DISSERTATION

UNDERSTANDING PROTECTED AREAS: AN ANALYSIS OF DRIVERS OF FOREST LOSS AND CONSERVATION TRENDS

Submitted by

Kathryn Ann Powlen

Department of Human Dimensions of Natural Resources

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Spring 2022

Doctoral Committee:

Advisor: Michael Gavin

Randall Boone
Kelly Jones
Jennifer Solomon

ABSTRACT

UNDERSTANDING PROTECTED AREAS: AN ANALYSIS OF DRIVERS OF FOREST LOSS AND CONSERVATION TRENDS

Global forests harbor much of the world's terrestrial biodiversity, provide critical ecosystem services, and directly support the livelihoods of over a billion people. Nonetheless, forest cover continues to decline rapidly, largely due to human-driven land use changes, such as conversion for agriculture, urban expansion, and increased forest market demands. Protected areas are one of the most common conservation tools used to counter global forest loss. However, forest conversion has been found to persist in protected areas globally. Understanding the diverse factors driving forest cover change in protected area is critical for ensuring forest conservation success. This dissertation contributes evidence to help advance our understanding of protected area performance through three empirical manuscripts. Each manuscript uses a unique approach to examine drivers of conservation outcomes in protected areas at different scales. All three manuscripts are focused on Mexico's protected area network.

The first manuscript uses a machine learning approach – random forest regression – to identify the main drivers of deforestation in protected areas across Mexico. By comparing the relative importance of multiple socioeconomic, biophysical, and protected area design characteristics in driving forest loss, this manuscript highlights the important role that placement characteristics, such as topography and proximity to development, can play in protected area conservation success. Additionally, results from this manuscript demonstrate the nonlinearity of the relationships between most forest loss predictors and observed deforestation.

The second manuscript uses a propensity score matching approach to quantify the influence of protected area management effectiveness on forest loss outcomes in protected areas across Mexico. This manuscript finds critical evidence that protected areas with high levels of management effectiveness reduce forest loss to a greater extent than those with lower management effectiveness. This manuscript also finds that multiple dimensions of management, such as effective planning, collaborative decision-making, equitable benefit sharing, as well as sufficient financial and human resources, can contribute to the reduction of forest loss.

The final manuscript examines how the COVID-19 pandemic influenced protected areas and conservation outcomes across Mexico. This manuscript measures protected area managers' perceptions of the impacts of the pandemic on protected area inputs, mechanisms, moderators, and non-compliance. We find a perceived decrease in human capacity, monitoring capacity, and tourism, and an increase in a number of non-compliant activities in 2020 compared to 2019. Understanding how protected areas are impacted by unexpected global events such as the COVID-19 pandemic is critical for building more resilient protected area networks in the future.

Together the three manuscripts demonstrate the range of factors that can influence protected area performance, including landscape characteristics, protected area management practices, and global events. By advancing our understanding of the factors influencing protected area performance, we can improve conservation planning, more strategically allocate resources, and more proactively protect key biodiversity areas in the future.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

Covering one-third of the total global land area, forests serve as a home for over 240 million people, support the livelihoods of 1.6 billion people, and provide critical ecosystem services for all humans on Earth (Chao, 2012; FAO & UNEP, 2020; Keenan et al., 2015). Over half of the world's remaining forests are located in tropical and sub-tropical countries, with 26% in temperate countries, and 22% in boreal countries (Keenan et al., 2015).

Forests are threatened on a global scale, with an estimated 6.5-7 million hectares deforested annually in tropical forests alone (FAO & UNEP, 2016). The conversion of primary vegetation has been estimated to have caused a 13% reduction in global species richness and 11% reduction in species abundance (Newbold et al., 2015). Additionally, continued widespread and increasing loss of forests will have profound and long-lasting impacts on climate change due to reduced carbon sequestration capacity.

Human activity is a significant driver of deforestation. Agriculture and large-scale commercial forestry operations have been estimated to account for almost three-fourths of the total global forest loss (Curtis et al., 2018). Direct threats to forests, or proximate pressures, have been found to vary by region (Curtis et al., 2018; Schulze et al., 2017). For example, a land cover change analysis using satellite imagery found commodity agriculture and cattle to be significant drivers of forest loss in tropical regions, while forestry plantations were the main driver in temperate and boreal forests (Curtis et al., 2018).

In response to the widespread loss of biodiversity and climate change impacts, forest conservation has become a global priority. Protected areas are a widely promoted tool to protect the world's remaining forest and have significantly expanded since the adoption of the Aichi

Targets by the Convention of Biological Diversity, which aimed to protect 17% of the world terrestrial surface and 10% of marine area by 2020 (i.e., Aichi Target 11) (Butchart et al., 2015; Convention on Biological Diversity, 2010). A recent evaluation found that while the total protected area coverage had almost been achieved, the designated areas were not necessarily ecologically representative, of particular importance, well-connected, or effectively and equitably managed (Secretariat of the Convention on Biological Diversity, 2020).

Additionally, while there has been significant growth in protected area networks, protected area evaluations have found varying levels of effectiveness (e.g., Heino et al., 2015; Jones et al., 2018; Joppa & Pfaff, 2011). Multiple recent analyses have found that global protected areas continue to face threats from human pressures within protected area boundaries (e.g. resource extraction, land conversion, urban development) (Geldmann et al., 2014; Geldmann et al., 2019; Jones et al., 2018). However, in general the amount of human pressure within protected areas has been found to be lower than the pressure experienced in similar unprotected areas (Geldmann et al., 2019; Jones et al., 2018), and smaller and sustainable use protected areas were found to experience human pressure more often than larger and stricter areas globally (Jones et al., 2018).

Recent studies have also found heterogenous results on the ability of protected areas to prevent forest loss. Several studies found lower deforestation rates in protected areas compared to non-protected areas (Barber et al., 2012; Ferraro et al., 2013; Leisher et al., 2013), while others have recorded increased deforestation rates inside protected area boundaries (Heino et al., 2015; Joppa & Pfaff, 2011; Leberger et al., 2019). In a literature review of 76 studies on protected area ecological effectiveness, with counterfactuals considered, Geldmann et al. (2013)

found strong evidence of protected areas' ability to maintain forest habitat, but "inconclusive" evidence on their ability to maintain species populations (Geldmann et al., 2013).

My dissertation contributes to the body of literature on protected areas by examining drivers of protected area performance from various angles, using Mexico as a focal country. I use novel methods (e.g., machine learning), best practice impact evaluation designs (e.g., propensity score matching), and a mixed methods approach to contribute rigorous evidence to the existing body of protected area research.

The dissertation is organized around three empirical manuscripts that seek to answer the overarching question, "what factors influence protected area forest conservation success?". Manuscript one identifies the main factors driving deforestation in protected areas using a machine learning approach, specifically examining the relative importance of socioeconomic, biophysical, and protected area design characteristics in determining forest loss outcomes. Manuscript two uses a propensity score matching approach to quantify the effect of protected area management effectiveness on forest loss outcomes. Manuscript three investigates how the COVID-19 pandemic has influenced protected area outcomes, using a detailed theory of change to understand how the pandemic's impact on protected area inputs and mechanisms influenced the level of non-compliance inside protected areas. All three manuscripts are conducted at the national level in Mexico.

This introduction aims to situate the three manuscripts within existing protected area literature and is organized into three sections, including Protected Area Evaluations & Manuscript Summaries, Study Site – Mexico, and Broader Impacts. The first section provides short summaries of each manuscript, highlighting the key contributions of each study. The second section summarizes conservation efforts and research in Mexico to date, while the final section outlines implications of the research for conservation science and practice going forwards. Following this introductory chapter, the dissertation is organized by manuscript, with each manuscript including an introduction to my research questions, a focused review of relevant literature, methods, and results.

Protected Area Evaluations & Manuscript Summaries

Understanding the factors that shape protected area performance has been identified as a top priority for the conservation of global biodiversity (Sutherland et al., 2009). Additionally, there has been a recent push for more evidence-based conservation research to inform practice (Pullin & Knight, 2001; Sutherland et al., 2004). Given the range of objectives that protected areas may hold (e.g., forest protection, species conservation, habitat connectivity), a variety of performance metrics have been used in existing literature examining drivers of protected area effectiveness (Ghoddousi et al., 2021). Forest cover change is one of the most commonly used metrics given the accessibility of high-resolution global forest loss data (e.g., Leberger et al., 2019; Spracklen et al., 2015; Yang et al., 2021). Alternative metrics used to examine protected area conservation success include species abundance or richness (e.g., Geldmann et al., 2013; Gray et al., 2016), normalized difference vegetation index (NDVI) (e.g., Muñoz Brenes et al., 2018; Tang et al., 2011), forest fire occurrence (e.g., Nolte & Agrawal, 2013; Román-Cuesta & Martínez-Vilalta, 2006), and land cover change more broadly (e.g., Joppa & Pfaff, 2011; Pfaff et al., 2017). Other studies have used proxies for human pressure including the Human Footprint (e.g., Jones et al., 2018), a temporal human pressure index (e.g., Geldmann et al., 2014, 2019), as well as an assessment of threat levels inside protected areas (e.g., Schulze et al., 2017). Existing research has also measured a number of social outcomes as protected area effectiveness metrics, often representing changes to human-wellbeing and equity (see Ghoddousi et al., 2021; Oldekop, et al., 2016; Pullin et al., 2013). Here I largely focus on the impacts of protected areas on forest cover change given the quality and quantity of data available, and due to the cascading impacts of forest loss on other measures of biodiversity (e.g. species diversity and abundance). In doing so, I recognize that not all impacts of protected areas will be captured by focusing on forest cover loss. For example, many species (particular large mammals) may be locally extirpated while forest cover remains intact, creating what Redford (1992) referred to as empty forests. Additionally, the positive and negative impacts that protected areas can have on the well-being of local human communities will not be fully captured by measuring protected area performance based on forest cover change.

In addition to the integration of diverse effectiveness indicators, there have been many advancements in protected area evaluation design in recent years, increasing accuracy through rigorous methodological approaches (e.g. Barnes et al., 2017; Geldmann et al., 2013; Jones et al., 2018; Joppa & Pfaff, 2011). For example, more recent protected area evaluations often address concerns of threat displacement (i.e., spillover effects) by including buffer zone comparisons (e.g., Andam et al., 2008; Fuller et al., 2019) and potential confounding factors by controlling for characteristics such as proximity to human pressure and physical characteristics of the landscape (e.g., Baldi et al., 2017; Joppa & Pfaff, 2009, 2011). An increasing number of studies have also used a quasi-experimental research design to more accurately quantify protected area effectiveness compared to a counterfactual, or what would have happened if the area was not protected (e.g., Ferraro, 2009; Ferraro & Pressey, 2015; Miteva et al., 2012). While these research approaches have increased our knowledge of protected area performance, many studies remain limited by methodological assumptions that oversimplify complex relationships, and omitted variable biases (dos Santos Ribas et al., 2020; Vaca et al., 2019).

Manuscript one overcomes these limitations by using machine learning to account for non-linear relationships and adjust for higher order interactions among multiple predictor variables while determining key drivers of forest loss outcomes in protected areas (Breiman, 2001; Hastie et al., 2017). In doing so, we identify the relative influence of socioeconomic, biophysical, and design characteristics (e.g., age and size) on protected area outcomes. We also demonstrate the complex relationships between forest loss and common predictor variables - often oversimplified in existing research - using accumulated local effect plots to map the conditional relationships between important drivers of deforestation and observed forest loss. In summary, this manuscript highlights the significant role that placement characteristics (e.g., slope and elevation, or proximity to urban areas and roads) can play in determining protected area success.

Existing research has frequently examined IUCN category as a determinant of protected area success and found evidence of both strict protected areas avoiding more forest loss than multi-use protected areas (e.g., Ferraro et al., 2013; Nolte et al., 2013; Pfaff et al., 2017), as well as multi-use protected areas avoiding more forest loss than strict protected areas (e.g., Blackman, 2015; Miranda et al., 2016; Pfaff et al., 2014). This has led to a call for a better understanding of the management factors that influence protected area performance beyond IUCN category designation (Macura et al., 2015).

Manuscript two responds to this call by examining the influence of five different dimensions of management on protected area performance. Specifically, we test the influence of management effectiveness on forest loss outcomes using a propensity score matching approach to control for the strong influence of placement characteristics highlighted in manuscript one. Matching methods are designed to account for hidden biases by systematically selecting treatment and control groups based on observable characteristics (Schleicher et al., 2019; Stuart, 2010). Understanding the degree to which management effectiveness can drive forest loss outcomes has important implications for conservation practice given the emphasis placed on effective and equitable protected area management in global conservation goals. Additionally, it is critical that we understand the influence of different dimensions of management to ensure we are setting the right goals for the greatest success in conservation practice.

In 2020, we experienced an unexpected global health crisis, the COVID-19 pandemic, which led to restrictions on human movement, ultimately having an indirect impact on the environment and conservation efforts. Understanding how and through what pathways protected areas were impacted by the pandemic is critical in order to design protected area networks that will be resilient to future unexpected events.

In manuscript three, we develop a detailed theory of change with the National Commission of Natural Protected Areas (Comisión Nacional de Áreas Naturales Protegidas; CONANP), Mexico's federal agency primarily responsible for management and monitoring of their protected area network, to provide evidence of the impact of the pandemic on protected areas in Mexico. Specifically, the theory of change was used to highlight the pathways through which the pandemic drove changes in protected area inputs, mechanisms, and moderators, and led to conservation outcomes. The findings of this manuscript highlight the complex web of factors that can influence protected area performance and can be used to understand potential impacts of future unexpected events, such as political instability and economic crises.

Study Site – Mexico

The focus of the three empirical manuscripts of my dissertation is on protected areas in Mexico because of the immense biodiversity that the country holds, the extensive protected area network that has been established across the country to protect this biodiversity, and the mixed evidence on whether or not the protected area network has been successful in delivering conservation outcomes to date (e.g., Blackman et al., 2015; Figueroa & Sanchez-Cordero, 2008; Figueroa et al., 2011; Pfaff et al., 2017).

Mexico is recognized as one of the world's few megadiverse countries. While representing only 1.4% of the Earth's surface, it hosts more than 10% of the world's biological diversity (Comisión Nacional de Conocimiento y Uso de la Biodiversidad, 2010). More specifically, Mexico ranks in the top five countries with the greatest diversity of vertebrates and vascular plants (Alonso Concheiro et al., 2006), and in the top three countries with the greatest diversity of reptiles (Flores-Villela & Canseco-Márquez, 2004). It has been estimated that about 33% of Mexico's terrestrial mammals, 60% of its amphibians, and 40% of its plants are endemic (USAID, 2002). However, Mexico's biodiversity and remaining forest cover face significant threats, as is true on a global scale (FAO & UNEP, 2016). Major threats include agricultural expansion, urbanization, and climate change.

Mexico is also incredibly culturally diverse, with about 22% of Mexico's total population identifying as Indigenous (Instituto Nacional de Estadística y Geografía, 2015). Mexico's cultural diversity has been found to closely correspond with its ecological diversity (Comisión Nacional de Conocimiento y Uso de la Biodiversidad, 2010). Much of Mexico's forests reside in Indigenous territories, and about one third of Mexico's federal protected areas include Indigenous territories (Comisión Nacional de Conocimiento y Uso de la Biodiversidad, 2010).

There are over 1,000 designated protected areas across Mexico, including UNESCO World Heritage Sites, Ramsar Wetlands of International Importance, and 32 different national-level designations (UNEP-WCMC, 2021). These areas vary widely in the levels of protection provided, from strict protection (IUCN categories I-IV) where limited human use is permitted, to sustainable use protected areas (IUCN categories V and VI) where human communities and their resource use activities are integrated into management objectives. Within the last decade, Mexico established four new UNESCO biosphere reserves, three new world heritage sites, and many other nationally recognized protected areas, including four national parks (UNEP-WCMC, 2021). These recent designations increased the total national coverage of protected areas in Mexico to 14.5% of terrestrial area and 21.6% of marine area.

My research focuses on a subset of Mexico's protected areas, specifically national protected areas with management plans. This includes 132 protected areas managed by CONANP. CONANP has made many advancements in improving their protected area network, despite limited resources and regular budget cuts. For example, CONANP recently developed a management effectiveness evaluation tool, with the help of senior scientists at the IUCN, to regularly monitor management across their protected area network every four years (Comisión Nacional de Áreas Naturales Protegidas, 2020b). CONANP has also been awarded the IUCN Green List Sustainability Standard for two of their protected areas, including National Park Zona Marina Archipiélago Espiritu Santo and Biosphere Reserve Isla San Pedro Mártir. The IUCN Green List is the most recent global protected area standard, with only 59 parks in 16 countries meeting requirements since 2015 (IUCN, 2021).

Similar to other regions of the world, researchers have found variability in the performance of Mexico's protected area network (Blackman et al., 2015; Bruner et al., 2001; Figueroa & Sanchez-Cordero, 2008; Figueroa et al., 2011; Pfaff et al., 2017; Sánchez-Cordero et al., 2011; Sims & Alix-Garcia, 2017). For example, Figueroa et al. (2011) analyzed 44 federal protected areas and found 70% to be successful at slowing rates of land use change compared to surrounding areas, while 80% were successful when compared to similar ecoregions. In an earlier study, Figueroa and Sanchez-Cordero (2008) found only 54% of 69 protected areas to be successful at slowing deforestation compared to a surrounding area. Neither study, however, considered drivers of performance beyond protected area type (i.e., national park, biosphere reserve, national monument, etc.).

More recently, researchers have controlled for placement biases when comparing land cover change in protected areas in Mexico by using a matching technique. Blackman et al. (2015) found heterogenous impacts within protected area boundaries and in surrounding areas (spillover effects) compared to non-protected areas. The authors concluded that larger, newer, mixed use protected areas, and protected areas with sufficient funds, were more successful at slowing deforestation. Conversely, Pfaff et al. (2017) found stricter protected areas to be more successful at slowing forest loss compared to mixed use protected areas when examining a slightly later time span. Both studies found elevation, slope and travel time to urban centers to be significant drivers of forest conversion (Blackman et al., 2015; Pfaff et al., 2017).

The three manuscripts of this dissertation help to advance our understanding of the factors driving the variation in performance in Mexico's protected area network. Manuscript one and two use forest loss as a metric of protected area performance given that rates of deforestation in protected areas in Mexico have been found to vary (e.g., Blackman et al., 2015) and deforestation is frequently reported as a critical threat by protected area managers in Mexico on management evaluations such as the Management Effectiveness Tracking Tool (see Stolton & Dudley, 2016). Manuscript 3 examines changes in seven different non-compliant activities impacting biodiversity outcomes to understand changes in protected area performance during the pandemic. Using these performance metrics, this dissertation examines a wide range of socioeconomic and biophysical factors known to influence forest loss outcomes globally, quantifies the influence of management dimensions previously unexamined in Mexico, and identifies the pathways through which unexpected global events, specifically the COVID-19 pandemic, can influence management capacity and non-compliance in protected areas.

Broader Impacts

Protected areas are one of the main instruments for conserving biodiversity in Mexico (García-Frapolli et al., 2009) and globally, with over 200,000 protected areas designated around the world (UNEP-WCMC et al., 2020). Moreover, global coverage of protected areas is projected to increase in the coming years - an increase in coverage has been proposed in early drafts of the post-2020 biodiversity targets (Convention on Biological Diversity, 2021) and 50 countries, including Mexico, pledged to help conserve 30% of the world's terrestrial and marine areas by 2030 in early 2021 (Campaign for Nature, 2021). If this expansion of protected area coverage is to be successful in delivering conservation goals, it is critical that we continue to advance our understanding of the factors that determine protected area performance.

My dissertation research contributes empirical evidence to better understand the complex relationships between various drivers of protected area performance. Specifically, across the three studies, we build evidence on the influence of various socioeconomic, biophysical, and management characteristics driving conservation outcomes. The findings of each manuscript can help to inform protected area planning and resource allocation decisions. Additionally, the findings can inform the design of future protected area evaluations by identifying key confounding factors and demonstrating approaches that can account for the complex relationships between drivers of protected area performance and protected area outcomes. Ultimately, the methodological contributions and findings of this dissertation can help to improve the accuracy of conservation evaluations not just in Mexico, but on a global scale.

Note on Authorship

The three empirical studies of this dissertation resulted in manuscripts with multiple co-authors. While each was a collaborative effort, I was the individual primarily responsible for the conceptualization of each study, the design and execution of the analyses, and the writing of each manuscript. Co-authors provided critical support through idea development and by providing feedback on each written manuscript. Manuscript one was coauthored by Jonathan Salerno, Kelly Jones, and Michael Gavin. Manuscript two was coauthored by Michael Gavin and Kelly Jones. Manuscript three was coauthored by Kelly Jones, Elva Ivonne Bustamante Moreno, Maira Abigail Ortíz Cordero, Jennifer Solomon, and Michael Gavin.

CHAPTER 2: THE INFLUENCE OF PROTECTED AREA PLACEMENT AND DESIGN CHARACTERISTICS ON FOREST LOSS OUTCOMES IN MEXICO

Chapter Summary

Protected areas are a commonly-used strategy to confront forest conversion and biodiversity loss. While determining drivers of forest loss outcomes is central to conservation success, our understanding has been limited by conventional modeling assumptions. Here, we use random forest regression to account for non-linear relationships and higher-order interactions while evaluating a range of potential drivers of deforestation in protected areas in Mexico. We find socioeconomic drivers, such as road density and human population density, and underlying biophysical conditions, such as distance to water, elevation, and slope, are stronger predictors of forest loss than protected area characteristics, such as age, type, and management effectiveness. We show that the relationships between most predictors and forest loss are non-linear. Our findings can help inform decisions on the allocation of protected area resources by strengthening management in protected areas with the highest risk of deforestation and help preemptively protect key biodiversity areas that may be vulnerable to deforestation in the future.

Introduction

Global forests harbor much of the world's terrestrial biodiversity, provide carbon sequestration and other critical ecosystem services, and directly support the livelihoods of over a billion people (FAO & UNEP, 2020; Fedele et al., 2021). Nonetheless, forest cover continues to decline rapidly, with an estimated 10 million hectares lost per year between 2015-2020 (FAO & UNEP, 2020). Human-driven land use changes, including forest conversion for agriculture, urban expansion, and increased forest market demands, have been found to be the primary cause of forest loss (Armenteras et al., 2017; Curtis et al., 2018). Protected areas are one of the most common conservation tools used to counter this loss, with 18% of the world's remaining forest under some form of protection (FAO & UNEP, 2020; UNEP-WCMC et al., 2020). However, forest conversion and biodiversity loss persists in protected areas globally, albeit often less than in unprotected areas (Geldmann et al., 2019; Wolf et al., 2021). Understanding the diverse factors driving the impacts of protected areas on forest cover change is critical to ensuring forest conservation success.

Existing research has identified a number of protected area design characteristics (e.g., size, strictness), socioeconomic drivers (e.g., distance to roads, human population density), and other underlying biophysical factors (e.g., slope, elevation, climate conditions) that influence protected area outcomes (e.g., Barnes et al., 2017; Geist & Lambin, 2002). However, previous methods used to examine these drivers have been limited by strict methodological assumptions, such as linear relationships and independence among predictors. This has often resulted in low explanatory power and biased protected area evaluations due to the oversimplification of complex non-linear relationships or the omission of key predictor variables (Andam et al., 2008; Vaca et al., 2019). Here we use a machine learning technique – random forest regression – to overcome existing limitations and advance our understanding of the drivers of forest cover change in protected areas in Mexico, a global biodiversity hotspot.

Specifically, we assess hypothesized drivers of forest loss related to protected area design characteristics, socioeconomic drivers, and underlying biophysical factors in influencing forest cover change in protected areas. Although high resolution satellite imagery has allowed researchers to analyze patterns of global environmental change (Pettorelli et al., 2014; Turner et al., 2003), we conduct our analysis at the country-level, given its higher relevance for protected area policy. Additionally, conducting a country-level analysis allows us to contribute unique empirical evidence on the importance of protected area design characteristics, beyond IUCN category, by integrating scores from a national-level management effectiveness evaluation, filling a critical gap previously identified in protected area research (Macura et al., 2015).

Identifying key drivers of forest loss in protected areas has implications for both the design of future protected areas and the management of existing ones. An understanding of the factors contributing to increased deforestation risk can lead to better informed protected area design and more strategic allocation of resources to forested areas with higher vulnerability. Additionally, our findings can help improve the design of protected area evaluations by providing critical information for variable selection to control for confounding factors. Ignoring key confounding variables in effectiveness evaluations can lead to over- or under-estimating protected area impact (see Andam et al., 2008; Baylis et al., 2016); by identifying the most important variables driving outcomes, we can increase the accuracy of future research.

Drivers of Protected Area Outcomes

An extensive body of literature exists that summarizes potential drivers of forest loss and other conservation outcomes (e.g., Aide et al., 2012; Barnes et al., 2017; Busch & Ferretti-Gallon, 2017; Geist & Lambin, 2002; Salafsky et al., 2008). For the purpose of this study, we summarize relevant drivers of protected area outcomes into three categories – protected area design characteristics, socioeconomic characteristics, and biophysical characteristics – to compare relative influence. Socioeconomic drivers of forest cover change serve as proxies for development pressure (e.g., human population density and population growth) and forest accessibility (e.g., proximity to roads), while biophysical drivers (e.g., slope and climate conditions) represent potential for economic productivity.

Protected Area Design characteristics

Existing literature has identified a variety of protected area characteristics that can influence protected area effectiveness, including age, size, level of strictness, enforcement capacity, stakeholder engagement, and management resources (Barnes et al., 2017; Ghoddousi et al., 2021). However, the estimated degree of influence and the direction of influence of many characteristics have varied across studies, potentially due to geographical differences, scale of analysis, and study design (e.g., control variables included, or outcome variable examined). For example, a recent study found that protected areas with higher management effectiveness prevented more forest loss than those with low management effectiveness across Mexico (Powlen et al., 2021) and similar patterns have been found between higher management effectiveness and vertebrate abundance on a global scale (Geldmann et al., 2018). However, the influence of management effectiveness on protected area outcomes has been less clear in other regions, such as the Amazon Basin (e.g., Carranza et al., 2014; Nolte & Agrawal, 2013).

Younger protected areas are often more successful than older protected areas due to management resources (financial and staff capacity) increasing in the first few years following establishment (Barnes et al., 2017). Research in Mexico has pointed to similar relationships between age and effectiveness, with Blackman et al. (2015) finding a negative correlation between avoided deforestation and age (Blackman et al., 2015). However, younger protected areas may be established in response to more recent threats, and thus could appear less successful than older areas if original threat level is not appropriately controlled for (Geldmann et al., 2018; Kere et al., 2017).

Larger protected areas are expected to be more successful due to their ability to fully protect a critical ecosystem or species range. Larger areas also experience a decreased risk of edge effects, or development pressure, encroachment, or the concentration of ecological stress along the boundary of a protected area (Barnes et al., 2016). Research in Mexico has found larger protected areas better conserve forest cover compared to smaller protected areas on average (Blackman et al., 2015). However, larger areas can require a greater amount of resources for monitoring and management, and were found to experience more forest loss than smaller protected areas in a recent global assessment (Wolf et al., 2021).

Protected area strictness refers to the regulations on resource use inside protected areas and can range from strict no-access zones to multi-use areas, which allow sustainable livelihood opportunities. Existing evidence has found strict protected areas to be more successful at the global-level (Jones et al., 2018) and in Mexico (e.g., Figueroa & Sanchez-Cordero, 2008; Pfaff et al., 2017). However, other studies have found conflicting evidence, with multi-use protected areas appearing more successful than strict protected areas in Mexico (e.g., Blackman, 2015; Sims & Alix-Garcia, 2017), as well as in other Latin American countries, such as Brazil and Peru (see Miranda et al., 2016; Pfaff et al., 2014). Blackman (2015) found that while multi-use protected areas had more heterogenous outcomes, those that provide sustainable livelihoods opportunities, such as forest concessions, resulted in less forest loss on average (Blackman, 2015).

Socioeconomic Characteristics

Proxies for development pressures and forest accessibility are often correlated, and both can increase biodiversity threats (e.g., urban areas contain larger human populations and higher road density). Proximity to roads and higher road density are expected to increase risk of deforestation in protected areas, due to increased accessibility for natural resource extraction or development opportunities (Joppa & Pfaff, 2009; Kere et al., 2017; Laurance et al., 2009).

Similarly, human population growth, human population density, and proximity to urban areas are also expected to increase biodiversity risk due to risk of encroachment, increased demand for resources, and a larger labor force available for extractive industries (Busch & Ferretti-Gallon, 2017). Alternatively, protected areas that provide tourism-related opportunities may incentivize compliance from local populations leading to less forest encroachment (Barnes et al., 2017). An increase in both accessibility and human populations may also lead to greater surveillance and enforcement efforts (Andam et al., 2008), which could decrease forest cover loss particularly when it is linked to non-compliant activities.

Land tenure, including usufruct rights, land ownership, and tenure security, have also been examined as a driver of forest conservation outcomes (e.g., Bonilla-Moheno et al., 2013; Robinson et al., 2014; Skutsch et al., 2014; Blackman et al., 2015; Barnes et al., 2017; Hajjar et al., 2021). Mexico has a communal tenure system, known as "*ejidos*", which provide usufruct rights over an area of land, requiring a group of ejidatarios to make land use decisions collectively (Bray et al., 2008). While some researchers have promoted community forest management as a key strategy for biological conservation in Mexico (e.g., Ellis & Porter-Bolland, 2008; Porter-Bolland et al., 2012), other studies have found no significant relationship between tenure and forest loss outcomes (e.g., Bray et al., 2008; Mas & Cuevas, 2013; Skutsch et al., 2014). Additionally, establishing overlapping protected areas may weaken tenure security or undermine existing tenure systems, leading to increased biodiversity risks (Geldmann et al., 2019).

Biophysical Characteristics

Physical characteristics of the landscape, such as slope and elevation, are often examined as a proxy for suitability for other land uses, such as agriculture and livestock grazing. Lands with lower agricultural preparation costs are often more likely to be deforested (Busch & Ferretti-Gallon, 2017; Joppa & Pfaff, 2009; Vaca et al., 2019). Climate-related variables, such as temperature and precipitation, are also often examined as proxies for suitability and potential productivity. Areas with more ideal climate conditions are expected to be more at risk of clearance for development or agricultural use (Aide et al., 2012; Busch & Ferretti-Gallon, 2017). Proximity to water has been linked to increased agricultural activities (Vaca et al., 2019) and can increase accessibility of forests via water transportation (Bax & Francesconi, 2018). Previous research has found biophysical variables – specifically, temperature and elevation – to be stronger predictors of land cover change than socioeconomic variable at the municipality level in Mexico (e.g., Bonilla-Moheno et al., 2012) and across Latin America (e.g., Aide et al., 2012).

Methods

We use random forest regression in order to further investigate the relationships between design characteristics, socioeconomic and biophysical variables, and forest cover change in protected areas. In doing so, we demonstrate how random forest regression can help advance our understanding of drivers of protected area outcomes due to its capacity to examine a large number of predictor variables at once, while adjusting for multicollinearity and non-linear relationships (Breiman, 2001).

Data

Data used in our analysis were gathered from publicly available sources (Table 2.1). This included five protected area design characteristics, 10 socioeconomic predictors, and six biophysical predictors. Our dependent variable was forest loss, accessed from Global Forest Watch (Hansen et al., 2013). We examined forest loss between 2015-2019, and aligned all other predictor variables with this time period.

Table 2.1: Summary of data and data sources.

Independent Variables	Source
Socioeconomic	
· Distance to roads	INEGI
· Distance to urban centers	INEGI
· Ejido tenure	INEGI
· Payment for ecosystem service (PES) enrollment	CONAFOR
· Population change	WorldPop
· Population density	WorldPop
· % population in extreme poverty	CONEVAL[1]
· % population in moderate poverty	CONEVAL
· Roads density	INEGI
· State	CONANP
Biophysical	
· Ecoregions	WWF
· Elevation	USGS
· Precipitation	WorldClim
· Proximity to water	INEGI[2]
· Slope	USGS
· Temperature	WorldClim
Design Characteristics	
· Age	CONANP
· Management effectiveness	CONANP
· Total area	CONANP
· Strictness (protected area type)	CONANP
Dependent Variable	**Source**
· Forest Cover Loss	GFW

Scores from CONANP's *i-efectividad* evaluation were used as our management effectiveness variables. The evaluation, conducted in 2017, is a standardized survey taken by protected area managers measuring five dimensions of management using 48 indicators. The five categories include: context and planning, administration and financial, use and benefits, governance and social participation, and management quality (see Comisión Nacional de Áreas Naturales Protegidas (2019) for more details). We used scores from each of the five dimensions

[1] CONEVAL - Consejo Nacional de Evaluación de la Política de Desarrollo Social
[2] INEGI - Mexico's National Institute of Statistics & Geography

and an overall score calculated by CONANP.

Poverty indicators were taken from a multidimensional poverty index developed by Mexico's National Council for the Evaluation of Social Development Policy (Consejo Nacional de Evaluación de la Política de Desarrollo Social; CONEVAL). The multidimensional index measures access to social services, such as education, health services, housing quality, and access to sufficient food, in addition to sufficient income. CONEVAL defines *moderate* poverty as having insufficient income and lack of access to at least *one* social service. *Extreme* poverty is measured as having insufficient income and lack of access to *three or more* services. The poverty values are estimated at the municipality level.

In addition to an extensive protected area network, Mexico has implemented a payment for ecosystem service (PES) program focused on watershed protection, biodiversity conservation, and carbon capture and storage since the early 2000s. Given the significant overlap with existing PES programs and protected areas across Mexico, and evidence that these programs have a positive and significant influence on forest conservation outcomes (e.g., Min-Venditti et al., 2017; Sims & Alix-Garcia, 2017), we examined PES as a predictor of protected area outcomes.

Data extraction was conducted in ArcMap Pro using 1km^2 grid cells to extract variable values. Grid cells were created within protected areas with management effectiveness scores from CONANP's *i-efectividad* management evaluation (n=77). We selected all cells in terrestrial protected areas with a baseline forest cover of 75% of the cell or greater in 2000 for a computationally feasible sample size. This excluded cells from 11 protected areas that were primarily marine or coastal and an additional 15 terrestrial protected areas in non-forested ecoregions. The final sample resulted in 30,888 grid cells in 51 protected areas. Grid cells with missing data were removed from the analysis. See Appendix Table A1 for more specific details about data sources and data extraction.

Analysis

Random forest is a machine learning approach that can be used to classify a categorical variable or predict a continuous or binary dependent variable (i.e., regression) (Breiman, 2001). Random forest regression is a strong exploratory approach for analyses where there are many potential predictor variables with higher-order interactions and non-linear relationships (Breiman, 2001; Strobl et al., 2009). It uses a bootstrap aggregating, or "bagging", approach to create multiple subsamples of a dataset for training and testing a model (Strobl et al., 2009). With the training data, the algorithm uses a split-variable randomization process to develop a collection of uncorrelated decision trees and averages the prediction across all trees (Hastie et al., 2017). Averaging the predictions across a diverse set of trees reduces the variance and bias and ultimately, increases prediction performance. The remaining test data are used to measure the model's predictive power. Using between 60-80% of the data is recommended for training, with the remaining 20-40% used for testing (Breiman, 2001). We used a 70:30 training-test split ratio.

Random forest is often referred to as an "off-the-shelf" machine learning algorithm due to its high predictive capability with low hyperparameter tuning requirements (Hastie et al., 2017). Optional tuning parameters for the model include the total numbers of trees (ntree) and the number of variables randomly sampled to split each tree node (mtry) (Breiman, 2001). Similar to Epstein et al. (2021), we used the *caret* package (Kuhn, 2008) in R (version 3.6.1) using RStudio (version 1.2.1335) to determine optimal tuning parameters and a 10-fold cross validation method to assess model accuracy (Epstein et al., 2021).

Our full model includes all sampling grid cells selected from forested protected areas across Mexico. To examine differences in deforestation predictors across forest type, we subset the data by ecoregion based on simplified terrestrial ecoregions from World Wildlife Fund (WWF) (Olson et al., 2001). The subsetting classified grid cells into five forest types: moist forest (*n*=15,087), dry forest (*n*=2,094), pine-oak forest (*n*=10,450), montane forest (*n*=592) and mangrove forest (*n*=1,541) (see Appendix Table A3 and A4 for more details). Separate random forest models were then run for each subgroup. Appendix Table A5 includes test and train data summaries for each model.

We present the mean absolute error (MAE) as a measure of model performance (Chai et al., 2014; Willmott & Matsuura, 2005). In addition to the MAE, we report total variance explained (R^2) and the importance values from each model. Random forest regression calculates importance values as the increase in node purity (IncNodePurity), or the reduction in the sum of square errors from splitting with each specific variable (Hastie et al., 2017). The values were adjusted using the caret package to fall along a 0-100 scale for interpretability.

The importance values are an estimate of the *level* of influence of each variable in the prediction and does not reflect the *direction* of influence. Therefore, random forest analyses are often paired with partial dependence plots (PDP) or accumulated local effect (ALE) plots to better depict the nature and direction of the relationship (Apley & Zhu, 2020; Hastie et al., 2017). We use ALE plots to present the conditional relationship between our predictors and forest loss due to the multicollinearity of many of our predictor variables (see Apley & Zhu, 2020; Strobl et al., 2008). We use the iml package (Molnar et al., 2018) to produce ALE plots for the top nine most important variables in the final model and include all other ALE plots in Appendix A.

Results

Descriptive Statistics

The final sample contained grid cells in 51 protected areas located in 27 different states. Five protected area management categories were represented, including biosphere reserves (74%), flora and fauna protection areas (14%), national parks (6%), natural resource protection areas (6%), and national monuments (0.001%). The ages of the protected areas ranged from six years to 86 years (mean: 35 years). The smallest area was 20 km^2 and the largest was 7,232 km^2, with a mean of 3,806 km^2. The median overall management effectiveness score was 74, with a minimum of 42 and maximum of 88 (mean: 72). The highest scoring management dimensions were governance and social participation (median: 87), management quality (median: 81), and use and benefits (median: 76).

The average coverage of *ejido* tenure in the grid cells was 40%, and the average overlap with PES enrollment was 65% (Table 2.2; see Appendix Table A6 for descriptive statistics by forest type). Population density was relatively low, and the population change rate was negative, on average. The median estimate for the percent of the population in extreme poverty was 23.5%, with around twice as many living in moderate poverty.

Table 2.2: Summary statistics of predictor variables.

Variable	Median	Mean	Standard Dev.	Min	Max
Socioeconomic					
Distance to Roads (km)	3.20	4.12	4.07	0.00	14.99
Distance to Urban Areas (km)	14.91	16.58	13.62	0.00	49.99
Ejido Tenure (%)	0.00	39.55	46.85	0.00	100.00
Extreme Poverty (%)	23.55	21.92	14.02	0.18	69.97
Moderate Poverty (%)	48.27	45.19	8.62	4.23	72.25
PES (%)	100.00	65.32	46.73	0.00	100.00
Pop. Change Rate ($\triangle$pop/km^2)	-0.01	-0.49	3.86	-205.23	8.38
Pop. Density (pop/km^2)	0.37	5.28	39.53	0.00	1,959.03
Road Density (0-5)	0.09	0.24	0.43	0.00	4.15
Biophysical					
Elevation (m)	600.00	906.52	853.16	1.00	3,618.00
Distance to Water (km)	1.07	2.06	2.73	0.00	14.99
Precipitation (mm)	1,154.00	1,240.35	570.07	281.00	3,100.00
Slope (degree)	2.69	4.64	5.30	0.00	31.85
Temperature (°C)	22.00	19.85	5.07	6.00	27.00
Design Characteristics					
Age (years)	32.00	35.27	16.41	6.00	86.00
Area (km^2)	3,312.00	3,806.00	2,379.00	20.00	7,231.00
Mngmt Effectiveness	74.00	72.24	11.28	42.00	88.00
ME: Context	71.00	69.22	12.73	41.00	95.00
ME: Admin	56.00	56.37	7.60	17.00	92.00
ME: Use	76.00	77.08	17.18	38.00	100.00
ME: Governance	87.00	83.1	17.67	30.00	100.00
ME: Mngmt Quality	81.00	77.91	15.93	38.00	90.00

A correlation analysis found multiple predictors to be correlated, further emphasizing the need for modelling methods that control for multicollinearity when exploring a variety of potential drivers of forest loss. Correlated variables occurred within the same variable category (e.g., socioeconomic, biophysical, design characteristics), including temperature and elevation (r = -0.95), population density and population change (r = -0.97), and the overall management effectiveness score with individual management categories (governance and social participation, r = 0.91; management quality, r = 0.92), as well as across categories, such as percent of the population in extreme poverty and precipitation (r = 0.76) and overall management score and elevation (r = -0.63). A full list of Pearson correlation coefficients is included in Appendix A (Appendix Table A7).

We find evidence of overall forest loss between 2015 and 2019, with a mean baseline forest loss of 1.19% per cell (median: 0) (Table 2.3). While the mean is relatively low, there were a few outliers, with 27 cells losing over 75% of forest cover, 11 of which lost over 90%. We find variation in the rate of forest loss by ecoregion, with the highest rates of deforestation occurring in moist forests (1.93%), followed by montane forests (1.72%) (Table 2.3). Dry forests (0.28%) and pine-oak forest (0.40%) experienced the lowest rates of forest loss across the five forest types.

Table 2.3: Forest loss summaries, calculated as percent of the baseline forest area lost per cell between 2015-2019.

Forest Type	Mean Forest Loss (%)	Standard Dev.	Max Forest Loss (%)
Moist Forest	1.93	7.00	98.97
Montane Forest	1.72	4.01	28.00
Mangrove Forest	0.53	3.48	81.54
Pine-oak Forest	0.40	2.58	68.56
Dry Forest	0.28	1.69	38.42
All Forests	1.19	5.45	98.97

Random Forest Model

The random forest model was able to predict about 60% of the variance in the full dataset, with model fit varying by forest type. The highest variance was explained in moist forests (R^2=0.61; MAE=1.38), followed by montane forests (R^2=0.43; MAE=1.57), and mangrove forests (R^2=0.28; MAE=0.92). The dry forest model had very low explanatory power, with only 12% of the variance explained (MAE=0.40) (Appendix Table A8).

Figure 2.1 presents variable importance using an inclusion cutoff value of 1.0 to increase figure interpretability. Three variables were under the 1.0 cutoff, including the overall management effectiveness score (0.84), the context and planning dimension of management effectiveness (0.72), and protected area strictness, with biosphere reserves having the strongest influence of all protected area types at 0.09. All biophysical and socioeconomic variables were above the cut-off in at least one category (e.g., moist forest, state of Tabasco). Notably, the top 12 variables of importance were all socioeconomic or biophysical variables, and the first nine had a substantially higher importance value than all remaining variables (importance value [IV] of top nine > 40).

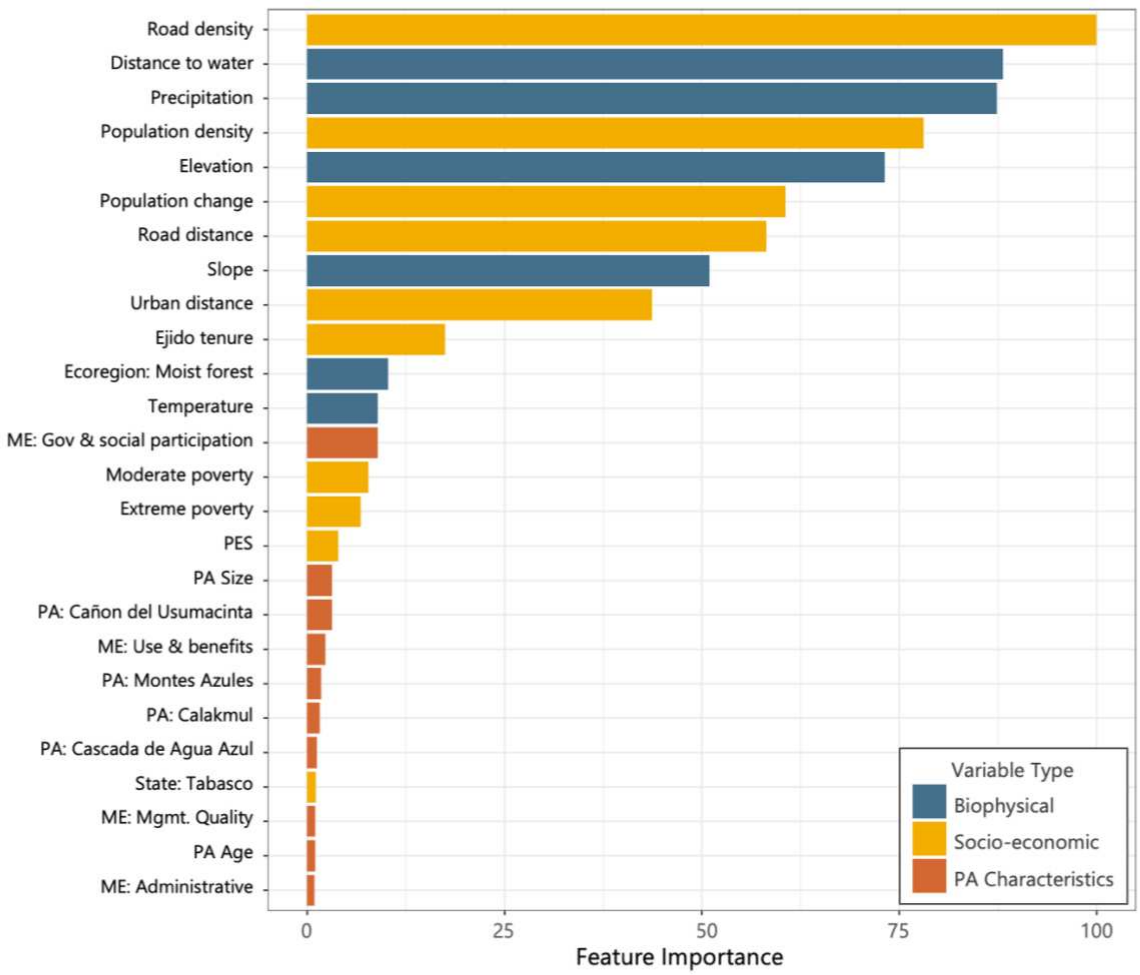


Figure 2.1: Variable importance (increase in node purity) from the final full forest model. Importance values are an estimate of the level of influence and do not indicate direction of influence. A 1.0 cutoff value of importance was used to increase figure interpretability. Management effectiveness components indicated by "ME: (component name)". Specific protected areas are indicated by "PA: (name)".

We found road density to have the highest importance in predicting forest loss (IV= 100), followed by the biophysical variables of distance to water (IV= 88) and precipitation (IV= 87) (Figure 2.1). Other key socioeconomic variables included population density (IV= 78), population change (IV= 60), and road distance (IV= 58). Percent of the population in moderate poverty (IV= 7), extreme poverty (IV= 8), and enrollment in PES programs (IV= 4) had the lowest influence, although still above the 1.0 cut-off and higher than most protected area design characteristics. Additional biophysical variables of high importance were elevation (IV= 73) and slope (IV= 51), with temperature (IV= 9) having the lowest influence of the biophysical variables.

The protected area design characteristic with the highest importance value was the governance and social participation dimension of management effectiveness (IV= 9). This reflects the degree to which all stakeholders' rights are recognized and respected, and the level of involvement from local communities and neighboring resource users in management decision-making. The second most influential design variable was protected area size (IV= 3), followed by a second management dimension, use and benefits (IV= 2), which measures the fair distribution of benefits for all stakeholders, including the promotion of sustainable use of natural resources in the area. In addition to these variables, a number of specific protected areas were found to be strong predictors of forest loss, which included Cañon del Usumacinta (IV= 3.1), Montes Azules (IV= 1.7), Calakmul (IV= 1.6), and Cascada de Agua Azul (IV= 1.2).

Accumulated Local Effects (ALE)

To better understand the relationships between the variables of highest importance and forest loss, we produce ALE plots for the nine strongest forest loss predictors (Figure 2.2). The results show that none of the relationships are linear. We find that higher road density increases the risk of forest loss. More specifically, we found a steep increase as road density begins to increase, with some variation, then leveling off after a road density of 1.5 (out of 5). We found a decreased risk of forest loss as distance from roads and urban areas increased until about 8km and 20km, respectively. Risk then gradually increased as protected areas become remote and farther from roads. There was high uncertainty in the influence of population density and population change on forest loss.

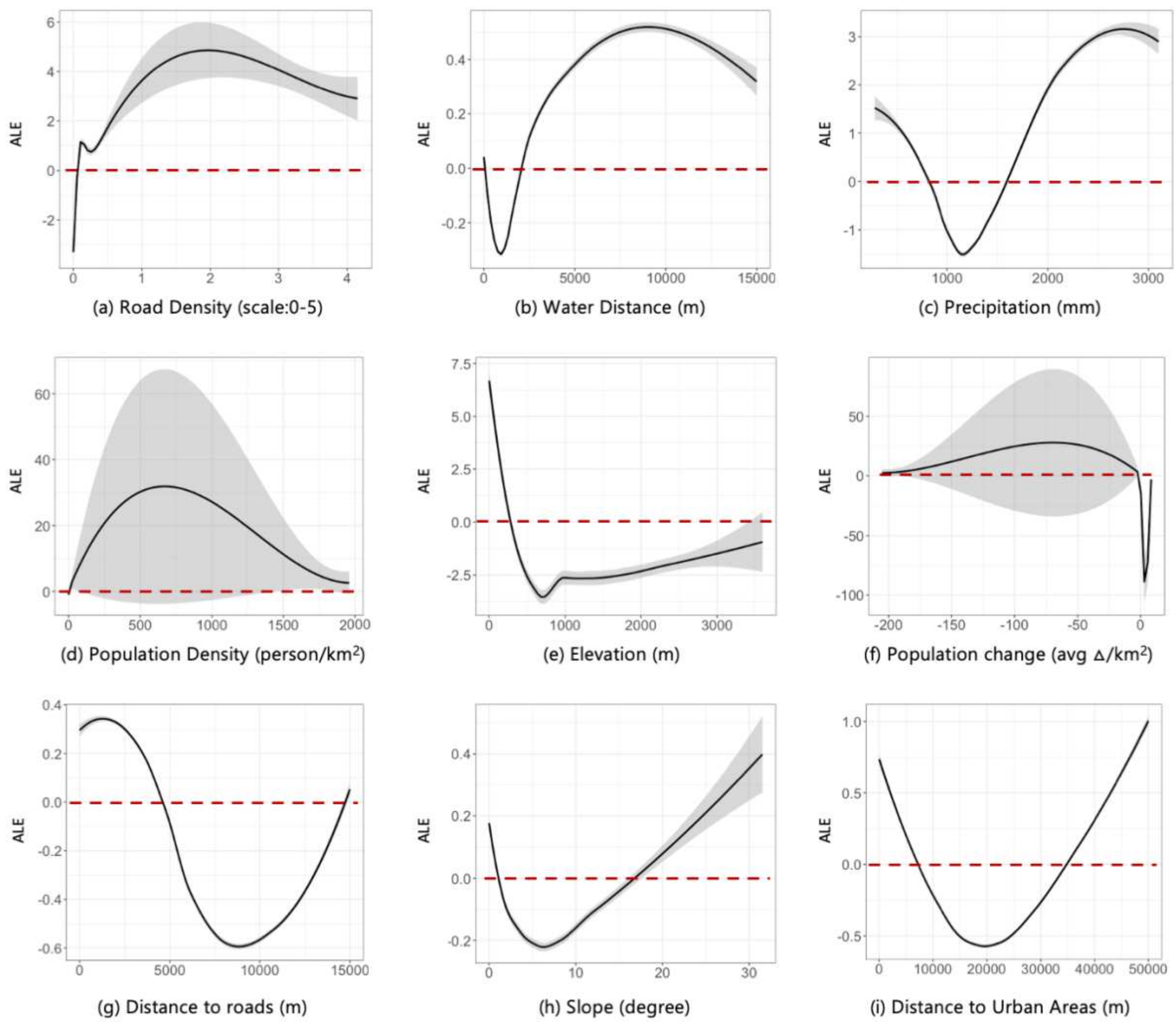


Figure 2.2: Accumulated local effect (ALE) plots displaying conditional relationships between predicted forest loss and top 9 variables of importance. ALE values represent the change in predicted forest loss at a given value compared to the average prediction. 95% confidence interval shaded in grey.

The risk of forest loss sharply declines within 1km of water, but then increased from around 1.25 km until approximately 7 km. The direction of the relationship between forest loss risk and precipitation varied, with a decrease in forest loss at low levels of precipitation, which begins to increase around 1,200 mm, before ultimately dropping off again at very high levels of precipitation of around 2,700 mm. We found a reduction in forest loss risk as elevation increased to about 800m, then leveling off. A similar pattern was found with slope and forest loss, with risk decreasing until around a 7-degree slope, then ultimately beginning to increase in risk, though with some uncertainty. ALE plots for additional predictor variables are included in Appendix A.

Forest Subgroup Analysis

While there was some variation across the forest type subgroups, the patterns of variable importance were qualitatively similar, with the five most important variables across all subgroup models being socioeconomic and biophysical characteristics (Figure 2.3). The most important variable for montane and pine-oak forest models were socioeconomic characteristics of accessibility (road density) and human pressure (urban distance). Biophysical characteristics were the most important variables for moist forests (precipitation), mangrove forests (distance to water), and dry forest models (distance to water). However, the socioeconomic variables of road density and population density were found to have equal importance in the moist forest and mangrove forest models respectively (both IV = 98). Protected area design characteristics were not ranked in the top five of any subgroup.

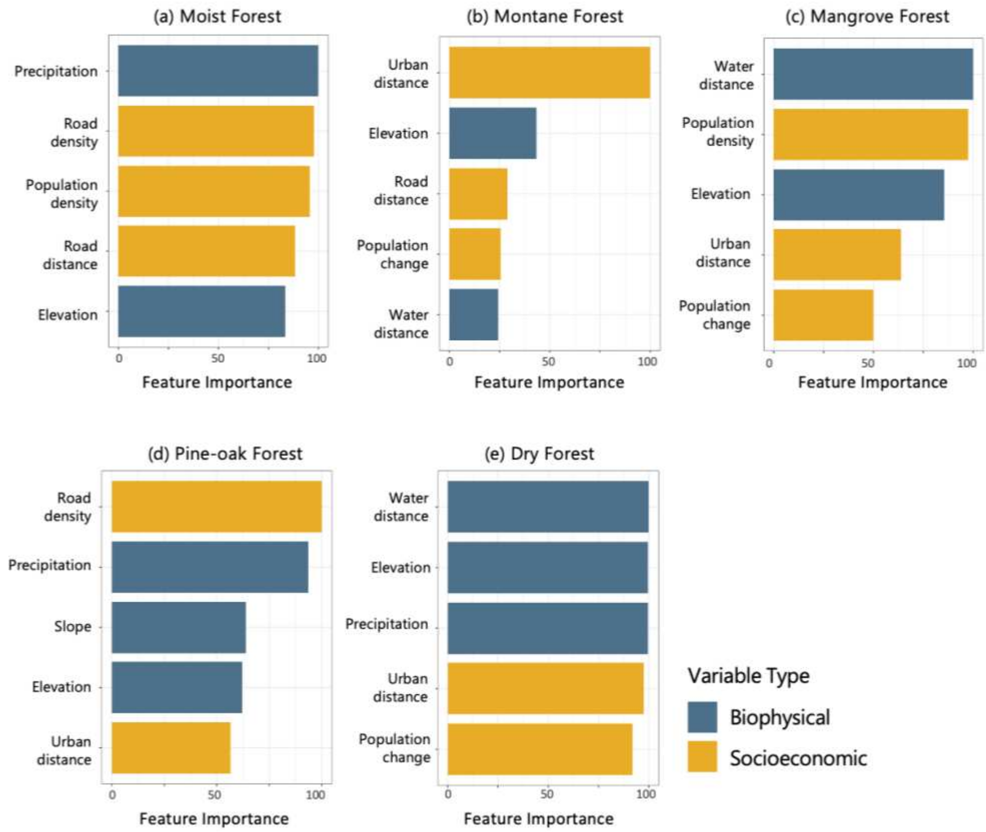


Figure 2.3: Top 5 variables of importance from forest type subgroups.

Discussion

Our study uses a novel approach to increase our understanding of the drivers of protected area outcomes. Random forest regression has been highlighted as a useful exploratory approach for identifying important predictors of marine protected area performance (e.g., Edgar et al., 2014; Franco et al., 2016; Gill et al., 2017), as well as to examine drivers of deforestation broadly (i.e., irrespective of protected areas) (e.g., Aide et al., 2012; Bax & Francesconi, 2018; Bonilla-Moheno et al., 2012), drivers of protected area placement (Baldi et al., 2017), factors leading to social and conservation protected area outcomes in a meta-analysis (Oldekop et al., 2016), and most recently, predictors of forest monitoring by forest-user groups (Epstein et al., 2021). However, its application for understanding drivers of terrestrial protected area outcomes remains relatively unexplored. Here we demonstrate its utility in advancing our understanding of the key variables driving forest loss inside protected areas.

Overall, we find that protected area placement, including the socioeconomic context and landscape characteristics, has substantial influence over protected area success. More specifically, we find that most socioeconomic and biophysical variables are stronger drivers of protected area outcomes than protected area design characteristics such as size, strictness, and management effectiveness (Figure 2.1). We found this pattern across all five forest types and the full model, with slight variations in the variables of importance across different forest types (Figure 2.3). Within protected area design characteristics, we find variables reflecting collaborative management and equity and protected area size to be the strongest predictors of forest loss, albeit with less explanatory power than socioeconomic and biophysical variables.

Our ALE plots provide evidence of the complexity of the relationships between various predictors and observed forest loss, suggesting that protected area evaluations are frequently oversimplifying these relationships by using conventional modeling approaches which assume linearity when examining drivers of forest loss outcomes in protected areas, including generalized linear models, probit regressions, or ordinary least squares regressions. We build upon the small number of studies that have examined the complexity of the relationship between potential drivers of forest loss and deforestation by using higher resolution data for a finer spatial scale of analysis, while also examining a new temporal period of forest loss (e.g., Bonilla-Moheno et al., 2012), as well as using ALE plots (rather than PDP plots) to estimate the conditional relationship of predictor variables and forest loss, accounting for multicollinearity among predictor variables (e.g., Bonilla-Moheno et al., 2012; Bax & Francesconi, 2018).

Socioeconomic Factors

We find socioeconomic variables to be strong predictors of forest loss across all models, including proxies for development pressures and forest accessibility (Figure 2.1). Existing research has often highlighted the negative effects of linear infrastructure, such as roads, on forest conservation (e.g., Busch & Ferretti-Gallon, 2017; Laurance et al., 2009; Mendoza-Ponce et al., 2018). In a meta-analysis of drivers of forest loss, Busch & Ferretti-Gallon (2017) found that the presence of roads was consistently correlated with higher forest loss across over 100 studies. Our results align with previous findings, identifying road density and road distance as strong predictors of forest loss outcomes (Figure 2.1) and demonstrating the increased risk of forest loss in areas closer to roads and with higher road density (Figure 2.2a and 2.2g). However, we also find that more remote areas (i.e., far from roads and urban areas) experience an increased risk of forest loss.

We found high levels of uncertainty in the relationship between forest loss and human populations (see Figure 2.2d and 2.2f). This uncertainty may reflect the complex and sometimes contradictory relationships between human population centers and forest cover change. For example, larger populations near protected areas can increase the demand for resources and employment opportunities in extractive industries (Busch & Ferretti-Gallon, 2017). Alternatively, neighboring populations can increase surveillance for conservation efforts and be encouraged to engage in more environmentally sustainable livelihoods (e.g., eco-tourism, forest concessions, honey production) (Andam et al., 2008; Barnes et al., 2017; Solorzano & Fleischman, 2018). Solorzano and Fleischman (2018) found that tenure legacies, political inequality, and economic opportunities can also influence community support for conservation efforts in biosphere reserves in Mexico and Guatemala. Future research should try to incorporate additional socioeconomic variables to those included here, such as tenure legacy, livelihood opportunities, and tourism rates, to attempt to clarify some of the uncertainty found in the ALE plots.

Biophysical Characteristics

Our model found that precipitation and distance to water had a strong influence on forest conservation outcomes. Precipitation has been found to be a key predictor of forest loss in previous studies in Mexico (Bonilla-Moheno et al., 2012; Roy Chowdhury, 2006) and across Latin America (Aide et al., 2012). Additionally, Bax and Francesconi (2018) found distance to rivers and precipitation to be the second and third most important variables in predicting forest loss in Peru, with similar non-linear patterns found using partial dependence plots. Water access from rivers can increase forest accessibility (similar to roads), influencing human settlement and resource extraction patterns (Bax & Francesconi, 2018). Precipitation can influence agricultural productivity, however, landscape wetness was found to be negatively correlated with deforestation in a recent meta-analysis due to higher rates of wetness decreasing agricultural suitability (Busch & Ferretti-Gallon, 2017). Our ALE plots demonstrate this relationship with greater detail, finding that risk of forest loss increases as precipitation increases followed by a potential decline around 2,700mm, though with less certainty. Additionally, we also found high levels of predicted forest loss at very low precipitation values, which could reflect higher fire risk. To test for this, we examined the relationship between fire burn scars and forest loss, but found little evidence of correlation with the data used (Appendix Table A9 and A10).

Protected areas are more often established in places less-suited to alternative land uses, such as higher elevations and areas with steeper slopes (Baldi et al., 2017; Joppa & Pfaff, 2009). While neither of these variables were the strongest determinants of forest loss in our analysis, we find that they do have some influence over protected area outcomes, similar to other research in Mexico (e.g., Pfaff et al., 2017). Our ALE results support prior research, finding high risk of forest loss at lower elevations and low slopes, depicting areas with potentially lower agricultural preparation costs and favorable conditions for livestock grazing. We also find a substantial increase in forest loss risk at steep slopes, which has also been linked to fire risk, since fire containment is more challenging in steeper landscapes (Vaca et al., 2019). Future research should expand on these findings to better understand what determines directional thresholds in each of the non-linear predictor variables.

Protected Area Design Characteristics

There has been a recent call to make protected areas more just and equitable (Franks & Schreckenberg, 2016; Jonas et al., 2021; Zafra-Calvo et al., 2017), with related indicators being integrated into the most recent protected area global Green List standards (IUCN, 2016). Community involvement in protected area decision-making has previously been found to increase support for conservation efforts, and ultimately to increase protected area success (Andrade & Rhodes, 2012; Solorzano & Fleischman, 2018). We find the most important protected area management variables to be governance and social participation, with use and benefits shortly below. In general, the relationships trended negative, with higher scores resulting in lower risks of forest loss, contributing evidence in support of efforts to make protected areas more collaborative and equitable. Additionally, given that our analysis found the main drivers of forest conservation outcomes to be proxies for human pressure, the involvement and equitable benefit sharing with all stakeholders may serve as a key response to these threats.

The administrative and financial management components were also ranked in the importance plot, albeit lower than expected. Financial resources and human capacity are consistently highlighted as key drivers for protected area success, and have been known to be limited on a global scale (e.g., Coad et al., 2019; Gill et al., 2017). Our findings continue to support existing research, highlighting the importance of sufficient management resources for protected area success, while also contributing concrete evidence on the importance of additional management characteristics, such as collaboration and shared decision-making.

Four individual protected areas were ranked as having a strong influence on forest loss outcomes, all experiencing higher levels of forest loss than expected. Two of the protected areas were biosphere reserves and the other two were flora and fauna protection areas. The four areas were all located in southern Mexico, but in three different states. Three of the areas were located either on (Cañón del Usumacinta, Calakmul) or close to (Montes Azules) the border with Guatemala. More research should be done to better understand the unique characteristics of these areas that may be driving these outcomes.

Study Implications

Our subgroup comparison showed that the variables used in our analysis, gathered from a review of relevant literature, explained the greatest variance for deforestation in moist forests. Additionally, we found the greatest rates of forest loss between 2015-2019 to be in moist forests, similar to previous research in Mexico (Bonilla-Moheno et al., 2012), Latin America (Aide et al., 2012), and global analyses (Hansen et al., 2013; Laurance et al., 2012; Spracklen et al., 2015). Given these rapid rates of forest loss, and the immense amount of biodiversity that moist tropical forests harbor, it is critical that we continue to advance our understanding of drivers of forest loss in this ecoregion. However, future research should also aim to better understand drivers in the other forest types, including dry forests and pine-oak forest, given that they also provide critical ecosystem services, are experiencing loss, and commonly-used predictor variables were found to have lower explanatory power for deforestation in these areas.

Our findings highlight the importance of placement characteristics in shaping protected area outcomes, including proximity to human populations, road access, waterways, and the physical characteristics of the landscape. This has important implications for protected area managers, as well as researchers. By combining results of our ALE plots, landscape-level patterns can be identified to determine areas with the highest deforestation risk (e.g., areas at low elevation with low slopes, areas close to urban areas and roads, areas with cooler temperatures and higher levels of precipitation) and resources can be appropriately allocated to protected areas that may face the greatest threat based on these characteristics. Additionally, given current rates of environmental change driven by factors such as urban sprawl and climate change, threats to global biodiversity are likely to shift, and less threatened protected areas may face increasing pressures in future. Identifying the important design and management characteristics that can counter this pressure will be key to future conservation success.

Researchers have called for more careful protected area effectiveness evaluations after finding evidence of protected area placement biases (see Joppa & Pfaff, 2009; Baldi et al., 2017). In response, impact evaluations that estimate a counterfactual (i.e., what would have happened if the area was not protected) are now commonly used to account for these biases (e.g., Andam et al., 2008; Baylis et al., 2016; dos Santos Ribas et al., 2020; Pressey et al., 2015; Schleicher et al., 2019). Our findings reinforce the need for counterfactuals in protected areas evaluations, given that many variables driving outcomes are external to protected area design. We demonstrate the utility of random forest as an exploratory method, which can be used to help inform matching or other counterfactual design measurements, in order to avoid omitted variable biases and, ultimately, design more accurate evaluations.

Limitations

Data availability is a common limitation when conducting spatial analysis with secondary data. Moreover, determining drivers of forest loss requires close temporal alignment of independent variables with observed loss (except for those which may have a lag effect), further narrowing appropriate data. We recognize that our list of predictors is not comprehensive and that there may be variables not included that can be strong predictors of forest loss. For example, a marginalization index from 2010 was found to influence forest loss in a previous study conducted at the municipality-level in Mexico (Bonilla-Moheno et al., 2012) and livestock density was negatively correlated with forest conservation in another (Mas & Cuevas, 2015). However, to our knowledge, neither were available for our time period of focus.

A second limitation to spatial analyses is the lack of spatial referencing of complex variables, such as tenure security, market forces, community dynamics, and other institutional variables (Vaca et al., 2019). We recognize that some variables included in our analysis may be oversimplified. We attempted to capture some complex institutional relationships by using a multidimensional poverty index, which considers access to social services in addition to income. However, we acknowledge that there may be other key social and institutional factors driving outcomes that are not accounted for, such as tenure security (see Robinson et al., 2014), overlap with Indigenous lands (see Garnett et al., 2018), and tenure and political trends pre-dating protected area establishment (see Solorzano & Fleischman, 2018).

Conclusion

We present evidence on the drivers of protected area forest conservation outcomes, finding socioeconomic and biophysical variables to be more influential than protected area design characteristics. Of protected area design characteristics, we find that variables reflecting inclusion of relevant stakeholders and the fair distribution of benefits to be strong predictors of outcomes. Our findings provide important information for protected area management and planning by identifying characteristics that can reduce protected area success and inform resource allocation to address those threats. We also strengthen the argument for protected area impact evaluation methods that calculate a counterfactual since we found that a number of external variables strongly influenced deforestation outcomes and can thus bias evaluation results. Finally, our study highlights a number of future research opportunities, including more investigation into thresholds determining the direction of influence of predictors, as well as building more evidence on drivers of forest loss across different forest types.

CHAPTER 3: MANAGEMENT EFFECTIVENESS POSITIVELY INFLUENCES FOREST CONSERVATION OUTCOMES IN PROTECTED AREAS

Chapter Summary

Understanding the factors that drive protected area outcomes is critical for increasing the success of global conservation efforts. Until recently, our understanding of the influence of management effectiveness has been restricted by the limited availability of standardized management data and study design limitations of prior evaluations. Here we use a quasi-experimental matching approach to test the influence of management effectiveness on forest cover change inside 46 protected areas in Mexico using the results of a recently developed national assessment. We test the influence of five management categories, including context and planning, administrative and finances, use and benefits, governance and social participation, and management quality, as well as an overall effectiveness score, using a subgroup analysis and an interaction term in multiple linear regression. Our results find that protected areas with higher management effectiveness have a greater effect on reducing deforestation compared to those with low management effectiveness, but that both types of protected areas experience less forest loss compared to similar unprotected areas. We find this trend in all five of the management categories and the overall score, with administrative and finance scores having the greatest effect on forest loss outcomes. Our findings suggest that forest conservation requires careful design andplanning, effective participation from multiple stakeholders and equal sharing of benefits, and sufficient human and financial capital in order to be effective at preventing forest loss.[3]

[3]Reference for publication: Powlen, K. A., Gavin, M. C., & Jones, K.W. (2021). Management effectiveness positively influences forest conservation outcomes in protected areas. *Biological Conservation* 260, 109192.

Introduction

Protected areas are a widely promoted tool to conserve the world's remaining forests, and have significantly expanded since the adoption of the Aichi Targets by the Convention of Biological Diversity (Butchart et al., 2015; Convention on Biological Diversity, 2010). While we are on track to reach global goals for protected area coverage, less progress has been made on other global goals, including minimal improvements in the loss and fragmentation of natural habitats and the restoration of ecosystems that provide essential services (Secretariat of the Convention on Biological Diversity, 2020). In light of this disconnect between protected area establishment and conservation metrics, it is critical that we gain a better understanding of what drives conservation outcomes for the effective pursuit of biodiversity goals.

In addition to increasing global terrestrial protected area coverage to 17%, the CBD calls for the *effective and equitable* management of protected areas (Convention on Biological Diversity, 2010). Management effectiveness is expected to lead to better conservation outcomes as more strategic planning, better monitoring capacity, improved accountability and transparency, and sufficient human and financial resources should theoretically result in more effective enforcement and governance (Coad et al., 2013; Coad et al., 2015; Dudley & Stolton, 2009; Geldmann et al., 2018; Nolte & Agrawal, 2013). However, until recently, these theoretical links remained largely untested due to limited data on *de facto* management (i.e., how management actions are carried out on the ground) and a lack of counterfactual evaluation. Our study overcomes both limitations by using a rigorous impact evaluation design to examine the influence of management effectiveness scores on protected area outcomes using the results of a recently developed national management effectiveness assessment in Mexico.

Management effectiveness assessments, known as Protected Area Management Effectiveness (PAME) tools, have been designed to increase and standardize protected area management monitoring (Coad et al., 2013, 2015; Geldmann et al., 2015, 2018; Hockings et al., 2015; Leverington et al., 2010). These assessments focus on the design and planning, capacity and resources, and decision-making processes of protected areas (Hockings et al., 2006; Stolton & Dudley, 2016). In addition to strengthening efforts to meet global conservation goals, many conservation organizations have adopted these assessments as a measurement of protected area success, and the results play an important role in conservation investments by large donors, such as the Global Environmental Facility (GEF) (Nolte & Agrawal, 2013).

Scores from management effectiveness assessments provide new opportunities to examine *de facto* management rather than *de jure* management (e.g., IUCN management categories) used in previous studies (Ferraro et al., 2013; Muñoz Brenes et al., 2018). To date, few impact evaluations have critically examined the relationship between *de facto* management and biodiversity outcomes (Coad et al., 2015). As of 2015, an estimated 17,700 PAME assessments had been conducted in over 9,000 protected areas (Coad et al., 2013), but a review from the same year found only nine studies, from peer-review and gray literature, that could be summarized as evidence on the relationship between PAME scores and biodiversity outcomes (Coad et al., 2015). Of those nine studies, only three studies used counterfactual evaluation, and all three of these studies found no correlation between management effectiveness and biodiversity outcomes (Coad et al., 2015).

Evidence from other existing impact evaluations have drawn inconsistent conclusions about the influence of management effectiveness on conservation outcomes. For example, Geldmann et al. (2018) found only management characteristics related to staff and budget had a significant relationship with vertebrate abundance in global protected areas, while other studies have found no relationship between management effectiveness scores and forest loss mitigation in Brazil (Nolte et al., 2013) or forest fire mitigation in the broader Amazon basin (Nolte & Agrawal, 2013). Additionally, while a few existing impact evaluations have attempted to link assessment scores to conservation outcomes on a global scale (e.g., Geldmann et al., 2018, 2019; Leverington et al., 2010), national-level evaluations have been largely concentrated in Brazil and the Amazon basin region (e.g., Carranza et al., 2014; Nolte & Agrawal, 2013; Nolte et al., 2013).

The limited empirical research critically examining the relationship between management effectiveness and conservation outcomes, as well as the importance of measuring management effectiveness for global conservation goals and conservation funding, warrants further investigation. We contribute to this body of evidence by conducting an evaluation of the impacts of management effectiveness on forest cover loss in 46 terrestrial protected areas in Mexico, a biodiversity hotspot. We link the results of a standardized management effectiveness assessment developed by Mexico's National Commission of Natural Protected Areas (CONANP) to forest loss data inside protected areas and use matching techniques to more accurately measure the influence of five different management dimensions, as well as an overall management score, on changes in forest cover.

Mexico provides a unique opportunity to examine the influence of management effectiveness on protected area performance due to recent advances in management effectiveness monitoring across its extensive protected area network, estimated at 14.5% of terrestrial area and 21.6% of marine area (UNEP-WCMC, 2021). Similar to other regions of the world, researchers have found variability in the performance of Mexico's protected area network (e.g., Blackman et al., 2015; Figueroa & Sanchez-Cordero, 2008; Figueroa et al., 2011; Pfaff et al., 2017;

Sánchez-Cordero et al., 2011; Sims & Alix-Garcia, 2017). For example, Pfaff et al. (2017) found stricter protected areas to be more successful at slowing forest loss compared to mixed-use protected areas in Mexico, while Blackman et al. (2015) found mixed-use protected areas were more successful at slowing deforestation, in addition to those that were larger and newer, over a slightly different time span.

Efforts to monitor management effectiveness in Mexico's protected area network have been ongoing since 2005 (Comisión Nacional de Áreas Naturales Protegidas, 2019). However, in 2016, CONANP developed a new national assessment (*i-efectividad*, or El Sistema Permanente de Evaluación de la Efectividad del Manejo de las Áreas Naturales Protegidas Federales de México) to collect standardized results using indicators from four existing international PAME evaluation frameworks. While the role of management effectiveness in protected area success has been examined in three marine protected areas in the Yucatan Peninsula (Herrejón et al., 2020), and financial resources have been examined as a driver of outcomes in 56 terrestrial protected areas across Mexico (Blackman et al., 2015), this is the first study to test the influence of a comprehensive suite of management dimensions on conservation outcomes in Mexico using the results of CONANP's recently developed assessment. By identifying the specific management factors that have the greatest influence on conservation outcomes, our results serve to inform more efficient investments in protected areas to ensure better protection of global biodiversity.

Methods

Data

Data extraction was completed using ArcMap 10.7 and data analysis was conducted using R statistical software. Similar to Nolte & Agrawal (2012), we created sampling grid cells of 1 km^2 and used the Global Forest Watch (GFW) forest cover data to randomly select 80,000 forested grid cells across Mexico for a computationally feasible final sample. Due to the distribution of ecoregions across Mexico, many of the grid cells included in our analysis were concentrated in southern Mexico. Grid cells in northern Mexico, which is primarily North America Desert, were more scarce.

The final sample consists of 60,000 cells outside of protected areas and 20,000 inside protected areas. Retaining a greater number of cells outside of protected areas increases the probability of strong matches with protected cells due to a greater variety of control group characteristics. We found no evidence of spillover effects, or the displacement of deforestation from protected areas to adjacent unprotected areas, within a 5km and 10km buffer around each protected area (Appendix Table B1). Therefore, we did not exclude grid cells within a buffer region of protected areas in the final sample.

We use protected area data from the World Database on Protected Areas (IUCN & UNEP-WCMC, 2019) and the scores of CONANP's management effectiveness evaluation to test the influence of management effectiveness on performance in all forested protected areas with scores available. At the time of our analysis, 76 of the 123 protected areas with existing management plans had available management effectiveness scores. Our sub-sample of the 46 forested protected areas represents 62% of the 76 protected areas with completed evaluations, accounting for 37% of all protected areas with management plans in Mexico (Figure 3.1, full list included in Appendix Table B2).

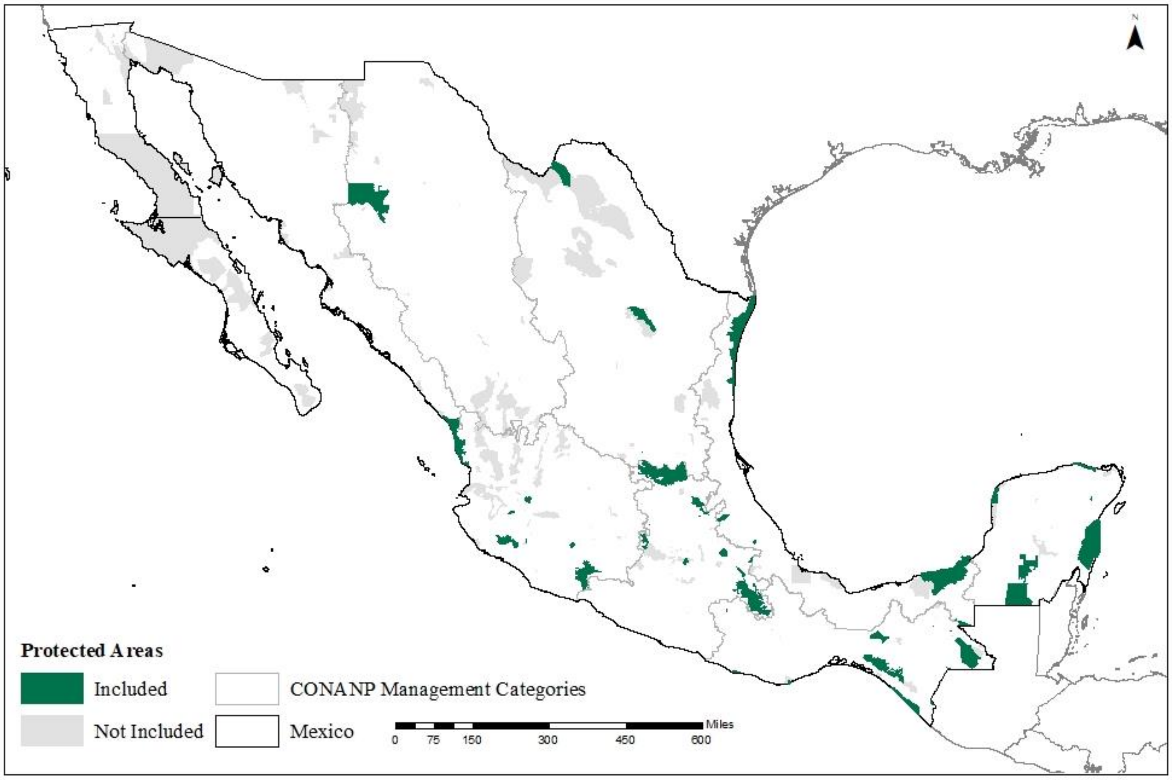


Figure 3.1: Map of the 46 protected areas included in the analysis. Management effectiveness subgroup were split at the median (i.e., high management effectiveness score ≥ 74 and low management effectiveness score < 74).

The management effectiveness evaluation, like many of the PAME tools, is a self-administered survey and responses are provided by management personnel. It consists of 48 indicators organized into five management categories, including context and planning, administration and finance, use and benefits, governance and social participation, and management quality, each category with a score on a scale from 0-100 (Table 3.1). We use scores from a one-time response in 2017.

Table 3.1: Examples of indicators in the five management categories listed in CONANP's management effectiveness evaluation.

Category	Indicator Examples
Context and Planning	Existence of a management plan, work plan, monitoring and evaluation plan, documentation of natural and cultural resources
Administration and Finance	Sufficient financial resources, human capacity, appropriate equipment
Use and Benefits	Economic benefits, sustainable use or production within the boundary, appropriate infrastructure for use and visitation
Governance and Social Participation	Recognition and respect of rights of all stakeholders, participation from local communities and neighboring resource users, education and outreach programs
Management Quality	Area is managed to objectives, sufficient information and active management strategies are used for threats or endemic species

For the outcome variable, we use data on annual forest cover loss from Global Forest Watch (GFW), the most comprehensive high-resolution data available on global forest cover (Hansen et al., 2013). We define protected area performance as forest loss between 2017-2019, assuming that management effectiveness did not change significantly in the two years after the CONANP assessment was conducted. Additionally, we recognize that changes in forest cover from 2017-2019 may also be due to management characteristics that predate 2017, for which we have no reliable data to test.

We include socioeconomic, ecological and climatological variables in our analysis to control for confounding factors, similar to prior protected area evaluations (e.g., Blackman et al., 2015; Nolte & Agrawal, 2013; Pfaff et al., 2017) and due to the significant differences found in the subgroups of our analysis (e.g., protected area and unprotected area). These variables include elevation, slope, distance to roads, road density, distance to urban centers, population density, average temperature, rainfall, and *ejido* (communal) land tenure (list of data sources included in Appendix Table B3).

Prior evaluations have found distance to roads and road density to have a negative influence on forest conservation outcomes due to roads increasing access and opportunities for extraction of forest resources (e.g., Joppa & Pfaff, 2009; Kere et al., 2017; Oliveira et al., 2007). Slope and elevation have been linked to agricultural and urban development suitability, similar to temperature and rainfall (e.g., Blackman, 2015; Joppa & Pfaff, 2009; Nolte & Agrawal, 2013). Flatter areas and more favorable weather conditions can increase forest clearing for agricultural production or other development. Proximity to urban areas and higher population density can increase deforestation due to space and resources needed to support the human population, as well as market integration opportunities (e.g., Leberger et al., 2019; Nolte & Agrawal, 2013; Waldron et al., 2017). Finally, land tenure has been found to influence conservation outcomes, with some community-owned forests producing better outcomes than protected areas (e.g., Durán-Medina et al., 2005; Porter-Bolland et al., 2012). We controlled for tenure in our analysis due to the substantial overlap of *ejidos* and protected areas in Mexico.

Analysis

To accurately measure causal effect relative to a counterfactual, impact evaluation design is needed to account for hidden biases in intervention placement (Baylis et al., 2016). Matching is one approach used to control for such biases, and can help account for non-randomly assigned treatment groups by increasing similarities among predictive variables, or observable covariates, within treatment and non-treatment groups (Austin, 2011; Schleicher et al., 2019; Stuart, 2010). We implement matching following the best practices outlined by Schleicher et al. (2019).

Prior to matching, we examined correlation coefficients between all socioeconomic, ecological, and climatological covariates to minimize potential multicollinearity and maximize model fit (Appendix Table B4). We selected six covariates that were not highly correlated and that were significant predictors of both forest loss and protected area status (Appendix Table B5). The final six covariates used in matching included elevation, slope, urban distance, road distance, average yearly rainfall, and *ejido* tenure.

We used two matching algorithms to match protected and unprotected cells: Propensity Score Matching and Mahalanobis Distance Matching. We used a one-to-one matching without replacement for both algorithms and tested a caliper of 0.2 standard deviations and 0.1 standard deviations when necessary to improve match quality (Imbens & Rubin, 2015; Stuart, 2010). We evaluated the quality of each match by calculating the standardized bias (SB) and examined potential biases from omitted variables using Rosenbaum bounds sensitivity test (Γ), a measure of the amount of change in a confounding factor required to undermine the statistical significance of the treatment effect (Rosenbaum, 2002).

The influence of management effectiveness on protected area outcomes was measured by (1) calculating average treatment effect (ATE) across matched management subgroups and (2) using an interaction term in a general linear regression model. For the subgroup analysis, let $D_{he}=1$ if the grid cell has a high management effectiveness score and equal to 0 if unprotected and $D_{le}=1$ if the grid cell has a low management effectiveness score and 0 if unprotected. The median management effectiveness score was used as the cutoff between high and low management effectiveness protected areas. Y is the continuous forest loss between 2017-2019. After selecting the most balanced match for each subgroup, we calculated ATE as the difference in mean outcomes between treatment and control cells, or $[\Sigma (Y|D_{he}=1)-\Sigma(Y|D_{he}=0)]$ and $[\Sigma(Y|D_{le}=1)-\Sigma(Y|D_{le}=0)]$, using t-tests.

To account for possible remaining imbalances, we also examined the significance of the treatment effect for each matched group using a multivariate linear regression, which included the six covariates used in matching as independent variables. Specifically, we regressed the binary treatment dummy variables (*D_{he}* and *D_{le}*) and the six covariates (*CoVar*) outlined above on Y, as follows:

Equation 1: $Y = \beta_0 + \beta_1 D_{he} + \beta_2 CoVar1 + \ldots + \beta_7 CoVar6 + U$

for the high management effectiveness subgroup and

Equation 2: $Y = \beta_0 + \beta_1 D_{le} + \beta_2 CoVar1 + \ldots + \beta_7 CoVar6 + U$

for the low management effectiveness subgroup.

We used robust standard errors, *U*, in both regressions after finding evidence of heteroscedasticity among the residuals using a Breusch-Pagan test.

Second, we used an interaction term in a multivariate linear regression to test for a moderating effect of management effectiveness. While both subgroup analysis and interaction effects are used to test for moderating effects in impact evaluation, the use of an interaction term allows for more variation in the moderator compared to a subgroup approach (Sills & Jones, 2018). The moderating effect of management effectiveness in this analysis is estimated as follows:

Equation 3: $Y = \beta_0 + \beta_1 (PA * D_c) + \beta_2 CoVar1 + \ldots + \beta_7 CoVar6 + U,$

where *PA* is a treatment dummy variable equal to 1 if the cell is within a protected area and 0 if else and D_c is a continuous management effectiveness score. We estimated the above regression separately for each of the five management categories, as well as for the overall management score. We used robust standard errors, U, after finding evidence of heteroscedasticity and the same six covariates listed above are included in each interaction model.

Additionally, to test the robustness of the interaction models, we created a binary dependent variable from the continuous percent forest loss, Y, where Y_b=1 for any loss and Y_b=0 for no forest loss. A logit regression and a constructed binary variable can be used to test the robustness of linear regression results when continuous data contains a large number of zeros, and is thus severely skewed to the right (Boulton & Williford, 2018). We therefore examined the moderating effect of each management score using Y_b as the dependent variable in a logit regression model similar to equation 3. We tested for spatial autocorrelation using Moran's I and the residuals of each interaction model (Legendre, 1993; Negret et al., 2020).

Results

The 20,000 protected area grid cells were located within 46 protected areas that were all established before 2010 and ages ranged from 11 to 83 years. The areas represented five protected area types: biosphere reserves (IUCN Category Ia and VI; 72%), national parks (IUCN Category II; 6%), national monuments (IUCN Category III; <1%), flora and fauna protection areas (IUCN Category VI; 17%) and natural resource protection areas (IUCN Category VI; <1%).

Management Scores

Management scores in all categories varied across the 46 protected areas (Figure 3.2). Using the median score of the 20,000 grid cells inside protected areas to create high and low subgroups, 34 protected areas fell within the low overall effectiveness score category (< 74) and 12 protected areas were in the high overall effectiveness category (>74). No protected area had an overall management score of less than 40. Across the five management categories, protected areas scored highest on governance and social participation and lowest on administration and finance (Figure 3.2).

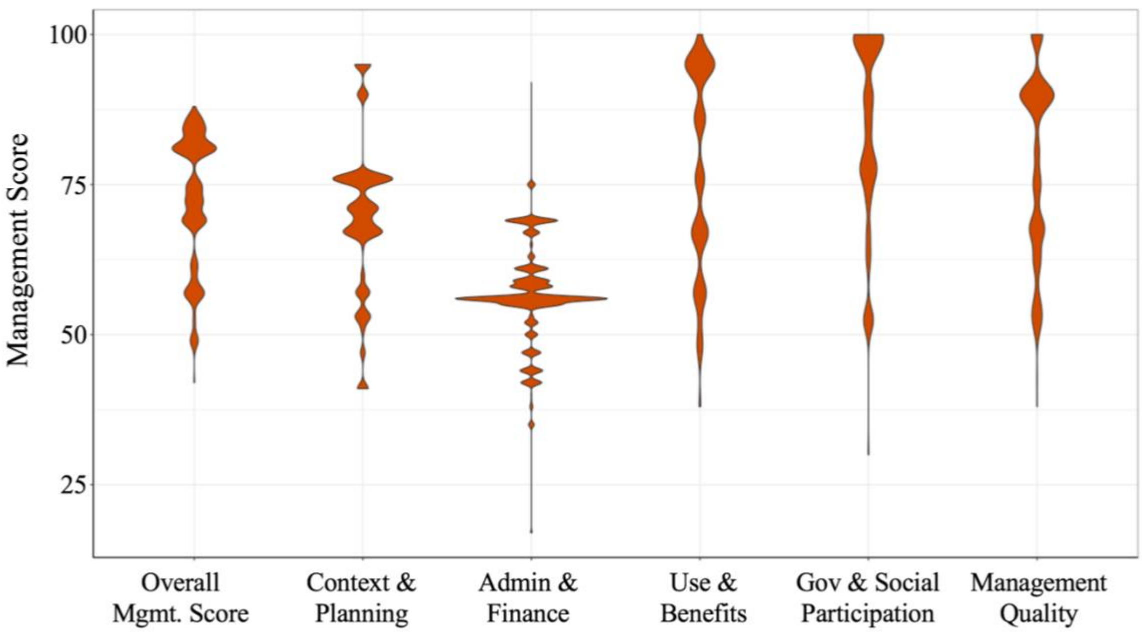


Figure 3.2: Distribution of scores for each management category and the overall score from the grid cells in the 46 protected areas.

Covariates and Matching

The socioeconomic, ecological and climatological covariates varied greatly across protected and unprotected cells, as well as high and low management effectiveness protected area cells (Figure 3.3, Appendix Table B6). A t-test found that cells within protected areas tend to be at higher elevations *($p<.001$)*, with lower slopes *($p<.0001$)*, further from urban areas *($p<.0001$)* and roads *($p<.0001$)*, and with lower road density *($p<.0001$)*. They were also found to have lower temperatures and a lower amount of rainfall, as well as a lower percentage of *ejido* tenure *($p<.0001$* for all covariates).

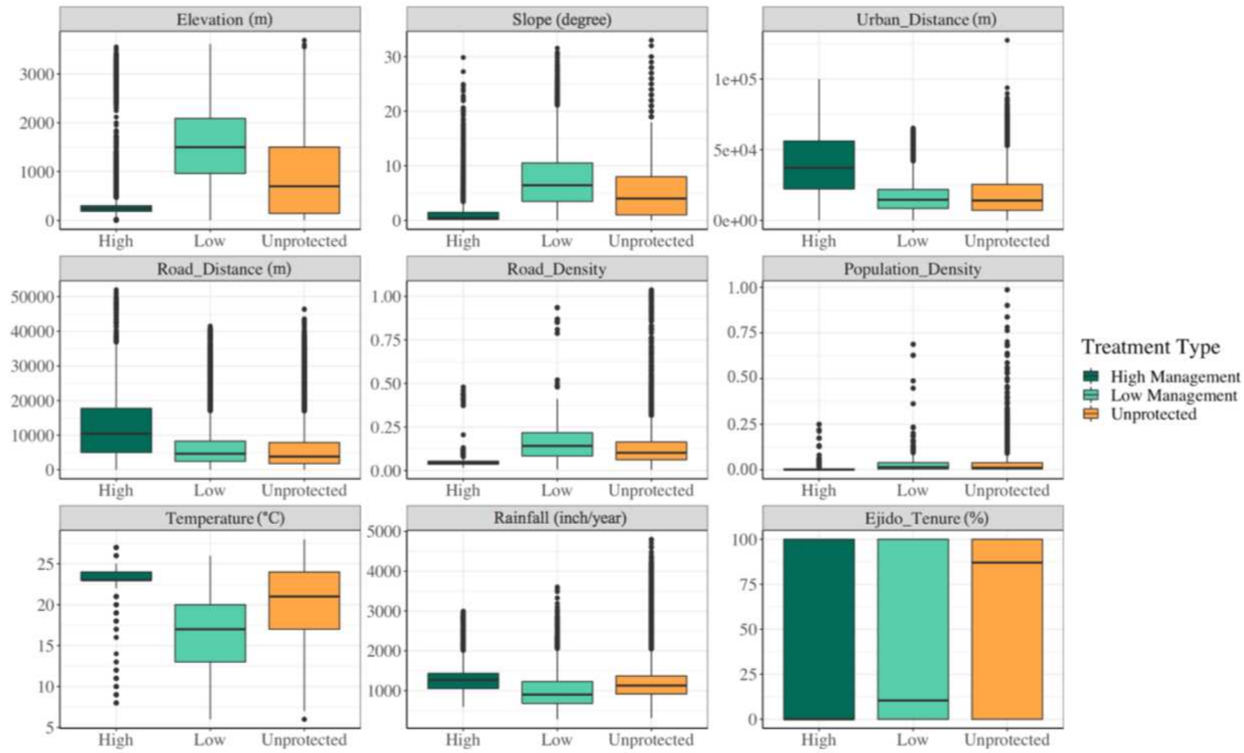


Figure 3.3: Boxplots displaying the variation in covariates across high and low management effectiveness subgroups and unprotected cells.

Cells in low management effectiveness protected areas were located at higher elevations with steeper slopes and closer to roads and urban areas compared to high management effectiveness protected areas (Appendix Table B6). They were also found to have a higher population density and road density, contained a higher percentage of *ejido* tenure, as well as less rainfall and lower temperatures on average ($p < .0001$ for all covariates).

The significant differences in covariates posed a challenge for well-balanced matches, with high management effectiveness being more challenging to match with unprotected cells than low management. Thus, we used a caliper in all protected area matches to improve match balance. We present the results from the best matching algorithms below (see Appendix Table B7, Appendix Table B8, Appendix Figure B1) for summaries of all matching algorithms tested and the associated post-matching balance).

Average Treatment Effect Estimates: Subgroup Analysis

Both high and low management effectiveness protected areas experienced significantly less deforestation than their matched controls using post-matching t-tests (Appendix Table B9). While high management effectiveness areas were found to have experienced more forest loss than low management effectiveness areas in absolute terms, the average treatment effect (relative to control cells) was significantly greater in high management effectiveness areas (Figure 3.4). These findings suggest that on average, while high management effectiveness protected areas are located in areas with greater threats than low management effectiveness protected areas, they are also more successful in deterring these threats than low management effectiveness areas.

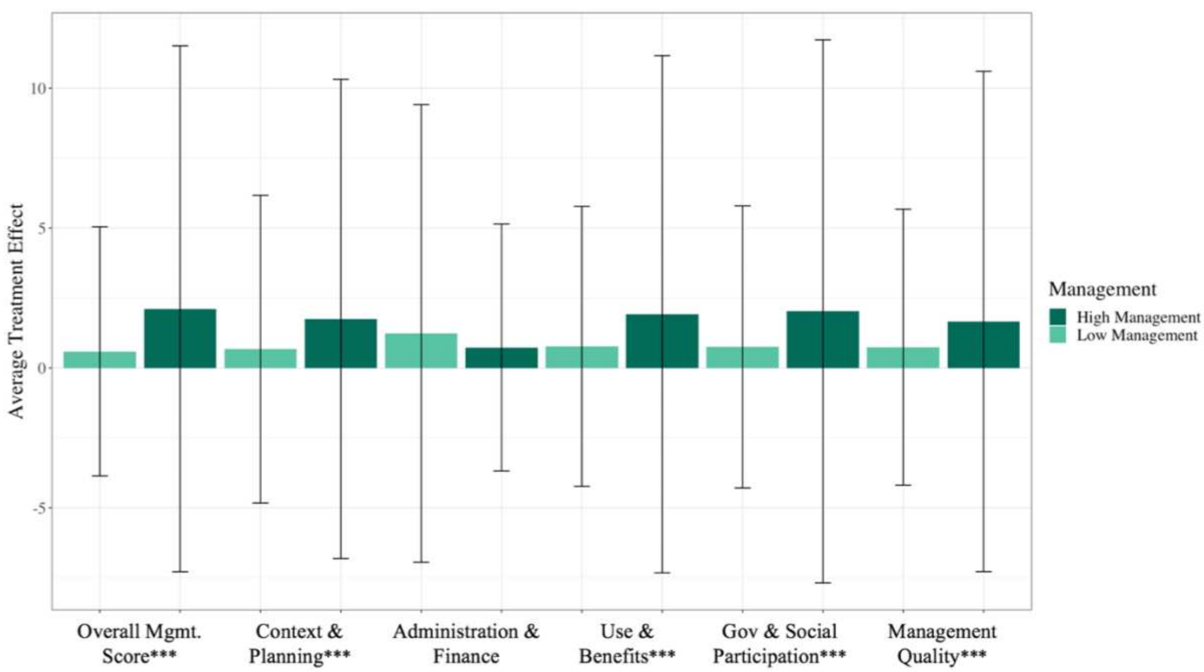


*Figure 3.4: Bar chart and error terms of average treatment effects (ATE), calculated as the difference in average forest loss in the treatment group and the control. Statistical significance was estimated using Wilcoxon Rank Sum analysis ($p<.0001$***, $p<.001$**, $p<.01$*).*

The average percent loss between 2017-2019 in high overall management cells was 1.19 compared to 3.30 in the matched unprotected cells ($p<.0001$), and 0.46 in low overall management cells compared to 1.05 in the matched unprotected cells ($p<.0001$). Similarly, average forest loss in the high and low matches of each of the five management categories was significantly less than their matched control group.

Although low management effectiveness cells experienced less deforestation than high management effectiveness cells in all categories except for context and planning and administration and finance, a Wilcoxon Rank Sum test found the ATE to be significantly higher in the high subgroups of the overall management scores (p <.0001), context and planning (p <.0001), use and benefits (p <.0001), governance and social participation (p <.0001), and management quality (p <.0001) compared to the ATE of the low management effectiveness subgroups (Figure 3.4). The ATE of the low administration subgroup was higher that of the high subgroup (low: -1.23, high: -0.73), however, no statistical significance was found.

The post-match linear regression model, used to control for remaining imbalances in covariates, found that both high and low management effectiveness protected areas significantly reduce deforestation in all models (p <.0001) (Table 3.2, full model results in Appendix Table B10 and B11). Across all management categories, the models indicate that less forest loss occurred in both high and low management effectiveness categories when compared to unprotected sites.

Table 3.2: High and low management effectiveness effects for individual management categories. Regression coefficients and robust standard errors shown for only the treatment variable of each model. Dependent variable is percent forest loss between 2017-2019 for all models.

	Overall Mgmt. Effectiveness	Context & Planning	Admin & Finance	Use & Benefits	Gov & Social Participation	Management Quality
High Management	-2.18*** (.106)	-1.77*** (.117)	-0.73*** (.049)	-2.01*** (.110)	-2.00*** (.115)	-1.81*** (.104)
Observations	14,046	10,232	15,476	12,958	12,866	10,820
	Overall Mgmt. Effectiveness	**Context & Planning**	**Admin & Finance**	**Use & Benefits**	**Gov & Social Participation**	**Management Quality**
Low Management	-0.50*** (.043)	-0.63*** (.049)	-1.32*** (.077)	-0.73*** (.047)	-0.71*** (.048)	-0.71*** (.047)
Observations	20,242	23,334	21,140	20,740	20,820	20,658

p <.0001*** p <.001** p <.01*

Average Treatment Effect Estimates: Interaction Effects

Our results found a significant moderating effect of management effectiveness (overall effectiveness and each sub-category) using an interaction term. Higher management effectiveness in each category was significantly correlated with a reduction in forest loss (coefficients range from -1.25e-02 to -1.84e-02, all p <.0001) (full results in Appendix Table B12). The administration and finance score was found to have the largest ATE on average, followed by context and planning, use and benefits, management quality and governance and social participation. The overall management score was also statistically significant at the <.0001 level.

While holding all else constant, a 10% increase in the administration and finance score was associated with the largest decrease in percent forest loss, of about 0.19% (Figure 3.5). A 10% increase in the context and planning score and the overall score was found to decrease the average forest loss by about 0.16% and 0.15%, respectively. We found similar effects for a 10% increase in the use and benefits and management quality score, which were both found to decrease average forest loss by 0.14%. Finally, a change in governance and social participation had the smallest effect, with a 10% increase in score decreasing forest loss by 0.13%. Full marginal effects results are presented in Appendix Table B13.

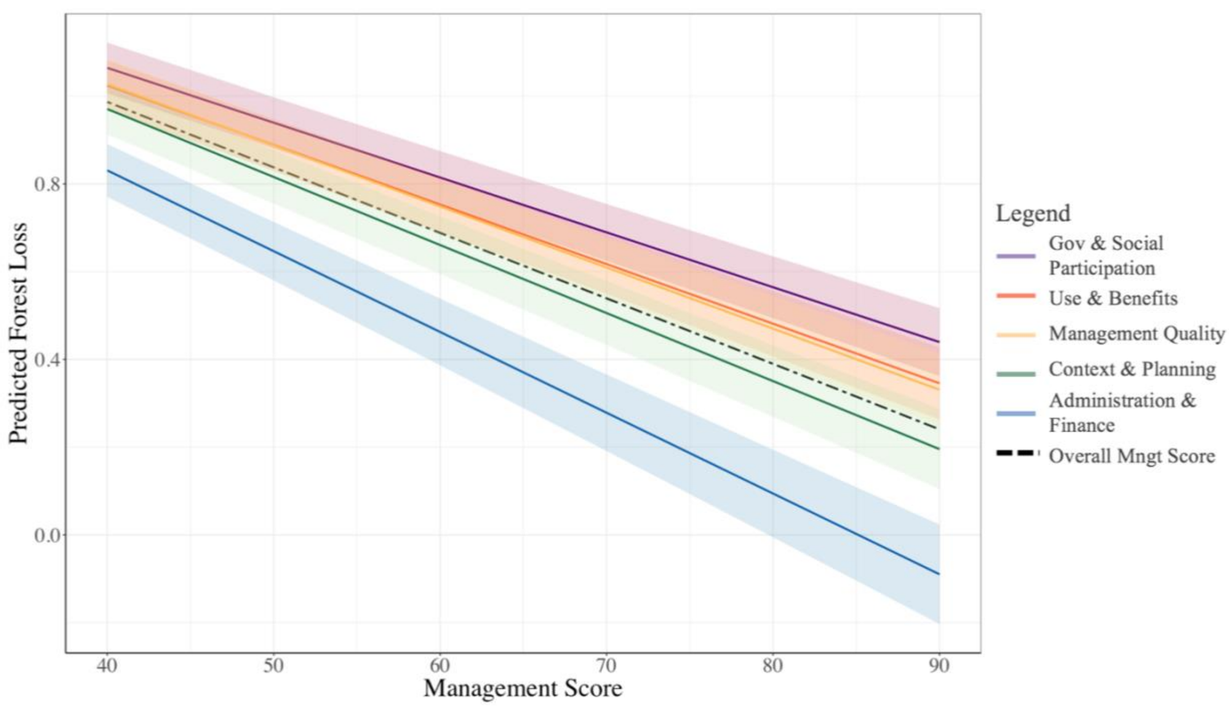


Figure 3.5: Marginal effect of each management category on predicted forest loss. Shaded area represents 95% confidence intervals for each model.

Robustness checks

The Rosenbaum bounds sensitivity test found that our analysis was sensitive to small changes in unobservable bias (Appendix Table B14). However, this test is not able to detect if there is unobservable bias present, only what would happen if there were omitted variables that affected both the treatment and outcome variables. When comparing subgroups, the unobservable heterogeneity would need to act differently across subgroups to bias our findings (Ferraro & Hanauer, 2011).

The results of the logit models also confirm the robustness of our interaction model results (Appendix Table B15). In the logit models, all interaction effects were found to have a negative effect on predicted forest loss (p <.0001). Additionally, we find no evidence of spatial clustering in the residuals of the interaction model, with all Moran indices equal to ~0.00 (Appendix Figure B2).

Discussion

Our study contributes to a growing number of impact evaluations designed to measure the influence of protected areas on conservation outcomes. More specifically, it adds to the small number of those studies that have measured the moderating effect of multiple dimensions of protected area management effectiveness on conservation outcomes (e.g., Coad et al., 2015; Geldmann et al., 2018; Muñoz Brenes et al., 2018).

We found that protected areas in general avoid more forest loss than their matched controls, meaning that protected areas are successfully reducing deforestation across Mexico. Moreover, we found that protected areas with higher overall management effectiveness scores, as well as those with higher scores in all five sub-categories, are associated with lower rates of forest loss (Figure 3.5). Our results emphasize the importance of improving effectiveness across multiple dimensions of management to ensure the greatest conservation outcomes. These findings also illustrate the predictive power of management assessments in monitoring terrestrial protected area effectiveness and support their use in conservation investment decisions.

Results of our covariate comparison suggest that, on average, protected areas with higher management effectiveness scores are located in areas potentially more suitable for agriculture compared to those with low management effectiveness scores (Figure 3.3). This includes areas at lower elevations with flatter landscapes, and areas with warmer temperatures and greater rainfall.

In their global analysis, Geldmann et al. (2019) also found protected areas with higher management effectiveness scores to contain flatter terrain and, in contrast to our findings, in areas with higher road density, on average.

As a result of these location characteristics, we found large differences in the absolute forest loss findings of our high and low management effectiveness subgroup analysis. Unprotected cells matched with high management effectiveness protected areas experienced a much higher amount of forest loss compared to the unprotected cells matched with low management effectiveness protected areas in almost all matches (Appendix Table B9). Additionally, protected areas with high management effectiveness also experience higher rates of forest loss than protected areas with low management effectiveness. In turn, we can conclude, that levels of management effectiveness are not randomly distributed. Rather, high management effectiveness appears to be more common in protected areas that face higher threats. This could be due to more investment in high risk areas but would require additional research to tease out the cause of this relationship.

When compared to a counterfactual in our subgroup analysis, protected areas with high management effectiveness are found to prevent a greater degree of forest loss compared to those with low management effectiveness, resulting in a higher treatment effect (Figure 3.4). Overall, while high management effectiveness areas experience more forest loss, they also prevent more loss than would have occurred without any management intervention. When controlling for imbalances in the matched pairs using a post-match regression and the interaction regression models, we found higher scores in all five management categories to be associated with lower rates of forest loss. These findings illustrate the importance of quasi-experimental impact evaluation methods that utilize a counterfactual to compare observed differences. The influence of each management category is discussed in turn below.

Influence of Management by Category

The management category with the greatest influence over forest loss was the administration and finance category, which measures whether or not the protected area has sufficient human and financial resources (Figure 3.5). Our results support prior research pointing to the importance of financial and administrative resources in protected areas (e.g., Barnes et al., 2016; Barnes et al., 2017; Blackman et al., 2015; Bruner et al., 2001; Coad et al., 2019; Gill et al., 2017) and in conservation more broadly (e.g., Waldron et al., 2017). Additionally, in a global management effectiveness impact evaluation, Geldmann et al. (2018) found "capacity and resources" to be the only management category significantly related to changes in vertebrate abundance. Financial resources are often interlinked with human capacity (e.g., number of staff and staff training) and can enable better management practices for planning and enforcement of protected area restrictions (Leverington et al., 2010). Thus, this analysis provides additional empirical support to the hypothesized relationship that financial and human capital are critical to achieving conservation outcomes.

The management category with the next strongest relationship with forest loss was context and planning. Planning has previously been highlighted as a critical component to increasing protected area ecological impact and has been linked to improved resource monitoring and adaptive capacity of management (Pressey et al., 2015). Muñoz Brenes et al. (2018) found planning to play a significant role in protected area outcomes in an impact evaluation examining management capacity in 12 protected areas across Central America. Given that effective planning requires sufficient resources, including time, human capacity, and appropriate equipment, management planning may be largely enabled by administrative and financial resources. The significance of our findings highlight the important role that effective planning can have in protected area success and encourages greater investment in this dimension of management.

The management quality category includes indicators on the protected area's ability to monitor and respond to specific threats as well as to fulfill management objectives in pursuit of protected area goals. An increase in the management quality score was associated with less forest loss. Since the early 2000s, there has been a growing awareness of the importance of monitoring and evaluation in the conservation field and the influence that these processes have on conservation intervention success (Ferraro & Pattanayak, 2006; Stem et al., 2005). Monitoring and evaluation can increase the ability of protected area management to adapt to specific threats by providing sufficient information for decision-making, thereby increasing the likelihood of achieving specific goals.

Higher management scores in the governance and social participation and the use and benefits categories were also found to decrease the probability of forest cover loss. The governance and social participation category reflects the degree of procedural equity in protected area management, or the level of inclusion and effective participation of diverse stakeholders in management decisions (Franks & Schreckenberg, 2016; Zafra-Calvo et al., 2017). The use and benefits category can be linked to distributive equity, or the distribution of cost and benefits across relevant stakeholders (Zafra-Calvo et al., 2017). Thus, while these categories contribute to overall management effectiveness, they can also be strong indicators of the level of equity in protected area management, another key component of the Aichi Target 11.

A global literature review of protected area socioeconomic and conservation outcomes found that protected areas with greater socioeconomic benefits and greater empowerment of local communities were more successful ecologically (Oldekop et al., 2016). Greater participation from local communities in decision-making has also been linked to more effective resource allocation, by identifying appropriate needs such as specific local capacity building or outreach and education programs (Andrade & Rhodes, 2012). Additionally, a study examining management effectiveness in three marine protected areas in Mexico found protected areas to be more successful at conserving manatee populations when management incorporated activities that produced socioeconomic benefits for the community, such as fishing and tourism (Herrejón et al., 2020). In addition to the strong evidence that exists on the links between equitable management and conservation outcomes, researchers have argued that equitable management is also important for moral reasons (Franks & Schreckenberg, 2016; Greiber et al., 2009; Vucetich et al., 2018).

Areas for Future Research

While we found all five management categories to have a significant influence on protected area outcomes, our interaction models were only able to explain a fraction of the observed forest loss (Appendix Table B12). Thus, while management effectiveness can influence protected area success, it may not be the main driver of success. Future research could try to incorporate additional data on potential institutional moderators of protected area effectiveness to increase the model's predictive power (Sills & Jones, 2018). For example, level of tenure security has been found to influence protected area outcomes in Brazil (Nolte et al., 2013), and Sims and Alix-Garcia (2017) found Mexico's payment for ecosystem services program helped reduce deforestation inside and outside of protected areas (Sims & Alix-Garcia, 2017).

Additionally, we found a greater number of protected areas with higher overall effectiveness scores in Southern Mexico, specifically in the states of Chiapas and Yucatán. Future research could test additional ecological, cultural, or socioeconomic moderators which may be driving these regional disparities.

We recognize that historical management trends, for which we do not have data, could have also influenced 2017-2019 forest loss. Future research on management effectiveness should focus on temporal changes in management using regularly conducted management surveys to better determine causality, as well as the interrelationships between different aspects of management effectiveness (i.e., if better planning and resources leads to better outcomes, or if better performing protected areas receive greater resources and thus are better able to plan). Our results should be interpreted with some caution due to the one-time survey response and lack of prior management data with which to examine longer term trends in the relationship between management effectiveness and protected area performance.

We recognize that our final sample is relatively small in terms of total protected areas. While the high overall management effectiveness subgroup contains over 7,000 grid cells, it only represents 12 protected areas. This limitation is in part due to our focus on changes in forest cover as a measure of protected area success. In turn, we were only able to examine forested protected areas. Future research should focus on expanding this analysis to include non-forested protected areas to test the external validity of our findings to increase sample representation across Mexico's protected area network.

Finally, we also acknowledge the limitation posed by potential biases in self-reported management assessments (Coad et al., 2015). Capturing the perceptions of stakeholders beyond protected area staff, similar to Herrejón et al. (2020), may more accurately measure different management categories, especially those addressing equity in power and benefit sharing. Ground truthing the scores of CONANP's management assessment should be a focus of future research.

Conclusion

Our study responds to calls for more rigorous evidence identifying the moderators that lead to protected area success by examining the role of management effectiveness in protected area success (Geldmann et al., 2013; Macura et al., 2015). In our sample of 46 terrestrial protected areas in Mexico, we find statistically significant and positive relationships between better management effectiveness and mitigation of forest loss. While many studies have previously identified the importance of sufficient financial resources for protected areas success, our findings highlight the importance of additional management components including planning and design, relationships with diverse stakeholders, equitably shared benefits, and adaptive management. We recognize that these management components are not mutually exclusive, and that often an improvement in one can enable an improvement in another (i.e., greater financial resources can lead to more training and human capacity building, which can lead to improved resource monitoring programs). However, our findings highlight that each dimension can have a significant impact on conservation outcomes, thereby emphasizing the importance to conservation planners of investing time and resources in each category to ensure the greatest conservation outcomes. Finally, our findings support the theory that standardized management effectiveness tools can be useful predictors of conservation outcomes, and thus can be an appropriate measurement for global monitoring.

CHAPTER 4: IMPACTS OF THE COVID-19 PANDEMIC ON PROTECTED AREA MANAGEMENT AND CONSERVATION OUTCOMES IN MEXICO

Chapter Summary

Protected areas are a widely used tool for biodiversity conservation and can be strained by unpredicted events such as the COVID-19 pandemic. Understanding the extent of the pandemic's effect on protected area inputs, mechanisms, and conservation outcomes is critical for recovery and future planning to buffer against these types of events. We use survey and focus group data to measure the perceived impact of the pandemic on Mexico's protected area network and outline the pathways that led to conservation outcomes. On average, across 62 protected areas, we find substantial changes in management capacity, monitoring, and tourism, and a slight increase in non-compliant activities. Our findings highlight the need to integrate short-term relief plans to support communities dependent on tourism, who were particularly vulnerable during the pandemic, and to increase access to technology and technical capacity to better sustain management activities during future unexpected events.

Introduction

Unexpected events such as the COVID-19 pandemic can have substantial impacts on conservation outcomes. These impacts can be difficult to predict and may vary over time. For example, global restrictions on human mobility led to positive impacts on the environment in the early months of the pandemic, including clearer skies, cleaner waterways, reduced ecosystem stress, and increased frequency of sensitive species sightings in human-dominated landscapes (e.g., Bates et al., 2020; Cheval et al., 2020; Corlett et al., 2020; Manenti et al., 2020; Rupani et al., 2020). However, as the pandemic and the associated restrictions continued, the narrative around environmental impacts grew increasingly negative, pointing to a rise in illegal activities such as wildlife trafficking and illegal logging, and growing pressure within many protected areas (e.g., Cumming et al., 2021; Hockings et al., 2020).

Research examining the impact of the pandemic in protected areas has found an increase in biodiversity threats, as well as negative outcomes on management capacity and tourism, with the impact often varying regionally (Buckley, 2020; Hockings et al., 2020; Jacobs et al., 2020; Lindsey et al., 2020; McCleery et al., 2020; Singh et al., 2021; Spenceley et al., 2021). For example, illegal logging, encroachment, and subsistence hunting were found to increase in South America and Africa, while gathering of non-timber forest products and grazing were found to be the primary threat in most other regions (Singh et al., 2021). Additionally, while Spenceley et al. (2021) found negative impacts on tourism, on average, the specific impacts, such as total reduction in visitors, reduction in tourism income, and changes in non-compliance behavior, were found to vary across their eight country case studies. Continued research is needed to fully understand the impacts of the pandemic on protected areas and examine how they vary geographically. In this paper we add to the growing empirical evidence by exploring the diverse impacts of the COVID-19 pandemic on conservation outcomes in protected areas across Mexico.

In addition to understanding the pandemic's impact on protected area outcomes, it is critical to understand *how* and *why* these impacts occurred. However, clear models identifying specific impact pathways, as well as protected area characteristics that may influence the level of impact, remain limited, with only a few studies presenting evidence of these links in South Africa (Smith et al., 2021) and for marine protected areas globally (Phua et al., 2021). We add to the body of knowledge on COVID-19 impacts on protected areas by summarizing the impacts of the pandemic perceived by protected area directors across Mexico. Specifically, we use data from a survey of 62 protected area directors to identify changes to protected area inputs (e.g., human and financial capacity), mechanisms (e.g., monitoring), and non-compliance activities (e.g., illegal logging) due to the COVID-19 pandemic. We then draw on qualitative data from focus groups and open-ended survey questions to understand how those changes link together. Understanding the pathways through which unexpected events such as the COVID-19 pandemic impact protected area performance can help protected area directors and conservation practitioners not only with the design of post-pandemic relief efforts, but also in planning for future crises, such as political instability, economic shocks, and the climate crisis.

Study Area

This study seeks to measure the impacts of the COVID-19 pandemic across Mexico's protected areas. Mexico is a megadiverse country and has an extensive protected area network, covering 14.5% of the country's terrestrial surface and 21.6% of their coastal and marine area. There are over 1,000 designated protected areas in Mexico. We focus on a subset of these areas, specifically those managed and monitored by the Comisión Nacional de Áreas Naturales Protegidas (CONANP; National Commission of Natural Protected Areas).

CONANP manages over 180 protected areas ranging in level of strictness. This includes national parks (IUCN Category II), national monuments (IUCN Category III), flora and fauna protection areas (IUCN Category VI), natural resource protection areas (IUCN Category VI), sanctuaries (IUCN Category II), and biosphere reserves (IUCN Category 1a and VI). These areas cover diverse ecoregions and protect unique ecological and cultural resources, such as critical habitat for endangered species and ancient Mayan archeological sites. The diversity in Mexico's protected areas creates a unique opportunity to investigate the full range of impacts - from tourism impacts to illegal natural resource extraction - of the pandemic on protected areas.

Methods

To measure the perceived impacts of the COVID-19 pandemic on Mexico's protected areas, we first developed a theory of change (TOC) to outline potential impacts of the pandemic on Mexico's protected area network with the help of CONANP and a review of existing literature (see Table 4.1). The TOC outlines how protected area inputs link to conservation outcomes through various mechanisms and moderators. A *mechanism* is the process through which the inputs lead to positive or negative outcomes, which can be enhanced or obstructed by *moderators*, or external factors (not affected by inputs), which can ultimately affect the ability to achieve a specific goal (Ferraro & Hanauer, 2015). The TOC was refined using data from two focus groups and used to guide the design of an online survey. Appropriate IRB approval was gained prior to data collection (ID: 19-8870H). We present the TOC as part of our results, adjusted to highlight the findings of our survey (Figure 4.2). The following sections outline the components of our TOC, justification for the inclusion of each component, and our hypothesized pandemic impacts.

Table 4.1: Main components of the TOC used in this study.

Category	Component
Inputs	Management inputs (human capacity, financial capacity)
Mechanisms	Monitoring activities, visitation
Moderators	Governmental & non-governmental organization programs, emergency funds or in-person support, advisory council
Outcomes	Non-compliance, ecological restoration

TOC Inputs: Human & Financial Capacity

Higher management capacity has been found to have a positive relationship with conservation outcomes in protected areas in Mexico (Powlen et al., 2021) and on a global scale

(Geldmann et al., 2018). Management capacity includes human and financial capacity, which influence the ability to carry out management activities such as monitoring and maintenance, and effective and collaborative decision-making abilities. Recent evaluations have noted several different negative impacts that the pandemic has had on human capacity, including anxiety, fatigue, and stress, communication challenges, as well as reduced financial capacity and increased financial uncertainty (Smith et al., 2021; Waithaka et al., 2021).

In addition, by March 2021, at least 24 countries had proposed budget cuts to protected area management agency budgets or environmental regulation rollbacks, including Mexico (see Cumming et al., 2021; Kroner et al., 2021). Researchers have predicted a similar reduction in philanthropic and international aid benefiting protected areas caused by the pandemic (e.g., Lindsey et al., 2020). Based on these findings, we chose to examine both human capacity and financial capacity as the primary management inputs for our TOC.

We hypothesized that the pandemic would lead to a reduction in *human capacity* in Mexico due to restrictions on mobility, illness, and a reduction in staff availability due to new tasks (e.g., increased cleaning and sanitization in public spaces, introduction of virtual technology) or familial reasons (e.g., lack of childcare, ill family members) (Jacobs et al., 2020). Additionally, we predicted a shift in government spending priorities, reducing the overall *financial capacity* of protected areas in 2020.

TOC Outcomes: Biodiversity Threats

Previous research has found biodiversity threats to have increased during the pandemic in protected areas across the globe, with some regional variation (e.g., Hockings et al., 2020; Singh et al., 2021; Waithaka et al., 2021). We identified a list of non-compliant activities that pose a threat to Mexico's protected area network using responses from the Management Effectiveness

Tracking Tool (see Stolton & Dudley, 2016), existing literature, and the authors' prior knowledge in order to measure changes in biodiversity threats in Mexico. Selected activities included human-caused fires, land clearing for agriculture, hunting, fishing, logging, mining, unapproved settlements, and unapproved camping or use of trails.

TOC Mechanisms: Tourism & Monitoring

Previous pandemic-related research has identified impacts on two key protected area mechanisms that can shape protected area performance – the ability to conduct monitoring activities and tourism (e.g., Bates et al., 2020; Hockings et al., 2020; McCleery et al., 2020; Mcginlay et al., 2020; Mitchell & Phillips, 2021; Spenceley et al., 2021). Monitoring is a critical mechanism for reducing non-compliant activities in protected areas. Tourism provides financial support to protected areas and livelihood opportunities to neighboring communities, in addition to increasing the overall human presence in protected areas, ultimately decreasing the likelihood of non-compliant activities. While we recognize that many other mechanisms can influence protected area performance, we focus on these two mechanisms and seek to understand how changes in each can lead to changes in the non-compliant activities previously identified.

Protected area monitoring can vary in terms of total area monitored, number of trips, number of personnel responsible for monitoring, and support from community monitoring groups. The reduction in staff availability, financial capacity, and mobility restrictions were expected to reduce the capacity for monitoring across all four dimensions. We also expected that the Procuraduría Federal de Protección al Ambiente (PROFEPA; Federal Attorney for Environmental Protection), the agency responsible for enforcement of protected area regulations, would experience similar reductions in staff availability and mobility, also reducing their capacity for enforcement. We expected that a reduction in monitoring and enforcement capacity by protected area staff and PROFEPA area would lead to an *increase* in non-compliance and threats to biodiversity.

As part of Mexico's response to the pandemic, protected areas were closed to the public between March and June 2020, with a slow reopening thereafter starting at 20% visitor capacity (Comisión Nacional de Áreas Naturales Protegidas, 2020a). We therefore predicted a decrease in the total number of visitors to protected areas in 2020. Based on early studies (e.g., Manenti et al., 2020), we expected this to lead to an improvement in ecosystem health due to reduced visitor-caused damage, as well as an increase in protected area staff's ability to complete other tasks. However, we also expected reduced visitation to decrease protected area financial capacity and income opportunities for local communities, potentially *increasing* the risk of non-compliant activities.

TOC Moderators

We expected that non-compliant activities would be moderated by additional income gained through government subsidies and sustainable development programs such as the Programa de Conservación para el Desarrollo Sostenible (Conservation for Sustainable Development Program; PROCODES), as well as support from non-governmental organizations, based on the experience of the research team. We predicted that reductions in government spending and human capacity would reduce the ability to carry out these programs. Fewer government support programs, in combination with less tourism-related business, was expected to *decrease* income for local communities. We expected the decrease in income for local communities to create a need for new livelihood activities, potentially *increasing* non-compliance and threatening biodiversity.

Focus groups

We conducted two virtual focus groups in February 2021 with 10 directors from different marine and terrestrial protected areas to verify the components of the TOC. Focus group participants were selected with the help of CONANP to represent a range of ecoregions and protected area types (e.g., national park, biosphere reserve). The focus groups gathered a range of information about the experiences of each director in their respective protected areas. Each focus group began by asking what changes to protected area management and activities were experienced due to the pandemic. We then used guiding questions to gather more information on the reported changes (Yin, 2015).

After receiving verbal permission from all participants, focus groups were recorded, transcribed, and translated from Spanish to English by a member of the research team. Transcriptions were coded using a multi-level coding scheme, grouping key themes into broader categories of protected area inputs, mechanisms, moderators, and outcomes (Yin, 2015).

Survey

We used Kobo Toolkit (Harvard Humanitarian Initiative, 2021) to create an electronic, Spanish-language survey to measure perceived changes in protected areas on a national scale. The design of the survey was guided by the TOC, focus groups, and CONANP's *i-efectividad* evaluation, a standardized survey used to monitor management effectiveness in protected areas nationally (Comisión Nacional de Áreas Naturales Protegidas, 2019). We distributed the survey via email to directors of all protected areas in Mexico that had a management plan, annual operating program, and budget (132 protected areas). The survey took 25 minutes to complete, on average. If the director was not able to take the survey, we invited other management staff with knowledge of management decisions and operations to participate.

The survey covered the management inputs, mechanisms, moderators, and outputs identified in Table 4.1. Question types included binary and multiple-choice formats to measure changes in inputs, mechanisms, moderators, and outcomes, and seven-point scale bars to measure the degree to which perceived changes were considered attributable to the pandemic. Additionally, multiple optional open-ended questions allowed respondents to expand on their responses or share additional thoughts (see Appendix C for additional details and the full survey).

The survey was piloted with five protected area directors before sending the survey to all protected areas in March 2021. Limited adjustments were made after piloting the survey, specifically increasing the number of optional open-ended responses. Therefore, piloted responses were included in the final sample. The survey stayed open for six weeks and seven reminders were sent via email.

One survey response from each protected area was used in the final analysis. If more than one response was received for a single protected area, we used the responses from the director of the protected area. If the director did not respond, we then used responses from the individual who had worked for the protected area the longest.

We used descriptive statistics to identify the degree of change in various protected area dimensions measured using structured questions. We translated and coded all open-ended questions using a multi-level thematic coding approach, similar to the focus group transcripts (Yin, 2015). Major patterns in the data were coded using open codes and then organized into broader themes. We used the codes to verify links in the TOC and to identify changes not previously included.

Results

We received responses from 62 protected areas, representing almost half of the protected areas with a management plan and annual operative budget in Mexico (47%) (Figure 4.1). The protected areas in our sample were primarily flora and fauna protected areas (FFPA; 37%), biosphere reserves (BR; 31%) and national parks (NP; 29%). One natural resource protected area (NRPA) and one sanctuary (S) also participated. Our sample was primarily terrestrial protected areas (77%), with only 8% marine and 13% mixed terrestrial and marine. The ages of the protected areas in our sample ranged from four to 84 years (median=29). Prior to 2020, respondents had worked at their respective protected areas between 1 and 34 years (median=8).

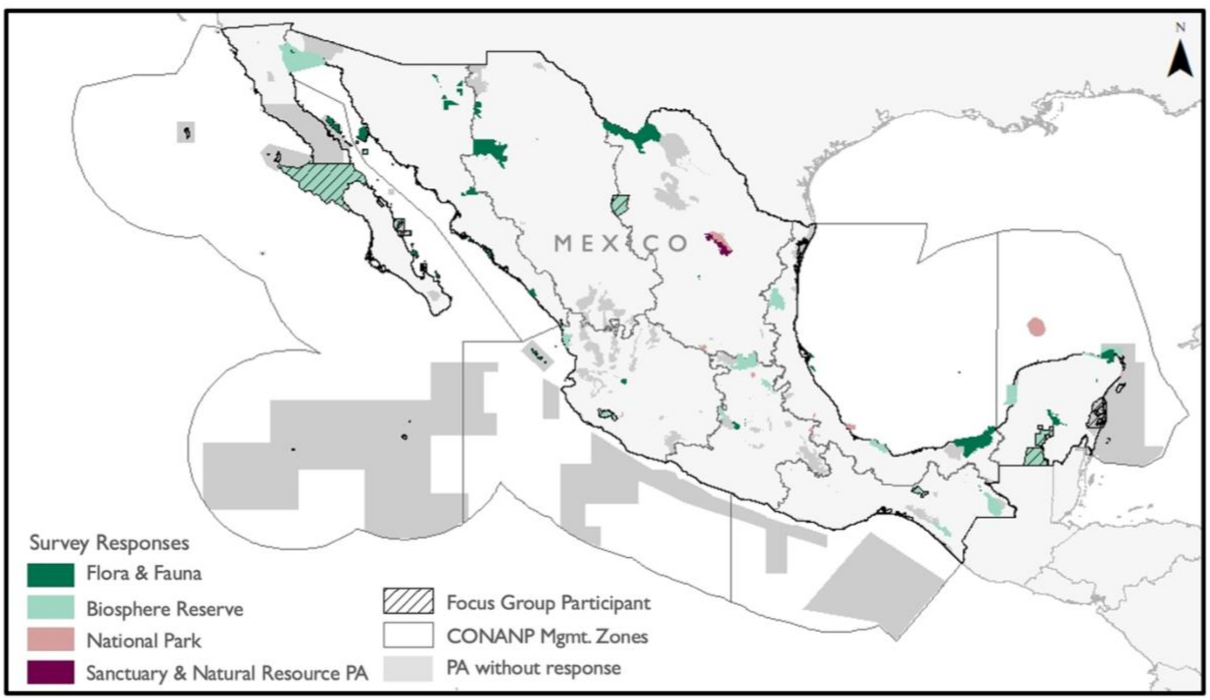


Figure 4.1: Map of protected areas that participated in focus groups and responded to the survey. Sample includes flora and fauna protection area (n=23), biosphere reserve (n=19), national park (n=18), sanctuary (n=1) and natural resource protection area (n=1).

On average, our results found that protected area directors perceived negative impacts on protected area management capacity, tourism, and support for local communities from the pandemic. Additionally, we found a perceived increase in non-compliance in 2020 compared to

2019, on average, across Mexico. However, as detailed below, we also note that impacts varied widely across different protected areas. Using our survey responses to identify substantial areas of change and qualitative data to link these changes to reported conservation outcomes, we highlight the potential pathways through which the COVID-19 pandemic has impacted protected areas (Figure 4.2).

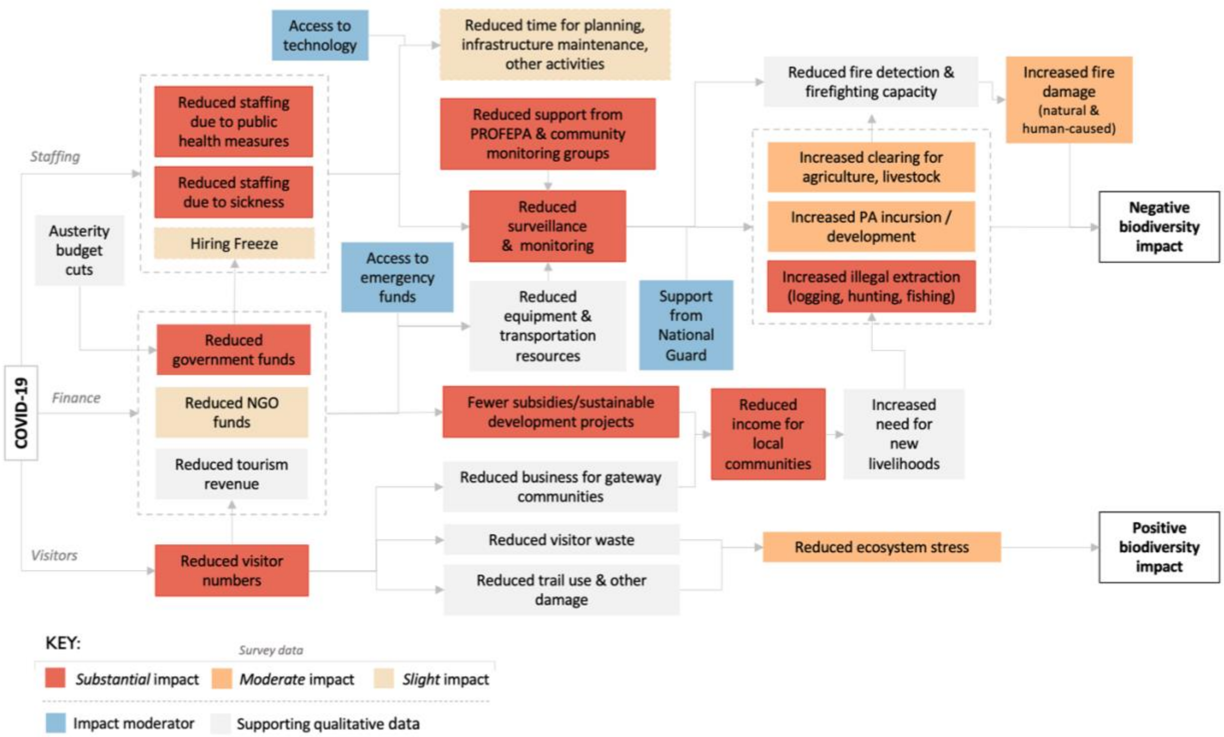


Figure 4.2: TOC, color coded to reflect findings from survey results. Substantial area of impact = change reported in over 50% of protected areas; moderate impact = change reported in 25-50% of protected areas; slight impact = change reported in less than 25% of protected areas. Supporting results from qualitative data presented in gray.

Inputs

Respondents reported that the most prevalent impacts of the pandemic on human capacity were illness (63%) and reduced time availability (52%) (Figure 4.3a). Of the 39 protected areas with staff becoming sick with the virus, 47% had less than 20% of staff become ill and 33%

reported between 20-40% of staff became ill. At one protected area, 60-80% of staff contracted the virus.

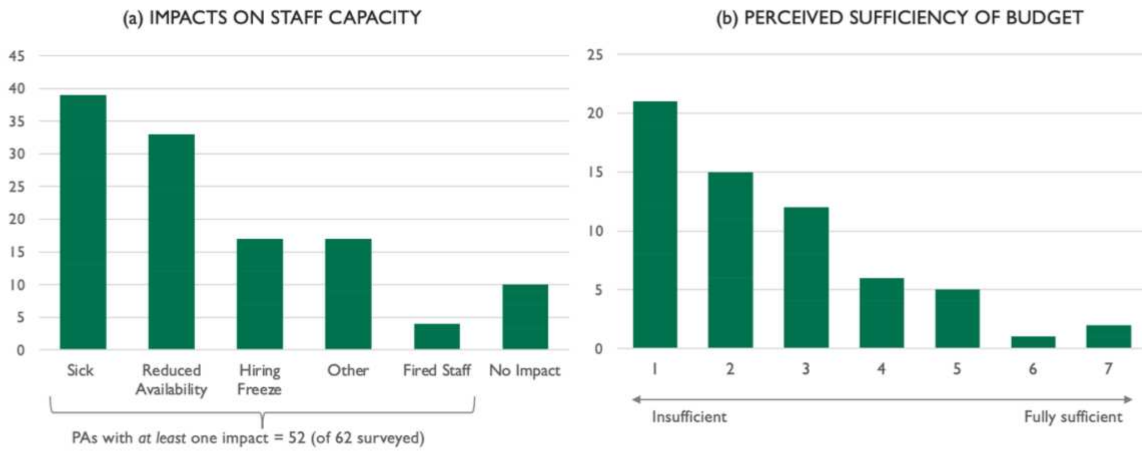


Figure 4.3: Count of protected areas who reported (a) perceived impacts on human capacity and (b) level of sufficiency of budget for basic needs in 2020 compared to 2019.

Less than a third of protected areas in our sample experienced hiring freezes on new positions (27%) and only three protected areas were forced to fire staff. No protected areas had staff on unpaid leave. Additional impacts reported by directors included various emotional impacts such as stress, depression, and anxiety caused by the uncertainty of the pandemic (n=4). Ten protected areas reported no impacts on their staff.

Seventy-seven percent of respondents reported a budget reduction in 2020 compared to 2019, with 42% reporting a significant reduction (Figure 4.4). Nineteen percent of respondents reported no change, and one protected area reported an increase. The average estimated budget reduction from 2019 to 2020 among all respondents was 39%. When rating the sufficiency of budgets, 77% of respondents rated the budget at a 3 out of 7 or lower, with an average rating of 2.5 (Figure 4.4). While many directors reported a decrease in financial capacity in 2020, few perceived the pandemic as the primary driver, with a median attribution of 2.5 out of 7 (Figure

4.3b). As one survey respondent stated, *"The COVID-19 pandemic aggravated and complicated our activities even more. They were already reduced due to lack of money and now also uncertain due to the pandemic."*

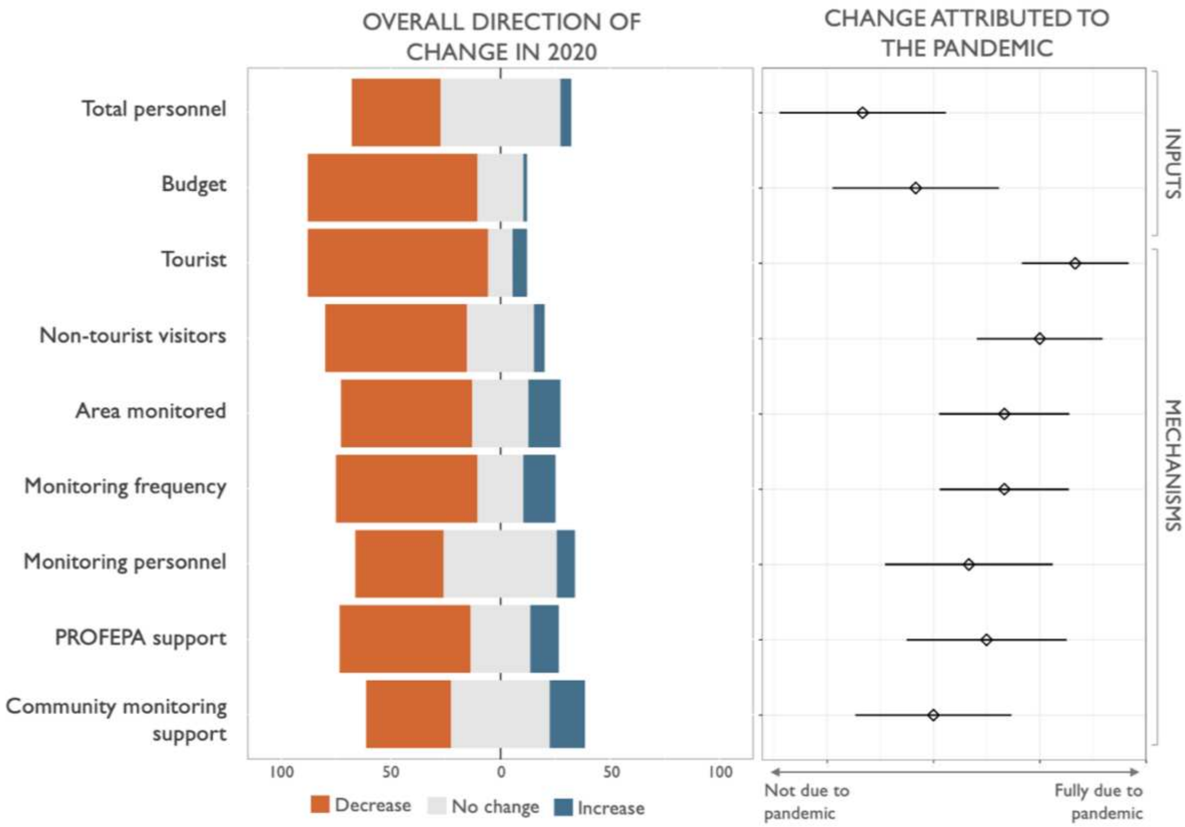


Figure 4.4: Portion of the participating protected areas that experienced changes to protected area inputs and mechanisms and the degree to which changes were attributed to the pandemic (median shown).

Mechanisms

Protected areas reported dramatic declines in the number of tourist and non-tourist visitors (e.g., researchers, maintenance, etc.) in 2020. Almost 91% of protected areas reported a reduction in tourism of 25% or greater, with little difference across protected area type. Thirty-six percent of protected areas reported a reduction of 75% or greater. Similarly, 76% of protected areas reported a reduction in non-tourist visitors, with about 19% reporting a reduction of 75% or greater. About 7% and 6% saw an increase in tourist and non-tourist visitors, respectively.

Directors most closely linked the change in tourist (median attribution of 7 out of 7) and non-tourist visitors (6 out of 7) to the pandemic. In addition to COVID-19 closures and other health and safety procedures, respondents reported that reduced visitation has likely been driven by reduced household spending on recreational activities (n=5), reduced budgets for research and project development (n=5), and a perceived increase in crime in and around protected areas (n=3) in an optional open-ended question.

Protected area directors perceived the reduction in tourism to have significant impacts on local community livelihoods, including tourism-related occupations and supporting industries. As one focus group participant explained, *"The pandemic did not directly impact the management of the protected area, but rather the economy of the communities. Since there is no tourism … their income fell to zero."*

As a second participant explained, the impacts went beyond just those directly engaged in tourism activities: "*Fisheries, like tourism service providers, were directly influenced by [changes in] tourism… There is a direct link between tourists and fishing. When there are no tourists,… there is no market where fishermen can sell their product.*"

On average, monitoring capacity of protected areas decreased in 2020 compared to 2019 (Figure 4.4). Approximately 60% of respondents reported a decrease in the frequency of monitoring, 53% reported a decrease in the total area monitored and 39% reported a decrease in the total number of staff responsible for monitoring. In contrast, 16% of respondents reported an increase in both the frequency and area monitored, and 11% reported an increase in the total number of staff.

On average, respondents estimated that the frequency of monitoring decreased, with a 23% reduction in the number of monitoring trips (median= -25%). The total area being monitored also decreased by almost 18%, and the number of staff responsible for monitoring fell by about 12% on average (area median= -25%; personnel median = 0% [i.e., no change]). Respondents estimated that the pandemic had the largest influence on the change in total area being monitored and the frequency of monitoring trips, with the median pandemic attribution rate of the change in both equal to 5 out of 7. The attribution rate for the change in the number of personnel responsible for monitoring was estimated at 4 out of 7.

The respondents perceived the reduction in monitoring capacity to be due to reduced human and financial capacity, reduced access to appropriate equipment, and the restricted ability to collaborate with groups that support these activities. As one respondent explained, *"Changes in the individuals responsible for inspection and surveillance and budget adjustments, coupled with problems generated by the COVID-19 pandemic, have hampered inspection and surveillance activities in the protected area."* A second respondent stated, *"Monitoring requires collaboration with local [groups], and this collaboration was reduced by the COVID pandemic."*

Over half of the protected areas in our study (57%) reported a decrease in the level of support provided by PROFEPA in 2020 compared to 2019. This reduction was partially attributed to the pandemic - specifically to the mobility restrictions, inability to be in the office, and reduced staff availability. However, respondents also reported a multi-year trend of decreasing PROFEPA capacity due to budget cuts which have left the organization under-resourced.

While community monitoring groups were present in almost all participating protected areas (89%), changes in the level of support provided by community groups varied across protected areas. Forty percent of respondents reported no change in the level of community monitoring support, 40% reported a decrease, and 20% reported an increase.

Moderators

Over half of the protected areas reported impacts to subsidy programs implemented by the protected area for local communities (57%), as well as impacts on other government programs (36%) and non-governmental programs (31%). About 25 of the 35 protected areas reporting changes to subsidy programs experienced an overall reduction in the value of subsidies provided. Six protected areas reported delays in subsidy delivery and four reported other impacts, such as reduced participation and freezes on new project enrollment.

Approximately 60% of protected areas perceived a reduction in other government programs, 23% reported a pause and 14% reported a delay. For non-governmental programs, the majority of directors reported a pause in implementation (42%), with 32% perceiving a reduction and 11% a delay. There was a high level of uncertainty in the impacts on non-subsidy government programs and non-governmental programs, with 27% and 31% reporting unknown impacts respectively.

Almost half (48%) of participating protected areas reported access to emergency funds which helped to compensate for the limited financial capacity in 2020. Fund-providing organizations included national and international conservation funds (e.g., Mexico's National Fund for the Conservation of Nature [FMCN] and the Global Environmental Facility [GEF]). Many protected areas also reported additional support to manage non-compliance, most commonly provided by the National Guard.

Additionally, access to technology (e.g., internet, computers, WhatsApp) emerged as an important moderator from our focus group and survey data. For those with access, technology allowed for the continuation of regular management activities, monitoring of subsidy programs, communicating health and safety guidelines to community members, and supporting and facilitating the collaborative decision-making processes of the advisory council. Other participants highlighted the lack of technology as a barrier to maintaining key management activities. For example, when talking about the advisory council, one respondent reported, *"Only one meeting could be held over the year and it was held virtually. Many of the counselors from local communities found it difficult to attend because they did not have internet and computers."*

Outcomes

Although responses varied, on average respondents reported that non-compliance increased across Mexico's protected area network in 2020 (Figure 4.5). The largest increase perceived by directors was in fishing, followed by hunting, the establishment of new settlements, logging, land clearance for agriculture, and mining. Directors perceived a slight decrease in the number of human-caused fires and unpermitted camping and trail use. The specific patterns of perceived changes in non-compliant activities did not appear to vary across different protected area types.

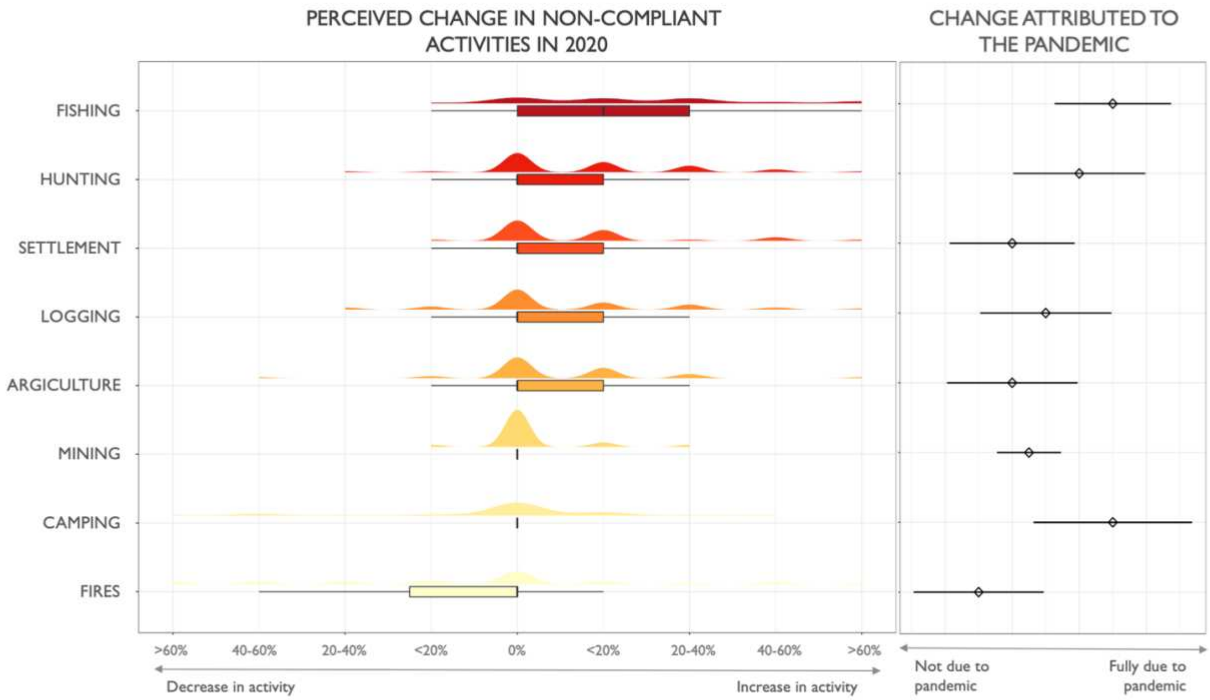


Figure 4.5: Raincloud plot showing perceived changes in non-compliance experienced in 2020 compared to 2019 and the degree to which they were attributed to the pandemic. The violin plot shows the distribution of responses, and the box plot summarizes those responses as quartiles. (Quartile$_1$ and Quartile$_3$ of mining and camping are equal to 0, resulting in no boxplot).

Although respondents reported increases across most non-compliant activities, the perceived degree of attribution to the pandemic varied. Changes in activities perceived to be most attributable to the pandemic included fishing (median=5 out of 7), camping and trail use (median=5), hunting (median=4), and logging (median=3). In an optional open-ended question, an increase in unpermitted water extraction and stone extraction were each reported by one respondent.

Many protected area directors perceived the lack of a presence of authority as the main reason for the perceived increases in non-compliant activities. One focus group participant stated, "*In March, April, and May, CONANP personnel were confined. However, essential activities continued, such as fishing. It was said to be taking place in the protected area and that* *irregular fishing activities had increased. We received many calls from other fishermen noticing*".

Similarly, a survey respondent noted: "*In the absence of… authorities such as PROFEPA, the National Guard, and the police who monitor the roads, we have detected an increase in illegal activities around the protected area, such as clearings, illegal construction, and trespassing*.". A second wrote, "*Budget cuts and staff illness reduced monitoring, and the poachers increased their activity*", also highlighting the perceived links between the lack of a presence of authority and increased non-compliance.

Other respondents highlighted the decrease in livelihood opportunities as a potential driver of non-compliance, stating: "*In the case of illegal fishing, [non-compliant activity] increased due to the need to obtain additional sources of economic income*"; and *"the impact of COVID on the economy increases demand for natural resources that are used and traded illegally."*

Discussion

We found that the COVID-19 pandemic had substantial impacts on many of the factors considered in our TOC. Specifically, we found considerable impacts on human capacity and well-being, such as staff illness, increased stress and anxiety, and an overall reduction in staff availability, similar to Smith et al. (2021) and Waithika et al. (2021) (Figure 4.3). Respondents also reported a decrease in financial capacity, with many respondents perceiving their annual budget to be insufficient for management needs (Figure 4.3). However, respondents did not perceive changes in financial capacity to be solely attributed to the pandemic. Rather, respondents felt the financial limitations resulting from the COVID-19 pandemic further compounded a more significant general trend in reduced capacity for protected areas.

These findings are in line with existing evidence on protected area capacity limitations found in Mexico and globally (Coad et al., 2019; Singh et al., 2020; Watson et al., 2014). A recent evaluation found that 50% of protected areas in Mexico experienced partially effective or ineffective management prior to the pandemic (CONANP et al., 2020) and Coad et al. (2019) found over 75% of the protected areas in their global analysis did not have adequate staff and financial resources. While CONANP has recently made significant progress in strengthening management effectiveness (Powlen et al., 2021), the agency has experienced multiple budget cuts over the past five years. Thus, as Cumming et al. (2021) argues, the current global crisis serves to "*magnify, intensify, and exacerbate existing structural and systemic financial constraints and weaknesses*", rather than introducing novel threats to protected areas (Cumming et al., 2021, p149).

Tourism, a key mechanism in our TOC, was significantly reduced in most protected areas across Mexico, similar to other regions of the world (e.g., Spenceley et al., 2021). These decreases were largely attributed to the pandemic, due to closures and capacity restrictions. Survey respondents and focus group participants perceived the reduction in tourism to have significant implications for local community livelihoods, reducing opportunities for tourism service providers, as well as linked activities, such as fishing. Additionally, survey respondents reported negative impacts on community programs, such as subsidies, further exacerbating the negative impacts on local communities. Previous research has also found local populations living in and around protected areas, especially those in remote areas, have been the most affected in terms of employment, income, and health (Mitchell & Phillips, 2021). Future research is needed to document community perspectives to fully understand the extent of this impact.

Survey respondents also reported substantial changes in monitoring, the second key mechanism. The reduction in monitoring, in addition to reduced tourism-related livelihoods, were perceived to be the main drivers of the increase in non-compliance, similar to the predictions in previous research (e.g., Buckley, 2020; Hockings et al., 2020; McCleery et al., 2020; Mitchell & Phillips, 2021). The perceived increase in subsistence and economic-driven activities, such as fishing, hunting, and logging, and decrease in unpermitted camping and trail use, support this assumption. In a global overview of the pandemic impacts in protected areas, Waithaka et al. (2021) also found an overall perceived increase in logging, poaching, settlements and fires.

Our results point to two potential avenues to reducing the impact of future global crises on protected areas, similar to those identified by Cumming et al. (2021) and Waithaka et al. (2021). The first involves providing protected area management with the skills and equipment required to adopt technological solutions that can help to maintain critical management activities in times of unexpected crises. Improved connectivity through remote working technology would help to maintain communication between protected area rangers, as well as between rangers and local communities. This would allow for administrative tasks to be completed remotely, new health and safety guidelines could be more easily shared, and non-compliant activities to be more easily reported.

Second, protected areas should consider integrating relief plans into their management strategies, which would cover basic needs in times of financial uncertainty (e.g., when government funds are redirected to other sectors) or to provide short-term support to communities, specifically those reliant on tourism and vulnerable to global economic fluctuations. Additionally, given the negative trends in institutional support from governments (see Kroner et al., 2021; Waithaka et al., 2021), it will be important that these efforts are supported by diverse funding mechanisms going forward. Planning in anticipation of future events should help build protected area networks that are more resilient to unexpected crises, ultimately leading to more positive biodiversity outcomes.

Limitations

The challenges in monitoring and measuring illicit behavior or non-compliance are well documented (e.g., Gavin et al., 2010; Solomon et al., 2015). Given the sensitivity of the topic and challenges of detecting certain activities, it is often best to triangulate evidence using diverse data sources. For example, while a fire occurrence may be easily spotted by smoke or a burn scar after an event, illegal hunting can be harder to detect. Given the recency of changes in our outcomes of interest, and the ongoing practical limitations to field research during the pandemic, data sources on biodiversity impacts of the pandemic remain limited. Therefore, perceived impacts reported by protected area managers and directors are the most accessible data source, and commonly used in existing literature (e.g., Singh et al., 2021; Smith et al., 2021; Waithaka et al., 2021).

We also recognize the potential biases introduced when using the perceptions of protected area managers to measure management conditions and perceived changes in management or outcomes. For example, protected area staff may be incentivized to exaggerate positive performance measures while providing more conservative answers for other indicators. Additionally, while protected area directors have access to the information gathered in this study, there is no guarantee that they referred to existing documents while responding to the survey questions. While we recognize these limitations, perceptions have been identified as an "indispensable form of evidence" to understand social impacts and ecological outcomes in conservation research (Bennett, 2016), and can provide valuable insight in understanding immediate impacts of significant events, such as the pandemic, especially when limited alternative forms of data are available.

Future Research & Conclusion

Given the challenges of measuring biodiversity threats, future research should attempt to triangulate these findings with additional perspectives and data sources, such as those from community members, tourism service providers, and satellite imagery. Additionally, given the potential time lag for changes to materialize, future research should continue to monitor changes in conservation outcomes and management trends in order to improve our understanding of COVID-19 impacts, the response of protected areas to unexpected events, and the length of recovery period required.

The COVID-19 pandemic has highlighted the importance of preparedness for shocks and stressors on protected areas. We now have an opportunity to critically examine how this has affected conservation efforts in order to better prepare in the future. Our research has identified potential pathways of impact on conservation outcomes perceived by protected area directors across Mexico's protected areas. Specifically, we found that the pandemic reduced human capacity and tourism, ultimately reducing monitoring capacity and financial benefits for communities in and around protected areas across Mexico. Additionally, we found an increase in multiple non-compliant activities in 2020, on average.

Moving forward, it will be critical to provide support for protected area directors to efficiently and effectively plan, design, and implement management activities, as well as to engage and collaborate with stakeholders to improve adaptive capacity in protected areas globally. Protected area planning should also begin to integrate relief plans and build technological capabilities in anticipation of future unexpected events and crises. Finally, in order to be effective, these plans will need to pay particular attention to impacts on local communities.

CHAPTER 5: CONCLUSION

The three empirical manuscripts of my dissertation advance our understanding of the factors shaping protected area outcomes. While the three manuscripts were focused on protected areas in Mexico, protected areas are one of the main instruments for conserving biodiversity globally, with about one-sixth of the world's terrestrial surface area under protection (Geldmann et al., 2019) and over 200,000 protected areas designated globally (Geldmann et al., 2019; UNEP-WCMC et al., 2020). Thus, the findings of each manuscript have broader implications for international conservation efforts. This conclusion explores the overarching themes of the three manuscripts, implications for conservation research and practice, and limitations and areas for future research. It is organized into four sections as follows: Overarching Themes, Implications for Research, Implications for Applied Conservation, and Limitations and Future Research.

Overarching Themes

Protected areas exist within complex social-ecological systems (Cumming et al., 2015). Landscape characteristics, such as slope, elevation, and climate conditions, can influence land use decisions. Certain ecological conditions can increase risk of noncompliance, deforestation and other human pressure inside protected area boundaries (Vaca et al., 2019). Institutions play a key role in managing these risks and ultimately influencing conservation outcomes in protected areas (Sills & Jones, 2018). Institutions can play direct roles, such as management, monitoring, and surveillance (e.g., CONANP, PROFEPA), or indirect ones, such as conservation organizations promoting sustainable livelihoods in local communities.

Research on protected area effectiveness has increasingly acknowledged these complex relationships and the critical role humans play in influencing outcomes. In doing so, researchers have used a variety of proxies to account for pressure from human development, natural resource accessibility, and suitability of the land for alternative uses while conducting protected area evaluations (e.g., Andam et al., 2008; Blackman, 2015; Geldmann et al., 2019; Pfaff et al., 2017). The three manuscripts of my dissertation build upon existing literature examining protected areas within social-ecological systems, while filling three critical knowledge gaps. Manuscript one identifies the specific socioeconomic, biophysical, and protected area design characteristics that have the strongest influence on forest loss outcomes in protected areas in Mexico and depicts the nonlinearity of those relationships. Manuscript two increases our understanding of the role of institutions in managing deforestation risk by quantifying the impact of effective management on forest loss in protected areas. Manuscript three explores the effect of unexpected global events on protected area management by examining the COVID-19 pandemic's influence on protected areas across Mexico.

In addition to the novel contribution of each standalone manuscript, the three manuscripts together demonstrate the multi-scalar nature of factors influencing protected areas outcomes, a common challenge to understanding of social-ecological systems (Cumming et al., 2015; Ostrom, 2009). For example, land use decisions inside protected areas are influenced by management decisions of the protected area, which are influenced by the policies and resources of the national park service. Additionally, land use decisions can be driven by national or global market forces, including prices of agricultural products or timber (Busch & Ferretti-Gallon, 2017).

Together, the three manuscripts of my dissertation demonstrate the local-to-global scale of factors influencing protected area outcomes. Manuscript one focuses on local-scale factors by examining the relationship between observed forest loss and socioeconomic, biophysical, and design characteristics of protected areas at the 1 km^2 scale. Manuscript two is conducted at the protected area-level, comparing forest loss outcomes in protected areas with high and low management effectiveness scores to understand the role of various dimensions of management in driving protected area performance. The third manuscript demonstrates the global scale, examining the effects of the current global health crisis on protected areas. It is important to note that there are a number of additional scales not represented in my research that can influence protected area outcomes, including various political scales such as municipalities or states.

Understanding local scale factors driving deforestation has been a focus of a number of existing reviews (e.g., Barnes et al., 2017; Busch & Ferretti-Gallon, 2017; Geist & Lambin, 2002). For example, Busch and Ferretti-Gallon (2017) found that biophysical characteristics, proximity to built infrastructure, land tenure, and demographic characteristics can influence deforestation rates. These findings have helped to improve the design of protected area evaluations by highlighting the important role that placement characteristics can play in conservation success. However, the ability to fully control for these factors in protected area evaluations has been limited by conventional modelling methods which assume independence among predictors and linear relationships (Vaca et al., 2019).

Manuscript one advances our understanding of the local scale factors driving forest loss in protected areas in Mexico using a machine learning technique to overcome previous research limitations. This manuscript highlights the important role that various socioeconomic and biophysical characteristics play in protected area performance. Specifically, we find that road density, human population density, population change, and distance to urban areas are key drivers of forest loss outcomes in protected areas, as well as biophysical variables such as distance to water, precipitation, elevation, and slope. Many socioeconomic and biophysical predictors were found to have a higher influence on forest loss outcomes than protected area design characteristics (e.g., protected area size, age, and IUCN category). These findings have important implications for decisions related to protected area placement, a topic discussed further in the next section.

Understanding protected area performance requires accounting for these confounding contextual factors while examining the specific protected area design characteristics that may also be driving outcomes. Protected area design characteristics that are frequently examined in existing research include ownership type (e.g., community, private, state), age, size, and IUCN category (Barnes et al., 2017; Ghoddousi et al., 2021; Macura et al., 2015). However, some have argued that IUCN categories are more representative of *de jure* management regimes, rather than *de facto* management (i.e., what is actually happening on the ground) (e.g., Ferraro et al., 2013; Muñoz Brenes et al., 2018). As such, there have been calls for the assessment of a broader suite of management variables beyond IUCN categories to better understand protected area performance (Macura et al., 2015).

Manuscript two responds to this call by contributing empirical evidence on the role of management effectiveness in avoiding forest loss using a novel nationally-employed protected area management evaluation, *i-efectividad,* which better captures *de facto* management. In this manuscript, we find that protected areas with high management scores avoid a greater amount of forest loss than protected areas with low management scores, expanding our understanding of protected area-level drivers. We find this for the overall management effectiveness score and across five different management dimensions.

Linking global events, such as the COVID-19 pandemic, to protected area outcomes can be challenging given the complex pathways through which the impacts can be felt in protected areas. Using a detailed theory of change, manuscript three captures this complexity by measuring changes in protected area inputs, mechanisms, moderators, and conservation outcomes. Globally, the COVID-19 pandemic led to periods of human confinement (Bates et al., 2020) and a dramatic reduction in tourism (WTTC, 2021). This led to reduced visitation for protected areas and reduced income for tourism-related business in and around protected areas (Spenceley et al., 2021). We find evidence of similar tourism impacts in Mexico during the first year of the pandemic, as well as a reduction in protected area monitoring capacity and an increase in non-compliant activities (e.g., illegal fishing, hunting, logging). Protected area managers perceived the increase in non-compliant activities to be linked to the reduction in tourism-related income and reduced presence of authority in protected areas during the pandemic.

Together, these three manuscripts demonstrate how factors at different scales shape protected area performance, which points to the overarching conclusion that protected areas do not operate in isolation. Protected area success is influenced by a combination of location characteristics, management characteristics, availability of human and financial resources, and global events. While international conservation goals continue to focus on the expansion of protected area networks, it is important to remember that protected area designation itself is not a panacea for preventing forest loss. To ensure success, conservation researchers and practitioners need to consider the broader context in which protected areas are designated in order to accurately assess their potential strengths and weaknesses, and to tailor conservation strategies accordingly.

Implications for Research

Impact evaluations which estimate a counterfactual have become the new standard for protected area effectiveness assessments (see Baylis et al., 2016; Pressey et al., 2015; Schleicher et al., 2019). Given the significant role that contextual variables played in predicting forest loss in manuscript one (e.g., road density, precipitation, elevation), and the significant differences found between protected area and unprotected areas in manuscript two, this dissertation provides strong evidence in support of counterfactual-based evaluations.

Manuscript one demonstrated the non-linearity of the relationships between most predictor variables and forest loss. A small number of studies have examined the complexity of the relationship between drivers of forest loss and observed deforestation using machine learning techniques (e.g., Bax & Francesconi, 2018; Bonilla-Moheno et al., 2012) or generalized additive models (e.g., Vaca et al., 2019). However, the majority of protected area evaluations continue to oversimplify these relationships when examining protected area outcomes by using conventional modeling approaches, such as generalized linear models, probit regressions, or ordinary least squares regressions. The findings from manuscript one suggest that future research should avoid analytical methods which oversimplify relationships between drivers of forest loss and observed outcomes to advance our understanding of what drives protected area outcomes.

In manuscript two we demonstrate how the evaluation of protected area effectiveness can be skewed if confounding factors (i.e., placement characteristics) are not appropriately controlled for. Specifically, we found higher rates of deforestation inside protected areas with higher management effectiveness scores when directly compared to deforestation rates in protected areas with low management effectives scores. However, after using a propensity score matching approach to estimate a counterfactual which accurately reflects the underlying threat of deforestation by considering multiple placement characteristics, we find the *avoided* forest loss (relative to the counterfactual) to be greater in protected areas with high management effectiveness scores compared to those with low scores, despite losing a higher percentage of forest cover overall. This finding has important implications for how protected area success is defined. *Total forest loss* may not present an accurate picture of how protected areas are performing. Instead, future research needs to account for placement characteristics influencing outcomes by comparing observed forest loss with an estimated counterfactual to better understand what would have happened if the protected area did not exist.

Implications for Applied Conservation

Aichi Biodiversity Target 11 calls for 17% of terrestrial and 10% of coastal and marine areas to be conserved through "*effectively and equitably managed, ecologically representative and well connected systems of protected areas or other effective area based conservation measures*" (Convention on Biological Diversity, 2010). Given the prioritization of *effective* and *equitably* managed areas, it is important that we understand what effective and equitable management means and how that translates to conservation outcomes. Manuscript two helps to answer this question and contributes critical evidence that protected areas with greater management capacity, including equity-related management dimensions, avoid more forest loss.

Manuscript three builds on these findings by highlighting the links between changes in management and biodiversity threats experienced during the COVID-19 pandemic. In this chapter, we found that disruptions to management operations such as monitoring and subsidy programs led to a perceived increase in non-compliance inside protected areas. By strengthening management capacity, protected areas will likely be more successful in avoiding deforestation generally and more resilient in the face of future unexpected shocks, such as political instability, economic fluctuations, and climate change.

The importance of placement characteristics found in manuscript one also has key implications for protected area planning. By identifying the key drivers of forest loss, practitioners can identify the forested protected areas that may be more at risk of deforestation (e.g., close to roads and urban areas) and focus on strengthening management effectiveness in those areas. Additionally, by understanding which characteristics make protected areas more vulnerable, conservation efforts can be more proactive in protecting key biodiversity areas, rather than reactively designating protected areas in response to biodiversity loss.

Limitations & Future Research

I was initially interested in Mexico's protected area network due to its recent growth, efforts to improve management monitoring, achievement of the Green List Global Standard in two protected areas, and the substantial overlap between protected areas and community-owned lands. It is estimated that up to 80% of forests in Mexico are community-owned (Bray et al., 2008) and that over half of the country's land area is under a form of communal tenure, primarily in rural areas (Morett-Sánchez & Cosío-Ruiz, 2017). Given this degree of overlap, protected areas in Mexico can have important equity implications. Equity is a general concern for protected area management, since many of the benefits from protected areas are global (i.e., carbon sequestration), while costs are often local (i.e., restrictions to resource use) (Bebber & Butt, 2017; Jones et al., 2017).

Equity considerations in conservation have increasingly gained attention over the last decade (Greiber et al., 2009; Martin et al., 2016; Vucetich et al., 2018). For example, the Convention on Biological Diversity has made equitable participation and reduced burdens on vulnerable populations key components to their strategic plan (Convention on Biological Diversity, 2010). Additionally, researchers and practitioners have developed frameworks for social equity in protected areas focused on governance and management, which include three recognized typologies of justice – distributive (i.e., distribution of costs and benefits experienced by stakeholders), participatory (i.e., equal participation in the rule-making processes and decision-making procedures, including who gets to participate and under what conditions) and recognition (i.e., level of respect and recognition given to all identities and cultures) (e.g. Franks & Schreckenberg, 2016; Zafra-Calvo et al., 2017).

While there is a push for increased equity in protected area governance, evidence on how those factors relate to environmental outcomes is limited. My initial research proposal sought to address this knowledge gap by building evidence on the theoretical links between just conservation and ecological outcomes using multiple stakeholder perspectives, such as managers, communities living in and around protected areas, and conservation organizations. However, given the travel restrictions of the COVID-19 pandemic, my ability to capture diverse perspectives was limited. Instead, the three manuscripts focus primarily on the perspective of protected area managers due to this population being more accessible than remote communities living inside protected areas. While the results of my research find equitable decision-making and benefit sharing to be important factors in protected area success (see manuscripts one and two), important perspectives are missing from all manuscripts. An area of future research that I would like to pursue is capturing the perspective of additional stakeholders to triangulate findings and better evaluate the role of equity-related management variables in determining protected area success.

The findings of the manuscripts presented in this dissertation could also be strengthened by expanding the protected area performance indicators given the range of objectives that protected areas hold. Manuscripts one and two use the Global Forest Watch annual forest loss data as the measure of protected area performance. Deforestation detected from land use/land cover (LULC) has become a common measurement of ecological performance due to the accessibility, and the temporal and spatial range of satellite imagery (e.g., Defries et al., 2005; Ferraro et al., 2013; Geldmann et al., 2013; Heino et al., 2015; Joppa & Pfaff, 2011; Macura et al., 2015; Nagendra, 2008; Porter-Bolland et al., 2012; Spracklen et al., 2015). However, changes in forest cover detected by satellite imagery can overlook human impacts, such as reduced forest productivity and illegal hunting. Land classified as 'forest' based on satellite imagery alone can have significantly reduced levels of fauna (i.e., "empty forests") – a long-standing concern in the conservation field (see Redford, 1992; Wilkie, et al., 2011). To overcome this limitation, researchers have promoted field-based measurements, such as species richness and abundance, to better capture human impact (see Coetzee, 2017; Geldmann et al., 2013, 2018; Gray et al., 2016; Pettorelli et al., 2005). Therefore, to increase the validity of our findings in manuscript one and two, future research should test alternative measures of conservation outcomes.

Protected areas can also have significant socioeconomic impacts on the communities living in and around them (Corrigan et al., 2018; Jones et al., 2017; McKinnon et al., 2016; Naidoo et al., 2019; Pullin et al., 2013). Broadly, socioeconomic impacts of protected areas may include changes in poverty, health, displacement, redistribution of power, and human rights (Jones et al., 2017). These impacts can be positive, such as the development of new economic opportunities (e.g., Oldekop et al., 2016; Pullin et al., 2013), or negative, such as increased conflict and stress in local communities (e.g., Pfaff et al., 2017; Ruiz-Mallén et al., 2015) or displacement (e.g., Jones et al., 2017). A recent meta-analysis found that protected areas were more likely to report positive conservation outcomes when there were simultaneous positive socioeconomic outcomes associated with the protected area designation (Oldekop et al., 2016). Therefore, future research should also consider socioeconomic impacts in addition to ecological outcomes in order to develop a more holistic concept of protected area success.

Concluding remarks

Global forests are under immense threat and protected areas are a key conservation strategy used to counter that threat. We have seen a significant expansion of area under protection over the past decade, and global conservation goals aim to continue this expansion in the future. Success in preventing forest loss and protecting biodiversity requires a strong understanding of what drives protected area outcomes. My dissertation research contributes empirical evidence to advance our understanding of protected area performance, using novel research methods to identify the strongest predictors of forest loss, quantify the role of effective management in preventing forest loss, and outline how unexpected events, specifically the current global health crisis, can impact protected areas. My research demonstrates the range of variables that can influence protected area outcomes, from local to global scales. A better understanding of the factors leading to protected area success will improve our ability to monitor progress and conserve ecosystems that are vital both for the health of the planet and for those who occupy it.

REFERENCES

Aide, T. M., Clark, M. L., Grau, R., López-Carr, D., Levy, M. A., Redo, D., … Muñiz, M. (2012). Deforestation and Reforestation of Latin America and the Caribbean (2001 – 2010). *Biotropica*, *45*(2), 262–271.

Alonso Concheiro, A., García Méndez, G., & Eccardi, F. (2006). *Capital natural y bienestar social*. Comision Nacional para el Conocimiento y Uso de la Biodiversidad.

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(42), 15–20. https://doi.org/www.pnas.org/cgi/doi/10.1073/pnas.0800437105

Andrade, G. S. M., & Rhodes, J. R. (2012). Protected areas and local communities: An inevitable partnership toward successful conservation strategies? *Ecology and Society*, *17*(4). https://doi.org/10.5751/ES-05216-170414

Apley, D. W., & Zhu, J. (2020). Visualizing the effects of predictor variables in black box supervised learning models. *Journal of the Royal Statistical Society B*, *82*(4), 1059–1086. https://doi.org/10.1111/rssb.12377

Armenteras, D., María Espelta, J., Rodríguez, N., & Retana, J. (2017). Deforestation dynamics and drivers in different forest types in Latin America: Three decades of studies (1980 – 2010). *Global Environmental Change*, *46*, 139–147. https://doi.org/10.1016/j.gloenvcha.2017.09.002

Austin, P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Mutivariate Behavioral Research*, *46*, 399–424. https://doi.org/10.1080/00273171.2011.568786

Baldi, G., Texeira, M., Martin, O. A., Grau, H. R., & Jobbágy, E. G. (2017). Opportunities drive the global distribution of protected areas. *PeerJ*, 1–24. https://doi.org/10.7717/peerj.2989

Barber, C. P., Cochrane, M. A., Souza, C., & Veríssimo, A. (2012). Dynamic performance assessment of protected areas. *Biological Conservation*, *149*(1), 6–14. https://doi.org/10.1016/j.biocon.2011.08.024

Barnes, M., Craigie, I. D., & Hockings, M. (2016). Towards Understanding Drivers of Wildlife

Population Trends in Terrestrial Protected Areas. In Luccas N. Joppa, J. E. M. Ballie, & J. G. Robinson (Eds.), *Protected Areas: Are They Safeguarding Biodiveristy?* (First). John Wiley & Sons, Ltd.

Barnes, M. D., Craigie, I. D., Dudley, N., & Hockings, M. (2017). Understanding local-scale drivers of biodiversity outcomes in terrestrial protected areas. *Annals of the New York Academy of Sciences*, *1399*(1), 42–60. https://doi.org/10.1111/nyas.13154

Barnes, M. D., Craigie, I. D., Harrison, L. B., Geldmann, J., Collen, B., Whitmee, S., … Woodley, S. (2016). Wildlife population trends in protected areas predicted by national socio–economic metrics and body size. *Nature Communications*, *7*, 1–9. https://doi.org/10.1038/ncomms12747

Bates, A. E., Primack, R. B., Moraga, P., & Duarte, C. M. (2020). COVID-19 pandemic and associated lockdown as a “Global Human Confinement Experiment” to investigate biodiversity conservation. *Biological Conservation*, *248*(108665). https://doi.org/10.1016/j.biocon.2020.108665

Bax, V., & Francesconi, W. (2018). Environmental predictors of forest change: An analysis of natural predisposition to deforestation in the tropical Andes region, Peru. *Applied Geography*, *91*, 99–110. https://doi.org/10.1016/j.apgeog.2018.01.002

Baylis, K., Honey-Roses, J., Borner, J., Corbera, E., Ezzine-de-Blas, D., Ferraro, P. J., … Wunder, S. (2016). Mainstreaming Impact Evaluation in Nature Conservation. *Conservation Letters*, *9*(1), 58–64. https://doi.org/10.1111/conl.12180

Bebber, D. P., & Butt, N. (2017). Tropical protected areas reduced deforestation carbon emissions by one third from 2000-2012. *Scientific Reports*, *7*(1). https://doi.org/10.1038/s41598-017-14467-w

Bennett, N. J. (2016). Using perceptions as evidence to improve conservation and environmental management. *Conservation Biology*, *30*(3), 582–592. https://doi.org/10.1111/cobi.12681

Blackman, A. (2015). Strict versus mixed-use protected areas: Guatemala’s Maya Biosphere Reserve. *Ecological Economics*, *112*, 14–24. https://doi.org/10.1016/j.ecolecon.2015.01.009

Blackman, A., Pfaff, A., & Robalino, J. (2015). Paper park performance: Mexico’s natural protected areas in the 1990s. *Global Environmental Change*, *31*, 50–61. https://doi.org/10.1016/j.gloenvcha.2014.12.004

Bonilla-Moheno, M., Aide, T. M., & Clark, M. L. (2012). The influence of socioeconomic, environmental, and demographic factors on municipality-scale land-cover change in Mexico. *Regional Environmental Change*, *12*, 543–557. https://doi.org/10.1007/s10113-011-0268-z

Bonilla-Moheno, M., Redo, D. J., Aide, T. M., Clark, M. L., & Grau, H. R. (2013). Vegetation change and land tenure in Mexico: A country-wide analysis. *Land Use Policy*, *30*(1), 355–364. https://doi.org/10.1016/j.landusepol.2012.04.002

Boulton, A. J., & Williford, A. (2018). Analyzing Skewed Continuous Outcomes With Many Zeros: A Tutorial for Social Work and Youth Prevention Science Researchers. *Journal of the Society for Social Work and Research*, *9*(4), 721–740. https://doi.org/10.1086/701235

Bray, D. B., Duran, E., Ramos, V. H., Mas, J., Velazquez, A., McNab, R. B., … Radachowsky, J. (2008). Tropical Deforestation, Community Forests, and Protected Areas in the Maya Forest. *Ecology and Society*, *13*(2).

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*, 5–32.

Bruner, A. G., Gullison, R. E., Rice, R. E., & Fonseca, G. A. B. (2001). Effectiveness of Parks in Protecting Tropical Biodiversity. *Science*, *291*(5501), 125–128.

Buckley, R. (2020). Conservation implications of COVID19: Effects via tourism and extractive industries. *Biological Conservation*, *247*(108640).

Busch, J., & Ferretti-Gallon, K. (2017). What Drives Deforestation and What Stops It? A Meta-Analysis. *Review of Environmental Economics and Policy*, *11*(1), 3–23. https://doi.org/10.1093/reep/rew013

Butchart, S. H. M., Clarke, M., Smith, R. J., Sykes, R. E., Scharlemann, J. P. W., Harfoot, M., … Burgess, N. D. (2015). Shortfalls and Solutions for Meeting National and Global Conservation Area Targets. *Conservation Letters*, *8*(5), 329–337. https://doi.org/10.1111/conl.12158

Campaign for Nature. (2021). *50 Countries Announce Bold Commitment to Protect at Least 30% of the World's Land and Ocean by 2030*. Paris. Retrieved from https://www.campaignfornature.org/50-countries-announce-bold-commitment-to-protect-at-least-30-of-the-worlds-land-and-ocean-by-2030

Carranza, T., Balmford, A., Kapos, V., Manica, A., & Busch, J. (2014). Protected Area Effectiveness in Reducing Conversion in a Rapidly Vanishing Ecosystem: The Brazilian Cerrado. *Conservation Letters*, *7*(3), 216–223. https://doi.org/10.1111/conl.12049

Carranza, T., Manica, A., Kapos, V., & Balmford, A. (2014). Mismatches between conservation outcomes and management evaluation in protected areas: A case study in the Brazilian Cerrado. *Biological Conservation*, *173*, 10–16. https://doi.org/10.1016/j.biocon.2014.03.004

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geoscience Model Development*, *7*, 1247–1250. https://doi.org/10.5194/gmd-7-1247-2014

Chao, S. (2012). *Forest Peoples: Numbers across the World*. United Kingdom.

Cheval, S., Adamescu, C. M., Georgiadis, T., Herrnegger, M., Piticar, A., & Legates, D. R. (2020). Observed and Potential Impacts of the COVID-19 Pandemic on the Environment. *International Journal of Environmental Research and Public Health*, *17*(11).

Coad, L., Leverington, F., Burgess, N. D., Cuadros, I. C., Geldmann, J., Marthews, T. R., … Hockings, M. (2013). Progress towards the CBD protected area management effectiveness targets. *Parks*, *19*(1), 13–24. https://doi.org/10.2305/IUCN.CH.2013.PARKS-19-1.LC.en

Coad, L., Leverington, F., Knights, K., Geldmann, J., Eassom, A., Kapos, V., … Hockings, M. (2015). Measuring impact of protected area management interventions: current and future use of the Global Database of Protected Area Management Effectiveness. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(20140281). https://doi.org/10.1098/rstb.2014.0281

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

Coetzee, B. W. T. (2017). Evaluating the ecological performance of protected areas. *Biodiversity and Conservation*, *26*(1), 231–236. https://doi.org/10.1007/s10531-016-1235-2

Comisión Nacional de Áreas Naturales Protegidas. (2019). *Documento técnico base del Sistema Permanente de Evaluación e la Efectividad del Manejo de las Áreas Naturales Protegidas Federales*. México.

Comisión Nacional de Áreas Naturales Protegidas. (2020a). *Compilación de medidas tomadas en la Comisión Nacional de Áreas Naturales Protegidas ante la pandemia del SARS-CoV-2 (COVID-19)*. Mexico City, MX. Retrieved from https://www.gob.mx/conanp información relativa al COVID-19, Comisión Nacional de Áreas Naturales Protegidas. (2020b). *Evaluación de la Efectividad del Manejo de las Áreas Naturales Protegidas de México: Primer Informe Nacional*. México.

Comisión Nacional de Conocimiento y Uso de la Biodiversidad. (2010). *Natural Capital of Mexico*. México.

CONANP, CONABIO, & SRE. (2020). *Progress towards achieving Achi Target 11 in Mexico*. Mexico City, MX.

Convention on Biological Diversity. (2010). *The Strategic Plan for Biodiversity 2011–2020 and the Aichi Biodiversity Targets. COP 10 Decision X/2.* Montreal, Canada.

Convention on Biological Diversity. (2021). *First Draft of the Post-2020 Global Biodiversity Framework*. Retrieved from https://www.cbd.int/article/draft-1-global-biodiversity-framework

Corlett, R. T., Primack, R. B., Devictor, V., Maas, B., Goswami, V. R., Bates, A. E., … Roth, R. (2020). Impacts of the coronavirus pandemic on biodiversity conservation. *Biological Conservation*, *246*(108571).

Corrigan, C., J. Robinson, C., Burgess, N. D., Kingston, N., & Hockings, M. (2018). Global Review of Social Indicators used in Protected Area Management Evaluation. *Conservation Letters*, *11*(2), 1–9. https://doi.org/10.1111/conl.12397

Cumming, G. S., Allen, C. R., Ban, N. C., Biggs, D., Biggs, H. C., Cumming, D. H. M., … Maciejews, K. (2015). Understanding protected area resilience: a multi-scale, social-ecological approach. *Ecological Applications*, *25*(2), 299–319.

Cumming, T., Seidl, A., Emerton, L., Spenceley, A., Kroner, R. G., Uwineza, Y., & Zyl, H. Van. (2021). Building Sustainable Finance for Resilient Protected and Conserved Areas: Lessons from COVID-19. *Parks*, *27*(Special Issue), 149–160.

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.

Defries, R., Hansen, A., Newton, A., & Hansen, M. (2005). Increasing isolation of protected areas in tropical forest over the past twenty years. *Ecological Applications*, *15*(1), 19–26.

dos Santos Ribas, L. G., Pressey, R. L., Loyola, R., & Bini, L. M. (2020). A global comparative analysis of impact evaluation methods in estimating the effectiveness of protected areas. *Biological Conservation*, *246*, 108595. https://doi.org/10.1016/j.biocon.2020.108595

Dudley, N., & Stolton, S. (2009). *The Protected Areas Benefits Assessment Tool: A methodology*.

Retrieved from
http://wwf.panda.org/what_we_do/where_we_work/amazon/publications/?174401/PABAT

Durán-Medina, E., Mas, J. F., & Velázquez, A. (2005). Land use/cover change in community-based forest management regions and protected areas in Mexico. In D. Bray, L. Merino, & D. Barry (Eds.), *The Community Forests of Mexico: Managing for Sustainable Landscapes*. Mexico City, MX: INE-SEMARNAT.

Edgar, G. J., Stuart-Smith, R. D., Willis, T. J., Kininmonth, S., Baker, S. C., Banks, S., … Edgar, S. C. (2014). Global conservation outcomes depend on marine protected areas with five key features. *Nature*, *506*. https://doi.org/10.1038/nature13022

Ellis, E. A., & Porter-Bolland, L. (2008). Is community-based forest management more effective than protected areas? A comparison of land use/land cover change in two neighboring study areas of the Central Yucatan Peninsula, Mexico. *Forest Ecology and Management*, *256*(11), 1971–1983. https://doi.org/10.1016/j.foreco.2008.07.036

Epstein, G., Gurney, G., Chawla, S., Anderies, J. M., Baggio, J., Unnikrishnan, H., … Cumming, G. S. (2021). Drivers of compliance monitoring in forest commons. *Nature Sustainability*, *4*, 450–456. https://doi.org/10.1038/s41893-020-00673-4

FAO, & UNEP. (2016). *State of the World's Forests 2016. Forest and agriculture: land-use challenges and opportunities.* Rome. https://doi.org/10.1146/annurev-environ-102014-021358

FAO, & UNEP. (2020). *The State of the World's Forests: Forests, biodiversity, and people*. Rome. https://doi.org/https://doi.org/10.4060/ca8642en

Fedele, G., Donatti, C. I., Bornacelly, I., & Hole, D. G. (2021). Nature-dependent people: Mapping human direct use of nature for basic needs across the tropics. *Global Environmental Change*, (xxxx), 102368. https://doi.org/10.1016/j.gloenvcha.2021.102368

Ferraro, P. J. (2009). *Counterfactual Thinking and Impact Evaluation in Environmental Policy*. (M. Birnbaum & P. Michwitz, Eds.), *Environmental Program and Policy Evaluation: Addressing methodological challenges. New Directions for Evaluation* (Vol. 122). https://doi.org/10.1002/ev

Ferraro, P. J., & Hanauer, M. M. (2011). Protecting ecosystems and alleviating poverty with parks and reserves: "Win-win" or tradeoffs? *Environmental and Resource Economics*, *48*(2), 269–286. https://doi.org/10.1007/s10640-010-9408-z

Ferraro, P. J., & Hanauer, M. M. (2015). Through what mechanisms do protected areas affect environmental and social outcomes? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1681). https://doi.org/10.1098/rstb.2014.0267

Ferraro, P. J., Hanauer, M. M., Miteva, D. A., Canavire-Bacarreza, G. J., Pattanayak, S. K., & Sims, K. R. E. (2013). More strictly protected areas are not necessarily more protective: Evidence from Bolivia, Costa Rica, Indonesia, and Thailand. *Environmental Research Letters*, *8*(2). https://doi.org/10.1088/1748-9326/8/2/025011

Ferraro, P. J., & Pattanayak, S. K. (2006). Money for nothing? A call for empirical evaluation of biodiversity conservation investments. *PLoS Biology*, *4*(4), 482–488. https://doi.org/10.1371/journal.pbio.0040105

Ferraro, P. J., & Pressey, R. L. (2015). Measuring the difference made by conservation initiatives: Protected areas and their environmental and social impacts. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1681), 4–8. https://doi.org/10.1098/rstb.2014.0270

Figueroa, F., & Sanchez-Cordero, V. (2008). Effectiveness of natural protected areas to prevent land use and land cover change in Mexico. *Biodiversity and Conservation*, *17*, 3223–3240. https://doi.org/10.1007/s10531-008-9423-3

Figueroa, F., Sánchez-Cordero, V., Illoldi-Rangel, P., & Linaje, M. (2011). Evaluación de la efectividad de las áreas protegidas para contener procesos de cambio en el uso del suelo y la vegetación. ¿Un índice es suficiente? *Revista Mexicana de Biodiversidad*, (82), 951–963.

Flores-Villela, O., & Canseco-Márquez, L. (2004). *Nuevas especies y cambios taxonómicos para la herpetofauna de Mexico*. *Acta Zoologica Mexicana (n.s.)* (Vol. 20).

Franco, A. Di, Thiriet, P., Di Carlo, G., Dimitriadis, C., Francour, P., Gutiérrez, N. L., … Guidetti, P. (2016). Five key attributes can increase marine protected areas performance for small-scale fisheries management. *Scientific Reports*, *6*(38135), 1–9. https://doi.org/10.1038/srep38135

Franks, P., & Schreckenberg, K. (2016). Advancing equity in protected area conservation. *The International Institute for Environment and Development (IIED)*, (February), 5–9. https://doi.org/10.13140/RG.2.1.2817.0649

Fuller, C., Ondei, S., Brook, B. W., & Buettel, J. C. (2019). First, do no harm: A systematic review of deforestation spillovers from protected areas. *Global Ecology and Conservation*, *18*(e00591). https://doi.org/10.1016/j.gecco.2019.e00591

García-Frapolli, E., Ramos-Fernández, G., Galicia, E., & Serrano, A. (2009). The complex reality of biodiversity conservation through Natural Protected Area policy: Three cases from the Yucatan Peninsula, Mexico. *Land Use Policy*, *26*(3), 715–722. https://doi.org/10.1016/j.landusepol.2008.09.008

Garnett, S. T., Burgess, N. D., Fa, J. E., Fernández-Llamazares, Á., Molnár, Z., Robinson, C. J., … Leiper, I. (2018). A spatial overview of the global importance of Indigenous lands for conservation. *Nature Sustainability*, *1*(7), 369–374. https://doi.org/10.1038/s41893-018-0100-6

Gavin, M. C., Solomon, J. N., & Blank, S. G. (2010). Measuring and Monitoring Illegal Use of Natural Resources. *Conservation Biology*, *24*(1), 89–100.

Geist, H. J., & Lambin, E. F. (2002). Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *BioScience*, *52*(2), 143–150.

Geldmann, J., Barnes, M., Coad, L., Craigie, I. D., Hockings, M., & Burgess, N. D. (2013). Effectiveness of terrestrial protected areas in reducing habitat loss and population declines. *Biological Conservation*, *161*, 230–238. https://doi.org/10.1016/j.biocon.2013.02.018

Geldmann, J., Coad, L., Barnes, M., Craigie, I. D., Hockings, M., Knights, K., … 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., … Burgess, N. D. (2018). A global analysis of management capacity and ecological outcomes in terrestrial protected areas. *Conservation Letters*, *11*(3), 1–10. https://doi.org/10.1111/conl.12434

Geldmann, J., Joppa, L. N., & Burgess, N. D. (2014). Mapping Change in Human Pressure Globally on Land and within Protected Areas. *Conservation Biology*, *28*(6), 1604–1616. https://doi.org/10.1111/cobi.12332

Geldmann, J., Manica, A., Burgess, N. D., Coad, L., & Balmford, A. (2019). A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. *PNAS*, *116*(46), 23209–23215. https://doi.org/10.1073/pnas.1908221116

Ghoddousi, A., Loos, J., & Kuemmerle, T. (2021). An Outcome-Oriented, Social–Ecological Framework for Assessing Protected Area Effectiveness. *BioScience*, *XX*(X), 1–12.

Gill, D. A., Mascia, M. B., Ahmadia, G. N., Glew, L., Lester, S. E., Barnes, M., … Whitmee, S.

(2017). Capacity shortfalls hinder the performance of marine protected areas globally. *Nature*, *543*(7647), 665–669. https://doi.org/10.1038/nature21708

Gray, C. L., Hill, S. L. L., Newbold, T., Hudson, L. N., Boïrger, L., Contu, S., … Scharlemann, J. P. W. (2016). Local biodiversity is higher inside than outside terrestrial protected areas worldwide. *Nature Communications*, *7*(12306). https://doi.org/10.1038/ncomms12306

Greiber, T., Janki, M., Orellana, M., Savaresi, A., & Shelton, D. (2009). *Conservation with Justice: A rights-based approach*. *IUCN Environmental Policy and Law Paper*. Gland, Switzerland. https://doi.org/10.2305/IUCN.CH.2009.EPLP.71.en

Hajjar, R., Oldekop, J. A., Cronkleton, P., Newton, P., Russell, A. J. M., & Zhou, W. (2021). A global analysis of the social and environmental outcomes of community forests. *Nature Sustainability*, *4*. https://doi.org/10.1038/s41893-020-00633-y

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., … Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693

Hastie, T., Tibshirani, R., & Friedman, J. (2017). *The Elements of Statistical Learning: Data mining, inference, and prediction* (Second). Springer.

Heino, M., Kummu, M., Makkonen, M., Mulligan, M., Verburg, P. H., Jalava, M., & Räsänen, T. A. (2015). Forest loss in protected areas and intact forest landscapes: A global analysis. *PLoS ONE*, *10*(10), 1–21. https://doi.org/10.1371/journal.pone.0138918

Herrejón, J. C. R., Morales-Vela, B., Ortega-Argueta, A., Pozo, C., & Olivera-Gómez, L. D. (2020). Management effectiveness in marine protected areas for conservation of Antillean manatees on the eastern coast of the Yucatan Peninsula, Mexico. *Aquatic Conservation: Marine Freshwater Ecosystems*, *30*, 1182–1193. https://doi.org/10.1002/aqc.3323

Hockings, M., Cook, C. N., & Leverington, F. (2015). Protected Area Management Effectiveness. In G. L. Worboys, M. Lockwood, A. Kothari, S. Feary, & I. Pulsford (Eds.), *Protected Area Governance and Management* (pp. 889–928). Canberra: ANU Press.

Hockings, M., Dudley, N., Elliott, W., Napolitano Ferreira, M., Mackinnon, K., Pasha, M. K. S., … Yang, A. (2020). Editorial Essay: COVID-19 and Protected and Conserved Areas. *Parks*, *26*(1), 7–24.

Hockings, M., Stolton, S., Leverington, F., Dudley, N., Courrau, J., & Valentine, P. (2006). *Evaluating effectiveness: A framework for assessing management effectiveness of protected* *areas*. *IUCN*. https://doi.org/10.2305/IUCN.CH.2006.PAG.14.en

Imbens, G. W., & Rubin, D. B. (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences*. New York, NY: Cambridge University Press.

Instituto Nacional de Estadística y Geografía. (2015). *Panorama Sociodemográfico de Mexico*.

IUCN. (2016). *The global standard for protected areas in the 21st Century, IUCN Green List of Protected and Conserved Areas: User Manual, Version 1.0*.

IUCN. (2021). IUCN Green List of Protected and Conserved Areas. Retrieved from https://www.iucn.org/theme/protected-areas/our-work/iucn-green-list-protected-and-conserved-areas

IUCN, & UNEP-WCMC. (2019). World Database on Protected Areas (WDPA). Cambridge (UK): UNEP World Conservation Monitoring Center. Available at: www.protectedplanet.net.

Jacobs, L., Blacketer, M. P., Peterson, B. A., Levithan, E., Russel, Z. A., & Brunson, M. (2020). Responding to COVID-19 and future times of uncertainty: Challenges and opportunities associated with visitor use, management, and research in parks and protected areas. *The Interdisciplinary Journal of Place-Based Conservation*, *36*(3). https://doi.org/10.5070/P536349860

Jonas, H. D., Ahmadia, G. N., Bingham, H. C., Briggs, J., Butchart, S. H. M., Cariño, J., … von Weizsäcker, C. (2021). Equitable and Effective Area-based Conservation: Towards the conserved area paradigm. *Parks*, *27*(1).

Jones, N., McGinlay, J., & Dimitrakopoulos, P. G. (2017). Improving social impact assessment of protected areas: A review of the literature and directions for future research. *Environmental Impact Assessment Review*, *64*, 1–7. https://doi.org/10.1016/j.eiar.2016.12.007

Jones, Venter, O., Fuller, R. A., Allan, J. R., Maxwell, S. L., Negret, P. J., & Watson, J. E. M. (2018). One-third of global protected land is under intense human pressure. *Science*, *360*(6390), 788–791. https://doi.org/10.1126/science.aap9565

Joppa, Lucas N., & Pfaff, A. (2009). High and far: Biases in the location of protected areas. *PLoS ONE*, *4*(12), 1–6. https://doi.org/10.1371/journal.pone.0008273

Joppa, Lucas N., & Pfaff, A. (2011). Global protected area impacts. *Proceedings of the Royal Society B: Biological Sciences*, *278*(1712), 1633–1638.

https://doi.org/10.1098/rspb.2010.1713

Keenan, R. J., Reams, G. A., Achard, F., Freitas, J. V. De, Grainger, A., & Lindquist, E. (2015). Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015. *Forest Ecology and Management*, *352*, 9–20. https://doi.org/10.1016/j.foreco.2015.06.014

Kere, E. N., Choumert, J., Combes Motel, P., Combes, J. L., Santoni, O., & Schwartz, S. (2017). Addressing Contextual and Location Biases in the Assessment of Protected Areas Effectiveness on Deforestation in the Brazilian Amazônia. *Ecological Economics*, *136*(2017), 148–158. https://doi.org/10.1016/j.ecolecon.2017.02.018

Kroner, R. G., Barbier, E. B., Chassot, O., Jr, L. C., Cruz-trinidad, A., Howard, J., … Rica, C. (2021). COVID-Era Policies and Economic Recovery Plans: Are governments building back better for protected and conserved areas? *Parks*, *27*(Special Issue), 135–148.

Kuhn, M. (2008). Building Predictive Models in R Using the caret Package. *Journal of Statistical Software*, *28*(5).

Laurance, W. F., Carolina Useche, D., Rendeiro, J., Kalka, M., Bradshaw, C. J. A., Sloan, S. P., … Zamzani, F. (2012). Averting biodiversity collapse in tropical forest protected areas. *Nature*, *489*(7415), 290–293. https://doi.org/10.1038/nature11318

Laurance, W. F., Goosem, M., & Laurance, S. G. W. (2009). Impacts of roads and linear clearings on tropical forests. *Trends in Ecology and Evolution*, *24*(12), 659–669. https://doi.org/10.1016/j.tree.2009.06.009

Leberger, R., Rosa, I. M. D., Guerra, C. A., Wolf, F., & Pereira, H. M. (2019). Global patterns of forest loss across IUCN categories of protected areas. *Biological Conservation*, *241*(108299). https://doi.org/10.1016/j.biocon.2019.108299

Legendre, P. (1993). Spatial autocorrelation: Trouble or new paradigm? *Ecology*, *74*(6), 1659–1673.

Leisher, C., Touval, J., Hess, S. M., Boucher, T. M., & Reymondin, L. (2013). Land and forest degradation inside protected areas in Latin America. *Diversity*, *5*, 779–795. https://doi.org/10.3390/d5040779

Leverington, F., Costa, K. L., Pavese, H., Lisle, A., & Hockings, M. (2010). A global analysis of protected area management effectiveness. *Environmental Management*, *46*(5), 685–698. https://doi.org/10.1007/s00267-010-9564-5

Lindsey, P., Allan, J., Brehony, P., Dickman, A., Robson, A., Begg, C., … Fitzgerald, K. (2020). Conserving Africa's wildlife and wildlands through the COVID-19 crisis and beyond. *Nature Ecology & Evolution*, *4*, 1300–1310. https://doi.org/10.1038/s41559-020-1275-6

Macura, B., Secco, L., & Pullin, A. S. (2015). What evidence exists on the impact of governance type on the conservation effectiveness of forest protected areas? Knowledge base and evidence gaps. *Environmental Evidence*, *4*(24), 1–29. https://doi.org/10.1186/s13750-015-0051-6

Manenti, R., Mori, E., Canio, V. Di, Mercurio, S., Picone, M., Caffi, M., … Rubolini, D. (2020). The good, the bad and the ugly of COVID-19 lockdown effects on wildlife conservation: Insights from the first European locked down country. *Biological Conservation*, *249*(108728). https://doi.org/10.1016/j.biocon.2020.108728

Martin, A., Coolsaet, B., Corbera, E., Dawson, N. M., Fraser, J. A., Lehmann, I., & Rodriguez, I. (2016). Justice and conservation: The need to incorporate recognition. *Biological Conservation*, *197*, 254–261. https://doi.org/10.1016/j.biocon.2016.03.021

Mas, J., & Cuevas, G. (2013). Análisis de los patrones de deforestación en México con regresiones ponderadas geográficamente. *Anais XVI Simpósio Brasileiro de Sensoriamento Remoto*, 6292–6299.

Mas, J. F., & Cuevas, G. (2015). Identifying Local Deforestation Patterns Using Geographically Weighted Regression Models. In C. Grueau & R. J. Gustavo (Eds.), *Geographical Information Systems Theory, Applications and Management* (pp. 36–49). Springer. https://doi.org/https://doi.org/10.1007/978-3-319-29589-3_3

McCleery, R. A., Fletcher Jr., R. J., Kruger, L. M., Govender, D., & Ferreira, S. M. (2020). Conservation needs a COVID-19 bailout. *Science*, *369*(6503), 515–517.

McGinlay, J., Gkoumas, V., Holtvoeth, J., Fuertes, R. F. A., Bazhenova, E., Benzoni, A., … Jones, N. (2020). The Impact of COVID-19 on the Management of European Protected Areas and Policy Implications. *Forest*, *11*(1214), 1–15.

McKinnon, M. C., Cheng, S. H., Dupre, S., Edmond, J., Garside, R., Glew, L., … Woodhouse, E. (2016). What are the effects of nature conservation on human well-being? A systematic map of empirical evidence from developing countries. *Environmental Evidence*, *5*(1), 1–25. https://doi.org/10.1186/s13750-016-0058-7

Mendoza-Ponce, A., Corona-Núñez, R., Kraxner, F., Leduc, S., & Patrizio, P. (2018). Identifying effects of land use cover changes and climate change on terrestrial ecosystems and carbon stocks in Mexico. *Global Environmental Change*, *53*, 12–23. https://doi.org/10.1016/j.gloenvcha.2018.08.004

Min-Venditti, A. A., Moore, G. W., & Fleischman, F. (2017). What policies improve forest cover? A systematic review of research from Mesoamerica. *Global Environmental Change*, *47*, 21–27. https://doi.org/10.1016/j.gloenvcha.2017.08.010

Miranda, J. J., Corral, L., Blackman, A., Asner, G., & Lima, E. (2016). Effects of Protected Areas on Forest Cover Change and Local Communities: Evidence from the Peruvian Amazon. *World Development*, *78*, 288–307. https://doi.org/10.1016/j.worlddev.2015.10.026

Mitchell, B. A., & Phillips, A. (2021). A global tragedy in search of answers: Editor's introduction. *Parks*, *27*(Special Issue), 7–12.

Miteva, D. A., Pattanayak, S. K., & Ferraro, P. J. (2012). Evaluation of biodiversity policy instruments: what works and what doesn't? *Oxford Review of Economic Policy*, *28*(1), 69–92. https://doi.org/10.1093/oxrep/grs009

Molnar, C., Bischl, B., & Casalicchio, G. (2018). iml: An R package for Interpretable Machine Learning. *JOSS*, *3*(26). https://doi.org/10.21105/joss.00786, https://joss.theoj.org/papers/10.21105/joss.00786.

Morett-Sánchez, J. C., & Cosío-Ruiz, C. (2017). Panorama de los ejidos y comunidades agrarias en méxico. *Agricultura, Sociedad y Desarrollo*, *14*, 125–152.

Muñoz Brenes, C. L., Jones, K. W., Schlesinger, P., Robalino, J., & Vierling, L. (2018). The impact of protected area governance and management capacity on ecosystem function in Central America. *PLoS One*, *13*(10).

Nagendra, H. (2008). Do parks work? Impact of protected areas on land cover clearing. *Ambio*, *37*(5), 330–337. https://doi.org/10.1579/06-R-184.1

Naidoo, R., Gerkey, D., Hole, D., Pfaff, A., Ellis, A. M., Golden, C. D., … Johnson, K. (2019). Evaluating the impacts of protected areas on human well-being across the developing world. *Science Advances*, 1–8.

Negret, P. J., Marco, M. Di, Sonter, L. J., Rhodes, J., Possingham, H. P., & Maron, M. (2020). Effects of spatial autocorrelation and sampling design on estimates of protected area effectiveness. *Conservation Biology*, *00*(0), 1–11. https://doi.org/10.1111/cobi.13522

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., … Purvis, A.

(2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*. https://doi.org/10.1038/nature14324

Nolte, C., Agrawal, A., Silvius, K. M., & Soares-Filho, B. S. (2013). Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proceedings of the National Academy of Sciences*, *110*(13), 4956–4961. https://doi.org/10.1073/pnas.1214786110

Nolte, Christoph, & Agrawal, A. (2013). Linking Management Effectiveness Indicators to Observed Effects of Protected Areas on Fire Occurrence in the Amazon Rainforest. *Conservation Biology*, *27*(1), 155–165. https://doi.org/10.1111/j.1523-1739.2012.01930.x

Nolte, Christoph, Agrawal, A., & Barreto, P. (2013). Setting priorities to avoid deforestation in Amazon protected areas: Are we choosing the right indicators? *Environmental Research Letters*, *8*(1). https://doi.org/10.1088/1748-9326/8/1/015039

Oldekop, J. A., Holmes, G., Harris, W. E., & Evans, K. L. (2016). A global assessment of the social and conservation outcomes of protected areas. *Conservation Biology*, *30*(1), 133–141. https://doi.org/10.1111/cobi.12568

Oliveira, P. J. C., Asner, G. P., Knapp, D. E., Almeyda, A., Galván-gildemeister, R., Keene, S., … Smith, R. C. (2007). Land-use Allocation Protected the Peruvian Amazon. *Science*, *317*, 1233–1237.

Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N., Underwood, E. C., … Kassem, K. R. (2001). Terrestrial Ecoregions of the World: A New Map of Life on Earth. *BioScience*, *51*(11), 933–938.

Ostrom, E. (2009). A General Framework for Analyzing Sustainability of Social-Ecological Systems. *Science*, *325*(5939), 419–422.

Pettorelli, N., Safi, K., & Turner, W. (2014). Satellite remote sensing, biodiversity research and conservation of the future. *Philosophical Transactions Royal Society B*, *369*(20130190).

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology and Evolution*, *20*(9). https://doi.org/10.1016/j.tree.2005.05.011

Pfaff, A., Robalino, J., Lima, E., Sandoval, C., & Herrera, L. D. (2014). Governance, Location and Avoided Deforestation from Protected Areas: Greater Restrictions Can Have Lower Impact, Due to Differences in Location. *World Development*, *55*, 7–20.

https://doi.org/10.1016/j.worlddev.2013.01.011

Pfaff, A., Santiago-Ávila, F., & Joppa, L. (2017). Evolving protected-area impacts in Mexico: Political shifts as suggested by impact evaluations. *Forests*, *8*(1), 1–14. https://doi.org/10.3390/f8010017

Phua, C., Andradi-brown, D. A., Mangubhai, S., Ahmadia, Gabby, N., Mahajan, S. L., Larsen, K., … Wells, S. (2021). Marine Protected and Conserved Areas in the Time of COVID. *Parks*, *27*, 85–102.

Porter-Bolland, L., Ellis, E. A., Guariguata, M. R., Ruiz-Mallén, I., Negrete-Yankelevich, S., & Reyes-García, V. (2012). Community managed forests and forest protected areas: An assessment of their conservation effectiveness across the tropics. *Forest Ecology and Management*, *268*, 6–17. https://doi.org/10.1016/j.foreco.2011.05.034

Powlen, K. A., Gavin, M. C., & Jones, K. W. (2021). Management effectiveness positively influences forest conservation outcomes in protected areas. *Biological Conservation*, *260*, 109192. https://doi.org/10.1016/j.biocon.2021.109192

Pressey, R. L., Visconti, P., & Ferraro, P. J. (2015). Making parks make a difference: poor alignment of policy, planning and management with protected-area impact, and ways forward. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1681). https://doi.org/10.1098/rstb.2014.0280

Pullin, A. S., Bangpan, M., Dalrymple, S., Dickson, K., Haddaway, N. R., Healey, J. R., … Oliver, S. (2013). Human well-being impacts of terrestrial protected areas. *Environmental Evidence*, *2*(19).

Pullin, A. S., & Knight, T. M. (2001). Effectiveness in conservation practice: Pointers from medicine and public health. *Conservation Biology*, *15*(1), 50–54. https://doi.org/10.1046/j.1523-1739.2001.99499.x

Redford, K. H. (1992). The Empty Forest. *BioScience*, *42*(6), 412–422.

Robinson, B. E., Holland, M. B., & Naughton-Treves, L. (2014). Does secure land tenure save forests? A meta-analysis of the relationship between land tenure and tropical deforestation. *Global Environmental Change*, *29*, 281–293. https://doi.org/10.1016/j.gloenvcha.2013.05.012

Román-Cuesta, R. M., & Martínez-Vilalta, J. (2006). Effectiveness of protected areas in mitigating fire within their boundaries: Case study of Chiapas, Mexico. *Conservation*

Biology, *20*(4), 1074–1086. https://doi.org/10.1111/j.1523-1739.2006.00478.x

Rosenbaum, P. R. (2002). Overt bias in observational studies. In *Observational Studies* (pp. 71–104). New York, NY: Springer.

Roy Chowdhury, R. (2006). Landscape change in the Calakmul Biosphere Reserve, Mexico: Modeling the driving forces of smallholder deforestation in land parcels. *Applied Geography*, *26*(2), 129–152. https://doi.org/10.1016/j.apgeog.2005.11.004

Ruiz-Mallén, I., Corbera, E., Calvo-Boyero, D., & Reyes-García, V. (2015). Participatory scenarios to explore local adaptation to global change in biosphere reserves: Experiences from Bolivia and Mexico. *Environmental Science and Policy*, *54*, 398–408. https://doi.org/10.1016/j.envsci.2015.07.027

Rupani, P. F., Nilashi, M., Abumalloh, R. A., Asadi, S., Samad, S., & Wang, S. (2020). Coronavirus pandemic (COVID-19) and its natural environmental impacts. *International Journal of Environmental Science and Technology*, *17*, 4655–4666. https://doi.org/10.1007/s13762-020-02910-x

Salafsky, N., Salzer, D., Stattersfield, A. J., Hilton-Taylor, C., Neugarten, R., Butchart, S. H. M., … Wilkie, D. (2008). A standard lexicon for biodiversity conservation: Unified classifications of threats and actions. *Conservation Biology*, *22*(4), 897–911. https://doi.org/10.1111/j.1523-1739.2008.00937.x

Sánchez-Cordero, V., Figueroa, F., Illoldi-Rangel, P., & Linaje, M. (2011). Efectividad del Sistema de Áreas Protegidas para conservar la vegetación natural. *Planeación Para La Conservación de La Biodiversidad Terrestre En México: Retos En Un País Megadiverso*, 59–86.

Schleicher, J., Eklund, J., Barnes, M. D., Geldmann, J., Oldekop, J. A., & Jones, J. P. G. (2019). Statistical matching for conservation science. *Conservation Biology*, *34*(3), 538–549. https://doi.org/10.1111/cobi.13448

Schulze, K., Knights, K., Coad, L., Geldmann, J., Leverington, F., Eassom, A., … Burgess, N. D. (2017). An assessment of threats to terrestrial protected areas. *Conservation Letters*, *11*(3), 1–10. https://doi.org/10.1111/conl.12435

Secretariat of the Convention on Biological Diversity. (2020). *Global Biodiversity Outlook 5*. Montreal.

Sills, E. O., & Jones, K. (2018). *Chapter 9 - Causal inference in environmental conservation:*

The role of institutions. *Handbook of Environmental Economics* (Vol. 4). Elsevier B.V. https://doi.org/10.1016/bs.hesenv.2018.09.001

Sims, K. R. E., & Alix-Garcia, J. M. (2017). Parks versus PES: Evaluating direct and incentive-based land conservation in Mexico. *Journal of Environmental Economics and Management*, *86*, 8–28. https://doi.org/10.1016/j.jeem.2016.11.010

Singh, R., Galliers, C., Moreto, W., Slade, J., Long, B., Aisha, H., … Ghosh, S. (2021). Impact of the COVID-19 Pandemic on Rangers and the Role of Rangers as a Planetary Health Service. *Parks*, *27*(Special Issue), 119–134. https://doi.org/10.2305/IUCN.CH.2021.PARKS-27-SIRS.en

Singh, R., Gan, M., Barlow, C., Long, B., Mcvey, D., De Kock, R., … Belecky, M. (2020). What do rangers feel? Perceptions from Asia, Africa and Latin America. *Parks*, *26.1*. https://doi.org/10.2305/IUCN.CH.2020.PARKS-26-1RS.en

Skutsch, M., Mas, J. F., Bocco, G., Bee, B., Cuevas, G., & Gao, Y. (2014). Deforestation and land tenure in Mexico: A response to Bonilla-Moheno et al. *Land Use Policy*, *39*, 390–396. https://doi.org/10.1016/j.landusepol.2013.11.013

Smith, M. K. S., Smit, I. P. J., Swemmer, L. K., Mokhatla, M. M., Freitag, S., Roux, D. J., & Dziba, L. (2021). Sustainability of protected areas: Vulnerabilities and opportunities as revealed by COVID-19 in a national park management agency. *Biological Conservation*, *255*(108985). https://doi.org/10.1016/j.biocon.2021.108985

Solomon, J. N., Gavin, M. C., & Gore, M. L. (2015). Detecting and understanding non-compliance with conservation rules. *Biological Conservation*, *189*. https://doi.org/10.1016/j.biocon.2015.04.028

Solorzano, C. R., & Fleischman, F. (2018). Institutional legacies explain the comparative efficacy of protected areas: Evidence from the Calakmul and Maya Biosphere Reserves of Mexico and Guatemala. *Global Environmental Change*, *50*, 278–288. https://doi.org/10.1016/j.gloenvcha.2018.04.011

Spenceley, A., Mccool, S., Newsome, D., Báez, A., Barborak, J. R., Blye, C.-J., … Zschiegner, A.-K. (2021). Tourism in Protected and Conserved Areas Amid the COVID-19 Pandemic. *Parks*, *27*(Special Issue), 103–118.

Spracklen, B. D., Kalamandeen, M., Galbraith, D., Gloor, E., & Spracklen, D. V. (2015). A Global Analysis of Deforestation in Moist Tropical Forest Protected Areas. *PLoS ONE*, *342*, 1–16. https://doi.org/10.1371/journal.pone.0143886

Stem, C., Margoluis, R., Salafsky, N., & Brown, M. (2005). Monitoring and evaluation in conservation: a review of trends and appraoches. *Conservation Biology*, *19*(2), 295–309. https://doi.org/10.1111/j.1523-1739.2005.00594.x

Stolton, S., & Dudley, N. (2016). *METT Handbook: A guide to using the Management Effectiveness Tracking Tool (METT). WWF-UK.*

Strobl, C., Boulesteix, A., Kneib, T., Augustin, T., & Zeileis, A. (2008). Conditional variable importance for random forests. *BMC Bioinformatics*, *9*(307), 1–11. https://doi.org/10.1186/1471-2105-9-307

Strobl, C., Malley, J., & Tutz, G. (2009). An Introduction to Recursive Partitioning: Rationale, Application and Characteristics of Classification and Regression Trees, Bagging and Random Forest. *Psychology Methods*, *14*(4), 323–348. https://doi.org/10.1037/a0016973.An

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Stat Science*, *25*(1), 1–21. https://doi.org/10.1214/09-STS313.Matching

Sutherland, W. J., Adams, W. M., Aronson, R. B., Aveling, R., Blackburn, T. M., Broad, S., … Watkinson, A. R. (2009). One hundred questions of importance to the conservation of global biological diversity. *Conservation Biology*, *23*(3), 557–567. https://doi.org/10.1111/j.1523-1739.2009.01212.x

Sutherland, William J., Pullin, A. S., Dolman, P. M., & Knight, T. M. (2004). The need for evidence-based conservation. *Trends in Ecology and Evolution*, *19*(6), 305–308. https://doi.org/10.1016/j.tree.2004.03.018

Tang, Z., Fang, J., Sun, J., & Gaston, K. J. (2011). Effectiveness of Protected Areas in Maintaining Plant Production. *PLoS One*, *6*(4), 1–8. https://doi.org/10.1371/journal.pone.0019116

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., & Steininger, M. (2003). Remote sensing for biodiversity science and conservation. *Trends in Ecology and Evolution*, *18*(6), 306–314. https://doi.org/10.1016/S0169-5347(03)00070-3

UNEP-WCMC. (2021). Protected Area Profile for Mexico from the World Database of Protected Areas. Retrieved from www.protectedplanet.net

UNEP-WCMC, IUCN, & NGS. (2020). *Protected Planet Live Report 2020*. Cambridge, UK; Gland, Switzerland; Washington D.C., USA. Retrieved from https://livereport.protectedplanet.net/

USAID. (2002). *Biodiversity and Tropical Forest Conservation, Protection, and Management in Mexico: Assessment and Recommendations*. Mexico City, MX.

Vaca, R. A., Golicher, D. J., Rodiles-Hernández, R., Castillo-Santiago, Á., Bejarano, M., & Navarrete-Gutiérrez, D. A. (2019). Drivers of deforestation in the basin of the Usumacinta River: Inference on process from pattern analysis using generalised additive models. *PLoS ONE*, *14*(9), 1–21.

Vucetich, J. A., Burnham, D., Macdonald, E. A., Bruskotter, J. T., Marchini, S., Zimmermann, A., & Macdonald, D. W. (2018). Just conservation: What is it and should we pursue it? *Biological Conservation*, *221*, 23–33. https://doi.org/10.1016/j.biocon.2018.02.022

Waithaka, J., Dudley, N., Álvarez, M., Mora, S. A., Chapman, S., Figgis, P., … Wong, M. (2021). Impacts of COVID-19 on Protected and Conserved Areas: A Global Overview and Regional Perspectives. *Parks*, *27*(Special Issue), 41–56.

Waldron, A., Miller, D. C., Redding, D., Mooers, A., Kuhn, T. S., Nibbelink, N., … Gittleman, J. L. (2017). Reductions in global biodiversity loss predicted from conservation spending. *Nature*, *551*(7680), 364–367. https://doi.org/10.1038/nature24295

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

Wilkie, D. S., Bennett, E. L., Peres, C. A., & Cunningham, A. A. (2011). The empty forest revisited. *Annals of the New York Academy of Sciences*, *1223*, 120–128. https://doi.org/10.1111/j.1749-6632.2010.05908.x

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*, 79–82.

Wolf, C., Levi, T., Ripple, W. J., Zárrate-charry, D. A., & Betts, M. G. (2021). A forest loss report card for the world's protected areas. *Nature Ecology & Evolution*, *5*. https://doi.org/10.1038/s41559-021-01389-0

WTTC. (2021). *WTTC research reveals global Travel & Tourism sector suffered a loss of almost US $4.5 trillion in 2020 due to the impact of COVID-19*. London, UK. Retrieved from https://wttc.org/Portals/0/Documents/Press Releases/Global Travel and Tourism sector suffered a loss of almost US4 trillion in 2020 due to the impact of COVID-

19.pdf?ver=2021-03-29-175141-243

Yang, H., Viña, A., Winkler, J. A., Chung, M. G., Huang, Q., Dou, Y., … Liu, J. (2021). A global assessment of the impact of individual protected areas on preventing forest loss. *Science of the Total Environment*, *777*. https://doi.org/10.1016/j.scitotenv.2021.145995

Yin, R. K. (2015). *Qualitative research from start to finish*. Guilford Publications.

Zafra-Calvo, N., Pascual, U., Brockington, D., Coolsaet, B., Cortes-Vazquez, J. A., Gross-Camp, N., … Burgess, N. D. (2017). Towards an indicator system to assess equitable management in protected areas. *Biological Conservation*, *211*, 134–141. https://doi.org/10.1016/j.biocon.2017.05.014

APPENDIX A

Appendix Table A1: Details of data used in the analysis.

Independent Variable	Year	Measurement	Source
Biophysical			
· Ecoregions*	2012	WWF category	WWF
· Precipitation	1970-2000	Year Total (mm)	WorldClim
· Temperature	1970-2000	Yearly Average (°C)	WorldClim
· Proximity to water*	2006	Euclidean (km)	INEGI
· Slope	--	Average (degree slope)	USGS
· Elevation	--	Average (m)	USGS
Socioeconomic			
· Ejido tenure	2010	% of cell	INEGI
· Population density	2015	Est. total humans	WorldPop
· Population change	2010-2019	Avg change/year/km^2	WorldPop
· % moderate poverty	2015	% municipal population	CONEVAL
· % extreme poverty	2015	% municipal population	CONEVAL
· Distance to roads*	2017	Euclidean (km)	INEGI
· Roads density*	2017	Scale: 0-5	INEGI
· Distance to urban centers	2017	Euclidean (km)	INEGI
· PES enrollment	2017	% of cell enrolled	CONAFOR
· State	2019	(N/A)	CONANP
Protected Area Design Characteristics			
· Age	2019	Years from decree date	CONANP
· Strictness	2019	IUCN Category	CONANP
· Total area	2019	Total terrestrial (ha)	CONANP
· Management effectiveness	2017	Score of protected area	CONANP
Dependent Variable	**Year**	**Measurement**	**Source**
· Forest Cover (baseline)	2000	% of cell	GFW
· Forest Cover Loss*	2015-19	% baseline lost	GFW

*more details below

More data details

Sample cells and missing data. Of the original 30,888 cells, 30,032 fell within forest ecoregions. A total of 28,630 of the forest cells had no missing data. The largest portion of missing data fell within pine-oak forests, resulting in the removal of 11% of the original pine-oak forest cells. Mangrove forest was the second highest, with about 6% of the original cells containing missing data.

The predictor variable with the largest portion of missing data was the multidimensional poverty index, which was missing values for two municipalities – Temósachic (included 1,117 cells) and Mezcalapa (17 cells). Prior to removing all cells with missing data, we confirmed that it would not lower the total number of protected areas considered in our final analysis.

Appendix Table A2: Summary of missing data.

Group	orig. count	w/o missing	missing (#)	missing (%)
Forest cells	30,032	28,630	1,402	4.67
Moist Forest	15,213	15,070	143	0.94
Montane Forest	599	592	7	1.17
Pine-Oak Forest	10,451	9,333	1,118	10.70
Mangrove Forest	1,636	1,541	95	5.81
Dry Forest	2,133	2,094	39	1.83

Forest cover loss (dependent variable). Forest cover loss between 2015-2019 was calculated using a baseline forest cover dataset from 2000. We first calculated the percent forest cover of each cell in 2000. We then calculated the percent forest loss between 2001-2014 and 2015-2019. The final forest loss dependent variable was calculated as:

% forest loss between 2015-2019 / [% forest cover (2000) - % forest loss between 2001-2014] * 100

Roads. Data of spatially referenced roads and other linear infrastructure were downloaded from a census report held by INEGI. A national layer of all roads was created by merging all state-level data files. We then selected five types of roads for our analysis, including avenue, boulevard, street, highway and private road. This removed infrastructure such as sidewalks, pedestrian street, horse corridors, and roundabouts. Distance was measured to the closest of any of the five road types. The road density data was created using the same five types of roads compiled as one "road density" measure using the line density tool in ArcGIS Pro.

Proximity to water. Hydrological data was acquired from INEGI, which included rivers, streams and canals. All were dissolved into a single line feature and closest distance to any of the three was used as the distance to water measurement.

Ecoregions. Our sampling grid cells overlapped with 32 different ecoregions from WWF's Terrestrial Ecoregion Classification. We manually grouped ecoregions into five categories for the forest subgroup analysis (Appendix Table 3). In doing so, we also removed 856 cells (from the 30,888) that fell in non-forest ecoregion categories. This included the following ecoregions: Central Mexican, Meseta Central, Tamaulipan and Tehuacán Valley matorral (*n*=733), Pantanos de Centla (*n*=73), Tamaulipan mezquital (*n*=35), Western Gulf coastal grasslands (*n=12*), and Chihuahuan desert (*n*=3). The full forest analysis also excluded these 856 cells. See Appendix Table 3 below for more details on each subgroup's ecoregions.

Appendix Table A3: Summary of the ecoregions included in each of the five forest types.

Moist Forests	*Montane Forests*	*Mangrove Forest*
Petén-Veracruz moist forests	Chiapas montane forests	Mesoamerican Gulf-Caribbean mangroves
Sierra Madre de Chiapas moist forests	Chimalapas montane forests	Northern Mesoamerican Pacific mangroves
Veracruz moist forests	Veracruz montane forests	Southern Mesoamerican Pacific mangroves
Yucatán moist forests		

Dry Forests	*Pine-Oak Forests*
Balsas dry forests	Central American pine-oak forests
Central American dry forests	Sierra Juarez and San Pedro Martir pine-oak forests
Chiapas Depression dry forests	Sierra Madre de Oaxaca pine-oak forests
Jalisco dry forests	Sierra Madre del Sur pine-oak forests
Sinaloan dry forests	Sierra Madre Occidental pine-oak forests
Southern Pacific dry forests	Sierra Madre Oriental pine-oak forests
Yucatán dry forests	Trans-Mexican Volcanic Belt pine-oak forests

Appendix Table A4: Forest type subgroup details

Forest type	*All forests*	*Moist forest*	*Pine-oak*	*Dry forest*	*Mangroves*	*Montane forest*
% Area of MX	56%	11%	24%	19%	1%	1%
# grid cells	30,032	15,087	10,450	2,094	1,541	592
# protected areas	51	19	30	15	8	5

Appendix Table A5: Forest loss summaries for the random forest train and test datasets (forest loss years: 2015-2019). A 70:30 training-test split ratio was used.

Group	*N*	Median	Mean	Max
All forests	28,630	0.00	1.23	98.97
Train	*20,041*	*0.00*	*1.21*	*95.54*
Test	*8,589*	*0.00*	*1.29*	*98.97*
Moist forests	15,070	0.00	1.94	98.97
Train	*10,549*	*0.00*	*1.95*	*98.97*
Test	*4,521*	*0.00*	*1.88*	*95.54*
Pine-oak forests	9,333	0.00	0.38	68.56
Train	*6,533*	*0.00*	*0.41*	*68.56*
Test	*2,800*	*0.00*	*0.39*	*45.37*
Dry forests	2,094	0.00	0.28	38.42
Train	*1,466*	*0.00*	*0.30*	*38.42*
Test	*628*	*0.00*	*0.22*	*16.19*
Mangrove Forest	1,541	0.00	0.53	81.54
Train	*1,079*	*0.00*	*0.50*	*81.54*
Test	*462*	*0.00*	*0.57*	*34.78*
Montane forests	592	0.00	1.73	28.00
Train	*414*	*0.00*	*1.84*	*28.00*
Test	*178*	*0.00*	*1.45*	*26.99*

Appendix Table A6: Descriptive statistics of forest subgroup samples

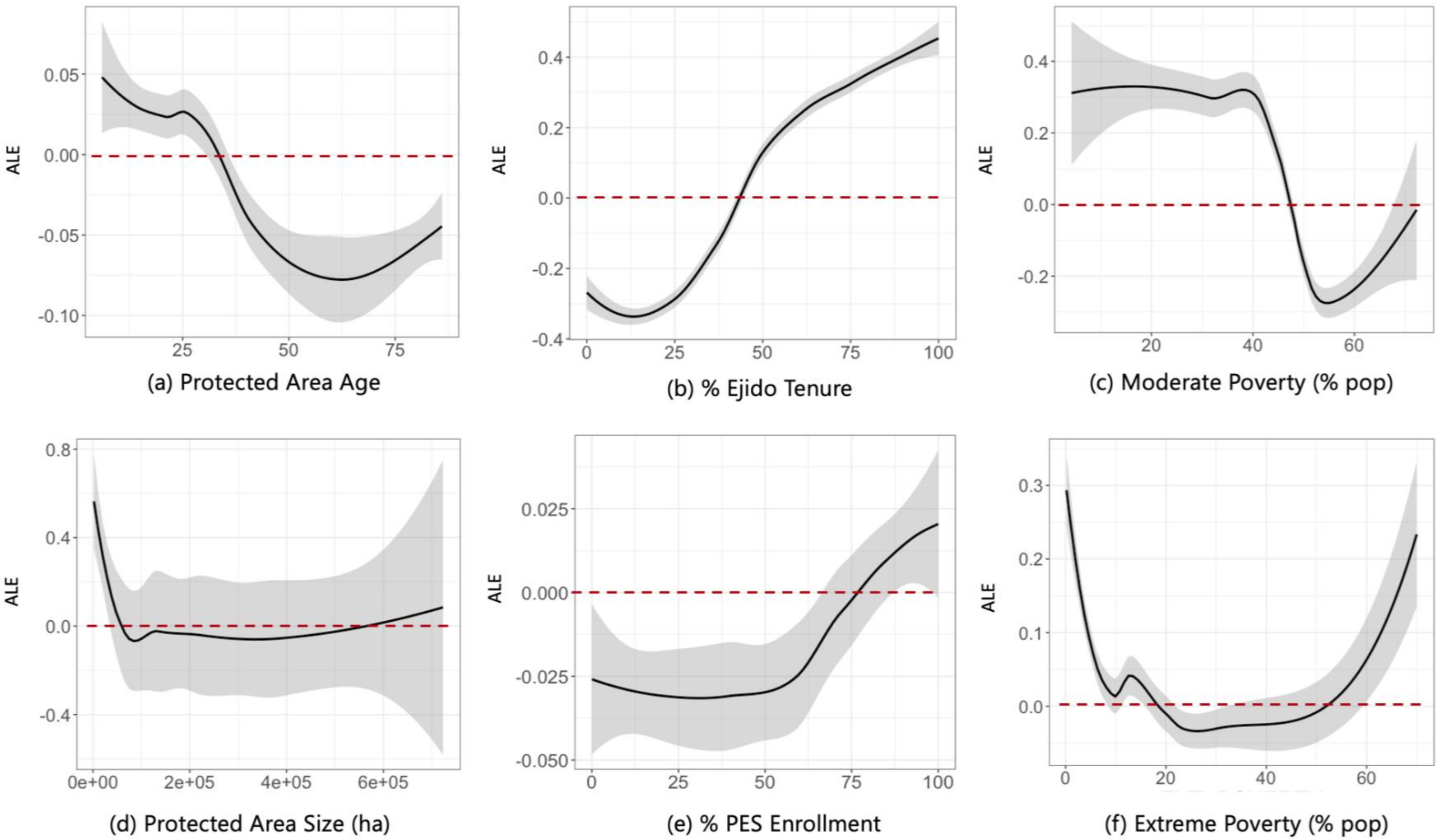
	Moist Forest		*Montane Forest*		*Dry Forest*		*Mangrove Forest*		*Pine-oak Forest*	
Variable	Median	*sd*	Median	*sd*	Median	*sd*	Median	*sd*	Median	*sd*
Precipitation (mm)	1275.00	*584.28*	2096.00	*655.03*	1019.00	*248.57*	1511.00	*255.50*	784.00	*326.60*
Temperature (°C)	23.00	*1.83*	20.00	*2.59*	22.00	*2.84*	25.00	*0.93*	15.00	*4.23*
Distance from water (km)	1.37	*3.32*	0.57	*0.54*	0.70	*0.64*	1.35	*3.48*	0.97	*0.96*
Slope (degree)	0.57	*3.67*	5.15	*3.94*	7.54	*5.30*	0.01	*0.18*	7.29	*5.25*
Elevation (m)	254.00	*380.65*	1032.50	*363.45*	847.50	*536.57*	1.00	*4.84*	1900.00	*639.60*
Population density (pop/km^2)	0.13	*14.78*	5.10	*212.75*	0.91	*25.53*	0.07	*11.86*	1.01	*34.00*
Population change (Δpop/km^2)	0.00	*1.46*	-0.23	*20.36*	-0.06	*2.63*	0.00	*1.11*	-0.05	*3.46*
Distance from road (km)	1.79	*4.47*	2.64	*3.95*	4.29	*2.47*	4.42	*4.94*	3.75	*3.39*
Road density (0-5)	0.03	*0.08*	0.16	*0.34*	0.20	*0.52*	0.06	*0.09*	0.31	*0.61*
Urban distance (km)	19.30	*15.94*	14.47	*11.04*	9.43	*7.26*	18.68	*11.24*	13.06	*9.78*
PES (% cell enrolled)	100.00	*48.74*	100.00	*40.39*	4.00	*48.56*	91.00	*48.07*	100.00	*37.62*
Ejido tenure (% cell)	0.00	*46.77*	0.00	*44.50*	50.00	*47.21*	0.00	*38.22*	21.00	*46.92*
Moderate poverty (% pop)	50.78	*6.34*	48.85	*8.20*	45.13	*7.04*	45.25	*10.29*	47.60	*11.08*
Extreme poverty (% pop)	23.55	*12.75*	36.65	*17.60*	16.12	*9.80*	18.23	*9.84*	10.61	*11.02*
PA Age (years)	32.00	*6.46*	43.00	*21.11*	26.00	*15.29*	27.00	*4.77*	24.00	*25.05*
PA Area (km^2)	5,728.08	*2,422.70*	3,312.00	*1,303.92*	1,673.09	*1,410.28*	3,749.84	*1,973.37*	2,083.81	*1,417.61*
Management eff.	81.00	*7.90*	75.00	*11.41*	72.00	*6.54*	75.00	*10.10*	69.00	*9.21*
ME: Context & planning	76.00	*10.12*	71.00	*9.03*	69.00	*10.64*	75.00	*17.36*	67.00	*12.34*
ME: Administrative	56.00	*5.89*	61.00	*4.81*	56.00	*7.56*	59.00	*9.03*	58.00	*9.66*
ME: Use & benefits	95.00	*12.33*	86.00	*8.35*	67.00	*10.03*	67.00	*18.20*	67.00	*10.00*
ME: Gov & social part.	97.00	*10.53*	78.00	*11.05*	80.00	*8.89*	73.00	*7.81*	77.00	*13.87*
ME: Management quality	90.00	*10.80*	81.00	*21.16*	67.00	*10.77*	80.00	*7.18*	67.00	*13.33*

Appendix Table A7: Pearson correlation coefficients between forest loss predictors.

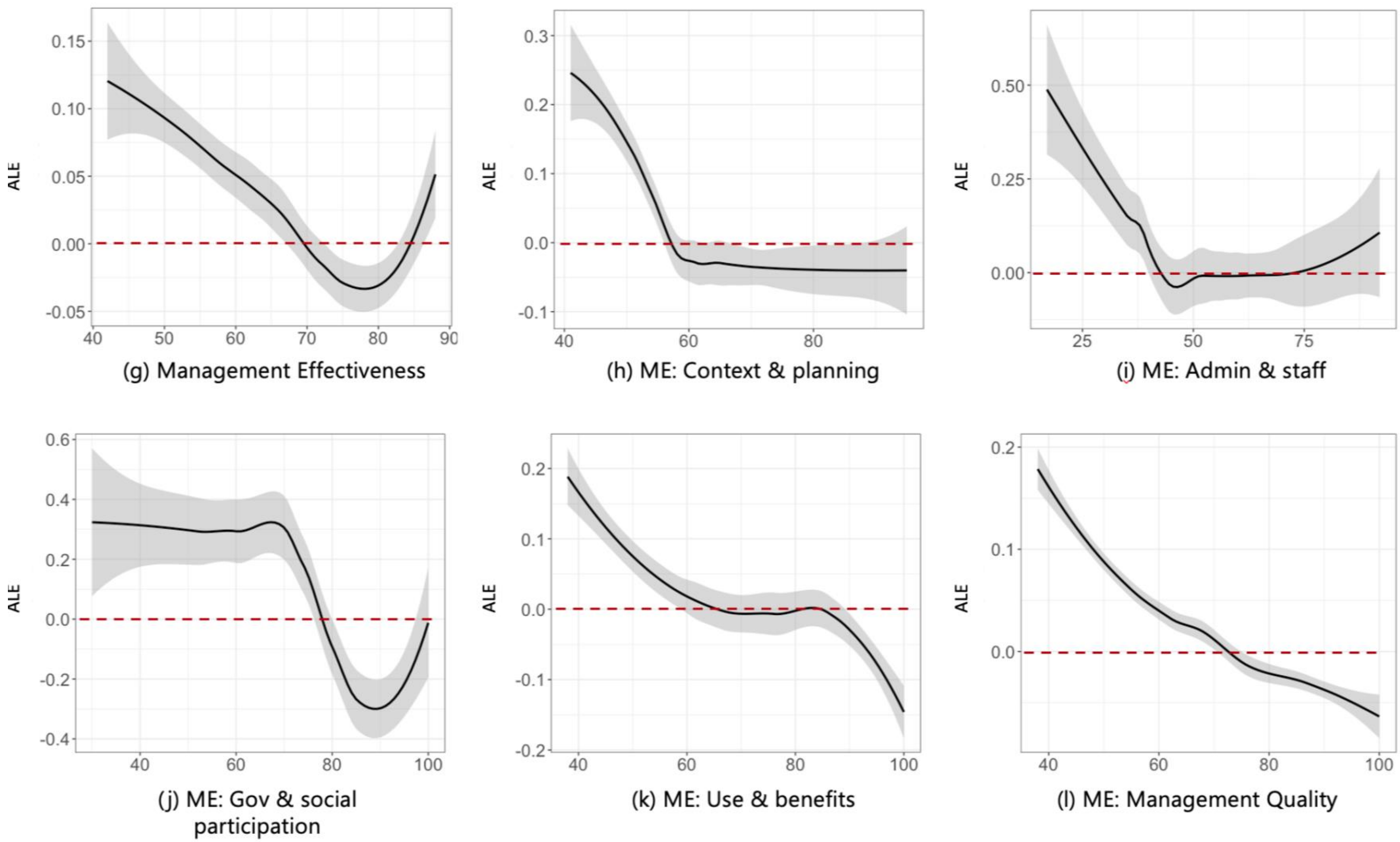
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
(1) Precipitation																					
(2) Temperature	.48																				
(3) Dist. to water	-.07	.24																			
(4) Slope	-.27	-.49	-.27																		
(5) Elevation	-.42	**-.95**	-.28	**.57**																	
(6) Pop density	.04	-.07	-.05	.04	.07																
(7) Pop change	-.04	.07	.05	-.04	-.07	**-.97**															
(8) Dist. to roads	.04	-.13	-.15	.08	.11	-.09	.09														
(9) Road density	-.22	-.45	-.15	.41	**.52**	.15	-.15	.01													
(10) Urban distance	.16	.12	-.13	-.13	-.16	-.08	.08	.17	-.21												
(11) PES	.11	-.23	-.24	.26	.28	-.01	.01	.32	.22	.05											
(12) Ejido	.17	-.14	-.14	.08	.16	-.03	.02	.11	-.04	-.02	.22										
(13) Moderate poverty	-.25	.10	.17	-.11	-.05	.02	-.02	-.13	-.16	-.09	-.12	-.13									
(14) Extreme poverty	**.76**	.44	-.04	-.21	-.35	-.03	.03	.01	-.28	.17	.13	.15	.03								
(15) PA Age	.18	-.35	-.08	-.09	.30	.12	-.11	.11	.12	-.01	.01	.05	-.11	.07							
(16) PA Size	-.08	.39	.40	-.47	-.48	-.11	.11	-.10	-.43	-.02	-.24	-.13	.32	.10	-.18						
(17) Overall ME	.33	**.60**	.25	-.42	**-.63**	-.09	.09	-.13	-.28	.11	-.17	-.06	-.03	.45	-.24	.43					
(18) ME: Context	.10	.48	.23	-.29	-.48	-.09	.09	-.16	-.21	.10	-.26	-.12	.00	.15	-.27	.27	**.83**				
(19) ME: Admin	-.20	-.01	-.05	-.09	.01	.05	-.05	-.10	-.19	.00	-.03	-.01	.26	-.08	-.06	.15	.22	.27			
(20) ME: Use	.21	**.52**	.33	-.48	**-.57**	-.07	.07	-.13	-.22	.10	-.23	-.14	.15	.41	-.11	**.52**	**.84**	**.60**	.06		
(21) ME: Govern.	.31	**.59**	.29	-.40	**-.61**	-.05	.05	-.14	-.21	.01	-.17	-.06	.05	.43	-.26	**.54**	**.91**	**.67**	.05	**.85**	
(22) ME: Quality	.44	**.61**	.23	-.41	**-.66**	-.12	.11	-.08	-.28	.12	-.10	-.04	-.14	.50	-.20	.42	**.92**	**.62**	.00	**.76**	**.85**

Appendix Table A8: Random forest model results of full forest model and forest subgroups. Root mean square error (RMSE) and mean absolute error (MAE) are presented. MAE represents the average magnitude of all errors, ignoring direction and weight, while RMSE weighs larger errors more heavily than small errors (see Willmott & Matsuura, 2005). We also present normalized values for both the RMSE and MAE (i.e. NRMSE and NMAE) in order to compare performance across models. We used the standard deviation of the outcome variable in the test set of each model to normalize each error measure.

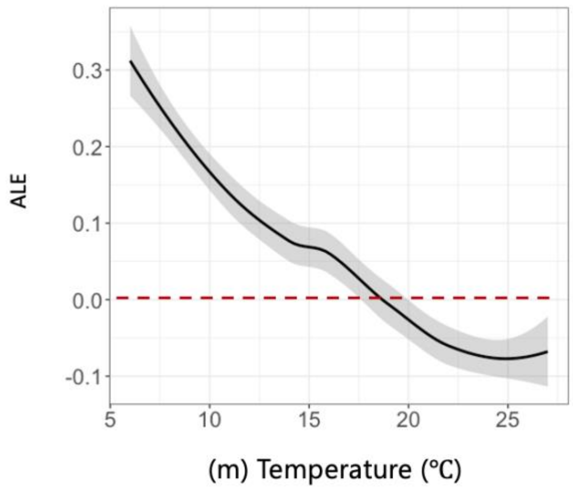
Forest type	All Forests	Moist forest	Montane forest	Mangroves	Pine-oak	Dry forest
N	*28,630*	*15,070*	*592*	*1,541*	*9,333*	*2,094*
R^2	59.37%	60.46%	48.25%	29.50%	25.17%	11.00%
RMSE	3.60	4.06	3.09	2.98	2.02	1.15
NRMSE	0.65	0.59	0.88	0.93	1.00	0.95
MAE	1.04	1.38	1.57	0.92	0.58	0.40
NMAE	0.19	0.20	0.45	0.29	0.29	0.34



Appendix Figure A1: ALE plots of all socioeconomic, biophysical and protected area design characteristics.



Appendix Figure A1 (continued): ALE plots of all socioeconomic, biophysical and protected area design characteristics.



Appendix Figure A1 (continued): ALE plots of all socioeconomic, biophysical and protected area design characteristics.

Appendix Table A9: Descriptive statistics of burn scar data across all sampling grid cells. Data was calculated as the total percent of 1 km^2 cell with burn scar between 2017-2019. Forest fire data was acquired from CONABIO, with the earliest available data starting in 2017.

Median	Mean	Standard Dev	Min	Max
0.00%	1.15%	9.25%	0.00%	100.00%

Appendix Table A10: Pearson correlation coefficients for percent of cell with burn scar and percent forest loss (2017-2019) for full forest and by forest subgroup.

All Forest	Moist	Dry	Montane	Mangrove	Pine-Oak
0.07	0.18	-0.01	-0.01	0.00	0.24

APPENDIX B

Appendix Table B1: Difference in Means (t-test) in percent forest loss from 2017-2019 in cells inside a 5km and 10km buffer around protected areas and the remaining unprotected cells.

	Unprotected	Buffer	Sig.
5km Buffer	1.86	2.07	--
10km Buffer	1.86	2.05	--

p <.001**   p <.01*

Appendix Table B2: List of protected areas included in the final analysis and the total number of cells in the final sample.

Protected Area	Type	Cells
Barranca de Metztitlán	Biosphere Reserve	200
Bonampak	Natural Monument	29
Boquerón de Tonalá	Flora and Fauna Protection Area	17
Calakmul	Biosphere Reserve	7575
Cañón del Usumacinta	Flora and Fauna Protection Area	312
Cascada de Agua Azul	Flora and Fauna Protection Area	17
Cofre de Perote o Nauhcampatépetl	National Park	32
Cumbres de Monterrey	National Park	1291
El Chico	National Park	14
El Potosí	National Park	11
El Tepozteco	National Park	152
Huatulco	National Park	47
La Encrucijada	Biosphere Reserve	445
La Montaña Malinche o Matlalcuéyatl	National Park	124
La Primavera	Flora and Fauna Protection Area	148
La Sepultura	Biosphere Reserve	997
Laguna de Términos	Flora and Fauna Protection Area	763
Laguna Madre y Delta del Río Bravo	Flora and Fauna Protection Area	100
Lagunas de Chacahua	National Park	34
Lagunas de Montebello	National Park	22
Maderas del Carmen	Flora and Fauna Protection Area	193

Mariposa Monarca	Biosphere Reserve	378
Marismas Nacionales	Biosphere Reserve	178
Metzabok	Flora and Fauna Protection Area	16
Montes Azules	Biosphere Reserve	3283
Otoch Ma'ax Yetel Kooh	Flora and Fauna Protection Area	36
Papigochic	Flora and Fauna Protection Area	925
Pico de Orizaba	National Park	4
Pico de Tancítaro	Flora and Fauna Protection Area	188
Ría Celestún	Biosphere Reserve	73
Ría Lagartos	Biosphere Reserve	112
Selva El Ocote	Biosphere Reserve	943
Sian Ka'an	Biosphere Reserve	1537
Sierra de Manantlán	Biosphere Reserve	1218
Sierra de Quila	Flora and Fauna Protection Area	104
Sierra de San Pedro Mártir	National Park	1
Sierra Gorda	Biosphere Reserve	3074
Sierra Gorda de Guanajuato	Biosphere Reserve	604
Tehuacán-Cuicatlán	Biosphere Reserve	753
Tutuaca	Flora and Fauna Protection Area	1650
Uaymil	Flora and Fauna Protection Area	558
Volcán Nevado de Colima	National Park	2
Volcán Tacaná	Biosphere Reserve	73
Yaxchilán	Natural Monument	2
Zicuarán-Infiernillo	Biosphere Reserve	461
Zona de Protección Forestal en… en los municipios de La Concordia, Ángel Albino Corzo, Villa Flores y Jiquipilas	Natural Resource Protection Area	1383
Zona Protectora Forestal Vedada Cuenca Hidrográfica del Río Necaxa	Natural Resource Protection Area	254

Appendix Table B3: Summary of data and data sources included in the analysis.

Indicators	Measurement Used	Source
· Ecoregions	(N/A)	WWF
· CONANP regions	(N/A)	CONANP
· Rainfall	Year Total	WorldClim
· Temperature	Yearly Average	WorldClim
· Ejido	% of cell	INEG
· Population density	Average	NASA - SEDAC
· Distance to roads	Euclidean	INEG– Census 2010
· Road density	Average	INEG – Census 2010
· Distance to urban centers	Euclidean	INEG – Census 2010
· Slope	Median	USGS Earth Explorer
· Elevation	Average	USGS Earth Explorer
· Protected areas	(N/A)	Protected Planet
· IUCN category	(N/A)	Protected Planet
· Management effectiveness	(N/A)	CONANP
· Forest Cover 2000	% of cell	GFW
· Forest Cover Loss 2017-2019	% of 2000 baseline lost	GFW

Appendix Table B4: Spearman correlation of all socioeconomic, ecological, and climatological variables considered for the propensity score model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Elevation (1)	1.00								
Slope (2)	0.69	1.00							
Urban Distance (3)	-0.15	-0.18	1.00						
Road Distance (4)	0.07	0.06	0.53	1.00					
Road Density (5)	0.06	0.09	-0.62	-0.55	1.00				
Population Density (6)	0.15	0.22	-0.70	-0.57	0.72	1.00			
Average Temperature (7)	-0.91	-0.59	0.13	-0.07	-0.05	-0.10	1.00		
Rainfall (8)	-0.35	-0.14	-0.04	-0.15	0.05	0.19	0.42	1.00	
Ejido Tenure (9)	0.00	-0.02	0.05	-0.02	-0.11	-0.03	0.04	0.00	1.00
% Forest Loss	-0.22	-0.15	-0.15	-0.34	0.19	0.25	0.22	0.39	0.06

Appendix Table B5: ***Model 1****: Logistic regression with a binary treatment (protected) dummy variable.* ***Model 2****: Linear regression with a continuous dependent variables of percent forest loss between 2017-2019. Each model includes the 6 covariates used in the matching algorithms as independent variables.*

	Model 1: Treatment (1-0)	Model 2: % Forest Loss
Elevation	2.081e-04*** (1.236e-05)	-1.119e-03*** (4.058e-05)
Slope	-8.666e-03*** (2.029e-03)	-1.531e-01*** (6.572e-03)
Urban Distance	2.970e-05*** (5.992e-07)	3.687e-05*** (2.061e-06)
Road Distance	3.324e-05*** (1.384e-06)	-2.345e-04*** (4.940e-06)
Rainfall	1.451e-04*** (1.636e-05)	2.510e-03*** (5.216e-05)
Ejido Tenure	-7.309e-03*** (1.840e-04)	6.042e-03*** (5.912e-04)
R^2	--	0.12
Observations	80,000	80,000

p <.0001*** *p* <.001** *p* <.01*

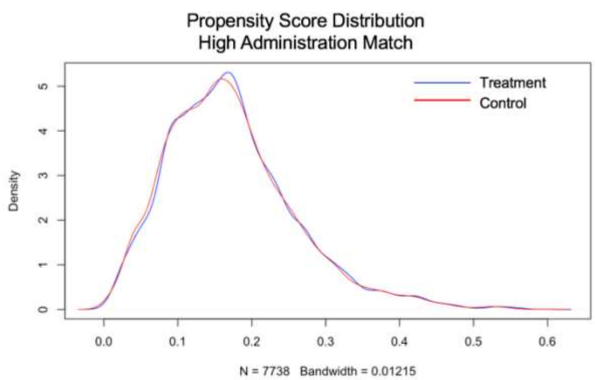
Appendix Table B6: Difference in means (t-test) between protected-unprotected cells and high-low management subgroups for all covariates.

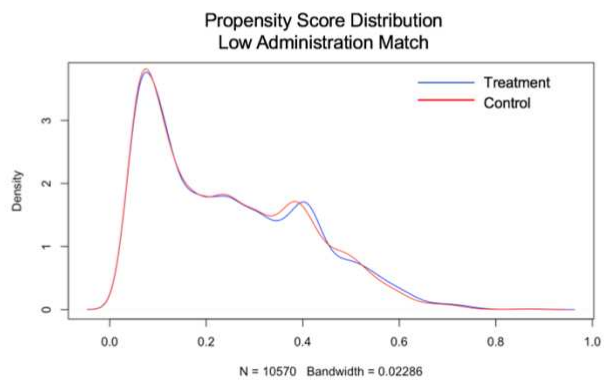
	Elevation	*Slope*	*Urban Distance*	*Road Distance*	*Road Density*	*Population Density*	*Average Temperature*	*Rainfall*	*Ejido Tenure*
Unprotected	911	5.00	17844	5886	0.13	46.0	19.8	1254.12	56.07
Protected	934	4.64	28283	9503	0.11	46.1	19.6	1232.12	41.12
Sig.	**	***	***	***	***	--	***	***	***
High	369	1.72	40280	12337	0.058	10.9	23.0	1454.60	38.17
Low	1483.70	7.48	16621.77	6748.8	0.156	80.4	16.37	1015.86	43.99
Sig.	***	***	***	***	***	***	***	***	***

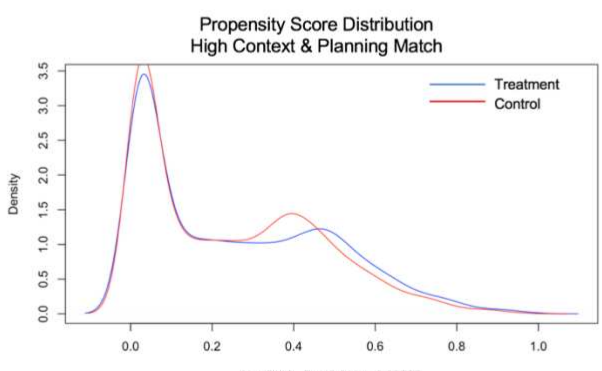
p <.0001***   *p* <.001**   *p* <.01*

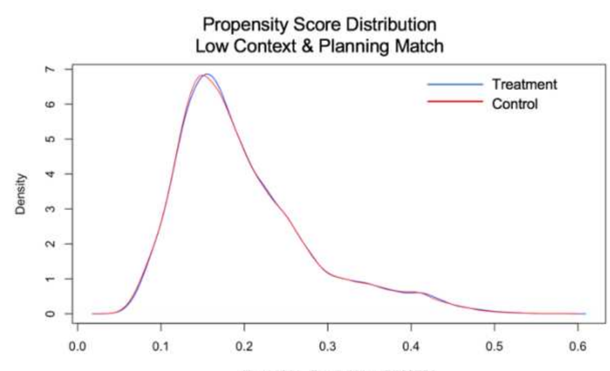
Appendix Table B7: List of algorithms and calipers used in best matches. 'PS' is Propensity Score Matching.

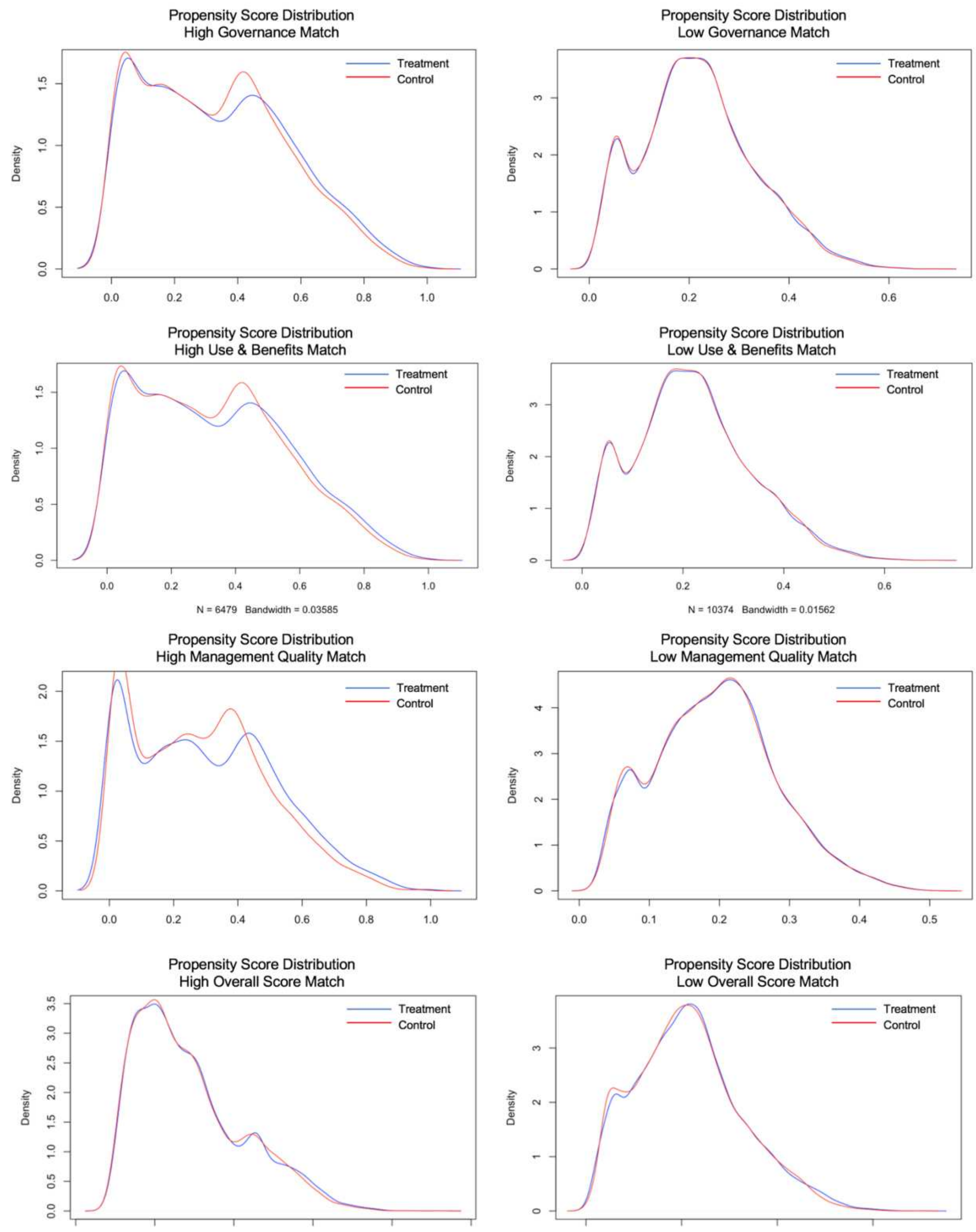
Match	High Mgmt. Effectiveness	#	Low Mgmt. Effectiveness	#
Overall Management	PS + .2 sd caliper	7,023	PS + .2 sd caliper	10,121
Context & Planning	PS + .2 sd caliper	5,116	PS + .1 sd caliper	11,667
Administration	PS + .2 sd caliper	7,738	PS + .1 sd caliper	10,570
Use & Benefits	PS + .1 sd caliper	6,479	PS + .1 sd caliper	10,370
Governance	PS + .1 sd caliper	6,433	PS + .1 sd caliper	10,410
Management Quality	PS + .2 sd caliper	7,044	PS + .1 sd caliper	10,329
Match	All Cells			
Protected - Unprotected	PS + .1 sd caliper	18,204		











Appendix Figure B1: Visual distribution of the propensity scores for the post-match balance of management subgroups for the most balanced match (Appendix Table B7).

Appendix Table B8: Mean standardized bias (SB) of high management and low management matches using propensity score matching (PS) with no caliper, PS with a 0.2 standard deviations caliper, PSM with a 0.1 standard deviations caliper, and Mahalanobis Matching (MM). SB is calculated as calculated as the difference in means in the treated and matched control subgroups as a percentage of the square root of the average of sample variances in both groups.

Protected – Unprotected Match

Covariate	**PS**	**PS + .2 SD Caliper**	**PS + .1 SD Caliper**	**MM**
Elevation	14.41	6.17	5.40	7.61
Slope	14.63	6.27	6.09	13.02
Urban Distance	16.41	3.92	1.44	28.70
Road Distance	10.95	0.52	2.61	23.38
Avg Rainfall	2.65	1.07	0.25	4.12
Ejido Tenure	8.40	5.94	5.34	6.56
# Matched Pairs	*20,000*	*18,395*	*18,204*	*20,000*

High Overall Management Score – Unprotected Match

Covariate	**PS**	**PS + .2 SD Caliper**	**PS + .1 SD Caliper**	**MM**
Elevation	20.51	12.59	11.69	29.08
Slope	27.20	13.75	13.10	40.30
Urban Distance	45.29	2.97	4.78	50.63
Road Distance	36.14	0.90	3.48	37.89
Avg Rainfall	14.51	4.54	4.91	12.21
Ejido Tenure	16.23	1.96	0.34	10.28
# Matched Pairs	*9,858*	*7,023*	*6,781*	*9,858*

Low Overall Management Score – Unprotected Match

Covariate	**PS**	**PS + .2 SD Caliper**	**PS + .1 SD Caliper**	**MM**
Elevation	5.20	2.96	3.64	5.75
Slope	0.45	1.31	0.04	3.77
Urban Distance	1.67	3.89	1.56	2.59
Road Distance	0.53	2.11	1.32	2.31
Avg Rainfall	8.71	5.21	6.95	6.77
Ejido Tenure	0.88	1.40	0.61	0.67
# Matched Pairs	*10,142*	*10,121*	*10,080*	*10,142*

High Context and Planning Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	28.92	17.44	18.62	33.10
Slope	30.81	10.93	9.61	33.23
Urban Distance	47.24	9.60	13.29	52.10
Road Distance	27.60	4.10	6.26	32.31
Avg Rainfall	12.88	2.11	1.25	20.62
Ejido Tenure	17.03	11.54	9.77	16.12
# Matched Pairs	*8,333*	*5,116*	*4,987*	*8.333*

Low Context and Planning Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	5.67	6.39	4.72	3.69
Slope	5.95	5.96	6.60	0.86
Urban Distance	2.88	3.70	3.79	7.75
Road Distance	2.80	4.22	4.00	10.73
Avg Rainfall	8.62	8.12	6.75	0.97
Ejido Tenure	4.43	2.27	3.47	2.23
# Matched Pairs	*11,667*	*11,660*	*11,644*	*11,667*

High Administration and Finance Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	0.08	0.67	1.24	1.60
Slope	4.12	2.75	1.13	3.35
Urban Distance	5.19	2.08	0.37	8.68
Road Distance	3.73	3.22	2.54	5.70
Avg Rainfall	0.75	3.46	0.19	0.70
Ejido Tenure	4.16	3.34	1.73	1.67
# Matched Pairs	*7,748*	*7,738*	*7,735*	*7,748*

Low Administration and Finance Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	17.24	7.86	7.69	11.52
Slope	18.93	7.32	6.19	15.95
Urban Distance	23.75	1.03	1.20	33.58
Road Distance	12.62	2.80	2.87	27.90
Avg Rainfall	3.57	2.56	2.23	6.17
Ejido Tenure	8.40	3.85	3.05	5.19

# Matched Pairs	*11,667*	*10,682*	*10,570*	*12,252*

High Use and Benefits Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	22.24	11.28	8.34	29.34
Slope	26.13	12.72	10.41	46.80
Urban Distance	49.10	4.85	0.02	53.63
Road Distance	39.03	4.51	0.08	40.06
Avg Rainfall	15.44	8.81	7.29	12.49
Ejido Tenure	17.10	5.20	2.86	11.15
# Matched Pairs	*9,521*	*6,715*	*6,479*	*9,521*

Low Use and Benefits Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	6.16	4.66	5.43	4.75
Slope	0.16	0.48	0.20	3.80
Urban Distance	0.21	1.01	1.19	2.58
Road Distance	0.13	0.06	1.01	2.30
Avg Rainfall	8.16	7.76	7.90	7.48
Ejido Tenure	1.17	0.42	2.29	0.55
# Matched Pairs	*10,479*	*10,424*	*10,374*	*10,479*

High Governance and Social Participation Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	21.45	9.75	8.57	29.83
Slope	26.39	13.14	12.07	47.15
Urban Distance	49.30	4.62	0.55	53.76
Road Distance	39.34	2.35	1.86	40.19
Avg Rainfall	16.06	7.10	6.83	12.59
Ejido Tenure	17.89	4.34	1.58	11.11
# Matched Pairs	*9,488*	*6,665*	*6,433*	*9,488*

Low Governance and Social Participation Score – Unprotected Match

Covariate	PS	PS + .2 SD Caliper	PS + .1 SD Caliper	MM
Elevation	6.45	4.24	5.32	4.97
Slope	0.30	0.89	0.24	3.81
Urban Distance	0.29	2.55	0.68	2.23

Road Distance	0.25	0.52	0.10	2.03
Avg Rainfall	8.57	6.50	7.60	7.10
Ejido Tenure	1.93	1.14	0.86	0.63
# Matched Pairs	*10,512*	*10,461*	*10,410*	*10,512*

High Management Quality Score – Unprotected Match

Covariate	**PS**	**PS + .2 SD Caliper**	**PS + .1 SD Caliper**	**MM**
Elevation	29.91	14.22	16.32	27.84
Slope	29.98	12.37	11.71	29.25
Urban Distance	41.77	1.30	5.27	49.13
Road Distance	27.22	6.94	8.52	28.15
Avg Rainfall	7.53	1.81	3.05	9.28
Ejido Tenure	14.19	1.33	2.30	10.54
# Matched Pairs	*9,671*	*7,044*	*6,795*	*9,671*

Low Management Quality Score – Unprotected Match

Covariate	**PS**	**PS + .2 SD Caliper**	**PS + .1 SD Caliper**	**MM**
Elevation	3.25	1.37	2.90	3.71
Slope	1.99	0.57	0.55	1.49
Urban Distance	0.59	4.48	3.07	6.26
Road Distance	1.37	5.16	1.99	2.97
Avg Rainfall	6.57	2.36	4.47	1.76
Ejido Tenure	0.92	3.08	2.40	0.37
# Matched Pairs	*10,329*	*10,329*	*10,329*	*10,329*

Appendix Table B9: Difference in means (t-tests) in percent forest loss from 2017-2019 between management subgroups and unprotected matched cells.

	Control	High	Low	Sig.
Overall Management				
High Match	3.30	1.19		***
Low Match	1.05		0.46	***
Context & Planning				
High Match	2.49	0.74		***
Low Match	1.42		0.75	***
Administration				
High Match	0.93	0.20		***
Low Match	2.39		1.16	***
Use & Benefits				
High Match	3.28	1.36		***
Low Match	1.15		0.38	***
Governance				
High Match	3.47	1.45		***
Low Match	1.13		0.38	***
Management Quality				
High Match	2.82	1.16		***
Low Match	1.22		0.48	***

p <.0001***

Appendix Table B10: Post-match linear regression results for high management – unprotected matches. Dependent variable is percent forest loss between 2017-2019. Regression coefficient presented and robust standard errors shown in parentheses.

	Model 1: Overall Score	Model 2: Context	Model 3: Administration	Model 4: Uses	Model 5: Governance	Model 6: Management
High Management Score (Binary)	-2.176e+00*** (1.064e-01)	-1.773e+00*** (1.169e-01)	-7.326e-01*** (4.943e-02)	-2.014e+00*** (1.102e-01)	-2.002e+00*** (1.151e-01)	-1.805e+00*** (1.038e-01)
Elevation	-3.600e-04*** (5.934e-05)	-4.775e-04*** (7.542e-05)	-7.391e-05 (3.781e-05)	-3.173e-04*** (6.874e-05)	-4.089e-04*** (6.652e-05)	-2.424e-04** (7.567e-05)
Slope	-6.508e-02*** (9.889e-03)	-3.124e-02* (7.788e-03)	-2.638e-02*** (4.581e-03)	-7.238e-02*** (2.281e-02)	-7.872e-02*** (1.301e-02)	-4.201e-02*** (7.500e-03)
Urban Distance	5.349e-05*** (4.234e-06)	5.851e-05*** (4.739e-06)	1.212e-05** (4.021e-06)	4.660e-05*** (4.282e-06)	4.938e-05*** (4.621e-06)	4.319e-05*** (3.949e-06)
Road Distance	-1.769e-04*** (6.105e-06)	-1.497e-04*** (7.722e-06)	-4.434e-05*** (5.843e-06)	-1.731e-04*** (6.336e-06)	-1.789e-04*** (6.443e-06)	-1.566e-04*** (5.615e-06)
Rainfall	1.266e-03*** (8.697e-05)	1.138e-03*** (1.590e-04)	8.928e-04*** (8.402e-05)	1.233e-03*** (9.480e-05)	1.208e-03*** (9.584e-05)	1.046e-03*** (8.401e-05)
Ejido Tenure	6.729e-03*** (1.232e-03)	7.814e-03*** (1.306e-03)	1.562e-03* (6.387e-04)	6.228e-03*** (1.265e-03)	7.412e-03*** (1.346e-03)	5.141e-03*** (1.188e-03)
R2	0.11	0.10	0.04	0.10	0.10	0.10
Observations	*14,046*	*10,232*	*15,476*	*12,958*	*12,866*	*10,820*

p <.0001*** p <.001** p <.01* p<.05°

VIF ≤ 2 for all coefficients in all models

Appendix Table B11: Post-match linear regression results for low management – unprotected matches. Dependent variable is percent forest loss between 2017-2019. Regression coefficient presented and robust standard errors shown in parentheses.

	Model 1: Overall Score	Model 2: Context	Model 3: Administration	Model 4: Uses	Model 5: Governance	Model 6: Management
Low Management Score (Binary)	-4.961e-01*** (4.317e-02)	-6.258e-01*** (4.869e-02)	-1.317e+00*** (7.727e-02)	-7.254e-01*** (4.757e-02)	-7.075e-01*** (4.824e-02)	-7.069e-01*** (4.735e-02)
Elevation	-1.719e-04*** (3.422e-05)	-8.584e-05* (3.787e-05)	-4.265e-04*** (4.460e-05)	-1.444e-04*** (3.753e-05)	-1.841e-04*** (3.673e-05)	-1.576e-04* (3.684e-05)
Slope	-3.751e-02*** (3.857e-03)	-4.448e-02*** (4.861e-03)	-4.672e-02*** (5.163e-03)	-4.307e-02*** (4.247e-03)	-3.952e-02*** (4.166e-03)	-4.853e-02** (4.476e-03)
Urban Distance	1.029e-05*** (2.679e-06)	1.878e-05*** (2.616e-06)	4.215e-05*** (3.460e-06)	1.680e-05*** (2.271e-06)	1.803e-05*** (3.536e-06)	1.784e-05*** (3.062e-06)
Road Distance	-3.927e-05*** (4.003e-06)	-7.235e-05*** (3.806e-06)	-1.410e-04*** (4.880e-06)	-4.542e-05*** (4.530e-06)	-4.739e-05*** (4.833e-06)	-5.274e-05*** (4.528e-06)
Rainfall	1.244e-03*** (6.424e-05)	1.279e-03*** (5.026e-05)	1.173e-03*** (6.933e-05)	1.412e-03*** (7.110e-05)	1.371e-03*** (7.898e-05)	1.551e-03*** (7.725e-05)
Ejido Tenure	1.977e-03*** (4.754e-04)	-1.774e-03*** (5.325e-04)	2.054e-03* (8.505e-04)	1.359e-03** (5.265e-04)	1.649e-03** (5.376e-04)	1.629e-03*** (5.262e-04)
R2	.06	0.09	0.09	0.07	0.11	0.07
Observations	*20,242*	*23,334*	*21,140*	*20,740*	*20,820*	*20,658*

p <.0001*** p <.001** p <.01* p<.05°

VIF < 2 for all coefficients in all models

Appendix Table B12: Full results for each management interaction linear regression model. Dependent variable is percent forest loss between 2017-2019. Regression coefficient presented and robust standard errors shown in parentheses.

	Overall Mngt Effectiveness	Context & Planning	Admin & Finance	Use & Benefits	Gov & Social Participation	Management Quality
Mngt (Interaction)	-1.49e-02*** (6.93e-04)	-1.55e-02*** (6.83e-04)	-1.84e-02*** (7.98e-04)	-1.39e-02*** (6.670e-04)	-1.25e-02*** (6.17e-04)	-1.36e-02*** (6.58e-04)
Elevation	-3.37e-04*** (2.82e-05)	-3.43e-04*** (2.83e-05)	-2.95e-04*** (2.81e-05)	-3.41e-04*** (2.83e-05)	-3.45e-04*** (2.82e-05)	-3.48e-04*** (2.83e-05)
Slope	-4.52e-02*** (3.47e-03)	-4.43e-02*** (3.46e-03)	-4.60e-02*** (3.47e-03)	-4.73e-02*** (3.50e-03)	-4.47e-02*** (3.47e-03)	-4.54e-02*** (3.48e-03)
Urban Distance	3.06e-05*** (2.53e-06)	3.05e-05*** (2.53e-06)	2.91e-05*** (2.53e-06)	3.19e-05*** (2.53e-06)	3.10e-05*** (2.53e-06)	3.09e-05*** (2.53e-06)
Road Distance	-1.10e-04*** (3.73e-06)	-1.10e-04*** (3.73e-06)	-1.12e-04*** (3.75e-06)	-1.10e-04*** (3.73e-06)	-1.11e-04*** (3.73e-06)	-1.08e-04*** (3.71e-06)
Rainfall	1.18e-03*** (5.38e-05)	1.15e-03*** (5.36e-05)	1.12e-03*** (5.35e-05)	1.17e-03*** (5.37e-05)	1.18e-03*** (5.39e-05)	1.21e-03*** (5.41e-05)
Ejido Tenure	3.09e-03*** (5.34e-04)	3.00e-03*** (5.34e-04)	3.17e-03*** (5.32e-04)	2.85e-03*** (5.37e-04)	3.08e-03*** (5.34e-04)	3.13e-03*** (5.33e-04)
R2	0.08	0.08	0.08	0.08	0.08	0.08

*p <.0001*** p <.001** p <.01**

Appendix Table B13: Marginal effects for each continuous management score interaction term. Dependent variable is percent forest loss between 2017-2019.

Overall Score				**Use and Benefits**			
Score	Predicted Forest Loss	SE	95% CI	Score	Predicted Forest Loss	SE	95% CI
40	0.99	0.03	[0.93, 1.04]	40	1.03	0.03	[0.97, 1.08]
50	0.84	0.03	[0.78, 0.90]	50	0.89	0.03	[0.83, 0.95]
60	0.69	0.03	[0.62, 0.75]	60	0.75	0.03	[0.69, 0.81]
70	0.54	0.04	[0.47, 0.61]	70	0.61	0.03	[0.54, 0.68]
80	0.39	0.04	[0.31, 0.47]	80	0.47	0.04	[0.40, 0.54]
90	0.24	0.05	[0.15, 0.33]	90	0.33	0.04	[0.25, 0.41]
Context & Planning				**Governance and Social Participation**			
Score	Predicted Forest Loss	SE	95% CI	Score	Predicted Forest Loss	SE	95% CI
40	0.97	0.03	[0.91, 1.03]	40	1.06	0.03	[1.01, 1.12]
50	0.82	0.03	[0.76, 0.88]	50	0.94	0.03	[0.88, 1.00]
60	0.66	0.03	[0.60, 0.73]	60	0.81	0.03	[0.75, 0.88]
70	0.51	0.04	[0.43, 0.58]	70	0.69	0.03	[0.62, 0.75]
80	0.35	0.04	[0.27, 0.43]	80	0.56	0.04	[0.49, 0.63]
90	0.20	0.05	[0.10, 0.29]	90	0.44	0.04	[0.36, 0.52]
Administrative and Finance				**Management Quality**			
Score	Predicted Forest Loss	SE	95% CI	Score	Predicted Forest Loss	SE	95% CI
40	0.83	0.03	[0.77, 0.89]	40	1.02	0.03	[0.97, 1.08]
50	0.65	0.03	[0.58, 0.71]	50	0.89	0.03	[0.83, 0.95]
60	0.46	0.04	[0.39, 0.54]	60	0.75	0.03	[0.69, 0.82]
70	0.28	0.04	[0.19, 0.37]	70	0.62	0.03	[0.55, 0.68]
80	0.09	0.05	[0.01, 0.19]	80	0.48	0.04	[0.41, 0.56]
90	-0.09	0.06	[-0.20, 0.02]	90	0.35	0.04	[0.26, 0.43]

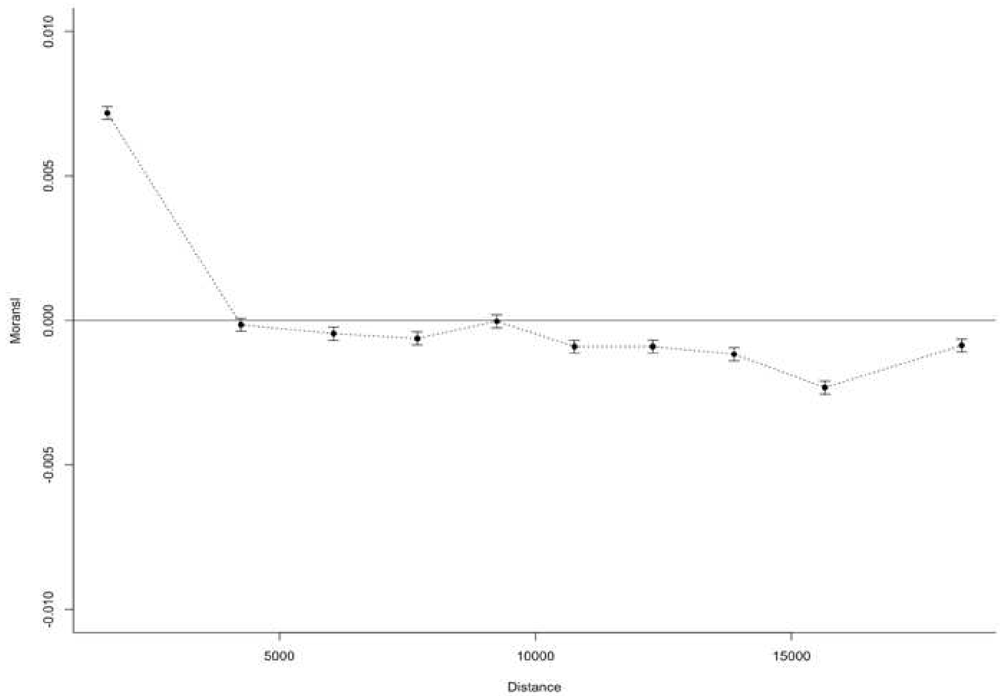
Appendix Table B14. Rosenbaum Sensitivity Test

	Wilcoxon Signed Rank P-value		*Hodges-Lehmann Point Estimate*	
Gamma	Lower Bound	Upper Bound	Lower Bound	Upper Bound
1.0	<.0001	<.0001	-1.566	-1.458
1.2	<.0001	<.0001	-1.666	0.034
1.4	<.0001	<.0001	-1.666	0.034
1.6	<.0001	<.0001	-1.666	0.034
1.8	<.0001	<.0001	-1.666	0.034
2.0	<.0001	<.0001	-1.666	0.034
2.2	<.0001	<.0001	-1.666	0.034
2.4	<.0001	.047	-1.666	0.034
2.6	<.0001	.862	-1.666	0.034

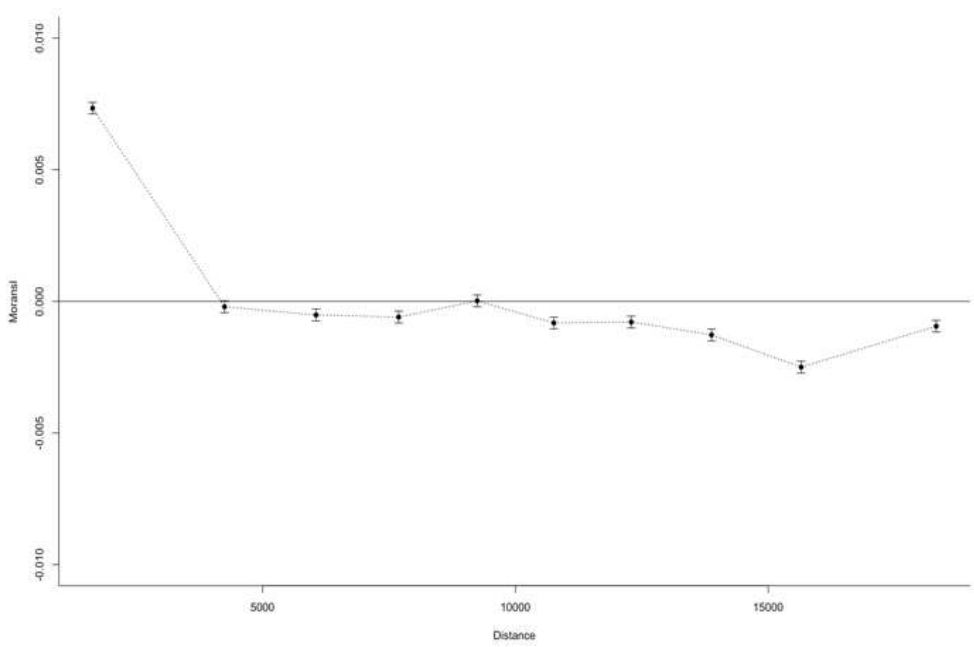
Appendix Table B15: Logit regression with binary forest loss dependent variable (any loss between 2017-19=1, else 0). Each model contains the full continuous management score of each category as the interaction term.

	Overall Mngt Effectiveness	Context & Planning	Admin & Finance	Use & Benefits	Gov & Social Participation	Management Quality
Management (Interaction)	-1.610e-02*** (3.973e-04)	-1.701e-02*** (4.175e-04)	-2.028e-02*** (5.105e-04)	-1.442e-02*** (3.720e-04)	-1.353e-02*** (3.424e-04)	-1.477e-02*** (3.661e-04)
Elevation	-2.147e-04*** (2.085e-05)	-2.222e-04*** (2.091e-05)	-1.940e-04*** (2.090e-05)	-2.108e-04*** (2.077e-05)	-2.183e-04*** (2.080e-05)	-2.214e-04*** (2.083e-05)
Slope	-1.170e-02*** (3.407e-03)	-1.015e-02** (3.410e-03)	-1.106e-02** (3.395e-03)	-1.310e-02*** (3.385e-03)	-1.158e-02*** (3.399e-03)	-1.295e-02*** (3.412e-03)
Urban Distance	6.734e-06*** (9.590e-07)	6.709e-06*** (9.588e-07)	5.169e-06*** (9.506e-07)	7.825e-06*** (9.617e-07)	7.140e-06*** (9.616e-07)	7.138e-06*** (9.611e-07)
Road Distance	-1.266e-04*** (2.997e-06)	-1.280e-04*** (3.000e-06)	-1.289e-04*** (3.000e-06)	-1.270e-04*** (2.994e-06)	-1.276e-04*** (2.998e-06)	-1.251e-04*** (2.997e-06)
Rainfall	1.269e-03*** (2.657e-05)	1.221e-03*** (2.614e-05)	1.191e-03*** (2.599e-05)	1.247e-03*** (2.629e-05)	1.271e-03*** (2.653e-05)	1.315e-03*** (2.700e-05)
Ejido Tenure	1.197e-03*** (2.969e-04)	1.114e-03*** (2.973e-04)	1.051e-03*** (2.965e-04)	9.566e-04** (2.963e-04)	1.204e-03*** (2.964e-04)	1.303e-03*** (2.967e-04)
R^2	--	--	--	--	--	--

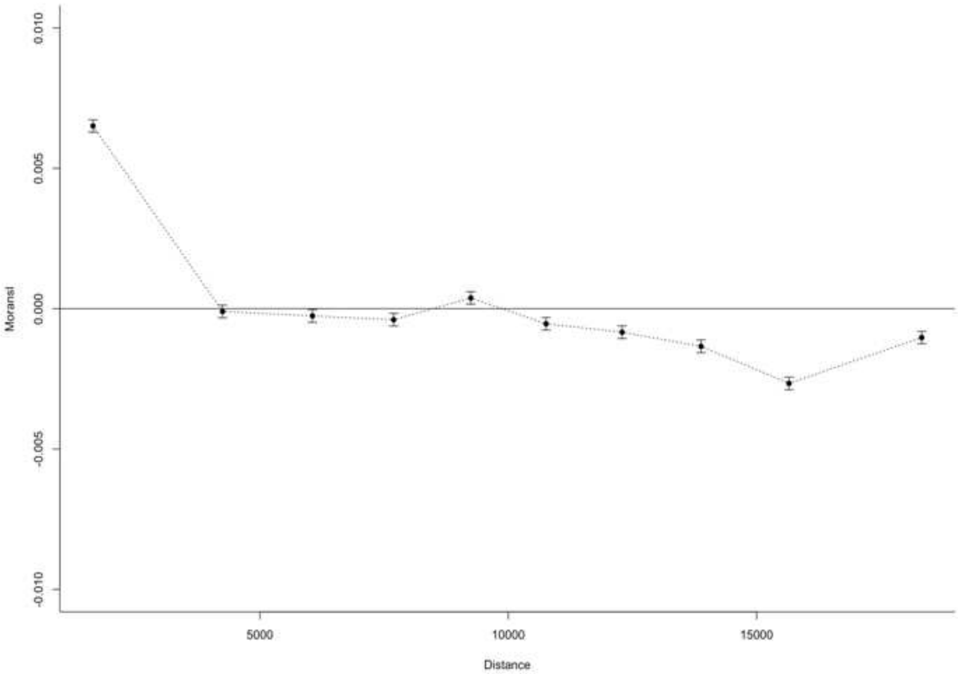
*p <.0001*** p <.001** p <.01**



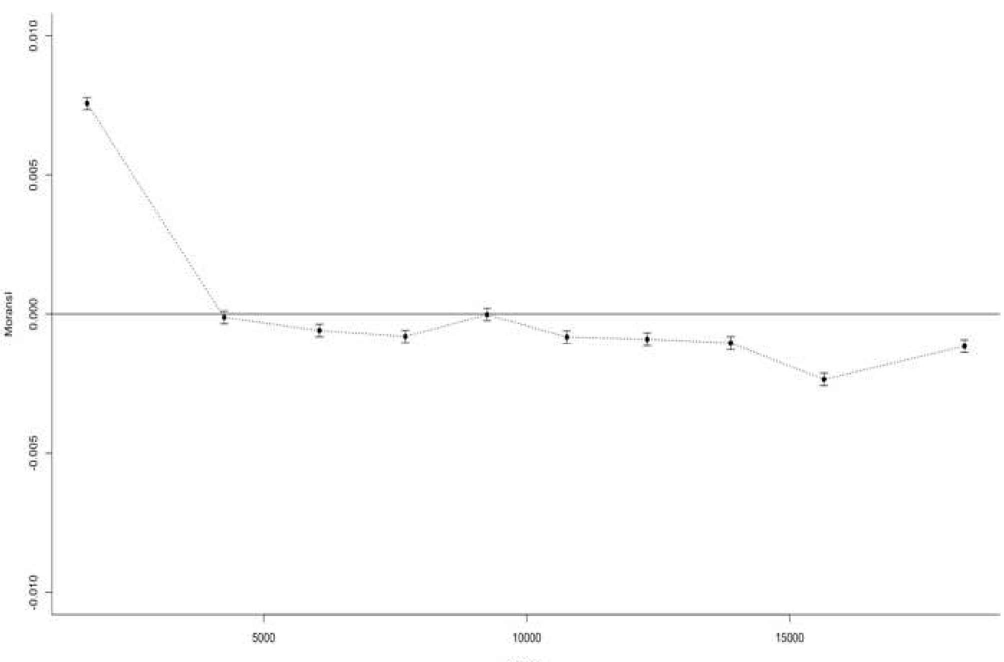
Appendix Figure B2a. Global Moran's I correlograms of the residuals of the overall management effectiveness score interaction term model.



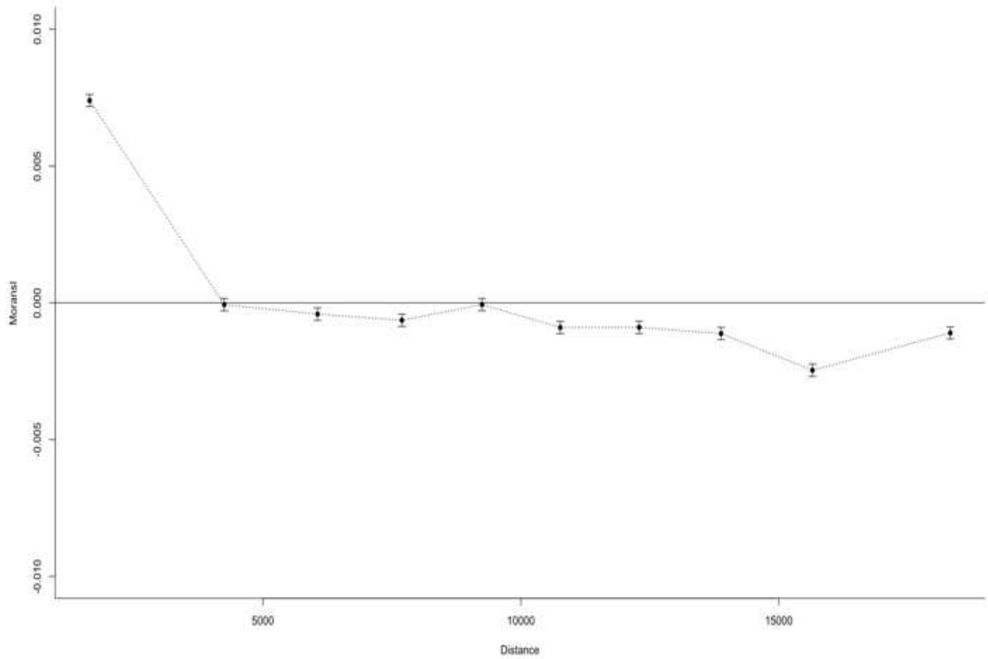
Appendix Figure B2b. Global Moran's I correlograms of the residuals of the context and planning score interaction term model.



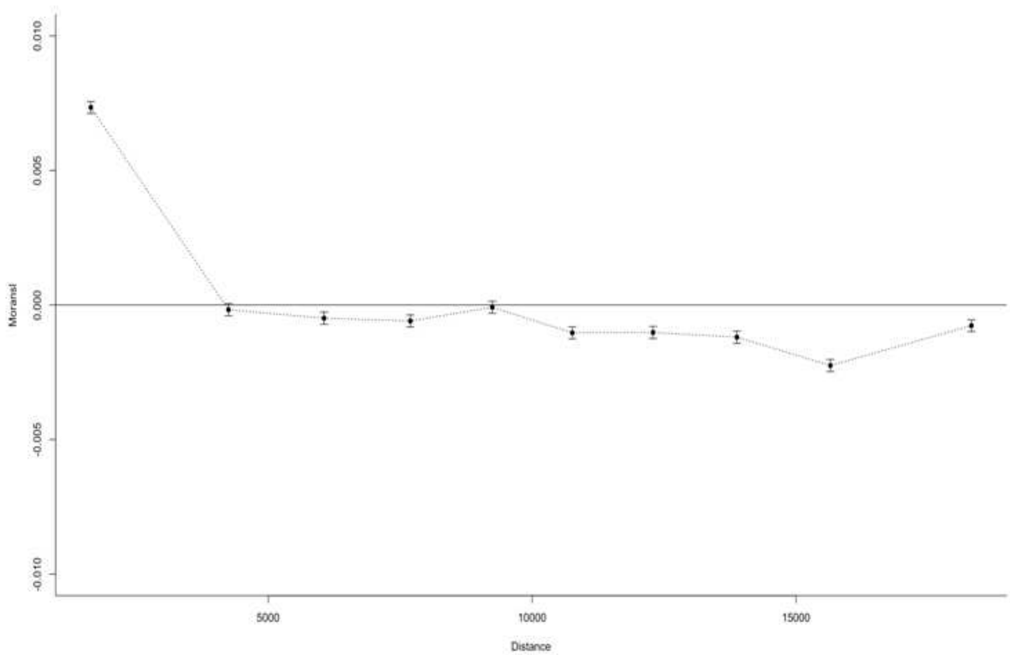
Appendix Figure B2c. Global Moran's I correlograms of the residuals of the administration and finance score interaction term model.



Appendix Figure B2d. Global Moran's I correlograms of the residuals of the use and benefits score interaction term model.



Appendix Figure B2e. Global Moran's I correlograms of the residuals of the governance and social participation score interaction term model.



Appendix Figure B2e. Global Moran's I correlograms of the residuals of the management quality score interaction term model.

APPENDIX C

Narrative summary of survey

Inputs

The survey recorded a range of impacts on protected area staff, such as changes in the total number of staff in 2020 compared to 2019 and the previous five years, and main reasons for those changes. Questions about financial capacity included changes to protected area operational budget in 2020 compared to 2019 and compared to the previous five years, expected budget changes, and the perceived sufficiency of the current budget. Additionally, managers were asked to estimate the degree to which changes in staff capacity and financial capacity were due to the pandemic on a 7-pt scale (1-not attributable to the COVID-19 pandemic to 7-fully attributable to the COVID-19 pandemic).

Mechanisms

The average annual number of tourist and non-tourist visitors over the past five years were collected for each protected area. For protected areas that receive visitors, the change in tourists and non-tourist visitors were measured in 2020 compared to 2019. Additionally, managers were asked to estimate the degree to which changes in either were due to the pandemic on a 7-pt scale (1-not attributable to the COVID-19 pandemic to 7-fully attributable to the COVID-19 pandemic).

Changes in three dimensions of monitoring were measured, including the frequency of monitoring, total area monitored, and the total number of staff responsible for monitoring. A similar question was also used to measure changes in community monitoring support and the level of support provided by PROFEPA, the government agency responsible for enforcement and sanctions. The degree to which changes in any of these factors were due to the pandemic were measured on a 7-pt scale.

Additionally, we recorded managers' perceptions of changes in the total amount of time spent on infrastructure maintenance in 2020, as well as changes in the capacity to continue active management, and necessary studies on natural resources.

Moderators

Moderators measured in the survey included perceived changes to advisory council operations, government programs, such as subsidy programs, and programs run by non-governmental organizations. The specific changes recorded include project delays, temporary freezes on project activities, and reduction in benefits. Additionally, the survey also recorded access to emergency funds in 2020 and the name of the supporting organization.

Outcomes

We measured the perceived change in 2020 in 8 different non-compliant activities, including human-caused fires, land clearing for agriculture, hunting, fishing, logging, mining, unapproved settlements and unapproved camping or use of trails, as well we the perceived level of threat from each activity for the 5 years prior. Finally, we measured perceived changes in ecosystem health in 2020 compared to 2019 on a 5-pt scale from much better to much worse. We recorded the degree to which changes in each activity and ecological improvements were due to the pandemic using a 7-pt scale.

Open-ended questions were included throughout the survey to allow the participant to expand on their responses or perceived changes.

Appendix Table C1: Full survey (translated from Spanish to English)

INPUTS		
Staff Capacity		
1. Did the average number of staff working at one time in the PA during 2020 increase or decrease compared to the average number of staff working at one time: - in 2019? - Between 2015-2019?	Multiple Choice – 2 part	A. Increase B. Decrease C. No change D. I don't know
a. If decrease (from 2019), how does the average number of staff working at one time in the PA during 2020 compared to the average number of staff working at one time in 2019. Please indicate the percent reduction from the 2019 on the bar below.	Scale	Scale from 0-100%
b. If decreased, to what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not at all due to COVID-19 7-Fully due to COVID-19
2. In what ways did COVID-19 impact your staff capacity in 2020? Select all that apply.	Select <u>all</u> that apply	A. Did not have an impact on management capacity B. Temporary job loss with pay C. Temporary job loss without pay D. Permanent job loss E. Hiring freeze / unable to contract for open positions F. Less availability of personnel (heath or family related) G. Employees were sick with the COVID-19 virus H. Other (If "other", please list.)
a. If D, what percentage of staff have been permanently laid off due to budget restrictions as a result of COVID?	Multiple choice	A. No staff have lost their job B. <20% of staff have lost their job C. 20-40% of staff have lost their job D. 40-60% staff have lost their job E. 60-80% staff have lost their job F. >80% of staff have lost their job
b. If G, what percentage of staff members became sick with the COVID-19 virus (at work or outside of the work setting)?	Multiple choice	A. No staff became ill with COVID B. <20% of staff became ill C. 20-40% of staff became ill D. 40-60% of staff became ill E. 60-80% of staff became ill F. >80% of staff became ill
3. Are there any other specific events that influenced the total number of staff working at the PA in 2020?	Binary & Open choice	Yes/No If so, please explain.
Financial Capacity		
4. On average, how does the PA budget in 2020 compare to the budget: - in 2019? - in the past 5 years?	Multiple choice – 2 part	A. Substantial decrease B. Decrease C. No change / about the same D. Increase E. Substantial increase
a. If the budget decreased in the past year, please estimate the percent reduction	Scale	Scale from 0-100%

experienced in the PA budget from 2019 to 2020.		
b. If decreased, to what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not at all due to COVID-19 7-Fully due to COVID-19
c. Do you feel the 2020 budget was sufficient for basic management needs?	Scale	7 pt scale 1-not sufficient 7-totally sufficient
5. Did you access to any emergency funds in 2020 (e.g., Fondo Mexicano)	Binary	Yes/No
a. If yes, please list the organization or group that you received emergency funds from.	Open-ended	(*list organization)*
6. Has the PA experienced or anticipate experiencing any changes to their budget in 2021 compared to the budget in 2020? - Experienced in 2021 - Anticipate experiencing in 2021	Multiple choice – 2 part	A. Increase B. No change / about the same C. Decrease D. Not sure
a. If yes, to what degree is/was this change or expected change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
MECHANISMS		
Visitation		
7. In the five years prior to the COVID-19 pandemic, about how many tourists visited the PA each year? (If there is no tourism, write "00".)	Open-ended	(*estimated number of tourists*)
a. On average, were there changes to the total number of tourists that visited the PA in 2020 compared to the total number in 2019?	Multiple choice	A. >75% increase in tourists B. 50-75% increase in tourists C. 25-50% increase in tourists D. <25% increase in tourists E. No changes F. <25% decrease in tourists G. 25-50% decrease in tourists H. 50-75% decrease in tourists I. >75% decrease in tourists
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
8. In the five years prior to the COVID-19 pandemic, about how many individuals entered the PA each year for non-tourism purposes (e.g., researchers, local community members, etc.)?	Open-ended	(*estimated number of non-tourist visitors*)
a. On average, were there changes to the number of individuals that entered the PA for non-tourism purposes in 2020 compared to the total number in 2019?	Multiple choice	A. >75% increase in visitors B. 50-75% increase in visitors C. 25-50% increase in visitors D. <25% increase in visitors E. No changes F. <25% decrease in visitors G. 25-50% decrease in visitors H. 50-75% decrease in visitors I. >75% decrease in visitors
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19

		7-Fully due to COVID-19
9. **OPTIONAL**: Are there any specific reasons that there was a change in the total number of individuals that entered the park (tourists and non-tourists) in 2020 other than the COVID-19 pandemic? If so, can you provide an example?	Open-ended	(*response not required)*
Management Capacity		
10. On average, were there any changes in the time spent on infrastructure maintenance in the year 2020 compared to the time spent in 2019 due to the COVID-19 pandemic?	Multiple choice	A. Very significantly increase (75% or greater) B. Significantly increase (50-75%) C. Moderate increase (25-50%) D. Slightly increase (<25%) E. No change F. Slightly decreased (<25%) G. Moderate increase (25-50%) H. Significantly decreased (50-75%) I. Very significantly decreased (75% or greater)
11. On average, were there any changes in the staff's ability to continue active management processes for natural resources in 2020 compared to 2019 due to the COVID-19 pandemic?	Multiple choice	A. Very significantly increase (75% or greater) B. Significantly increase (50-75%) C. Moderate increase (25-50%) D. Slightly increase (<25%) E. No change F. Slightly decreased (<25%) G. Moderate increase (25-50%) H. Significantly decreased (50-75%) I. Very significantly decreased (75% or greater)
12. On average, were there any changes in the staffs ability to continue necessary studies on natural resources in 2020 compared to 2019 due to the COVID-19 pandemic?	Multiple choice	A. Very significantly increase (75% or greater) B. Significantly increase (50-75%) C. Moderate increase (25-50%) D. Slightly increase (<25%) E. No change F. Slightly decreased (<25%) G. Moderate increase (25-50%) H. Significantly decreased (50-75%) I. Very significantly decreased (75% or greater)
13. On average, how does the adequacy and availability of the management equipment in 2020 compare to that of 2019 due to the COVID-19 pandemic?	Select all that apply	A. Equipment is in better condition B. Equipment is more available C. No change D. Equipment is less available E. Equipment is in worse condition
14. Were changes in the following processes in 2020 due any other specific reasons besides COVID-19: - Time spent on infrastructure maintenance - Active management processes - Continuation of necessary studies on natural resources	Multiple choice – multiple part	A. Yes – increase B. No C. Yes - decrease

a. If yes, please explain what influenced this change.	Open-ended	
15. **OPTIONAL**: Were there any other activities or updates that the management staff was able to make progress or not make progress on due to COVID-19 changes? If so, please explain.	Open ended	*(response not required)*
Monitoring		
16. On average, have there been any changes in the **frequency** of monitoring and surveillance in 2020 compared to 2019 in the PA?	Multiple choice	A. Very significantly increase (60% or greater) B. Significantly increase (40-60%) C. Moderate increase (20-40%) D. Slightly increase (<20%) E. No change F. Slightly decreased (<20%) G. Moderate increase (20-40%) H. Significantly decreased (40-60%) I. Very significantly decreased (60% or greater)
a. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
17. On average, have there been any changes in the **total area** of monitoring and surveillance in 2020 compared to 2019 in the PA?	Multiple choice	A. Very significantly increase (60% or greater) B. Significantly increase (40-60%) C. Moderate increase (20-40%) D. Slightly increase (<20%) E. No change F. Slightly decreased (<20%) G. Moderate increase (20-40%) H. Significantly decreased (40-60%) I. Very significantly decreased (60% or greater)
a. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
18. On average, have there been any changes in the **total number of staff responsible** for monitoring and surveillance in 2020 compared to 2019 in the PA?	Multiple choice	A. Very significantly increase (60% or greater) B. Significantly increase (40-60%) C. Moderate increase (20-40%) D. Slightly increase (<20%) E. No change F. Slightly decreased (<20%) G. Moderate increase (20-40%) H. Significantly decreased (40-60%) I. Very significantly decreased (60% or greater)
a. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
19. **OPTIONAL**: Would you like to provide an example(s) of non-pandemic related reasons that there were changes in the frequency, area or total number of personal responsible for monitoring in 2020?	Open-ended	*(response not required)*

20. Does the PA receive any community support for monitoring and surveillance?	Binary	Yes/No
a. If yes, on average have there been any changes in the **total amount of support from community monitoring** in 2020 compared to 2019?	Multiple choice	A. Very significantly increase (60% or greater) B. Significantly increase (40-60%) C. Moderate increase (20-40%) D. Slightly increase (<20%) E. No change F. Slightly decreased (<20%) G. Moderate increase (20-40%) H. Significantly decreased (40-60%) I. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
c. **OPTIONAL**: Would you like to provide an example(s) of non-pandemic related reasons that there were changes in community support for monitoring and surveillance in 2020?	Open-ended	*(response not required)*
21. On average, have you experienced a change in the support and response provided by PROFEPA in 2020?		A. Very significantly increase (75% or greater) B. Significantly increase (50-75%) C. Moderate increase (25-50%) D. Slightly increase (<25%) E. No change F. Slightly decreased (<25%) G. Moderate increase (25-50%) H. Significantly decreased (50-75%) I. Very significantly decreased (75% or greater)
a. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
b. **OPTIONAL**: Would you like to provide an example(s) of non-pandemic related reasons that there were changes in the support and response provided by PROFEPA in 2020?	Open-ended	*(response not required)*
22. Have you received support from other actors in response to reports of illegal activity (ex., National guard or other international communities) in 2020?	Binary	Yes/No If yes, please list examples.
Community Engagement & Benefits		
23. In 2019, did the PA provide environmental education programs?	Binary	Yes/No
a. If so, how did availability of programs change in 2020 due to the COVID-19 pandemic?	Multiple choice	A. Very significantly increase (75% or greater) B. Significantly increase (50-75%) C. Moderate increase (25-50%) D. Slightly increase (<25%) E. No change F. Slightly decreased (<25%) G. Moderate increase (25-50%)

		H. Significantly decreased (50-75%) I. Very significantly decreased (75% or greater) J. Completely stopped
24. In 2019, did the PA conduct activities that provided economic benefits to local communities?	Multiple choice	A. No B. Few economic benefits C. Many economic benefits
a. If so, were there any changes to the economic benefits that these activities provided in 2020 due to the COVID-19 pandemic?	Multiple choice	A. Very significantly increase (75% or greater) B. Significantly increase (50-75%) C. Moderate increase (25-50%) D. Slightly increase (<25%) E. No change F. Slightly decreased (<25%) G. Moderate increase (25-50%) H. Significantly decreased (50-75%) I. Very significantly decreased (75% or greater) J. Completely stopped
b. **OPTIONAL**: Would you like to add any additional comments on changes to environmental education programs or other economic benefits in 2020?	Open-ended	
MODERATORS		
25. Were there any changes in the following programs due to the COVID-19 pandemic… - Government subsidy programs - Other government programs - Non-governmental programs	Multiple choice – 3 part	A. Yes B. No C. Not applicable D. I don't know
a. If so, to what extent have **government** subsidy programs been affected by COVID-19… - In communities in the PA - In communities around the PA	Multiple choice – 2 part	A. Have currently paused all programs B. Subsidies were delayed C. Programs were trimmed D. Other (please list) E. Not sure / they are not any
b. If so, to what extent have **other government** programs been affected by COVID-19… - In communities in the PA - In communities around the PA	Multiple choice – 2 part	A. Have currently paused all programs B. Subsidies were delayed C. Programs were trimmed D. Other (please list) E. Not sure / they are not any
c. If so, to what extent have **non-governmental** sustainable development programs been affected by COVID-19… - In communities in the PA - In communities around the PA	Multiple choice – 2 part	A. Have currently paused all programs B. Subsidies were delayed C. Programs were trimmed D. Other (please list) E. Not sure / they are not any
26. **OPTIONAL**: Would you like to add any additional comments about changes to government subsidy programs, other government programs or non- government programs in the PA in 2020?	Open-ended	

27. Did the advisory council experience any changes to meetings due to COVID-19? If so, please elaborate.	Multiple choice	A. There is no advisory council B. Very significantly increase (75% or greater) C. Significantly increase (50-75%) D. Moderate increase (25-50%) E. Slightly increase (<25%) F. No change G. Slightly decreased (<25%) H. Moderate increase (25-50%) I. Significantly decreased (50-75%) J. Very significantly decreased (75% or greater)
a. Are there any other changes that the advisory council experienced that you would like to elaborate on?	Open ended	*(response not required)*
OUTCOMES		
Fires		
28. In the five years prior to 2020, how much of a threat was fires in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. In 2020, were there any changes in the occurrence of **human-caused** fires compared to 2019?	Multiple choice	J. Very significantly increase (60% or greater) K. Significantly increase (40-60%) L. Moderate increase (20-40%) M. Slightly increase (<20%) N. No change O. Slightly decreased (<20%) P. Moderate increase (20-40%) Q. Significantly decreased (40-60%) R. Very significantly decreased (60% or greater)
b. In 2020, were there any changes in the occurrence of **natural-caused** fires compared to 2019?	Multiple choice	A. Very significantly increase (60% or greater) B. Significantly increase (40-60%) C. Moderate increase (20-40%) D. Slightly increase (<20%) E. No change F. Slightly decreased (<20%) G. Moderate increase (20-40%) H. Significantly decreased (40-60%) I. Very significantly decreased (60% or greater)
29. Generally speaking, how does the **total area burned** in 2020 compare to 2019?	Multiple choice	A. Very significantly increase (60% or greater) B. Significantly increase (40-60%) C. Moderate increase (20-40%) D. Slightly increase (<20%) E. No change F. Slightly decreased (<20%) G. Moderate increase (20-40%) H. Significantly decreased (40-60%) I. Very significantly decreased (60% or greater)

a. To what degree was this change in total area burned due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
Other Illegal Activities		
30. In the five years prior to 2020, how much of a threat was illegal **agricultural land clearing** in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. On average, how does the threat level for **agricultural land clearing** in the PA in 2020 compare to the threat level in 2019?	Multiple choice	A. Does not apply B. Very significantly increase (60% or greater) C. Significantly increase (40-60%) D. Moderate increase (20-40%) E. Slightly increase (<20%) F. No change G. Slightly decreased (<20%) H. Moderate increase (20-40%) I. Significantly decreased (40-60%) J. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
31. In the five years prior to 2020, how much of a threat was illegal **logging** in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. On average, how does the threat level for **logging** in the PA in 2020 compare to the threat level in 2019?	Multiple choice	A. Does not apply B. Very significantly increase (60% or greater) C. Significantly increase (40-60%) D. Moderate increase (20-40%) E. Slightly increase (<20%) F. No change G. Slightly decreased (<20%) H. Moderate increase (20-40%) I. Significantly decreased (40-60%) J. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
32. In the five years prior to 2020, how much of a threat was **illegal hunting** in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. On average, how does the threat level for **illegal hunting** in the PA in 2020 compare to the threat level in 2019?	Multiple choice	A. Does not apply B. Very significantly increase (60% or greater) C. Significantly increase (40-60%) D. Moderate increase (20-40%) E. Slightly increase (<20%) F. No change G. Slightly decreased (<20%) H. Moderate increase (20-40%)

		I. Significantly decreased (40-60%) J. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
33. In the five years prior to 2020, how much of a threat was **illegal fishing** in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. On average, how does the threat level for **illegal fishing** in the PA in 2020 compare to the threat level in 2019?	Multiple choice	A. Does not apply B. Very significantly increase (60% or greater) C. Significantly increase (40-60%) D. Moderate increase (20-40%) E. Slightly increase (<20%) F. No change G. Slightly decreased (<20%) H. Moderate increase (20-40%) I. Significantly decreased (40-60%) J. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
34. In the five years prior to 2020, how much of a threat was illegal **mining** in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. On average, how does the threat level for **mining** in the PA in 2020 compare to the threat level in 2019?	Multiple choice	A. Does not apply B. Very significantly increase (60% or greater) C. Significantly increase (40-60%) D. Moderate increase (20-40%) E. Slightly increase (<20%) F. No change G. Slightly decreased (<20%) H. Moderate increase (20-40%) I. Significantly decreased (40-60%) J. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
35. In the five years prior to 2020, how much of a threat was **illegal settlements** in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. On average, how does the threat level for **illegal settlements** in the PA in 2020 compare to the threat level in 2019?	Multiple choice	A. Does not apply B. Very significantly increase (60% or greater) C. Significantly increase (40-60%) D. Moderate increase (20-40%) E. Slightly increase (<20%) F. No change

		G. Slightly decreased (<20%) H. Moderate increase (20-40%) I. Significantly decreased (40-60%) J. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
36. In the five years prior to 2020, how much of a threat was **illegal camping and unpermitted use of trails** in the PA?	Scale	4pt scale: 1 - Not a threat 4 - A severe threat + (does not apply)
a. On average, how does the threat level for **illegal camping and unpermitted use of trails** in the PA in 2020 compare to the threat level in 2019?	Multiple choice	A. Does not apply B. Very significantly increase (60% or greater) C. Significantly increase (40-60%) D. Moderate increase (20-40%) E. Slightly increase (<20%) F. No change G. Slightly decreased (<20%) H. Moderate increase (20-40%) I. Significantly decreased (40-60%) J. Very significantly decreased (60% or greater)
b. To what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
37. For the activities that saw an increase in 2020, please list all groups responsible.	Select all that apply	A. Community members in the PA B. Community members next to the PA C. Domestic visitors D. International visitors E. Tourism companies F. Other enterprises G. Other (please list)
38. **OPTIONAL:** Were there any other specific reasons, excluding COVID-19, that resulted in changes in these illegal activities? If so, please explain.	Open-ended	(*no response required)*
39. **OPTIONAL**: Did you experience an increase in any illegal activities in 2020 that were not previously mentioned? If so, please list examples.	Open-ended	(*no response required)*
Ecological Restoration		
40. Has there been any changes in the health of any species being monitored in the PA in 2020 compared to 2019?	Multiple choice	A. Significantly improved B. Slightly improved C. No change D. Slightly worsened E. Significantly worsened F. Unknown G. Not applicable
a. If yes, to what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19

41. Has there been any changes in the general health of the ecosystem being monitored in the PA in 2020 compared to 2019?	Multiple choice	A. Significantly increased B. Slightly increased C. No change D. Slightly decreased E. Significantly decreased F. Unknown G. Not applicable
a. If yes, to what degree was this change due to the COVID-19 pandemic?	Scale	7pt continuous scale: 1-Not due to COVID-19 7-Fully due to COVID-19
Other		
42. **OPTIONAL**: Are there any other ecological changes or management changes that the PA experiences due to COVID-19 that you would like mention?	Open ended	(*no response required)*
43. **OPTIONAL**: Do anticipate any other ecological changes or management changes that the PA experiences due to COVID-19 in the year 2021 that you would like mention?	Open ended	(*no response required)*