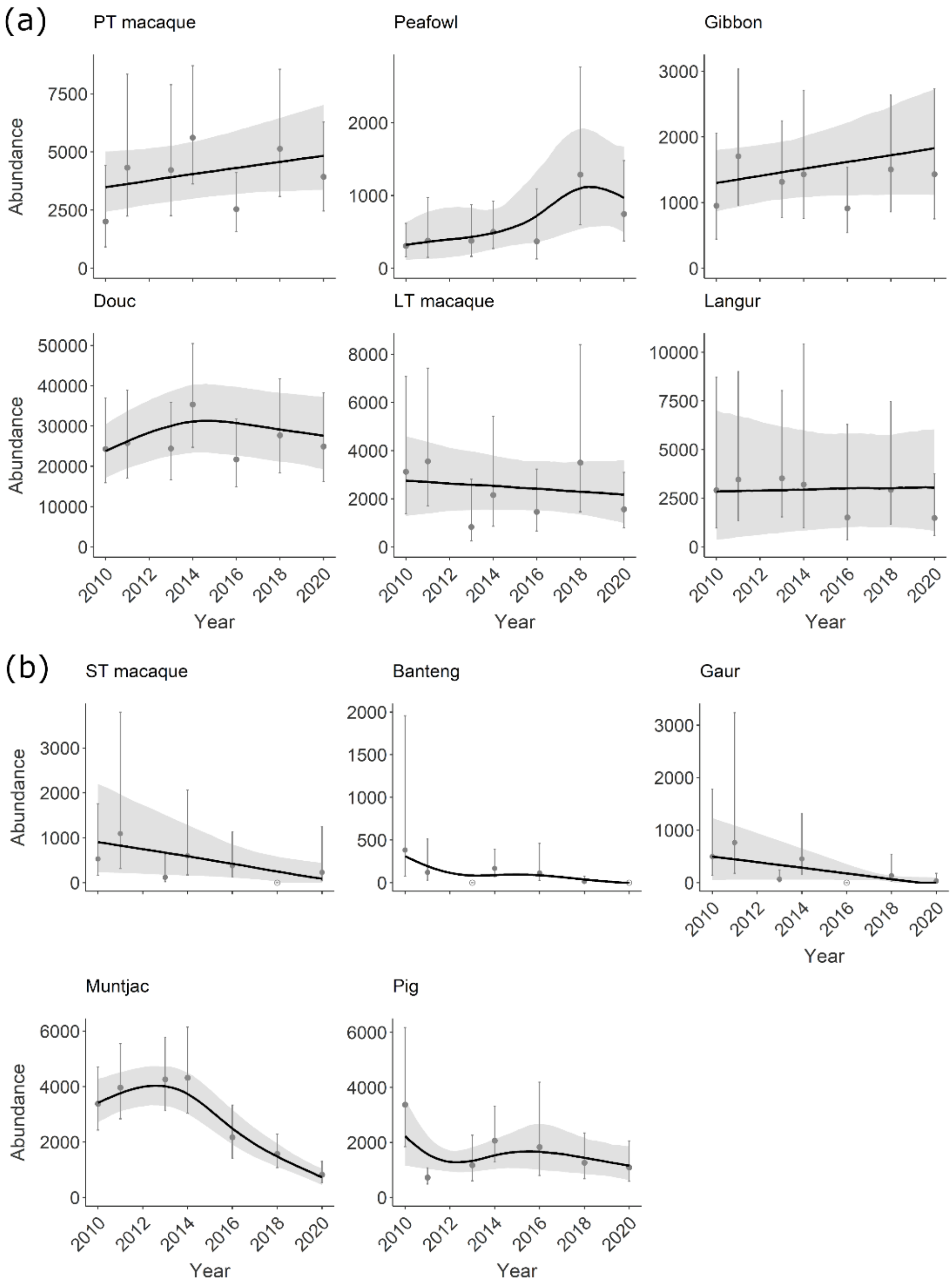

Figure 4.2. Annual abundance estimates (gray points) and population trend (black line) for 11 species in Keo Seima Wildlife Sanctuary between 2010 and 2020. A – Species with increasing or stable population trends, B – species with declining population trends. Hollow points denote zero observations in that year. Error bars around the annual abundance estimates, and gray error ribbons around the trend lines, denote 95% confidence intervals. Bootstrapping was not possible for banteng and so confidence intervals were not produced. PT macaque = northern pig-tailed macaque, peafowl = green peafowl, Gibbon = southern yellow-cheeked crested gibbon, Douc = black shanked douc, LT macaque = long-tailed macaque, Langur = Germain's silver langur, ST macaque = stump-tailed macaque, muntjac = northern red muntjac, pig = wild pig.

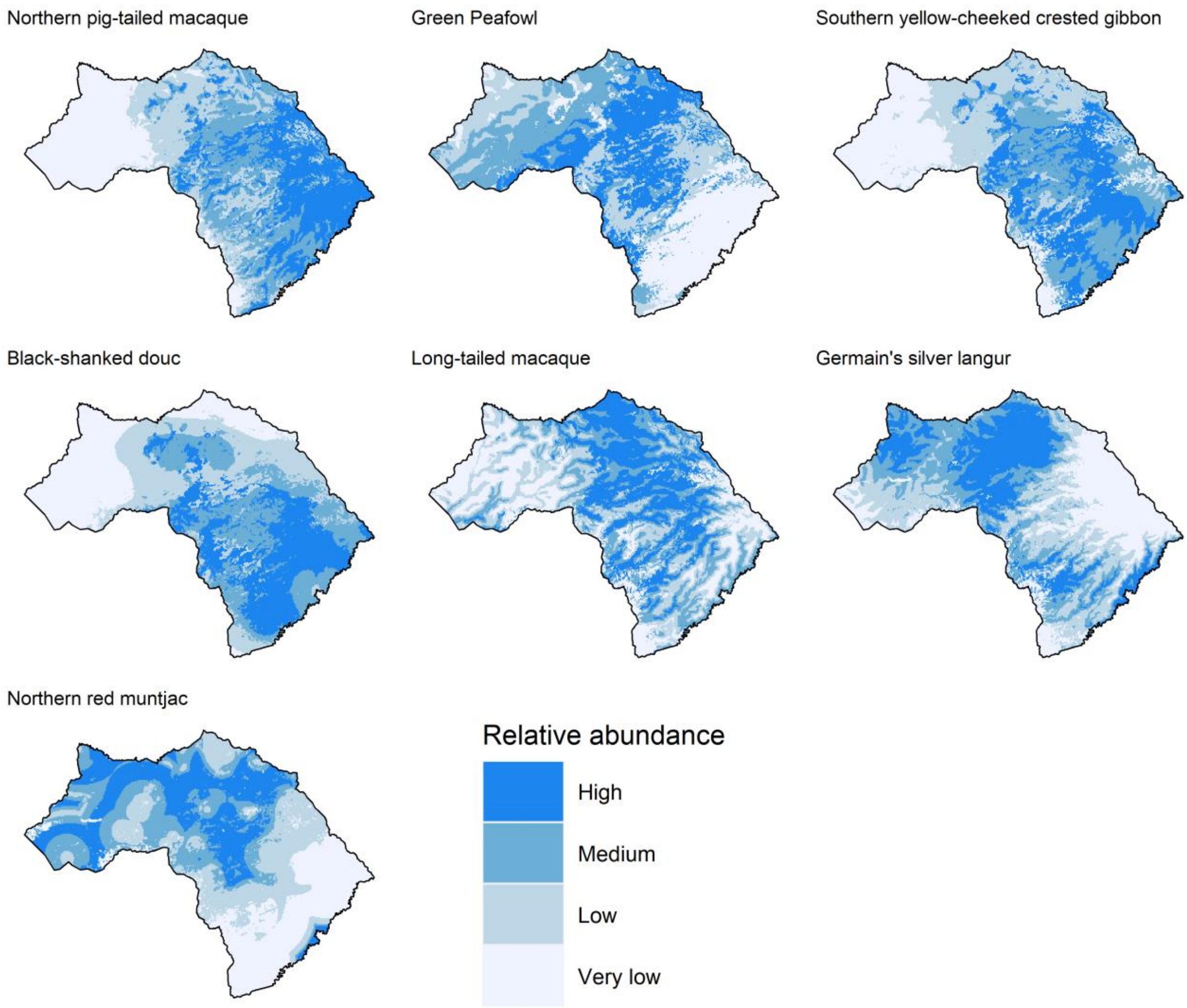

Figure 4.3. Predicted spatial distribution and relative abundance for 7 species in Keo Seima Wildlife Sanctuary from the study period in 2010 – 2020. Relative abundance categories denote predicted species-specific abundance above the 75% quantile ("High"), between the 50 and 75% quantile ("Medium"), between the 25 and 50% quantile ("Low"), and below the 25% quantile ("Very low"). See Supporting Information for corresponding maps of coefficient of variation for the above species.

4.4. DISCUSSION

Long term monitoring of biological populations is critical for conservation science and policy (Hughes et al. 2017). Multi-year datasets provide baselines against which conservation efforts can be judged (Magurran et al. 2010) and are important for monitoring PA effectiveness (Geldmann et al. 2018). We have presented population estimates and temporal trends for 11 species over one decade in a large and globally significant PA. These include the first robust estimates for one critically endangered (douc), one endangered (langur), and two vulnerable (PT and ST macaques) primates from anywhere in their ranges. We are aware of only one other study in the literature that presents long-term wildlife population trends in SEA based on absolute abundance estimates rather than uncalibrated indices (Duangchantrasiri et al., 2016; also see Groenenberg et al. 2020). Therefore, our results provide critical information for global status assessments, underpin evaluations of management effectiveness in KSWS, and inform management options in PAs with similar threats regionally.

Spatial modeling indicated that species distributions vary widely, with no clear commonality among species with declining population trends or among those with stable populations. This lack of commonality suggests that population trends are not associated with a particular habitat or area within KSWS, but rather are driven by factors associated with species ecology and behavior. The exception is the border with Vietnam, which is a spatial attribute associated with declining abundance. The declining species in our study are ungulates and the single primate that is predominantly ground dwelling, whereas arboreal and semi-arboreal primates and peafowl have stable or increasing populations. These results indicate that ground-based threats are likely to be the primary drivers of species decline, in particular implicating snares and free-ranging domestic dogs.

4.4.1. Declining populations

Models for all species except langur showed decreased relative abundance closer to the Vietnamese border. Douc, gibbon, and PT macaque prefer evergreen and semi-evergreen forest (Nadler et al. 2007; Rawson et al. 2009), which dominate the border area. Long-tailed macaque is a generalist occupying a range of habitats (Hansen et al. 2019). Therefore, higher densities would be expected near the border based on habitat characteristics alone. The likely explanation for the contradictory pattern observed is that parts of KSWS in close proximity to the border have been hotspots for illegal cross-border activities throughout the study period, including illegal logging and hunting with firearms and snares (Evans et al. 2013; O'Kelly et al. 2018a; Ibbett et al. 2020). Snare density increases with proximity to the Vietnamese border (O'Kelly et al. 2018b), with high volumes of illegal incursions into KSWS driven by demand for wild meat and wildlife products from Vietnam (Shairp et al. 2016). Snaring is prevalent in Cambodian PAs more generally (Coad et al. 2019a; Belecky & Gray 2020). The scale of the snaring problem in a given area is difficult to quantify due to inherent biases in snare removal data resulting from issues with detectability and sampling, although reliable methods have recently been developed (O'Kelly et al., 2018a, 2018b). In 2015 nearly 28,000 snares were removed from Southern Cardamom National Park in southern Cambodia (Gray et al. 2018). In KSWS, 36% of survey respondents reported engaging in hunting and 20% reported laying snares to protect crops (Ibbett et al. 2020). These data suggest that snares may be a primary contributor to regional wildlife population declines.

There is substantial evidence that free-ranging and feral dogs can have negative effects on wildlife populations (Young et al. 2011; Hughes & Macdonald 2013), and these effects are particularly severe in SEA (Doherty et al. 2017). Domestic dogs are commonly used by local communities in Cambodia for hunting inside PAs (Coad et al. 2019a; Ibbett et al. 2020). In KSWS, 79% of households own dogs and nearly 50% of households take dogs with them into the forest (Ibbett et al. 2020). The number of domestic dogs in KSWS may be as high as 4,000, corresponding to 1.36 km^{-2} (Ibbett et al. 2020), which would make the density of domestic dogs several times greater than that of any monitored ungulate. Therefore, it is likely that free-ranging and feral dogs, in addition to widespread snaring, are contributing to declines in ground-based species in KSWS.

The population trend for pig, although exhibiting an overall decline, follows a fluctuating pattern that possibly reflects factors additional to the threats mentioned above. Pigs are highly fecund, and their density-dependent populations can fluctuate dramatically based on food availability and disease (Gentle et al., 2019; Sánchez-Cordón et al., 2019). African Swine Fever is a plausible contributing factor to pig declines, as the disease has been recorded in Cambodia and can have severe negative effects on wild pig populations (Ikeda et al. 2020; Marinov et al. 2020). Pigs are resilient to relatively high levels of hunting, so the population may be able to rebound quickly if the decline is due to disease or food shortages (Steinmetz et al., 2010).

Although the most prevalent direct causes of wildlife mortality in KSWS are likely to be snares and free-ranging dogs, the broader drivers are more complex. Food insecurity, shifting livelihood strategies, a preference for wild over domestic meat, traditional medicines, targeted hunting by outsiders, increasing debt burdens caused by agricultural and socioeconomic fluctuations, changing perceptions of law enforcement effectiveness, and increased access to local markets are all interacting factors that contribute to hunting of wildlife in KSWS (Ibbett et al., 2020).

4.4.2. Stable and increasing populations

We found that gibbon, douc, PT macaque, LT macaque, langur, and peafowl showed stable or increasing population trends. Arboreal primates and birds are less vulnerable than ground-based mammals to hunting with snares and dogs but can be targeted with firearms. The number of firearms in Cambodia has reduced in recent years, and access to firearms has become more difficult (Dyke 2006). Although some species, including langur and LT macaque, are used in traditional medicine, human consumption of primates is less common in Cambodia than in neighboring Vietnam (Alves et al. 2010). The reduction in firearms and the absence of a strong cultural propensity for primate consumption together may have allowed arboreal primate populations to remain stable. Nevertheless, hunting of primates with firearms, as well as traditional projectile weapons such as crossbows, persists in KSWS (Ibbett et al., 2020), and it is likely to increase if there is continued unregulated movement of people from Vietnam into KSWS with associated illegal hunting and logging activities. The relative scarcity of primates in adjacent Vietnamese PAs means that KSWS has the potential to become a source for the primate trade in Vietnam.

During the study period there has been large-scale deforestation outside the study area, driven primarily by industrial-scale agriculture in the form of land concessions, and subsequent leakage of illegal land clearance around concessions. In 2010, a Reduced Emissions from Deforestation and Forest Degradation (REDD+) project was initiated in KSWS. This project has provided financial incentives to the RGC and local communities to reduce forest loss in the study area; consequently, forest cover has remained largely intact. An estimated 25,000 ha of forest loss has been avoided because of the REDD+ project (McMahon et al. 2020). Maintenance of forest cover is likely to be another factor supporting stable and increasing population trends for arboreal primates, particularly of gibbon, douc, and langur, which are forest-dependent. Our abundance estimates for douc and gibbon suggest that populations in KSWS are likely to be the largest cohesive populations of these species globally (Rawson et al. 2020; Duc et al. 2020a), although for douc these are the first peer-reviewed abundance estimates published. Abundance estimates for langur suggest KSWS is also a globally important site for this species, although comparison between sites is challenging due to a lack of published population estimates (Duc et al. 2020b; Moody 2018).

It is not clear what is causing the apparent difference in trends between LT and PT macaque, but there are several possibilities. Widespread live capture of LT macaques to supplement so-called "monkey farms" (Lee, 2011) in Vietnam and China, which in turn supply the international biomedical and laboratory trade, is known to have been occurring in Cambodia since 2003 (Eudey, 2008). This practice was reported from the northeast of the country, and specifically in KSWS, from 2006 onwards (Lee, 2011; Pollard et al., 2007; Rawson, 2007), but there has been little evidence of this practice in KSWS in recent years. A second plausible explanation is the tolerance of LT macaque to a range of habitats, including urban and agricultural areas (Eudey, 2008), which in KSWS will expose the species to a higher density of snares and dogs and opportunistic hunting in parts of its range. PT macaques, although adaptable, prefer dense evergreen and semi-evergreen forest where available, and are therefore less exposed to anthropogenic threats. A decline in LT macaque over time may be reducing resource competition with PT macaque, thus facilitating population increase in PT macaque.

Peafowl are predominantly ground-based, yet they have experienced a population increase over the study period. Population recovery of peafowl is rarely recorded in the literature as this species is suffering from habitat loss and hunting across its range, generally leading to population declines (e.g., Sukumal et al. 2015). Nevertheless, when threats are reduced, population recovery can occur (e.g., Sukumal et al. 2017). It is unclear what has caused the increase in peafowl abundance in KSWS. The population density in KSWS is much lower than other areas, even within Cambodia (see Loveridge et al. 2017), suggesting scope for substantial population increases under favorable conditions. Peafowl mortality resulting from ground-based human threats could be lower than that of ungulates for several reasons. They are less vulnerable to dogs, as they can retreat into trees when approached; and they prefer open deciduous habitat which is found in the central, northern, and western regions of KSWS, out of reach of the Vietnam border and the larger human population centers in the south of KSWS.

4.4.3. Implications for Keo Seima Wildlife Sanctuary

Keo Seima Wildlife Sanctuary has been officially protected for nearly two decades, and over the last decade has benefited from a greater level of conservation investment than most other PAs in Cambodia. KSWS has one of the largest law enforcement teams within any Cambodian PA, as well as a range of other programs including indigenous land tenure, community protected areas, ecotourism development, and REDD+. Despite operational budgets that are relatively high in the context of Cambodia, the resources available to KSWS managers are well below international benchmarks. For example, KSWS has less than 10% of the recommended law enforcement ratio of one ranger per $5km^2$ (IUCN, 2016). Our results demonstrate that charismatic and ecologically important species are heading rapidly towards local extirpation – trends that are replicated in other Cambodian PAs (Groenenberg et al. 2020). Substantially more investment, particularly into ranger staffing levels, will be required to reverse current species trends. Recent developments in the voluntary carbon markets, and Cambodia's decision to support both project and national REDD+ programs suggest this may be achieved in a sustainable manner through REDD+.

Historically, law enforcement efforts in KSWS have been disproportionately focused on illegal logging of luxury timber; this trend has been seen in PAs across the country and was a result of national policies and widespread media attention targeting the economically valuable timber trade. These efforts take place at the expense of combatting wildlife crime, with less attention focussed on addressing species declines. Although there have been successes in reducing deforestation compared to the without-project scenario, and an extensive indigenous community land titling program that has increased indigenous tenure within KSWS, there have been no initiatives dedicated to reducing illegal hunting that have focused on community engagement. Community-led law enforcement patrols have been operational in KSWS throughout most of the study period, but these have largely prioritised illegal logging and forest clearance.

The monitoring program in KSWS represents a long-term commitment by RGC and WCS to provide PA managers with rigorous data to inform management action. Our results suggest that for effective conservation management to provide benefits to forests, biodiversity, and communities, increases in scale across all interventions are needed and, within law enforcement, the need for a greater focus on poaching, targeting illegal hunting with snares, weapons, and dogs. Most people in KSWS hunt wildlife for subsistence, as a source of additional income, for medicinal purposes, or to protect crops (Ibbett et al 2020). Therefore, the community-focused conservation programs within KSWS, which include community engagement and livelihood development, should explore and develop approaches to reduce the community reliance on wild meat, promote domestic sources of protein, improve food security and livelihoods more generally, and offer non-lethal crop protection strategies. Such approaches may be more effective and enduring than law enforcement alone. For detailed management recommendations for KSWS and the Eastern Plains Landscape more broadly, see Griffin & Nuttall (2020) and Groenenberg et al. (2020).

4.4.4. Broader implications for SEA

Ten of the 11 species monitored in KSWS are estimated to have declining global populations (Table 4.1, www.iucnredlist.org), yet our results show that 6 of these species have stable or increasing populations in KSWS. The remaining 5 ground-based species have decreasing population trends in KSWS that mirror global population trends. The striking divide we have uncovered between ground-based and arboreal species has important conservation implications for these species throughout their range. Significant declines in KSWS of species such as muntjac, which are generally widespread and common, are concerning as they suggest that sustained anthropogenic pressure can lead to population collapses, even for resilient species. Equally, results for arboreal primates and peafowl from KSWS suggest that when hunting pressure remains low and forest cover is maintained, species populations within a site can remain stable.

Our findings will be valuable for future IUCN Red List assessments and regional conservation planning. We have demonstrated how robust monitoring within KSWS has provided critical information for assessing the impact of past management action, for example reduced forest loss through the REDD+ program, by linking it to species outcomes such as stable primate populations. Our results can guide future management decisions including increased anti-snare efforts and strategic, targeted deployment of resources based on species distributions.

These results also have wider implications for both species conservation and PA management. First, the species trends and potential drivers of population declines seen in KSWS are likely to be replicated in PAs across SEA. Hunting of wildlife for consumption, trophies, and trade is widespread in SEA and has resulted in species extinctions (Brook et al. 2014). Hunting with snares and free-ranging dogs (hunting and feral dogs) in particular represent two of the most serious threats to wildlife populations across SEA. Population declines in terrestrial mammals driven by snaring and free-ranging dogs are likely to be occurring in PAs across SEA where pressure from such threats is high, conservation investment and resources are low, and awareness is limited by inadequate monitoring. In

PAs across the region where these threats are known to exist, this study suggests that managers should target resources at anti-snare efforts and management of free-ranging dogs to protect populations of terrestrial species.

Second, monitoring of biodiversity via appropriate indicators is essential to allow the attribution of species outcomes to conservation action. The establishment of a robust monitoring framework is prioritised in the Post-2020 Global Biodiversity report (CBD 2020a). Monitoring is particularly important within PAs as their primary function is the conservation of biodiversity. Continued efforts to increase global PA coverage, driven by Aichi Target 11 (CBD 2010), have seen some success with over 15% of the Earth's terrestrial surface and 7% of oceans legally protected (UNEP-WCMC et al. 2020). Yet evidence linking management action to biodiversity outcomes within PAs is sparse (Geldmann et al. 2018). For PAs where protection of wildlife is a primary objective, long-term datasets on wildlife populations are critical for understanding population dynamics, evaluating extinction risk, informing management action, and assessing interventions (Magurran et al. 2010; White 2019). Despite the significant contribution that long-term datasets make to conservation research and policy, investment in the collection of such data is falling (Hughes et al. 2017). There is an urgent need for robust long-term wildlife monitoring data in SEA to understand the effects that hunting, wildlife trade, and other threats are having on already-fragmented populations, to support conservation decision-making and assessment, and ultimately to avoid species extinctions.

4.5. ACKNOWLEDGEMENTS

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4.6. SUPPORTING INFORMATION

4.6.1 Data collection on line transects

Effort varied among transects within years, and among years, depending on transect location and available resources each year (Table S4.1). A total of 40 transects were surveyed. For clustered animals, perpendicular distances were recorded from the line transect to the geometric centre of the group. The primary data recorded for each observation on a line transect were: Transect ID, species, distance from transect to individual/cluster, angle of the transect, angle of the individual/cluster, and cluster size (if applicable). Transect 20 was discarded for all analyses as it was located outside the survey area, resulting in the loss of 5 observations across the study period.

Table S4.1. Team composition for line transect surveys. Team members have been anonymised.

	Team member	A	B	C	D	E	F	G	H	I	J	K
Survey												
2010		X	X	X	X					X		
2011		X	X	X	X					X		X
2013		X	X	X	X	X						
2014		X	X	X	X	X	X	X				
2016		X	X	X	X	X	X	X	X			
2018			X	X	X	X	X				X	
2020			X	X	X	X			X		X	

Square line transects can potentially cause detection bias around the corners, as animals on the inner side of the corner could be detected twice. Although double-counting does not in itself violate distance-sampling assumptions, bias may arise if the two sightings are non-independent, for example if the second sighting occurs because animals are still present at the location of the first sighting. To assess whether there was evidence of corner-bias in our data, we tested for differences in density of observations between corner areas and non-corner areas. The corner samples were obtained from all transect sections within 50 m of a corner, and the non-corner samples were obtained by two methods: firstly, as all transect sections not within 50 m of a corner; and secondly by using 50 m transect sections around each of 1000 randomly-selected points, discarding any that overlapped with corner areas. For either method, observation density was calculated for the corner and non-corner samples and compared using a t-test. Neither method resulted in a significant difference in observation density between corner areas and non-corner areas, so no further action was taken to address corner effects.

4.6.2. Detection function model selection

Observation-level covariate data were collected during line transect surveys for inclusion in the detection function modelling process: observer and cluster size (all years), and habitat and time of day (2013 onwards). Evidence of lumping at a distance of 0 m was detected for some species: douc, muntjac, langur, LT macaque, PT macaque, and pig, which can result in biased estimates (Buckland et al., 2001). For these species, models were run using the raw distance data followed by models where distance data were grouped into distance bins. If the abundance estimates from the two sets of models were very similar (< ± 1 SE) then the unbinned results were used. If the results were different (> ± 1 SE) then the binned results were used (Buckland et al., 2015, 2001).

4.6.3. Temporal trend analysis and bootstrapping approach

Uncertainty in distance sampling is comprised predominantly of encounter rate variance (ERV), variance in the estimation of the detection function, and the mean cluster size (Buckland et al., 2001; Fewster et al., 2009). For sites such as KSWS which exhibit high heterogeneity in habitat types, ERV is likely to be high, yet dependent on the particular spatial attributes of the survey design (i.e., transect layout). Bootstrapping is an effective method for quantifying the range of uncertainty arising from the above processes (O. N. P. Hamilton et al., 2018). Many of the study species were known to exhibit spatial heterogeneity in abundance, and this variation could be broadly associated with habitat. We therefore employed a bootstrap scheme based on habitat strata, such that every bootstrap resample had a similar habitat composition to that of the original sample. This ensured that the bootstrap resamples would reflect the key property of the systematic sampling design, namely that all realisations of the design have representative habitat coverage. A detailed description of principles of variance estimation for systematic survey designs is given in Fewster (2011).

To implement the bootstrap scheme, transects were first categorised by broad habitat type (“dense” or “open” forest). Transects within each habitat category were sampled with replacement until the effort across all years in the sample first equalled or exceeded the effort across all years for that habitat category in the original data, producing a single bootstrap replicate. A detection function model was fitted to the replicate data using the same key function and truncation distance used in the abundance estimation above. A GAM was fitted to the resulting abundance estimates and used to predict a smooth temporal abundance trend across the study period for that replicate. Prior to the bootstrapping, GAMs with either one, two, or three degrees of freedom were fitted to the original abundance estimates for each species and AIC was used to determine the best fit. This same model formulation was used for each replicate of that species. From 2000 bootstrap replicates, we obtained 2000 replicate GAM trend curves. The overall estimated trend curve and 95% confidence intervals were taken on a pointwise basis from the 50%, 2.5%, and 97.5% quantiles of these 2000 curves.

4.6.4. Covariates used in the spatial models

The distances from a segment to the nearest variable location (e.g., water body, Vietnam border) were measured from the centre of the segment. The variables tested in the spatial models were within-segment habitat (dense forest, open forest, non-forest, deforested, water), elevation, distance to water bodies, distance to human settlements, distance to ranger stations, and distance to the Vietnamese border. A habitat class was assigned to a transect segment or a prediction grid cell when it covered more than 50% of the spatial unit. If a cell or segment had equal amounts of two habitat classes, then the dominant class in the surrounding area was chosen. A digital elevation model was used to assign elevation values to line transect segments and prediction grid cells, and the locations of ranger stations, human settlements and the Vietnam border were provided by the Ministry of Environment of the Royal Government of Cambodia. Spatial data on rivers were provided by WCS. Distances from prediction grid cells and transect segments to the nearest variable point location were calculated using QGIS ("QGIS Geographic Information System," 2020).

4.6.5. Creation of transect segments and the prediction grid

Each line transect was divided into 40 equally sized contiguous spatial segments measuring 100m x 100m (n = 1560) and wildlife observations were allocated to the segment within which they fell. Segment size was based on 2 x effective strip width W which was truncated to 50m (Buckland et al., 2004). In addition to their primary numerical IDs (i.e. 1 - 39), transects were given unique IDs for each multi-day visit across all years (n = 349) in order to reduce confounding temporal effects when testing model results for autocorrelation (Buckland et al., 2004). To improve autocorrelation assessment further each segment was also given a unique ID for each multi-day visit (n = 14,240), resulting in multiple IDs for each spatial segment representing temporal replication of surveys within that segment. Spatial trends for the entire study area were predicted over a grid with a cell size of 200 x 200m (n = 70,024). The size of the study area and available computing power precluded a prediction grid with cell size matching the transect segment size, and so the smallest practical size that was appropriate for the scale of the covariates was selected. The prediction grid was produced using QGIS (*QGIS Geographic Information System*, 2018, version 3.4.0). Each prediction grid cell and transect segment was assigned a value for each variable.

4.6.6 Details on spatial modelling process, model selection, and autocorrelation

Model building started with fully saturated models, with model complexity being reduced in a step-wise fashion. Terms were removed if their estimated degrees of freedom (EDF) had been shrunk to <1, or if they were insignificant ($p>0.05$). If a covariate's EDF was close to 1 the model was re-run with that covariate as a parametric term to check if model fit was improved. Model selection was done using a combination of diagnostic plot assessment and AIC for Tweedie and negative binomial distributions, and analysis of variance for the quasi-Poisson distribution. The habitat variable was retained in all models based on the authors' understanding of the importance of habitat for the species in this study. Each final model was tested for autocorrelation. If significant autocorrelation existed models would be re-fit with the following terms in succession until autocorrelation was reduced: univariate or bivariate smooths of the location (x,y), first-order autoregressive covariance structure, autoregressive moving average error structure. The best model from each of the three distribution groups was tested against the other two using AIC (Tweedie and negative binomial) and analysis of variance (quasi-Poisson), resulting in a single final model. Variance for the final model was estimated by summing the GAM uncertainty estimation with the detection function uncertainty estimation via the delta method (Buckland et al., 2004).

Table S4.2. Total effort (distance walked) in each survey year and the number of observed clusters for all recorded species*

Year	Effort (km^2)	BAN	BSD	ELD	GAU	GPF	GSL	LTM	PIG	PTM	RMJ	SAM	STM	YCG	Total
2010	1600	5	333	0	13	26	36	36	53	26	169	6	7	19	729
2011	1476	3	461	0	9	16	36	35	28	57	175	3	11	47	881
2013	1260	0	265	1	2	16	34	7	26	43	167	5	1	21	588
2014	1292	8	535	0	7	25	36	28	41	80	181	7	6	34	988
2016	1272	3	437	2	1	12	17	17	32	49	93	0	7	24	694
2018	1280	1	338	1	2	41	21	23	23	73	58	3	0	32	616
2020	1280	0	333	0	1	31	13	24	19	73	35	0	2	29	560
Total	9460	**20**	**2702**	**4**	**35**	**167**	**193**	**170**	**222**	**401**	**878**	**24**	**34**	**206**	**5056**

* BAN = Banteng, BSD = Black-shanked douc, ELD = Eld's deer, GAU = Gaur, GSL = Germain's silver langur, LTM = Long-tailed macaque, PIG = Wild pig, PTM = Pig-tailed macaque, RMJ = Northern red muntjac, SAM = Sambar, STM = Stump-tailed macaque, YCG = Yellow-cheeked crested gibbon

Table S4.3. Encounter rate for each recorded species* in each survey year. Encounter rate is calculated as n/L where n is the total number of observed individuals and L is the total length of transect walked (effort).

Year	BSD	BAN	ELD	GAU	GPF	GSL	LTM	PIG	PTM	RMJ	SAM	STM	YCG	Mean
2010	0.7200	0.0244	0.0000	0.0119	0.0238	0.0769	0.1113	0.0938	0.0619	0.1125	0.0044	0.0200	0.0231	0.0988
2011	1.1098	0.0068	0.0000	0.0183	0.0237	0.0996	0.1321	0.0203	0.1877	0.1287	0.0020	0.0298	0.0793	0.1414
2013	0.8222	0.0000	0.0016	0.0016	0.0325	0.1278	0.0389	0.0341	0.1635	0.1444	0.0056	0.0032	0.0405	0.1089
2014	1.6664	0.0093	0.0000	0.0108	0.0286	0.1432	0.0759	0.0627	0.2539	0.1401	0.0070	0.0163	0.0712	0.1912
2016	0.9717	0.0063	0.0024	0.0008	0.0228	0.0558	0.0527	0.0590	0.1226	0.0731	0.0000	0.0102	0.0417	0.1092
2018	1.0570	0.0008	0.0016	0.0031	0.0805	0.1414	0.1602	0.0406	0.2047	0.0500	0.0023	0.0000	0.0641	0.1389
2020	1.0758	0.0000	0.0000	0.0008	0.0430	0.0734	0.0680	0.0367	0.1797	0.0273	0.0000	0.0063	0.0641	0.1212
Mean	1.0604	0.0068	0.0008	0.0068	0.0364	0.1026	0.0913	0.0496	0.1677	0.0966	0.0030	0.0122	0.0548	0.1299

* BAN = Banteng, BSD = Black-shanked douc, ELD = Eld’s deer, GAU = Gaur, GSL = Germain’s silver langur, LTM = Long-tailed macaque, PIG = Wild pig, PTM = Pig-tailed macaque, RMJ = Northern red muntjac, SAM = Sambar, STM = Stump-tailed macaque, YCG = Yellow-cheeked crested gibbon

Table S4.4. Model formulation, abundance and density estimates from conventional distance sampling for the 11 key species. N is the estimate for individual abundance, and D is the estimate for individual density. For each of N and D the associated parameters are: se = standard error, cv = coefficient of variation, and lcl and ucl = lower and upper 95% confidence intervals respectively.

Year	Species*	Data pooling	Key term**	Adjustment term ***	Covariates$	N	n_se	n_cv	n_lcl	n_ucl	D	d_se	d_cv	d_lcl	d_ucl
2010	BSD	annual	Hn	-	-	24289	5127	0.21	15936	37021	12.92	2.73	0.21	8.48	19.69
2011	BSD	annual	Hn	-	-	25795	5299	0.21	17098	38917	13.72	2.82	0.21	9.10	20.70
2013	BSD	annual	Hn	-	-	24444	4699	0.19	16653	35881	13.00	2.50	0.19	8.86	19.09
2014	BSD	annual	Hn	-	Observer + Habitat	35351	6283	0.18	24754	50486	18.80	3.34	0.18	13.17	26.85
2016	BSD	annual	Hr	-	AM/PM	21744	4117	0.19	14877	31782	11.57	2.19	0.19	7.91	16.91
2018	BSD	annual	Hn	-	observer + habitat	27720	5697	0.21	18406	41747	14.75	3.03	0.21	9.79	22.21
2020	BSD	annual	Hr	-	observer	24929	5352	0.22	16241	38266	13.26	2.85	0.22	8.64	20.35
2010	YCG	pooled	Hn	-	year	952	378	0.40	441	2055	0.51	0.20	0.40	0.24	1.09
2011	YCG	pooled	Hn	-	Cluster size	1707	492	0.29	960	3033	0.91	0.26	0.29	0.51	1.61
2013	YCG	pooled	Hn	-	year	1317	356	0.27	772	2245	0.70	0.19	0.27	0.41	1.19
2014	YCG	pooled	Hn	-	Cluster size	1431	462	0.32	756	2709	0.76	0.25	0.32	0.40	1.44
2016	YCG	pooled	Hn	-	Cluster size	912	239	0.26	541	1536	0.49	0.13	0.26	0.29	0.82
2018	YCG	pooled	Hn	-	year	1505	429	0.29	858	2637	0.80	0.23	0.29	0.46	1.40
2020	YCG	pooled	Hn	-	year	1432	474	0.33	750	2735	0.76	0.25	0.33	0.40	1.46
2010	GSL	pooled	Hn	-	size + year	2912	1703	0.59	974	8712	1.55	0.91	0.59	0.52	4.63
2011	GSL	pooled	Hn	-	size + year	3468	1735	0.50	1335	9009	1.85	0.92	0.50	0.71	4.79
2013	GSL	pooled	Hn	-	size + year	3524	1499	0.43	1547	8029	1.87	0.80	0.43	0.82	4.27
2014	GSL	pooled	Hn	-	size + year	3205	2040	0.64	985	10425	1.71	1.09	0.64	0.52	5.55

2016	GSL	pooled	Hn	-	size + year	1515	1213	0.80	365	6292	0.81	0.65	0.80	0.19	3.35
2018	GSL	pooled	Hn	-	size + year	2935	1435	0.49	1153	7475	1.56	0.76	0.49	0.61	3.98
2020	GSL	pooled	Hn	-	size + year	1487	720	0.48	588	3758	0.79	0.38	0.48	0.31	2.00
2010	LTM	pooled	Hn	-	size + year	3125	1324	0.42	1379	7080	1.66	0.70	0.42	0.73	3.77
2011	LTM	pooled	Hn	-	size + year	3557	1348	0.38	1704	7425	1.89	0.72	0.38	0.91	3.95
2013	LTM	pooled	Hn	-	size + year	830	553	0.67	245	2812	0.44	0.29	0.67	0.13	1.50
2014	LTM	pooled	Hn	-	size + year	2160	1038	0.48	860	5424	1.15	0.55	0.48	0.46	2.89
2016	LTM	pooled	Hn	-	size + year	1460	598	0.41	660	3231	0.78	0.32	0.41	0.35	1.72
2018	LTM	pooled	Hn	-	size + year	3504	1598	0.46	1461	8403	1.86	0.85	0.46	0.78	4.47
2020	LTM	pooled	Hn	-	size + year	1566	549	0.35	792	3097	0.83	0.29	0.35	0.42	1.65
2010	PTM	pooled	Hn	-	Cluster size + Year	2008	818	0.41	913	4417	1.07	0.44	0.41	0.49	2.35
2011	PTM	pooled	Hr	-	Cluster size	4320	1437	0.33	2237	8343	2.30	0.77	0.33	1.19	4.44
2013	PTM	pooled	Hn	-	Cluster size + Year	4224	1345	0.32	2262	7889	2.25	0.72	0.32	1.20	4.20
2014	PTM	pooled	Hr	-	Cluster size	5615	1226	0.22	3622	8705	2.99	0.65	0.22	1.93	4.63
2016	PTM	pooled	Hr	-	Cluster size	2539	612	0.24	1568	4112	1.35	0.33	0.24	0.83	2.19
2018	PTM	pooled	Hn	-	Cluster size + Year	5138	1322	0.26	3085	8557	2.73	0.70	0.26	1.64	4.55
2020	PTM	pooled	Hn	-	Cluster size + Year	3929	930	0.24	2457	6284	2.09	0.49	0.24	1.31	3.34
2010	STM	pooled	Hr	-	-	529	344	0.65	159	1758	0.28	0.18	0.65	0.09	0.94
2011	STM	pooled	Hr	-	-	1093	742	0.68	315	3796	0.58	0.40	0.68	0.17	2.02
2013	STM	pooled	Hr	-	-	116	117	1.00	22	631	0.06	0.06	1.00	0.01	0.34
2014	STM	pooled	Hr	-	-	598	404	0.68	173	2064	0.32	0.22	0.68	0.09	1.10
2016	STM	pooled	Hr	-	-	375	222	0.59	124	1134	0.20	0.12	0.59	0.07	0.60

2018	STM	pooled	Hr	-	-	0	0	0.00	0	0	0.00	0.00	0.00	0.00	0.00
2020	STM	pooled	Hr	-	-	230	231	1.01	42	1246	0.12	0.12	1.01	0.02	0.66
2010	BTG	pooled	Uni	SimPoly	-	382	367	0.96	75	1956	0.20	0.20	0.96	0.04	1.04
2011	BTG	pooled	Uni	SimPoly	-	121	99	0.81	29	511	0.07	0.05	0.81	0.02	0.27
2013	BTG	pooled	Uni	SimPoly	-	0	0	0.00	0	0	0.00	0.00	0.00	0.00	0.00
2014	BTG	pooled	Uni	SimPoly	-	167	74	0.45	71	392	0.09	0.04	0.45	0.04	0.21
2016	BTG	pooled	Uni	SimPoly	-	113	89	0.79	28	461	0.06	0.05	0.79	0.02	0.25
2018	BTG	pooled	Uni	SimPoly	-	14	14	1.02	3	77	0.01	0.01	1.02	0.00	0.04
2020	BTG	pooled	Uni	SimPoly	-	0	0	0.00	0	0	0.00	0.00	0.00	0.00	0.00
2010	GAU	pooled	Hn	-	-	497	348	0.70	139	1778	0.26	0.19	0.70	0.07	0.95
2011	GAU	pooled	Hn	-	-	763	624	0.82	180	3236	0.41	0.33	0.82	0.10	1.72
2013	GAU	pooled	Hn	-	-	66	47	0.72	18	242	0.04	0.03	0.72	0.01	0.13
2014	GAU	pooled	Hn	-	-	453	257	0.57	156	1313	0.24	0.14	0.57	0.08	0.70
2016	GAU	pooled	Hn	-	-	0	0	0.00	0	0	0.00	0.00	0.00	0.00	0.00
2018	GAU	pooled	Hn	-	-	131	105	0.80	32	541	0.07	0.06	0.80	0.02	0.29
2020	GAU	pooled	Hn	-	-	33	33	1.01	6	179	0.02	0.02	1.01	0.00	0.10
2010	PIG	pooled	Hr	-	year	3377	1039	0.31	1846	6177	1.80	0.55	0.31	0.98	3.29
2011	PIG	pooled	Hr	-	year	729	145	0.20	492	1080	0.39	0.08	0.20	0.26	0.57
2013	PIG	pooled	Hr	-	year	1175	392	0.33	610	2262	0.63	0.21	0.33	0.33	1.20
2014	PIG	pooled	Hr	-	year	2067	493	0.24	1288	3316	1.10	0.26	0.24	0.69	1.76
2016	PIG	pooled	Hr	-	year	1832	783	0.43	801	4188	0.97	0.42	0.43	0.43	2.23
2018	PIG	pooled	Hr	-	year	1267	399	0.32	683	2348	0.67	0.21	0.32	0.36	1.25

2020	PIG	pooled	Hr	-	year	1100	355	0.32	587	2063	0.59	0.19	0.32	0.31	1.10
2010	RMJ	pooled	Hn	-	-	3383	557	0.17	2434	4703	1.80	0.30	0.17	1.30	2.50
2011	RMJ	pooled	Hn	-	-	3967	666	0.17	2836	5550	2.11	0.35	0.17	1.51	2.95
2013	RMJ	pooled	Hn	-	-	4258	650	0.15	3137	5780	2.27	0.35	0.15	1.67	3.07
2014	RMJ	pooled	Hn	-	-	4317	760	0.18	3036	6138	2.30	0.40	0.18	1.62	3.27
2016	RMJ	pooled	Hn	-	-	2173	466	0.21	1417	3334	1.16	0.25	0.21	0.75	1.77
2018	RMJ	pooled	Hn	-	-	1573	295	0.19	1082	2288	0.84	0.16	0.19	0.58	1.22
2020	RMJ	pooled	Hn	-	-	825	188	0.23	524	1300	0.44	0.10	0.23	0.28	0.69
2010	GPF	pooled	Hn	-	year + size	308	110	0.36	154	617	0.16	0.06	0.36	0.08	0.33
2011	GPF	pooled	Hn	-	year + size	380	187	0.49	148	972	0.20	0.10	0.49	0.08	0.52
2013	GPF	pooled	Hn	-	year + size	377	165	0.44	162	877	0.20	0.09	0.44	0.09	0.47
2014	GPF	pooled	Hn	-	year + size	500	156	0.31	271	926	0.27	0.08	0.31	0.14	0.49
2016	GPF	pooled	Hn	-	year + size	370	213	0.58	125	1093	0.20	0.11	0.58	0.07	0.58
2018	GPF	pooled	Hn	-	year + size	1288	508	0.40	599	2770	0.69	0.27	0.40	0.32	1.47
2020	GPF	pooled	Hn	-	year + size	745	262	0.35	375	1481	0.40	0.14	0.35	0.20	0.79

* YCG – Yellow-cheeked crested gibbon, BSD – Black-shanked douc langur, GSL – Germain's silver langur, LTM – Long-tailed macaque, PTM – Pig-tailed macaque, STM – Stump-tailed macaque, BTG – Banteng, GAU – Gaur, PIG – Wild pig, RMJ – Northern red muntjac, GPF – Green peafowl.

** Hn – Half normal, Uni – Unifom, Hr – Hazard rate.

*** Cos – Cosine, SimPoly – Simple polynomial

$ To create the 'year' covariate the years were treated as numeric and scaled and centred. 'AM/PM' represented the time of day the survey was conducted (morning or afternoon).

+ Grp – group abundance estimated, Ind – Individual abundance estimated

Table S4.5. Model formulation and deviance explained for the final spatial model for each species

Species*	Distribution**	Model***	Deviance Explained (%)
GPF	NB	s(DB) + Hab + DW	24.4
BSD	QP	s(DS) + s(DB) + s(Dst) + s(E) + s(x) + s(y) + Hab	28.5
RMJ	NB	s(DS) + s(DB) + s(Dst) + Hab	16.3
YCG	NB	s(DB) + s(DW) + s(x) + s(y) + Hab + Dst	18.5
GSL	NB	s(DW) + s(Dst) + s(x,y) + Hab + E	66.1
LTM	NB	s(DW) + s(DB) + s(E) + Hab + Dst	32.5
PTM	NB	s(DW) + s(E) + s(x) + s(y) + Hab + DB	19.7

* YCG – Yellow-cheeked crested gibbon, BSD – Black-shanked douc langur, GSL – Germain's silver langur, LTM – Long-tailed macaque, PTM – Pig-tailed macaque, RMJ – Northern red muntjac, GPF – Green peafowl.

** NB – negative binomial, QP – quasi-Poisson

*** DB – distance to Vietnam border, Hab – Habitat, DW – distance to water, DS – distance to human settlement, Dst – distance to ranger station, E – elevation, XY – xy coordinates

Table S4.6. Model outputs for the final spatial model for green peafowl. Values are on the log scale

	Parametric coefficients				Smooth terms		
Parameter*	**Estimate**	**SE**	**Z value**	***p***	**edf**	**χ^2**	***p***
Intercept (Habitat D)	-1.52	0.32	-47.3	$<2 \times 10^{-16}$			
Habitat DEF	2.61	1.65	1.59	0.11			
Habitat NF	1.59	0.56	2.83	4.7×10^{-3}			
Habitat O	2.0	0.34	5.90	4×10^{-9}			
Habitat W	-37.1	8.2×10^{6}	0.00	1.0			
Distance to water	-5.3×10^{-4}	2.8×10^{-4}	-1.9	0.05			
Distance to border					3.34	35.7	1.1 ×10-8

* Habitat abbreviations: D – dense forest, O – open forest, DEF – deforested, NF – non-forest, W - water

Table S4.7. Model outputs for the final spatial model for black-shanked douc. Values are on the log scale

	Parametric coefficients				Smooth terms		
Parameter*	**Estimate**	**SE**	**T value**	***p***	**edf**	***F***	***p***
Intercept (Habitat D)	-11.46	0.31	-37.31	$<2 \times 10^{-16}$			
Habitat DEF	-0.70	0.79	-0.85	0.40			
Habitat NF	-1.84	0.42	-4.34	1.4×10^{-5}			
Habitat O	-1.53	0.11	-13.75	$<2 \times 10^{-16}$			
Habitat W	-2.0	0.95	-2.10	0.04			
Distance to settlement					2.81	3.19	9.6×10^{-4}
Distance to border					3.51	4.74	9.6×10^{-5}
Distance to ranger station					2.95	12.47	1.6×10^{-13}
Elevation					3.61	3.58	2.5×10^{-3}
X					7.33	5.10	5.0×10^{-9}
Y					7.90	8.88	$<2 \times 10^{-16}$

* Habitat abbreviations: D – dense forest, O – open forest, DEF – deforested, NF – non-forest, W - water

Table S4.8. Model outputs for the final spatial model for northern red muntjac. Values are on the log scale

	Parametric coefficients				Smooth terms		
Parameter	**Estimate**	**SE**	**Z value**	***p***	**edf**	**χ^2**	***p***
Intercept (Habitat D)	-12.14	0.09	-142.56	2×10^{-16}			
Habitat DEF	-36.95	1.2×10^{7}	0.00	1.0			
Habitat NF	0.35	0.28	1.24	0.214			
Habitat O	0.38	0.13	3.0	2.7×10^{-3}			
Habitat W	-37.7	8.2×10^{6}	0.00	1.0			
Distance to settlement					6.32	46.02	5.03×10^{-10}
Distance to border					4.50	118.81	$<2 \times 10^{-16}$
Distance to ranger station					3.10	12.65	0.002

* Habitat abbreviations: D – dense forest, O – open forest, DEF – deforested, NF – non-forest, W - water

Table S4.9. Model outputs for the final spatial model for yellow-cheeked crested gibbon. Values are on the log scale

	Parametric coefficients				Smooth terms		
Parameter*	**Estimate**	**SE**	**Z value**	***p***	**edf**	**χ^2**	***p***
Intercept (Habitat D)	-13.90	0.36	-38.10	$<2 \times 10^{-16}$			
Habitat DEF	-42.91	0.00	-Inf	$<2 \times 10^{-16}$			
Habitat NF	-2.65	0.97	-2.72	0.007			
Habitat O	-1.44	0.27	-5.32	1.0×10^{-7}			
Habitat W	0.56	1.03	0.55	0.59			
Distance to ranger station	8.4×10^{-5}	3.7×10^{-5}	2.23	0.02			
Distance to border					2.14	6.51	0.001
Distance to water					0.89	6.22	0.006
X					2.46	12.41	2.4×10^{-5}
Y					2.96	14.81	1.7×10^{-5}

* Habitat abbreviations: D – dense forest, O – open forest, DEF – deforested, NF – non-forest, W - water

Table S4.10. Model outputs for the final spatial model for Germain's silver langur. Values are on the log scale

	Parametric coefficients				**Smooth terms**		
Parameter*	**Estimate**	**SE**	**Z value**	***p***	**edf**	**χ^2**	***p***
Intercept (Habitat D)	-8.62	2.04	-4.22	2.4×10^{-5}			
Habitat DEF	-53.63	1.2×10^{7}	0.00	0.99			
Habitat NF	-0.66	0.86	-0.76	0.45			
Habitat O	-2.11	0.35	-6.02	1.7×10^{-9}			
Habitat W	1.04	9.5×10^{-3}	1.20	0.23			
Elevation	-0.03	9.5×10^{-3}	-3.57	3.6×10^{-4}			
Distance to water					3.04	28.74	1.6×10^{-7}
Distance to ranger station					0.87	2.66	0.008
XY					18.00	110.50	$<2 \times 10^{-16}$

* Habitat abbreviations: D – dense forest, O – open forest, DEF – deforested, NF – non-forest, W - water

Table S4.11. Model outputs for the final spatial model for long-tailed macaque. Values are on the log scale

	Parametric coefficients				**Smooth terms**		
Parameter*	**Estimate**	**SE**	**Z value**	***p***	**edf**	**χ^2**	***p***
Intercept (Habitat D)	-14.76	0.33	-45.05	$<2 \times 10^{-16}$			
Habitat DEF	-33.46	0.00	-Inf	$<2 \times 10^{-16}$			
Habitat NF	-1.91	1.04	-1.84	0.065			
Habitat O	-1.19	0.29	-4.10	4.5×10^{-5}			
Habitat W	1.81	1.12	1.63	0.10			
Distance to ranger station	1.5×10^{-4}	3.2×10^{-5}	4.75	2.04×10^{-6}			
Distance to water					2.35	23.17	2.1×10^{-6}
Distance to border					3.86	34.45	2.1×10^{-4}
Elevation					1.16	3.53	0.059

* Habitat abbreviations: D – dense forest, O – open forest, DEF – deforested, NF – non-forest, W - water

Table S4.12. Model outputs for the final spatial model for pig-tailed macaque. Values are on the log scale

	Parametric coefficients				Smooth terms		
Parameter*	**Estimate**	**SE**	**Z value**	***p***	**edf**	**χ^2**	***p***
Intercept (Habitat D)	-21.03	3.85	-5.47	4.5×10^{-8}			
Habitat DEF	-1.02	1.37	-0.75	0.46			
Habitat NF	-2.35	0.55	-4.30	1.8×10^{-5}			
Habitat O	-1.31	0.21	-6.28	3.3×10^{-10}			
Habitat W	-0.55	0.97	-0.56	0.57			
Distance to border	3.3×10^{-4}	1.5×10^{-4}	2.18	0.03			
Distance to water					3.36	18.80	8.3×10^{-5}
Elevation					3.27	25.89	1.1×10^{-6}
X					4.23	17.60	1.9×10^{-4}
Y					2.20	10.82	9.7×10^{-4}

* Habitat abbreviations: D – dense forest, O – open forest, DEF – deforested, NF – non-forest, W - water

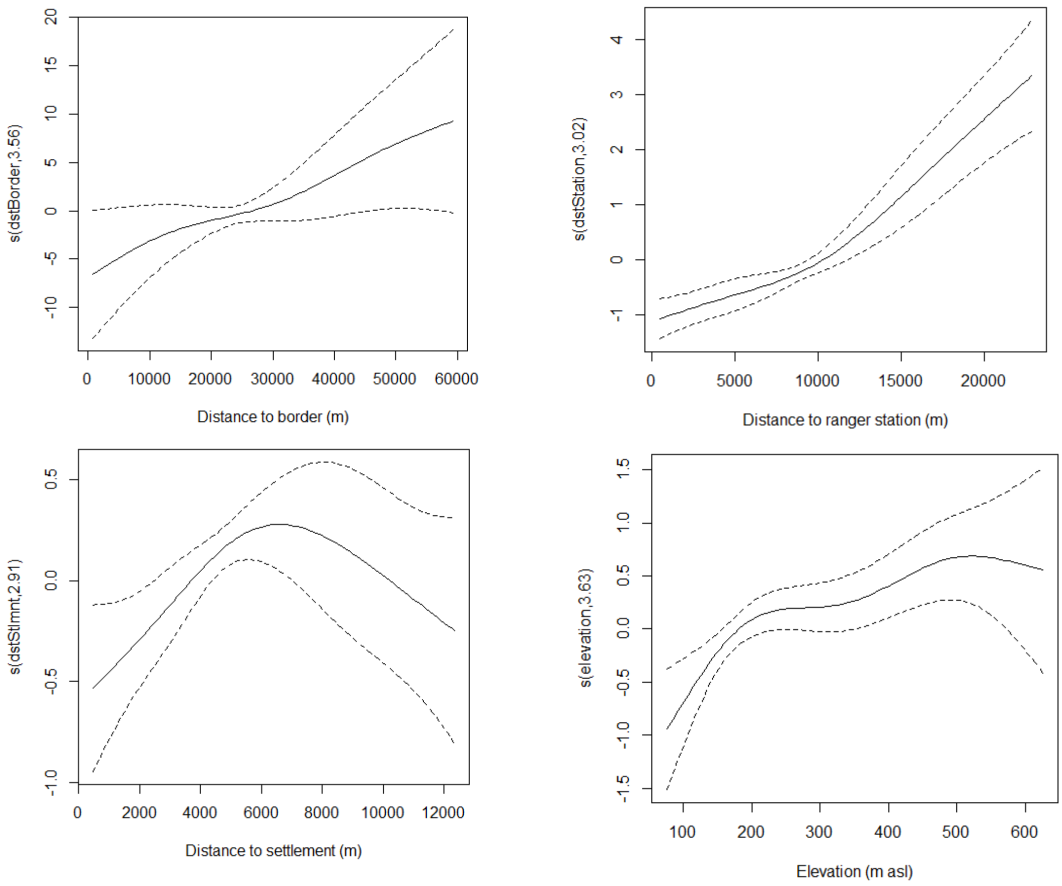

Figure S4.1. Smooth plots for black-shanked douc. X axes are the covariates and the Y axes are abundance on the link (log) scale

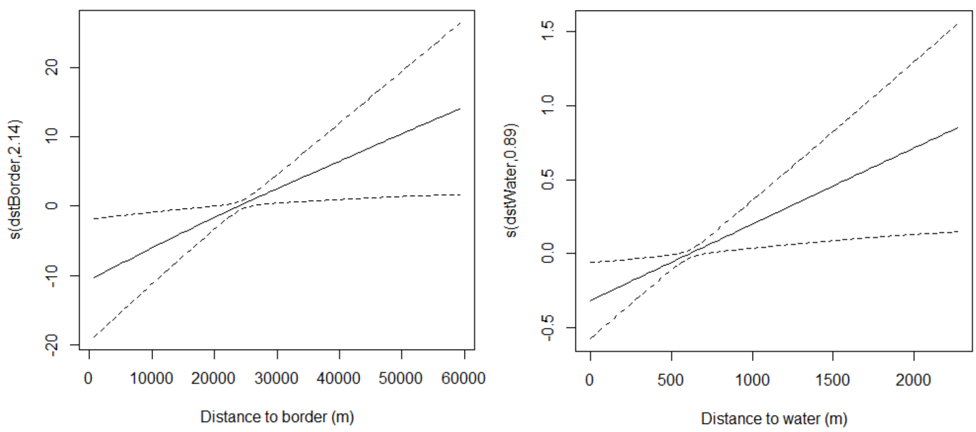

Figure S4.2. Smooth plots for yellow-cheeked crested gibbon. X axes are the covariates and the Y axes are abundance on the link (log) scale

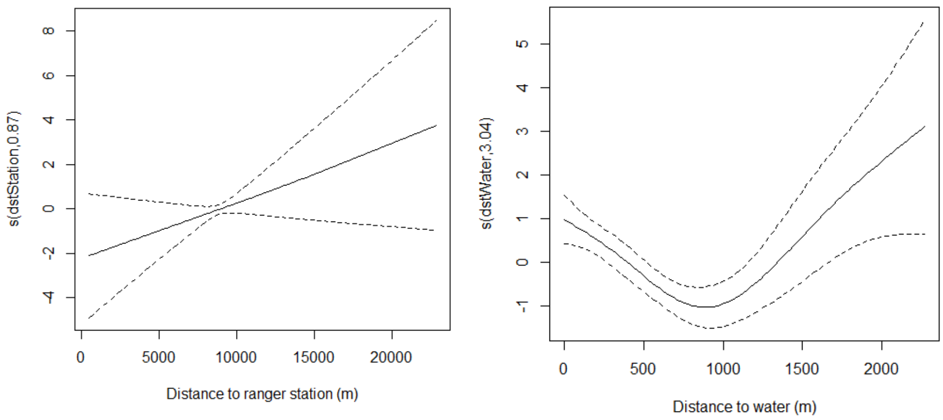

Figure S4.3. Smooth plots for Germain's silver langur. X axes are the covariates and the Y axes are abundance on the link (log) scale

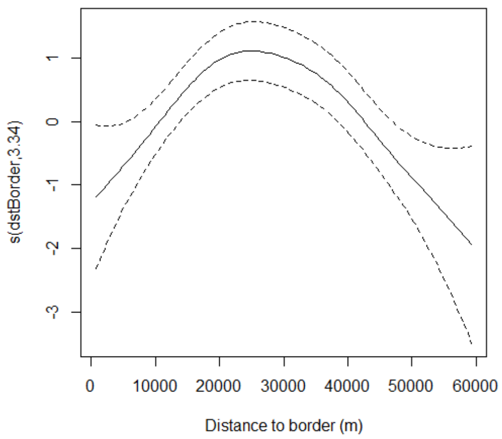

Figure S4.4. Smooth plots for green peafowl. X axes are the covariates and the Y axes are abundance on the link (log) scale

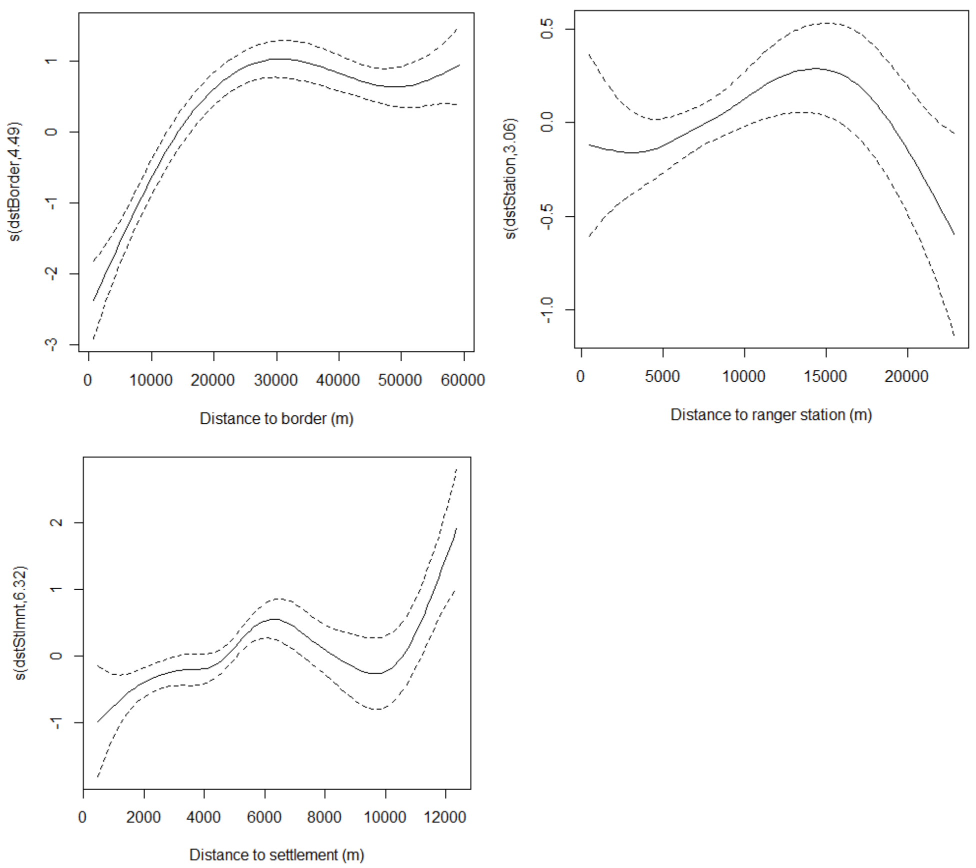

Figure S4.5. Smooth plots for northern red muntjac. X axes are the covariates and the Y axes are abundance on the link (log) scale

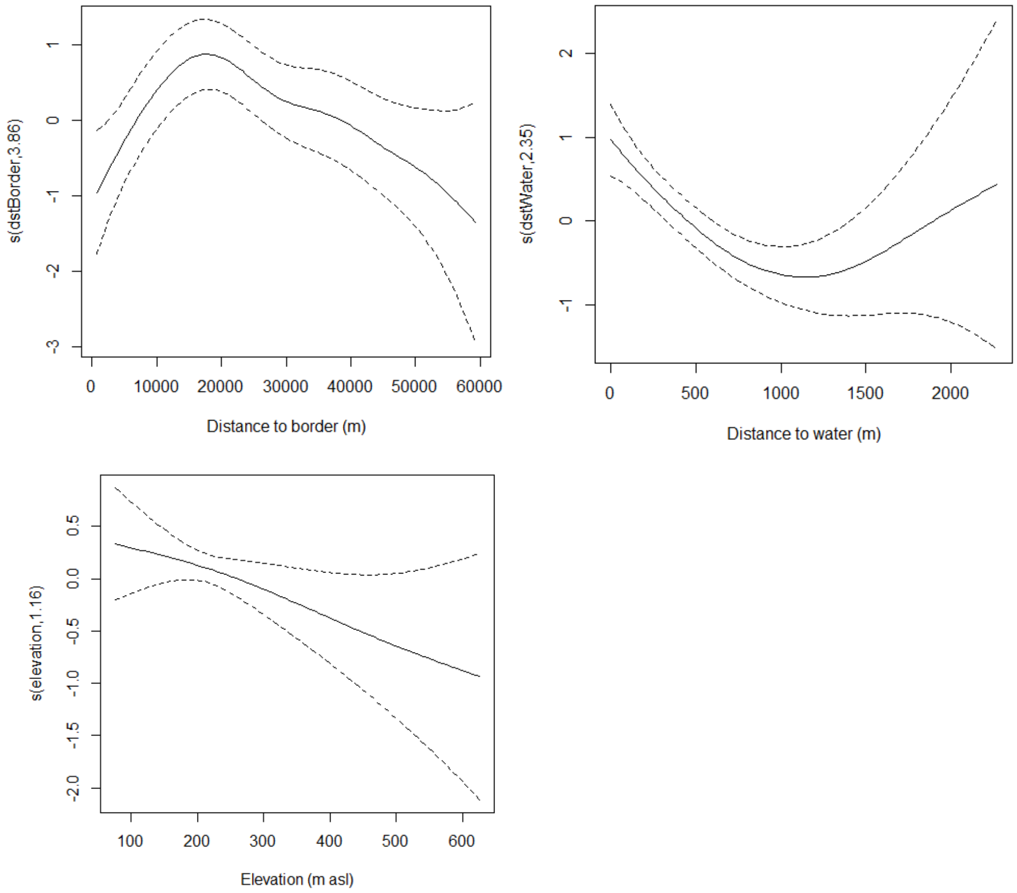

Figure S4.6. Smooth plots for long-tailed macaque. X axes are the covariates and the Y axes are abundance on the link (log) scale

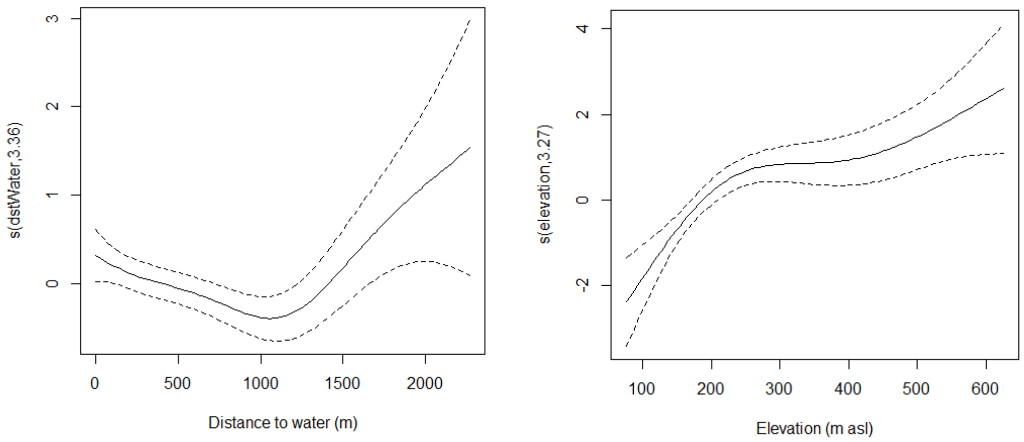

Figure S4.7. Smooth plots for pig-tailed macaque. X axes are the covariates and the Y axes are abundance on the link (log) scale

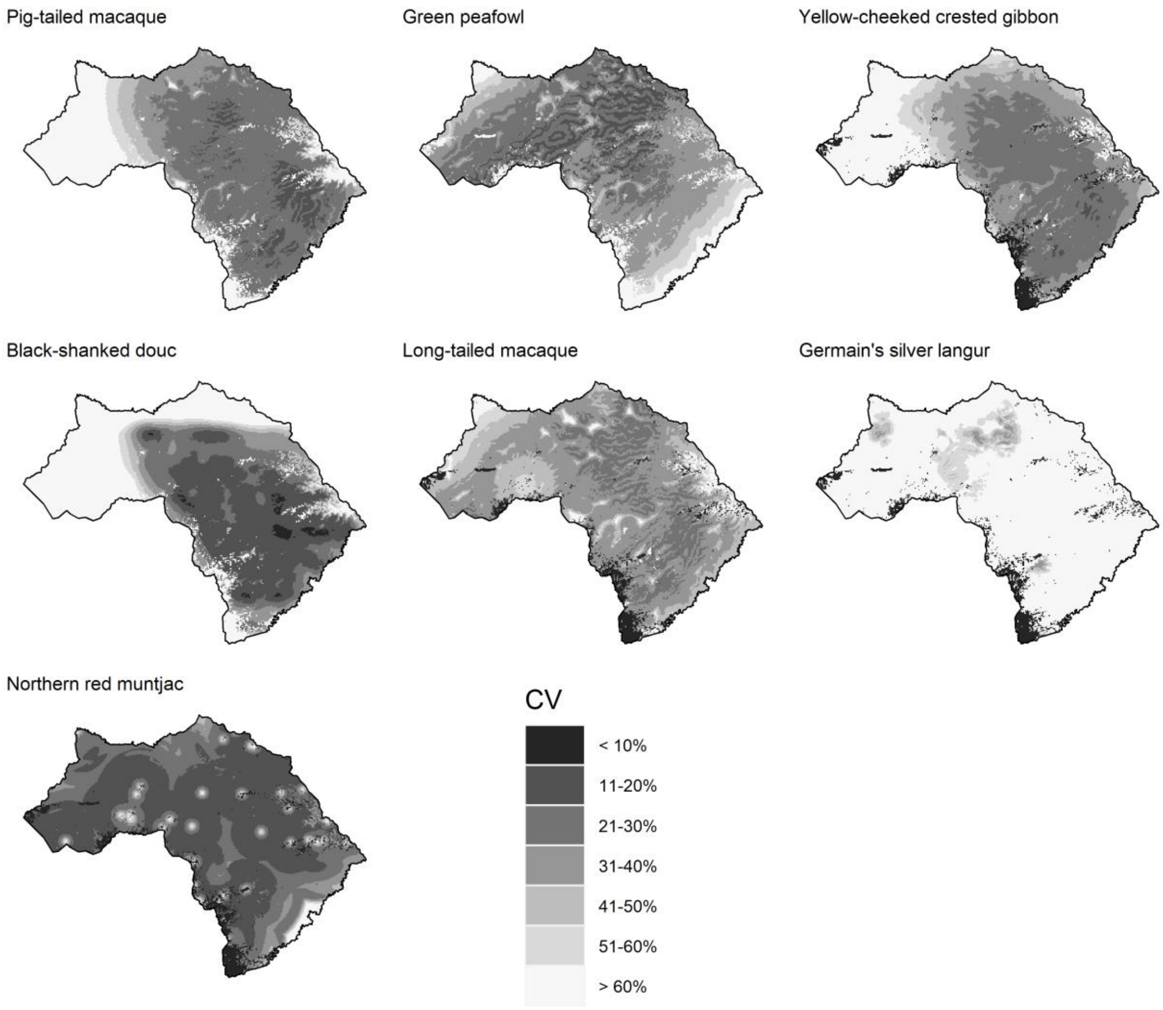

Figure S4.8. Coefficient of variation for the spatial model predictions presented in Figure 4.3 of the main chapter

Table 4.1 in the main chapter provides details of published population estimates for the 11 focal species. Table 4.1 is limited to peer-reviewed publications, estimates that account for imperfect detection, have some form of error estimation (standard errors, confidence intervals), and are absolute estimates (as opposed to relative indices). There are, however, many reports and other publications that provide valuable information on the species, but for one or several of the reasons above were excluded from Table 4.1. The table below (Table S4.13) provides some of these additional references, although it is not an exhaustive list.

Table S4.13. Additional references for the 11 species monitored in Keo Seima Wildlife Sanctuary

Common name	Scientific name	Additional references
Southern yellow-cheeked crested gibbon	*Nomascus gabriellae*	Gray et al., 2010; Rawson et al., 2011; Thinh et al., 2010; Traeholt et al., 2005
Black-shanked douc	*Pygathrix nigripes*	Duc et al., 2008; Hoang, 2007; Nadler et al., 2007; Pollard et al., 2007
Germain's silver langur	*Trachypithecus germaini*	Fiore, 2013; Moody, 2018; Timmins et al., 2013
Long-tailed macaque	*Macaca fascicularis*	Karuppannan et al., 2014; Riley et al., 2015; Saren et al., 2019
Northern pig-tailed macaque	*Macaca leonina*	Chetry et al., 2003; Coudrat and Nekaris, 2013; Nguyen et al., 2012; Sharma et al., 2014
Stump-tailed macaque	*Macaca arctoides*	Nguyen et al., 2012; Syamil et al., 2019; Toyoda et al., 2020
Banteng	*Bos javanicus*	Hedges and Meijaard, 1999; Journeaux et al., 2018; Nguyen, 2009; Pedrono et al., 2009
Gaur	*Bos gaurus*	Ahrestani and Karanth, 2014; Choudhury, 2002; Gray et al., 2012; Karanth and Kumar, 2015; Nguyen, 2009
Northern red muntjac	*Muntiacus vaginalis*	Karanth and Nichols, 2000; Pei et al., 2010; Steinmetz et al., 2010; Teng et al., 2005
Wild pig	*Sus scrofa*	Ariefiandy et al., 2016; Gentle et al., 2019; Ickes, 2001 (and refs within); Ikeda et al., 2020; O'Brien et al., 2003; Sánchez-Cordón et al., 2019
Green peafowl	*Pavo muticus*	Brickle, 2002; Goes, 2009; Hernowo, 2011; McGowan et al., 1998; Shwe et al., 2020; van Balen et al., 1995

Chapter 5

Conservation funding in dynamic social-ecological landscapes

5.0 ABSTRACT

Short-term grants are the dominant funding mechanism for conservation projects around the world. Researchers, practitioners, and managers rely on unpredictable, time-limited, and highly competitive grants to fund and maintain conservation initiatives, leading to unstable project budgets over the long term. These ad-hoc funding sources makes investment and strategic planning challenging, with negative consequences for nature and stakeholders. Advanced modelling techniques have been applied extensively to spatial conservation investment problems (i.e., where to invest), but to my knowledge there are no quantitative studies that explore the consequences of short-term grant cycles on biodiversity or compare them to plausible alternatives. Therefore, in this chapter I use a generalised management strategy evaluation approach to explore the effects of different long-term funding strategies on forest cover in a simulated conservation landscape with a growing human population. I found that the funding scenario that mimicked the short-term grant cycle performed the worst out of all five scenarios, with 93% of all simulations resulting in complete forest loss. In contrast, two scenarios that reflected different levels of unpredictability in funding resulted in complete forest loss 1% and 25% of the time, and the scenario that reflected stable, predictable funding never experienced complete forest loss. My results demonstrate the negative effect of initial underfunding on long-term project success, and that the effects of uncertainty and unpredictability in funding from year to year is dependent on the ability to maintain core budgets at a certain level. The results further demonstrate that stable, predictable budgets perform best in terms of minimising forest loss over time. This study provides a rare theoretical insight into the implications of short-term grant cycles and unpredictable funding on biodiversity. I demonstrate that in the context of increasing human pressure on conservation landscapes, stable funding is likely to deliver greater conservation outcomes in the long-term than funding based on grant cycles. My results highlight the importance of developing alternative, sustainable funding mechanisms that can provide predictable budgets to landscape managers over multi-decadal timeframes, allowing for strategic and well-planned deployment of resources.

5.1. INTRODUCTION

Global conservation funding is inadequate to eliminate biodiversity loss (Echols et al., 2019; Waldron et al., 2013). Currently, the majority of conservation funding around the world comes from either governmental, intergovernmental, or philanthropic entities, where funds are distributed via grants (Huwyler et al., 2016; Larson et al., 2021; Sayer and Wells, 2004). In response to the global climate and ecological crises, novel approaches to funding environmental projects (including projects related to climate change, biodiversity, and sustainable development) have emerged. These new mechanisms are largely focussed on leveraging private sector investment via conservation finance (Huwyler et al., 2016), green bonds, public-private partnerships, impact investing, and government-led incentives for private sector investment such as new policy, subsidies, loans, and risk mitigation mechanisms (Clark et al., 2018). It is expected that these new approaches will affect both the quantity of funding available and the distribution mechanisms, moving away from short-term grants towards longer-term, sustainable financing (Echols et al., 2019). Although the development of alternative financing models for the environment is both necessary and promising, they are being developed within a global economy in which government policies, business models, and free-market capitalism still incentivise the environmental degradation the models are attempting to reduce (Clark et al., 2018). It is therefore likely that in the short- to medium-term, conservation practitioners will remain largely reliant on traditional grant-based funding to implement conservation activities.

5.1.1. Grant-based conservation funding

To see positive environmental gains, conservation action is often required over decades (Isaac et al., 2018; Santana et al., 2014). This is significantly longer than the duration of conservation grants which often cover periods of a few years (Blom et al., 2010). Yet, grant-based funding is the dominant mechanism for conservation investment largely because funders are hesitant to provide long-term institutional support to government agencies that they consider lack the necessary infrastructure, processes, and technical and human resources. Project- or grant-based funding however, allows donors to maintain control over finances and programme implementation, standardise approaches, and measure progress (Sayer and Wells, 2004). This means that conservation projects often lack funding that is continuous or stable over periods greater than a given grant cycle. Very little research has been done to assess the effects of unstable, non-linear budgets on biodiversity outcomes, nor the effects of alternative funding strategies. Given the inadequate funding for conservation, to have the greatest positive effect on biodiversity as possible, managers and conservationists need to ensure the investment of scarce resources is strategic and efficient, and they must strive to maximise the biodiversity outcomes of each dollar spent (Bruner et al., 2004; McBride et al., 2007; Waldron et al., 2013).

Grants for conservation activities vary in size and duration, with larger, long-term grants (between three and five years) often requiring significant investments in staff time for the development of applications, and substantial administrative capacity to manage the grant if it is awarded. Such grants are often awarded by international financial institutions or international development agencies and often come with complex rules governing procurement, accounting, and reporting. These requirements often preclude smaller organisations that do not have in-house fundraising teams or large financial management and administrative capacity (Sanders et al., 2021). Alternatively, conservation organisations can apply for smaller, short-term grants (usually between one and three years) which are often targeted towards specific species, habitats, or activities. The smaller grants require less staff time for the application process and subsequent grant management yet can be limited in the amount of the award that can be spent on overheads, fixed costs, and other core project expenditure such as salaries, fuel, office space, and utilities (Sanders et al., 2021). This results in the core operational budgets of smaller projects or organisations comprising small percentages of multiple short-term grants, leading to insecure and unstable core budgets that can fluctuate from year to year. Budgets such as this prohibit long-term strategic planning for investment of funds and conservation action (Emerton et al., 2006). There is a paucity of research into the long-term implications of grant-based funding on the effectiveness of conservation projects, or how financial unpredictability may affect biodiversity outcomes over time.

5.1.2. The effects of grant-based funding on conservation projects

Investing conservation funds strategically over time is made difficult when funding is based on short-term grants that generally last between one and five years, with little or no guarantee of future renewal of funding (Hodge and Adams, 2016; Sayer et al., 2017). Most conservation projects or initiatives, even in wealthy countries with relatively well-funded protected area networks, rely on such short-term grants to launch programmes, conduct research, and implement key activities such as training, engagement, enforcement, and outreach (Emerton et al., 2006). This funding model results in long-term budgets that are non-linear, unpredictable, do not necessarily track changes in threat levels, and rarely reflect the time required to see positive conservation outcomes (Blom et al., 2010; Sayer et al., 2017). The financial stability of a conservation project or organisation is therefore reliant on the ability to leverage external funding through grant applications, which are inherently competitive and have low success rates (Sayer and Wells, 2004; Sohn, 2019). This funding mechanism means that conservation projects go through periods of relative affluence when conservation activities (such as enforcement, policy interventions, and community engagement) can increase in scope and scale, ultimately leading to net benefits for nature (Coad et al., 2019b; Kearney et al., 2020; Lindsey et al., 2017). The same projects will inevitably go through periods of financial hardship, which often occur between grants (Lambin et al., 2019).

When conservation projects experience periods of inadequate funding, expenditure is restricted to core activities, additional activities wind down, staff redundancies occur, research and monitoring activities decrease, and new initiatives end (Bruner et al., 2004; Waithaka et al., 2021). These periods can have serious negative effects on conservation projects (Fernandes et al., 2017; Wittemyer, 2011). Organisations lose talented staff and thus institutional knowledge, trust between stakeholders and the project or organisation can be lost as commitments may not be met, local participation in project activities can end (Sayer and Wells, 2004), and stakeholders may view the project and the implementing organisation(s) as unreliable due to inconsistent support (Waithaka et al., 2021). In many parts of the world where unregulated or illegal activities such as forest clearance and hunting of wildlife threaten conservation landscapes, periods of financial hardship can cause increases in these activities as project support for enforcement, engagement, outreach, and overall project visibility decreases (Bang and Khadakkar, 2020; Henschel et al., 2014).

The cycle of organisations applying for grants to maintain budgets leads to 'projectification', whereby control over conservation activities, interventions, and strategic direction is ceded to funders (Sanders et al., 2021), as conservation organisations adapt to funding trends and specific funder interests in an effort to remain competitive in grant applications, and maintain project funding (Hodge and Adams, 2016; Rodríguez et al., 2007). If financial and operational control is external in grant-funded projects that involve partnerships with government agencies, local organisations or communities, then host country authorities and other local partners will be unlikely to embrace responsibility, nor have any sense of ownership or genuine partnership (Hodge and Adams, 2016). There is also often a lack of transparency and coordination between funders and grant distributors which reduces cohesion and makes strategic allocation of funds at a broader scale difficult (Brockington and Scholfield, 2010; Laufer and Jones, 2021; Sayer et al., 2017). Nevertheless, many conservation projects are unable to fund activities through other means.

5.1.3. The research gap

Site-level assessments of investment priorities are relatively common, and form an important part of a manager's toolkit for developing strategy (see Ervin, 2003; Utami et al., 2020). Yet studies that provide broader theoretical insights into long-term investment strategies in the context of finite resources are lacking. There is a large body of literature that explores prioritising conservation investment over space, or the 'conservation resource allocation problem' (Wilson et al., 2006), with approaches including return on investment (Armsworth et al., 2018; Murdoch et al., 2010), heuristic algorithms (Meir et al., 2004; Wilson et al., 2006), regression models (Fishburn et al., 2013), and impact mapping (Tulloch et al., 2020). The next question, which is equally important yet largely unanswered, is that once land has been selected or acquired for conservation, how should the authority responsible for its management invest finite conservation resources over the next five, ten, thirty, or fifty years to minimise biodiversity loss?

One of the main challenges associated with assessing future conservation implementation and predicting outcomes is the inherent uncertainty surrounding future conditions (McBride et al., 2007). Previous studies have investigated the effects of investment uncertainty (transaction uncertainty and performance uncertainty) on the optimal allocation of conservation funds to land acquisition (McBride et al., 2007), and uncertainty surrounding future site conditions (availability and ecological condition) and how this influences the optimal combination of short- and long-term conservation contracts with private landowners (Lennox and Armsworth, 2011). Yet the uncertainty surrounding changing social-ecological conditions within a single site or landscape over time, and how this may affect biological resources given different investment strategies by the management authority, has yet to be investigated.

The global human population is increasing, particularly around protected areas and other ecologically rich landscapes (Wittemyer et al., 2008), and increasing human populations within these areas increase pressure on natural resources (Lindsey et al., 2014). Therefore, understanding how the funds available to landscape managers to invest over multi-decadal timeframes affect system dynamics in the context of increasing human pressure and uncertainty will be critical for developing strategies that maximise conservation gains. I am not aware of any previous studies that have investigated the effects of funding cycles and consequent investment strategies by managers within social-ecological systems. Lessons can be learnt from empirical studies that examine past strategies and the subsequent observed outcomes (Santana et al., 2014), but using such data to project future social-ecological conditions and system dynamics is at best challenging, and at worst misleading (Mouquet et al., 2015). In contrast to empirical studies, simulation modelling offers an analytical environment within which system dynamics can be stress tested without any real-world consequences.

5.1.4. Simulation modelling for testing social-ecological system dynamics

Conservationists have for many years relied on both theory and empirical generalisations to make urgent decisions when appropriate data have been lacking (Doak and Mills, 1994). Perhaps borne out of necessity in the past, theoretical models are now seen as important tools for ecologists and conservation biologists to improve understanding of their study systems (Green et al., 2005). Mathematical models offer the opportunity to take the well-studied component parts of a complex system and reassemble them in ways that capture their fundamental properties whilst allowing for the interrogation of system dynamics (Wilson, 1999). Such models require complex systems to be carefully simplified so that hypotheses can be tested within a manageable environment whilst ensuring fundamental processes are honoured. Social-ecological systems (SES) are fundamentally complex, dynamic systems that are characterised by non-linear relationships and feedbacks between multiple social and ecological sub-systems (Berkes et al., 2000). It is implausible to build a model that captures all components of a SES, and therefore simplified models that simulate the fundamental dynamics are required to test social-ecological theory. Generalised Management Strategy Evaluation (GMSE) is a modelling framework that allows the construction of simplified social-ecological systems that are comprised of four fundamental sub-systems, allowing for a huge variety of theoretical investigations (Bunnefeld et al., 2011; Duthie et al., 2018a).

In this study, I build a widely applicable mechanistic model of a generic conservation landscape and use it to investigate the dynamics between different conservation funding situations, the resulting investment strategies by landscape managers, and forest loss, in the context of increasing human populations over a period of 50 years. I use the GMSE modelling framework (Duthie et al., 2018a) to test the effects of five realistic investment strategies available to the landscape management authority that are designed to reflect real-world conservation funding scenarios: 1) a uniform management budget that does not increase or decrease over the study period, 2) a management budget that increases linearly over time, 3) a management budget that fluctuates in a predictable and regular way, reflecting short-term grant cycles, 4) a management budget that fluctuates randomly and unpredictably, but with only minor variation from the starting value, reflecting a core budget that increases or decreases via short-term grants, and 5) a management budget that fluctuates randomly and unpredictably with high variation from the starting value, reflecting a highly variable budget that has no core quantity, and is therefore entirely governed by short-term grants of varying sizes and durations. To disentangle and emphasise potential effects of the different investment strategies on forest loss, I simplify the system so that the actions of the human stakeholders are the only factors influencing forest loss, and I push the investment scenarios to their extremes. This modelling framework is generalised in such a way as to be applicable to landscape managers and conservationists around the world who are reliant on non-linear and unpredictable funding cycles and offers theoretical insights into the consequences of the business-as-usual conservation funding mechanisms.

5.2. METHODS

5.2.1. GMSE

GMSE is designed to simulate dynamic decision-making by stakeholders in a social-ecological system (Duthie et al., 2018a). The stakeholders are a) the "manager" who represents an appropriate authority, for example a protected area manager or a natural resource manager, and b) the "users" who represent independent actors such as farmers or hunters. Additionally, there is a natural "resource" population, for example animals or trees, that requires management. In each simulation, the manager is attempting to get the resource population as close to a pre-determined value as possible, and the users are trying to maximise their utility on the landscape. Simulations in GMSE are comprised of four submodels that govern the social-ecological system, each of which can be individually parameterised (Figure 5.1). The individual actors (manager, users, resources) are discrete, and events in the landscape are probabilistic, thus introducing stochasticity.

The submodels are (1) the natural resource model, which is used to simulate the biological population within the system. The natural resource model can simulate complex spatially explicit biological populations that have individual traits such as age, and population-level traits such as carrying capacity and related density-dependent mortality. (2) The observation model represents the observation process, and the associated error, whereby the manager estimates the size of the natural resource population. The manager sets policy based on the estimates rather than the actual population size, thus introducing uncertainty that exists in the real world. (3) The manager model uses the genetic algorithm (GA, see below) to develop management policies that attempt to reduce deviation of the natural resource population from the target population size. The manager achieves this by dynamically altering the cost of actions for the users thereby increasing or decreasing the ability of the users to act on the resources. (4) The user model, in which after the manager has set the policy, each user calls the GA to develop a strategy for that time step that maximises their utility (e.g., maximises their yield) given the constraints imposed by the manager. Users can choose to act on the natural resources (e.g., cull or scare), which can affect the resource population (e.g., if they choose to cull) or resources on the landscape cell (e.g., if they choose to scare, forcing some resources onto another cell). These changes then feed into the natural resource submodel in the next time step. For detailed explanations of the submodels, see Duthie et al (2018) and the documentation for the GMSE R package.

The primary approach to altering system dynamics is via the manager and user budgets. The relative power between the manager and the users is largely driven by the relative budgets that each actor has access to. Generally, when the manager has a high relative budget, they have a greater ability to set policies that will influence the resource population in the desired way. For example, if the resource population is below the target, a manager with a relatively high budget can increase the costs of culling for the users, thus reducing the users' ability to cull, and in turn allowing the resource population to recover. Conversely, if users have a relatively high budget, then they are more likely to be able to afford to take actions such as culling, even if the manager is setting the costs of such actions as high as possible. The budgets, and the associated dynamics, can be used to replicate various real-world systems and scenarios such as conservation conflicts, power dynamics, and lobbying (Cusack et al., 2020; Duthie et al., 2018a; Nilsson et al., 2021).

5.2.2. Genetic algorithm (GA)

The GA is the process that mimics human decision-making, and through which the manager develops policy and users decide upon actions. The GA is called once for each decision-making actor on the landscape (the manager and *n* users) in each time step. Each call to the GA results in a policy decision (for the manager) or an action decision (for each user). Final manager and user strategies are selected within each call of the GA through a process that mimics evolution by natural selection (Duthie et al., 2018b; Hamblin, 2013). Each GA call comprises multiple iterations (Figure 5.1). The first iteration initialises many possible strategies, followed by a process of cross-over and mutation (mixing of strategies, and generation of alternate strategies) between the initialised strategies, ensuring that budgets are not exceeded. High fitness strategies are selected via a fitness function and a tournament, and the resulting strategies form the starting layers of the next iteration, where the process is repeated. The fitness functions for manager and users rank different strategies based on their predicted effect on the resource population (for the manager), and an individual's landscape yield (for the users).

The process continues until a minimum number of iterations has been run and a convergence criterion is met (Duthie et al., 2018b). This process results in adaptive, but not necessarily optimal, strategies for the manager and the users. The GA takes the manager's budget constraints, user action histories, and the predicted consequences of each action on the resource population and uses the process described above to develop a strategy for the manager to reduce deviation from the target resource population size. Once the manager's policy is established, users will individually call the GA to decide upon actions that maximise their utility (e.g., agricultural yield). Users can choose from several options depending on the parameters set by the researcher. These include tending their crops or acting on the natural resources (e.g., cull, scare), all of which will have some effect on their yield. Their ability to act on the natural resource is governed by both the user budget, and the manager's policy, in each time step.

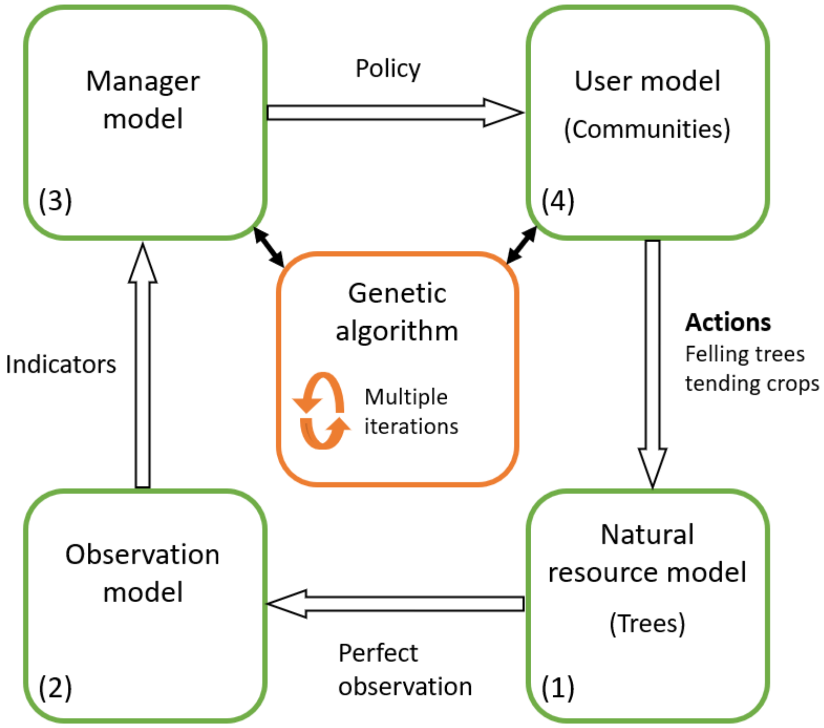

Figure 5.1. Conceptual flow diagram showing the four submodels and the genetic algorithm, and how they interact in a single time step in GMSE. Adapted from Duthie et al., (2018).

5.2.3. Model parameterisation

5.2.3.1. Landscape

In this study, I have used the GMSE modelling framework to explore the effects of different investment strategies and funding models available to a conservation manager on forest resources, in the context of finite funds and increasing anthropogenic pressure caused by an increasing human population. I simulated a forested landscape of 100 × 100 cells, where we assumed one cell was equivalent to 1 hectare, resulting in a landscape of 10,000 ha (or 100 km^2). I allocated 30 "users" to the landscape, which in this case represented 30 villages or communities, each of which had an approximately equal area of spatially explicit land upon which they could act. This resulted in each village having approximately 333 ha (3.33 km^2) of land. I assumed the users represented agricultural communities whose primary livelihood is farming. I simulated scenarios over 50 time steps, which I assumed represented 50 years.

5.2.3.2. Resource population

The flexibility of GMSE allows for the biological resource to represent a population of a wide range of taxa. In this study, I assumed the resources were trees, that the manager's goal was to protect as many trees as possible from being felled (i.e., maintain the resource population at the starting value), and that the users were able to increase their agricultural yield by felling trees on their land. I tested the landscape with a tree density that was realistic for a tropical forested landscape (50 trees ha^{-1}, n = 1,125,000), but because the number of users on the landscape was relatively low, due to each user representing a community rather than an individual farmer, the absolute number of trees felled was too low to see clear differences between scenarios. I therefore reduced the total number of trees to 100,000 to ensure trends in felling were clear to see.

Trees were randomly distributed across the landscape (with multiple trees allowed on any given cell), reflecting natural variation. The population dynamics of trees is difficult to capture over a 50-year time period due to slow growth and recruitment relative to animals. Furthermore, I wanted to eliminate any "noise" around the deforestation signal so that the only driver of forest loss was the effect of user actions on the trees. Therefore, I removed the effects of natural recruitment or natural deaths (density-dependent and density-independent), resulting in a static population (excluding the effects of the users). If trees were present on a landscape cell, they reduced the agricultural yield that could be harvested by the user. Each tree reduced the cell's yield by Y_r = 8%, with the cumulative reduction in yield governed by the exponential function:

$$y = (1 - Y_r)^{R_T}$$

Where y is the yield of the cell when trees are present and R_T is the number of trees remaining on the cell. Therefore, if there are 50 trees on a given cell, the cell's yield is 1.5% of the total possible yield. If there are 25 trees remaining on a given cell then the cell's yield increases to 12.4%, and so on.

5.2.3.3. Users

GMSE allows for each user to represent an individual actor or agent, who makes decisions about their actions based on individual circumstances. However, the number of users on a landscape cannot be changed during a simulation, and so to simulate increasing human populations I assumed that each user represented a village or community rather than an individual. I assumed that a population increase in a real-world community would result in increased human and financial resources, and increased demand for land (e.g., for housing and agriculture). These combined effects would increase the community's desire and ability to clear forest land. This allowed me to employ the user budget to simulate population increases. The user budget is the primary parameter that governs a user's ability to take actions, such as felling trees. Therefore, a user budget that increases during the simulation represents an increase in the user's power to act, thus simulating population increases.

The only actions the users were permitted to take were 1) tend crops, and 2) fell trees. The decision about which action to take in each time step was governed by trade-offs in cost versus benefit (computed within the GA, see above). The parameter that defined how much a user could increase their yield by tending their crops was set to 0.01 (1%). This contrasts with the parameter governing the yield reduction for a single tree (8%, see section above). Different ranges of these parameters were tested for sensitivity (Supporting Information Figures S5.1 to S5.4), with the final values chosen to deliberately ensure that felling trees would have a much higher positive effect on yield than simply tending crops. This was both to reflect the fact that in the real world expanding agricultural area will generally increase yield more than tending existing agricultural land, and to simulate strong exogenous drivers of deforestation that are found around the world, particularly in the tropics (Ceddia 2019, Davis et al 2015).

5.2.3.4. Manager

In our study, the manager represents a person or organisation that has a remit to conserve forest land and the authority to set and implement policy that affects the ability of users to take actions. I set the resource population target (which the manager tries to maintain) at the same value as the starting number of trees, and because there was no natural tree regeneration (natural population increase), the manager's goal is to reduce forest loss as much as possible in every time step. These parameters were set to simulate a conservation landscape in which there is pressure on forest resources, and authorities are trying to eliminate, or reduce as much as possible, forest loss. This could, for example, represent a protected area, which contains both forest and local communities.

In each time step, the manager called the GA and identified a policy, which was reflected in the cost for users to fell trees, that attempted to reduce forest loss as much as possible. I assumed the manager's budget reflected the actual budget of the authority, and could represent a monetary budget, available non-monetary resources (e.g., law enforcement resources), or a combination of these. In each of the different scenarios, the manager's budget varied according to the funding scenario I was simulating. I assumed that the manager achieved perfect detection of resources, so there was no error associated with the observation submodel. This was to keep the simulations as simple as possible. In the age of free, high resolution satellite imagery that is available every few weeks, it is plausible that a manager has near-perfect deforestation detection over a landscape.

5.2.4. Scenarios

I designed 5 scenarios with dynamic manager budgets that simulated different funding regimes that a manager or authority with responsibility over a conservation landscape may encounter in the real world (Table 5.1, Figure 5.2). Scenarios 1 to 3 aimed to test three primary funding models and scenarios 4 and 5 aimed to test the effects of uncertainty and variability in funding. Before running the final 5 scenarios I tested several null scenarios to ensure the landscape was operating as expected (Supporting Information, figures S5.5 to S5.7). Due to the nature of the GA (i.e., identifying one out of multiple possible near-optimal solutions), and that each actor on the landscape calls the GA in each time step, stochasticity in decision-making is explicitly built into the simulations. Therefore, each simulation was run 100 times to quantify variation in results. The manager budget, user budget, number of felling actions, the cost of felling actions, and the number of trees remaining at each time step were extracted for each replicate simulation. For each parameter, the 50, 2.5, and 97.5% percentiles across all replicates were calculated and used to represent the median and lower and upper confidence intervals, respectively.

For all scenarios, I ensured that the total cumulative budget for the manager was equal across all scenarios (Table 5.1). This was to eliminate the possibility of one scenario outperforming another simply because the manager had access to a greater total budget over the simulation period. In all scenarios, I assumed the same level of human population increase over time, and so for each scenario the user budget increases linearly with the same starting point and slope (Table 5.1, Figure 5.2). The absolute values for the user budget are arbitrary and can be set in such a way as to meet the objectives of the study. I tested various starting values and slopes for the user budget, increasing the parameter values until the absolute number of trees felled was sufficient to see clear differences between scenarios.

The manager and user budgets are not equal nor necessarily proportional, as they are used in very different ways (Duthie et al., 2018a). Therefore, equal budgets do not necessarily equate to equal power to affect the system. The differences in manager and user budgets relative to each other is what governs the differences and changes in power to affect the system. It is important to recognise the incomparability between the absolute values of the manager and user budgets, and therefore to differentiate the two parameters in this study I will refer to the user budget as “community resources”.

All simulations were conducted using the R package GMSE (Duthie et al 2018, v0.6.2.0), and all associated analyses described below were conducted in R (v4.0.4, R Core Team, 2021). Relevant parameter values used in the simulations can be seen in the Supporting Information (section 3).

5.2.4.1. Scenario 1

This scenario assumed that the manager budget does not change over the simulation period (Figure 5.2). This scenario was designed to represent a conservation landscape in which the authority has a regular and predictable budget over time with which to invest in policy, but one which does not increase or decrease in response to changing threats or grant cycles. This scenario could represent a government-funded landscape which has a finite but regular budget that is not reliant on short-term grants.

5.2.4.2. Scenario 2

This scenario assumed that the budget available to the manager starts low but increases with increasing pressure on the landscape (Figure 5.2). This scenario could represent a statutory authority in a conservation landscape in which the authority is provided regular and predictable budget increases with which to invest in policy. In this scenario the management authority is not reliant on short-term grants. The shape of the manager budget (starting point, slope) was calculated to ensure that the total cumulative budget was equal to the other scenarios (Table 5.1).

5.2.4.3. Scenario 3

This scenario assumed that the budget available to the manager increases and decreases in a regular and predictable way, regardless of the changing pressure on the landscape (Figure 5.2). This scenario was designed to replicate a conservation landscape in which the management authority is reliant on regular grant cycles. The scenario assumes that the authority conducts successful fundraising at regular intervals, and thus has a varying yet predictable budget with which to invest in policy implementation. The cycle length (i.e., the wavelength) is approximately 5 years, reflecting larger grants that are often provided by statutory funding agencies or international bodies. These large, longer-term grants require a high investment in staff time to apply for, and high administrative capacity to manage once implemented, and so are generally won by large, international organisations, government agencies, or collaborations between such partners, where the required resources already exist. To simulate this funding cycle, I produced a sine wave of the form:

$$M_b = 350 \times sin(0.5t) + 400$$

Where M_b is a vector of resulting manager budget values, and *t* is a vector of time steps (1, 2, …, 49, 50).

5.2.4.4. Scenario 4

This scenario assumed that the budget available to the manager increased and decreased in unpredictable and irregular ways (Figure 5.2). This was to simulate a conservation landscape in which the management authority relies partly on grant funding for policy implementation, and so applies for a range of different grants which vary in size and duration but is not necessarily successful at any given time. This scenario assumes the management authority has some level of core funding, and so the budget never decreases to zero. This scenario could reflect any number of conservation landscapes around the world, where project budgets are subject to the success of funding applications, resulting in variable and unpredictable resources for project activities and policy implementation. To simulate this scenario, I used a Fourier series approach to create irregular curves by summing multiple sine waves of different frequency (f), delay (φ), and strength (A). I produced three sine waves for each replicate simulation by randomly sampling values for the above parameters (Supporting Information). The three sine waves were summed to produce a random complex wave, using,

$$B(t) = C + \sum_{i=1}^{3} b_i\,(t)$$

Where $B(t)$ is the manager budget at time t, b_i is a function defined by a sine wave i at time t, and C is a constant. Each of the 100 replicates produced a different complex wave (Figure 5.2 shows 10 examples, see Supporting Information section 4 for all 100 waves used in the simulations).

5.2.4.5. Scenario 5

This scenario is a more extreme example of scenario 4 and aimed to test the effect of increased variation and uncertainty in manager budgets on deforestation and system dynamics. I increased the range of the available values from which the frequencies and component strengths for the three sine waves could be sampled, thus increasing the potential amplitude of each wave, and making the changes in wave frequency more extreme (Figure 5.2 shows 10 examples, see Supporting Information section 4 for all 100 waves used in the simulations). To simulate this scenario, I produced a set of three random sine waves which were used to produce a new complex wave for each replicate, using the same approach and formula as in Scenario 4 (Supporting Information).

5.2.4.6. Standardisation

Manager budgets in Scenario 1 had a constant value which summed to 25,000 over the 50 time steps, and for scenarios 2 to 5 I standardised the manager budgets to 25,000, using,

$$S\_M_{b_i} = 25000 \times \frac{M_{b_i}}{\sum_{i=1}^{50} M_{b_i}}$$

Where $S\_M_{b_i}$ is the standardised manager budget at time i, $M_{b_i}$is the manager budget M_b at time step i produced in the above sections.

5.2.5. Maximum harvest under maximum conflict

The maximum harvest under maximum conflict (MHMC) was calculated for each time step in each scenario to improve our understanding of the power dynamics between the manager and the communities. The MHMC is a single value for each time step that is based on the manager and user budgets at that time step. It is the maximum number of trees a user can harvest if the manager uses all their budget to reduce felling, and the user uses all their budget to fell trees. The manager uses 10 budget points to increase the cost of felling by 1. There is always a minimum cost of an action of 10. Therefore, the cost of an action for the user, assuming the manager is using all their budget to increase the cost of the action, will be,

$$nUA = \frac{C_r}{\left(\frac{M_b}{10}\right) + 10}$$

where nUA is the number of user actions (i.e., the number of trees felled), C_r is the community resources (user budget), and M_b is the manager budget.

Table 5.1. Details of the five funding scenarios. In all scenarios, the community resources started at a value of 2000 and increased with a slope of 75, resulting in a cumulative total of 191,875

Scenario	Description	Manager budget	
		Starting value	Total cumulative budget
1	Manager budget remains constant (i.e., does not increase) over time. Community resources increases linearly	500	25,000
2	Manager budget increases linearly, reflecting a regular and predictable increase in resources over time. Community resources increase linearly	126.9	25,000
3	Manager budget increases and decreases in a predictable way, reflecting reliable funding cycles. Community resources increases linearly	499.3	25,000
4	Manager budget increases and decreases unpredictably, reflecting unreliable and unpredictable funding streams over time. Community resources increase linearly	Variable	25,000
5	Manager budget increases and decreases unpredictably, reflecting unreliable and unpredictable funding streams over time. Community resources increase linearly	Variable	25,000

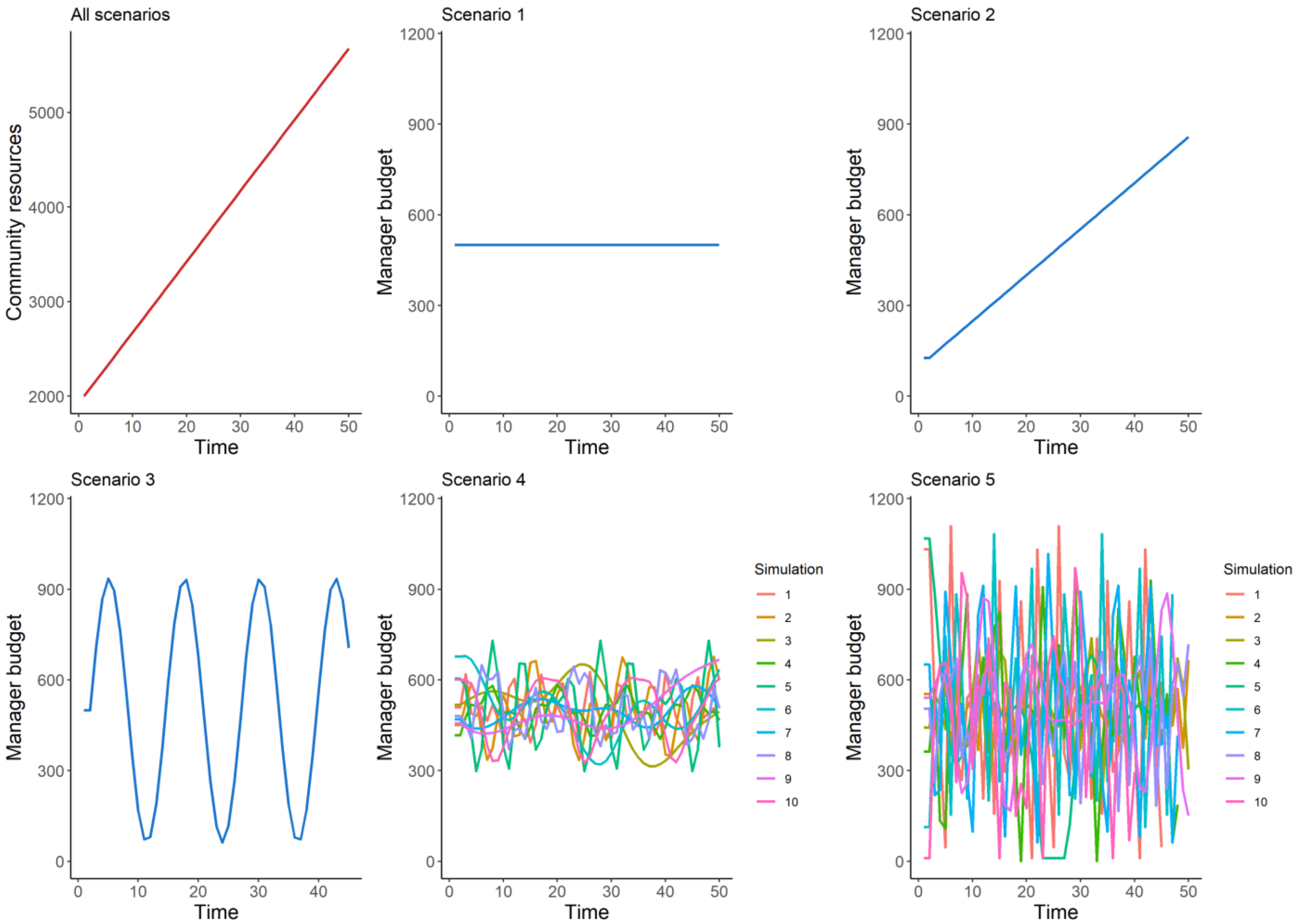

Figure 5.2. Manager budgets and community resources (user budget) for the five scenarios. Scenarios 4 and 5 have a different manager budget for each replicate simulation, and so this figure shows 10 examples for each.

5.3. RESULTS

The parameter settings used in the simulations ensured that communities would try and fell trees, thus increasing their yield, if it was possible to do so given the policy set by the manager. The values and positive slope of the community resources ensured that communities had sufficient power to clear the majority of the forest by the end of the 50 time steps in all scenarios (Table 5.2). These extreme parameter settings resulted in clear differences in the deforestation trajectories between the scenarios (Figures 5.3 and 5.4).

5.3.1. Scenarios 1 to 3

Of the three primary funding models, scenario 1 was the most effective at minimising deforestation over the 50 time steps (Figure 5.3). In all time steps, excluding time steps 4 to 9, scenario 1 retained the highest number of trees. This is despite having a felling count that increased linearly throughout the simulation (Figure 5.5). The increasing felling count in scenario 1 resulted in the loss of trees accelerating over time (Figure 5.3). Conversely, scenario

2 had a decelerating felling count over time (Figure 5.5) as the manager budget increased, resulting in a deforestation rate that slowed over time (Figure 5.3). Nevertheless, the low starting manager budget values for scenario 2, which were lower than scenario 1 for the first half of the simulation period, resulted in higher deforestation overall (Figure 5.3). Scenario 2 performed worse than all other scenarios (including scenarios 4 and 5) for the first half of the simulation period (Figure S5.11), highlighting the effects of chronic underfunding. The fluctuations in the manager budget in scenario 3 is reflected in both the rate of deforestation (Figure 5.3) and the felling count (Figure 5.5). During periods of high manager budget, the felling count and deforestation rate decreases, and during periods of low manager budget, the felling count and deforestation rate increase. Despite the peaks in manager budget in scenario 3 regularly reaching values much higher than the manager budget in scenario 1, this funding model had worse outcome in terms of forest loss than scenarios 1 and 2 (Figure 5.3) and resulted in complete loss of forest cover in 93% of simulations (Table 5.2). This can be explained by the felling count which shows that during periods of very low manager budget, the number of trees lost is between two and three times greater than any point in scenarios 1 and 2 (Figure 5.5).

5.3.2. Scenarios 4 and 5

Scenarios 4 and 5 showed the potential effects of unpredictable and uncertain funding models on forest loss. Scenario 4 had less variation in manager budgets than scenario 5, and the simulations were more likely to have retained greater forest cover at any given time step than scenario 5 (Figure 5.4) across the 100 simulations. Interestingly, deforestation rates for scenario 4 were very similar to those of scenario 1, and scenario 4 outperformed scenarios 2 and 3 in most cases (Figure S5.11). This suggests that unpredictable variation in manager budgets is not necessarily catastrophic, provided fluctuations are small and that some level of core funding means that manager budgets do not drop too low (Figure 5.2). Scenario 5 showed that large uncertainty and variability in manager budget could have very serious negative effects on forest cover over time (Figure 5.4). Despite many of the scenario 5 replicates having very high peaks in manager budgets (Figure 5.2), most simulations resulted in a worse outcome than scenario 4 in terms of forest cover. Of the 100 simulations, complete forest loss occurred 25 times (25%) in scenario 5 (Table 5.2). As with scenario 3, the driver of forest loss can be seen in the felling counts for scenario 5, which reach extremely high levels during periods of low manager budget (Figure 5.5).

5.3.3. Maximum harvest under maximum conflict (MHMC)

The MHMC calculations revealed some of the power dynamics within each of the scenarios (Figure 5.6). The maximum number of trees that the communities could fell at a given time step decreased over time in scenario 2, reflecting the increasing manager budget that provided increasing power to the manager to set policy and affect the number of felling actions. The rate at which the MHMC value decreased in scenario 2 was itself decreasing, stabilising to a near-constant rate by the end of the simulation period. This reflects the increases in community resources over time, which were increasing at a faster rate than the increase in the manager budget (Figure 5.2), resulting in decreasing power for the manager. Scenarios 1 and 4 had the most stable MHMC values, reflecting the relatively stable manager budgets. The MHMC values for scenarios 3 and 5 reflected the fluctuating and highly variable manager budgets and demonstrated how the rate of forest loss could increase during periods of low manager funding. When the manager had little funding there was an increase in the potential number of trees the communities could fell, assuming the manager was using all their budget to reduce felling and the communities were using all their budget to fell trees (Figure 5.6).

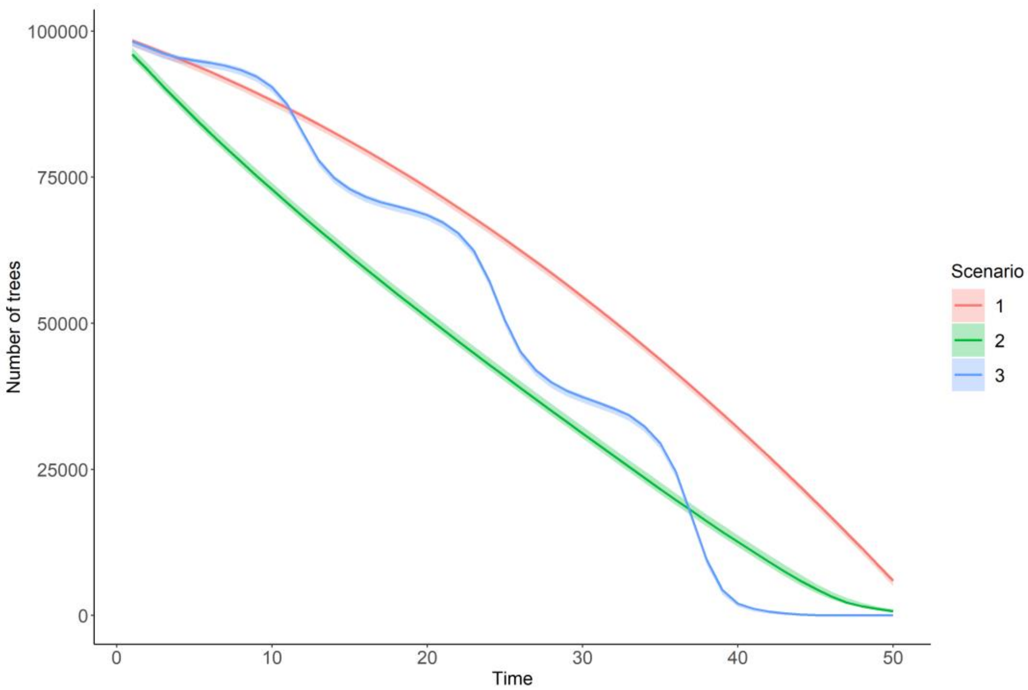

Figure 5.3. The number of trees remaining at each time step for scenarios 1, 2, and 3. Solid lines and faded ribbons are the 50, 2.5, and 97.5 percentiles from the 100 runs, respectively.

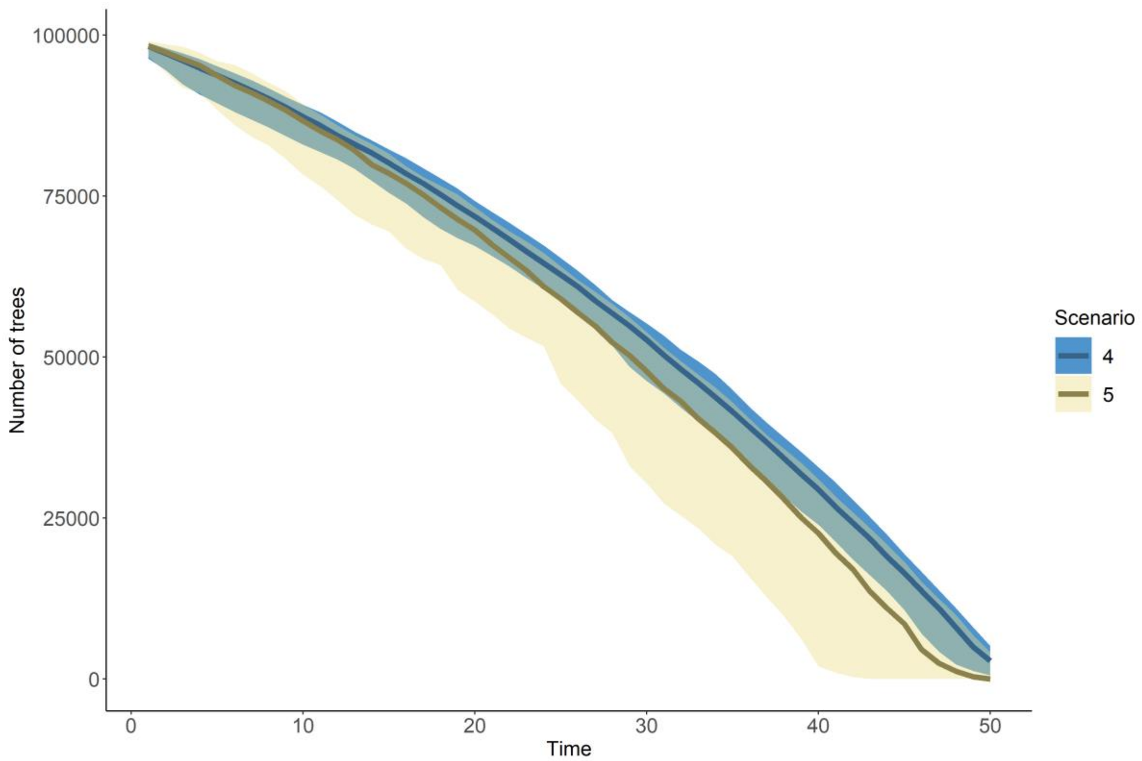

Figure 5.4. The number of trees remaining at each time step for scenarios 4 and 5. Solid lines and faded ribbons are the 50, 2.5, and 97.5 percentiles from the 100 runs, respectively.

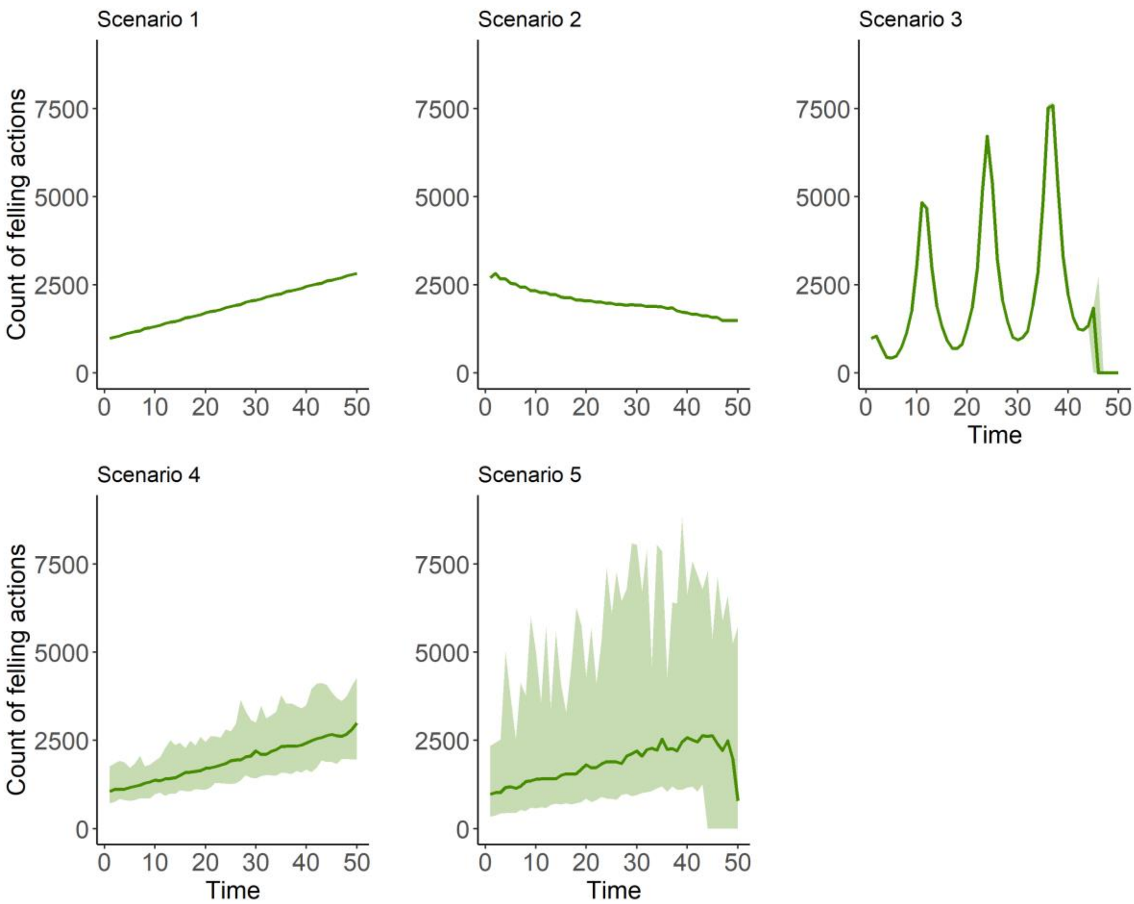

Figure 5.5. The count of felling actions taken by all communities at each time step for the five scenarios. Solid lines and faded ribbons are the 50, 2.5, and 97.5 percentiles from the 100 runs, respectively.

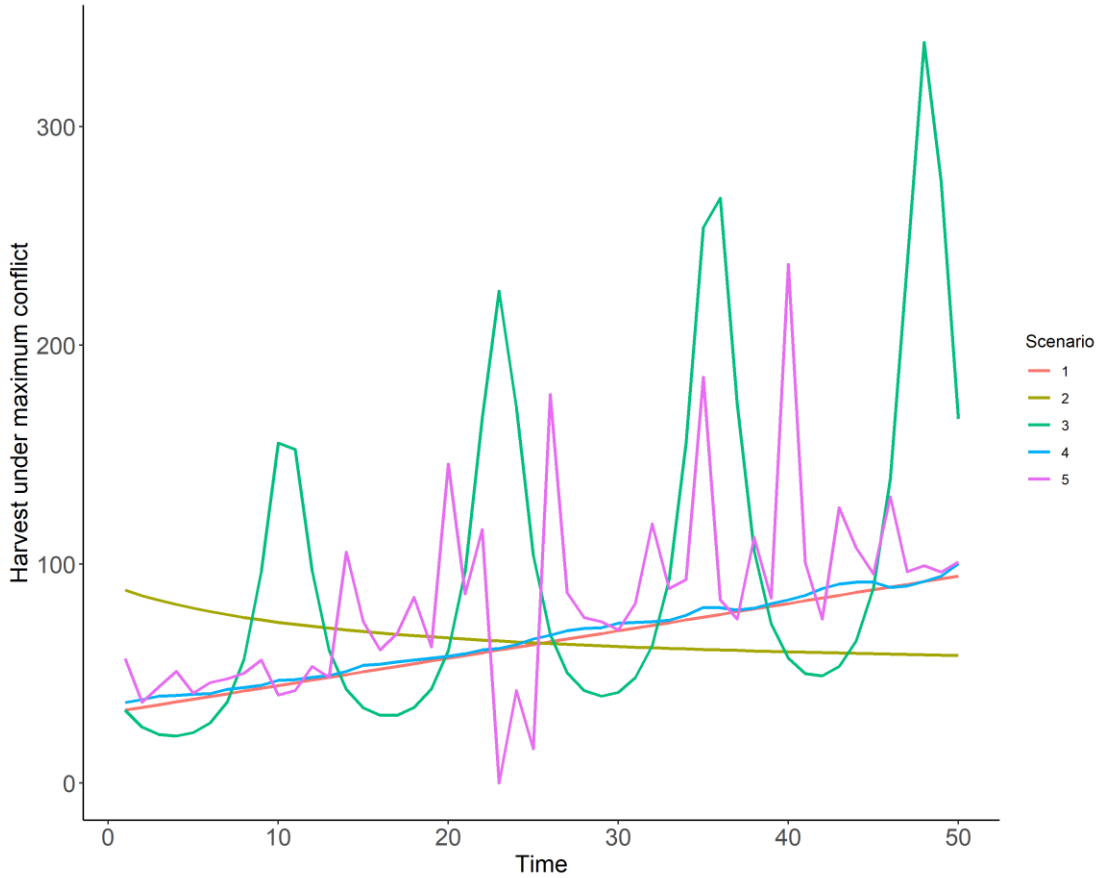

Figure 5.6. Calculated maximum harvest under maximum conflict (MHUMC) for all five scenarios. MHUMC is calculated using: community resources / ((manager budget/10) + 10). The value is the maximum number of trees that could be felled if the manager was using all their available budget to prevent felling, and the community were using all their available resources to fell trees. The lines for scenarios 4 and 5 (which had different manager budgets for each replicate simulation) represent the mean MHMC value at each time step across all replicate simulations.

Table 5.2. Summary of the number of trees remaining at time step 50 (2.5, 50, 97.5 percentiles), and the number of simulations that resulted in complete forest loss, from the 100 replicates for each of the five scenarios.

Scenario	Trees remaining after 50 time steps			Complete forest loss (no. of simulations)
	Mean	2.5 percentile	97.5 percentile	
1	5857	4660	6412	0
2	715	281	1202	0
3	0	0	0	93
4	2823	545	5152	1
5	8	0	4159	25

5.4. DISCUSSION

Global funding for nature conservation is far below what is required to halt biodiversity loss (Freeling and Connell, 2020; Laufer and Jones, 2021), and the funding that is available is rarely stable or sustainable over periods of more than a few years. To maximise conservation gains, it is necessary to provide conservation managers, and conservation funders, with insights into the trade-offs between different approaches to long-term investment of limited resources in the context of increasing anthropogenic pressure on natural resources. To our knowledge, no studies have investigated the potential long-term consequences of existing funding mechanisms for conservation projects and organisations. Our results therefore provide crucial theoretical insight that researchers can use to develop future hypothesis testing and data collection, and funders, conservation bodies, and landscape managers can use to develop more effective long-term investment strategies.

I have demonstrated that the dominant funding mechanism for conservation in the world today – the short-term grant cycle – is not optimal for conservation investment within social-ecological landscapes where there are competing objectives and increasing anthropogenic pressure on natural resources. In circumstances where project budgets experience negative peaks caused by gaps in grant funding, and where there is no core budget, biodiversity loss is accelerated. In these circumstances, managers are unable to maintain power to affect the system or set policies that benefit nature over the long-term. Increased uncertainty and variability around the shape of fluctuating budget curves inevitably increases uncertainty around the state of biodiversity over the long-term. Brief periods of high budgets in the grant cycle scenarios result in only brief periods of success where rates of forest loss decrease, and in the context of increasing human pressure on the landscape, these are insufficient to mitigate for the periods of low funding. Chronic underfunding, particularly in the early stages of a landscape conservation programme, can lead to serious negative effects on natural resources. Severe forest loss at the start of a project period, with all the associated losses of biodiversity, ecosystem process and services, leads to very poor project success over a 50-year period. Even when project budgets increase over time, the damage caused during initial periods of underfunding is difficult to remedy.

5.4.1 Primary scenarios (scenarios 1 to 3)

Our results have demonstrated that in a situation where human pressure on a landscape is increasing over time, and assuming managers across all scenarios have access to the same total budget, the most effective funding strategy for a conservation manager is a stable, predictable budget. A constant budget is preferable to an increasing budget that starts too low, even when the increasing budget exceeds the value of the stable budget halfway through the study period.

If a manager's budget is too low at the start of the study period, initial forest loss is very high. The manager is able to reduce the rate of forest loss as their budget increases over time, but they are not able to make sufficient gains over 50 years to render the strategy better than a stable budget.

Likewise, a fluctuating manager budget that reflects predictable grant cycles performs worse over 50 years than a stable budget. During periods of high budget, managers can develop effective policies that reduce forest loss. However, these periods are not sufficiently long, and budgets not sufficiently high, to offset the damage that is done during periods of low funding. Furthermore, the rate of forest loss during periods of low funding increases over time, as community resources increase. If the manager was focussed on the conservation of a wildlife population that exhibited reproduction and thus population growth, the periods of high budget, and therefore more effective protective policies, may be sufficient to maintain a healthy population as there would be periods of recovery. However, I assumed that the loss of primary forest could not be effectively reversed within a period of 50 years. These simulations could be further parameterised to include realistic forest regrowth or regeneration based on a specific landscape or ecosystem, but this would decrease the generality of the results and therefore was not attempted here.

Providing a manager with a stable budget that allows the development and maintenance of policies that minimise deforestation over the long-term is the best approach in this study. Stable, predictable budgets in the real world allow conservationists and landscape managers to maintain staffing levels, invest in long-term relationships and partnerships with stakeholders (Armitage et al., 2020), maintain enforcement levels, and design policies and interventions that are strategic and adaptive over periods greater than short-term grant cycles (Blom et al., 2010; Sanders et al., 2021). Conservation projects that are initially underfunded yet receive increasing resources will still spend many years working to reach the same levels of protection as they would have had, had they been provided an adequate, stable budget at the start. Our results predict that it could be several decades before the deforestation trajectories of the two alternative projects meet, and the increasing budget starts to pay dividends.

I do however acknowledge that I have made assumptions in our models about the timescales within which actions and decisions are made, and the time it takes for the effects of those actions to occur. Therefore, inferences regarding the timescales associated with forest loss within and between scenarios should be seen as examples and treated with caution. Projects that repeatedly experience severe funding shortages due to grant cycles will not have the same capacity for long-term investment and strategic planning as projects with stable funding, resulting in greater losses for biodiversity.

5.4.2. Uncertainty and unpredictability in funding

Scenarios 4 and 5 highlight two common funding situations for conservation organisations and projects (Hodge and Adams, 2016). Scenario 4 represents a situation where the management authority has some level of core funding that ensures the operational budget does not drop below a certain level, despite budget uncertainty over time. This is a common scenario for large, international conservation organisations or statutory authorities, which have long-term support for core operational budgets. They can increase their budgets at any given time through grant applications which can be used to support existing activities, initiate new programmes, bolster enforcement, or extend engagement and collaboration with stakeholders, all of which will have a positive effect on biodiversity conservation on the landscape (Andrade and Rhodes, 2012; Moore et al., 2018; Steinmetz et al., 2014). Likewise, grant funding will inevitably end within a few years, and there is no guarantee that future bids will be successful, resulting in decreases in overall budgets. However, the maintenance of budgets above a certain level means that core conservation activities do not cease, and the manager is able to minimise forest loss to a level similar to the manager in scenario 1.

Conversely, scenario 5 represents a situation where the management authority has no core budget and is therefore entirely reliant on uncertain and unpredictable grant funding over time. This is the reality for many small organisations, grass roots projects, or poorly supported statutory authorities which rely on the ability of other partner organisations to leverage external funding. In this study, the manager in all scenario 5 replicates has the same cumulative total budget over the 50 years as the other scenarios, yet the shape of the budget curve is random. This leads to large and highly unpredictable positive and negative peaks in some cases. My results show that there is large variability in the overall success of the manager in scenario 5 to minimise forest loss. In some cases, they can maintain a forest loss trajectory similar to scenarios 1 and 4, yet more often the rate of forest loss is worse, regularly leading to complete forest loss.

The results from scenarios 4 and 5 translate logically to the real world; if a conservation project or organisation has no core budget support, it is entirely reliant on the success of fundraising efforts. Winning sufficient funding via short-term grants to support adequate long-term conservation management is neither reliable nor straightforward (Sohn, 2019). When long-term budgets are unpredictable, uncertain, and highly variable, landscape managers are often unable to maintain core activities, guarantee continued support for communities and other stakeholders, plan investments strategically, assess impacts, or target investments at the most relevant drivers of biodiversity loss (Barnes et al., 2018; Gill et al., 2017; Gollin and Probst, 2015; McCarthy et al., 2012). In contrast, when core budgets are guaranteed, managers can maintain core activities and investments over the long-term which provides stability and minimises biodiversity loss.

5.4.3. Advantages of simulation studies

Simulation studies allow us to investigate possible biodiversity outcomes from a variety of scenarios over time periods much longer than for which we generally have empirical data for. Monitoring data for conservation projects rarely exist over timeframes as long as 50 years, and managers are therefore required to assess conservation actions using monitoring data from significantly shorter periods. This study has demonstrated that this can be misleading. For example, if a manager was provided forest monitoring data for scenario 3 between years two and six, or between years 14 and 18, it would be reasonable to conclude that the existing investment strategy and associated conservation interventions were working, as the rate of forest loss was decreasing. If a manager was given forest monitoring data from any four-year period from scenario 1, they could reasonably conclude that the investment strategy and associated conservation interventions were not working, as the rate of forest loss was increasing. Neither manager could be justifiably criticised for their inference; they are drawing conclusions from the best available data, which is what conservationists around the world must do every day. Nevertheless, our results have demonstrated that these inferences are likely flawed, and that the manager from scenario 1 will have greater success in minimising forest loss over the long-term if they maintain their strategy.

5.4.4. The way forward

The global conservation community requires a huge increase in funding, and a fundamental shift in the constancy of funding, if it is to halt the decline in biodiversity and minimise the worst impacts of climate change (Echols et al., 2019; Larson et al., 2021). I have demonstrated that a funding model that relies on short term grant funding, which is a common mechanism in the conservation sector, is unlikely to be the most effective way of financing landscape conservation. In addition to the landscape-level challenges of short-term grants that I have demonstrated here, the lack of communication, cohesion, and national, regional, and global coordination between funders that administer conservation grants results in poor strategic allocation of funding across larger spatial scales (Laufer and Jones, 2021). Greater coordination between funders, or indeed less reliance on numerous, disparate funders, will allow more thoughtful and strategic assessments regarding allocation of conservation funds, thus maximising environmental return-on-investment (Echols et al., 2019).

If global funding for conservation increases, the mechanisms by which this funding is distributed need to be carefully considered to ensure biodiversity gains per dollar are maximised. Our results suggest that simply increasing the number of short-term grants available within a competitive application framework is unlikely to provide the maximum gains. Alternative funding mechanisms are needed which provide stable and predictable budgets over multi-decadal timeframes thus allowing organisations and authorities to devise and implement strategic, long-term interventions and policies that benefit nature and people (Sayer and Wells, 2004).

There is a wide range of funding sources available to conservationists, yet government and philanthropic sources are the most common (Clark et al., 2018). The fragility of government funding has been exposed during the Covid-19 global pandemic; around the world there have been shrinking national economies, dramatic increases in emergency government spending, and governments forced to prioritise sectors of the economy for support and recovery (Evans et al., 2020). Ironically, a global pandemic that was most likely caused by overexploitation of the natural environment (Lytras et al., 2021) is likely to cause a decrease in government spending on conservation, at least in the short term (Corlett et al., 2020; Evans et al., 2020). There is increasing recognition that broadening the sources of conservation funding is necessary to both increase global spending on the environment and to diversify the sources, thus stabilising funding against inevitable future economic shocks (Echols et al., 2019).

There are numerous sources of funding that are available for conservationists to explore. Funding for the environment from philanthropic entities is increasing (Gruby et al., 2021), and the influence of private foundations is growing (Betsill et al., 2021). As independent organisations, foundations have the potential to adapt their funding strategies and mechanisms to maximise effectiveness. If conservationists can provide evidence to support certain investment strategies, private foundations and other philanthropic entities are theoretically able to adapt accordingly. The idea of charitable giving that is evidence-based and results-orientated is already growing with the social movement known as 'effective altruism' (Freeling and Connell, 2020), giving the conservation sector an opportunity to shape the charitable funding landscape using empirical evidence. Global environmental agendas have driven the creation of global funds such as the BioCarbon Fund managed by the world bank (www.biocarbonfund-isfl.org), the Global Environment Facility (www.thegef.org), and the Green Climate Fund (www.greenclimate.fund), all of which still operate within the grant-based model, yet are large enough to operate at a variety of spatial and temporal scales (Clark et al., 2018).

Payment for environmental services (PES) schemes are market-based mechanisms that can provide additional, and potentially long-term, funding for conservation by providing financial incentives for certain land management practices that preserve benefits generated by natural systems (Redford and Adams, 2009). Over the last two decades, the number of PES programmes have expanded rapidly around the world, with over 550 active programmes covering watersheds, biodiversity and habitats, and forest and carbon (Salzman et al., 2018). In contrast to traditional grant-based funding, PES has the potential to provide steady, long-term funds for conservation (Hein et al., 2013). This potential is, however, contingent on the motivations of participants of a given scheme and their willingness to participate over the long-term (Fisher, 2012).

There are many case studies that demonstrate successful PES projects (e.g., Clements and Milner-Gulland, 2015; Ingram et al., 2014; Jayachandran et al., 2016; Zheng et al., 2013), yet a lack of effective monitoring of PES programmes globally means there is still insufficient evidence that these market-based mechanisms provide a net benefit to nature (Ingram et al., 2014; Salzman et al., 2018). Although likely an important component of the conservation toolbox, and a potential source of stable, long-term funding for conservation, the development of PES projects should be careful, context-specific, and designed with robust monitoring to ensure long-term effectiveness (Hein et al., 2013; Redford and Adams, 2009).

Another promising avenue for market-based environmental funding is private finance, the power of which is yet to be fully realised (Clark et al., 2018). This is largely because the environmental sector has thus far failed to provide projects that are investable, scalable, and low risk (McFarland, 2018). Leveraging of private sector finance is increasing, and is being achieved through a variety of mechanisms including 1) national development banks which provide credit and finance to underfunded areas of society (Torres and Zeidan, 2016); 2) blended finance, which combines public and private finance through traditional mechanisms such as public-private partnerships, and through more novel mechanisms including development finance institutions (Clark et al., 2018); 3) custom-built partnerships between the private sector and governments, civil society, and non-governmental organisations, for example the Tropical Landscapes Finance Facility (www.tlffindonesia.org), which provide long-term financing to support sustainable land use; 4) green bonds, which raise funds for projects that contribute to a more sustainable economy and deliver benefits to the environment (Sachs et al., 2019), 5) conservation finance, which is a broad term that describes financial solutions that deliver conservation gains *and* financial return for investors. An undeveloped field, conservation finance has huge potential as a private sector investment opportunity that delivers conservation goals, using mechanisms such as substitute funds, marine protected area bonds, and conservation impact bonds (Huwyler et al., 2016); 6) carbon market instruments such as REDD+ and the Green Climate Fund (Sachs et al., 2019); 7) other ‘green finance’ mechanisms such as impact investing, fiscal policy, green central banking, and community-based green funds (Sachs et al., 2019).

Although in relative infancy, private sector investment for conservation and the environment is underway, with global players in both conservation and finance recognising the potential. An example is the NatureVest collaboration between The Nature Conservancy and JP Morgan

Chase which focusses on identifying and financing investable projects that deliver for investors and the environment (Kaiser, 2015). To successfully leverage private sector finance, the conservation sector (and the environmental sector more broadly) needs to dramatically increase the number and scale of projects that have low-risk rates of return and conservation impacts that are clear and measurable, thus making them attractive investments.

There is currently a large gap between the global ambitions for environmental recovery and the money available to fulfil those ambitions. In this study I have demonstrated that stable, long-term funding is more effective for the management of social-ecological landscapes than short-term, unreliable grant funding. Yet funding streams that provide such long-term financial stability are rare. Increasing the quantity of funding available for conservation and moving towards more sustainable investment strategies is going to require paradigm shifts across national and global policies and economies.

5.5. ACKNOWLEDEMENTS

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5.6. SUPPORTING INFORMATION

5.6.1 Sensitivity testing for parameters res_consume and tend_crop_yield

The two parameters *res_consume* and *tend_crop_yield* are important because they influence the decision making of the users. *Res_consume* governs the quantity of crops each resource consumes on a given landscape cell at a given time step, thus reducing the users yield on that cell by a certain amount. *Tend_crop_yield* governs the amount a user can increase their yield on a given cell by tending their crops, as opposed to taking another action such as felling.

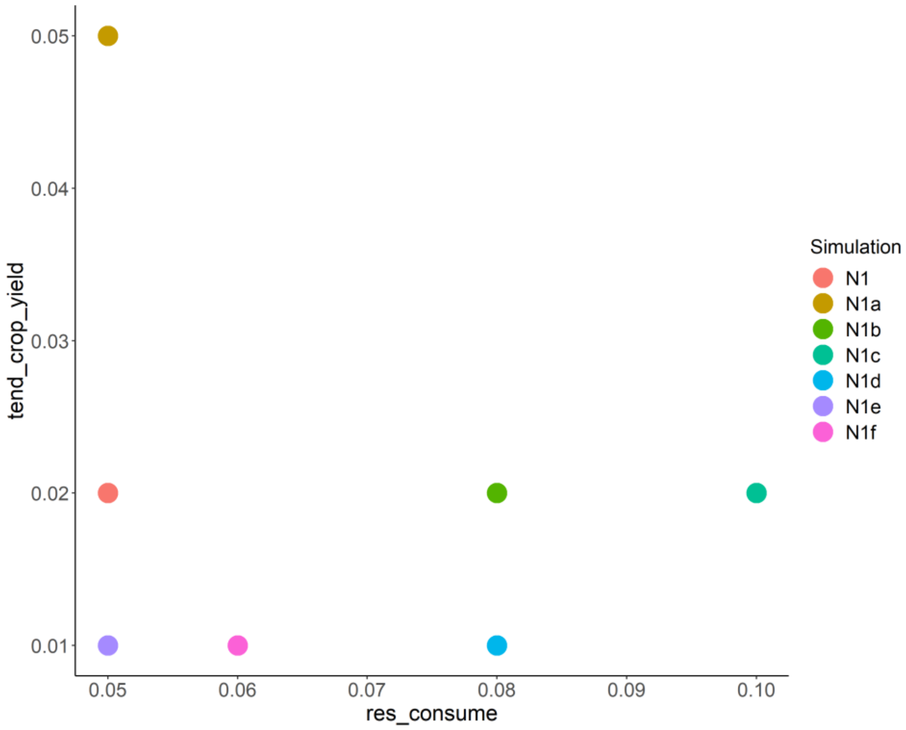

Figure S5.1. Parameter values for res_consume and tend_crop_yield that were tested prior to the final simulations.

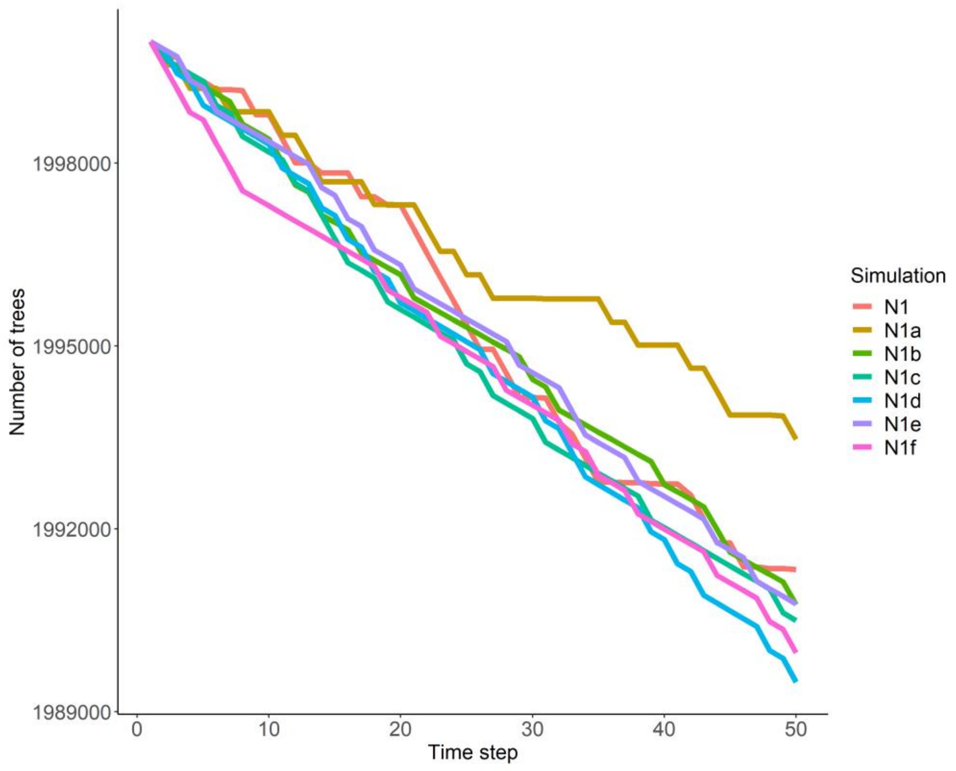

Figure S5.2. The number of trees remaining at each time step for each of the simulations from plot S5.1. above.

N1a results in the fewest trees being lost, which was expected as N1a has no incentive to fell trees (equal parameter values). N1 and N1b:f are all similar in their loss of trees. Interestingly, the simulation with the highest *res_consume* (N1c) does not end up with the fewest trees, and that is because *tend_crop_yield* is higher than some of the others and so users will be more likely to choose to tend crops when costs of felling are very high. The simulation with the most trees lost is N1d, where *tend_crop_yield* is very low (0.01) and *res_consume* is quite high (0.08). This is closely followed by N1f which although has a lower *res_consume* value than N1b and N1c, it also has a lower *tend_crop_yield* value. This quite nicely shows the interaction between the two parameters. This further demonstrates that small incremental changes in *tend_crop_yield* are more influential than similar increases in *res_consume*.

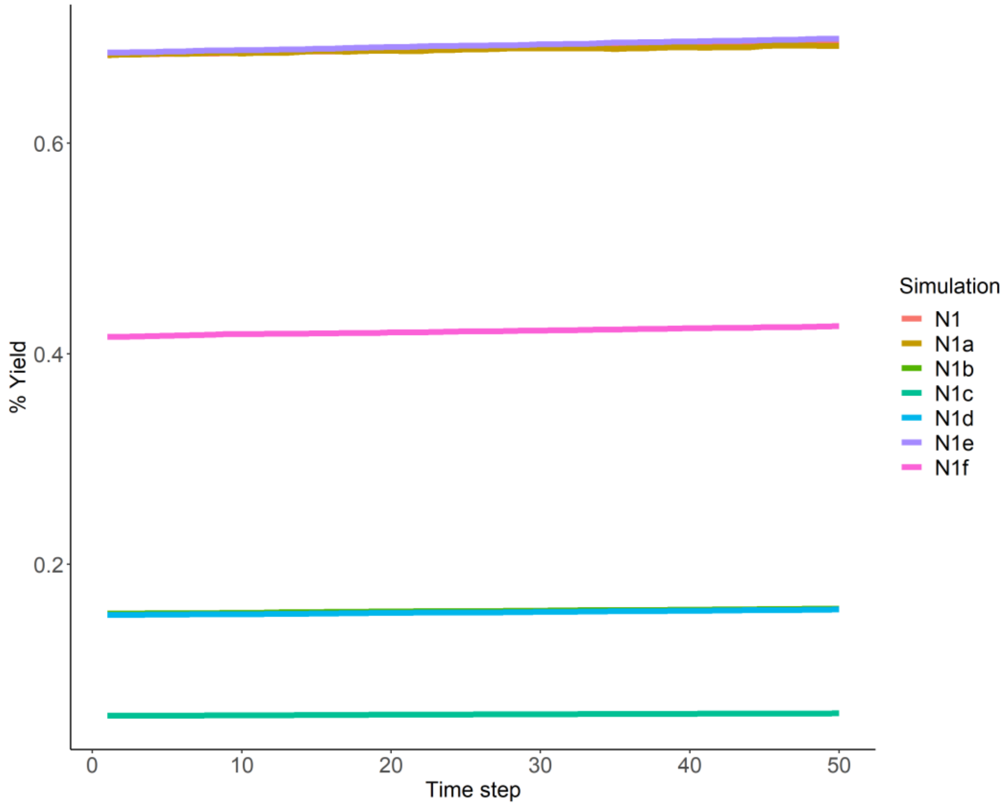

Figure S5.3. The total yield for each user at each time step, as a percentage of the total available yield, for each of the simulations from plot S5.1.

Yield is lowest in N1c, as this simulation has the highest value for *res_consume* (0.1), followed by N1b and N1d (0.08). N1f is on its own in the middle (0.06). The highest yields are for N1, N1a, and N1e, where *res_consume* is 0.05 for all. For this last group, we see that N1e is increasing slightly faster, as *tend_crop_yld* is set lower than N1 and N1a, and so users are more likely to fell trees as tending crops has less value.

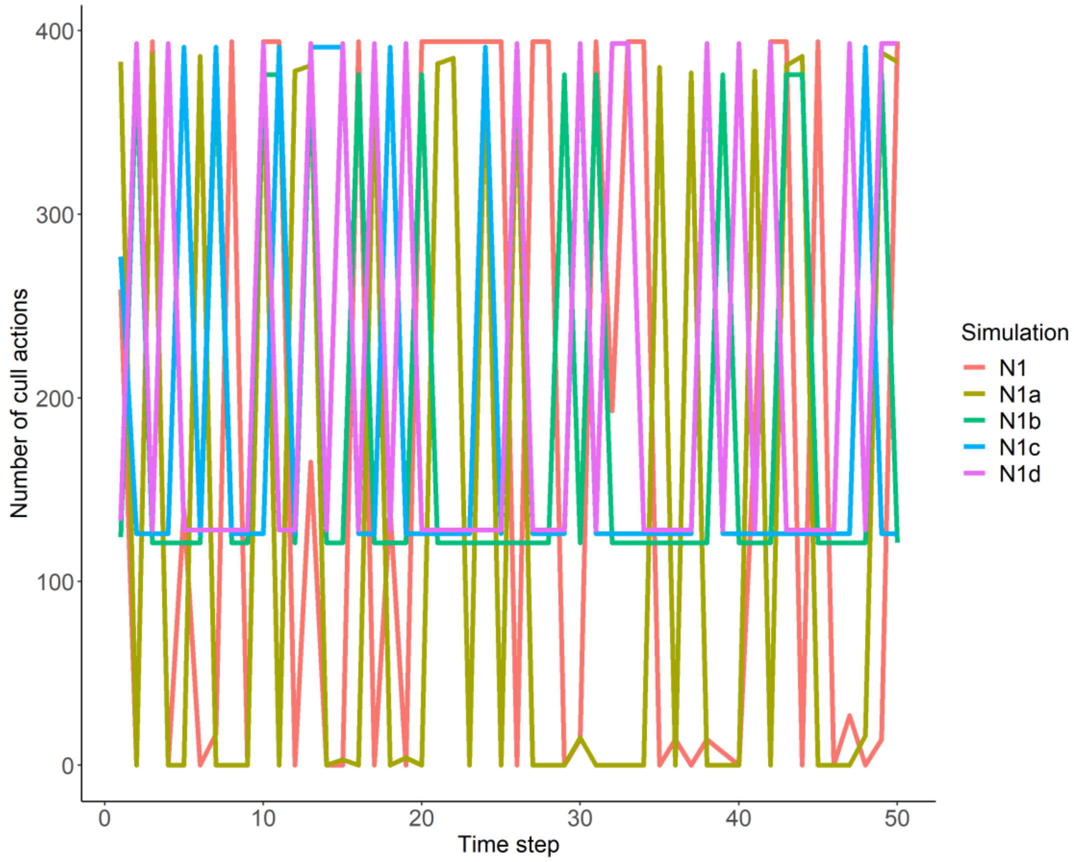

Figure S5.4. The total number of culling (felling) actions taken by users at each time step for each of the simulations from plot S5.1.

The simulations appear to be broadly split between N1 and N1a, and the rest. N1 and N1a show much more variation in the number of felling actions, with the number of felling actions regularly dropping to 0. For simulation N1a, which has the two parameters set equally at 0.05, we see regular spells of 0 felling actions, where the users are choosing to tend crops (as that produces the same benefits in terms of yield). This happens less frequently with simulation N1, and in simulation N1 there are no occasions when number of cull actions remain at 0 for more than a single time step. This is because *tend_crop_yield* is lower than *res_consume*, and so it is more beneficial to fell trees. For all of the other simulations though, there appears to be a minimum number of culls below which they never drop (just over 100). Even simulation N1e, which is very similar to N1 in terms of parameters, never drops below a certain value of cull actions.

5.6.2. Null scenarios

N1

The null scenario N1 had the manager and user budgets (community resources) as stable and equal. Both budgets were set to 500.

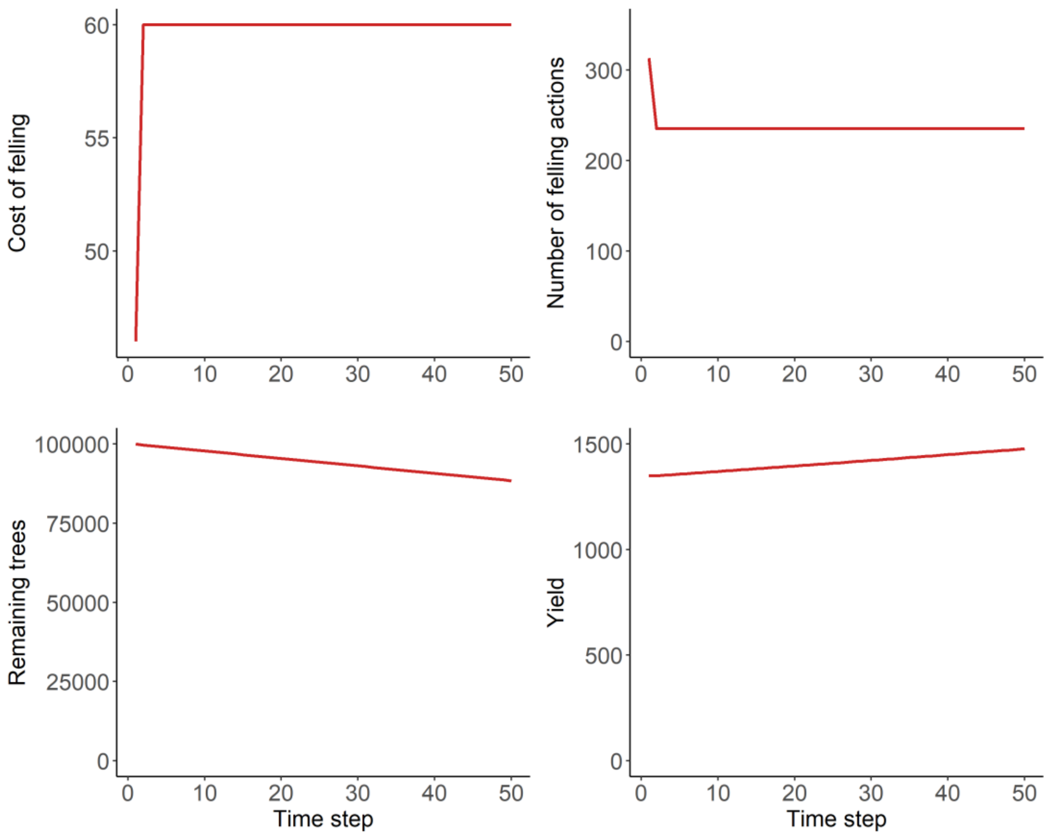

Figure S5.5. Summary results from null scenario N1. The cost of a felling action at each time step (top left), number of felling actions at each time step (top right), the number of trees remaining on the landscape at each time step (bottom left), and the total yield from all users at each time step (bottom right).

The results of scenario N1 were as expected – the manager uses all of their budget to reduce felling by time step 2, which coincides with the number of felling actions dropping between time step 1 and time step 2. The stable budgets for both the manager and user results in a stabilisation of felling costs and number of felling actions, as neither user nor manager loses or gains power over the other. The manager is unable to entirely stop felling taking place, and therefore there is a steady decrease in the number of trees remaining. This results in a steady increase in the yield that the users get from the landscape over time.

N2

The null scenario N2 tested the situations when either the manager or user had a decreasing budget, whilst the other was stable. The scenario was therefore split into two sub-scenarios. N2a had the manager budget stable, and the user budget (community resources) decreasing linearly. N2b had the user budget (community resources) stable, and the manager budget decreasing linearly.

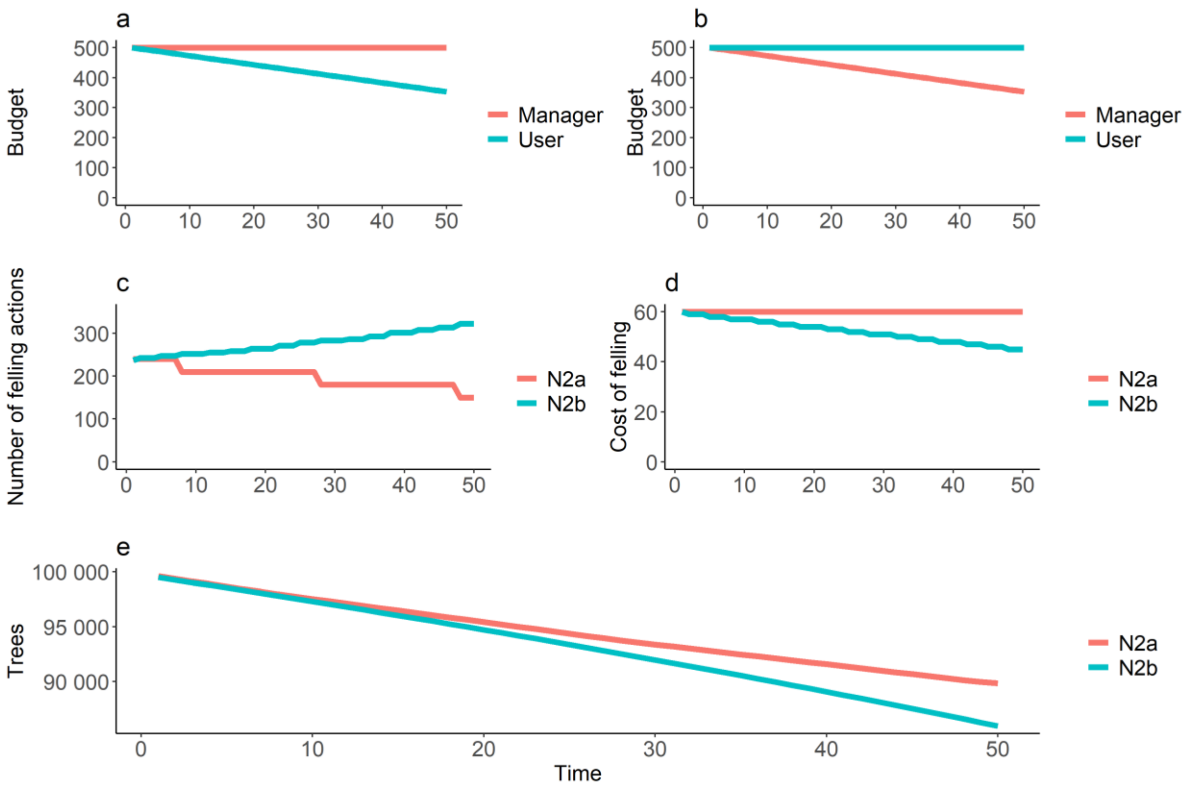

Figure S5.6. summary results from null scenario N2a and N2b. a – budgets at each time step for N2a, b – budgets at each time step for N2b, c – the number of felling actions at each time step for both scenarios, d – the cost of felling actions at each time step for both scenarios, e – the number of trees remaining at each time step for both scenarios.

The results from null scenarios N2a and N2b were as expected. When the manager budget was stable and the user budget (community resources) were decreasing, the cost of felling remained stable over time, but due to the decreasing community resources the number of felling actions decreased over time. The rate of forest loss in N2a was decreasing over time as the community lost power to take actions (i.e., fell trees). When the community resources were stable, but the manager budget decreased over time, the cost of felling trees decreased over time as the manager had less budget at each time step with which to set the cost of felling actions. This resulted in an increasing number of felling actions over time, and a rate of forest loss that was increasing.

N3

The final null scenario, N3, had the manager budget increasing linearly and the user budget (community resources) stable.

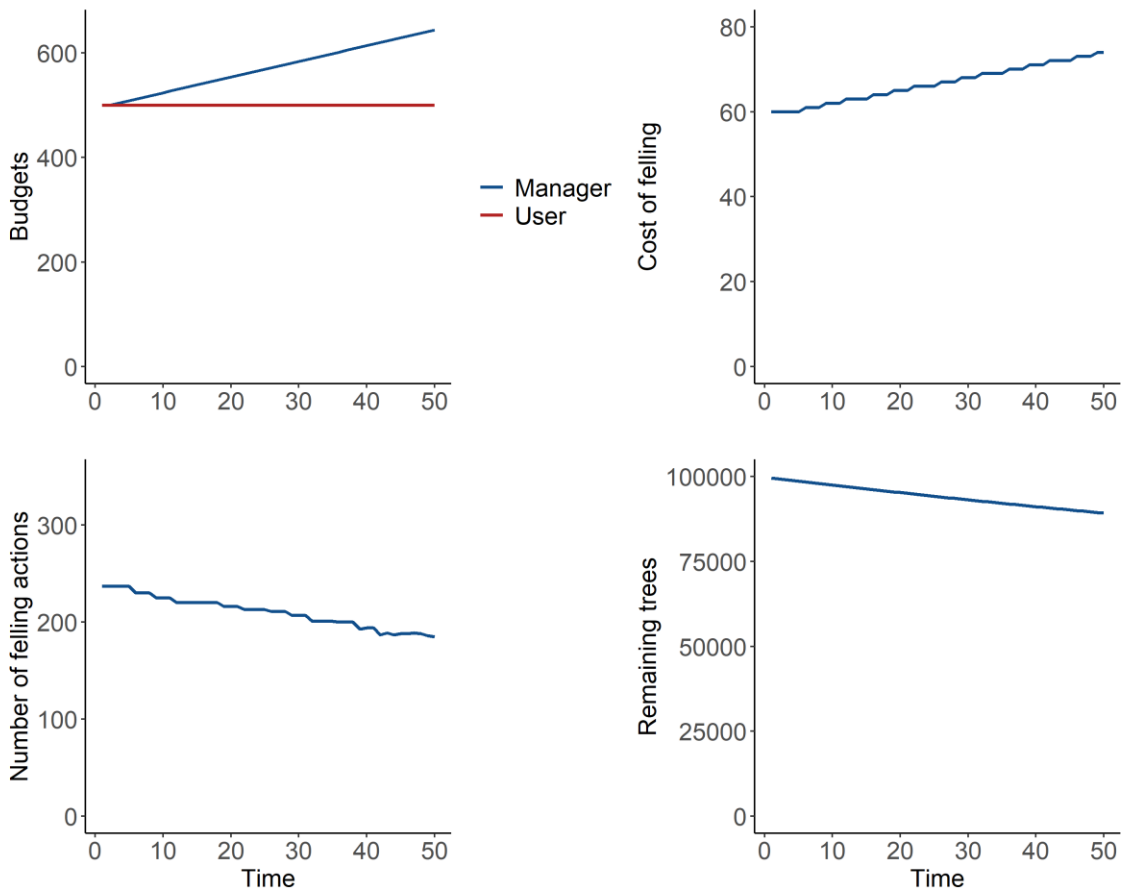

Figure S5.7. Summary results from null scenario N3. The budget at each time step for both the manager and the users (top left), the cost of a felling action at each time step (top right), the total number of felling actions at each time step (bottom left), and the number of trees remaining on the landscape at each time step (bottom right).

The results from N3 were as expected; the power of the manager to affect the system increased as the manager budget increased and the community resources remained stable. This led to a steady increase in the cost of felling actions for the community, and therefore a steady decrease in the number of felling actions. The relative differences between the manager budget and community resources were never large enough to completely eliminate felling actions, and therefore forest loss was still occurring.

5.6.3. Parameter values

The below parameter values were used in all null and final scenarios. See the GMSE package documentation for further details on *gmse()* and *gmse_apply()* parameter values. All genetic algorithm parameters were kept at their default value.

Table S5.1. GMSE parameter values used in all final simulations.

Parameter	**Valuea**
time_max	50
land_dim_1	100
land_dim_2	100
res_movement	0
agent_view	150
agent_move	50
res_move_type	0
res_death_type	0
lambda	0
observe_type	2
times_observe	1
obs_move_type	1
res_min_age	0
res_move_obs	FALSE
res_consume	0.08
move_agents	TRUE
minimum_cost	10
usr_budget_range	User budget / 10
manage_target	100000
RESOURCE_ini	100000
culling	TRUE
tend_crops	TRUE
tend_crop_yield	0.01
stakeholders	30
land_ownership	TRUE
public_land	0
manage_freq	1
group_think	FALSE

5.6.4. Manager budgets

Scenarios 4 and 5 used a Fourier series approach to produce random complex waves that mimicked unpredictable manager budgets over time. Three sine waves were produced for each simulation replicate, and were summed to produce a single complex wave. Sine waves for both scenarios were created using,

$$b_i(t) = A_i \sin\left(\frac{2\pi}{T} t f_i + \varphi_i\right).$$

Where $b_i(t)$ is the trajectory at time t for wave i, T is the total number of time steps (t), A_i is the strength of wave i, f_i is the frequency of wave i, and φ_i is the delay of wave i.

The frequency values (f_i) for each sine wave were sampled from a uniform distribution, for scenario 4 using,

$$f_i \sim U(0.01, 0.08).$$

And scenario 5 using,

$$f_i \sim U(0.01, 0.2).$$

Delay values (φ_i) for each sine wave were sampled from a uniform distribution, for scenario 4 and 5 using,

$$\varphi_i \sim U(0, 180).$$

Wave strength (A_i) for each sine wave were sampled from a uniform distribution, for scenario 4 using,

$$A_i \sim U(1, 150).$$

And scenario 5 using,

$$A_i \sim U(1, 300).$$

Figure S5.8 below shows an example, where the budget B (black line) is determined by the sum of the three $b_i(t)$ coloured lines.

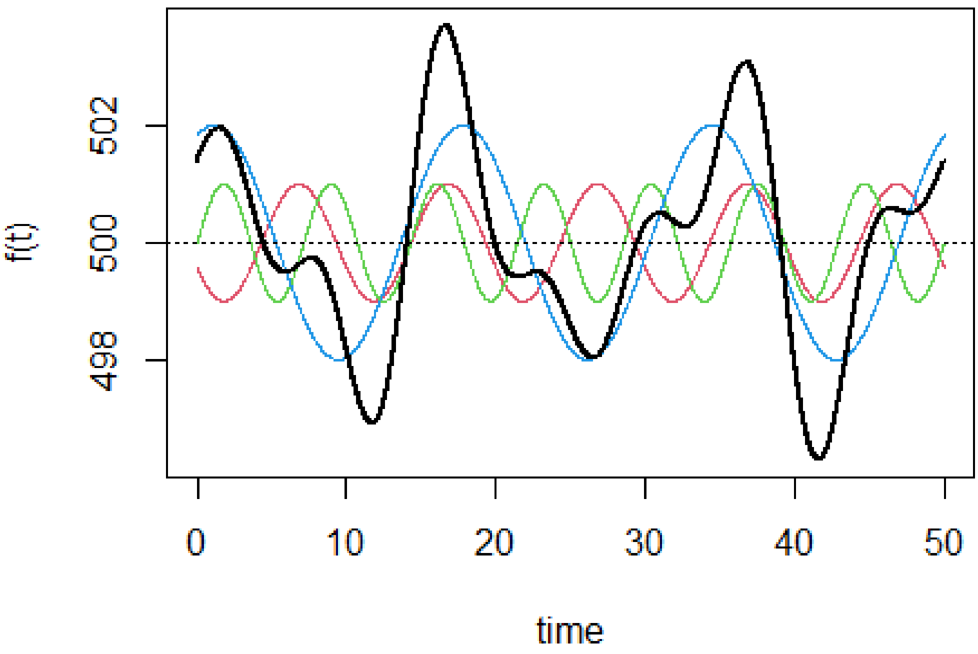

Figure S5.8. An unpredictable manager budget B (black line), produced by the sum of three sine waves ($b_i(t)$, coloured lines).

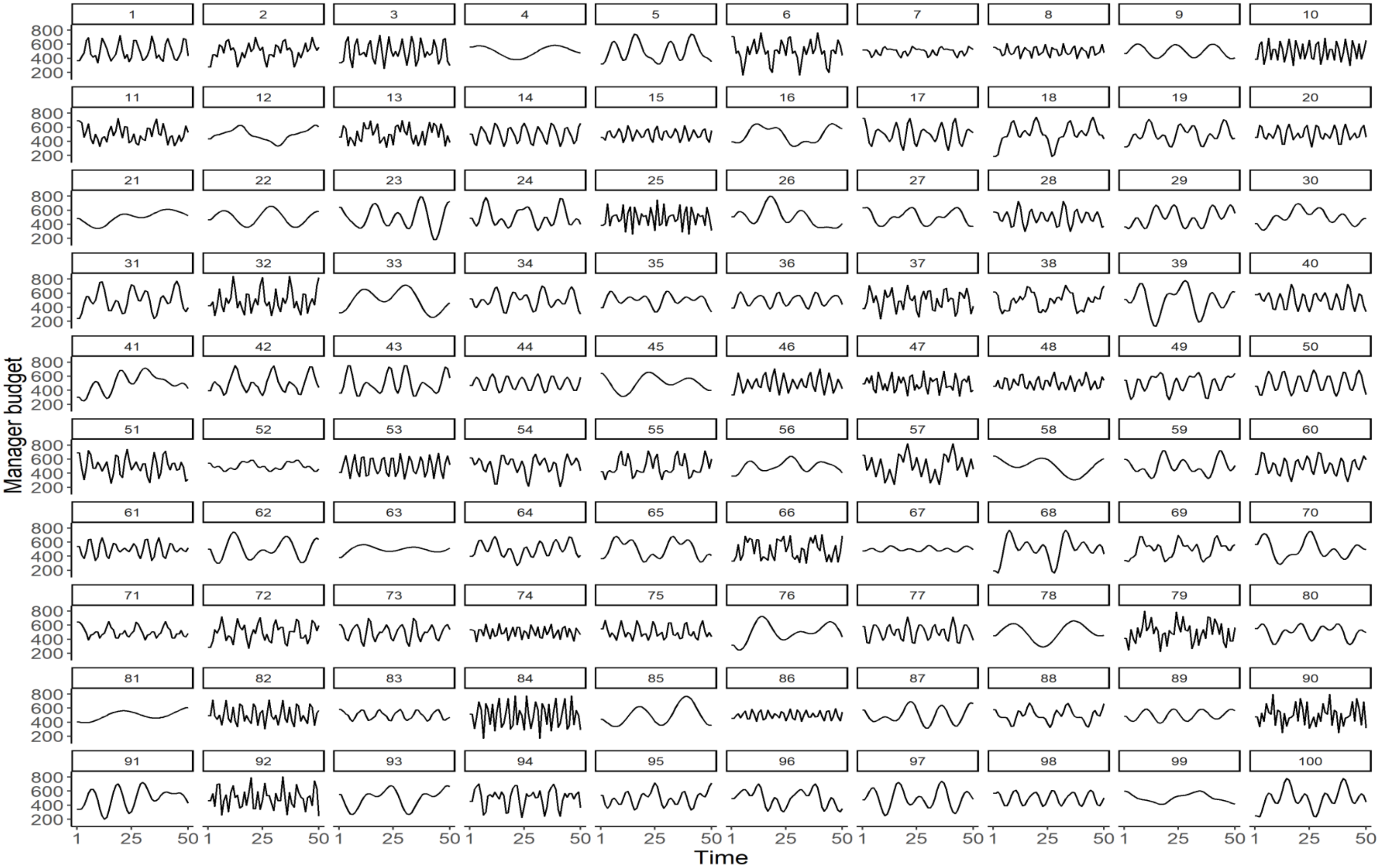

Figure S5.9. Manager budgets for each of the 100 replicate simulations for scenario 4. Each budget was produced using three randomly produced sine waves and an Inverse Fourier Transform.

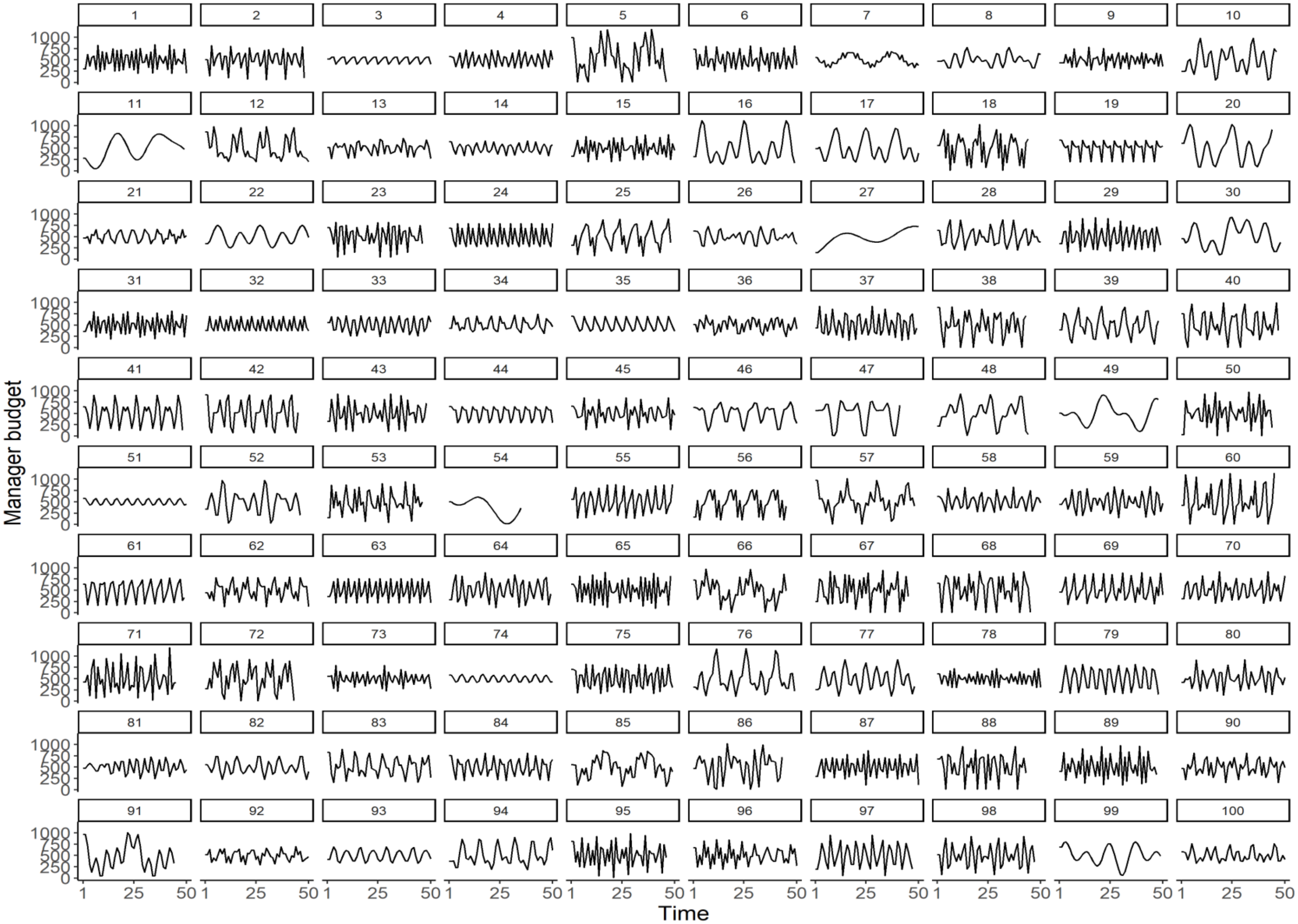

Figure S5.10. Manager budgets for each of the 100 replicate simulations for scenario 5. Each budget was produced using three randomly produced sine waves and an Inverse Fourier Transform.

5.6.5. Results

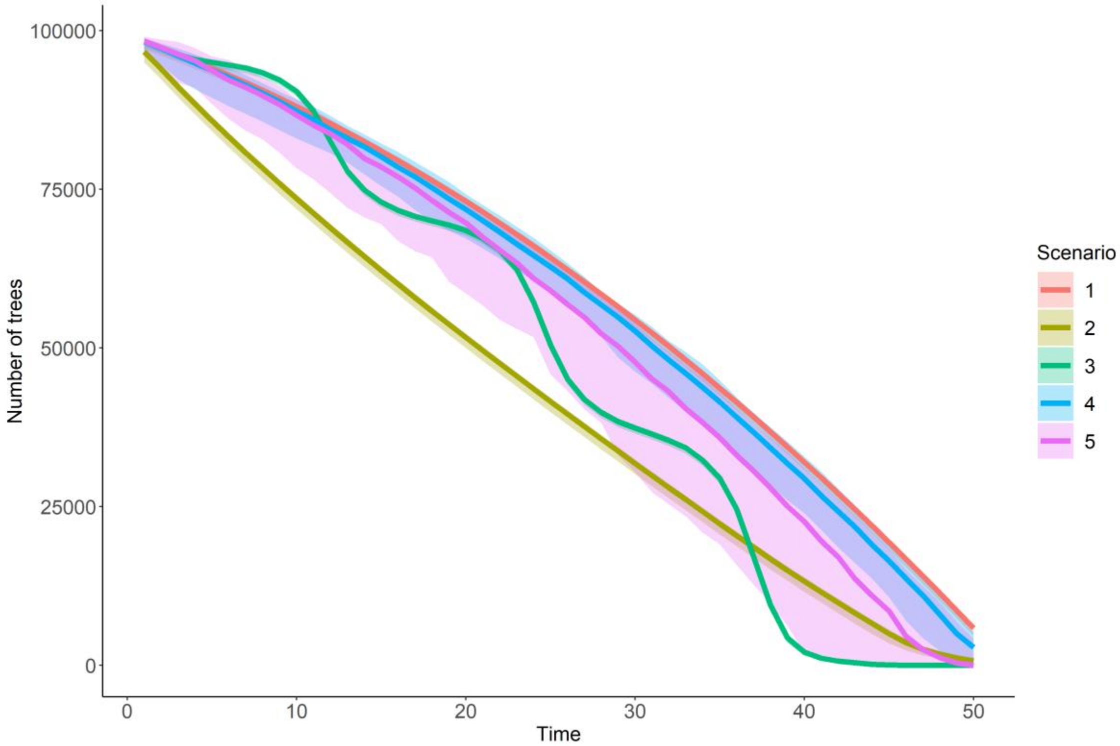

Figure S5.11. Remaining trees at each time step for all five scenarios. Thick lines and confidence ribbons are the 50, 2.5, and 97.5 percentiles taken from the 100 replicates for each scenario.

Chapter 6
General discussion

6.1 Background

Southeast Asia is one of the most biologically diverse regions of the world, and its extensive tropical forest cover is critically important for biodiversity conservation, ecosystem services, human livelihoods, and carbon sequestration (Hughes, 2018, 2017; Mukul et al., 2016). Yet the region is facing enormous pressure from human activities which are driving wildlife population declines and deforestation at some of the fastest rates in the world (Hoffmann et al., 2010; Hughes, 2017). In many ways, Cambodia epitomises the challenges facing the wider region; it has high biodiversity value and forest cover that are threatened by rapid economic development, a boom in commercial agriculture, large rural populations, high levels of poverty and inequality, and weak governance. Yet by virtue of Cambodia's traumatic recent history, it can offer a unique perspective on the drivers of biodiversity loss and opportunities for action. The rebuilding of the country, including government, laws and policies, the economy, and society after the Peace Accords in 1991 means that it is possible to examine the effects of such rapid change from a known baseline, and over a much shorter temporal scale than would be possible in other countries.

Cambodia's post-war economic recovery has had dramatic effects on poverty reduction, agricultural production, and food security, which have benefited the Cambodian people (Eliste and Zorya, 2015). The country, however, still faces numerous challenges. Many of these challenges stem from the initial period of reconstruction in the 1990s when establishing the rule of law, ensuring there was sufficient food for the surviving population, and rebuilding basic infrastructure were prioritised at the expense of transparent governance, accountability, inclusion, and participation (World Bank, 2014). Furthermore, economic recovery and the expansion of the agricultural sector were prioritised over environmental protection (Eliste and Zorya, 2015). The state of Cambodia today reflects the consequences of these decisions; there is a booming economy and an affluent urban population, yet inequality is increasing (World Bank, 2014), many rural areas remain poor and have yet to benefit from economic growth (Solcomb, 2010), the political system is one of the most corrupt in the world (Transparency International, 2021), governance and policy implementation is weak (Milne and Mahanty, 2015), and environmental governance is poor (Milne and Mahanty, 2015; Riggs et al., 2018).

Cambodia still holds globally significant biodiversity (Chapter 4; Gray et al., 2012; Moody, 2018), and still retains large areas of forest cover that is critical for wildlife and local people (MoE, 2020), particularly many of the country's indigenous population (Coad et al., 2019a; Ibbett et al., 2020). As the country continues to develop, the business-as-usual scenario will lead to continued loss of forests and wildlife declines. Yet, with the right knowledge about relationships between development and forest loss, and with evidence to support better landscape and protected area (PA) management, there are opportunities to develop new policy frameworks, and better implement existing policies, to ensure environmental protection into the future. The research described in this thesis has contributed original, policy-relevant knowledge to support decision-making, policy development, and landscape management in Cambodia. I have revealed important relationships between economic development and commercial agriculture at the national scale (Chapter 2), which is one of the most important drivers of forest loss across the world (Curtis et al., 2018; Hoang and Kanemoto, 2021), and I have highlighted the complexity of the relationships between socioeconomic development and forest cover, with important methodological lessons for future research (Chapter 3). Leading an international team of researchers and practitioners, I harnessed one of the longest and most robust wildlife monitoring datasets in SEA, and revealed a significant pattern of decline in ground-based mammals within one of Cambodia's flagship PAs (Chapter 4; Nuttall et al., 2021). Finally, I have provided novel theoretical insights into the effects of unstable and unpredictable funding for landscape managers in the context of increasing anthropogenic pressure within a dynamic conservation landscape (Chapter 5). In the following sections, I summarise the key findings and evaluate their implications for conservation in Cambodia.

6.2 Economic development and forests

6.2.1 Results summary and implications

Chapters 2 and 3 investigated the relationships between economic and socioeconomic development and forests cover and loss across Cambodia. Chapter 2 identified important relationships between changes in various parts of the economy and agricultural commodity prices, and the expansion of commercial agriculture in the form of economic land concessions (ELCs). There was a positive relationship between new ELC allocations and 1) growth in the agricultural sectors proportion of national GDP, 2) increases in foreign direct investment, 3) increases in development flows to the environment sector, and 4) increases in market and producer prices for rubber, sugar, corn, and rice. In Chapter 3, I did not identify any socioeconomic factors that could effectively predict forest cover at either the provincial level or the commune level. Nevertheless, the socioeconomic models in combination with the cluster analysis showed that there were certain characteristics of both provinces and communes that could predict high forest cover. Generally, areas of high elevation and low human population density are more likely to have high forest cover, and provinces that are close to international borders, contain large, remote communes, and contain PAs and ELCs, are more likely to be highly forested. When viewed together, the results from Chapters 1 and 2 provide insights that have important policy implications.

First, provinces with ELCs are more likely to be highly forested, which is counterintuitive in the context of the law governing ELCs. Legally, leases for ELCs are only allowed on "degraded" or "marginal" land which has low biodiversity value (Neef and Touch, 2012; RGC, 2001). My results do not explicitly demonstrate which ELCs were placed on forested land, nor do I quantify forest loss as a direct result of ELCs, but this has been demonstrated elsewhere (Appendix; Beauchamp et al., 2018; Davis et al., 2015). Based on my results from Chapter 3, the rapid expansion of ELCs, which was driven by economic growth, the international commodity market, and foreign investment, will probably have disproportionately affected remote, rural, forested provinces with largely poor, indigenous populations. Rural communities in Cambodia, particularly indigenous minorities, rely heavily on forest resources for their livelihoods (Coad et al., 2019a; Ibbett et al., 2020; Nguyen et al., 2015), and many forests are culturally and spiritually significant for local people (Evans et al., 2013; Milne, 2012). The allocation of ELCs on forested land has therefore had negative effects on local people. The case for poverty reduction and economic development through commercial agriculture, which is one of the prerequisites for the granting of ELC leases (RGC, 2001), is demonstrably weak in Cambodia, and there is evidence that ELCs have not only infringed on local land rights but have also been used as a tool for the commercial capture of smallholder farmland (Scheidel, 2016). Increasing inequality and an expanding wealth gap between the wealthy political class and the rural poor, in combination with the many criticisms of ELCs in Cambodia, suggest that the expansion of ELCs has probably had negligible effects on poverty reduction for rural communities.

Second, Chapter 3 demonstrated that the presence of both ELCs and PAs predicted high forest cover within a province, suggesting that ELCs were more likely to be granted in provinces where there was existing forest cover and high biodiversity value. Despite a legal framework that prohibits ELC allocation within PAs (RGC, 2001), almost every PA in the country has had ELCs granted within their borders (RGC unpublished data, www.opendevelopmentcambodia.net). Obscure legal mechanisms, opaque processes, and weak governance have all contributed to the downgrading of important PAs via ELCs, to the detriment of biodiversity (Appendix; Beauchamp et al., 2018; Davis et al., 2015; Riggs et al., 2018). International conservation organisations and donors have invested heavily into the PA estate for two decades, and yet have been largely unsuccessful in resisting ELC allocation within PAs (although see Appendix). This is supported by Chapter 2, which showed that, counterintuitively, ELC allocation increased with greater development flows to the environment sector. Donor aid and investment into the environment failed to reduce the rapid expansion of ELCs, many of which resulted in the loss of PA land (Appendix; Beauchamp et al., 2018; Conservation International and World Wildlife Fund, 2021; Global Witness, 2013; Riggs et al., 2018). Once ELCs are allocated on forested land, even within PAs, the areas are often rapidly deforested to make way for commercial crops (Beauchamp et al., 2018; Davis et al., 2015), with negative effects on biodiversity, carbon storage, and ecosystem services.

Agricultural sector growth, foreign investment, and entry into the global market post-1993 have been critical parts of Cambodia's economic recovery and efforts in reducing poverty and increasing food security (Eliste and Zorya, 2015), and my results have suggested that the commercial agricultural sector has been a major beneficiary of this development. Commercial agriculture can bring economic benefits (Li et al., 2018; Taylor et al., 2019), but it is also the primary driver of global deforestation (Curtis et al., 2018). In Cambodia, ELCs have been criticised for driving deforestation (Beauchamp et al., 2018; Davis et al., 2015; Magliocca et al., 2019), downgrading PAs (Appendix; Beauchamp et al., 2018; Watson et al., 2014), and their negative effects on local land rights (De Schutter, 2011; Neef et al., 2013; Neef and Touch, 2012; Oldenburg and Neef, 2014; Scheidel, 2016). Economic land concessions in Cambodia have also received significant negative media attention which has suggested the industry suffers from corruption and nepotism (e.g., Global Witness, 2013; Vrieze and Kuch, 2012). Cambodia's legal framework that governs ELCs and PAs is theoretically sound, although translating law into environmentally sustainable commercial agriculture and effective PA management requires equally robust policy implementation and governance, both of which are lacking to a certain degree.

Examples of sustainable agriculture already exist, both in Cambodia and globally. The Ibis Rice programme in Cambodia (www.ibisrice.com) harnesses the demand for high quality jasmine rice and adds value through 'organic' and 'wildlife-friendly' certifications which increase the price above market value. In return, approximately 1,500 individual farmers from the Northern Plains adhere to conservation agreements which prohibit forest clearance, hunting, and any other activities or practices that have negative effects on the environment. Studies have demonstrated the success of the programme (Clements and Milner-Gulland, 2015), and it has continued to expand to other parts of Cambodia in recent years. In Vietnam, sustainable agricultural practices are becoming more popular (Van Thanh and Yapwattanaphun, 2015), agroforestry approaches have increased the sustainability of rubber production in Indonesia and Thailand (Penot et al., 2017), and in South America, market forces and consumer demand have driven novel forms of multistakeholder governance that have had positive effects on the sustainability of beef production (Buckley et al., 2019). Lessons from across the tropics suggest that movement towards sustainable agriculture is often swiftest under conditions of hybrid governance, where governments, the private sector, and civil society collaborate to design effective interventions (Erbaugh et al., 2019).

Continued economic development is important for Cambodia to reduce poverty and ensure adequate provision of education, employment, and healthcare. The agricultural sector will continue to play a major role in both economic development and food security, yet environmental sustainability must be a priority if deforestation rates are to decrease (Erbaugh et al., 2019). Investment into modern agricultural practices such as irrigation, mechanisation, and high-quality seed has already resulted in increased yields in some parts of Cambodia, and in combination with better market access, has begun stimulating the diversification of crop production to include more profitable crops (Eliste and Zorya, 2015). Reducing deforestation from agriculture is a complex challenge, requiring a combination of market forces, legal reforms, and effective policy and implementation at multiple scales from multinational corporations and supply chain responsibility, to national governments, and local action with the support of civil society (Erbaugh et al., 2019).

6.2.2 Methodological notes

In Chapter 2, I did not find any significant relationships between the predictor variables representing economic development and direct forest loss. In the chapter I discussed various explanations for this lack of effects, but the most plausible is that there has been a genuine disconnect between economic development and direct forest loss, particularly in the early years of economic recovery. Despite impressive economic growth rates, Cambodia's economy between 1993 and the early 2000s was still in relative infancy compared with its neighbours (Solcomb, 2010), and therefore it is likely that factors such as GDP growth, foreign investment, and development support were not yet at a scale large enough to have a direct influencing effect on land use change (LUC). Particularly in the first half of the study period covered by Chapter 2 (1993 to ~2004), economic growth, investment, and development aid was focussed on rebuilding the institutions and government infrastructure required to govern the country (World Bank, 2014), and so these factors will have had less influence on forest loss, and indeed other land management decisions and LUC, in the rural provinces than might be seen in studies from other countries with more established economies (e.g., Bonilla-Bedoya et al., 2018; Ewers, 2006; Fan and Ding, 2016; Gong et al., 2013; Kuang et al., 2016). Previous studies from Cambodia have highlighted some national-scale factors, including human population increases and tourism policies, that have influenced LUC in certain parts of the country (Dasgupta et al., 2005; Gaughan et al., 2009), whilst others have supported my hypothesis and pointed to more local-scale factors influencing deforestation such as the repatriation of Khmer Rouge soldiers, families moving back to their homelands, and resettling of refugees, all of which drove deforestation via small-holder agricultural expansion (Hought et al., 2012; Kong et al., 2019).

In Chapter 3, I did not detect any strong relationships between socioeconomic variables and forest cover at the scale of the commune. As discussed in the chapter, it is plausible that the socioeconomic variables I selected were appropriate but that there was a genuine lack of effects. Alternatively, an explanation could be that socioeconomic variables can predict forest cover, but the variables available to me were not appropriate and therefore were not effective predictors of forest cover. However, this is unlikely as many of the variables used have been shown to be effective predictors in other parts of Asia (e.g., Bonilla-Bedoya et al., 2018; Dasgupta et al., 2005; Kristensen et al., 2016; Mena et al., 2006; Rowcroft, 2008). The more likely explanation is that the extreme between-commune (and within-province) variation, coupled with a very large number of random effect levels at the commune level, meant that estimating a single coefficient with a representative effect size and direction was unlikely. Modelling the relationships at a coarser scale (province) resulted in three socioeconomic predictor variables being retained in the final model, albeit with weak effects, but also revealed complex interactions between the direction of effects and scale. The challenges that I discovered with modelling highly complex spatiotemporal landscapes at fine resolutions highlight important lessons for future researchers.

First, when utilising generalised linear mixed models (GLMMs) in such a scenario, it is critical to interrogate and report details of between-group variance, as these can offer insights into the predictive efficacy of a model. Between-group variance often goes unreported in the LUC literature (e.g., Bhattarai and Hammig, 2004), reducing the transparency of the results. Second, given large variation in predictor and response values over space, researchers should explore the option of spatial stratification, whereby regions with similar variable ranges are modelled independently. Not only will this reduce the challenges mentioned above but may offer useful insights into regional differences in effects. Third, researchers must select the scale of their analysis carefully, as there are likely complex interactions between drivers and effects at different scales, as demonstrated in Chapter 3. Importantly, Chapter 3 demonstrates that inferences drawn from a particular model should not be considered true at scales different from that which the model was applied.

6.3 Protected area and landscape management

6.3.1 Results summary and implications

In Chapters 4 and 5 I investigated the dynamics of different aspects of conservation landscapes, and my results have important implications both for protected area management in Cambodia, and the management of conservation landscapes around the world. In Chapter 4, I used one of the most robust wildlife monitoring data sets from SEA to model the temporal population trends and spatial distributions of a suite of species from the Keo Seima Wildlife Sanctuary (KSWS) between 2010 and 2020. My results confirmed that the site is a global stronghold for several threatened species, particularly the black-shanked douc (*Pygathrix nigripes*) and southern yellow-cheeked crested gibbon (*Nomascus gabriellae*). Keo Seima Wildlife Sanctuary probably holds the largest single populations of these two highly threatened primates, making conservation at the site of particular importance. Critically, my results from Chapter 4 revealed that ground-based species were largely in decline, some severely.

There are examples of robust wildlife research and monitoring from Cambodia, including for large herbivores and ungulates (Gray and Phan, 2011; Gray, 2012; Gray et al., 2016; Gray et al., 2012; O'Kelly et al., 2012), carnivores (Gray, 2013; Gray et al., 2014; Kamler et al., 2021; Rostro-García et al., 2021, 2018), primates (Gray et al., 2010; Moody, 2018; Moody et al., 2011), and birds (Gray et al., 2014; Handschuh and Rainey, 2010; Loveridge et al., 2018, 2017; Nuttall et al., 2017). Yet my results from Chapter 4 represent the first modelled wildlife population trends over time from Cambodia, and one of the few examples of population trends using absolute population estimates (as opposed to relative indices) from SEA. My results also present the first population estimates for four species from anywhere in their range: black-shanked douc (*Pygathrix nigripes,* Critically Endangered), Germain's silver langur (*Trachypithecus germaini*, Endangered), northern pig-tailed macaque (*Macaca leonine,* Vulnerable), and stump-tailed macaque (*Macaca arctoides,* Vulnerable). Therefore, my results are of critical importance for conservation status assessments and protected area management in the region. The results from Chapter 4 are timely, providing further empirical evidence to support the growing literature that wildlife populations across Cambodia are in decline (Groenenberg et al., 2020; Loveridge et al., 2018; Rostro-García et al., 2016). Furthermore, Chapter 4 provides rare insights into the causes of declines for certain groups of species. My results demonstrate that ground-based species are in decline, whereas arboreal species are not. This pattern implicates ground-based threats as those of most conservation concern.

I did not test empirically the drivers of declines in Chapter 4, but there is sufficient evidence in the literature to suggest that hunting using snares and dogs, as well as predation by free-ranging dogs, are likely to be major causes (Belecky and Gray, 2020; Coad et al., 2019a; Gray et al., 2018, 2017; Ibbett et al., 2020). These inferences are important for PAs across Cambodia, where landscapes are managed under similar conditions of growing human populations, under-resourced law enforcement, and weak PA governance. Keo Seima Wildlife Sanctuary is arguably one of the most well-resourced PAs in Cambodia, suggesting that ground-based wildlife populations in PAs with fewer resources and sparser conservation interventions are likely to be in similar, if not worse, conditions. There needs to be rapid management action in KSWS to avoid wildlife extirpations. In the short-term, law enforcement resources need to be targeted in the areas of KSWS that are important for the declining species, and efforts need to focus on hunting with snares and dogs. In the longer term, conservation interventions need to reduce the reliance of local people on wild meat as a protein source, diversify and improve livelihoods, and support non-lethal forms of crop protection. The challenges facing KSWS are shared with PAs across the region (Gray et al., 2017; Groenenberg et al., 2020; Harrison et al., 2016), and therefore the implications from Chapter 4, as well as any possible solutions, will be relevant for many Southeast Asian PAs.

In Chapter 5, I presented what I believe to be the first example of an assessment of the conservation implications of grant-based funding in a formal quantitative model. My results support what many conservation practitioners already believe to be true (based on my experience in the conservation sector) – that reliable, predictable, and generally stable management funds over time will provide better long-term conservation outcomes than fluctuating and unpredictable funding. My results demonstrated this in the context of a dynamic social-ecological landscape with increasing human pressure. This context is common for conservation landscapes around the world, making my results relevant for conservationists and landscape managers in Cambodia and further afield, and will contribute valuable evidence to support the development of more sustainable conservation financing.

Protected areas in Cambodia can generally be divided into two categories: those with the support of large conservation non-governmental organisations (NGOs), and those without external support. The PAs with no support from NGOs receive nominal support from the Cambodian government, and therefore have minimal law enforcement or conservation activity. In contrast, the PAs with NGO support receive relatively extensive financial input, leveraged by the NGO from international donors, which supports government salaries, equipment, technical capacity, and conservation activities. The ability to raise funds for PA management has led to positive conservation outcomes relative to unsupported PAs (see Appendix for an example). However, my results from Chapter 4 highlight that PA management, even in a relatively well-funded PA, is far from optimal. The conservation funds raised by NGOs in Cambodia are short-term, grant-based sources of income, which results in fluctuations in available funds over time. In Chapter 5, I demonstrate that the grant-based funding model employed within PAs in Cambodia, and across the world, is not likely to produce the best possible long-term conservation outcomes.

As with conservation landscapes around the world, PAs in Cambodia will need to secure long-term, reliable funding if they are to halt wildlife declines and reduce rates of deforestation (Sayer and Wells, 2004). Efforts to secure sustainable conservation financing are already underway in Cambodia. Keo Seima Wildlife Sanctuary is one of several Reduced Emissions from Deforestation and Forest Degradation in Developing Countries (REDD+) sites in the country and in 2016 was the first to sell carbon credits (Washington, 2019). Continued validation of avoided deforestation resulting from the project has resulted in more sales since 2016. The income from these sales is distributed between the Cambodian government's forest conservation fund, the core management budget of KSWS, the local communities within the REDD+ project area, an operating reserve, and a permanence reserve (Washington, 2019). These funds incentivise government and local communities to reduce deforestation, support the ongoing management of the PA, and critically, ensure that steady funding is available over the long term. An assessment of the project states that conservation activities within KSWS are now able to be adaptive, flexible, and innovative, as the programme is no longer subject to the priorities of external funders (WCS, 2021). Despite some valid criticisms of REDD+ in the region, particularly related to the displacement of deforestation (Ingalls et al., 2018), the KSWS project demonstrates that REDD+ can be a mechanism for reduced deforestation and sustainable financing within PAs.

6.3.2. Methodological notes

Distance sampling is one of the most popular approaches to estimating the abundance of biological populations (Knights et al., 2021), and therefore has an extensive literature. Relatively few studies, however, take analytical steps beyond the production of point estimates of density or abundance, for example by explicitly modelling temporal trends (e.g., Campbell et al., 2015; Drummond and Armstrong, 2019). Distance sampling studies can be expensive to conduct, and so in many cases surveys are not continued beyond one or two years (e.g., Gray et al., 2012; Jathanna et al., 2003; Tomas et al., 2021), precluding the investigation of temporal trends. In Chapter 4, and in the subsequent publication, I demonstrated, with my co-authors, a practical yet robust approach to modelling population trends over time when distance sampling surveys have been conducted over multiple time steps. Furthermore, we have demonstrated how the same survey data can be used for both temporal and spatial modelling, thus extracting maximum utility for conservation management out of expensive monitoring data. By publishing in an open access journal, and making our R code and data publicly available, we hope that this study will benefit as many wildlife researchers as possible.

Long-term wildlife monitoring is expensive, and line transect surveys are especially resource heavy. Changing methodologies during a long-term study will always carry a risk of incomparability, however it is worth noting that there have been advances in distance sampling-based approaches. Distance sampling surveys can be conducted using remote sensing camera traps, which has the potential to greatly reduce the effort of field teams (Bessone et al., 2020; Cappelle et al., 2021; Harris et al., 2020; Howe et al., 2017; Palencia et al., 2021). There are other methods for estimating population density using camera traps (e.g., Rowcliffe et al., 2008, 2011), however retaining the distance sampling approach would be advisable to maintain comparability. The wildlife monitoring team from KSWS already have significant experience using camera traps, and therefore it may be worth the Wildlife Conservation Society (WCS) and their government partners conducting a cost-benefit analysis to assess the plausibility of altering the method of data collection in the future.

Huge leaps in computing power and the development of powerful and flexible statistical computing software over the last few decades has made the investigation of complex systems more tenable. The simulation of large datasets and the development and implementation of complex models are now accessible to any researcher with a personal computer, increasing researchers' abilities to simulate and model complex systems to gain theoretical insights that can benefit conservation (Green et al., 2005). The GMSE package from Duthie et al (2018), implemented in R, is an example of a modelling framework that has been developed to increase access to complex individual-based models that can explore and test a large range of theoretical questions relating to social-ecological systems.

The GMSE package allowed me, in Chapter 5, to investigate a component of conservation – the grant or funding cycle – that dominates project planning and the management and maintenance of which requires huge proportions of staff time and resources that could otherwise be focussed on designing and implementing conservation interventions. Conducting an empirical study with real data that provided the same insights as Chapter 5 would require long-term datasets that very rarely exist, and certainly do not exist across a broad sample of projects around the world. Simulation modelling allowed me to generalise the conservation landscape and simulate sufficient data such that theoretical insights were obtained that could be relevant to landscapes across the world. I hope that this chapter, and any publication that follow, will provide both a valuable contribution to the conservation financing field, and a good example of the utility of simulating social-ecological systems.

6.4 Impact of this thesis

This PhD project was a CASE studentship in collaboration with WCS Cambodia Programme. Analyses of the wildlife monitoring data from Chapter 4 have been limited to annual point estimates of abundance for the 11 species that have been reported to government and donors. Spatial modelling has been carried out for one species and published (Nuttall et al., 2017). However, the modelling of temporal trends for all species was requested to allow for unambiguous statements of population trends (“decreasing”, “stable”, “increasing”), and the spatial models were requested to support the strategic deployment of ranger patrols. The results, interpretation, and implications I presented in Chapter 4 were critical outputs for WCS as they have directly informed the management of KSWS, and they, and the peer-reviewed publication, have been well received. The results have been widely shared within Cambodia via news and media, and importantly they have been shared with senior government officials. Importantly, both the positive aspect of the results (primate and green peafowl populations are largely stable or increasing), and the negative aspect (ground-based species are in decline) have been highlighted, and I hope that the results will have a genuine impact on policy and the management of KSWS.

The publication of the results in a scientific journal has allowed the scale and quality of the KSWS monitoring programme to be internationally recognised, and the publication of population estimates and trends for species with no prior estimates will be invaluable for regional IUCN status assessments. All my R code is publicly available, and I conduced the analysis in close collaboration with Olly Griffin from WCS. This was done so that WCS technical advisers can repeat the analyses in the future, ensuring that what I accomplished during my PhD continues to benefit WCS and KSWS for many years.

Chapter 2 demonstrated how rapid economic development in a post-conflict nation can have significant effects on the expansion of commercial agriculture and, therefore, deforestation. Interestingly, the approval of new ELCs in Cambodia has decreased dramatically in recent years in response to a moratorium issued by the Prime Minister. Therefore, my results from Chapter 2 have less value in explicitly informing immediate current policy around commercial agriculture in Cambodia. However, they provide a formal analysis which suggests that these reductions in new ELCs should be maintained. Commercial agriculture is one of the most important drivers of deforestation around the world (Curtis et al., 2018; Hoang and Kanemoto, 2021), and my results will provide an important case study demonstrating the relationships between economic development and commercial agriculture, particularly in developing countries of SEA, and post-conflict nations.

WCS operates in many parts of Cambodia, and the results from Chapter 3 will provide important insights into the relationships between socioeconomics and forest cover. Importantly, Chapter 3 showed that in the Northern Plains (NP) of Cambodia, there has been socioeconomic development with little resulting forest loss. The WCS have some important conservation programmes in the NPs, including ecotourism initiatives and the Ibis Rice Payment for Environmental Services (PES) programme (www.ibisrice.com). The results from Chapter 3 may provide confirmation that these programmes are having the desired effect of increasing socioeconomic status in an environmentally sustainable way. This will allow WCS to investigate the development of similar programmes elsewhere in the country, for example in the Eastern Plains (where KSWS is located) where Chapter 3 demonstrated socioeconomic development was low, forest cover was high, and forest loss was high.

Chapter 5 has the potential to make a significant contribution to the conservation and green financing fields. I believe that this is the first study that explicitly models the effects of short-term funding cycles on conservation outcomes, and therefore will provide valuable theoretical insights for landscape managers and those working to develop sustainable financing for conservation. This chapter will be prioritised for publication in a peer-reviewed journal, and I hope it will be widely read. As a former conservation practitioner, I know that there is virtually universal agreement that short-term funding cycles are not optimal for long-term conservation management. It is always beneficial to have peer-reviewed publications that provide evidence to support calls for change, and to provide objective assessments of the pros and cons under certain circumstances.

6.5 Future research

This thesis has highlighted research that would be beneficial for conservation in Cambodia and more broadly. Chapters 2 and 3 modelled forest cover and loss across Cambodia, but they did not attempt to predict where forests would be lost in the future. There are some powerful tools for spatial predictive modelling of deforestation, such as cellular automata, maximum entropy, and machine learning (Basse et al., 2014; Bonilla-Bedoya et al., 2018; de Souza and De Marco, 2014), which could provide valuable information on spatial deforestation patterns, high risk areas, and the fine-scale predictors of deforestation for conservation managers across Cambodia.

The data and modelling framework from Chapter 3 could be used to investigate the socioeconomic predictors of forest cover from smaller, discrete regions of Cambodia. Smaller regions are likely to have less variance in predictor and response variables, and therefore the models may be able to identify specific regional predictors more effectively. If true, these predictions could be valuable for developing conservation or development interventions that are targeted and appropriate to the region.

Chapter 4 demonstrated that ground-based wildlife was in decline, and I suggest that hunting with snares and dogs, and predation by free-ranging dogs, are likely the main drivers of these declines. A study that was designed to specifically identify the main causes of mortality, and therefore demonstrate causation of population declines, would provide evidence for PA managers to design effective countermeasures.

In Chapter 5 I used the GMSE modelling framework to test theories on a generalised landscape. The GMSE package has sufficient flexibility to allow for customisation of the landscape to reflect a real-world conservation landscape or PA. For KSWS, using GMSE to investigate the implications of the REDD+ benefit sharing mechanism (i.e., how funds are distributed) on deforestation and local livelihoods in different contexts would be valuable for supporting future decisions relating to the REDD+ project. Alternatively, GMSE could be used more generally to investigate the dynamics of a social-ecological system when a PES scheme is applied. There is still debate surrounding the efficacy of PES schemes (Ingram et al., 2014; Salzman et al., 2018), and so simulation modelling could provide an opportunity to explore and test underlying theories.

6.6 Concluding remarks

Cambodia has a traumatic recent past; one that still exists in living memory. I had the privilege to live and work in Cambodia for four years, and I have seen the scars that have been left on the landscape, the people, and the nation as a whole. The civil war has had a significant and lasting effect on the politics and society of the country, with many of the issues surrounding governance and policy deeply interwoven with the conflict and its aftermath (de Zeeuw, 2010). Cambodia still has extensive forest cover and diverse wildlife, but these are under ever increasing pressure from humans. The results from my thesis support what I have experienced as a conservation practitioner and wildlife biologist working in the country; the broadest drivers of environmental degradation are poor governance, ineffective policies and policy implementation, and chronic underfunding for the environment sector.

Chapter 2 confirmed that economic recovery and agricultural expansion have been prioritised over sustainable natural resource management, and Chapter 3 confirmed that rural areas have seen relatively few socioeconomic benefits from that recovery. I have demonstrated that commercial agriculture has been a major beneficiary of government economic policy, and other studies have demonstrated that local people have often seen land conflict and forest loss from ELCs, rather than the economic development the Land Law states they should bring.

Chapter 4 confirmed that wildlife, even in one of the best funded PAs in the country, is under extreme pressure from human activities. Chapter 5 provided evidence, albeit theoretical, that the conventional grant-based funding mechanism for conservation – which is the dominant mechanism in Cambodia – is not likely to support the most effective conservation management of landscapes and PAs over the long-term. Although not unique to Cambodia, this approach to funding conservation activities is largely due to insufficient government resourcing of the PA network.

The main insights from this thesis, described above, can be attributed to policy that is poorly designed or poorly implemented, weak and ineffective governance, or indeed both. The insights from Chapter 5 could offer at least one solution to reverse the general decline of Cambodia's forests and wildlife: long-term sustainable funding for conservation landscapes. To reduce deforestation rates and ensure wildlife populations do not face local extinction, Cambodia's leaders will need to prioritise the development of both economic and environmental policies that safeguard what remains of the country's natural environment. Critically, they will need to provide the resources and governance structures to ensure they are implemented effectively.

Literature cited

Abdullah, S.A., Nakagoshi, N., 2007. Forest fragmentation and its correlation to human land use change in the state of Selangor, peninsular Malaysia. Forest Ecology and Management 241, 39–48. https://doi.org/10.1016/j.foreco.2006.12.016

Adams, D., Adams, K., Ullah, S., Ullah, F., 2019. Globalisation, governance, accountability and the natural resource 'curse': Implications for socio-economic growth of oil-rich developing countries. Resources Policy 61, 128–140. https://doi.org/10.1016/j.resourpol.2019.02.009

Ahrestani, F.S., Karanth, K.U., 2014. Gaur Bos gaurus (C.H. Smith, 1827), in: Ecology, Evolution and Behvaiour of Wild Cattle, Wildlife Ecology and Conservation. Cambridge University Press, Cambridge, UK, pp. 174–193.

Alston, J.M., Pardey, P.G., 2014. Agriculture in the Global Economy. Journal of Economic Perspectives 28, 121–146. https://doi.org/10.1257/jep.28.1.121

Alves, R.R.N., Souto, W.M.S., Barboza, R.R.D., 2010. Primates in traditional folk medicine: a world overview. Mammal Review 40, 155–180. https://doi.org/10.1111/j.1365-2907.2010.00158.x

Amnesty International, 2021. Cambodia: Widespread illegal logging in Prey Lang rainforest amid ban on community patrols [WWW Document]. Amnesty International. URL https://www.amnesty.org/en/latest/news/2021/02/cambodia-widespread-illegal-logging-in-prey-lang-rainforest-amid-ban-on-community-patrols/ (accessed 12.10.21).

Andrade, G.S.M., Rhodes, J.R., 2012. Protected Areas and Local Communities: an Inevitable Partnership toward Successful Conservation Strategies? Ecology and Society 17. https://doi.org/10.5751/ES-05216-170414

Ariefiandy, A., Forsyth, D.M., Purwandana, D., Imansyah, J., Ciofi, C., Rudiharto, H., Seno, A., Jessop, T.S., 2016. Temporal and spatial dynamics of insular Rusa deer and wild pig populations in Komodo National Park. J Mammal 97, 1652–1662. https://doi.org/10.1093/jmammal/gyw131

Armitage, D., Mbatha, P., Muhl, E.-K., Rice, W., Sowman, M., 2020. Governance principles for community-centered conservation in the post-2020 global biodiversity framework. Conservation Science and Practice 2, e160. https://doi.org/10.1111/csp2.160

Armsworth, P.R., Jackson, H.B., Cho, S.-H., Clark, M., Fargione, J.E., Iacona, G.D., Kim, T., Larson, E.R., Minney, T., Sutton, N.A., 2018. Is conservation right to go big? Protected area size and conservation return-on-investment. Biological Conservation 225, 229–236. https://doi.org/10.1016/j.biocon.2018.07.005

Ayebare, S., Plumptre, A.J., Kujirakwinja, D., Segan, D., 2018. Conservation of the endemic species of the Albertine Rift under future climate change. Biological Conservation 220, 67–75. https://doi.org/10.1016/j.biocon.2018.02.001

Backstrom, A.C., Garrard, G.E., Hobbs, R.J., Bekessy, S.A., 2018. Grappling with the social dimensions of novel ecosystems. Frontiers in Ecology and the Environment 16, 109–117. https://doi.org/10.1002/fee.1769

Baghai, M., Miller, J.R.B., Blanken, L.J., Dublin, H.T., Fitzgerald, K.H., Gandiwa, P., Laurenson, K., Milanzi, J., Nelson, A., Lindsey, P., 2018. Models for the collaborative management of Africa's protected areas. Biological Conservation 218, 73–82. https://doi.org/10.1016/j.biocon.2017.11.025

Bal, P., Tulloch, A.I., Addison, P.F., McDonald-Madden, E., Rhodes, J.R., 2018. Selecting indicator species for biodiversity management. Frontiers in Ecology and the Environment 16, 589–598. https://doi.org/10.1002/fee.1972

Baltzer, M., Dao, N.T., Shore, R.G., 2001. Towards a vision for biodiversity conservation in the forests of the lower Mekong ecoregion complex. IUCN.

Bang, A., Khadakkar, S., 2020. Opinion: Biodiversity conservation during a global crisis: Consequences and the way forward. PNAS 117, 29995–29999. https://doi.org/10.1073/pnas.2021460117

Barfuss, W., Donges, J.F., Wiedermann, M., Lucht, W., 2017. Sustainable use of renewable resources in a stylized social–ecological network model under heterogeneous resource distribution. Earth System Dynamics; Gottingen 8, 255–264. http://dx.doi.org/10.5194/esd-8-255-2017

Barnes, M.D., Glew, L., Wyborn, C., Craigie, I.D., 2018. Prevent perverse outcomes from global protected area policy. Nature Ecology & Evolution 1. https://doi.org/10.1038/s41559-018-0501-y

Barrett, C.B., Gibson, C.C., Hoffman, B., McCUBBINS, M.D., 2006. The Complex Links between Governance and Biodiversity. Conservation Biology 20, 1358–1366. https://doi.org/10.1111/j.1523-1739.2006.00521.x

Bartoń, K., 2020. MuMIn: Multi-Model Inference.

Basse, R.M., Omrani, H., Charif, O., Gerber, P., Bódis, K., 2014. Land use changes modelling using advanced methods: Cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale. Applied Geography 53, 160–171. https://doi.org/10.1016/j.apgeog.2014.06.016

Beauchamp, E., Clements, T., Milner-Gulland, E.J., 2018. Exploring trade-offs between development and conservation outcomes in Northern Cambodia. Land Use Policy 71, 431–444. https://doi.org/10.1016/j.landusepol.2017.11.021

Behrens, A., Giljum, S., Kovanda, J., Niza, S., 2007. The material basis of the global economy: Worldwide patterns of natural resource extraction and their implications for sustainable resource use policies. Ecological Economics, Special Section - Ecosystem Services and Agriculture 64, 444–453. https://doi.org/10.1016/j.ecolecon.2007.02.034

Belecky, M., Gray, T.N.E., 2020. Silence of the snares - Southeast Asia's snaring crisis. World Wide Fund for Nature, Gland, Switzerland.

Bergin, S., 2009. The Khmer Rouge and the Cambodian Genocide. The Rosen Publishing Group.

Berkes, F., Folke, C., Colding, J., 2000. Linking social and ecological systems: management practices and social mechanisms for building resilience. Cambridge University Press.

Bernhard, K.P., Smith, T.E.L., Sabuhoro, E., Nyandwi, E., Munanura, I.E., 2021. Effects of integrated conservation–development projects on unauthorized resource use in Volcanoes National Park, Rwanda: a mixed-methods spatio-temporal approach. Oryx 55, 613–624. https://doi.org/10.1017/S0030605319000735

Bessone, M., Kühl, H.S., Hohmann, G., Herbinger, I., N'Goran, K.P., Asanzi, P., Da Costa, P.B., Dérozier, V., Fotsing, E.D.B., Beka, B.I., Iyomi, M.D., Iyatshi, I.B., Kafando, P., Kambere, M.A., Moundzoho, D.B., Wanzalire, M.L.K., Fruth, B., 2020. Drawn out of the shadows: Surveying secretive forest species with camera trap distance sampling. Journal of Applied Ecology 57, 963–974. https://doi.org/10.1111/1365-2664.13602

Betsill, M.M., Enrici, A., Le Cornu, E., Gruby, R.L., 2021. Philanthropic foundations as agents of environmental governance:a research agenda. Environmental Politics 0, 1–22. https://doi.org/10.1080/09644016.2021.1955494

Bhattacharya, P., Pradhan, L., Yadav, G., 2010. Joint forest management in India: Experiences of two decades. Resources, Conservation and Recycling 54, 469–480. https://doi.org/10.1016/j.resconrec.2009.10.003

Bhattarai, M., Hammig, M., 2004. Governance, economic policy, and the environmental Kuznets curve for natural tropical forests. Environment and Development Economics 9, 367–382. https://doi.org/10.1017/S1355770X03001293

Blom, B., Sunderland, T., Murdiyarso, D., 2010. Getting REDD to work locally: lessons learned from integrated conservation and development projects. Environmental Science & Policy 13, 164–172. https://doi.org/10.1016/j.envsci.2010.01.002

Bodin, Ö., Robins, G., McAllister, R., Guerrero, A., Crona, B., Tengö, M., Lubell, M., 2016. Theorizing benefits and constraints in collaborative environmental governance: a transdisciplinary social-ecological network approach for empirical investigations. Ecology and Society 21. https://doi.org/10.5751/ES-08368-210140

Boillat, S., Gerber, J.-D., Oberlack, C., Zaehringer, J.G., Ifejika Speranza, C., Rist, S., 2018. Distant Interactions, Power, and Environmental Justice in Protected Area Governance: A Telecoupling Perspective. Sustainability 10, 3954. https://doi.org/10.3390/su10113954

Bonilla-Bedoya, S., Estrella-Bastidas, A., Molina, J.R., Herrera, M.Á., 2018. Socioecological system and potential deforestation in Western Amazon forest landscapes. Science of The Total Environment 644, 1044–1055. https://doi.org/10.1016/j.scitotenv.2018.07.028

Borcard, D., Gillet, F., Legendre, P., 2018. Cluster Analysis, in: Borcard, D., Gillet, F., Legendre, P. (Eds.), Numerical Ecology with R, Use R! Springer International Publishing, Cham, pp. 59–150. https://doi.org/10.1007/978-3-319-71404-2_4

Borges, S., Souza, F., Moreira, M., Camargo, Y., 2019. Alterar limites e categorias de áreas protegidas é necessariamente ruim? Um estudo de caso em duas unidades de conservação estaduais da Amazônia brasileira. Novos Cadernos NAEA 22. https://doi.org/10.5801/ncn.v22i2.3954

Borras, S.M., Franco, J.C., 2011. Political Dynamics of Land-grabbing in Southeast Asia: 56.

Brickell, K., Springer, S. (Eds.), 2016. The Handbook of Contemporary Cambodia. Routledge, London. https://doi.org/10.4324/9781315736709

Brickle, N.W., 2002. Habitat use, predicted distribution and conservation of green peafowl (Pavo muticus) in Dak Lak Province, Vietnam. Biological conservation 105, 189–197.

Brockington, D., Scholfield, K., 2010. Expenditure by conservation nongovernmental organizations in sub-Saharan Africa. Conservation Letters 3, 106–113. https://doi.org/10.1111/j.1755-263X.2010.00094.x

Broegaard, R.B., Rasmussen, L.V., Dawson, N., Mertz, O., Vongvisouk, T., Grogan, K., 2017. Wild food collection and nutrition under commercial agriculture expansion in agriculture-forest landscapes. Forest Policy and Economics, Forest, Food, and Livelihoods 84, 92–101. https://doi.org/10.1016/j.forpol.2016.12.012

Brook, B.W., Sodhi, N.S., Bradshaw, C.J.A., 2008. Synergies among extinction drivers under global change. Trends in Ecology & Evolution 23, 453–460. https://doi.org/10.1016/j.tree.2008.03.011

Brooks, M.E., Kristensen, K., Benthem, K.J. van, Magnusson, A., Berg, C.W., Nielsen, A., Skaug, H.J., Mächler, M., Bolker, B.M., 2017. glmmTMB Balances Speed and Flexibility Among Packages for Zero-inflated Generalized Linear Mixed Modeling. The R Journal 9, 378–400.

Bruner, A.G., Gullison, R.E., Balmford, A., 2004. Financial Costs and Shortfalls of Managing and Expanding Protected-Area Systems in Developing Countries. BioScience 54, 1119–1126. https://doi.org/10.1641/0006-3568(2004)054[1119:FCASOM]2.0.CO;2

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L., Thomas, L., 2004. Advanced Distance Sampling: Estimating abundance of biological populations. Oxford University Press, New York, NY.

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L., Thomas, L., 2001. Introduction to Distance Sampling: Estimating abundance of biological populations. Oxford University Press, New York, NY.

Buckland, S.T., Rextad, E.A., Marques, T.A., Oedekoven, C.S., 2015. Distance sampling: methods and applications. Springer Science+Business Media, New York, NY.

Buckley, K.J., Newton, P., Gibbs, H.K., McConnel, I., Ehrmann, J., 2019. Pursuing sustainability through multi-stakeholder collaboration: A description of the governance, actions, and perceived impacts of the roundtables for sustainable beef. World Development 121, 203–217. https://doi.org/10.1016/j.worlddev.2018.07.019

Bunnefeld, N., Hoshino, E., Milner-Gulland, E.J., 2011. Management strategy evaluation: a powerful tool for conservation? Trends in Ecology & Evolution 26, 441–447. https://doi.org/10.1016/j.tree.2011.05.003

Burnham, K.P., Anderson, D.R., 2007. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach. Springer Science & Business Media.

Campbell, G.S., Thomas, L., Whitaker, K., Douglas, A.B., Calambokidis, J., Hildebrand, J.A., 2015. Inter-annual and seasonal trends in cetacean distribution, density and abundance off southern California. Deep Sea Research Part II: Topical Studies in Oceanography, CCE-LTER: Responses of the California Current Ecosystem to Climate Forcing 112, 143–157. https://doi.org/10.1016/j.dsr2.2014.10.008

Cappelle, N., Howe, E.J., Boesch, C., Kühl, H.S., 2021. Estimating animal abundance and effort–precision relationship with camera trap distance sampling. Ecosphere 12, e03299. https://doi.org/10.1002/ecs2.3299

Caravaggio, N., 2020a. Economic growth and the forest development path: A theoretical re-assessment of the environmental Kuznets curve for deforestation. Forest Policy and Economics 118, 102259. https://doi.org/10.1016/j.forpol.2020.102259

Caravaggio, N., 2020b. A global empirical re-assessment of the Environmental Kuznets curve for deforestation. Forest Policy and Economics 119, 102282. https://doi.org/10.1016/j.forpol.2020.102282

Ceballos, G., Ehrlich, P.R., Raven, P.H., 2020. Vertebrates on the brink as indicators of biological annihilation and the sixth mass extinction. PNAS 117, 13596–13602. https://doi.org/10.1073/pnas.1922686117

Ceccherini, G., Duveiller, G., Grassi, G., Lemoine, G., Avitabile, V., Pilli, R., Cescatti, A., 2020. Abrupt increase in harvested forest area over Europe after 2015. Nature 583, 72–77. https://doi.org/10.1038/s41586-020-2438-y

Ceddia, M.G., 2019. The impact of income, land, and wealth inequality on agricultural expansion in Latin America. PNAS 116, 2527–2532. https://doi.org/10.1073/pnas.1814894116

Ceddia, M.G., Gunter, U., Corriveau-Bourque, A., 2015. Land tenure and agricultural expansion in Latin America: The role of Indigenous Peoples' and local communities' forest rights. Global Environmental Change 35, 316–322. https://doi.org/10.1016/j.gloenvcha.2015.09.010

CEPF, 2020. Ecosystem profile: Indo-Burma Biodiversity Hotspot, 2020 update. Critical Ecosystem Partnership Fund.

Chambers, J., Aguila Mejía, M.D., Ramírez Reátegui, R., Sandbrook, C., 2020. Why joint conservation and development projects often fail: An in-depth examination in the Peruvian Amazon. Environment and Planning E: Nature and Space 3, 365–398. https://doi.org/10.1177/2514848619873910

Chandler, D., 2008. A History of Cambodia. Routledge.

Chapman, P.M., Tobias, J.A., Edwards, D.P., Davies, R.G., 2018. Contrasting impacts of land-use change on phylogenetic and functional diversity of tropical forest birds. Journal of Applied Ecology 55, 1604–1614. https://doi.org/10.1111/1365-2664.13073

Chassagne, F., Hul, S., Deharo, E., Bourdy, G., 2016. Natural remedies used by Bunong people in Mondulkiri province (Northeast Cambodia) with special reference to the treatment of 11 most common ailments. Journal of Ethnopharmacology 191, 41–70. https://doi.org/10.1016/j.jep.2016.06.003

Chetry, D., Medhi, R., Biswas, J., Das, D., Bhattacharjee, P.C., 2003. Nonhuman Primates in the Namdapha National Park, Arunachal Pradesh, India. International Journal of Primatology 24, 383–388. https://doi.org/10.1023/A:1023057401967

Chhair, S., Ung, L., 2013. Economic history of industrialization in Cambodia (Working Paper No. No.7), WIDER. World Institue for Development Economics Research.

Chhun, S., Kumar, V., Martin, R.J., Srean, P., Hadi, B.A.R., 2020. Weed management practices of smallholder rice farmers in Northwest Cambodia. Crop Protection 135, 104793. https://doi.org/10.1016/j.cropro.2019.04.017

Choudhury, A., 2002. Distribution and conservation of the Gaur Bos gaurus in the Indian Subcontinent. Mammal Review 32, 199–226. https://doi.org/10.1046/j.1365-2907.2002.00107.x

Clark, R., Reed, J., Sunderland, T., 2018. Bridging funding gaps for climate and sustainable development: Pitfalls, progress and potential of private finance. Land Use Policy 71, 335–346. https://doi.org/10.1016/j.landusepol.2017.12.013

Clark, W.A., 2011. Clarifying the spiritual value of forests and their role in sustainable forest management. Journal for the Study of Religion, Nature & Culture 5, 18–38.

Clement, F., Orange, D., Williams, M., Mulley, C., Epprecht, M., 2009. Drivers of afforestation in Northern Vietnam: Assessing local variations using geographically weighted regression. Applied Geography 29, 561–576. https://doi.org/10.1016/j.apgeog.2009.01.003

Clements, T., Milner-Gulland, E.J., 2015. Impact of payments for environmental services and protected areas on local livelihoods and forest conservation in northern Cambodia. Conservation Biology 29, 78–87. https://doi.org/10.1111/cobi.12423

CNIS, 2019. General Population Census of the Kingdom of Cambodia 2019 (National Census). National Institute of Statistics, Ministry of Planning, Phnom Penh, Cambodia.

Coad, L., Lim, S., Nuon, L., 2019a. Wildlife and Livelihoods in the Cardamom Mountains, Cambodia. Front. Ecol. Evol. 7. https://doi.org/10.3389/fevo.2019.00296

Coad, L., Schleicher, J., Milner-Gulland, E.J., Marthews, T.R., Starkey, M., Manica, A., Balmford, A., Mbombe, W., Bineni, T.R.D., Abernethy, K.A., 2013. Social and Ecological Change over a Decade in a Village Hunting System, Central Gabon. Conservation Biology 27, 270–280. https://doi.org/10.1111/cobi.12012

Coad, L., Watson, J.E., Geldmann, J., Burgess, N.D., Leverington, F., Hockings, M., Knights, K., Marco, M.D., 2019b. Widespread shortfalls in protected area resourcing undermine efforts to conserve biodiversity. Frontiers in Ecology and the Environment 17, 259–264. https://doi.org/10.1002/fee.2042

Conca, K., 2001. Consumption and Environment in a Global Economy. Global Environmental Politics 1, 53–71. https://doi.org/10.1162/152638001316881403

Conservation International, World Wildlife Fund, 2021. PADDDtracker.org Data Release Version 2.1 (May 2021). Arlington, Virginia: Conservation International, Washington, DC: World Wildlife Fund.

Corlett, R.T., Primack, R.B., Devictor, V., Maas, B., Goswami, V.R., Bates, A.E., Koh, L.P., Regan, T.J., Loyola, R., Pakeman, R.J., Cumming, G.S., Pidgeon, A., Johns, D., Roth, R., 2020. Impacts of the coronavirus pandemic on biodiversity conservation. Biological Conservation 246, 108571. https://doi.org/10.1016/j.biocon.2020.108571

Coudrat, C., Nekaris, K.A.-I., 2013. Modelling Niche Differentiation of Co-Existing, Elusive and Morphologically Similar Species: A Case Study of Four Macaque Species in Nakai-Nam Theun National Protected Area, Laos. Animals 3, 45–62. https://doi.org/10.3390/ani3010045

Crawley, M.J., 2007. The R Book. Wiley, Chichester, UK.

Cropper, M., Griffiths, C., 1994. The Interaction of Population Growth and Environmental Quality. The American Economic Review 84, 250–254.

Culas, R.J., 2012. REDD and forest transition: Tunneling through the environmental Kuznets curve. Ecological Economics 79, 44–51. https://doi.org/10.1016/j.ecolecon.2012.04.015

Culas, R.J., 2007. Deforestation and the environmental Kuznets curve: An institutional perspective. Ecological Economics 61, 429–437. https://doi.org/10.1016/j.ecolecon.2006.03.014

Curtis, P.G., Slay, C.M., Harris, N.L., Tyukavina, A., Hansen, M.C., 2018. Classifying drivers of global forest loss. Science 361, 1108–1111. https://doi.org/10.1126/science.aau3445

Cusack, J., Duthie, A., Minderman, J., Jones, I., Pozo, R., Rakotonarivo, O., Redpath, S., Bunnefeld, N., 2020. Integrating conflict, lobbying, and compliance to predict the sustainability of natural resource use. Ecology and Society 25. https://doi.org/10.5751/ES-11552-250213
Dasgupta, S., Deichmann, U., Meisner, C., Wheeler, D., 2005. Where is the Poverty–Environment Nexus? Evidence from Cambodia, Lao PDR, and Vietnam. World Development 33, 617–638. https://doi.org/10.1016/j.worlddev.2004.10.003
Davis, K.F., Yu, K., Rulli, M.C., Pichdara, L., D'Odorico, P., 2015. Accelerated deforestation driven by large-scale land acquisitions in Cambodia. Nature Geoscience 8, 772–775. https://doi.org/10.1038/ngeo2540
Dawson, N., Martin, A., Danielsen, F., 2018. Assessing Equity in Protected Area Governance: Approaches to Promote Just and Effective Conservation. Conservation Letters 11, e12388. https://doi.org/10.1111/conl.12388
Dawson, T.P., Rounsevell, M.D.A., Kluv\'ankov\'a-Oravsk\'a Tatiana, Chobotov\'a Veronika, Stirling, A., 2010. Dynamic properties of complex adaptive ecosystems: implications for the sustainability of service provision. Biodivers.Conserv. 19, 2843–2853. https://doi.org/10.1007/s10531-010-9892-z"
de Groot, R.S., Wilson, M.A., Boumans, R.M.J., 2002. A typology for the classification, description and valuation of ecosystem functions, goods and services. Ecological Economics 41, 393–408. https://doi.org/10.1016/S0921-8009(02)00089-7
de Koning, M., Nguyen, T., Lockwood, M., Sengchanthavong, S., Phommasane, S., 2017. Collaborative Governance of Protected Areas: Success Factors and Prospects for Hin Nam No National Protected Area, Central Laos. Conservation and Society 15, 87–99.
De Schutter, O., 2011. How not to think of land-grabbing: three critiques of large-scale investments in farmland. The Journal of Peasant Studies 38, 249–279. https://doi.org/10.1080/03066150.2011.559008
de Souza, R.A., De Marco, P., 2014. The use of species distribution models to predict the spatial distribution of deforestation in the western Brazilian Amazon. Ecological Modelling 291, 250–259. https://doi.org/10.1016/j.ecolmodel.2014.07.007
de Zeeuw, J., 2010. 'Sons of war': parties and party systems in post-war El Salvador and Cambodia. Democratization 17, 1176–1201. https://doi.org/10.1080/13510347.2010.520549
DeCesare, N.J., Newby, J.R., Boccadori, V.J., Chilton-Radandt, T., Thier, T., Waltee, D., Podruzny, K., Gude, J.A., 2016. Calibrating minimum counts and catch-per-unit-effort as indices of moose population trend. Wildlife Society Bulletin 40, 537–547. https://doi.org/10.1002/wsb.678
Deininger, K., Byerlee, D., 2011. Rising Global Interest in Farmland: Can It Yield Sustainable and Equitable Benefits? World Bank Publications.
Di Marco, M., Venter, O., Possingham, H.P., Watson, J.E.M., 2018. Changes in human footprint drive changes in species extinction risk. Nat Commun 9, 4621. https://doi.org/10.1038/s41467-018-07049-5
Dixon, K.M., Cary, G.J., Worboys, G.L., Banks, S.C., Gibbons, P., 2019. Features associated with effective biodiversity monitoring and evaluation. Biological Conservation 238, 108221. https://doi.org/10.1016/j.biocon.2019.108221
Djoudi, H., Vergles, E., Blackie, R.R., Koame, C.K., Gautier, D., 2015. Dry forests, livelihoods and poverty alleviation: understanding current trends. International Forestry Review 17, 54–69. https://doi.org/10.1505/146554815815834868
Doak, D.F., Mills, L.S., 1994. A Useful Role for Theory in Conservation. Ecology 75, 615–626. https://doi.org/10.2307/1941720
Dressler, W.H., Wilson, D., Clendenning, J., Cramb, R., Keenan, R., Mahanty, S., Bruun, T.B., Mertz, O., Lasco, R.D., 2017. The impact of swidden decline on livelihoods and ecosystem services in Southeast Asia: A review of the evidence from 1990 to 2015. Ambio 46, 291–310. https://doi.org/10.1007/s13280-016-0836-z

Drummond, F.M., Armstrong, D.P., 2019. Use of distance sampling to measure long-term changes in bird densities in a fenced wildlife sanctuary. New Zealand Journal of Ecology 43.
Duc, M.H., Bang, T.V., Covert, H.H., Truong, L.H., Toan, T.Q., 2008. Conservation status of primates in Ta Kou Nature Reserve, in: Distribution and Status. Presented at the Conservation of Primates in Indochina, Cuc Phuong National Park, Vietnam.
Duckworth, J.W., Hedges, S., 1998. Tracking tigers: a review of the status of tiger, Asian elephant, gaur, and banteng in Vietnam, Lao, Cambodia and Yunnan Province (China), with recommendations for future conservation action. WWF Indochina Programme, Hanoi, Vietnam.
Duthie, A.B., Cusack, J.J., Jones, I.L., Minderman, J., Nilsen, E.B., Pozo, R.A., Rakotonarivo, O.S., Moorter, B.V., Bunnefeld, N., 2018a. GMSE: An r package for generalised management strategy evaluation. Methods in Ecology and Evolution 9, 2396–2401. https://doi.org/10.1111/2041-210X.13091
Duthie, A.B., Cusack, J.J., Jones, I.L., Minderman, J., Nilsen, E.B., Pozo, R.A., Rakotonarivo, O.S., Van Moorter, B., Bunnefeld, N., 2018b. Supporting Information 1 from Duthie et al. 2018. The genetic algorithm of GMSE. Methods in Ecology and Evolution 9.
Ear, S., 2011. Growth in the rice and garment sectors, in: Cambodia's Economic Transformation, NIAS Studies in Asian TopicsNordic Institute of Asian Studies. Nordic Institute of Asian Studies, Leifsgade 33, DK-2300 Copenhagen S, Denmark.
Ear, S., 2007. The Political Economy of Aid and Governance in Cambodia. Asian Journal of Political Science 15, 68–96. https://doi.org/10.1080/02185370701315624
Echols, A., Front, A., Cummins, J., 2019. Broadening conservation funding. Wildlife Society Bulletin 43, 372–381. https://doi.org/10.1002/wsb.1003
Edwards, P.J., 1998. Conservation in Cambodia. Oriental Bird Club Bulletin. URL https://www.orientalbirdclub.org/cambodia (accessed 12.6.21).
Efford, M.G., Fewster, R.M., 2013. Estimating population size by spatially explicit capture-recapture. Oikos 122, 918–928. https://doi.org/10.1111/j.1600-0706.2012.20440.x
EIA, 2012. Rosewood robbery: The case for Thailand to list Rosewood on CITES. Environmental Investigations Agency, London, UK.
Einoder, L.D., Southwell, D., Gillespie, G.R., Fisher, A., Lahoz-Monfort, J.J., Wintle, B.A., 2018. Optimising broad-scale monitoring for trend detection: review and re-design of a long-term program in northern Australia, in: Monitoring Threatened Species and Ecological Communities. Csiro Publishing, Victoria, Australia.
Eliste, P., Zorya, S., 2015. Cambodian agriculture in transition: Opportunities and risks. World Bank Group, Washington DC, USA.
Emerton, L., Bishop, J., Thomas, L., 2006. Sustainable financing of protected areas - A global review of challenges and options, Best Practice Protected Area Guidlines. IUCN, Gland, Switzerland.
Erbaugh, J., Bierbaum, R., Castilleja, G., da Fonseca, G.A.B., Hansen, S.C.B., 2019. Toward sustainable agriculture in the tropics. World Development 121, 158–162. https://doi.org/10.1016/j.worlddev.2019.05.002
Ervin, J., 2003. Rapid Assessment of Protected Area Management Effectiveness in Four Countries. BioScience 53, 833–841. https://doi.org/10.1641/0006-3568(2003)053[0833:RAOPAM]2.0.CO;2
Estoque, R.C., Ooba, M., Avitabile, V., Hijioka, Y., DasGupta, R., Togawa, T., Murayama, Y., 2019. The future of Southeast Asia's forests. Nature Communications 10, 1829. https://doi.org/10.1038/s41467-019-09646-4
Eudey, A.A., 2008. The Crab-Eating Macaque (Macaca fascicularis): Widespread and Rapidly Declining. prco 23, 129–132. https://doi.org/10.1896/052.023.0115
Evans, K.L., Ewen, J.G., Guillera-Arroita, G., Johnson, J.A., Penteriani, V., Ryan, S.J., Sollmann, R., Gordon, I.J., 2020. Conservation in the maelstrom of Covid-19 – a call to action to solve the

challenges, exploit opportunities and prepare for the next pandemic. Animal Conservation 23, 235–238. https://doi.org/10.1111/acv.12601

Evans, T., O'Kelly, H., Men, S., Nut, M., Pet, P., Pheakdey, P., Pollard, E., 2013. Seima Protection Forest, in: Evidence-Based Conservation: Lessons from the Lower Mekong. Routledge, London, UK, pp. 157–185.

Everett, T., Ishwaran, M., Ansaloni, G.P., Rubin, A., 2010. Economic growth and the environment (MPRA paper), DEFRA Evidence and Analysis Series.

Ewers, R.M., 2006. Interaction effects between economic development and forest cover determine deforestation rates. Global Environmental Change 16, 161–169. https://doi.org/10.1016/j.gloenvcha.2005.12.001

Faguet, J.-P., 2014. Decentralization and Governance. World Development, Decentralization and Governance 53, 2–13. https://doi.org/10.1016/j.worlddev.2013.01.002

Fan, Q., Ding, S., 2016. Landscape pattern changes at a county scale: A case study in Fengqiu, Henan Province, China from 1990 to 2013. CATENA 137, 152–160. https://doi.org/10.1016/j.catena.2015.09.012

FAO, 2021. Food and Agricultural Organisation of the United Nations [WWW Document]. FAOSTAT. URL https://www.fao.org/faostat/en/#data/QCL (accessed 11.25.21).

FAO, 2020. Global Forest Resources Assessment 2020: Main report. FAO, Rome, Italy. https://doi.org/10.4060/ca9825en

Fernandes, G.W., Vale, M.M., Overbeck, G.E., Bustamante, M.M.C., Grelle, C.E.V., Bergallo, H.G., Magnusson, W.E., Akama, A., Alves, S.S., Amorim, A., Araújo, J., Barros, C.F., Bravo, F., Carim, M.J.V., Cerqueira, R., Collevatti, R.G., Colli, G.R., da Cunha, C.N., D'Andrea, P.S., Dianese, J.C., Diniz, S., Estrela, P.C., Fernandes, M.R.M., Fontana, C.S., Giacomin, L.L., Gusmão, L.F.P., Juncá, F.A., Lins-e-Silva, A.C.B., Lopes, C.R.A.S., Lorini, M.L., de Queiroz, L.P., Malabarba, L.R., Marimon, B.S., Junior, B.H.M., Marques, M.C.M., Martinelli, B.M., Martins, M.B., de Medeiros, H.F., Menin, M., de Morais, P.B., Muniz, F.H., Neckel-Oliveira, S., de Oliveira, J.A., Oliveira, R.P., Pedroni, F., Penha, J., Podgaiski, L.R., Rodrigues, D.J., Scariot, A., Silveira, L.F., Silveira, M., Tomas, W.M., Vital, M.J.S., Pillar, V.D., 2017. Dismantling Brazil's science threatens global biodiversity heritage. Perspectives in Ecology and Conservation 15, 239–243. https://doi.org/10.1016/j.pecon.2017.07.004

Ferrari, S., Cribari-Neto, F., 2004. Beta Regression for Modelling Rates and Proportions. Journal of Applied Statistics 31, 799–815. https://doi.org/10.1080/0266476042000214501

Ferreguetti, Á.C., Pereira-Ribeiro, J., Prevedello, J.A., Tomás, W.M., Rocha, C.F.D., Bergallo, H.G., 2018. One step ahead to predict potential poaching hotspots: Modeling occupancy and detectability of poachers in a neotropical rainforest. Biological Conservation 227, 133–140. https://doi.org/10.1016/j.biocon.2018.09.009

Fewster, R.M., 2011. Variance Estimation for Systematic Designs in Spatial Surveys. Biometrics 67, 1518–1531. https://doi.org/10.1111/j.1541-0420.2011.01604.x

Fewster, R.M., Buckland, S.T., Burnham, K.P., Borchers, D.L., Jupp, P.E., Laake, J.L., Thomas, L., 2009. Estimating the Encounter Rate Variance in Distance Sampling. Biometrics 65, 225–236. https://doi.org/10.1111/j.1541-0420.2008.01018.x

Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A., 2013. Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environmental Modelling & Software, Thematic Issue on Spatial Agent-Based Models for Socio-Ecological Systems 45, 1–7. https://doi.org/10.1016/j.envsoft.2013.03.017

Fiore, R.R., 2013. A survey of Indochinese langurs (Trachypithecus germaini) in Phu Quoc National Park, Vietnam. University of Colorado Boulder, Boulder, Colorado, USA.

Fishburn, I.S., Boyer, A.G., Kareiva, P., Gaston, K.J., Armsworth, P.R., 2013. Changing spatial patterns of conservation investment by a major land trust. Biological Conservation 161, 223–229. https://doi.org/10.1016/j.biocon.2013.02.007

Fisher, J., 2012. No pay, no care? A case study exploring motivations for participation in payments for ecosystem services in Uganda. Oryx 46, 45–54. https://doi.org/10.1017/S0030605311001384
Folke, C., Hahn, T., Olsson, P., Norberg, J., 2005. ADAPTIVE GOVERNANCE OF SOCIAL-ECOLOGICAL SYSTEMS. Annual Review of Environment and Resources 30, 441–473. https://doi.org/10.1146/annurev.energy.30.050504.144511
Fox, J., Castella, J.-C., 2013. Expansion of rubber (Hevea brasiliensis) in Mainland Southeast Asia: what are the prospects for smallholders? The Journal of Peasant Studies 40, 155–170. https://doi.org/10.1080/03066150.2012.750605
Fox, J., Vogler, J.B., 2005. Land-Use and Land-Cover Change in Montane Mainland Southeast Asia. Environmental Management 36, 394–403. https://doi.org/10.1007/s00267-003-0288-7
Freeling, B.S., Connell, S.D., 2020. Funding Conservation through an Emerging Social Movement. Trends in Ecology & Evolution 35, 3–6. https://doi.org/10.1016/j.tree.2019.09.002
Frewer, T., Chan, S., 2014. GIS and the 'Usual Suspects'-[Mis]understanding Land Use Change in Cambodia. Hum Ecol 42, 267–281. https://doi.org/10.1007/s10745-013-9639-z
Fukushima, C.S., Mammola, S., Cardoso, P., 2020. Global wildlife trade permeates the Tree of Life. Biological Conservation 247, 108503. https://doi.org/10.1016/j.biocon.2020.108503
Fuller, R.A., McDonald-Madden, E., Wilson, K.A., Carwardine, J., Grantham, H.S., Watson, J.E.M., Klein, C.J., Green, D.C., Possingham, H.P., 2010. Replacing underperforming protected areas achieves better conservation outcomes. Nature 466, 365–367. https://doi.org/10.1038/nature09180
Fuller, R.J., Williamson, T., Barnes, G., Dolman, P.M., 2017. Human activities and biodiversity opportunities in pre-industrial cultural landscapes: relevance to conservation. Journal of Applied Ecology 54, 459–469. https://doi.org/10.1111/1365-2664.12762
Galvin, K.A., Thornton, P.K., Pinho, J.R. de, Sunderland, J., Boone, R.B., 2006. Integrated Modeling and its Potential for Resolving Conflicts between Conservation and People in the Rangelands of East Africa. Hum Ecol 34, 155–183. https://doi.org/10.1007/s10745-006-9012-6
Gatto, M., Wollni, M., Qaim, M., 2015. Oil palm boom and land-use dynamics in Indonesia: The role of policies and socioeconomic factors. Land Use Policy 46, 292–303. https://doi.org/10.1016/j.landusepol.2015.03.001
Gaughan, A.E., Binford, M.W., Southworth, J., 2009. Tourism, forest conversion, and land transformations in the Angkor basin, Cambodia. Applied Geography 29, 212–223. https://doi.org/10.1016/j.apgeog.2008.09.007
Geist, H., Lambin, E., 2003. Is poverty the cause of tropical deforestation? The International Forestry Review 5, 64–67.
Geist, H.J., Lambin, E.F., 2002. Proximate Causes and Underlying Driving Forces of Tropical DeforestationTropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. BioScience 52, 143–150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2
Geldmann, J., Coad, L., Barnes, M., Craigie, I.D., Hockings, M., Knights, K., Leverington, F., Cuadros, I.C., Zamora, C., Woodley, S., Burgess, N.D., 2015. Changes in protected area management effectiveness over time: A global analysis. Biological Conservation 191, 692–699. https://doi.org/10.1016/j.biocon.2015.08.029
Geldmann, J., Coad, L., Barnes, M.D., Craigie, I.D., Woodley, S., Balmford, A., Brooks, T.M., Hockings, M., Knights, K., Mascia, M.B., McRae, L., Burgess, N.D., 2018. A global analysis of management capacity and ecological outcomes in terrestrial protected areas. Conservation Letters 11, e12434. https://doi.org/10.1111/conl.12434
Gelman, A., Hill, J., 2006. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press.
Gentle, M., Pople, A., Scanlan, J.C., Carter, J., 2019. The dynamics of feral pig (Sus scrofa) populations in response to food supply. Wildl. Res. 46, 191–204. https://doi.org/10.1071/WR17176

Gill, D.A., Mascia, M.B., Ahmadia, G.N., Glew, L., Lester, S.E., Barnes, M., Craigie, I., Darling, E.S., Free, C.M., Geldmann, J., Holst, S., Jensen, O.P., White, A.T., Basurto, X., Coad, L., Gates, R.D., Guannel, G., Mumby, P.J., Thomas, H., Whitmee, S., Woodley, S., Fox, H.E., 2017. Capacity shortfalls hinder the performance of marine protected areas globally. Nature 543, 665–669. https://doi.org/10.1038/nature21708
Global Witness, 2013. Rubber Barons: How Vietnamese companies and international financiers are driving a land grabbing crisis in Cambodia and Laos. Global Witness.
Goes, F., 2009. The status and distribution of green peafowl Pavo muticus in Cambodia. Cambodian Journal of Natural History 1, 7–15.
Golden Kroner, R.E., Krithivasan, R., Mascia, M.B., 2016. Effects of protected area downsizing on habitat fragmentation in Yosemite National Park (USA), 1864 – 2014. Ecology and Society 21.
Golden Kroner, R.E., Qin, S., Cook, C.N., Krithivasan, R., Pack, S.M., Bonilla, O.D., Cort-Kansinally, K.A., Coutinho, B., Feng, M., Garcia, M.I.M., He, Y., Kennedy, C.J., Lebreton, C., Ledezma, J.C., Lovejoy, T.E., Luther, D.A., Parmanand, Y., Ruíz-Agudelo, C.A., Yerena, E., Zambrano, V.M., Mascia, M.B., 2019. The uncertain future of protected lands and waters. Science 364, 881–886. https://doi.org/10.1126/science.aau5525
Gollin, D., Probst, L.T., 2015. Food and agriculture: shifting landscapes for policy. Oxford Review of Economic Policy 31, 8–25. https://doi.org/10.1093/oxrep/grv012
Gong, C., Yu, S., Joesting, H., Chen, J., 2013. Determining socioeconomic drivers of urban forest fragmentation with historical remote sensing images. Landscape and Urban Planning 117, 57–65. https://doi.org/10.1016/j.landurbplan.2013.04.009
Gray, T.N., Phan, C., 2011. Habitat preferences and activity patterns of the larger mammal community in Phnom Prich Wildlife Sanctuary, Cambodia. The Raffles Bulletin of Zoology 59, 311–318.
Gray, T.N.E., 2013. Activity patterns and home ranges of Indochinese Leopard Panthera pardus delacouri in the Eastern Plains Landscape, Cambodia. Nat. Hist. Bull. Siam Soc. 59, 39–47.
Gray, T.N.E., 2012. Studying Large Mammals With Imperfect Detection: Status and Habitat Preferences of Wild Cattle and Large Carnivores in Eastern Cambodia. Biotropica 44, 531–536. https://doi.org/10.1111/j.1744-7429.2011.00846.x
Gray, T.N.E., Hughes, A.C., Laurance, W.F., Long, B., Lynam, A.J., O'Kelly, H., Ripple, W.J., Seng, T., Scotson, L., Wilkinson, N.M., 2018. The wildlife snaring crisis: an insidious and pervasive threat to biodiversity in Southeast Asia. Biodivers Conserv 27, 1031–1037. https://doi.org/10.1007/s10531-017-1450-5
Gray, T.N.E., Lynam, A.J., Seng, T., Laurance, W.F., Long, B., Scotson, L., Ripple, W.J., 2017. Wildlife-snaring crisis in Asian forests. Science 355, 255–256. https://doi.org/10.1126/science.aal4463
Gray, T.N.E., Phan, C., Long, B., 2010. Modelling species distribution at multiple spatial scales: gibbon habitat preferences in a fragmented landscape: Gibbon distribution in fragmented landscapes. Animal Conservation 13, 324–332. https://doi.org/10.1111/j.1469-1795.2010.00351.x
Gray, Thomas N.E., Phan, C., Pin, C., Prum, S., 2012. Establishing a monitoring baseline for threatened large ungulates in eastern Cambodia. Wildlife Biology 18, 406–413. https://doi.org/10.2981/11-107
Gray, T.N.E, Pin, C., Pan, C., Crouthers, R., Kamler, J.F., Prum, S., 2014. Camera-trap records of small carnivores from eastern Cambodia, 1999–2013. Small Carnivore Conservation 50, 20–24.
Gray, T. N. E., Pollard, E.H.B., Evans, T.D., Goes, F., Grindley, M., Omaliss, K., Nielsen, P.H., Orn, S., Phan, C., Sanh, S., 2014. Birds of Mondulkiri, Cambodia: distribution, status, and conservation. Forktail 30, 66–78.
Gray, T.N.E., Prum, S., Phan, C., 2016. Density and Activity Patterns of the Globally Significant Large Herbivore Populations of Cambodia's Eastern Plains Landscape, in: Ahrestani, F.S., Sankaran,

M. (Eds.), The Ecology of Large Herbivores in South and Southeast Asia. Springer Netherlands, Dordrecht, pp. 207–222.
Gray, Thomas N. E., Prum, S., Pin, C., Phan, C., 2012. Distance sampling reveals Cambodia's Eastern Plains Landscape supports the largest global population of the Endangered banteng Bos javanicus. Oryx 46, 563–566. https://doi.org/10.1017/S0030605312000567
Green, J.L., Hastings, A., Arzberger, P., Ayala, F.J., Cottingham, K.L., Cuddington, K., Davis, F., Dunne, J.A., Fortin, M.-J., Gerber, L., Neubert, M., 2005. Complexity in Ecology and Conservation: Mathematical, Statistical, and Computational Challenges. BioScience 55, 501–510. https://doi.org/10.1641/0006-3568(2005)055[0501:CIEACM]2.0.CO;2
Green, W.N., 2020. Financial landscapes of agrarian change in Cambodia. Geoforum. https://doi.org/10.1016/j.geoforum.2020.02.001
Griffin, O., Nuttall, M., 2020. Status of Key Speceis in Keo Seima Wildlife Sanctuary 2010-2020 (Status report). Wildlife Conservation Society, Phnom Penh, Cambodia.
Grimsditch, M., Schoenberger, L., 2015. New actions and existing policies: The implementation and impacts of Order 01. NGO Forum.
Groenenberg, M., Crouthers, R., Yoganand, K., 2020. Population status of ungulates in the Eastern Plains Landscape. Srepok Wildlife Sanctuary and Phnom Prich Wildlife Sanctuary, Cambodia (Technical Report). WWF-Cambodia, Phnom Penh, Cambodia.
Grogan, K., Pflugmacher, D., Hostert, P., Kennedy, R., Fensholt, R., 2015. Cross-border forest disturbance and the role of natural rubber in mainland Southeast Asia using annual Landsat time series. Remote Sensing of Environment 169, 438–453. https://doi.org/10.1016/j.rse.2015.03.001
Grogan, K., Pflugmacher, D., Hostert, P., Mertz, O., Fensholt, R., 2019. Unravelling the link between global rubber price and tropical deforestation in Cambodia. Nature Plants 5, 47–53. https://doi.org/10.1038/s41477-018-0325-4
Gruby, R.L., Enrici, A., Betsill, M., Le Cornu, E., Basurto, X., 2021. Opening the black box of conservation philanthropy: A co-produced research agenda on private foundations in marine conservation. Marine Policy 132, 104645. https://doi.org/10.1016/j.marpol.2021.104645
Gryseels, C., Kuijpers, L.M.F., Jacobs, J., Peeters Grietens, K., 2019. When 'substandard' is the standard, who decides what is appropriate? Exploring healthcare provision in Cambodia. Critical Public Health 29, 460–472. https://doi.org/10.1080/09581596.2019.1591614
Hamada, K., Kasuya, M., 1992. The reconstruction and stbilization of the postwar Japanese economy: Possible lessons for Eastern Europe? (Center Discussion Paper No. 672). Yale University Economic Growth Center, New Haven, CT.
Hamblin, S., 2013. On the practical usage of genetic algorithms in ecology and evolution. Methods in Ecology and Evolution 4, 184–194. https://doi.org/10.1111/2041-210X.12000
Hamilton, C.M., Bateman, B.L., Gorzo, J.M., Reid, B., Thogmartin, W.E., Peery, M.Z., Heglund, P.J., Radeloff, V.C., Pidgeon, A.M., 2018. Slow and steady wins the race? Future climate and land use change leaves the imperiled Blanding's turtle (Emydoidea blandingii) behind. Biological Conservation 222, 75–85. https://doi.org/10.1016/j.biocon.2018.03.026
Hamilton, O.N.P., Kincaid, S.E., Constantine, R., Kozmian-Ledward, L., Walker, C.G., Fewster, R.M., 2018. Accounting for uncertainty in duplicate identification and group size judgements in mark–recapture distance sampling. Methods in Ecology and Evolution 9, 354–362. https://doi.org/10.1111/2041-210X.12895
Hammer, P., 2008. Living on the Margins: Minorities and Borderlines in Cambodia and Southeast Asia, Mainland Southeast Asia at its Margins: MinorityGroups and Borders. Centre for Khmer Studies, Siem Reap, Cambodia.
Handschuh, M., Rainey, H., 2010. Clutch size of sarus crane Grus antigone in ther Northern Plains of Cambodia and incidence of clutches with three eggs. Cambodian Journal of Natural History 2, 103–105.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853. https://doi.org/10.1126/science.1244693

Harris, G.M., Butler, M.J., Stewart, D.R., Rominger, E.M., Ruhl, C.Q., 2020. Accurate population estimation of Caprinae using camera traps and distance sampling. Sci Rep 10, 17729. https://doi.org/10.1038/s41598-020-73893-5

Harrison, R.D., Sreekar, R., Brodie, J.F., Brook, S., Luskin, M., O'Kelly, H., Rao, M., Scheffers, B., Velho, N., 2016. Impacts of hunting on tropical forests in Southeast Asia. Conservation Biology 30, 972–981. https://doi.org/10.1111/cobi.12785

Harrison, X.A., Donaldson, L., Correa-Cano, M.E., Evans, J., Fisher, D.N., Goodwin, C.E.D., Robinson, B.S., Hodgson, D.J., Inger, R., 2018. A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ 6, e4794. https://doi.org/10.7717/peerj.4794

He, J., Lang, R., Xu, J., 2014. Local Dynamics Driving Forest Transition: Insights from Upland Villages in Southwest China. Forests 5, 214–233. https://doi.org/10.3390/f5020214

Hearn, A.J., Cushman, S.A., Goossens, B., Macdonald, E., Ross, J., Hunter, L.T.B., Abram, N.K., Macdonald, D.W., 2018. Evaluating scenarios of landscape change for Sunda clouded leopard connectivity in a human dominated landscape. Biological Conservation 222, 232–240. https://doi.org/10.1016/j.biocon.2018.04.016

Hedges, S., Meijaard, E., 1999. Reconnaissance survey for Banteng (Bos javanicus) and banteng survey methods training project, Kayan-Mentarang National Park, East Kalimantan, Indonesia. World Wide Fund for Nature - Indonesia and Centre for International Forestry Research, Kalimantan, Indonesia.

Hein, L., Miller, D.C., de Groot, R., 2013. Payments for ecosystem services and the financing of global biodiversity conservation. Current Opinion in Environmental Sustainability, Terrestrial systems 5, 87–93. https://doi.org/10.1016/j.cosust.2012.12.004

Heinrich, S., Ross, J.V., Gray, T.N.E., Delean, S., Marx, N., Cassey, P., 2020. Plight of the commons: 17 years of wildlife trafficking in Cambodia. Biological Conservation 241, 108379. https://doi.org/10.1016/j.biocon.2019.108379

Henschel, P., Coad, L., Burton, C., Chataigner, B., Dunn, A., MacDonald, D., Saidu, Y., Hunter, L.T.B., 2014. The Lion in West Africa Is Critically Endangered. PLOS ONE 9, e83500. https://doi.org/10.1371/journal.pone.0083500

Hernowo, J.B., 2011. Population analysis of the javan green peafowl (Pavo muticus muticus Linnaeus 1758) in Baluran and Alas Purwo National Parks, East Java. Biodiversitas, Journal of Biological Diversity 12, 99–106. https://doi.org/10.13057/biodiv/d120207

Hoang, D.M., 2007. Ecology and Conservation Status of the Black-shanked douc (Pygathrix nigripes) in Nui Chua and Phuoc Binh National Parks, Ninh Thuan Province, Vietnam. The University of Queensland, Brisbane, Australia.

Hoang, N.T., Kanemoto, K., 2021. Mapping the deforestation footprint of nations reveals growing threat to tropical forests. Nature Ecology & Evolution 1–9. https://doi.org/10.1038/s41559-021-01417-z

Hodge, I., Adams, W.M., 2016. Short-Term Projects versus Adaptive Governance: Conflicting Demands in the Management of Ecological Restoration. Land 5, 39. https://doi.org/10.3390/land5040039

Hoffmann, M., Hilton-Taylor, C., Angulo, A., Böhm, M., Brooks, T.M., Butchart, S.H.M., Carpenter, K.E., Chanson, J., Collen, B., Cox, N.A., Darwall, W.R.T., Dulvy, N.K., Harrison, L.R., Katariya, V., Pollock, C.M., Quader, S., Richman, N.I., Rodrigues, A.S.L., Tognelli, M.F., Vié, J.-C., Aguiar, J.M., Allen, D.J., Allen, G.R., Amori, G., Ananjeva, N.B., Andreone, F., Andrew, P., Ortiz, A.L.A., Baillie, J.E.M., Baldi, R., Bell, B.D., Biju, S.D., Bird, J.P., Black-Decima, P., Blanc, J.J., Bolaños, F., Bolivar-G, W., Burfield, I.J., Burton, J.A., Capper, D.R., Castro, F., Catullo, G., Cavanagh, R.D., Channing, A., Chao, N.L., Chenery, A.M., Chiozza, F., Clausnitzer, V., Collar, N.J., Collett, L.C., Collette, B.B., Fernandez, C.F.C., Craig, M.T., Crosby, M.J., Cumberlidge, N., Cuttelod, A., Derocher, A.E., Diesmos, A.C., Donaldson, J.S., Duckworth, J.W., Dutson, G., Dutta, S.K., Emslie, R.H., Farjon, A., Fowler, S., Freyhof, J., Garshelis, D.L., Gerlach, J., Gower, D.J., Grant, T.D., Hammerson, G.A., Harris, R.B., Heaney, L.R., Hedges, S.B., Hero, J.-M., Hughes, B., Hussain, S.A., M, J.I., Inger, R.F., Ishii, N., Iskandar, D.T., Jenkins, R.K.B., Kaneko, Y., Kottelat, M., Kovacs, K.M., Kuzmin, S.L., Marca, E.L., Lamoreux, J.F., Lau, M.W.N., Lavilla, E.O., Leus, K., Lewison, R.L., Lichtenstein, G., Livingstone, S.R., Lukoschek, V., Mallon, D.P., McGowan, P.J.K., McIvor, A., Moehlman, P.D., Molur, S., Alonso, A.M., Musick, J.A., Nowell, K., Nussbaum, R.A., Olech, W., Orlov, N.L., Papenfuss, T.J., Parra-Olea, G., Perrin, W.F., Polidoro, B.A., Pourkazemi, M., Racey, P.A., Ragle, J.S., Ram, M., Rathbun, G., Reynolds, R.P., Rhodin, A.G.J., Richards, S.J., Rodríguez, L.O., Ron, S.R., Rondinini, C., Rylands, A.B., Mitcheson, Y.S. de, Sanciangco, J.C., Sanders, K.L., Santos-Barrera, G., Schipper, J., Self-Sullivan, C., Shi, Y., Shoemaker, A., Short, F.T., Sillero-Zubiri, C., Silvano, D.L., Smith, K.G., Smith, A.T., Snoeks, J., Stattersfield, A.J., Symes, A.J., Taber, A.B., Talukdar, B.K., Temple, H.J., Timmins, R., Tobias, J.A., Tsytsulina, K., Tweddle, D., Ubeda, C., Valenti, S.V., Dijk, P.P. van, Veiga, L.M., Veloso, A., Wege, D.C., Wilkinson, M., Williamson, E.A., Xie, F., Young, B.E., Akçakaya, H.R., Bennun, L., Blackburn, T.M., Boitani, L., Dublin, H.T., Fonseca, G.A.B. da, Gascon, C., Lacher, T.E., Mace, G.M., Mainka, S.A., McNeely, J.A., Mittermeier, R.A., Reid, G.M., Rodriguez, J.P., Rosenberg, A.A., Samways, M.J., Smart, J., Stein, B.A., Stuart, S.N., 2010. The Impact of Conservation on the Status of the World's Vertebrates. Science 330, 1503–1509. https://doi.org/10.1126/science.1194442

Holdo, R.M., Holt, R.D., Fryxell, J.M., 2009. Grazers, browsers, and fire influence the extent and spatial pattern of tree cover in the Serengeti. Ecological Applications 19, 95–109. https://doi.org/10.1890/07-1954.1

Holling, C.S., 1973. Resilience and Stability of Ecological Systems. Annu.Rev.Ecol.Syst. 4, 1–23.

Hooper, D.U., Adair, E.C., Cardinale, B.J., Byrnes, J.E.K., Hungate, B.A., Matulich, K.L., Gonzalez, A., Duffy, J.E., Gamfeldt, L., O'Connor, M.I., 2012. A global synthesis reveals biodiversity loss as a major driver of ecosystem change. Nature. https://doi.org/10.1038/nature11118

Hooper, D.U., Chapin III, F.S., Ewel, J.J., Hector, A., Inchausti, P., Lavorel, S., Lawton, J.H., Lodge, D.M., Loreau, M., Naeem, S., Schmid, B., Setälä, H., Symstad, A.J., Vandermeer, J., Wardle, D.A., 2005. Effects of Biodiversity on Ecosystem Functioning: A Consensus of Current Knowledge. Ecological Monographs 75, 3–35. https://doi.org/10.1890/04-0922

Hought, J., Birch-Thomsen, T., Petersen, J., de Neergaard, A., Oelofse, M., 2012. Biofuels, land use change and smallholder livelihoods: A case study from Banteay Chhmar, Cambodia. Applied Geography 34, 525–532. https://doi.org/10.1016/j.apgeog.2012.02.007

Howe, E.J., Buckland, S.T., Després-Einspenner, M.-L., Kühl, H.S., 2017. Distance sampling with camera traps. Methods in Ecology and Evolution 8, 1558–1565. https://doi.org/10.1111/2041-210X.12790

Hughes, A.C., 2018. Have Indo-Malaysian forests reached the end of the road? Biological Conservation 223, 129–137. https://doi.org/10.1016/j.biocon.2018.04.029

Hughes, A.C., 2017. Understanding the drivers of Southeast Asian biodiversity loss. Ecosphere 8, e01624. https://doi.org/10.1002/ecs2.1624

Hughes, C., Un, K., 2011. Cambodia's Economic Transformation (No. 49), NIAS Studies in Asian Topics. Nordic Institute of Asian Studies, Leifsgade 33, DK-2300 Copenhagen S, Denmark.

Humphreys, S., 2009. Human Rights and Climate Change. Cambridge University Press.

Huwyler, F., Kappeli, J., Tobin, J., 2016. Conservation finance from niche to mainstream: The building of an institutional asset class. Credit Suisse and McMinsey Center for Business and Environment, Zurich, Switzerland.

Ibbett, H., Keane, A., Dobson, A.D.M., Griffin, O., Travers, H., Milner-Gulland, E.J., 2020. Estimating hunting prevalence and reliance on wild meat in Cambodia's Eastern Plains. Oryx 1–11. https://doi.org/10.1017/S0030605319001455

Ickes, K., 2001. Hyper-abundance of Native Wild Pigs (Sus scrofa) in a Lowland Dipterocarp Rain Forest of Peninsular Malaysia1. Biotropica 33, 682–690. https://doi.org/10.1111/j.1744-7429.2001.tb00225.x

Ikeda, T., Asano, M., Kuninaga, N., Suzuki, M., 2020. Monitoring relative abundance index and age ratios of wild boar (*Sus scrofa*) in small scale population in Gifu prefecture, Japan during classical swine fever outbreak. Journal of Veterinary Medical Science advpub. https://doi.org/10.1292/jvms.20-0083

Imai, N., Furukawa, T., Tsujino, R., Kitamura, S., Yumoto, T., 2018. Factors affecting forest area change in Southeast Asia during 1980-2010. PLOS ONE 13, e0197391. https://doi.org/10.1371/journal.pone.0197391

Ingalls, M.L., Meyfroidt, P., To, P.X., Kenney-Lazar, M., Epprecht, M., 2018. The transboundary displacement of deforestation under REDD+: Problematic intersections between the trade of forest-risk commodities and land grabbing in the Mekong region. Global Environmental Change 50, 255–267. https://doi.org/10.1016/j.gloenvcha.2018.04.003

Ingram, J.C., Wilkie, D., Clements, T., McNab, R.B., Nelson, F., Baur, E.H., Sachedina, H.T., Peterson, D.D., Foley, C.A.H., 2014. Evidence of Payments for Ecosystem Services as a mechanism for supporting biodiversity conservation and rural livelihoods. Ecosystem Services 7, 10–21. https://doi.org/10.1016/j.ecoser.2013.12.003

IPCC, 2019. Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

Ironside, J., 2008. Development - In Whose Name? Cambodia’s Economic Development and its Indigneous Communities - From Self-Reliance to Uncertainty, in: Living on the Margins: Minorities and Borderlines in Cambodia and Southeast Asia. Centre for Khmer Studies, Siem Reap, Cambodia, pp. 91–128.

Isaac, N.J.B., Brotherton, P.N.M., Bullock, J.M., Gregory, R.D., Boehning-Gaese, K., Connor, B., Crick, H.Q.P., Freckleton, R.P., Gill, J.A., Hails, R.S., Hartikainen, M., Hester, A.J., Milner-Gulland, E.J., Oliver, T.H., Pearson, R.G., Sutherland, W.J., Thomas, C.D., Travis, J.M.J., Turnbull, L.A., Willis, K., Woodward, G., Mace, G.M., 2018. Defining and delivering resilient ecological networks: Nature conservation in England. Journal of Applied Ecology 55, 2537–2543. https://doi.org/10.1111/1365-2664.13196

IUCN, 2019. Recognising and reporting other effective area-based conservation measures (No. 3), Protected Area Technical Report Series. IUCN, Gland, Switzerland.

IUCN, 2016. Establishment, recognition and regulation of the career of park rangers, in: Motion Number 032, Resolution Number WCC-2016_Rec-103. Presented at the World Conservation Congress, Honolulu, Hawai’i, USA.

Jathanna, D., Karanth, K.U., Johnsingh, A.J.T., 2003. Estimation of large herbivore densities in the tropical forests of southern India using distance sampling. Journal of Zoology 261, 285–290. https://doi.org/10.1017/S0952836903004278

Jayachandran, S., de Laat, J., Lambin, E.F., Stanton, C.Y., 2016. Cash for Carbon: A Randomized Controlled Trial of Payments for Ecosystem Services to Reduce Deforestation (Working Paper No. 22378), Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w22378

Jensen, C., 2006. Foreign Direct Investment and economic transition: Panacea or pain killer? Europe-Asia Studies 58, 881–902. https://doi.org/10.1080/09668130600831084

Jiao, T., Williams, C.A., Ghimire, B., Masek, J., Gao, F., Schaaf, C., 2017. Global climate forcing from albedo change caused by large-scale deforestation and reforestation: quantification and attribution of geographic variation. Climatic Change 142, 463–476. https://doi.org/10.1007/s10584-017-1962-8

Johnson, C.N., Balmford, A., Brook, B.W., Buettel, J.C., Galetti, M., Guangchun, L., Wilmshurst, J.M., 2017. Biodiversity losses and conservation responses in the Anthropocene. Science 356, 270–275. https://doi.org/10.1126/science.aam9317

Journeaux, K.L., Gardner, P.C., Lim, H.Y., Wern, J.G.E., Goossens, B., 2018. Herd demography, sexual segregation and the effects of forest management on Bornean banteng Bos javanicus lowi in Sabah, Malaysian Borneo. Endangered Species Research 35, 141–157. https://doi.org/10.3354/esr00882

Kaimowitz, D., Fauné, A., 2003. Contras and Comandantes. Journal of Sustainable Forestry 16, 21–46. https://doi.org/10.1300/J091v16n03_02

Kaiser, C., 2015. NatureVest: Natural Capital Investment Solutions to Transform The Way We Protect Nature. Social Research 82, 749–760.

Kamler, J.F., Minge, C., Rostro-García, S., Gharajehdaghipour, T., Crouthers, R., In, V., Pay, C., Pin, C., Sovanna, P., Macdonald, D.W., 2021. Home range, habitat selection, density, and diet of golden jackals in the Eastern Plains Landscape, Cambodia. Journal of Mammalogy 102, 636–650. https://doi.org/10.1093/jmammal/gyab014

Karanth, K.U., Kumar, N.S., 2015. Population estimation of tigers in Wayanad Wildlife Sanctuary, Kerala. Centre for Wildlife Studies / Wildlife Conservation Society, Bangalore, India.

Karanth, K.U., Nichols, J.D., 2000. Ecological status and conservation of tigers in India: Final technical report submitted to US Fish and Wildlife Service, Washington DC, and Wildlife Conservation Society, New York. Centre for Wildlife Studies, Bangalore, India.

Karuppannan, K., Saaban, S., Mustapa, A.R., Zainal Abidin, F.A., Azimat, N.A., Keliang, C., 2014. Population status of Long-tailed macaque (Macaca Fascicularis) in Peninsular Malaysia. Primatology 3.

Kearney, S.G., Adams, V.M., Fuller, R.A., Possingham, H.P., Watson, J.E.M., 2020. Estimating the benefit of well-managed protected areas for threatened species conservation. Oryx 54, 276–284. https://doi.org/10.1017/S0030605317001739

Kellner, K.F., Swihart, R.K., 2014. Accounting for Imperfect Detection in Ecology: A Quantitative Review. PLOS ONE 9, e111436. https://doi.org/10.1371/journal.pone.0111436

Khuc, Q.V., Tran, B.Q., Meyfroidt, P., Paschke, M.W., 2018. Drivers of deforestation and forest degradation in Vietnam: An exploratory analysis at the national level. Forest Policy and Economics 90, 128–141. https://doi.org/10.1016/j.forpol.2018.02.004

Kiernan, B., 2003. The demography of genocide in Southeast Asia. Critical Asian Studies 35, 585–597.

Kim, D.-H., Sexton, J.O., Townshend, J.R., 2016. Accelerated deforestation in the humid tropics from the 1990s to the 2000s. Geophysical Research Letters 3495–3501. https://doi.org/10.1002/2014GL062777@10.1002/(ISSN)1944-8007.2015EdHighlights

Kitamura, Y., Edwards, B.D., Sitha, C., Williams, J.H., 2016. The political economy of schooling in Cambodia: Issues of quality and equity, International and Development Education. Palgrave Macmillan.

Knights, K., McCarthy, M.A., Camac, J., Guillera-Arroita, G., 2021. Efficient effort allocation in line-transect distance sampling of high-density species: When to walk further, measure less-often and gain precision. Methods in Ecology and Evolution 12, 962–970. https://doi.org/10.1111/2041-210X.13589

Kong, R., Diepart, J.-C., Castella, J.-C., Lestrelin, G., Tivet, F., Belmain, E., Bégué, A., 2019. Understanding the drivers of deforestation and agricultural transformations in the Northwestern uplands of Cambodia. Applied Geography 102, 84–98. https://doi.org/10.1016/j.apgeog.2018.12.006

Krishnadas, M., Agarwala, M., Sridhara, S., Eastwood, E., 2018. Parks protect forest cover in a tropical biodiversity hotspot, but high human population densities can limit success. Biological Conservation 223, 147–155. https://doi.org/10.1016/j.biocon.2018.04.034

Kristensen, S.B.P., Busck, A.G., van der Sluis, T., Gaube, V., 2016. Patterns and drivers of farm-level land use change in selected European rural landscapes. Land Use Policy 57, 786–799. https://doi.org/10.1016/j.landusepol.2015.07.014
Kuang, W., Liu, J., Dong, J., Chi, W., Zhang, C., 2016. The rapid and massive urban and industrial land expansions in China between 1990 and 2010: A CLUD-based analysis of their trajectories, patterns, and drivers. Landscape and Urban Planning 145, 21–33. https://doi.org/10.1016/j.landurbplan.2015.10.001
Kugelman, M., Levenstein, S.L., 2012. The global farms race: land grabs, agricultural investment, and the scramble for food security. The global farms race: land grabs, agricultural investment, and the scramble for food security.
Kull, C.A., 2017. Forest transitions: a new conceptual scheme. Geographica Helvetica 72, 465–474. https://doi.org/10.5194/gh-72-465-2017
Lambin, E.F., Meyfroidt, P., 2010. Land use transitions: Socio-ecological feedback versus socio-economic change. Land Use Policy, Forest transitions 27, 108–118. https://doi.org/10.1016/j.landusepol.2009.09.003
Lambin, X., Horrill, J.C., Raynor, R., 2019. Achieving large scale, long-term invasive American mink control in northern Scotland despite short term funding, in: Proceedings of the International Conference on Island Invasives. Presented at the Island invasives: scaling up to meet the challenge, IUCN, Dundee, Scotland, UK, pp. 651–657.
Larson, L.R., Peterson, M.N., Furstenberg, R.V., Vayer, V.R., Lee, K.J., Choi, D.Y., Stevenson, K., Ahlers, A.A., Anhalt-Depies, C., Bethke, T., Bruskotter, J.T., Chizinski, C.J., Clark, B., Dayer, A.A., Dunning, K.H., Ghasemi, B., Gigliotti, L., Graefe, A., Irwin, K., Keith, S.J., Kelly, M., Kyle, G., Metcalf, E., Morse, W., Needham, M.D., Poudyal, N.C., Quartuch, M., Rodriguez, S., Romulo, C., Sharp, R.L., Siemer, W., Springer, M.T., Stayton, B., Stedman, R., Stein, T., Deelen, T.R.V., Whiting, J., Winkler, R.L., Woosnam, K.M., 2021. The future of wildlife conservation funding: What options do U.S. college students support? Conservation Science and Practice n/a, e505. https://doi.org/10.1111/csp2.505
Laufer, A.E., Jones, M.D., 2021. Who pays for marine conservation? Processes and narratives that influence marine funding. Ocean & Coastal Management 203, 105504. https://doi.org/10.1016/j.ocecoaman.2020.105504
Lee, B.P.Y.-H., 2011. A possible decline in population of the long-tailed macaque (Macaca fascicularis) in northeastern Cambodia, in: Monkeys on the Edge - Ecology and Management of Long-Tailed Macaques and Their Interface with Humans, Science. Cambridge University Press, New York, USA, pp. 83–86.
Lendrum, P.E., Northrup, J.M., Anderson, C.R., Liston, G.E., Aldridge, C.L., Crooks, K.R., Wittemyer, G., 2018. Predation risk across a dynamic landscape: effects of anthropogenic land use, natural landscape features, and prey distribution. Landscape Ecol 33, 157–170. https://doi.org/10.1007/s10980-017-0590-z
Lennox, G.D., Armsworth, P.R., 2011. Suitability of short or long conservation contracts under ecological and socio-economic uncertainty. Ecological Modelling 222, 2856–2866. https://doi.org/10.1016/j.ecolmodel.2011.04.033
Leung, B., Hargreaves, A.L., Greenberg, D.A., McGill, B., Dornelas, M., Freeman, R., 2020. Clustered versus catastrophic global vertebrate declines. Nature 1–5. https://doi.org/10.1038/s41586-020-2920-6
Li, J., Zhang, Z., Jin, X., Chen, J., Zhang, S., He, Zong, Li, S., He, Zhiming, Zhang, H., Xiao, H., 2018. Exploring the socioeconomic and ecological consequences of cash crop cultivation for policy implications. Land Use Policy 76, 46–57. https://doi.org/10.1016/j.landusepol.2018.04.009
Li, R., Buongiorno, J., Turner, J.A., Zhu, S., Prestemon, J., 2008. Long-term effects of eliminating illegal logging on the world forest industries, trade, and inventory. Forest Policy and Economics 10, 480–490. https://doi.org/10.1016/j.forpol.2008.04.003
Licadho, 2019. Economic Land Concessions in Cambodia.

Lindenmayer, D.B., Gibbons, P., Bourke, M., Burgman, M., Dickman, C.R., Ferrier, S., Fitzsimons, J., Freudenberger, D., Garnett, S.T., Groves, C., Hobbs, R.J., Kingsford, R.T., Krebs, C., Legge, S., Lowe, A.J., Mclean, R., Montambault, J., Possingham, H., Radford, J., Robinson, D., Smallbone, L., Thomas, D., Varcoe, T., Vardon, M., Wardle, G., Woinarski, J., Zerger, A., 2012. Improving biodiversity monitoring. Austral Ecology 37, 285–294. https://doi.org/10.1111/j.1442-9993.2011.02314.x

Lindsey, P.A., Nyirenda, V.R., Barnes, J.I., Becker, M.S., McRobb, R., Tambling, C.J., Taylor, W.A., Watson, F.G., t'Sas-Rolfes, M., 2014. Underperformance of African Protected Area Networks and the Case for New Conservation Models: Insights from Zambia. PLOS ONE 9, e94109. https://doi.org/10.1371/journal.pone.0094109

Lindsey, P.A., Petracca, L.S., Funston, P.J., Bauer, H., Dickman, A., Everatt, K., Flyman, M., Henschel, P., Hinks, A.E., Kasiki, S., Loveridge, A., Macdonald, D.W., Mandisodza, R., Mgoola, W., Miller, S.M., Nazerali, S., Siege, L., Uiseb, K., Hunter, L.T.B., 2017. The performance of African protected areas for lions and their prey. Biological Conservation 209, 137–149. https://doi.org/10.1016/j.biocon.2017.01.011

Linkie, M., Martyr, D., Harihar, A., Mardiah, S., Hodgetts, T., Risdianto, D., Subchaan, M., Macdonald, D., 2018. Asia's economic growth and its impact on Indonesia's tigers. Biological Conservation 219, 105–109. https://doi.org/10.1016/j.biocon.2018.01.011

Little, L.R., Kuikka, S., Punt, A.E., Pantus, F., Davies, C.R., Mapstone, B.D., 2004. Information flow among fishing vessels modelled using a Bayesian network. Environmental Modelling & Software 19, 27–34. https://doi.org/10.1016/S1364-8152(03)00100-2

Liu, Y., Feng, Y., Zhao, Z., Zhang, Q., Su, S., 2016. Socioeconomic drivers of forest loss and fragmentation: A comparison between different land use planning schemes and policy implications. Land Use Policy 54, 58–68. https://doi.org/10.1016/j.landusepol.2016.01.016

Lomborg, B., 2001. The Skeptical Environmentalist: Measuring the Real State of the World. Cambridge University Press.

Lonn, P., Mizoue, N., Ota, T., Kajisa, T., Yoshida, S., 2018. Biophysical Factors Affecting Forest Cover Changes in Community Forestry: A Country Scale Analysis in Cambodia. Forests 9, 273. https://doi.org/10.3390/f9050273

Loucks, C., Mascia, M.B., Maxwell, A., Huy, K., Duong, K., Chea, N., Long, B., Cox, N., Seng, T., 2008. Wildlife decline in Cambodia, 1953–2005: exploring the legacy of armed conflict. Conservation Letters 2, 82–92. https://doi.org/10.1111/j.1755-263X.2008.00044.x

Loveridge, R., Kidney, D., Ty, S., Eang, S., Eames, J.C., Borchers, D., 2017. First systematic survey of green peafowl Pavo muticus in northeastern Cambodia reveals a population stronghold and preference for disappearing riverine habitat. Cambodian Journal of Natural History 2, 157–167.

Loveridge, R., Ryan, G.E., Sum, P., Grey-Read, O., Mahood, S.P., Mould, A., Harrison, S., Crouthers, R., Ko, S., Clements, T., Eames, J.C., Pruvot, M., 2018. Poisoning causing the decline in South-East Asia's largest vulture population. Bird Conservation International 1–14. https://doi.org/10.1017/S0959270918000126

Luck, G.W., Smallbone, L.T., O'Brien, R., 2009. Socio-Economics and Vegetation Change in Urban Ecosystems: Patterns in Space and Time. Ecosystems 12, 604. https://doi.org/10.1007/s10021-009-9244-6

Lytras, S., Xia, W., Hughes, J., Jiang, X., Robertson, D.L., 2021. The animal origin of SARS-CoV-2. Science 373, 968–970. https://doi.org/10.1126/science.abh0117

MacKenzie, D.I., Nichols, J.D., Hines, J.E., Knutson, M.G., Franklin, A.B., 2003. Estimating Site Occupancy, Colonization, and Local Extinction When a Species Is Detected Imperfectly. Ecology 84, 2200–2207. https://doi.org/10.1890/02-3090

MacKenzie, D.I., Nichols, J.D., Lachman, G.B., Droege, S., Royle, J.A., Langtimm, C.A., 2002. Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. Ecology 83, 2248. https://doi.org/10.2307/3072056

Magliocca, N.R., Van Khuc, Q., Ellicott, E.A., de Bremond, A., 2019. Archetypical pathways of direct and indirect land-use change caused by Cambodia's economic land concessions. Ecology and Society 24.

Malakoutikhah, S., Fakheran, S., Hemami, M.-R., Tarkesh, M., Senn, J., 2018. Altitudinal heterogeneity and vulnerability assessment of protected area network for climate change adaptation planning in central Iran. Applied Geography 92, 94–103. https://doi.org/10.1016/j.apgeog.2018.02.006

Mannan, A., Liu, J., Zhongke, F., Khan, T.U., Saeed, S., Mukete, B., ChaoYong, S., Yongxiang, F., Ahmad, A., Amir, M., Ahmad, S., Shah, S., 2019. Application of land-use/land cover changes in monitoring and projecting forest biomass carbon loss in Pakistan. Global Ecology and Conservation 17, e00535. https://doi.org/10.1016/j.gecco.2019.e00535

Mascia, M.B., Pailler, S., 2011. Protected area downgrading, downsizing, and degazettement (PADDD) and its conservation implications. Conservation Letters 4, 9–20. https://doi.org/10.1111/j.1755-263X.2010.00147.x

Mascia, M.B., Pailler, S., Krithivasan, R., Roshchanka, V., Burns, D., Mlotha, M.J., Murray, D.R., Peng, N., 2014. Protected area downgrading, downsizing, and degazettement (PADDD) in Africa, Asia, and Latin America and the Caribbean, 1900–2010. Biological Conservation 169, 355–361. https://doi.org/10.1016/j.biocon.2013.11.021

Mather, A.S., 1992. The Forest Transition. Area 24, 367–379.

McBride, M.F., Wilson, K.A., Bode, M., Possingham, H.P., 2007. Incorporating the Effects of Socioeconomic Uncertainty into Priority Setting for Conservation Investment. Conservation Biology 21, 1463–1474. https://doi.org/10.1111/j.1523-1739.2007.00832.x

McCarthy, D.P., Donald, P.F., Scharlemann, J.P.W., Buchanan, G.M., Balmford, A., Green, J.M.H., Bennun, L.A., Burgess, N.D., Fishpool, L.D.C., Garnett, S.T., Leonard, D.L., Maloney, R.F., Morling, P., Schaefer, H.M., Symes, A., Wiedenfeld, D.A., Butchart, S.H.M., 2012. Financial Costs of Meeting Global Biodiversity Conservation Targets: Current Spending and Unmet Needs. Science 338, 946–949. https://doi.org/10.1126/science.1229803

McFarland, B., 2018. The future of tropical forest conservation finance, in: Conservation of Tropical Rainforests, Palgrave Studies in Environmental Policy and Regulation. Palgrave Macmillan, Cham.

McGowan, P.J.K., Duckworth, J.W., Xianji, W., Van Balen, B., Xiaojun, Y., Mohd, Khan, K.M., Yatim, S.H., Thanga, L., Setiawan, I., Kaul, R., 1998. A review of the status of the Green Peafowl Pavo muticus and recommendations for future action. Bird Conservation International 8, 331–348. https://doi.org/10.1017/S0959270900002100

McSweeney, C., New, M., Lizcano, G., 2010a. UNDP Climate Change Country Profiles: Cambodia. United Nations Development Program.

McSweeney, C., New, M., Lizcano, G., 2010b. The UNDP Climate Change Country Profiles Improving the Accessibility of Observed and Projected Climate Information for Studies of Climate Change in Developing Countries. Bulletin of the American Meteorological Society 91, 157–166.

Meacham, M., Queiroz, C., Norström, A.V., Peterson, G.D., 2016. Social-ecological drivers of multiple ecosystem services: what variables explain patterns of ecosystem services across the Norrström drainage basin? Ecology and Society 21.

Meir, E., Andelman, S., Possingham, H.P., 2004. Does conservation planning matter in a dynamic and uncertain world? Ecology Letters 7, 615–622. https://doi.org/10.1111/j.1461-0248.2004.00624.x

Mena, C.F., Bilsborrow, R.E., McClain, M.E., 2006. Socioeconomic Drivers of Deforestation in the Northern Ecuadorian Amazon. Environmental Management 37, 802–815. https://doi.org/10.1007/s00267-003-0230-z

Meyfroidt, P., Lambin, E.F., 2008. Forest transition in Vietnam and its environmental impacts. Global Change Biology 14, 1319–1336. https://doi.org/10.1111/j.1365-2486.2008.01575.x

Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington DC, USA.
Milne, S., 2015. Cambodia's Unofficial Regime of Extraction: Illicit Logging in the Shadow of Transnational Governance and Investment. Critical Asian Studies 47, 200–228. https://doi.org/10.1080/14672715.2015.1041275
Milne, S., 2013a. Under the leopard's skin: Land commodification and the dilemmas of Indigenous communal title in upland Cambodia. Asia Pacific Viewpoint 54, 323–339. https://doi.org/10.1111/apv.12027
Milne, S., 2013b. Under the leopard's skin: Land commodification and the dilemmas of Indigenous communal title in upland Cambodia. Asia Pacific Viewpoint 54, 323–339. https://doi.org/10.1111/apv.12027
Milne, S., 2012. Grounding Forest Carbon: Property Relations and Avoided Deforestation in Cambodia. Hum Ecol 40, 693–706. https://doi.org/10.1007/s10745-012-9526-z
Milne, S., Mahanty, S., 2015. Conservation and Development in Cambodia: Exploring frontiers of change in nature, state and society. Routledge.
Milner-Gulland, E.J., 2011. Integrating fisheries approaches and household utility models for improved resource management. PNAS 108, 1741–1746. https://doi.org/10.1073/pnas.1010533108
MoE, 2020. Cambodia Forest Cover 2018. Ministry of Environment, Royal Government of Cambodia, Phnom Penh, Cambodia.
MoE, UNEP, 2009. Cambodia Environment Outlook. Ministry of Environment, Royal Government of Cambodia, United Nations Environment Programme, Phnom Penh, Cambodia.
Mokany, K., Ferrier, S., Harwood, T.D., Ware, C., Marco, M.D., Grantham, H.S., Venter, O., Hoskins, A.J., Watson, J.E.M., 2020. Reconciling global priorities for conserving biodiversity habitat. PNAS. https://doi.org/10.1073/pnas.1918373117
Moody, J.E., 2018. Population genetics, biogeography, and conservation of the Indochinese silvered langur, Trachypithecus germaini, in Cambodia: Is the Mekong river a taxonomic boundary? (PhD). Fordham University, New York, USA.
Moody, J.E., Dara, A., Coudrat, C.N., Evans, T., Gray, T., Maltby, M., Soriyun, M., Hor, N.M., O'Kelly, H., Bunnat, P., others, 2011. A summary of the conservation status, taxonomic assignment and distribution of the indochinese silvered langur trachypithecus germaini (sensu lato) in cambodia. Asian Primates Journal 2, 21–28.
Moore, C.T., Kendall, W.L., 2004. Costs of detection bias in index-based population monitoring. Animal Biodiversity and Conservation 27, 287–296.
Moore, J.F., Mulindahabi, F., Masozera, M.K., Nichols, J.D., Hines, J.E., Turikunkiko, E., Oli, M.K., 2018. Are ranger patrols effective in reducing poaching-related threats within protected areas? Journal of Applied Ecology 55, 99–107. https://doi.org/10.1111/1365-2664.12965
Morea, J.P., 2019. A framework for improving the management of protected areas from a social perspective: The case of Bahía de San Antonio Protected Natural Area, Argentina. Land Use Policy 87, 104044. https://doi.org/10.1016/j.landusepol.2019.104044
Mouquet, N., Lagadeuc, Y., Devictor, V., Doyen, L., Duputié, A., Eveillard, D., Faure, D., Garnier, E., Gimenez, O., Huneman, P., Jabot, F., Jarne, P., Joly, D., Julliard, R., Kéfi, S., Kergoat, G.J., Lavorel, S., Gall, L.L., Meslin, L., Morand, S., Morin, X., Morlon, H., Pinay, G., Pradel, R., Schurr, F.M., Thuiller, W., Loreau, M., 2015. REVIEW: Predictive ecology in a changing world. Journal of Applied Ecology 52, 1293–1310. https://doi.org/10.1111/1365-2664.12482
Mukul, S.A., Rashid, A.Z.M.M., Uddin, M.B., Khan, N.A., 2016. Role of non-timber forest products in sustaining forest-based livelihoods and rural households' resilience capacity in and around protected area: a Bangladesh study†. Journal of Environmental Planning and Management 59, 628–642. https://doi.org/10.1080/09640568.2015.1035774
Mundkur, T., Carr, P., Sun, H., Chhim, S., 1995. Surveys for large waterbirds in Cambodia, March-April 1994 (Species Survival Commission). IUCN.

Murdoch, W., Ranganathan, J., Polasky, S., Regetz, J., 2010. Using return on investment to maximize conservation effectiveness in Argentine grasslands. PNAS 107, 20855–20862. https://doi.org/10.1073/pnas.1011851107
Nadler, T., Thanh, V.N., Streicher, U., 2007. Conservation status of Vietnamese primates. Vietnamese Journal of Primatology 7–26.
Nakagawa, S., Schielzeth, H., 2017. A general and simple method for obtaining R2 from generalized linear mixed-effects models. Methods in Ecology and Evolution 133–142. https://doi.org/10.1111/j.2041-210x.2012.00261.x@10.1111/(ISSN)2041-210X.STATSTOO
Neef, A., Touch, S., 2012. Land Grabbing in Cambodia: Narratives, Mechanisms, Resistance. Presented at the International Conference on Global Land Grabbing 2, Land Deals Politics Initiative, Ithaca, NY, USA, p. 23.
Neef, A., Touch, S., Chiengthong, J., 2013. The Politics and Ethics of Land Concessions in Rural Cambodia. J Agric Environ Ethics 26, 1085–1103. https://doi.org/10.1007/s10806-013-9446-y
Nelson, G.C., Dobermann, A., Nakicenovic, N., O'Neill, B.C., 2006. Anthropogenic drivers of ecosystem change: An overview. Ecology and Society 11.
Nguyen, M.H., 2009. The status of Vulnerable gaur Bos gaurus and Endangered banteng Bos javanicus in Ea So Nature Reserve and Yok Don and Cat Tien National Parks, Vietnam. Oryx 43, 129–135. https://doi.org/10.1017/S0030605307000440
Nguyen, T.T., Do, T.L., Bühler, D., Hartje, R., Grote, U., 2015. Rural livelihoods and environmental resource dependence in Cambodia. Ecological Economics 120, 282–295. https://doi.org/10.1016/j.ecolecon.2015.11.001
Nguyen, T.T., Nguyen, L.D., Lippe, R.S., Grote, U., 2017. Determinants of Farmers' Land Use Decision-Making: Comparative Evidence From Thailand and Vietnam. World Development 89, 199–213. https://doi.org/10.1016/j.worlddev.2016.08.010
Nguyen, V.M., Nguyen, H.V., Hamada, Y., 2012. Distribution of macaques (Macaca sp.) in central Vietnam and at the Central Highlands of Vietnam. Vietnamese Journal of Primatology 2, 78–83.
Nilsson, L., Bunnefeld, N., Minderman, J., Duthie, A.B., 2021. Effects of stakeholder empowerment on crane population and agricultural production. Ecological Modelling 440, 109396. https://doi.org/10.1016/j.ecolmodel.2020.109396
Nuno, A., Bunnefeld, N., Milner-Gulland, E., 2014. Managing social–ecological systems under uncertainty: implementation in the real world. Ecology and Society 19. https://doi.org/10.5751/ES-06490-190252
Nuttall, M., Nut, M., Ung, V., O'kelly, H., 2017. Abundance estimates for the endangered Green Peafowl Pavo muticus in Cambodia: identification of a globally important site for conservation. Bird Conservation International 27, 127–139. https://doi.org/10.1017/S0959270916000083
Nuttall, M.N., Griffin, O., Fewster, R.M., McGowan, P.J.K., Abernethy, K., O'Kelly, H., Nut, M., Sot, V., Bunnefeld, N., 2021. Long-term monitoring of wildlife populations for protected area management in Southeast Asia. Conservation Science and Practice n/a, e614. https://doi.org/10.1111/csp2.614
O'Brien, R.M., 2017. Dropping Highly Collinear Variables from a Model: Why it Typically is Not a Good Idea*. Social Science Quarterly 98, 360–375. https://doi.org/10.1111/ssqu.12273
O'Brien, T.G., Kinnaird, M.F., Wibisono, H.T., 2003. Crouching tigers, hidden prey: Sumatran tiger and prey populations in a tropical forest landscape. Animal Conservation 6, 131–139. https://doi.org/10.1017/S1367943003003172
O'Kelly, H.J., Evans, T.D., Stokes, E.J., Clements, T.J., Dara, A., Gately, M., Menghor, N., Pollard, E.H.B., Soriyun, M., Walston, J., 2012. Identifying Conservation Successes, Failures and Future Opportunities; Assessing Recovery Potential of Wild Ungulates and Tigers in Eastern Cambodia. PLoS ONE 7, e40482. https://doi.org/10.1371/journal.pone.0040482

O’Kelly, H.J., Rowcliffe, J.M., Durant, S., Milner-Gulland, E.J., 2018a. Experimental estimation of snare detectability for robust threat monitoring. Ecol Evol 8, 1778–1785. https://doi.org/10.1002/ece3.3655
O’Kelly, H.J., Rowcliffe, J.M., Durant, S.M., Milner-Gulland, E.J., 2018b. Robust estimation of snare prevalence within a tropical forest context using N-mixture models. Biol.Conserv. 217, 75–82. https://doi.org/10.1016/j.biocon.2017.10.007
Oldenburg, C., Neef, A., 2014. Reversing Land Grabs or Aggravating Tenure Insecurity: Competing Perspectives on Economic Land Concessions and Land Titling in Cambodia. Law & Dev. Rev. 7, 49–78.
Onojeghuo, A.O., Blackburn, G.A., 2011. Forest transition in an ecologically important region: Patterns and causes for landscape dynamics in the Niger Delta. Ecological Indicators 11, 1437–1446. https://doi.org/10.1016/j.ecolind.2011.03.017
Ota, T., Lonn, P., Mizoue, N., 2020. A country scale analysis revealed effective forest policy affecting forest cover changes in Cambodia. Land Use Policy 95, 104597. https://doi.org/10.1016/j.landusepol.2020.104597
Otis, D.L., 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs 62, 1–135.
Packman, C.E., Showler, D.A., Collar, N.J., Virak, S., Mahood, S.P., Handschuh, M., Evans, T.D., Chamnan, H., Dolman, P.M., 2014. Rapid decline of the largest remaining population of Bengal Florican Houbaropsis bengalensis and recommendations for its conservation. Bird Conservation International 24, 429–437. https://doi.org/10.1017/S0959270913000567
Palencia, P., Rowcliffe, J.M., Vicente, J., Acevedo, P., 2021. Assessing the camera trap methodologies used to estimate density of unmarked populations. Journal of Applied Ecology 58, 1583–1592. https://doi.org/10.1111/1365-2664.13913
Paudel, N.S., Jana, S., Rai, J.K., 2012. Contested law: Slow Response to Demands for Reformulating Protected Area Legal Framework in Nepal. Journal of Forest and Livelihood 10, 88–100. https://doi.org/10.3126/jfl.v10i1.8603
Pedrono, M., Tuan, H.M., Chouteau, P., Vallejo, F., 2009. Status and distribution of the Endangered banteng Bos javanicus birmanicus in Vietnam: a conservation tragedy. Oryx 43, 618–625. https://doi.org/10.1017/S0030605309990147
Pei, K.J.-C., Lai, Y.-C., Corlett, R.T., Suen, K.-Y., 2010. The larger mammal faune of Hong Kong: Species survival in a highly degraded landscape. Zoological Studies 49, 253–264.
Pellissier, V., Mimet, A., Fontaine, C., Svenning, J.-C., Couvet, D., 2017. Relative importance of the land-use composition and intensity for the bird community composition in anthropogenic landscapes. Ecology and Evolution 7, 10513–10535. https://doi.org/10.1002/ece3.3534
Pendrill, F., Persson, U.M., Godar, J., Kastner, T., 2019. Deforestation displaced: trade in forest-risk commodities and the prospects for a global forest transition. Environ. Res. Lett. 14, 055003. https://doi.org/10.1088/1748-9326/ab0d41
Penot, E., Chambon, B., Wibawa, G., 2017. A history of rubber agroforestry systems development in Indonesia and Thailand as alternatives for sustainable agriculture and income stability. Presented at the International Rubber Research and Development Board, Bali, Indonesia.
Phillips, R., Davy, D., 2021. Transnational neoliberalism in Asian civil society: Microfinance and poverty in Cambodia, in: Transnational Civil Society in Asia. Routledge.
Phipps, M., 1994. Cross-border wildlife trade in Ratankiri Province, Cambodia. IBRU Boundary and Security Bulletin 96–97.
Phromma, I., Pagdee, A., Popradit, A., Ishida, A., Uttaranakorn, S., 2019. Protected area co-management and land use conflicts adjacent to Phu Kao – Phu Phan Kham National Park, Thailand. Journal of Sustainable Forestry 38, 486–507. https://doi.org/10.1080/10549811.2019.1573689

Poffenberger, M., 2006. People in the forest: community forestry experiences from Southeast Asia. International Journal of Environment and Sustainable Development 5, 57–69. https://doi.org/10.1504/IJESD.2006.008683

Pollard, E., Clements, T., Nut, M., Sok, K., Rawson, B., 2007. Status and conservation of globally threatened primates in the Seima Biodiversity Conservation Area, Cambodia. Wildlife Conservation Society, Phnom Penh, Cambodia.

Pollock, K.H., Nichols, J.D., Simons, T.R., Farnsworth, G.L., Bailey, L.L., Sauer, J.R., 2002. Large scale wildlife monitoring studies: statistical methods for design and analysis. Environmetrics 13, 105–119. https://doi.org/10.1002/env.514

Pollock, K.J., Nichols, J.D., Brownie, C., Hines, J.E., 1990. Statistical inference for capture-recapture experiments. Wildlife Monographs 107, 3–97.

Price, S., 2020. War and Tropical Forests: Conservation in Areas of Armed Conflict. CRC Press.

QGIS Geographic Information System, 2020.

Qin, S., Kroner, R.E.G., Cook, C., Tesfaw, A.T., Braybrook, R., Rodriguez, C.M., Poelking, C., Mascia, M.B., 2019. Protected area downgrading, downsizing, and degazettement as a threat to iconic protected areas. Conservation Biology 33, 1275–1285. https://doi.org/10.1111/cobi.13365

R Core Team, 2021. R: A language and environment for statistical computing.

Rawson, B., 2007. Surveys, Trade and Training in Voensei Division, Ratanikiri Province, Cambodia. Conservation International / Forestry Administration, Phnom Penh, Cambodia.

Rawson, B.M., Insua-Cao, P., Manh Ha, N., Thinh, V.N., Duc, M.H., Mahood, S.P., Geissmann, T., Roos, C., 2011. The conservation status of gibbons in Vietnam. Fauna and Flora International / Conservation International, Hanoi, Vietnam.

Redford, K.H., Adams, W.M., 2009. Payment for Ecosystem Services and the Challenge of Saving Nature. Conservation Biology 23, 785–787. https://doi.org/10.1111/j.1523-1739.2009.01271.x

Redo, D.J., Grau, H.R., Aide, T.M., Clark, M.L., 2012. Asymmetric forest transition driven by the interaction of socioeconomic development and environmental heterogeneity in Central America. PNAS 109, 8839–8844. https://doi.org/10.1073/pnas.1201664109

RGC, 2002. The Law on Forestry, NS/RKM/0802/016.

RGC, 2001. The Law on Land, NS/RKM/0801/14.

RGC, 1996. Law on environmental protection and natural resource managment, PRK/NS-RKM-1296/36.

Riedel, J., Turley, W.S., 1999. The Politics and Economics of Transition to an Open Market Economy in Viet Nam. OECD, Paris. https://doi.org/10.1787/634117557525

Riggs, R.A., Langston, J.D., Sayer, J., 2018. Incorporating governance into forest transition frameworks to understand and influence Cambodia's forest landscapes. Forest Policy and Economics 96, 19–27. https://doi.org/10.1016/j.forpol.2018.08.003

Riley, C.M., Jayasri, S., Michael, D., 2015. Results of a nationwide census of the long-tailed macaque (Macaca fascicularis) population of Singapore. Raffles Bulletin of Zoology 63, 503–515.

Rodríguez, J.P., Taber, A.B., Daszak, P., Sukumar, R., Valladares-Padua, C., Padua, S., Aguirre, L.F., Medellín, R.A., Acosta, M., Aguirre, A.A., Bonacic, C., Bordino, P., Bruschini, J., Buchori, D., González, S., Mathew, T., Méndez, M., Mugica, L., Pacheco, L.F., Dobson, A.P., Pearl, M., 2007. Globalization of Conservation: A View from the South. Science 317, 755–756. https://doi.org/10.1126/science.1145560

Rostro-García, S., Kamler, J.F., Ash, E., Clements, G.R., Gibson, L., Lynam, A.J., McEwing, R., Naing, H., Paglia, S., 2016. Endangered leopards: Range collapse of the Indochinese leopard (Panthera pardus delacouri) in Southeast Asia. Biological Conservation 201, 293–300. https://doi.org/10.1016/j.biocon.2016.07.001

Rostro-García, S., Kamler, J.F., Crouthers, R., Sopheak, K., Prum, S., In, V., Pin, C., Caragiulo, A., Macdonald, D.W., 2018. An adaptable but threatened big cat: density, diet and prey

selection of the Indochinese leopard (Panthera pardus delacouri) in eastern Cambodia. Royal Society Open Science 5, 171187. https://doi.org/10.1098/rsos.171187
Rostro-García, S., Kamler, J.F., Minge, C., Caragiulo, A., Crouthers, R., Groenenberg, M., Gray, T.N.E., In, V., Pin, C., Sovanna, P., Kéry, M., Macdonald, D.W., 2021. Small cats in big trouble? Diet, activity, and habitat use of jungle cats and leopard cats in threatened dry deciduous forests, Cambodia. Ecology and Evolution 11, 4205–4217. https://doi.org/10.1002/ece3.7316
Rowcliffe, J.M., Field, J., Turvey, S.T., Carbone, C., 2008. Estimating animal density using camera traps without the need for individual recognition. Journal of Applied Ecology 45, 1228–1236. https://doi.org/10.1111/j.1365-2664.2008.01473.x
Rowcliffe, M.J., Carbone, C., Jansen, P.A., Kays, R., Kranstauber, B., 2011. Quantifying the sensitivity of camera traps: an adapted distance sampling approach: Quantifying camera trap sensitivity. Methods in Ecology and Evolution 2, 464–476. https://doi.org/10.1111/j.2041-210X.2011.00094.x
Rowcroft, P., 2008. Frontiers of Change: The Reasons Behind Land-use Change in the Mekong Basin. ambi 37, 213–218. https://doi.org/10.1579/0044-7447(2008)37[213:FOCTRB]2.0.CO;2
Rudel, T.K., Coomes, O.T., Moran, E., Achard, F., Angelsen, A., Xu, J., Lambin, E., 2005. Forest transitions: towards a global understanding of land use change. Global Environmental Change 15, 23–31. https://doi.org/10.1016/j.gloenvcha.2004.11.001
Sachs, J., Woo, W., Yoshino, N., Taghizadeh-Hesary, F., 2019. Importance of green finance for achieving sustainable development goals and energy security, in: Handbook of Green Finance: Energy Security and Sustainable Development, Sustainable Development. Springer, Tokyo.
Sachs, J.D., Warner, A.M., 2001. The curse of natural resources. European Economic Review, 15th Annual Congress of the European Economic Association 45, 827–838. https://doi.org/10.1016/S0014-2921(01)00125-8
Salzman, J., Bennett, G., Carroll, N., Goldstein, A., Jenkins, M., 2018. The global status and trends of Payments for Ecosystem Services. Nat Sustain 1, 136–144. https://doi.org/10.1038/s41893-018-0033-0
Sánchez-Cordón, P.J., Nunez, A., Neimanis, A., Wikström-Lassa, E., Montoya, M., Crooke, H., Gavier-Widén, D., 2019. African Swine Fever: Disease Dynamics in Wild Boar Experimentally Infected with ASFV Isolates Belonging to Genotype I and II. Viruses 11, 852. https://doi.org/10.3390/v11090852
Sanders, M.J., Miller, L., Bhagwat, S.A., Rogers, A., 2021. Conservation conversations: a typology of barriers to conservation success. Oryx 55, 245–254. https://doi.org/10.1017/S0030605319000012
Santana, J., Reino, L., Stoate, C., Borralho, R., Carvalho, C.R., Schindler, S., Moreira, F., Bugalho, M.N., Ribeiro, P.F., Santos, J.L., Vaz, A., Morgado, R., Porto, M., Beja, P., 2014. Mixed Effects of Long-Term Conservation Investment in Natura 2000 Farmland. Conservation Letters 7, 467–477. https://doi.org/10.1111/conl.12077
Saren, P.C., Basu, D., Mukherjee, T., 2019. Population status and distribution assessment of Nicobar Long-tailed macaque Macaca fascicularis umbrosus (Miller, 1902) in Nicobar group of Islands. Zoological Survey of India 199, 227–233.
Sayer, J., Wells, M., 2004. The pathology of projects, in: Getting Biodiversity Projects to Work: Towards More Effective Conservation and Development. Columbia University Press, New York, USA, pp. 35–48.
Sayer, J.A., Margules, C., Boedhihartono, A.K., Sunderland, T., Langston, J.D., Reed, J., Riggs, R., Buck, L.E., Campbell, B.M., Kusters, K., Elliott, C., Minang, P.A., Dale, A., Purnomo, H., Stevenson, J.R., Gunarso, P., Purnomo, A., 2017. Measuring the effectiveness of landscape approaches to conservation and development. Sustain Sci 12, 465–476. https://doi.org/10.1007/s11625-016-0415-z

Scheffers, B.R., Oliveira, B.F., Lamb, I., Edwards, D.P., 2019. Global wildlife trade across the tree of life. Science 366, 71–76. https://doi.org/10.1126/science.aav5327

Scheidel, A., 2016. Tactics of land capture through claims of poverty reduction in Cambodia. Geoforum 75, 110–114. https://doi.org/10.1016/j.geoforum.2016.06.022

Schreckenberg, K., Franks, P., Martin, A., Lang, B., 2016. Unpacking equity for protected area conservation. PARKS 22, 11–28. https://doi.org/10.2305/IUCN.CH.2016.PARKS-22-2KS.en

Sharma, N., Madhusudan, M.D., Sinha, A., 2014. Local and Landscape Correlates of Primate Distribution and Persistence in the Remnant Lowland Rainforests of the Upper Brahmaputra Valley, Northeastern India. Conservation Biology 28, 95–106. https://doi.org/10.1111/cobi.12159

Shevade, V.S., Loboda, T.V., 2019. Oil palm plantations in Peninsular Malaysia: Determinants and constraints on expansion. PLOS ONE 14, e0210628. https://doi.org/10.1371/journal.pone.0210628

Shrestha, S., Shrestha, U.B., Bawa, K., 2018. Socio-economic factors and management regimes as drivers of tree cover change in Nepal. PeerJ 6, e4855. https://doi.org/10.7717/peerj.4855

Shwe, N.M., Sukumal, N., Oo, K.M., Dowell, S., Browne, S., Savini, T., 2020. Importance of isolated forest fragments and low intensity agriculture for the long-term conservation of the green peafowl Pavo muticus. Oryx 1–7. https://doi.org/10.1017/S0030605319000267

Siddig, A.A., Ellison, A.M., Jackson, S., 2015. Calibrating abundance indices with population size estimators of red back salamanders (Plethodon cinereus) in a New England forest. PeerJ 3, e952. https://doi.org/10.7717/peerj.952

Smith, A.D.M., Fulton, E.J., Hobday, A.J., Smith, D.C., Shoulder, P., 2007. Scientific tools to support the practical implementation of ecosystem-based fisheries management. ICES J Mar Sci 64, 633–639. https://doi.org/10.1093/icesjms/fsm041

Smith, S., Hunt, J., Rivard, D., 1993. Risk Evaluation and Biological Reference Points for Fisheries Management, Canadian Special Publication of Fisheries and Aquatic Sciences. NRC Research Press. https://doi.org/10.1139/9780660149561

Sodhi, N.S., Posa, M.R.C., Lee, T.M., Bickford, D., Koh, L.P., Brook, B.W., 2010. The state and conservation of Southeast Asian biodiversity. Biodiversity and Conservation 19, 317–328. https://doi.org/10.1007/s10531-009-9607-5

Sodhy, P., 2004. Modernization and Cambodia. Journal of Third World Studies 21, 153–174.

Sohn, E., 2019. Secrets to writing a winning grant. Nature 577, 133–135. https://doi.org/10.1038/d41586-019-03914-5

Solcomb, M., 2011. The privatization of Cambodia’s rubber industry, in: Cambodia’s Economic Transformation, NIAS Studies in Asian Topics. Nordic Institute of Asian Studies, Leifsgade 33, DK-2300 Copenhagen S, Denmark.

Solcomb, M., 2010. An economic histroy of Cambodia in the twentieth century. NUS Press, National University of Singapore.

Steffen, W., Broadgate, W., Deutsch, L., Gaffney, O., Ludwig, C., 2015. The trajectory of the Anthropocene: the great acceleration. The Anthropocene Review 2, 81–98.

Steinmetz, R., Chutipong, W., Seuaturien, N., Chirngsaard, E., Khaengkhetkarn, M., 2010. Population recovery patterns of Southeast Asian ungulates after poaching. Biological Conservation 143, 42–51. https://doi.org/10.1016/j.biocon.2009.08.023

Steinmetz, R., Srirattanaporn, S., Mor-Tip, J., Seuaturien, N., 2014. Can community outreach alleviate poaching pressure and recover wildlife in South-East Asian protected areas? Journal of Applied Ecology 51, 1469–1478. https://doi.org/10.1111/1365-2664.12239

Stern, D.I., 2004. The Rise and Fall of the Environmental Kuznets Curve. World Development 32, 1419–1439. https://doi.org/10.1016/j.worlddev.2004.03.004

Stevens, D., Dragićević, S., 2007. A GIS-Based Irregular Cellular Automata Model of Land-Use Change. Environ Plann B Plann Des 34, 708–724. https://doi.org/10.1068/b32098

Stibig, H.-J., Achard, F., Carboni, S., Raši, R., Miettinen, J., 2014. Change in tropical forest cover of Southeast Asia from 1990 to 2010. Biogeosciences 11, 247–258. https://doi.org/10.5194/bg-11-247-2014

Sukumal, N., Dowell, S.D., Savini, T., 2017. Micro-habitat selection and population recovery of the Endangered Green Peafowl Pavo muticus in western Thailand: implications for conservation guidance. Bird Conservation International 27, 414–430. https://doi.org/10.1017/S095927091600037X

Sukumal, N., McGowan, P.J.K., Savini, T., 2015. Change in status of green peafowl Pavo muticus (Family Phasianidae) in Southcentral Vietnam: A comparison over 15 years. Global Ecology and Conservation 3, 11–19. https://doi.org/10.1016/j.gecco.2014.10.007

Sullivan, M., 2011. China's aid to Cambodia, in: Cambodia's Economic Transformation, NIAS Studies in Asian Topics. Nordic Institute of Asian Studies, Leifsgade 33, DK-2300 Copenhagen S, Denmark.

Sun, C., 2014. Recent growth in China's roundwood import and its global implications. Forest Policy and Economics 39, 43–53. https://doi.org/10.1016/j.forpol.2013.11.006

Sunderlin, W.D., Angelsen, A., Belcher, B., Burgers, P., Nasi, R., Santoso, L., Wunder, S., 2005. Livelihoods, forests, and conservation in developing countries: An Overview. World Development, Livelihoods, forests, and conservation 33, 1383–1402. https://doi.org/10.1016/j.worlddev.2004.10.004

Syamil, A.R., Mohid-Ridwan, A.R., Amsah, M.A., Abdul-Latiff, M.A.B., Md-Zain, B.M., 2019. Population census and age category character of Stump-tailed macaque, Macaca arctoides, in Northern Peninsular Malaysia. Biodiversitas Journal of Biological Diversity 20. https://doi.org/10.13057/biodiv/d200903

Symes, W.S., Rao, M., Mascia, M.B., Carrasco, R.L., 2016. Why do we lose protected areas? Factors influencing protected area downgrading, downsizing and degazettment (PADDD) in the tropics and sub-tropics. Global Change Biology n/a-n/a. https://doi.org/10.1111/gcb.13089

Taylor, J.E., Whitney, E., Zhu, H., 2019. Local-economy impacts of cash crop promotion. IFAD.

Teng, L.-W., Liu, Z.-S., Song, Y.-L., Zeng, Z.-G., Li, S.-Y., Lin, X.-M., 2005. Population size and characteristics of Indian muntjac (Muntiacus muntjak) at Hainan Datian National Nature Reserve. Acta Theriologica Sinica 25, 138–142.

Thinh, V.N., Rawson, B., Hallam, C., Kenyon, M., Nadler, T., Walter, L., Roos, C., 2010. Phylogeny and distribution of crested gibbons (genus Nomascus) based on mitochondrial cytochrome b gene sequence data. American Journal of Primatology 72, 1047–1054. https://doi.org/10.1002/ajp.20861

Timmins, R.J., Steinmetz, R., Poulsen, M.K., Evans, T.D., Duckworth, J.W., Boonratana, R., 2013. The Indochinese Silvered Leaf Monkey Trachypithecus germaini (Sensu lato) in Lao PDR. prco 26, 75–87. https://doi.org/10.1896/052.026.0112

Tittensor, D.P., Walpole, M., Hill, S.L.L., Boyce, D.G., Britten, G.L., Burgess, N.D., Butchart, S.H.M., Leadley, P.W., Regan, E.C., Alkemade, R., Baumung, R., Bellard, C., Bouwman, L., Bowles-Newark, N.J., Chenery, A.M., Cheung, W.W.L., Christensen, V., Cooper, H.D., Crowther, A.R., Dixon, M.J.R., Galli, A., Gaveau, V., Gregory, R.D., Gutierrez, N.L., Hirsch, T.L., Höft, R., Januchowski-Hartley, S.R., Karmann, M., Krug, C.B., Leverington, F.J., Loh, J., Lojenga, R.K., Malsch, K., Marques, A., Morgan, D.H.W., Mumby, P.J., Newbold, T., Noonan-Mooney, K., Pagad, S.N., Parks, B.C., Pereira, H.M., Robertson, T., Rondinini, C., Santini, L., Scharlemann, J.P.W., Schindler, S., Sumaila, U.R., Teh, L.S.L., van Kolck, J., Visconti, P., Ye, Y., 2014. A mid-term analysis of progress toward international biodiversity targets. Science 346, 241–244. https://doi.org/10.1126/science.1257484

Tomas, W.M., Berlinck, C.N., Chiaravalloti, R.M., Faggioni, G.P., Strüssmann, C., Libonati, R., Abrahão, C.R., do Valle Alvarenga, G., de Faria Bacellar, A.E., de Queiroz Batista, F.R., Bornato, T.S., Camilo, A.R., Castedo, J., Fernando, A.M.E., de Freitas, G.O., Garcia, C.M., Gonçalves, H.S., de Freitas Guilherme, M.B., Layme, V.M.G., Lustosa, A.P.G., De Oliveira, A.C., da Rosa Oliveira, M., de Matos Martins Pereira, A., Rodrigues, J.A., Semedo, T.B.F., de Souza, R.A.D., Tortato, F.R., Viana, D.F.P., Vicente-Silva, L., Morato, R., 2021. Distance sampling surveys reveal 17 million vertebrates directly killed by the 2020's wildfires in the Pantanal, Brazil. Sci Rep 11, 23547. https://doi.org/10.1038/s41598-021-02844-5

Top, N., Mizoue, N., Ito, S., Kai, S., Nakao, T., Ty, S., 2009. Effects of population density on forest structure and species richness and diversity of trees in Kampong Thom Province, Cambodia. Biodivers Conserv 18, 717–738. https://doi.org/10.1007/s10531-008-9535-9

Torres, E., Zeidan, R., 2016. The life-cycle of national development banks: The experience of Brazil's BNDES. The Quarterly Review of Economics and Finance, Special Issue: Is there a Brazilian Development "Model"? 62, 97–104. https://doi.org/10.1016/j.qref.2016.07.006

Toyama, H., Kajisa, T., Tagane, S., Mase, K., Chhang, P., Samreth, V., Ma, V., Sokh, H., Ichihashi, R., Onoda, Y., Mizoue, N., Yahara, T., 2015. Effects of logging and recruitment on community phylogenetic structure in 32 permanent forest plots of Kampong Thom, Cambodia. Philosophical Transactions of the Royal Society B: Biological Sciences 370, 20140008. https://doi.org/10.1098/rstb.2014.0008

Toyoda, A., Maruhashi, T., Malaivijitnond, S., Koda, H., 2020. Dominance status and copulatory vocalizations among male stump-tailed macaques in Thailand. Primates 61, 685–694. https://doi.org/10.1007/s10329-020-00820-7

Traeholt, C., Bunthoeun, R., Rawson, B.M., Samuth, M., Virak, C., Vuthin, S., 2005. Status review of pileated gibbon, Hylobates pileatus and yellow-cheeked crested gibbon, Nomascus gabriellae, in Cambodia. Flora and Fauna International, PO Box 1380, Phnom Penh, Cambodia.

Transparency International, 2021. Corruption Perceptions Index. Transparency International, Berlin, Germany.

Tsujino, R., Kajisa, T., Yumoto, T., 2019. Causes and history of forest loss in Cambodia. International Forestry Review 21, 372–384. https://doi.org/10.1505/146554819827293178

Tulloch, V.J.D., Turschwell, M.P., Giffin, A.L., Halpern, B.S., Connolly, R., Griffiths, L., Frazer, M., Brown, C.J., 2020. Linking threat maps with management to guide conservation investment. Biological Conservation 245, 108527. https://doi.org/10.1016/j.biocon.2020.108527

Ty, T.V., Sunada, K., Ichikawa, Y., Oishi, S., 2012. Scenario-based Impact Assessment of Land Use/Cover and Climate Changes on Water Resources and Demand: A Case Study in the Srepok River Basin, Vietnam—Cambodia. Water Resour Manage 26, 1387–1407. https://doi.org/10.1007/s11269-011-9964-1

UNEP-WCMC, IUCN, 2020. The World Database on Protected Areas. UNEP-WCMC & IUCN, Cambridge, UK.

Utami, N.W.F., Wirawan, I.G.P., Firn, J., Kepakisan, A.N.K., Kusdyana, I.P.G.A., Nicol, S., Carwardine, J., 2020. Prioritizing management strategies to achieve multiple outcomes in a globally significant Indonesian protected area. Conservation Science and Practice 2, e157. https://doi.org/10.1111/csp2.157

van Balen, S., Prawiradilaga, D.M., Indrawan, M., 1995. The distribution and status of green peafowl Pavo muticus in Java. Biological Conservation 71, 289–297. https://doi.org/10.1016/0006-3207(94)00048-U

Van Den Hoek, J., Ozdogan, M., Burnicki, A., Zhu, A.-X., 2014. Evaluating forest policy implementation effectiveness with a cross-scale remote sensing analysis in a priority conservation area of Southwest China. Applied Geography 47, 177–189. https://doi.org/10.1016/j.apgeog.2013.12.010

Van Thanh, N., Yapwattanaphun, C., 2015. Banana Farmers' Adoption of Sustainable Agriculture Practices in the Vietnam Uplands: The Case of Quang Tri Province. Agriculture and Agricultural Science Procedia, 1st International Conference on Asian Highland Natural Resources Management (AsiaHiLand) and 2nd IDRC-SEARCA Upland Fellowship and

Conference Chiang Mai, Thailand January 7 - 9, 2015 5, 67–74. https://doi.org/10.1016/j.aaspro.2015.08.010
van Vliet, N., Mertz, O., Heinimann, A., Langanke, T., Pascual, U., Schmook, B., Adams, C., Schmidt-Vogt, D., Messerli, P., Leisz, S., Castella, J.-C., Jørgensen, L., Birch-Thomsen, T., Hett, C., Bech-Bruun, T., Ickowitz, A., Vu, K.C., Yasuyuki, K., Fox, J., Padoch, C., Dressler, W., Ziegler, A.D., 2012. Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: A global assessment. Global Environmental Change, Adding Insult to Injury: Climate Change, Social Stratification, and the Inequities of Intervention 22, 418–429. https://doi.org/10.1016/j.gloenvcha.2011.10.009
Venter, O., Sanderson, E.W., Magrach, A., Allan, J.R., Beher, J., Jones, K.R., Possingham, H.P., Laurance, W.F., Wood, P., Fekete, B.M., Levy, M.A., Watson, J.E.M., 2016. Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. Nat Commun 7, 12558. https://doi.org/10.1038/ncomms12558
Vrieze, P., Kuch, N., 2012. Carving up Cambodia: One concession at a time. The Cambodia Daily 4–11.
Waithaka, J., Dudley, N., Alvarez, M., Arguedas Mora, S., Chapman, S., Figgis, P., Fitzsimons, J., Gallon, S., Gray, T.N.E., Kim, M., Pasha, M.K.S., Perkin, S., Roig-Boixeda, P., Sierra, C., Valverde, A., Wong, M., 2021. Impacts of COVID-19 on protected and conserved areas: A global overview and regional perspectives. PARKS 27, 41–56.
Waldron, A., Mooers, A.O., Miller, D.C., Nibbelink, N., Redding, D., Kuhn, T.S., Roberts, J.T., Gittleman, J.L., 2013. Targeting global conservation funding to limit immediate biodiversity declines. PNAS 110, 12144–12148. https://doi.org/10.1073/pnas.1221370110
Walls, S.C., Barichivich, W.J., Chandler, J., Meade, A.M., Milinichik, M., O'Donnell, K.M., Owens, M.E., Peacock, T., Reinman, J., Watling, R.C., Wetsch, O.E., 2019. Seeking shelter from the storm: Conservation and management of imperiled species in a changing climate. Ecology and Evolution 9, 7122–7133. https://doi.org/10.1002/ece3.5277
Walston, J., Davidson, P., Men, S., 2001. A wildlife survey of Southern Mondulkiri Province, Cambodia. Wildlife Conservation Society, Wildlife Conservation Society Cambodia program, Phnom Penh.
Wardle, D.A., Bardgett, R.D., Callaway, R.M., Van der Putten, W.H., 2011. Terrestrial Ecosystem Responses to Species Gains and Losses. Science 332, 1273–1277. https://doi.org/10.1126/science.1197479
Washington, H., 2019. KSWS REDD+ Benefit sharing manual. Wildlife Conservation Society, Phnom Penh, Cambodia.
Watson, J.E.M., Dudley, N., Segan, D.B., Hockings, M., 2014. The performance and potential of protected areas. Nature 515, 67–73. https://doi.org/10.1038/nature13947
WCS, 2021. USAID Keo Seima Conservation Project (Final Report). Wildlife Conservation Society and USAID, Phnom Penh, Cambodia.
Wharton, C.H., 1957. An ecological study of the Kouprey (Novibos sauveli: Urbain). Monographs of the Institute of Science and Technology Monograph 5, 111 pp.
White, E.R., 2019. Minimum Time Required to Detect Population Trends: The Need for Long-Term Monitoring Programs. BioScience 69, 40–46. https://doi.org/10.1093/biosci/biy144
WHO, 2019. Financial health protection in Cambodia (2009-2016): Analysis of data from the Cambodia Socioeconomic Survey. World Health Organisation, Manilla, Phillipines.
Widyono, B., 2015. United Nations Transitional Authority in Cambodia (UNTAC). The Oxford Handbook of United Nations Peacekeeping Operations. https://doi.org/10.1093/oxfordhb/9780199686049.013.38
Wiedmann, T., Lenzen, M., 2018. Environmental and social footprints of international trade. Nature Geosci 11, 314–321. https://doi.org/10.1038/s41561-018-0113-9
Wilcove, D.S., Giam, X., Edwards, D.P., Fisher, B., Koh, L.P., 2013. Navjot's nightmare revisited: logging, agriculture, and biodiversity in Southeast Asia. Trends in Ecology & Evolution 28, 531–540. https://doi.org/10.1016/j.tree.2013.04.005

Wilkinson, C.L., Yeo, D.C.J., Tan, H.H., Fikri, A.H., Ewers, R.M., 2018. Land-use change is associated with a significant loss of freshwater fish species and functional richness in Sabah, Malaysia. Biological Conservation 222, 164–171. https://doi.org/10.1016/j.biocon.2018.04.004
Williams, M., 2003. Deforesting the Earth: From Prehistory to Global Crisis. University of Chicago Press.
Wilson, E.O., 1999. Consilience: The Unity of Knowledge. Vintage Books.
Wilson, K.A., McBride, M.F., Bode, M., Possingham, H.P., 2006. Prioritizing global conservation efforts. Nature 440, 337–340. https://doi.org/10.1038/nature04366
Wittemyer, G., 2011. Effects of Economic Downturns on Mortality of Wild African Elephants. Conservation Biology 25, 1002–1009. https://doi.org/10.1111/j.1523-1739.2011.01713.x
Wittemyer, G., Elsen, P., Bean, W.T., Burton, A.C.O., Brashares, J.S., 2008. Accelerated Human Population Growth at Protected Area Edges. Science 321, 123–126. https://doi.org/10.1126/science.1158900
Woinarski, J.C.Z., 2018. A framework for evaluating the adequacy of monitoring programs for threatened species, in: Monitoring Threatened Species and Ecological Communities. Csiro Publishing, Victoria, Australia.
Wood, S., 2006. Generalized Additive Models: An Introduction with R. CRC Press.
World Bank, 2014. Where have all the poor gone? Cambodia poverty assessment 2013. World Bank Group, Washington DC, USA.
Wunder, S., Angelsen, A., Belcher, B., 2014. Forests, Livelihoods, and Conservation: Broadening the Empirical Base. World Development, Forests, Livelihoods, and Conservation 64, S1–S11. https://doi.org/10.1016/j.worlddev.2014.03.007
Xu, W., Pimm, S.L., Du, A., Su, Y., Fan, X., An, L., Liu, J., Ouyang, Z., 2019. Transforming Protected Area Management in China. Trends in Ecology & Evolution 34, 762–766. https://doi.org/10.1016/j.tree.2019.05.009
Xu, X., Jain, A.K., Calvin, K.V., 2019. Quantifying the biophysical and socioeconomic drivers of changes in forest and agricultural land in South and Southeast Asia. Global Change Biology 25, 2137–2151. https://doi.org/10.1111/gcb.14611
Yang, X., Zheng, X.-Q., Lv, L.-N., 2012. A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata. Ecological Modelling 233, 11–19. https://doi.org/10.1016/j.ecolmodel.2012.03.011
Youn, Y.-C., Choi, J., de Jong, W., Liu, J., Park, M.S., Camacho, L.D., Tachibana, S., Huudung, N.D., Bhojvaid, P.P., Damayanti, E.K., Wanneng, P., Othman, M.S., 2017. Conditions of forest transition in Asian countries. Forest Policy and Economics, Forest transition in Asia 76, 14–24. https://doi.org/10.1016/j.forpol.2016.07.005
Zaehringer, J.G., Lundsgaard-Hansen, L., Thein, T.T., Llopis, J.C., Tun, N.N., Myint, W., Schneider, F., 2020. The cash crop boom in southern Myanmar: tracing land use regime shifts through participatory mapping. Ecosystems and People 16, 36–49. https://doi.org/10.1080/26395916.2019.1699164
Zeb, A., Armstrong, G.W., Hamann, A., 2019. Forest conversion by the indigenous Kalasha of Pakistan: A household level analysis of socioeconomic drivers. Global Environmental Change 59, 102004. https://doi.org/10.1016/j.gloenvcha.2019.102004
Zeng, Z., Estes, L., Ziegler, A.D., Chen, A., Searchinger, T., Hua, F., Guan, K., Jintrawet, A., Wood, E.F., 2018. Highland cropland expansion and forest loss in Southeast Asia in the twenty-first century. Nature Geoscience 1. https://doi.org/10.1038/s41561-018-0166-9
Zheng, H., Robinson, B.E., Liang, Y.-C., Polasky, S., Ma, D.-C., Wang, F.-C., Ruckelshaus, M., Ouyang, Z.-Y., Daily, G.C., 2013. Benefits, costs, and livelihood implications of a regional payment for ecosystem service program. PNAS 110, 16681–16686. https://doi.org/10.1073/pnas.1312324110

Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A., Smith, G.M., 2009. Mixed effects models and extensions in ecology with R, Statistics for Biology and Health. Springer Science+Business Media, New York, USA.

Appendix A - Protected area downgrading, downsizing, and degazettement in Cambodia: Enabling conditions and opportunities for intervention

This appendix is a manuscript that has been in development for several years and has not been written as a formal part of my PhD. It is based in Cambodia and covers themes and topics that are relevant to this thesis, and therefore may be of interest to readers. It will soon be submitted to the journal Conservation Science and Practice as a 'perspectives and notes' article. The author list is: Matthew Nuttall, Harri Washington, Rachel Golden Kroner, Erick Olsson, Keziah Hobson, Joel Merrimen, Alex Diment, Ung Vises, Nils Bunnefeld.

A.1. ABSTRACT

The sustainability of protected areas (PAs) is challenged by their downgrading, downsizing, and degazettement (PADDD), which has been documented worldwide. Case studies of national and local enabling conditions that allow ecologically destructive PADDD events are of great value to the conservation community and may help to prevent future events. Using information collected from legal documents, we identified 39 PADDD events affecting two adjacent PAs in northeastern Cambodia which affected each PA differently, despite similar economic, environmental, social and biological conditions. Important differences in local context led to eventual degazettement (100% loss) of one PA and downsizing (loss of 6%) of the other, the remainder of which remains protected. This case study confirms the contribution of securing Indigenous land tenure to effective PA management and demonstrates the importance of investing in site-level capacity to ensure that social and biological conditions are monitored and proposed PADDD events can be successfully challenged.

A.2. INTRODUCTION

Protected areas (PAs) are cornerstones of biodiversity conservation efforts (Watson et al., 2014). Globally, protected land- and seascape coverage continues to increase (UNEP-WCMC and IUCN, 2020). PAs can only effectively contribute to conservation and improved human well-being in the long term if they are durable entities, invulnerable to fluctuating economic demands and political agendas. However, a framework for tracking and evaluating the tempering, reduction, and loss of PAs via legal mechanisms has highlighted a widespread and pervasive phenomenon (Golden Kroner et al., 2019; Mascia et al., 2014; Mascia & Pailler, 2011). The PA downgrading, downsizing, and degazettement (PADDD) framework defines *downgrading* as the decrease in legal restrictions on human use within a PA; *downsizing* as the reduction in size of a PA via a legal boundary change; and *degazettement* as complete loss of protection (Mascia & Pailler, 2011). Since 1892, more than 4,200 PADDD events have occurred in at least 74 countries, affecting over 3.4 million km^2 of protected land

and ocean, more than 500,000 km^2 of which represent a complete loss of legal protection (Conservation International and World Wildlife Fund, 2021; Golden Kroner et al., 2019). Some PADDD events, including consolidation and optimisation of PA networks (Fuller et al., 2010) and securing indigenous land rights (Borges et al., 2019), have not adversely affected biodiversity. Nevertheless, the majority (61%) of global PADDD events were enacted to enable or expand industrial-scale economic activities, especially agriculture, resource extraction, and infrastructure (Golden Kroner et al., 2019).

Southeast Asia (SEA) has exceptional faunal diversity and harbours a greater number of threatened species than any other continental area (Gray et al., 2018). Deforestation rates in SEA are among the highest globally and are accelerating (Hughes, 2017; Kim et al., 2015), driven predominantly by industrial-scale agriculture, mining, and infrastructure development (Estoque et al., 2019). Between 1910 and 2013, at least 255 PADDD events were enacted in SEA (www.padddtracker.org). Their proximate causes include industrial agriculture, infrastructure, and rural settlements, yet their impacts on conservation outcomes are poorly understood (Golden Kroner et al., 2019).

PADDD may accelerate forest loss (as observed in Malaysia and Peru, Forrest et al. 2015), or forest loss may put PAs at higher risk of PADDD (as observed in Brazil, Tesfaw et al. 2018). These dynamics make it difficult to predict the causal impacts of PADDD on biodiversity loss, to assess risk, and to design proactive responses to prevent or mitigate effects of potentially damaging PADDD events. Case studies evaluating national and local enabling conditions that are precursors to destructive PADDD events are of great value (Golden Kroner et al., 2019; Qin et al., 2019). Insights into political, social, economic, and environmental conditions surrounding PADDD events, particularly from case studies, can provide data to generate hypotheses describing the contexts within which PADDD events lead to positive and negative biodiversity outcomes. Such hypotheses can then be tested and used to develop frameworks for NGOs, businesses, and the public to create conditions and influence decisions that reduce negative PADDD events. Transparent reporting of successful or unsuccessful opposition to events will help conservation managers to foresee and prevent PADDD within their PAs.

This paper aims to elucidate conditions and mechanisms surrounding two PADDD events in Cambodia through a comparative case study and generate conservation lessons that may apply to other regions. We collected and reviewed legal documents (see Supporting Information for further details on methods) detailing 39 PADDD events that were enacted over less than a decade (2009‒2018) in two adjacent PAs in northeastern Cambodia. Based on our experience (MN, KH, HW, AD, UV) at the site, we describe the political and economic contexts of these events at national and local levels, and the different conditions affecting each PA that allowed partially successful responses to PADDD events at one site, and significant biodiversity loss at the other. We highlight examples of PADDD events from these PAs that had both positive and negative impacts on biodiversity, and a legal process that lacks transparency and due process. Finally, we discuss the relevance of these lessons to the wider conservation community.

A.3. Case study

A.3.1 Study sites

The Eastern Plains Landscape is one of the largest contiguous PA networks in SEA, with six PAs covering close to 1 million hectares (Figure 1, O'Kelly et al., 2012). Keo Seima Wildlife Sanctuary (hereafter 'Keo Seima'), located in Mondulkiri and Kratie provinces, became a PA in 2002 and remains protected (Figure 1). Snuol Wildlife Sanctuary (hereafter 'Snuol'), in Kratie Province, became a PA in 1993, but after 28 downgrading and downsizing events was degazetted in 2018. Both sites were originally designated as PAs because surveys highlighted the presence of important biodiversity (Baltzer et al., 2001; Walston et al., 2001). Subsequent monitoring in Keo Seima between 2010 and 2020 emphasised its global importance for several threatened species, including the largest single population of the endangered Yellow-cheeked crested gibbon (Nuttall et al., 2021). Keo Seima has had relatively well-funded management and an extensive conservation programme since 2002, largely due to the presence of an international conservation organisation (the Wildlife Conservation Society, WCS) that was able to leverage external funding. Close collaboration between WCS and the Royal Government of Cambodia (RGC) in Keo Seima from 2002 secured long-term funding and technical capabilities to support conservation activities. Snuol received little funding or investment in personnel from the RGC and no external organisations worked at the site. Thus, it never had an active conservation programme, and its law enforcement activities were less substantial than in other NGO-supported PAs in the Eastern Plains Landscape.

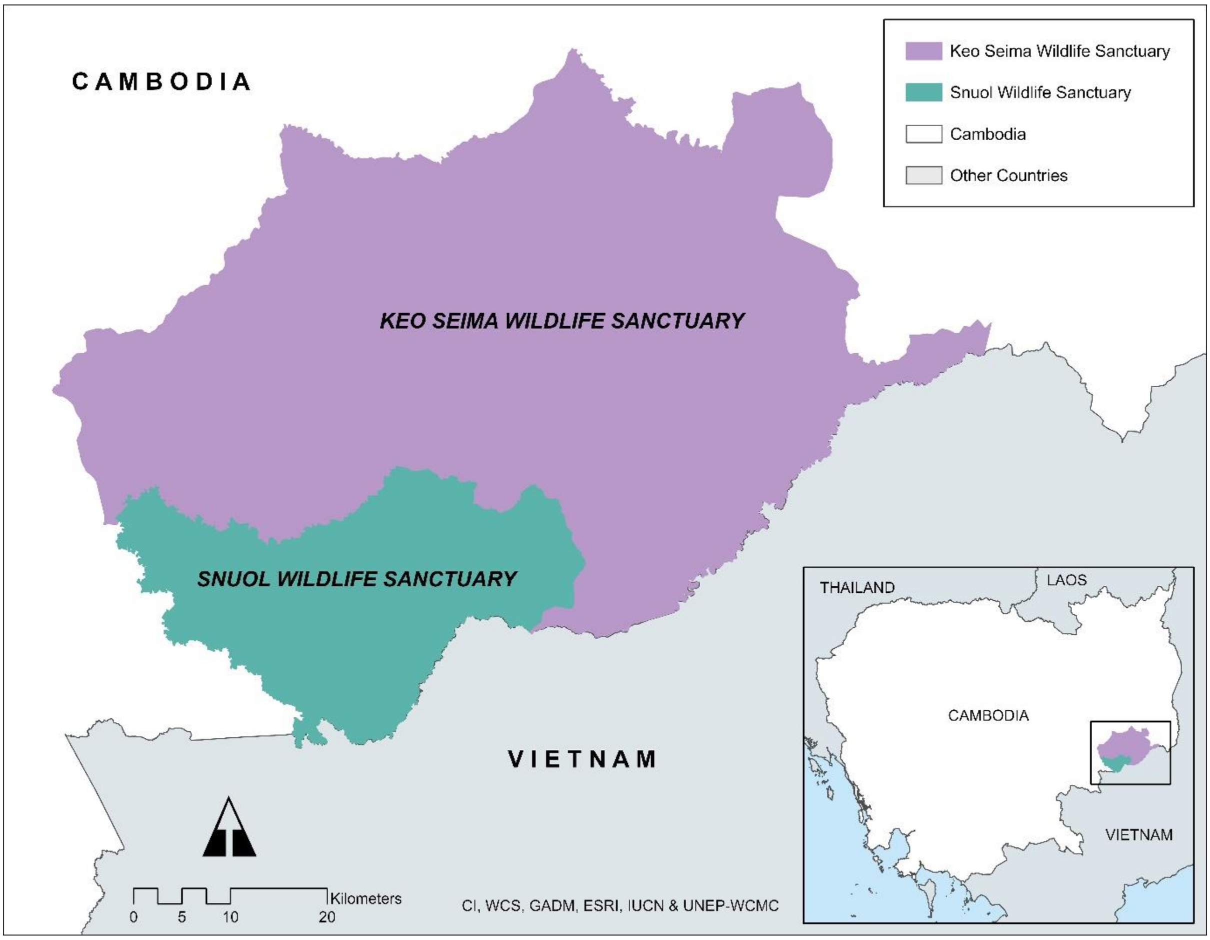

Figure A1. Keo Seima Wildlife Sanctuary and Snuol Wildlife Sanctuary in eastern Cambodia

A.3.2. Enabling conditions of PADDD events - National

The first democratic elections following decades of war and civil unrest were held in Cambodia in 1993, after which the country moved beyond post-conflict status and experienced rapid economic growth (Hughes & Un, 2011). The civil war and subsequent tumultuous years left Cambodia with no official public records of land ownership, resulting in many years of insecure land tenure and conflict (Chandler, 2008). National policies emerged that would pave the way for PADDD events to occur in both PAs. From the mid-2000s, the government pursued the development of agro-industrial land concessions to encourage economic growth (Neef et al., 2013). Such concessions contributed to the economy initially through export of timber cleared from forests, which fed regional and global timber demand (Li et al., 2008; Sun, 2014), and then through agricultural production and export (Borras & Franco, 2011; Fox & Castella, 2013). There has been widespread criticism of these industrial-scale economic land concessions (hereafter ‘economic concessions’), including their impacts on deforestation (Davis et al., 2015), the opaque legal mechanisms behind the awarding of concessions, and apparent disregard for local land rights and protected areas (Global Witness, 2013; Neef et al., 2013; Oldenburg and Neef, 2014; Vrieze and Kuch, 2012). By 2013, 1.2 million hectares of land in

Cambodia had been leased for economic concessions, 346,000 hectares of which were located within PAs (Beauchamp et al., 2018; Conservation International and World Wildlife Fund, 2021; Watson et al., 2014). At the request of development partners, the RGC responded by introducing social land concessions (hereafter 'social concessions'), aiming to provide secure land tenure and increase land distribution to families and individuals (Oldenburg & Neef, 2014).

The Land Law, enacted in 2001, contains provisions for securing the land rights of indigenous people. By 2012, three communities had been awarded an Indigenous Communal Land Title (hereafter 'Indigenous title'), and many others were partway through the process (Milne, 2013b). Indigenous titles provide legal tenure over traditional lands for Indigenous communities, emphasising communal ownership and management and allowing traditional rotational agriculture (Milne, 2013b). In addition to economic concessions, social concessions, and Indigenous titles, a further land acquisition scheme, Directive 01, was launched in 2012 to rapidly distribute individual land titles, predominantly to rural families. The mechanism aimed to provide land tenure to families living around economic concessions, seeking to prevent or resolve conflict between economic concession companies and residents. More than 600,000 individual land titles were issued in two years, providing secure land tenure for many families (Grimsditch & Schoenberger, 2015). However, the scheme faced criticisms of inaccurate land measurements, procedural inconsistencies, a lack of transparency, failure to address conflicts, and issuing titles within protected areas (Grimsditch & Schoenberger, 2015; Milne, 2013).

These four land tenure mechanisms (economic concession, social concession, Indigenous title, Directive 01) led to rapid and widespread changes in land ownership and use nationwide (Grimsditch & Schoenberger, 2015; Neef et al., 2013). The mechanisms were operationalised quickly and in parallel, which, in conjunction with poor administration and a lack of transparency in legal procedures, has had many negative consequences for PAs, primarily forest loss resulting from private or commercial land titling within PA boundaries. A traditionally top-down approach to policy implementation (despite decentralisation efforts, see Faguet (2014)), and thus limited autonomy for sub-national government, reduced the effectiveness of local application of these mechanisms. Finally, implementation of land tenure mechanisms requires input from multiple government ministries. Coupled with a historical division of responsibility for environmental management between two different ministries, this requirement has led to complex jurisdictional stalemates when conflicts arise in PAs.

A3.3. Enabling conditions - Local

The rapid increase in economic and social concessions and nationwide implementation of Directive 01 drove dramatic changes to infrastructure and land use at the local scale, particularly in rural areas such as the Eastern Plains Landscape. Despite legal restrictions on awarding economic and social concessions inside PAs, exceptions apply in certain circumstances, including when areas are considered ecologically ‘degraded’. These exceptions were used frequently in the Eastern Plains Landscape and elsewhere in the country to facilitate the awarding of concessions inside PAs, despite little evidence to support claims of such degradation. Economic concessions require large workforces and infrastructure, and both social concessions and Directive 01 offered opportunities for landless families to acquire farmland. Improved transport infrastructure, often developed by economic concession companies, increased the accessibility of previously remote areas such as the Eastern Plains Landscape. In combination, these factors led to large-scale migration into the landscape, increasing population density, urbanisation, and land speculation, all of which have negative consequences for ecological values of PAs (Evans et al., 2013; Symes et al., 2016).

Economic concessions were established within both Keo Seima and Snuol. Forests inside economic concession boundaries in both PAs were cleared rapidly, followed by escalating loss of surrounding forest. In Keo Seima, the law enforcement capacity of PA authorities was overwhelmed by the volume of people—both those employed by economic concession companies and opportunistic migrants—and the speed of illegal forest clearance, resulting in significant forest loss. The situation was exacerbated by regular conflict between PA authorities and economic concessionaires regarding concession boundaries. In Snuol, once all the forest within economic concession boundaries had been cleared, social concessions were awarded on the same land, which allowed in-migrants to settle. Meanwhile, the rapid loss of forests adjacent to economic concessions led to much of the PA being designated as ‘degraded’, thus facilitating the allocation of further social concessions. Insufficient law enforcement capacity in both Keo Seima and Snuol allowed land speculation and illegal forest clearance to also occur in parts of the PAs not adjacent to economic concessions. Directive 01 was then used to apply for individual titles to cleared land, even though the plots were inside PA boundaries. Implementation of Directive 01 in both PAs lacked transparency, regulation, and communication between titling officials and PA authorities, allowing many applications for land titles within the PAs to succeed, thus inappropriately legalising these land claims.

A3.4. PADDD events in Keo Seima and Snuol

In Keo Seima, 178.56 km^2 of the PA has been either downgraded or downsized (Table 1), resulting in complete loss of primary lowland evergreen and semi-evergreen forest across most of the areas affected. In Snuol, most of the forest was clear-felled by 2014, representing a significant loss of evergreen and semi-evergreen forest. Despite their adjacent locations and similar political and local contexts, the number and extent of PADDD events enacted in Keo Seima and Snuol differ significantly (Table 1). Keo Seima lost approximately 6% of its total area and remains an important area for biodiversity (Nuttall et al., 2021), while Snuol lost approximately 80% of its area to downgrading and downsizing events between 2009 and 2013, before being entirely degazetted in

2018. Eight of the PADDD events in Keo Seima resulted from the awarding of Indigenous titles, which are considered beneficial for both Indigenous land rights and conservation (Schreckenberg et al., 2016). Secure land tenure for Indigenous communities allowed clear demarcation between community land and PA land, provided legal agricultural land for the communities involved, and strengthened the ability of these communities to prevent in-migration, illegal clearing by outsiders, and allocation of concessions. Many of the PADDD events in Snuol were enacted as a result of forest clearance; social concessions were awarded on previously cleared economic concessions, and other cleared land became classified as 'degraded' and was thereby also eligible to be awarded as social concessions. No Indigenous titles were granted in Snuol.

Table A1. Protected area downgrading, downsizing, and degazettement (PADDD) events occurring in two adjacent protected areas in northeastern Cambodia.

Protected area	Year gazetted	Original PA extent (km^2)	Number of PADDD events				Years of PADDD event occurrence	Area affected (%)
			Downgrade[a]	Downsize[b]	Degazette	Total		
Keo Seima Wildlife Sanctuary	2002	2926.9	3	8	-	11	2012-2013	6.1
Snuol Wildlife Sanctuary	1993	750.89	17	10	1	28	2009-2018	100

[a] Economic concessions and social concessions
[b] Directive 01 and indigenous titles

A.3.5. Responses to PADDD events

WCS has worked with the RGC since 1999, providing financial, technical, and management support both nationally and across multiple conservation landscapes, including in Keo Seima but not in Snuol. The governance and management of Keo Seima is a hybrid of the 'project co-management' and 'financial-technical support' models of PA management (see Baghai et al., 2018), with close working relationships between government and NGO staff. This long-term collaboration, where NGO and government staff work in close-knit teams and share office space, fostered a working relationship that facilitated rapid formal and informal sharing of information about PADDD events that were being considered by the government.

The NGO–government collaboration provided Keo Seima with well-resourced technical teams that were able to react quickly to information about newly proposed PADDD events. Geographic Information Systems (GIS) staff had access to government-approved spatial data (e.g., delineated PA boundaries) and up-to-date habitat and land-cover data, allowing accurate spatial interrogation of proposed events (concessions and Directive 01 land parcels). Biodiversity monitoring staff had previously collected, and analysed biodiversity data spanning multiple years, produced a species list, and had reliable population estimates and areas of occurrence for several key species, highlighting the regional and global importance of the site. Community engagement staff had collected detailed demographic and socioeconomic data for communities within Keo Seima, strongly demonstrating the importance of the forest for livelihoods and Indigenous culture, and had supported indigenous communities in Keo Seima through the Indigenous titling process, which strengthened local land rights. Finally, law enforcement staff had evidence (e.g., reports, patrol records) of attempts to prevent the illegal clearance of many of the proposed Directive 01 land parcels within Keo Seima. The technical teams compiled this evidence, supporting data, and other appropriate documentation into persuasive reports highlighting the importance of Keo Seima for environmental protection and land rights, and the weaknesses in the proposals for concessions or titles based on the defined legal process for awarding each (e.g., consideration of environmental impact assessments, Indigenous land rights, intactness of forest areas). This coherent strategy allowed some proposed events to be prevented.

In contrast, Snuol did not benefit from a collaboration between an NGO (or any other partners) and the RGC, and had none of the above data, resources, or technical teams, which precluded effective interventions to stop proposed PADDD events. Snuol was degazetted in 2018 and has since lost what little forest cover remained.

A.4. DISCUSSION

Understanding the conditions within which PADDD events occur is critical for conservationists to anticipate and challenge events that are likely to have negative effects on biodiversity (Golden Kroner et al., 2019). This case study demonstrates how PADDD events shaped by the same political and economic conditions affected two adjacent PAs in very different ways. Overall, the events resulted in deforestation and have had negative consequences for biodiversity in both PAs. However, one PA was subsequently degazetted, while the other continues to be protected.

Ineffective governance of PAs is common wherever top-down decision-making, lack of procedural obligations, local power dynamics, and poor transparency make successful opposition to proposed PADDD events challenging (Dawson et al., 2018; de Koning et al., 2017; Morea, 2019; Paudel et al., 2012). The PADDD events in this case study were challenging for PA staff to manage and prevent because legal processes, including information about proposed boundary and regulatory changes, were often not transparent, with little or no opportunity for participation by local people, PA management, or NGOs. Although it is difficult to make generalisations about drivers of PADDD (Qin et al., 2019), many of the legal and institutional challenges that precluded effective and transparent opposition to these PADDD events are not unique to Cambodia. Legal frameworks that are weak, opaque, and poorly understood also exist in other countries, and often result in loopholes or gaps in environmental law that allow misinterpretation or abuse (Boillat et al., 2018; W. Xu et al., 2019).

The case study presented here provides important insights into policies and conditions that acted as precursors to multiple PADDD events, and the tools that were available for opposition to these events. It provides further evidence of the important role that Indigenous land tenure can play in increasing equity and securing land in and around PAs against economic land speculation (Schreckenberg et al., 2016). Future research to compile additional PADDD case studies, either focused on one site (e.g., Golden Kroner et al., 2016), in a comparative framework (as in this analysis), or other analytical approaches would reveal further insights on the contextual factors shaping PADDD events.

The example described in this paper demonstrates that national policies that aim for rapid and widespread land titling can have unintended negative consequences for PAs, especially in the context of top-down governance and weak legal institutions. These types of policies require robust tracking by independent actors (e.g., NGOs) so that conservationists can react quickly to threats to PA integrity, and to improve transparency and accountability. Collaboration with central governments to, where necessary, reform policies that control PADDD within PAs would be valuable (Qin et al., 2019).

In this case study, the long-term relationship between WCS and the RGC in Keo Seima meant that the management team had political capital to expend on leveraging central government support and pushing for opposition to proposed PADDD events. Long-term working relationships (within government and between government and external partners) that foster collaboration, trust, and investment are vital to conservation management. Long-term investment in technical teams (e.g., monitoring and research, law enforcement, community engagement) is critically important for functioning PAs (Geldmann et al., 2015). Our case study demonstrates that PA management teams need appropriate capacity and access to current datasets describing social and biological features of the PA. Managers that lack sufficient human and information resources will be unable to mount effective opposition to proposed and environmentally damaging PADDD events and will therefore struggle to ensure long-term integrity of PAs in the face of increasing economic and social pressures.

A.5. ACKNOWLEDGEMENTS

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