DISSERTATION

BIG DATA ANALYSIS AND COUPLED HUMAN-NATURAL SYSTEMS MODELING TO EXAMINE THE INFLUENCE OF SOCIOECONOMIC AND ENVIRONMENTAL FACTORS ON PROTECTED AREAS

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ABSTRACT

BIG DATA ANALYSIS AND COUPLED HUMAN-NATURAL SYSTEMS MODELING TO EXAMINE THE INFLUENCE OF SOCIOECONOMIC AND ENVIRONMENTAL FACTORS ON PROTECTED AREAS

This dissertation aims to deepen our understanding of how human and environmental factors affect protected areas through a social-ecological systems approach. This dissertation comprises two topics. The first consists of determining the level of landscape changes in protected areas and identifying the anthropogenic and environmental factors associated with these changes. The other topic explores the potential impacts of climate change and land management on ecosystems, agropastoral families' livelihoods, and livestock grazing behavior in the Peruvian Andes. I used a social-ecological systems analytical approach to have an interdisciplinary perspective on how the biophysical and socioeconomic contexts of protected areas impact their conservation effectiveness and influence the pressures they face. My analyses used innovative analytical approaches, including big data analysis and agent-based modeling, to offer new insights into these critical issues.

In Chapter 2, I quantified changes in the landscape of protected areas worldwide and identified the critical anthropogenic and biophysical factors associated with these changes. I estimated landscape metrics for about 11,000 protected areas for 2000 and 2020 using open-source spatial data and performed random forest analyses. Changes in the landscape of protected areas and their associated socioeconomic and environmental factors differed by region and cover classes. In general, landscape changes were mainly influenced by anthropogenic factors, such as the level of human development, agricultural expansion, population density, and the protected area's regulation level. The main biophysical factors critical in explaining landscape changes were slope and precipitation.

In Chapter 3, I examined the ecological impacts of climate change in a mountain landscape in the Andes of Peru. I parametrized an ecosystem-process model (L-Range) to Andean environmental conditions to capture ecosystem responses to climate change. Climate change impacts on Andean ecosystems vary by cover class, topographic position, and climate scenario. Shrublands and woodlands will become more productive, whereas wetlands are projected to experience a decline in primary production. However, under the most extreme climate scenario, all cover classes will undergo a reduction in primary production.

In Chapter 4, I explored the potential economic and ecological impacts of various land management scenarios in a valley of Huascaran National Park in the Andes of Peru used as grazing lands by a local community. I built the Agent-based model of laNd management Dynamics and Ecosystem Services (ANDES) that represents livestock grazing behavior, grazing management, and household economies. I coupled the ANDES/L-Range models to deepen my understanding of how new management scenarios and future climate conditions would impact ecosystems and families' economies. Families' incomes were reduced under the scenarios involving a reduction in livestock population. The biomass availability was markedly higher only under the scenarios that involved livestock population reduction and the implementation of new rotational grazing schemes. These findings reveal that not only livestock numbers should be adjusted but also livestock distribution.

In Chapter 5, I analyzed how different grazing management schemes impact livestock forage consumption, grazing behavior, and body condition of cattle and sheep. I analyzed information derived from the Livestock Grazing Behavior sub-model of ANDES. Livestock responses to grazing management varied by species. Forage consumption and body condition were the highest under the scenarios that implied livestock population reduction. Moreover, livestock mortality was the lowest under these scenarios. In general, the below-optimal performance of livestock across all management scenarios suggests adjusting stocking rate and grazing frequency.

The key insights derived from Chapters 3, 4, and 5 are as follows. The Andean ecosystems' response to climate change will exhibit considerable variability. While a reduction in primary production is anticipated across most cover classes, except for woodlands, the impacts of climate change will also be influenced by the ecosystem's landscape setting. Livestock management practices, particularly those that involve reducing livestock numbers, will result in better animal body condition. The implementation of regulatory policies, such as reducing livestock populations and limiting park land access, will have significant economic repercussions on families, especially middle-aged and elderly individuals, whose income primarily relies on livestock production.

My study provides critical information for the sustainable management and conservation of protected areas and can serve as the basis for designing integrative policies that balance conservation and sustainable development. The development of conservation and sustainability policies must address the factors impacting protected areas and their surroundings. To achieve this, these policies should incorporate diverse perspectives and foster engagement with local communities.

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DEDICATION

A mi padre y madre, José y Gladys por confiar en mi desde siempre!

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CHAPTER 1: INTRODUCTION

Protected areas provide a variety of benefits to society, including biodiversity and ecosystem conservation, as well as climate change mitigation. These areas are also vital for conserving places of cultural significance and value (Fan et al., 2019) and promoting sustainable development. The establishment of many protected areas has often followed an exclusionary management approach that failed to integrate sociocultural and political factors, leading to conflicts with local communities (Andrade et al., 2012). For example, in the Andes of Peru, the establishment of Huascarán National Park in 1975 created a new political, spatial, and legal framework for land uses and resource allocation, impacting neighboring communities and altering traditional land and livestock management (Lipton, 2014). Moreover, because consultation with local communities was limited and consent was not sought before the park's establishment, the later efforts to incorporate these communities into conservation efforts led to various responses from the local population (Rasmussen et al., 2019).

The long-term conservation potential of protected areas has historically relied on their ability to maintain biotic and abiotic conditions. However, as they are embedded in social-ecological systems, their conservation potential is threatened by anthropogenic and environmental factors, such as land cover change and changes in precipitation and temperature. Land cover change is a multi-scale process that affects ecosystems and can alter ecological processes and biological communities. Changes in land cover are a significant issue for protected areas because their conservation effectiveness depends on maintaining ecosystem structure and function over time (Guerra et al., 2019). Human impact in protected areas is a widespread issue, with about a third of the protected areas worldwide under high levels of human pressure (Jones et al., 2018). Urban and agricultural expansion in the lands surrounding protected areas are the main threat of land cover change in protected areas (Busch & Ferretti-Gallon, 2023; Geldmann et al., 2019).

Climate change is also a major threat to PAs' effectiveness, i.e., PAs ability to reduce biodiversity loss and ecosystem degradation, or their effectiveness. Approximately 27% of the world's protected areas will undergo high rates of climate and land-use changes by 2050, with large environmental and land-use changes in protected areas in tropical regions and grassland biomes (Asamoah et al., 2021). The magnitude of climate change impacts also depends on the landscape setting of protected areas and the ecosystems and natural resources these areas comprise. Protected areas in mountain regions that encompass glaciers are more susceptible to climate change than those without them (Diaz et al., 2003). In the tropical Andes, for example, the mass balance of glaciers is significantly influenced by variations in temperature and precipitation (Stansell et al., 2013). Glaciers in this region are particularly sensitive to climate change due to their snowlines being situated near the 0°C isotherm—the altitude at which the temperature is exactly 0°C. Consequently, even minor changes in temperature or precipitation can lead to significant alterations in mass balance (Stansell et al., 2013). Additionally, the relatively constant temperatures throughout the year, along with the distinct dry and wet seasons in the Andes, bring tropical glaciers closer to melting conditions, further impacting their mass balance (Vuille et al., 2008).

Climate projections show that mountain regions with small areas of glacier cover will lose more than 80% of their current glacial mass by 2100 (Intergovernmental Panel on Climate Change [IPCC], 2019). Huascarán National Park, located in the Andes of Peru, has experienced significant changes since 1930, losing approximately 46% of its glacier cover (Silverio et al., 2017). Currently, glaciers occupy only about 14% of the park's area (Chimner et al., 2019). The impacts of climate change go beyond ecological effects, such as changes in ecosystem functioning, composition, extent, and distribution. They also have sociocultural and economic repercussions, including alterations in cultural practices, traditions and livelihoods.

The overarching goal of my dissertation is to gain insights into the role of human and environmental factors in the conservation of protected areas at both global and local levels using a social-ecological system approach. Social-ecological systems frameworks can help analyze different components of a coupled system, identify thresholds and tipping points, and deepen our knowledge for developing research and policies (Carpenter et al., 2009). Additionally, this dissertation aimed to generate information that can serve as a foundation for developing integrative conservation and sustainability policies that consider social and ecological aspects while promoting the sustainable use of natural resources.

For my analysis, I used big data and agent-based modeling. Although these analytical approaches have been used in the natural resource management field for some time, the way I applied them is novel. The global case study represents the first effort to identify the economic and biophysical factors associated with changes in the landscape of protected areas at global and regional levels, and by cover class (forests, grasslands, shrublands, and wetlands), using machine learning algorithms and open-source big data. The local case study in the Andes of Peru represents a significant initial effort to model the responses of Andean ecological and human systems to climate change and land management. More importantly, it is the first modeling effort to use a coupled human-natural systems modeling approach to study these factors in the Peruvian Andes.

The rapid rate of data generation and the development of new analytical and computational methods create opportunities to study complex systems at high resolution and various scales (Farley et al., 2018). Big data analyses can help foster new understandings of complex systems and provide critical information for decision-making processes (LaDeau et al., 2017). For example, Jaung and Carrasco (2022) employed machine learning techniques to analyze content from 25,019 newspapers about people's perceptions of nature in 13 countries across Asia. They found that information in newspapers about nature tends to be depicted in terms of its benefit to society, highlighting the human-centric point of view when discussing nature and overlooking the intrinsic value of species and ecosystems. Similarly, Kim et al. (2019) used big data to identify spatial visitation patterns in 38 heritage parks in Southeast Asia by analyzing geotagged photographs, aiming to generate key information to support the parks’ sustainable management.

Agent-based modeling is another powerful tool for analyzing social-ecological systems. We can simulate individual and collective behaviors and explore the properties of a system that arise from the interaction among individuals and from individuals with their environment, such as non-linearity, emergence, and feedback. Researchers have used agent-based models to analyze the impacts of human activities on natural systems across multiple scales. For instance, Brown et al. (2022) developed a country-level agent-based model for the United Kingdom to assess the effects of future climate conditions and land management scenarios, along with their socioeconomic impacts. In contrast, Steger et al. (2022) co-designed an agent-based model with community managers in Ethiopia to enhance their understanding of the factors driving shrub encroachment and to analyze potential management actions.

This dissertation consists of four main chapters. It begins with this introductory section (Chapter 1) that frames the research and ends with a concluding section (Chapter 6) that presents the main findings and reflects on the challenges and implications of our analyses. The first main chapter (Chapter 2) offers a global analysis of changes in the landscape of protected areas, focusing on identifying the human and biophysical factors associated with these changes. The subsequent three chapters (Chapters 3, 4, and 5) examine the potential impacts of climate change and land management on ecosystems, agropastoral families' economies, and livestock grazing behavior in the Peruvian Andes.

My analysis of landscape changes in protected areas aimed to determine fragmentation levels and identify regions and cover classes experiencing significant changes. I also examined the roles of anthropogenic and environmental factors contributing to these landscape changes. Through a case study in the Andes of Peru, i.e., a valley of a national park used as grazing lands by a local community, I provide an interdisciplinary analysis of the interactions between human and environmental systems and their potential responses to future climate conditions and land management. This case study exemplifies the complex and dynamic nature of land management and conservation in a protected area, highlighting how climate change poses a threat to both human and natural systems. Finally, my analyses emphasize the importance of considering biophysical and sociocultural contexts for the effective conservation and sustainable management of protected areas and their surroundings.

CHAPTER 2: GLOBAL ANALYSIS OF LANDSCAPE CHANGE IN PROTECTED AREAS

1. Introduction

Protected areas (PAs), defined by the International Union for Conservation of Nature (IUCN) as "*...clearly defined geographical spaces, recognized, dedicated, and managed through legal or other effective means to achieve the long-term conservation of nature with associated ecosystem services and cultural values*" (Dudley, 2008, p. 8) reflect efforts of society to reduce biodiversity loss and ecosystem degradation (Cumming, 2016; Fan et al., 2019). PAs are critical ecosystem services and biological resource providers and are crucial for climate change mitigation. PAs are also essential for vulnerable human communities to conserve places of cultural significance and value (Fan et al., 2019). Over the past three decades, the number of PAs has increased considerably. Currently, about 271,140 terrestrial PAs cover about 16% of the world's land surface (World Database in Protected Areas [WDPA], 2022). Despite the significant increase of PAs worldwide, land degradation, habitat and biodiversity loss are occurring at alarming rates (Guan et al., 2021), with about 30% of global PAs under intense human pressure (Jones et al., 2018). PAs are part of complex social-ecological systems. Thus, they are not exempt from socioeconomic and environmental drivers of change, such as population growth, land degradation, land use change, and shifts in temperature and precipitation patterns. Therefore, PAs' ability to reduce biodiversity loss and ecosystem degradation, hereafter PAs "effectiveness", is influenced by direct and indirect pressures within and outside the PA's boundaries (Barnes et al., 2017). Consequently, the analysis of drivers of change in PAs associated with human pressure represents a fundamental topic that needs to be studied and has implications for achieving conservation and biodiversity targets and sustainable development (Elleason et al., 2021; Guan et al., 2021; Mammides, 2020).

Global analyses of PAs performance and human pressure in PAs and their surroundings have focused on estimating PAs land cover changes; however, to the best of my knowledge, no studies at this level of analysis have quantified changes in PAs landscape composition and structure in response to socioeconomic and environmental changes. Moreover, several global, regional, and national studies have primarily focused on quantifying cover changes in protected forests, with few exceptions at the global level (Fluet-Chouinard et al., 2023; Reis et al., 2017) and at regional and national levels, where studies have aimed at analyzing land cover changes in protected wetlands (Tanneberger et al., 2021; Lu et al., 2016). Thus, to fill this research gap, I estimated aggregation metrics, area and edge metrics, core area metrics, and diversity metrics to explore landscape change in the world's PAs from 2000 to 2020 for protected forests, grasslands, shrublands, and wetlands at the global and regional levels. The quantification of landscape change for different periods is critical to analyze cover class changes and fragmentation levels and identify potential degradation threads (Kubacka et al., 2022; Townsend et al., 2009).

Additionally, several studies on land cover change in PAs conducted at the global, regional, and local levels focus on estimating human pressure, e.g., urban and cropland expansion, and its associated factors within and outside PAs (e.g., Busch & Ferretti-Gallon, 2023; Geldmann et al. 2019; Guerra et al., 2019; Jones et al., 2018; Kubacka et al., 2022; Schulze et al., 2018; Yang et al.2021). These factors can be classified into socioeconomic variables, biophysical features, and PAs' design features. The most analyzed socioeconomic factors of land cover change in PAs include population density, Gross Domestic Product, agricultural expansion, and accessibility. The main PA biophysical features studied are elevation, slope, and precipitation. Studies of PAs effectiveness analyze PAs design factors, such as location, size, and the IUCN management category. However, few studies have explored this complex and dynamic relationship using machine learning techniques like random forest (Fidler et al., 2022; Powlen, 2022). Random forest is a non-parametric multivariate classification and regression algorithm, robust to outliers and overtraining due to the random selection of explanatory variables (Breiman, 2001; Touw et al., 2013). Moreover, random forest can help estimate each variable's relative importance in predicting a model response (Hastie et al., 2017), reducing potential variable selection bias. Consequently, random forest is a suitable approach to analyzing the relationship between human and natural drivers of change in PAs, where non-linear and dynamic interactions among environmental and socioeconomic variables, PA attributes, and ecological responses are expected (Gill et al., 2017; Powlen, 2022; Sanchez-Cuervo et al., 2013). Thus, I performed random forest analyses to explore the level of association between socioeconomic variables, biophysical features, and PAs' design characteristics, and the different landscape metrics.

In particular, my study addresses the following questions: How much change has the landscape of global PAs undergone from 2000 to 2020? How do these patterns vary by region? Are these changes similar for protected forests, grasslands, shrublands, and wetlands? To what extent can these changes be associated with socioeconomic and biophysical factors and PAs design features? To answer these questions, I estimated metrics at the landscape and cover class level for global and regional PAs for 2000 and 2020 and performed random forest analyses. In my analysis, I worked with a sample of 11,457 PAs established in or by 2000 with a known IUCN management category that did not include nor intersect with Indigenous Peoples' lands nor had the Indigenous Peoples' or local communities' governance type. The IUCN management category is a design feature of PAs that represents different levels of protection—ranging from strict nature reserves (e.g., category Ia) to areas with more permissible land use (e.g., categories V and VI).

I hypothesize that most landscape changes in protected areas are associated with socioeconomic factors, such as Gross Domestic Product, population density, and proximity to cities, and protected areas' design features, such as the level of regulation and topographic setting, i.e., slope and elevation. The environmental factors I think are responsible for landscape changes in protected areas are variations in precipitation and temperature patterns. I also hypothesize that protected areas in regions with low level of human development, economic inequality, and high population, i.e., high levels of human pressure, have undergone more negative changes, such as increases in the patchiness of the landscape. At the cover-class level, I expect that protected forests and wetlands will be the cover classes with more landscape changes over the past two decades with respect to the other cover classes, i.e., protected grasslands and shrublands.

1.1 Brief history of PAs

Setting aside natural areas for protection or restricted use has a long history and different origins. For thousands of years, societies have conferred special status or use to specific areas like sacred sites, hunting preserves, and communal lands (Chape et al., 2008; Holdgate & Phillips, 1999). Reserve areas were usually assigned to ensure a continuing provision of natural resources and for recreational or aesthetic purposes to benefit royalty or the colonial elites. For instance, around 300 BC, reserves were established through royal decrees in India to protect forests and wildlife. In the Middle East, nomadic people developed the “Al Hema”, a sustainable land management system implemented for at least 2000 years that controlled the use of rangelands and prevented overgrazing (Al-Rowaily, 1999; Chape et al., 2008). Reserve areas were established in Europe through the declaration of royal hunting grounds for preserving lands for the gentry (Chape et al., 2008; Doran & Richardson, 2010).

In other parts of the world, such as China and Japan land was set aside for religious elites (Doran & Richardson, 2010). In Africa, religious and cultural factors were important for preserving forests. For instance, “Kaya” forests on the coast of Kenya have been protected for more than 400 years by the Mijikenda tribe to serve as areas for burials and traditional ceremonies. Also, in Cameroon and Ivory Coast, forests have been preserved from cultivation to revere deities (Sayer, 1992).

The movement that gave rise to "modern" protected areas started in the nineteenth century in the newly colonized nations of North America, Australia, New Zealand, and South Africa (Phillips, 2004). In the nineteenth century, the protection of natural areas followed urbanization in the western world by the creation of parks in cities, such as Victoria Park in London (1842) and Central Park in New York (1853). Most reserve areas in many countries were established mainly for recreational purposes (Doran & Richardson, 2010). For instance, Yellowstone (USA), the world’s first national park, was established in

1872 "…Yellowstone is hereby reserved and withdrawn from settlement, occupancy, or sale...and dedicated and set apart as a public park or pleasuring-ground for the benefit and enjoyment of the people" (Yellowstone National Park Protection Act, 1872). In southern and eastern Africa, restricted-used areas were set aside with the primary goal of serving as game reserves by European colonies (Chape et al., 2008). These "modern" PAs were also established to reduce the ecological impacts of the western colonization of Africa, the Americas, Asia, Australia, and Oceanic islands. These PAs were established to conserve the remaining local ecosystems reduced by colonization, i.e., the creation of cities, farms, and plantations (Grove, 1995, cited by Chape et al., 2008).

In the mid-19th century, the establishment of PAs in different countries was affected by social and historical events and technological development (Doran & Richardson, 2010), which modified the function and role of PAs (Chape et al., 2008). Reserved woodlands were considered part of a mosaic of agricultural lands and developed areas in Europe, while in North America, protected areas were located far from developed areas (Doran & Richardson, 2010). After the Second World War, in 1948, with the increasing number of PAs worldwide, creating a global organization that works as an international network of specialists and entities to help strengthen conservation efforts was necessary. Thus, the International Union for the Protection of Nature (IUPN), currently known as the International Union for Conservation of Nature (IUCN), was created (World Commission on Protected Areas, 2010). In 1958, the IUPN established a provisional committee on national parks, whose status was raised two years later with the creation of the Commission on National Parks. The Commission initially gave significant attention to Africa. Conservationists worldwide called for action to protect Africa's wildlife after African countries moved to independence following turbulent periods of struggle. This initiative resulted in the creation of conservation areas such as Serengeti National Park in Tanzania (World Commission on Protected Areas, 2010).

The concept of PAs and conservation significantly evolved since establishing the first "modern" national park (Holdgate & Phillips, 1999). The first IUCN definition of PAs emphasized preventing or eliminating unsustainable resource use or PAs occupation by people (Chape et al. 2008). Nonetheless, over the past decades, the concept of PAs has evolved, acknowledging the role of people in and as part of landscapes and ecosystems (Chape et al. 2008). This change was influenced by international agreements and events, such as the Stockholm Conference on Environment and the adoption of the World Heritage Convention in 1972 and the 1992 United Nations Conference on Environment and Development. With these agreements, the concept of nature protection broadened to one that considers PAs part of a complex management system that allows for different levels of human interactions and use. These agreements also resulted in the formulation of specific PA management categories that distinguished different approaches for conserving natural areas and considering PAs as strategies for sustainable development (Chape et al., 2008), recognizing that local communities have the right to maintain their livelihoods (Elleason et al., 2021).

In 1992 at the IVth World Parks Congress (IUCN, 1992), a new definition of PA was established: "An area of land and/or sea especially dedicated to the protection and maintenance of biological diversity, and natural and associated cultural resources, and managed through legal or other effective means." Currently, the IUCN defines PAs as: "…clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values" (Dudley, 2008).

In 1994, the IUCN developed standardized guidelines for the planning, establishment, and management of PAs based on six categories (Ia, Ib, II, III, IV, V, and VI). These categories were intended to represent different levels of regulatory protection from strict nature reserves, e.g., category Ia, to areas with more permissible land use, e.g., categories V and VI, (Table 2.1) (Appendix A) (Appendix Table A1) (Chape et al., 2008; Dudley, 2008). However, this change was not very welcomed by some stakeholders who argued that multiple-purpose PAs were less effective because they allow higher levels of human presence (Elleason et al., 2021; Guan et al., 2021; Shafer, 2015).

Almost every country currently has implemented legislation for PAs and designated sites for protection. Different denominations are used at the country level to describe PAs. There are also international networks of PAs at the global and regional levels, such as PAs under the World Heritage and Ramsar Conventions and Nature 2000 in Europe (Phillips, 2004).

Table 2.1. *Brief description of the IUCN PAs management categories*

Category	Description
Ia (Strict nature reserve)	Strictly PAs set aside to protect biodiversity. Human visitation, use, and impacts are strictly controlled.
Ib (Wilderness area)	Large unmodified or slightly modified PAs managed to retain their natural character.
II (National Park)	PAs set aside to protect large-scale ecological processes. Permits visitors use for cultural, scientific, education, and recreational purposes.
III (Natural monument or feature)	PAs created to protect a specific natural monument.
IV (Habitat/species management area)	PAs established to conserve particular species or habitats.
V (Protected landscape)	PAs managed to conserve landscapes and safeguard the interaction between humans and natural processes.
VI (PAs with sustainable use of natural resources)	PAs set aside to conserve ecosystems, habitats, and associated cultural values and traditional management.

Adapted from Dudley (2008)

2. Data and methods

2.1 Selection criteria of PAs

I adopted the IUCN's definition of PAs and used the March 2022 edition of the World Database on Protected Areas (WDPA) as the spatial data source for the distribution of PAs. This database includes vector data in the form of polygons and point records of terrestrial and marine PAs (UN Environment Programme World Conservation Monitoring Centre [UNEP-WCMC] and IUCN, 2022). I selected terrestrial polygon data of PAs at the country level, excluding those in the Arctic and Antarctic, because my study involved analyzing socioeconomic variables, such as human and livestock population, proximity of PAs to cities, and Gross Domestic Product. I confined my work to PAs established in or by 2000 and PAs with a known IUCN management category. Additionally, I eliminated some duplicate data and fixed geometries. I did not include PAs polygons whose boundaries were delineated based on point data since these do not represent their actual limits. To avoid overlapping PAs polygons, I excluded PAs that shared boundaries or were within 3 km from each other. To analyze landscape changes in protected areas established by federal or state authorities, I selected PA polygons that did not overlap with Indigenous Peoples' lands and were not under Indigenous or local community governance. Governance type data was obtained from the WDPA database (WDPA, 2022).

Finally, I eliminated PAs smaller than 1.44 km^2, the minimum area required to estimate landscape metrics. I imported the WDPA dataset and selected the PAs that matched the criteria explained above using the "Select Layer by Attribute" tool of ArcGIS Pro v. 2.9.2. After this selection, I obtained data on establishment year, size, and IUCN management category of a sample of 11,457 terrestrial PAs (Figure 2.1) (Appendix Table A9).

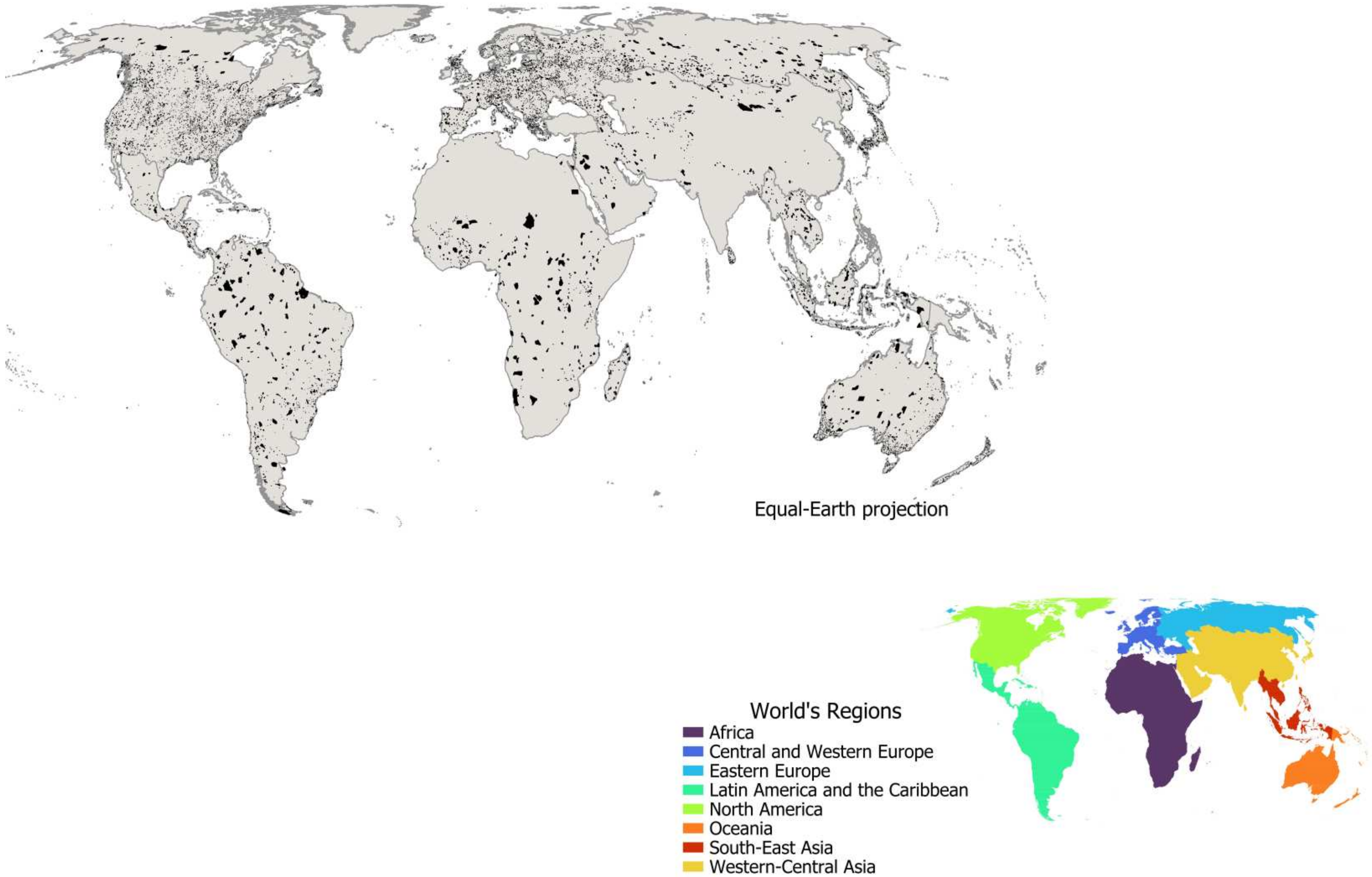

Figure 2.1. *Distribution of PAs (shaded areas) by region.*

2.2 Data collection and pre-processing

2.2.1. Drivers of land cover change

Based on a literature review focused on the analysis of deforestation, human settlements, and crop and mining activities in PAs and their surroundings (e.g., Guan et al., 2021; Luckeneder et al., 2021; Sze et al., 2022; and Vijaya & Armsworth, 2020), I identified a set of socioeconomic and biophysical variables and PA design factors that I hypothesize influenced changes in PA landscapes (Table 2.2). Detailed information about the datasets spatial-temporal resolution used in the analysis, their summarizing value, and their estimation can be found in Appendix Table A5.

Socioeconomic factors

I worked with 13 socioeconomic factors: total annual burnt area, mean Human Development Index, mean Gross Domestic Product, mean Global Inequality, mean population density, total livestock population expressed as tropical animal units, mean nighttime lights level, mean road density, mean travel time to the nearest city, and distance of PAs to Indigenous Peoples Lands, to mining areas, crops zones, and roads. Except for the total annual burnt area and the distance variables, the remaining variables were extracted from a buffer area around each PA (see below). The distance variables were calculated from the PAs boundaries to the nearest Indigenous Peoples' Lands, mining areas, croplands, and road polygons within a 0, 2.5, 5, 7.5, and 10 km. and represented in the dataset for analysis as 1s (“Present”) or 0s (“Absent”).

The Gross Domestic Product measures the monetary or market value of finished goods and services produced by a country. The Human Development Index is a composite measure of the human development of a country's or region's achievements in health, knowledge, and standard of living. The Human Development Index ranges from 0 to 1. Higher values of this index indicate that a region has high human development (Kummu et al., 2018). The variable nighttime light level, recorded as digital numbers, can help characterize the intensity of socioeconomic activities at local, regional, and global scales, such as electricity consumption, urbanization, carbon emission, and light pollution. The digital number values range from 0 to 63, with 0 representing complete darkness and 63 extensively bright areas (Li et al., 2020b). The Global Inequality variable is a proxy of economic inequality. This variable results from estimating the spatial variation in the average nighttime light emitted per person. In my analysis, this variable helps complement and fill the data gap of traditional estimates of economic income (Mirza et al., 2020).

Biophysical variables

The eight biophysical attributes analyzed are mode of elevation, mode of slope, mode of the Topographic Position Index, the average precipitation for 1999-2000 and 2019-2020, the average maximum temperature for 1999-2000 and 2019-2020, and the coefficient of variation of precipitation and minimum and maximum temperature from 1995 to 2020. The Topographic Position Index is calculated by comparing the elevation of a given pixel to its surrounding. This index allowed us to differentiate topographical features, such as flat and middle slope areas, ridgetops and hilltops, and valleys and canyon bottoms. The coefficient of variation is a measure of data dispersion. It is the ratio of the standard deviation to the mean. The higher the coefficient of variation, the greater the data dispersion. With the coefficient of variation variable, I explored the role of precipitation or temperature variability patterns on landscape changes that the average climatic variables could not capture.

PAs design features

The design features in my analysis include PAs size and the IUCN management category; this last variable has been used in several studies of PAs' effectiveness at regional and global levels, e.g., Elleason et al., 2021 and Guan et al., 2022.

Table 2.2. *Socioeconomic, biophysical and PAs design variables included in the analysis.*

Category	Variables	Data estimated/extracted from	Data Source
Biophysical	Elevation	PAs boundary	Amatulli et al., (2018)
	Slope		
	Topographic Position Index		
	Precipitation and temperature (mean and the coefficient of variation)		Karger et al., (2017)
Socioeconomic	Annual burnt area inside PAs	PAs boundary	Giglio et al., (2018)
	Human Development Index	Proportional-area buffer	Kummu et al., (2020)
	Gross Domestic Production per capita		
	Global Inequality		Mirza et al., (2021)
	Population density		Warszawski et al., (2017)
	Travel time to nearest city between 5,000 and 10,000 people		Nelson et al., (2019)
	Total livestock population (cattle, sheep, goat, horses, and buffaloes)		Gilbert et al., (2018a-2018f)
	Nighttime lights level in the vicinity of PAs		Li et al., (2020)
	Road density		Meijer et al., (2018)
	Near distance of PAs to Indigenous Peoples Lands	From PAs boundary to a 0, 2.5, 5, 7.5 and 10 km distance	Garnett et al., (2018)
	Near distance of PAs to mining areas		Maus et al., (2022)
	Near distance of PAs to crop zones		Defourny et al. (2017)
	Near distance of PAs to roads		Meijer et al., (2018)
PAs design feature	IUCN management category	PAs attribute	UNEP-WCMC & IUCN (2022)
	Size		

2.2.2. Data pre-processing

I estimated the correlation coefficients of these variables to reduce potential multicollinearity and redundancy to yield more interpretable models (Kuhn & Johnson, 2013). I used the *cor* function of the "corrplot" package (Wei et al., 2017) to perform the Pearson correlation analysis and the *ggcorrplot* function of the "ggcorrplot" package (Kassambara, 2019) to generate a heatmap to examine the correlation between the different quantitative explanatory variables (Appendix A3). I used the *cor_test* function of the "Rstatix" package (Kassambara, 2021) for the correlation analysis of the categorical variables (Appendix Table A4). Collinearity, the non-independence of predictor variables, is a common characteristic in ecological datasets. Correlation coefficient values of about 0.7 (absolute value) can substantially distort model estimation and predictions (Dormann et al., 2013). To prevent multicollinearity from causing statistical and inferential problems, variables with correlation coefficients greater than 0.85 (in absolute terms) were excluded from the analysis. The final variables included in the analysis are listed in Table 2 and explained in detail in Appendix Table A5. All analyses were performed in R (version 4.1.1) using RStudio (version 1.4.17.17).

Once I identified the final variables for the analysis, I imported them as spatial layers into ArcGIS Pro v. 2.9.2 for pre-processing. I projected all spatial data to the Equal Earth projection (Šavrič et al., 2019) at a 300 m resolution. For the cases in which datasets did not have information for 2000 or 2020, I worked with available data even if they did not match the exact years of the analysis, favoring data from years nearest my analysis period. Data used in my analysis were gathered from open-data sources, with the exception of Indigenous Peoples' Lands (IPL), obtained from Garnett et al. (2018). While acknowledging that many lands worldwide were historically Indigenous, this study defines “Indigenous lands” as those currently acknowledged through formal means. The IPL map (Garnet et al., 2018) used here is derived from publicly available information, which may not reflect the full extent of Indigenous territories. Therefore, lands not mapped as Indigenous should not be assumed to be non-Indigenous, as this determination could not be made based solely on the available data.

I extracted pixel values from raster data using the *extrac*t function of the "raster" package (Hijmans et al., 2015) in R using RStudio. For calculating the distance of PAs to different spatial layers, e.g., the proximity of PAs to mining areas, I used the “Near" tool in ArcGIS Pro v. 2.9.2. In this case, the layers that were in raster format were vectorized to be able to estimate the distances between them and PAs. To estimate road density in the areas surrounding PAs, I use the “Line density” tool in ArcGIS Pro v. 2.9.2. I created a proportional-area buffer representing 25% of the area of PAs to analyze how socio-economic and biophysical factors in the vicinity of PAs affect their landscape composition and structure. I used the Python module of ArcGIS Pro v. 2.9.2 for creating the 25% proportional-area buffer. The rationale for generating this was the marked difference in the distribution of PA sizes, e.g., 1.4 vs. 1000 km^2, which can affect the estimation of the impacts of drivers of change in PAs and their surroundings.

Lastly, to study regional variations in the distribution of PAs and socioeconomic and biophysical factors, I grouped the PAs using the World Bank's regions as a reference (Baldi et al., 2017). The regions in the analysis are Africa, South-East Asia, Western-Central Asia, Central and Western Europe, Eastern Europe, Latin America and the Caribbean, North America, and Oceania (Fig. 1).

2.3 Data analysis

2.3.1. Land cover dataset acquisition and preprocessing

To determine and quantify temporal land cover change patterns in PAs at the landscape and class level at a high resolution, I used the land cover raster dataset from the European Space Agency Climate Change Initiative Land Cover (ESA-CCI-LC) project. This dataset contains land cover data at annual time steps from 1992 to 2020 at 300 m resolution with a standardized classification and validation methodology. This dataset includes 37 land cover classes, with typology that follows the classification system developed by the Food and Agricultural Organization (FAO) of the United Nations (UN) and has an overall accuracy of about 71.1% (Defourny et al., 2017). For the analysis, I worked with landcover data for 2000 and 2020. I reclassified the original vegetation cover classes into four major categories

(Appendix Table A2): forest, grasslands, shrublands, and wetlands. The reclassification was done to facilitate the interpretation of land-cover transitions (Hu et al., 2021) and to quantify changes more accurately at the landscape and class levels. For the reclassification, I used as reference the vegetation cover classification systems used by previous studies (Liu et al., (2018) and Zhou et al., (2021)). These reclassified data were then used to calculate landscape metrics.

2.3.2. Landscape metrics estimation

The performance of PAs in mitigating biodiversity loss and ecosystem degradation or effectiveness can be assessed using metrics such as species richness and abundance, land-use and land-cover change, and management effectiveness assessments (Barnes et al., 2017). Management effectiveness is typically evaluated using both qualitative indicators (e.g., progress toward management standards) and quantitative indicators (e.g., budget, staff numbers, biological metrics) (Coad et al., 2015). However, obtaining accurate and representative data for these indicators, particularly for species abundance and questionnaire-based assessments, poses a significant challenge (Ferreira et al., 2020). On the contrary, using landscape metrics derived from land cover surfaces created from satellite imagery, such as aggregation, shape, and edge metrics, is accurate and unbiased for detecting landscape changes (Cardille & Turner, 2017; Zhang et al., 2013). Moreover, estimating landscape metrics for different periods can help quantify trends of landscape change, such as variations in the number of land cover classes and fragmentation levels (Kubacka et al., 2022) and identify potential degradation threats (Townsend et al., 2009). Estimating landscape metrics requires establishing the scale of analysis, which includes the spatial extent of the analysis, the grain size, and thematic resolution. The spatial extent of analysis refers to the units that will be examined. The grain size is the finest resolution (pixel size) of raster data used to detect the components of a landscape (Turner et al., 1989). The thematic resolution is the number of classes into which the different landscape resources are grouped (Kopp & Allen, 2021). For this study, the units of analysis are the PAs, the grain size for the estimation of landscape metrics is 300 m, and the thematic resolution is ten land cover classes. I used only the vegetation cover classes, i.e., forests, grasslands, shrublands, and wetlands, for estimating landscape metrics and detecting changes in the cover of PAs at the landscape and the cover-class level.

I calculated metrics at the landscape and class level using the "landscapemetrics" package (Hesselbarth et al., 2019) in R (version 4.1.1) (R Core Team, 2022) and RStudio (version 1.4.17.17) (RStudio Team, 2022) to calculate metrics. The metrics calculated at the landscape level were total area, the aggregation index, mean of the core area index, patch density, the largest patch index, and the modified Simpson's diversity index. At the class or land cover type level, the metrics estimated were total class area, patch density, and the largest patch index (Table 2.3). These metrics were used as the response variable in my analyses. To quantify landscape changes over time, I calculated these metrics for 2000 and 2020. I selected these metrics based on a literature review of previous landscape ecology studies that analyzed redundancy (e.g., Cushman et al., 2008; Su et al., 2014) and effectiveness (e.g., Kubacka et al., 2022; Peng et al., 2020; Wang et al., 2014) of various landscape metrics. I analyzed the correlation coefficients of the landscape metrics to reduce potential multicollinearity (Appendix A6 and A7). Appendix Table A8 describes in detail the metrics estimated.

__Table 2.3.__ Landscape and class-level metrics used in the analysis

Level	Metric	Interpretation
Landscape	Aggregation index (AI)(%)	AI = 0 for maximally disaggregated landscapes. AI = 100 for maximally aggregated landscapes.
	Mean of core area index (CAI) (%)	CAI_MN = 0 when all patches have no core area. CAI_MN = 100 with an increasing percentage of core area within patches.
	Modified Simpson's diversity index (MSDI)	MSIDI = 0 if only one patch is present
	Patch density (PD) (Number per 100 ha)	Increases as the landscape gets patchier.
	Largest patch index (LPI) (%)	LPI = 0 when the largest patch is becoming small. LPI = 100 only when one patch is present
	Total area (CA) (ha)	CA > 0 Increases, without limit, as the patch areas of class i become large.
Cover class	Patch density (PD) (Number per 100 ha)	Increases as the landscape gets patchier.
	Largest patch index (LPI) (%)	LPI = 0 when the largest patch is becoming small. LPI = 100 only when one patch is present
	Total area (CA) (ha)	CA > 0 Increases, without limit, as the patch areas of class i become large.

Adapted from McGarigal (2015)

The largest patch index and patch density are indicators of the fragmentation level of a landscape. The largest patch index quantifies the percentage of the total landscape area comprised by the largest patch of a specific class. Patch density indicates a landscape's aggregation level, i.e., how patchy or disaggregated a landscape is (McGarigal, 2015). A landscape is fragmented when it has an increasing number of patches per area and a reduction in the size of large and continuous patches (Garcia et al., 2017). The modified Simpson's diversity index is a metric of landscape composition, and it is the proportion of the landscape occupied by a patch type. It is zero when there is only one patch type in the landscape, i.e., no patch diversity. This index increases as the number of patch types increases, and the area occupied by patch types becomes more evenly distributed (McGarigal, 2015). The core area and largest patch indices can help identify the landscape areas that may serve as habitats, i.e., areas with significant resources for a particular species or areas for the occurrence of natural processes such as aquifer recharge (Leitao & Ahem, 2002). The core area index is the percentage of the core area in relation to patch area. The mean of the core area index is zero when patches in the landscape do not have a core area and approaches 100 with the increasing core area percentage within patches (McGarigal, 2015).

To determine landscape change patterns at the cover-class level, I selected PAs that in 2000 included at least one of the different land cover classes under analysis, i.e., forests, grasslands, shrublands, and wetlands. Thus, for estimating changes in global PAs with forest cover, I worked with 9 748 PAs. Similarly, to calculate landscape metrics for grasslands, shrublands, and wetlands I worked with 4 226, 3 405, and 3 032 PAs, respectively.

2.3.3.Differences in metrics at the landscape level by region and year

I performed Kruskal-Wallis tests to determine if there were significant differences in the value of landscape metrics (Table 3) across all regions (global PAs) for each year under analysis, i.e., 2000 and 2020. Next, I performed the Friedman tests to determine if there were significant differences in the values of the landscape metrics for each region and year. I selected these non-parametric tests because the landscape metrics data did not meet the assumptions for performing ANOVA tests, i.e., normality of residuals and equal variance within groups (McDonald, 2009).

2.3.4. Differences in metrics at the cover-class level by region and year

I performed Kruskal-Wallis tests to determine if there were significant differences in the value of metrics at the cover class level (Table 3) across global PAs for each year under analysis. Then, I performed Friedman tests to determine if there were significant differences in the metrics values for each land cover class, i.e., forests, grasslands, shrublands, and wetlands, for each year and region under analysis. The tests were performed in R using the *kruskal.test* and *friedman.test* functions of the "rstatix" package (Kassambara, 2021).

2.4. Analysis of socioeconomic and environmental drives of landscape change

2.4.1 Random Forest

I used random forest (RF), a machine learning algorithm (Breiman, 2001), to determine and rank the importance of the different socioeconomic and environmental factors associated with landscape change. RF is a non-parametric multivariate classification and regression method that does not require any assumptions about the statistical distribution of the data (Breiman, 2001) and is less sensitive to outliers, noise, or overtraining because of the random selection of candidate variables (Touw et al., 2013). Thus, RF can be used to analyze non-linear relationships among many predictor variables. Another advantage of RF analysis is the statistical weight information provided for each variable (Breiman, 2001; Catani et al., 2013). These features make RF an optimal approach to analyzing the complex relationship between human and natural drivers of change in PAs, in which non-linear and dynamic interactions among environmental and socioeconomic variables, PA attributes, and ecological responses are expected (Gill et al., 2017; Powlen, 2022; Sanchez-Cuervo et al., 2013).

RF is a data-driven machine learning method in which variables and samples for model training are randomly selected using techniques such as bootstrap sampling (bagging) to generate an ensemble of decision trees (Breiman, 2001). Only a restricted number of candidate predictors is randomly selected for creating each decision tree, permitting each variable to appear in different contexts with different covariates. Thus, if a variable is important only under a specific context, it still has the chance to be incorporated into the analysis once the "stronger" variables are not part of the analysis, which is critical when predictors are highly correlated (Levshina, 2021). Typically, about 75% of the data for each model iteration are used for training, while the remaining 25% or out-of-bag data are used to estimate the RF's goodness of fit (Breiman, 2001; Grekousis et al., 2022; Hengl et al., 2018). This process is repeated several hundred to thousands of times with different permutations of input variables (Breiman, 2001). The partitioning finishes when the final or terminal nodes include samples belonging to the same class or category or containing a specific number of samples. A classification tree grows until the final nodes are pure, even if that results in terminal nodes containing one sample (Breiman, 2001; Grekousis et al., 2022; Touw et al., 2013).

RF and other regression models involving recursive binary partitioning are not exempt from overfitting and a selection bias towards covariates. The overfitting issue can be avoided by creating conditional inference trees developed by Horthorn et al., (2006). Conditional Random Forests (CRF) are an ensemble of multiple conditional inference trees. The selection of variables in conditional inference trees is based on the strength of their relationship to the model response, measured through independent hypothesis testing. Thus, if there is no significant relationship, no split will be implemented (Horthorn et al., 2006). In CRF models, the inference trees are fitted to bootstrap samples of the learning dataset. The aggregation is done by estimating the average of observation weights from each tree, in contrast to the standard RF models, in which tree aggregation is done by averaging predictions directly. Thus, CRF models guarantee no overfitting and no need for pruning or cross-validation (Horthorn et al., 2006). Moreover, CRF models have lower error rates than standard RF but are more computationally demanding (Speiser et al., 2019). In general, only a few predictor variables in data mining analysis substantially influence a model response. Thus, it is helpful to estimate each variable's relative contribution or importance in predicting a model response (Hastie et al., 2017).

Though partial and marginal variable importance concepts are mainly discussed in linear regression frameworks, these concepts also apply to RF models. Marginal importance refers to the impact of a predictor variable without considering any other predictor. Partial importance, also called conditional importance, is the impact of a predictor variable over all the other predictors in the model. If all predictors are independent, there is no difference between the marginal and partial importance. Nonetheless, when predictors are correlated, the marginal and partial importance will vary (Debeer & Strobl, 2020). Although the concept of variable importance is straightforward for linear regression models, it is less evident for RF models due to factors such as the lack of a statistical population model and the non-linearity of the predictors' effects.

Variable importance in RF models should be considered as quantifications of the magnitude or impact of a predictor variable in the accuracy of the prediction, i.e., their scope of interpretation is limited to the fitted RF model (Debeer & Strobl, 2020). The importance of variables in RF is estimated based on changes in the model accuracy, measured as the mean square error (MSE), when a variable is not considered in the analysis (Liaw & Wiener, 2002; Watmough et al., 2019). The analysis and interpretation of the important variables for a single tree are straightforward; however, interpreting the importance of each predictor is more complex in an ensemble of trees or RF models. The importance of a variable can be measured in RF by estimating the Gini impurity (Strobl et al., 2009). The Gini impurity measures how well an element would be correctly categorized if it is randomly classified (Disha & Waheed, 2022). This measure evaluates the discriminatory power of a variable by the accumulated Gini gain over all splits and trees (Hastie et al., 2017). Thus, the variable with the lowest Gini impurity is selected to separate samples at each "parental node" (Breiman, 2001; Grekousis et al., 2022; Touw et al., 2013). However, the Gini impurity is subject to bias since it favors continuous variables over categorical ones, and within categorical variables, it favors variables with many classes (Strobl et al., 2007).

The most common measure of variable importance for RF is the permutation accuracy importance (Hapfelmeier et al., 2014). This measure is calculated by comparing the prediction accuracy of a tree before and after random permutation of the specific predictor of interest (Strobl et al., 2007). The values of the predictors are randomly permuted for the out-of-bag observations and then are used to get new predictions for determining the importance of a specific predictor variable. Next, the measure of the importance of a predictor variable is estimated by calculating the difference between the misclassification rate for the modified and original out-of-bag data, divided by the standard error (Cutler et al., 2007). If the predictor is relevant or important, the accuracy should decline as the original relationship to the response is eliminated by the random permutation (Strobl et al., 2007). The average of differences of all trees estimates the final importance score. Large values of the permutation accuracy importance suggest a strong association between the variable of interest and the response. In contrast, zero or even small negative values indicate that the variable of interest is unimportant for predicting the response (Strobl et al., 2009).

Once the most important variables have been identified, the next step is to analyze their dependence on the predicted response (Hastie et al., 2017). Partial dependence plots are the most common visualization method for analyzing and interpreting machine learning models (Apley & Zhu, 2020). These plots show the marginal effect of a variable on the machine learning model output (Friedman, 2001), depicting the prediction function in a way that the relationship between the outcome and the variable of interest of a model can be more easily understood (Cutler et al., 2007; Greenwell et al., 2017). However, the primary assumption of these kinds of plots is the independence of variables. Therefore, using accumulated local effects plots represents a better approach since they average the difference in predictions to block the effect of correlated variables and are less computationally expensive (Apley & Zhu, 2020; Mangalathu et al., 2022).

I performed CRF analyses at the global and regional levels for 2000 and 2020 for the landscape level and cover-class level metrics. At the regional level, I implemented CRF models for the class-level metrics for all the regions only for protected forests. Moreover, because some regions had a small number of PAs for a specific cover class, I performed specific cover class CRF analyses for each region: North America (CRF models for all cover classes), South-East Asia and Western-Central Asia (CRF models only for protected forests), Central and Western Europe and Eastern Europe (CRF models for all cover classes except for protected shrublands), and Oceania and Latin America and the Caribbean (CRF models only for protected forests and shrublands).

For the CRF analyses, I used the *cforest* function from the “party” package (Hothorn, Hornik, & Zeileis, 2006). Seven predictor variables were randomly selected from the complete set of 23 variables at each node, which performed slightly better than when five variables were selected. I created 1000 trees in each forest to ensure the stability of the results. I used the “perimp” package (Debeer et al., 2022) to estimate the unconditional variable importance. I only estimated the local accumulated effects of the most important variables for the CRF. For the estimation of the local effects, I used the *GetAleData* function from the “moreparty” package (Robette, 2020). I performed these analyses in R (version 4.1.1) using RStudio (version 1.4.17.17).

3. Results

3.1 Descriptive statistics of PAs

From the 11 457 sample of PAs analyzed, the region with the highest number of PAs was North America (30.00%), followed by Central and Western Europe and Eastern Europe, with 21.20 and 17.70% of the number of PAs, respectively. Western-Central Asia, South-East Asia, and Africa had the lowest number of PAs (Appendix Table A9). Most PAs (72.10%) were located in low elevation areas. PAs located at high and very high elevations were less common, representing only 3.80 and 0.10% of the total PAs. More than half of PAs (56.62%) in the sample were in valleys and canyon bottoms; PAs located in ridgetops and hilltops represented 32.73% of the total sample. In contrast, PAs located in flat and middle slope areas were only 10.65% of the total sample. The majority (85.60%) of PAs had a slope value of less than 10%, while only 1.60% had a slope value of more than 20% (Appendix Table A10). The smallest PA had an area of 1.44 km^2, and the largest has an area of 83 511 km^2.

All six IUCN categories were represented in the 11 457 PAs sample, from strictly protected PAs (e.g., categories I and II) to multiple-use PAs (categories V and VI). The IV (Habitat/species management area) and V (Protected landscape) IUCN categories were the most common classes in the sample, representing 29.9 and 24.6% of the PAs, respectively. The Ia, II, and III IUCN categories represented 12.4, 9.8, and 13.3% of the total PAs. The categories Ib and VI were the least common IUCN categories, representing only 4.2 and 5.8% of the PAs, respectively (Figure 2.2). The distribution of IUCN categories varied by region. Oceania had the highest number of PAs (45.5%) with strict regulatory protection, i.e., the Ia category or Strict Nature Reserve. In South-East Asia, this IUCN management category represented 30.3% of PAs, followed by the II IUCN category or National Park, which represents 19.6% of PAs. The predominant IUCN management category of PAs in Eastern Europe, Central and Western Europe, Africa, and Western-Central Asia is IV or Habitat/Species Management areas, representing 58.3, 55.9, 41.3, and 37.6% of PAs, respectively. In North America, the most common IUCN category is V or Protected Landscape, representing 55.3% of the PAs. In contrast, the two common IUCN management categories of PAs in Latin America and the Caribbean are VI or Protected Areas with Sustainable Use of Natural Resources and the II IUCN category, representing 26.8 and 25.2% PAs (Appendix Table A11).

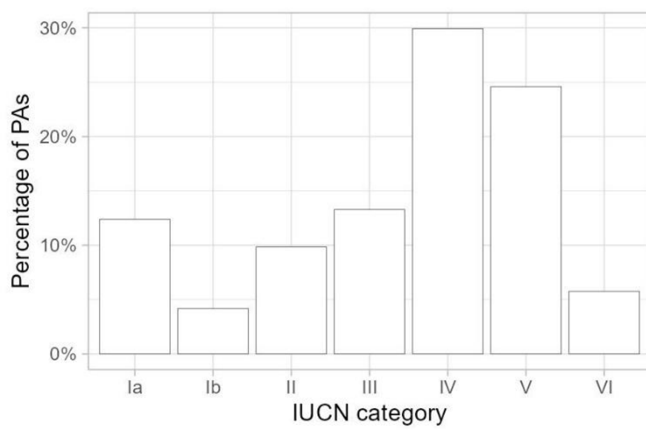

Figure 2.2. *Distribution of PAs by IUCN management category*

In the 11 457 PAs sample, the number of PAs that included forest in their cover is 9 748 PAs. The number of PAs with a cover class of grasslands, shrublands, or wetlands, is 4 226, 3 405, and 3 032, respectively. Hereafter, I will refer to these PAs as protected forests, grasslands, shrublands, and wetlands. The distribution of IUCN management categories by cover class is similar. For all cover classes, except for protected shrublands, the predominant IUCN categories were IV and V, i.e., areas established to protect habitats, species, or landscapes. The most common IUCN categories for protected forests were IV and V, representing 29.5 and 23.3% of the PAs, respectively. In the case of protected grasslands, the predominant IUCN categories were the same as PAs with forest cover. However, the percentage of PAs with the V IUCN category was slightly higher vs. the IV category, representing 33.0 and 31.2% of the total PAs, respectively. In the case of protected shrublands, the two most common IUCN categories were IV and Ia, with 20.1 and 18.5% of PAs, respectively. The predominant IUCN management categories for PAs with wetland cover were IV and V, representing 30.7 and 24.9% of PAs, respectively (Figure 2.3).

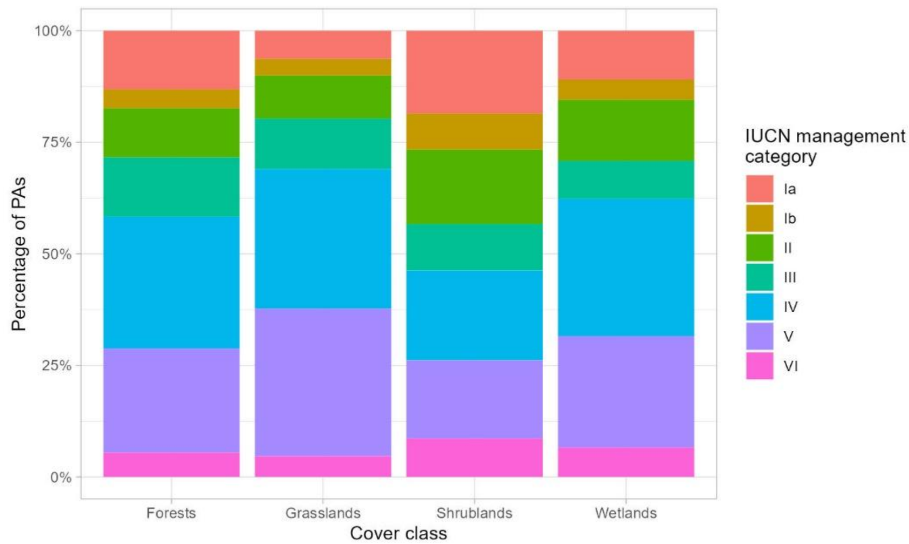

Figure 2.3. *Distribution of PAs by cover class and IUCN management category*

The distribution of PAs by cover class varies by region. Approximately 28.7, 21.0, and 18.4% of protected forests are found in North America, Central and Western Europe, and Eastern Europe, respectively. The highest number of PAs with the grassland cover type were also in these regions, with 35.5, 23.8, and 15.6% of the PAs, respectively. Similarly, these regions have the highest percentage of PAs with wetland cover, representing 33.0, 19.6, and 18.6% of the PAs, respectively. In the case of shrublands, the regions with the highest number of PAs with this cover type are North America, Oceania, and Latin America and the Caribbean, with 29.8, 24.8, and 13.7% of PAs, respectively (Appendix Table A12).

3.2 Changes in metrics at the landscape and cover-class level from 2000 to 2020

3.2.1 Non-parametric tests results

I found significant differences among regions for each landscape metric under analysis, i.e., largest patch index, patch density, aggregation index, core area index, and the Modified Simpson's diversity index, for 2000 and 2020 (Appendix Table A13). At the regional level, there were significant differences for all landscape metrics for 2000 and 2020 (Appendix Table A14). Results from the Kruskal-Wallis tests found significant differences among regions for each cover class, i.e., protected forests, grasslands, shrublands, and wetlands, and each class-level metric, i.e., class area, patch density, and the largest patch index, for 2000 and 2020 (Appendix Table A15). The Friedman test results show significant differences in the value of most class-level metrics for the different cover types for most regions. There were no significant differences for the largest patch metric for protected grasslands in Africa, protected shrublands in Western-Central Asia, and protected shrublands and wetlands in South-East Asia (Appendix Table A16).

3.2.2. Quantification of landscape change in PAs

Approximately 50% of protected forests, wetlands, grasslands, and shrublands did not have changes in their cover size from 2000 to 2020, with grasslands as the cover class with the highest PAs percentage (61.78%) with a constant cover size. Of all cover types, protected wetlands had the highest percentage of PAs (27.41%) with an increase in their cover. In contrast, protected shrublands had the highest percentage of PAs (27. 08%) with a reduced cover size. Protected grasslands (75.51%) and shrublands (62.11%) had the highest percentage of PAs, with a constant value of the largest patch index metric for 2000 and 2020. Except for protected shrublands, a similar percentage of PAs of the other cover classes had increases and decreases in the value of this metric. In the case of protected shrublands, the percentage of PAs with a decrease in this metric was higher than those with an increase, with 21.67 and 16.21%, respectively. Protected forests and grasslands were the cover types with the highest percentage of

PAs, both with approximately 72.50% of the PAs, with constant patch density values for 2000 and 2020. The percentage of PAs of all cover classes with patch density increases was higher than those with decreases in this metric. However, protected wetlands (34.63%) had the highest increase in patch density compared to the other cover classes (Table 2.4).

Table 2.4. Changes in landscape metrics for 2000 and 2020 for protected forests, grasslands, shrublands, and wetlands.

Cover class	Total PAs	PAs (%) Class Area increment	PAs (%) Class Area decrement	PAs (%) constant Class Area	PAs (%) Largest Patch Index increment	PAs (%) Largest Patch Index decrement	PAs (%) constant Largest Patch Index	PAs (%) Patch Density increment	PAs (%) Patch Density decrement	PAs (%) constant Patch Density
Forests	9 748	24.56	26.41	49.04	21.14	23.89	54.97	15.96	11.55	72.49
Grasslands	4 226	19.92	18.29	61.78	11.31	13.18	75.51	19.24	8.26	72.50
Shrublands	3 405	22.91	27.08	50.01	16.21	21.67	62.11	22.85	12.69	64.46
Wetlands	3 032	27.41	19.43	53.17	27.90	26.25	45.84	34.63	21.67	43.70

PAs in Africa, Central-Western Europe, Latin America and the Caribbean, Oceania, and Western-Central Asia, increased their forest cover from 2000 to 2020, with Africa with the highest percentage of PAs (57.84%) that increased their forest cover. In the case of protected grasslands, Eastern Europe, North America, and Oceania were the regions with grassland cover increases, with Eastern Europe with the highest percentage of PAs (25.95%) that increased their grassland cover. PAs in Eastern Europe, Latin America and the Caribbean, and North America increased their shrubland cover, with Eastern Europe with the highest percentage of PAs (51.11%) with an increased shrubland cover. In the case of protected wetlands, PAs in all regions except North America and Western-Central Asia increased their cover, with Eastern Europe having the highest percentage of PAs (49.74%) with an increase in this cover class (Appendix Table A17).

Protected forests in Africa, Central-Western Europe, Latin America and the Caribbean, and Oceania increased the largest patch index metric from 2000 to 2020. Protected forests in Africa had the highest percentage of PAs (50.90%) with an increased value in this metric. In the case of protected grasslands, only PAs in Oceania increased the value of the largest patch index metric. The only regions where protected shrublands had an increase in the value of this metric were Eastern Europe (34.44%) and North America (19.49%). In the case of protected wetlands, PAs in Africa, Central-Western Europe, Latin America and the Caribbean, and Eastern Europe were the regions with increases in the value of this metric. Eastern Europe had the highest percentage of PAs (57.49%), experiencing an increase in the largest patch index (Appendix Table A17).

Protected forests in all regions had increases in patch density from 2000 to 2020, with Africa (33.93%) and South-East Asia (31.65%) with the highest percentages of PAs with increases in this metric. Similarly, in the case of protected grasslands, PAs in all regions increased patch density, with Western-Central Asia with the highest percentage of PAs (43.14%) with the largest increase in this metric. Protected shrublands in all regions increased patch density, with South-East Asia (52.00%) and Eastern Europe (49.44%), as the regions with the highest percentages of PAs with increases in this metric. In the case of protected wetlands, all regions, except for Western-Central Asia, increased patch density. However, the percentage of PAs in Western-Central Asia with increased or decreased patch density was similar. In contrast, Eastern Europe had the highest percentage of protected wetlands (62.99%) with increased patch density (Appendix Table A17).

3.3. Global CRF models for the landscape-level metrics

The variance explained by the global CRF models for the five landscape metrics ranged from 23.86% to 48.09%. The highest variance was explained for patch density (48.09%), followed by the aggregation index metric (34.50%). The CRF models for the largest patch index and the modified Simpson's diversity index had the lowest explanatory power, with 23.86 and 29.11%, respectively. The variance explained for the 2000 models was slightly higher than for the 2020 models.

The CRF models for patch density and the aggregation index for 2000 and 2020 shared the same top-five most important variables but in a different order. PAs slope and distance to croplands were among the five most important explanatory variables common for all CRF models. Except for the core area index and the modified Simpson's diversity index CRF models, PAs size was the most important variable common to all metrics models. The IUCN management category was a top variable common for all CRF models except for the modified Simpson's diversity index model. The five most important variables of the modified Simpson's diversity index models also included other variables not determined as important for the other CRF models, such as total livestock tropical units and the mean maximum temperature (Table 2.5) (Appendix Table A18).

Table 2.5. *Conditional Random Forest models performance for landscape-level metrics for global PAs and their top-five most important explanatory variables*

	Patch density		**Aggregation index**		**Core area index**		**Modified Simpson's diversity index**		**Largest patch index**	
Model performance	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Coeff. of determination (R^2) (%)	48.09	47.86	34.50	33.92	32.31	31.21	29.67	29.11	24.65	23.86
Variable importance										
PAs size	1	1	1	1					1	
Human Development Index	2	2	2	2	2	3				
Distance to croplands	3	3	3	3	1	1	1	1		1
Slope	4	4	5	5	3	2	2	2	2	2
IUCN management category	5	5	4	4	5	5			3	3
Gross Domestic Product					4	4			5	5
Elevation							5	4		
Topographic Position Index								5	4	4
Total livestock tropical units							4	3		
Mean maximum temperature							3			

Colors and numbers display the importance of the CRF models' top five most important variables (1 & Red: most important to 5 & Green: less important).

3.4 Global CRF models of class-cover metrics

At the cover-class level, the CRF models for protected forests had higher performance than the other models, except for the patch density metric. In particular, the class-area CRF model for this cover class had the highest coefficient of determination explained (61.82%) with respect to the other metrics and cover class models. The CRF model for protected shrublands had the highest variance explained (53.96%) for the patch density metric (Table 2.6) (Appendix Table A19).

Table 2.6. *Coefficient of determination of the 2000 and 2020 CRF models for metrics at the cover class level of global PAs*

Cover class	**Landscape metric**	**Coefficient of determination (R^2) (%)**	
		2000	**2020**
Forest	Class area	60.24	61.82
	Patch density	46.13	45.18
	Largest patch index	41.65	40.51
Grassland	Class area	31.23	31.70
	Patch density	46.00	46.09
	Largest patch index	30.00	30.75
Shrubland	Class area	38.51	34.81
	Patch density	52.88	53.06
	Largest patch index	35.84	37.63
Wetland	Class area	9.42	9.41
	Patch density	47.46	46.59
	Largest patch index	32.04	31.71

3.5 Global CRF models for protected forests

The CRF models for the class area metric had the best performance compared to the other models. The class area and the patch density CRF models shared three of the most important five variables, i.e., mean precipitation, PAs size, and the Human Development Index. Only the CRF models for the class area and the largest patch index metrics shared the same most important variables for 2000 and 2020.

The largest patch index CRF model only shared one top variable (the IUCN management category) with the other models (Table 2.7) (Appendix Table A20).

Table 2.7. *Conditional Random Forest models performance for class-level metrics for global protected forests and their top-five most important explanatory variables*

	Class area		**Patch density**		**Largest patch index**	
Model performance	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Coefficient of determination (R^2) (%)	60.24	61.82	46.13	45.18	41.65	40.51
Variable importance						
Mean precipitation	1	1		5		
PAs size	2	2	1	1		
CV of prec. 95-20	3	4				
Human Development Index	4	3	2	2		
Road density	5	5				
Gross Domestic Product			3	4		
IUCN management category			4	3	3	3
Elevation			5			
Slope					1	1
Distance to croplands					2	2
Maximum temperature					4	4
Topographic Position Index					5	5

CV: Coefficient of variation

3.6 Global CRF models for protected grasslands

The CRF models for the patch density metric had the highest variance compared to the other metrics. The Human Development Index was the top variable common to all CRF models. Another variable important for the class area and patch density models was PAs size. The patch density and the largest patch index models also shared as important variables Gross Domestic Product and total livestock tropical units (Table 2.8) (Appendix Table A20).

__Table 2.8.__ Conditional Random Forest models performance for class-level metrics for global protected grasslands and their top-five most important explanatory variables

	Class area		**Patch density**		**Largest patch index**	
Model performance	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Coefficient of determination (R^2) (%)	31.23	31.70	46.00	46.09	30.00	30.75
Variable importance						
PAs size	1	1	1	1		
Human Development Index	2	2	2	2	3	4
Mean precipitation	3	3				
Mean maximum temperature	4	4				
Total annual burned area	5					
Slope		5				
Gross Domestic Product			3	5	2	2
Road density			4	3		
Total livestock tropical units			5	4	1	1
Elevation					4	5
IUCN management category					5	3

3.7 Global CRF models for protected shrublands

The CRF models for the patch density metric had the best performance compared to the other models. The class area and the patch density CRF models shared two of the most important five variables, i.e., PAs size and the Human Development Index. The CRF models for patch density and the largest patch index shared three top variables, i.e., the Human Development Index, the IUCN management categories, and Gross Domestic Product. Only the patch density CRF model had the same top-five important variables for 2000 and 2020 (Table 2.9) (Appendix Table A20).

Table 2.9. Conditional Random Forest models performance for class-level metrics for global protected shrublands and their top-five most important explanatory variables

	Class area		Patch density		Largest patch index	
Model performance	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Coefficient of determination (R^2) (%)	38.51	34.81	52.88	53.06	35.84	37.63
Variable importance						
PAs size	1	1	1	1		
Mean precipitation	2	2				
Total annual burned area	3					
Slope	4	3				
Mean maximum temperature	5	4			1	1
Human Development Index		5	2	2	3	
IUCN management category			3	3	5	3
Gross Domestic Product			4	4	2	4
Road density			5	5		
Elevation					4	5
Distance to croplands						2

3.8 Global CRF models for protected wetlands

The CRF models for the patch density had the best performance compared to the other models. The CRF model of class area only explained 9.42% of the variance. PAs size was the only variable common to the class area and patch density CRF models. The most important variables common to the patch density and the largest patch index models were distance to roads, Gross Domestic Product, and the IUCN management category (Table 2.10) (Appendix Table A20).

Table 2.10. *Conditional Random Forest models performance for class-level metrics for global protected wetlands and their top-five most important explanatory variables*

	Class area		Patch density		Largest patch index	
Model performance	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Coefficient of determination (R^2) (%)	9.42	9.41	47.46	46.59	32.04	31.71
Variable importance						
Mean precipitation	1	1				
PAs size	2	2	1	1		
Human Development Index	3			2		
Mean maximum temperature	4					
Road density	5					
Slope		3			1	1
Elevation		4			4	3
Distance to roads		5	5	4	5	4
Gross Domestic Product			2	5	3	
Human Development Index			3			
IUCN management category			4	3		5
Distance to croplands					2	2

3.9 Regional CRF models for landscape-level metrics

Generally, the CRF models for the different regions did not show large differences between 2000 and 2020. (Table 2.11) (Table S1). Most CRF metric models for Oceania and North America had higher coefficients of determination than the other regions. The CRF models for patch density for all regions, except for PAs in Asia, had the highest variance explained compared to the models for the other metrics. North America and Central and Western Europe had the highest variance explained for this metric. The core area index CRF models for Oceania had the highest coefficient of determination with respect to the other regions. In the case of the aggregation index models, Eastern Europe, Oceania, and North America had the highest variance explained. Lastly, Oceania, Latin America and the Caribbean, and North America had the highest variance explained for the CRF models for the modified Simpson's diversity index.

Table 2.11. *Coefficient of determination of the 2000 and 2020 CRF models for metrics at the cover class level for regional PAs*

Region	**Landscape metric**	**Coefficient of determination (R^2) (%)**	
		2000	**2020**
Africa	Aggregation index	23.27	26.08
	Patch density	38.94	37.52
	Core area index	9.19	6.30
	Largest patch index	21.64	15.93
	Modified Simpson's diversity index	19.49	16.12
South-East Asia	Aggregation index	23.78	24.40
	Patch density	21.35	19.92
	Core area index	27.87	24.11
	Largest patch index	32.71	16.88
	Modified Simpson's diversity index	28.24	25.00
Western-Central Asia	Aggregation index	30.39	28.59
	Patch density	34.56	35.69
	Core area index	28.28	28.06
	Largest patch index	21.36	20.31
	Modified Simpson's diversity index	36.42	35.97
Central Western Europe	Aggregation index	27.20	26.97
	Patch density	38.51	38.71
	Core area index	22.94	25.34
	Largest patch index	20.65	24.30
	Modified Simpson's diversity index	23.49	24.75
Eastern Europe	Aggregation index	36.00	34.11
	Patch density	37.64	37.35
	Core area index	34.27	32.94
	Largest patch index	20.02	17.96
	Modified Simpson's diversity index	25.66	25.87
Latin America and the Caribbean	Aggregation index	28.59	28.07
	Patch density	42.87	42.79
	Core area index	29.54	26.27
	Largest patch index	25.76	28.33
	Modified Simpson's diversity index	33.51	36.24
North America	Aggregation index	31.48	31.88
	Patch density	44.95	47.17
	Core area index	30.20	29.92
	Largest patch index	31.25	30.71
	Modified Simpson's diversity index	30.91	31.16
Oceania	Aggregation index	32.79	31.27
	Patch density	50.62	49.26
	Core area index	50.79	43.33
	Largest patch index	31.43	30.61
	Modified Simpson's diversity index	40.50	41.80

The most important socioeconomic and biophysical variables and PAs design features for the different CRF models of landscape-level metrics, i.e., aggregation index, core area index, patch density, largest patch index, and the modified Simpson's diversity index, varied by region and year. However, PAs size was the only top variable common to all CRF models. Here I list the three most important variables for the patch density CRF models since, in general, they had the highest variance explained for all regions. Africa, South-East Asia, Central and Western Europe, Eastern Europe, and Oceania were the regions where the three most important variables were the same for the 2000 and 2020 patch density CRF models (Table 2.12) (Table S2).

The most critical variables for the patch density 2000 and 2020 CRF models for Africa were PAs size, mean precipitation, and road density. For Western-Central Asia, the two most important variables common for the 2000 and 2020 models were PAs size and nighttime lights value. In the case of the patch density CRF models for South-East Asia, the three top variables were PAs size, the coefficient of variation of maximum temperature, and the Human Development Index. The three most important variables for explaining the variance of the 2000 and 2020 patch density CRF models for Central and Western Europe were PAs size, Human Development Index, and elevation. For Eastern Europe, the three most critical variables for the patch density CRF models were PAs size, distance to croplands, and the IUCN management category. In the case of Latin America and the Caribbean, PAs size and nighttime lights value were the two most important variables common for the 2000 and 2020 CRF models. The two most important variables for North America's patch density CRF models were PAs size and distance to croplands. The three most critical variables for the 2000 patch density CRF model for Oceania were PAs size, distance to croplands, and the IUCN management category.

Table 2.12. *Conditional Random Forest models performance for landscape-level metrics for regional PAs and their top-three most important explanatory variables*

	Africa									
	Patch density		**Aggregation index**		**Core area index**		**Modified Simpson's diversity index**		**Largest patch index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance										
Coefficient of determination (R2) (%)	38.94	37.52	23.27	26.08	9.19	6.30	19.49	16.12	21.64	15.93
Variable importance										
PAs size	1	1	1	2						
Mean precipitation	2	2	2	1		1				
Road density	3	3	3	3						
Distance to croplands					1	3				
Mean maximum temperature					2					
CV max. temp 95 - 20					3	2		2		
CV prec 95 - 20							1			
CV min. temp 95 - 20							2			
Human Development Index							3			
Total livestock tropical units								1	2	
Distance to Indigenous Peoples' Lands								3	1	1
Global inequality									3	
Distance to roads										2
IUCN management category										3

(Continued)

	Western-Central Asia									
	Patch density		**Aggregation index**		**Core area index**		**Modified Simpson's diversity index**		**Largest patch index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance										
Coefficient of determination (R2) (%)	34.56	35.69	30.39	28.59	28.28	28.06	36.42	35.97	21.36	20.31
Variable importance										
PAs size	1	2	1	1						
Road density	2		3	2						
Nighttime lights value	3	3	2							
Elevation		1		3						2
Distance to croplands					1	1				
Human Development Index					2	3	1	1	1	
Gross Domestic Product					3	2	2	2	3	1

	South-East Asia									
	Patch density		**Aggregation index**		**Core area index**		**Modified Simpson's diversity index**		**Largest patch index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance										
Coefficient of determination (R2) (%)	21.35	19.92	23.78	24.40	27.87	24.11	28.24	25.00	32.71	16.88
Variable importance										
PAs size	1	1		1	2	1				
CV max. temp 95 20	2	3								
Human Development Index	3	2								
Elevation			3				3	3	2	
Road density			1							
Total livestock tropical units			2	2						
Nighttime lights value				3						
Distance to croplands					1	2				3
Mean precipitation					3	3				
Total annual burned area							1	1	1	
Slope							2	2	3	1
Gross Domestic Product										2

	Central and Western Europe									
	Patch density		**Aggregation index**		**Core area index**		**Modified Simpson's diversity index**		**Largest patch index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance										
Coefficient of determination (R2) (%)	38.51	38.71	27.20	26.97	22.94	25.34	23.49	24.75	20.65	24.30
Variable importance										
PAs size	1	1	3	3						
Human Development Index	2	2	1	1	2	2		2		
Elevation	3	3	2	2	3		3	3		
Distance to croplands					1	1	1	1	1	1
Gross Domestic Product						3	2			
Mean precipitation									2	
Distance to roads									3	3
Topographic Position Index										2

	Eastern Europe									
	Patch density		Aggregation index		Core area index		Modified Simpson's diversity index		Largest patch index	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance										
Coefficient of determination (R2) (%)	37.64	37.35	36.00	34.11	34.27	32.94	25.66	25.87	20.02	17.96
Variable importance										
PAs size	1	1	1	1	2	2				
Distance to croplands	2	3	2	2	1	1	1	1	1	1
IUCN management category	3	2	3	3	3	3				
Slope							2	3		3
Topographic Position Index							3	2	2	2
Human Development Index									3	

	Latin America and the Caribbean									
	Patch density		**Aggregation index**		**Core area index**		**Modified Simpson's diversity index**		**Largest patch index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance										
Coefficient of determination (R2) (%)	42.87	42.79	28.59	28.07	29.54	26.27	33.51	36.24	25.76	28.33
Variable importance										
PAs size	1	1				2				
Nighttime lights value	2	2	1	1						
Mode elevation	3									
Road density		3								
Total livestock tropical units			2	2						
Mode slope			3				3	2	2	2
Human Development Index				3	3					
Distance to croplands					1	1	1	3	1	1
Mean maximum temperature					2					
Gross Domestic Product						3				
CV min. temp 95 - 20							2	1	3	3

North America									
Patch density		Aggregation index		Core area index		Modified Simpson's diversity index		Largest patch index	
2000	2020	2000	2020	2000	2020	2000	2020	2000	2020
44.95	47.17	31.48	31.88	30.20	29.92	30.91	31.16	31.25	30.71
1	1								
2	2	1	1	1	1	1	1	1	1
3		2	2	2	2	3			3
	3	3	3	3				3	
					3	2	2	2	2
							3		

	Oceania									
	Patch density		**Aggregation index**		**Core area index**		**Modified Simpson's diversity index**		**Largest patch index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance										
Coefficient of determination (R2) (%)	50.62	49.26	32.79	31.27	50.79	43.33	40.50	41.80	31.43	30.61
Variable importance										
PAs size	1	1	1	2					1	
Distance to croplands	2	2	2		1	1	1	2		
IUCN management category	3	3	3	1						
CV prec 95 - 20				3						
Slope					2	2	2	1	2	2
Human Development Index					3	3				
CV max. temp 95 - 20							3	3	3	1
Mean maximum temperature										3

3.10 Regional CRF models for class-level metrics

Here I present the main findings of the CRF models for class area, patch density, and the largest patch index for protected forests since the models for this cover class had the highest variance explained (Table 2.13). Table S10 the results of the specific cover-class CRF models by region, excluding the CRF forest models results: North America (models for protected grasslands, shrublands, and wetlands), Central and Western Europe and Eastern Europe (models for protected grasslands and wetlands), and Latin America and the Caribbean and Oceania (models only for protected shrublands).

The variance explained for the different models for the class-level metrics for protected forests varied by region and year. In general, the variation explained for the 2000 and 2020 CRF models did not largely vary. The three regions with the highest variance explained for the class-area CRF models were Eastern Europe (68.06%), Africa (55.88%), and Latin America and the Caribbean (46.68%). In the case of the patch density models, the three regions with the highest variance explained were Eastern Europe (49.48%), Western-Central Asia (45.50%), and North America (41.24%). Western-Central Asia (57.71%), Oceania (54.02%), and North America (46.14%) were the regions with the highest variance explained for the largest patch index CRF models.

Table 2.13. *Conditional Random Forest models results for protected forests for 2000 and 2020 regional PAs*

Region	**Landscape metric**	**Coefficient of determination (R^2) (%)**	
		2000	**2020**
Africa	Class area	44.86	55.88
	Patch density	25.03	27.90
	Largest patch index	41.42	37.13
South-East Asia	Class area	39.80	37.93
	Patch density	39.18	43.29
	Largest patch index	43.44	40.82
Western-Central Asia	Class area	41.83	29.39
	Patch density	45.50	41.32
	Largest patch index	56.44	57.71
Central Western Europe	Class area	42.74	48.65
	Patch density	32.14	41.39
	Largest patch index	35.46	36.74
Eastern Europe	Class area	65.27	68.06
	Patch density	49.48	44.70
	Largest patch index	37.52	34.56
Latin America and the Caribbean	Class area	46.68	46.04
	Patch density	35.82	34.17
	Largest patch index	38.28	40.60
North America	Class area	40.98	59.03
	Patch density	41.24	39.62
	Largest patch index	46.14	45.63
Oceania	Class area	20.18	9.90
	Patch density	43.98	31.58
	Largest patch index	53.59	54.02

To analyze the role of socioeconomic and biophysical factors and PA design features in explaining the variation of class-level metrics models for protected forests, I list the first two to three most important variables for the class-area models since the models for this metric had, in general, a better performance compared to the other metrics. PAs mean precipitation and size were the two most important variables common to the 2000 and 2020 class-area models for protected forests for all regions. Latin America and the Caribbean, and North America were the only regions that shared three top variables for the 2000 and 2020 CRF models (Table 14).

Table 2.14. *Conditional Random Forest models performance for landscape-level metrics for regional protected forests and their top-three most important explanatory variables*

	Africa					
	Patch density		**Class area**		**Largest Patch Index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance						
Coefficient of determination (R^2) (%)	25.03	27.90	44.86	55.88	41.42	37.13
Variable importance						
Mean precipitation	1	1	1	1		
PAs size	2	2	2	2		
Total annual burned area	3		3			
CV prec 95 - 20		3		3		3
Distance to Indigenous Peoples' Lands					1	2
Mean maximum temperature					2	1
Slope					3	

	Western-Central Asia					
	Patch density		**Class area**		**Largest Patch Index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance						
Coefficient of determination (R^2) (%)	45.50	41.32	41.83	29.39	56.44	57.71
Variable importance						
Mean precipitation	1		1	1		
PAs size	2	1	2	2		
Human Development Index	3		3		2	2
Mean maximum temperature		2		3		
IUCN management category		3				
Slope					1	1
Gross Domestic Product					3	3

	South-East Asia					
	Patch density		**Class area**		**Largest Patch Index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance						
Coefficient of determination (R^2) (%)	39.18	43.29	39.80	37.93	43.44	40.82
Variable importance						
PAs size	1	1	1	1		
Mean precipitation	2	2	2	2		
Mean maximum temperature	3		3		3	3
Human Development Index		3		3		
Slope					1	1
Elevation					2	2

	Central and Western Europe					
	Patch density		**Class area**		**Largest Patch Index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance						
Coefficient of determination (R^2) (%)	32.14	41.39	42.74	48.65	35.46	36.74
Variable importance						
PAs size	1	1	1	1		
Mean precipitation	2	2	2	2		
IUCN management category	3	3	3	3		
Distance to croplands					1	
Slope					2	1
Human Development Index					3	
Distance to croplands						2
Topographic Position Index						3

	Eastern Europe					
	Patch density		**Class area**		**Largest Patch Index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance						
Coefficient of determination (R^2) (%)	49.48	44.70	65.27	68.06	37.52	34.56
Variable importance						
Mean precipitation	1	1	1	1		
PAs size	2	2	2	2		
IUCN management category	3		3			
Mean maximum temperature		3		3		
Slope					1	1
Distance to croplands					2	2
Topographic Position Index					3	3

	Latin America and the Caribbean					
	Patch density		**Class area**		**Largest Patch Index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance						
Coefficient of determination (R^2) (%)	35.82	34.17	46.68	46.04	38.28	40.60
Variable importance						
Mean precipitation	1	1	1	1		
PAs size	2	2	2	2		
Global Inequality	3	3	3	3		
IUCN management category					1	1
Slope					2	
Distance to croplands					3	2
Human Development Index						3

	North America					
	Patch density		**Class area**		**Largest Patch Index**	
	2000	**2020**	**2000**	**2020**	**2000**	**2020**
Model performance						
Coefficient of determination (R^2) (%)	41.24	39.62	40.98	59.0 3	46.14	45.63
Variable importance						
PAs size	1	1	1	1		
Mean precipitation	2	2	2	2		
Mean maximum temperature	3	3	3	3		
Slope					1	1
Distance to croplands					2	2
IUCN management category					3	
Elevation						3

	Oceania					
	Patch density		Class area		Largest Patch Index	
	2000	2020	2000	2020	2000	2020
Model performance						
Coefficient of determination (R^2) (%)	43.98	31.58	20.18	9.90	53.59	54.02
Variable importance						
Mean precipitation	1	1	1	2		
PAs size	2	2	2	1		
Total annual burned area	3		3			
Distance to roads		3		3		
Mean maximum temperature					1	1
Slope					2	2
Distance to croplands					3	
CV max. temp 95 - 20						3

3.11 Accumulated local effects (ALE) for global and regional patch density and class-area for global and regional protected forests

It is important to note that the ALE plots show the effect of one variable on the prediction of a machine learning model, and they do not include potential interactions between multiple variables. Thus, their interpretation should be made carefully. The ALE plots show the non-linear relationship between the most important variables for the 2020 patch density global CRF model and the class-area 2020 model for global protected forests (Figures 2.4 and 2.5). In the case of the relationship between the most important variables of the patch density CRF model, slope and PAs size had a negative association with this metric. The landscape of PAs with a slope of less than 10% is patchier than those with a higher slope value. Similarly, patch density in small PAs tends to be higher than in larger PAs. The Human Development Index had a positive relationship with patch density. PAs for which surrounding areas had higher values of the Human Development Index had high patch density. PAs with a Human Development Index of 0.87 or more are patchier than those with a lower value of this index; this can be associated with more human pressure in PAs' surroundings, e.g., agriculture and urban expansion.

In the case of the relationship between the most important variables of the class area CRF model for global protected forests, there is a positive relationship between mean precipitation and the increase in forest cover. PAs with a mean precipitation of less than 125 mm for 2019 and 2020 reduced their forest cover. A similar pattern was found for the relationship between forest area and the coefficient of variation of precipitation from 1995 to 2020. PAs with high variation in precipitation had less forest cover. A marked reduction in forest cover occurs when the coefficient of variation of precipitation was larger than 10%. High road density in the vicinity of PAs also negatively affected forest cover. In the case of the Human Development Index, a decline in the cover of protected forests was associated with high values (above 0.75) of this index.

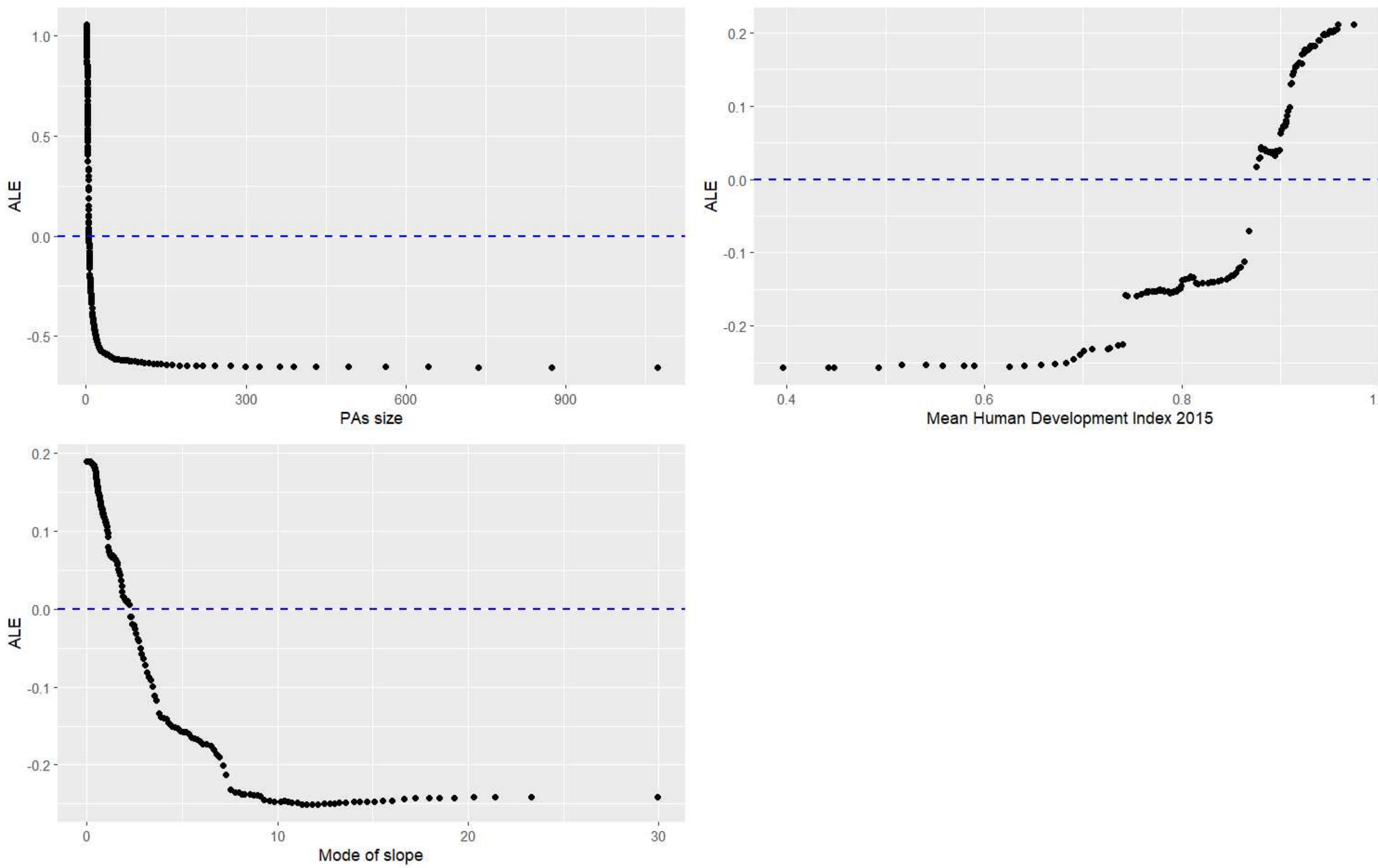

Figure 2.4. *Accumulated local effects (ALE) plots for the 2020 patch density CRF model for global PAs*

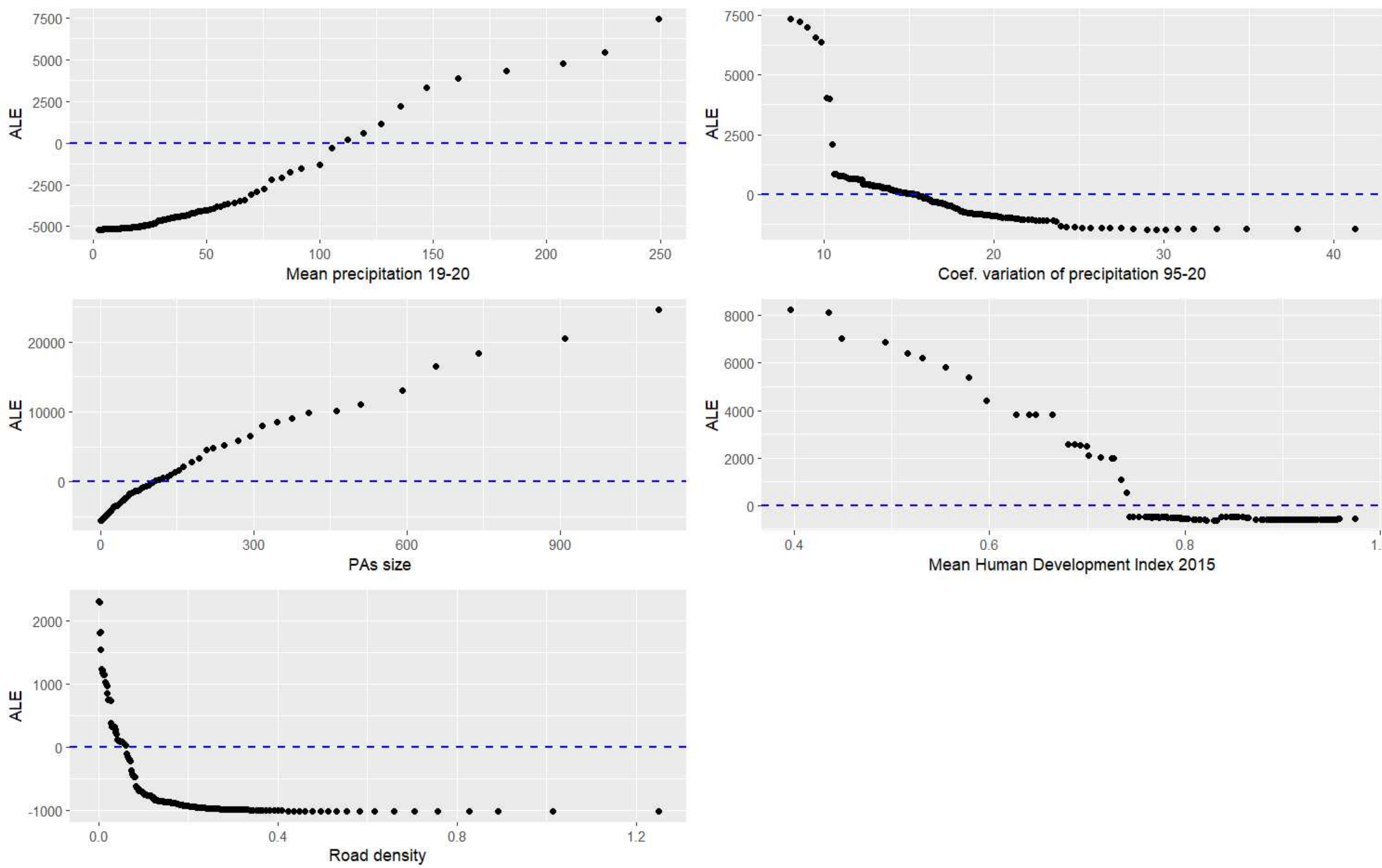

Figure 2.5. *Accumulated local effects (ALE) plots for the 2020 class-area CRF model for global protected forests*

In the case of the patch density CRF model for North America (Figure 2.6), PAs with more slope had lower patch density. Moreover, PAs that received more precipitation had a patchier landscape. Small PAs (< 10 ha) had higher patch density values than larger PAs. The ALE plots for the class-area CRF model for protected forests for this region (Figure 2.7) shows that the extension of forest cover was related to the size of PAs. Thus, small PAs (< 10 ha) had a less forest cover. The forest cover of PAs with higher mean precipitation for 2019 and 2020 was more extensive than those with less precipitation. PAs with flat slopes had the highest forest cover compared to those in steeper areas. Road density in the vicinity of the PAs did not negatively impact forest coverage.

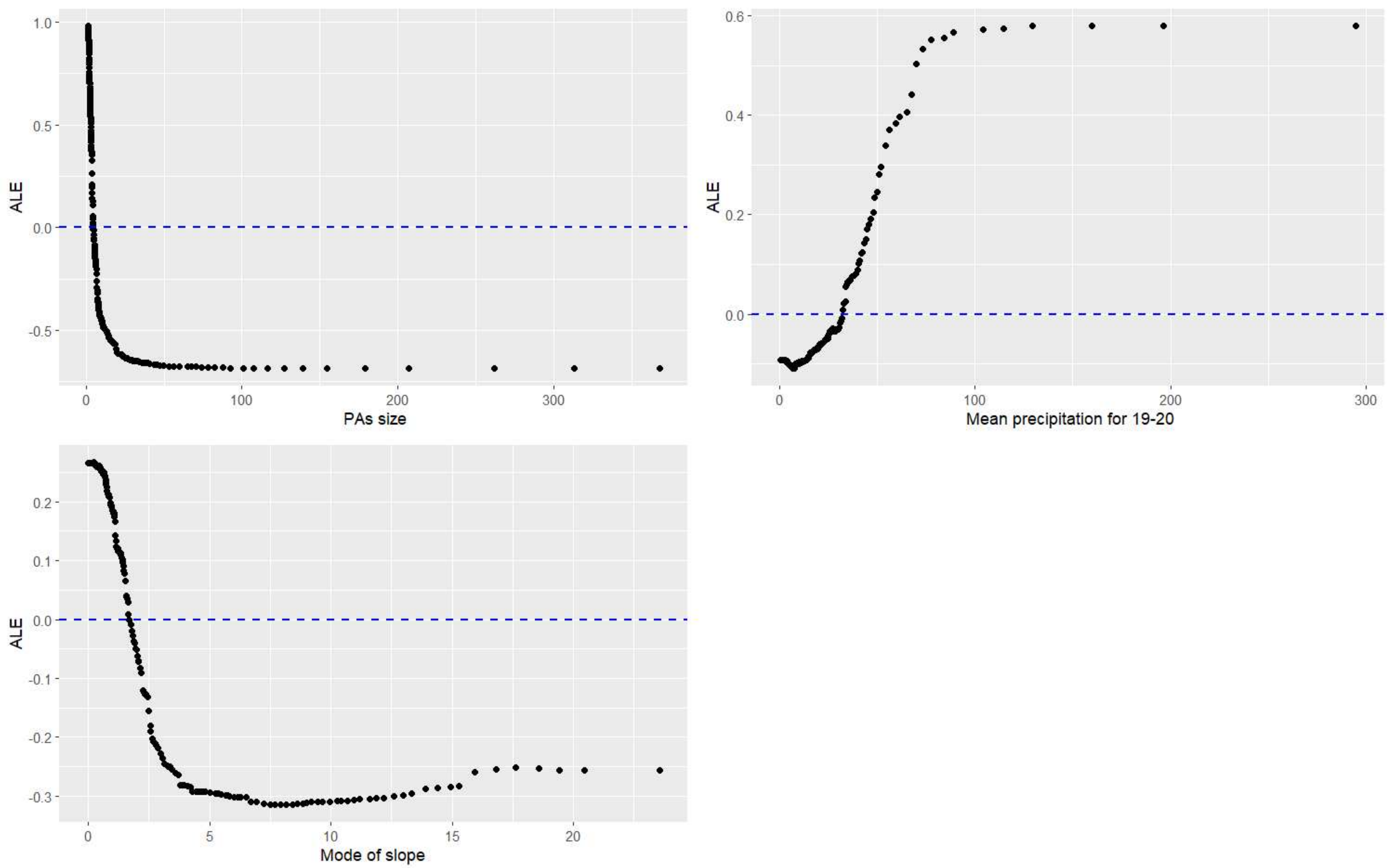

Figure 2.6. *Accumulated local effects (ALE) plots for the 2020 patch density CRF model for North America*

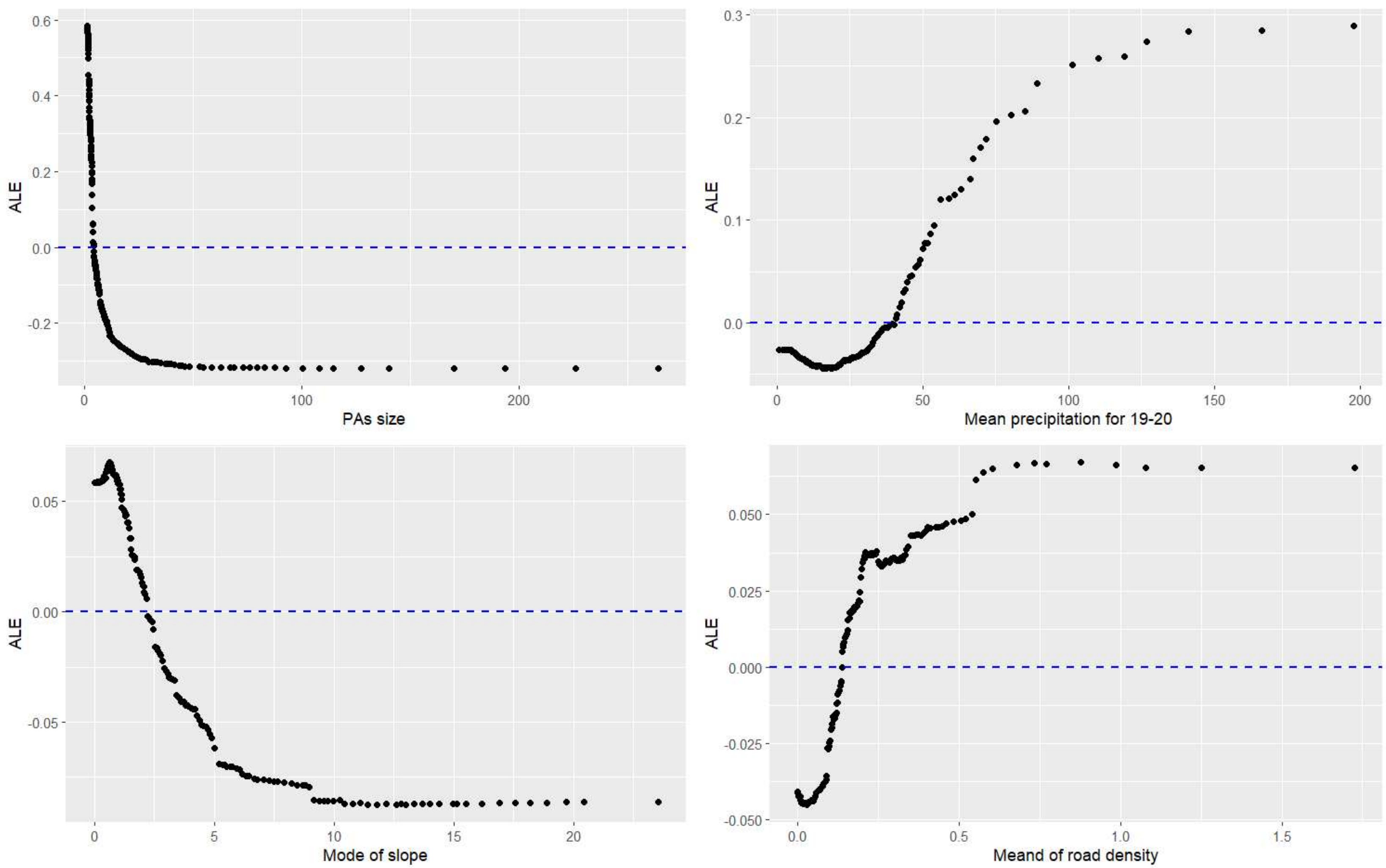

Figure 2.7. Accumulated local effects (ALE) plots for the 2020 class-area CRF model for protected forests in North America

4. Discussion

4.1 Landscape changes in protected forests, grasslands, shrublands, and wetlands

Over the past twenty years, the cover size of approximately 50% of global protected forests, grasslands, shrublands, and wetlands has remained constant, with protected grasslands experiencing fewer changes in their size than other cover classes. In contrast, protected wetlands increased their cover size while protected shrublands and forests had more decreases than increases in their cover. Globally, Africa has the highest percentage of PAs that increased their forest cover, and Eastern Europe has the highest percentage of PAs with increased grasslands, shrublands, and wetlands cover.

Although my findings show that 50% of PAs have not had land cover changes from 2000 to 2020, my results also evidence the dynamic nature of land cover change in PAs and how it varies among cover types and regions. Guerra et al. (2019) found that approximately 4.89% of the world's land surface has changed from one cover class to another from 1992 to 2015, with 97.9% of land conversion from one type to another persisting through time. The cover classes most impacted were forests, shrublands, sparse vegetation, and areas with natural or cropland-dominated mosaics, with forests and shrublands experiencing a decrease in their cover with -1.52 and -2.78%, respectively. These findings align with my results that show that protected shrublands and forests have had more cover losses than gains. Leberger et al. (2020) found an increasing trend in the annual rate of forest loss per PA between 2000 and 2014 that varied by level of protection and region. Findings from another study show that from 2000 to 2015, only 30.5% of forest loss in PAs was prevented; however, forest loss rates in PAs (11.2%) were higher than the global average (5.6%) (Yang et al., 2021). The extent of forest loss in PAs reduced by 3% between 2000 and 2012, with a high regional and country-level variation. For instance, forest loss in PAs in North America, Australia, Oceania, and Central America exceeded 5%, while PAs in South America and Southeast Asia prevented forest loss (Heino et al., 2015).

In the case of the largest patch index metric, protected forests, grasslands, and shrublands had a decline in the value of this metric from 2000 to 2020, while an opposite pattern was found for protected wetlands. However, wetlands had the lowest percentage of PAs with a constant value of this metric. Protected forests in Africa had the highest percentage of PAs with an increased value in the largest patch index metric. In the case of grasslands, only PAs in Oceania increased the value of this metric. Eastern Europe and North America had the highest percentages of protected shrublands that experienced an increase in this metric. Protected wetlands in Eastern Europe had the highest percentage of PAs, with increases in the largest patch index metric. These findings suggest that the dominant landscape of PAs in these regions has shifted in the past twenty years, revealing that other cover classes may have increased their extent or dominance. This shift could have significantly impacted PAs landscape composition and configuration, altering ecosystem processes and species habitats. However, the cause of these landscape changes, i.e., human activities or natural processes, will determine how ecosystems will respond to these stressors. For instance, landscape changes caused by unsustainable socioeconomic activities could have had more detrimental and irreversible changes with respect to natural-triggered landscape changes.

All cover classes experienced increases in patch density from 2000 to 2020; however, protected wetlands had the highest number of PAs with an increase in the value of this metric, which contradicts the findings of increases in the largest patch index. However, this pattern may result from changes in the structure of the landscape that may occur in different zones, time scales, and triggering factors, i.e., human activities or natural processes. For instance, PAs edges are more prone to human pressure than core areas and, therefore, more susceptible to fragmentation. Protected forests in Africa and South-East Asia had the highest percentages of PAs with increases in patch density with respect to the other regions. In the case of grasslands, Western-Central Asia had the highest percentage of PAs with increases in this metric. Protected shrublands in South-East Asia and Eastern Europe had the highest percentages of PAs with increases in patch density. In the case of protected wetlands, all regions, except for Western-Central Asia, experienced increases in patch density, with Eastern Europe with the highest percentage of protected wetlands with increased patch density. Overall, my findings indicate that from 2000 to 2020, global protected forests, shrublands, and grasslands have undergone fragmentation with large variations at the regional level. Evidence of this fragmentation pattern is the reduction in the percentage of global PAs with high values of the largest patch index and an increase in the number of PAs with increases in patch density.

4.2 Factors associated with landscape change in PAs

The CRF models for 2000 had a slightly better performance, i.e., a marginally higher explained variance, than the 2020 models. I could not find data for some variables for 2020, e.g., Gross Domestic Product and Human Development Index. Thus, I used available data favoring datasets from years nearest my analysis period, which could have affected the models' performance. Distance to croplands and mean Gross Domestic Product were two of the most important explanatory variables common for all landscape metrics models for 2000 and 2020. This finding suggests that over the 20 years of analysis, these two variables played a critical role in explaining changes in the landscape of global PAs.

In the case of the CRF models for the different regions, the models for patch density had the best performance, i.e., the highest variance explained, for all regions. Moreover, there were no marked differences between the 2000 and the 2020 models, opposing the results found at the global level. This suggests that at the regional level, the lack of data for some variables for a specific year did not influence the models' performance.

4.2.1 Socioeconomic factors

The socioeconomic factors important in explaining the variance of the patch density, aggregation index, and core area index CRF models, i.e., models with a percentage of variance explained of 48.09, 34.50, and 32.31% of the variance for 2000, in global PAs were distance to croplands and the Human Development Index. The 2020 CRF models for the modified Simpson's diversity index and the largest patch index had the lowest variance explained, with 29.33 and 24.65%, respectively. In the case of the modified Simpson's diversity index models, the two most important socioeconomic factors were distance to croplands and total livestock tropical units. For the largest patch index CRF models, the most important socioeconomic predictors were distance to croplands and Gross Domestic Product. These results show how the impacts of human activities in the vicinity of PAs have influenced changes in the landscape of global PAs for the past 20 years. They also reveal the role of economic growth and human development in exerting pressure on ecosystems worldwide, especially when considering cropland expansion as a major global factor responsible for changes in the landscape of PAs.

At the regional level, the socioeconomic factors important in explaining the patch density CRF models, i.e., the models with the highest variance explained for all regions and all the landscape-level metrics, included distance to croplands, the Human Development index, and Gross Domestic Product. The regional models captured variables not considered important for the global CRF models, such as nighttime light value, travel time to the nearest city, population density, and distance to Indigenous Peoples' Land. These findings evidence the regional variations of the socioeconomic variables that the global CRF models could not capture. Although, to the best of my knowledge, no similar studies have applied RF to analyze landscape changes in global PAs, my findings can be supported with information from previous research. For instance, Geldmann et al. (2019) found that slope, road density, the Human Influence Index, and the Human Development Index were factors that most contributed to the global PAs performance to prevent human activities impacts from 1995 to 2010, estimated based on the Temporal Human Pressure Index (Geldmann et al., 2014), with agricultural expansion as the principal factor associated with increased human pressure. This result was corroborated by Vijay and Armsworth (2021), who found that cropland expansion inside PAs is responsible for about 18% of the human pressure in global PAs. Similarly, results from a country-level assessment (Mammides, 2020) of factors associated with human activities' impacts on global PAs, e.g., population density, agricultural land, land area, conservation spending, and Gross Domestic Product, reveal that more than half of PAs in most countries have experienced intense human pressure, with population density, agricultural land, and national land area showing the strongest association with human pressure within PAs. Additionally, the occurrence of reported threats in PAs across 149 countries was associated with mean travel time to major cities, inequality-adjusted human development, control of corruption, and mean elevation, with an increased likelihood of PAs with multiple threats in countries with low inequality-adjusted human development (Schulze et al., 2018).

4.2.2. Biophysical factors

Slope was the most important biophysical variable that helped explain the CRF models for all metrics at the global level. The other biophysical variables common to all metrics and part of the ten most important variables of the models were elevation, the Topographic Position Index, and mean precipitation. In my analysis, as in previous studies, slope, elevation, and topographic position index, can be considered factors that influence PAs accessibility and, therefore, influence the human pressure on PAs and their surroundings. Additionally, environmental factors, such as precipitation and temperature, determine the spatial distribution of natural resources and influence ecosystems' response to external pressures, determining PAs' vulnerability to human activities or natural events. At the regional level, the most critical biophysical variables that helped explain the patch density CRF models for all landscape-level metrics were the same as for the global CRF models; however, the coefficients of variation of maximum temperature and precipitation from 1995 to 2020 were also critical for explaining the regional CRF models' variance. These results also evidence the ability of the regional CRF models to capture the variance of the biophysical features for explaining changes in the landscape at this scale of analysis that otherwise could remain unnoticed.

Yang et al. (2021) analyzed landscape and management factors influencing PAs' ability to prevent forest loss in 54 792 PAs worldwide from 2000 to 2015. They found that higher elevation, low soil carbon stocks, and a longer travel time to the nearest city were the most critical predictors of forest loss prevention. PAs at high elevations or with low soil organic carbon, i.e., PAs with low agricultural productivity, have lower pressure for forest harvest or land conversion. In the case of biophysical factors such as precipitation and temperature, several studies have analyzed them as proxies for land suitability and productivity (Busch & Ferretti-Gallon, 2017; Nzunda & Midtgaard, 2017). Natural areas with more suitable climatic conditions for development and agricultural production are more prone to land use change (Busch & Ferretti-Gallon, 2017). Additionally, PAs with low accessibility, i.e., areas located at higher elevations and long distances from major cities, are under fewer threats, e.g., unsustainable hunting, disturbance from recreational activities, and natural system modifications from fire or fire suppression, than PAs close to urban areas (Schulze et al., 2018). Long distances to roads and towns, low Gross Domestic Product, and steep slopes were associated with low levels of deforestation in mainland Tanzania from 1995 to 2010. Proximity to roads and cities and gentler slopes facilitate access to forests and greater tree harvest (Nzunda and Midtgaard, 2017).

4.2.3. PAs design features

The two PAs design features analyzed, i.e., the IUCN management category and PAs size, were among the ten most important variables for all global CRF models for 2000 and 2020. The IUCN management category variable, except for the modified Simpson's diversity index CRF model, was in the top-five most important variables for all the CRF models. These findings suggest that the level of protection or regulation is critical in explaining landscape changes in global PAs. Nonetheless, at the regional level, the mean PAs size was the most critical variable for all regional CRF models for 2000 and 2020. However, the IUCN management category was only in the top three of the most critical variables for the Africa, Eastern Europe, North America, and Oceania landscape-level CRF models. In some cases, this variable was one of the three most important variables only for a specific year, i.e., 2000 or 2020. Interestingly, the distribution of the IUCN management categories for these regions was markedly different. In the case of Oceania, the main IUCN management category was Ia (Strict Nature Reserve); for North America, the main IUCN category was V (Protected Landscape), while for Eastern Europe, the most common IUCN management category was IV (Habitat/Species Management areas). This difference in the level of regulation of PAs in these regions impedes us from determining the role of this variable in explaining changes in the landscape of PAs. In my analysis, I explored the relationship between landscape metrics and the IUCN management category, independent of the specific level of regulation, i.e., the six IUCN categories. Thus, I cannot specify which protection level better explains landscape pattern changes in PAs. Nevertheless, the IUCN management category was a critical design feature for global and regional CRF models.

Studies about the IUCN management categories and PAs' effectiveness are not conclusive. In some cases, the performance of the most regulated PAs to reduce human pressure is better than less strict PAs. In other studies, an opposite relation is found, while other assessments could not find marked differences between strictness levels and PAs performance (Barnes et al., 2016; Guan et al., 2016). For instance, Elleason et al. (2021) did not find significant differences in human pressure and forest cover loss between the six IUCN management categories. Similarly, Guan et al. (2022) found that the level of human settlement in global PAs was not necessarily different between the various IUCN management categories. However, Vijay and Armsworth (2021) found that approximately 22% of cropland expansion in global PAs occurred in those conservation areas with strict IUCN management categories (I-IV). However, cropland expansion was more common in multiple-use PAs (V-VI). These contradictory findings can result from various factors, such as the different approaches for grouping PAs based on protection level. For example, some studies classify IUCN categories III and IV as strictly protected, while others consider them multiple-use PAs. Furthermore, many studies have analyzed the performance of PAs in different geographic areas, e.g., Global South and Global North. However, evidence suggests that PAs effectiveness varies across regions (Elleason et al., 2021; Guan et al., 2021;

Leberger et al., 2020). Finally, assessments of PAs performance and regulation level have been made using different indicators and indices, such as changes in land-cover types, species presence, and abundance (Elleason et al., 2021; Guan et al., 2021), challenging the comparison of findings among studies.

The location and size of PAs influence the level of human pressure and the ability to reduce land degradation. Large PAs located near dense urban areas face intense human pressure and have a higher probability of downgrading, downsizing, and/or degazetting (Gonzales-Garcia et al., 2022; Symes, 2016). The ability of PAs to reduce habitat degradation and favor habitat restoration is affected by their size, with small-size PAs following the dominant land-use change pattern (Maiorano et al., 2008). For instance, Geldmann (2015) found that the management effectiveness of PAs has a significant positive correlation with their size. Larger PAs have proportionally less edge to pressure and, if located in remote areas, are less prone to be impacted by human activities.

4.3 Factors associated with landscape change in global and regional protected forests, grasslands, shrublands, and wetlands

The CRF model for the class-area metric for protected forests had the highest percentage of variance explained (61.82%), followed by shrublands (38.51%) and grasslands (31.70%). Surprisingly, the class-area model for protected wetlands had a very low explained variance (9.41%). The common variables for all cover types that helped explain the variance in the models were PAs size, the Human Development Index, and mean precipitation. Interestingly, the CRF model for shrublands was the only one where the total annual burned area was an important variable. Despite the low variance for the class-area model of protected wetlands, the most important variables for the CRF models were similar among cover classes.

The CRF model for patch density for protected shrublands had the highest percentage of variance explained (53.06%), followed by wetlands (47.46%), forests (46.13%), and grasslands

(46.09%). The common variables for all cover types that helped explain the models' variance were PAs size, the Human Development Index, and Gross Domestic Product. Except for protected grasslands, the IUCN management category was also important for all models for this metric. The CRF model for protected grasslands was the only one where the total livestock tropical units was an important variable.

The CRF model for the largest patch index for protected forests had the highest percentage of variance explained (41.65%), followed by shrublands (37.63%), wetlands (32.04%), and grasslands (30.75%). The only common variable for all cover types that helped explain the variance in the models for this metric was the IUCN management category. Except for protected grasslands, distance to croplands was important for the other models of the other cover classes. A common important variable for the CRF models for protected forests and shrublands was mean maximum temperature. Interestingly, the CRF model for protected forests was the only one for which the topographic position index was important. Similarly, only the CRF model for protected grasslands had total livestock tropical units as an important variable.

In the previous section, I discussed the role of different socioeconomic and biophysical variables and PAs design features, such as Gross Domestic Product, slope, and PAs size, as factors influencing human pressure in PAs and their surroundings. However, the CRF models for the different cover classes included other important variables, e.g., mean precipitation, mean maximum temperature, total livestock tropical units, and total annual burned area. In the case of precipitation and temperature, these environmental factors influence ecosystem processes, properties, and responses to external factors. For example, PAs in arid and semiarid sites responded positively to increments in precipitation and negatively to rising temperatures from 1982 to 2012, with an opposite response for humid ecosystems, showing a different time and sensibility response of ecosystems to changes in climatic regimes (Dieguez & Paruelo, 2017). Deforestation in PAs, changes in the presence of secondary vegetation, and fire occurrence in the Amazon can result from urban and agricultural expansion, infrastructure projects, illegal logging, and cattle production (Paiva et al., 2020). In the case of burned areas in PAs, Mansuy et al. (2019) found that fire activity inside and outside PAs in North America from 1984 to 2014 can be mainly explained by climatic and landscape variables, e.g., mean annual precipitation and topographic position index, and anthropogenic factors, e.g., human footprint and human population.

Moreover, at the regional level, other socioeconomic variables were also relevant in explaining the variance of the CRF models. For instance, distance to Indigenous Peoples' lands was a top variable for Africa's modified Simpson's diversity index (landscape-level metric) and largest patch index (protected forests) models. Sze et al. (2022) found that global deforestation and forest degradation in Indigenous lands from 2010 to 2018 decreased relative to unprotected areas across the tropics. Also, deforestation was avoided and forest degradation was reduced in Indigenous lands to comparable levels of PAs and Protected Indigenous areas, except for lands in Africa. The proximity of PAs to Indigenous Peoples' lands could have reduced PAs' exposure to external pressure and provided them protection from human activities. The Global Inequality variable was also important for explaining the variance of Africa's largest-patch index (landscape-level metric) model and the path density and class area models for protected forests for Latin America and the Caribbean. These findings indicate that PAs in regions with high-income inequality are more prone to fragmentation, which also was corroborated by the higher percentage of protected forests in these two regions experiencing increases in patch density from 2000 to 2020. Development in countries with high levels of inequality tends to aggravate deforestation rates. In contrast, in countries with an egalitarian distribution of incomes, the negative impacts of economic growth and development can be ameliorated (Koop & Tole, 2001).

Caveats

Factors that could have influenced my results include datasets' availability and spatial-temporal resolution. For some variables, such as livestock population, Gross Domestic Product, and Human Development Index, I could not find datasets that matched the years of my analysis. Thus, I worked with data from the years nearest my analysis period. Further, for some variables, such as the ones previously mentioned, the available datasets had a coarser resolution than the other variables included in my analysis. Even though I identified different socioeconomic and biophysical factors associated with land cover changes and human pressure in PAs and their vicinity, my list of explanatory variables is not exhaustive and cannot confirm causation. Additionally, I could not find PAs polygon data for some countries, such as Cuba and North Korea, and I could not find complete polygon data for some countries, such as China and India. The unbalanced distribution of PAs could have also affected my findings. In my sample, Eastern Europe, Central-Western Europe, and North America are the regions with 68.9% of PAs. Finally, a more comprehensive evaluation of the role of human and biophysical factors on changes in the landscape of PAs would include aspects I could not capture in my analysis, such as PAs threats, management effectiveness assessments, and environmental governance.

5. Conclusion

My findings show that 50% of PAs globally have experienced changes in landscape metrics from 2000 to 2020, varying by land cover class and region. Moreover, globally protected forests, grasslands, shrublands, and wetlands have faced cover losses, gains, and fragmentation. The minimal difference in the variance explained for most of the 2000 and 2020 models for all metrics, cover classes, and regions, as well as the similar top explanatory variables for both years under analysis, indicates that, in general, the factors associated with landscape change in PAs have not considerably varied over the past two decades. Moreover, in my analysis, I identified, from the vast list of variables associated with landscape changes, the most important anthropogenic and biophysical factors and PAs design features influencing landscape changes. My findings evidence the critical role of cropland expansion, Gross Domestic Product, Human Development Index, PAs size, the IUCN management category, and slope on influencing landscape changes of global and regional PAs for 2000 and 2020. In the case of protected forests, grasslands, wetlands, and shrublands, other important variables that help explain changes in their landscape include livestock population in their vicinity and the mean of maximum temperature and precipitation. At the regional level, top variables that were not considered important for the global models were listed as relevant for explaining the variance of the landscape-level and class-level metrics models, e.g., nighttime light value, travel time to the nearest city, population density, and the coefficients of variation of maximum temperature and precipitation from 1995 to 2020.

Information from my study allows us to identify the regions and protected cover classes that have undergone changes over the past twenty years and may be facing degradation, crucial information that can serve as a basis for PAs effectiveness assessments and developing global and regional conservation and sustainable management PAs targets. The development of comprehensive and holistic conservation and sustainable policy and planning needs to address factors associated with human pressure in PAs and their vicinity, incorporate multiple views and perspectives, and engage with local communities. Further studies are required to analyze the specific role of the various socioeconomic and biophysical variables and PAs design features on changes in the composition and configuration of the PAs landscapes and their complex dynamic. In addition, more detailed spatial-temporal and in-situ assessments will allow a deep understanding of the processes and threats PAs undergo and develop specific management and conservation actions. It is also critical to study to what extent and how ecological processes and biodiversity could have been impacted by landscape changes. My findings also reveal the dynamic, non-linear, and geographical relationship between socioeconomic and biophysical variables and landscape changes. In this way, my study demonstrates the advantage of using RF analysis as an exploratory method to capture complex interactions among variables while reducing variable selection bias. Nonetheless, because traditional RF does not address spatial heterogeneity, to explore the spatial variation between the socioeconomic and biophysical factors associated with PAs landscape change, I suggest performing the Geographical Random Forest (GRF) analysis (Georganos et al., 2021). GRF can be used as an exploratory tool to analyze local variations caused by the spatial heterogeneity of the data.

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CHAPTER 3: POTENTIAL ECOLOGICAL IMPACTS OF CLIMATE CHANGE ON ANDEAN MOUNTAIN ECOSYSTEMS

1. Introduction

Rapid changes in topography and climate make mountain ecosystems particularly sensitive to climate change (Beniston, 2003), with mountain regions encompassing glaciers, snow, and permafrost being more susceptible than regions without these elements (Diaz et al., 2003). Mountain glaciers represent the most visible indicator of climate change because of their fast response to climate fluctuations (Beniston, 2003; Vuille et al., 2008). Mountain glaciers are essential in providing water to lowland regions and regulating seasonal precipitation (Vuille et al., 2008). However, the glacier volume in these regions has decreased due to temperature rise (Stocker et al., 2013). From 2000 to 2019, the global glacier mass loss, excluding Greenland and Antarctica, was 267 ± 16 gigatonnes per year (Hugonnet et al., 2021). Due to climate change, the mass balance of glaciers, i.e., inputs of snow and ice and outputs from melting processes, has been altered. This change has affected glaciers' thickness and triggered their retreat, significantly impacting the hydrological processes and the water supply to downstream basins (Beniston, 2003).

Tropical glaciers, such as the ones located in the Andes, are more sensitive to climate than glaciers in other regions because of the absence of seasonal snow cover outside glacier areas, high solar radiation throughout the year, and the long dry season in some areas (Vuille et al., 2018). Projections indicate that regions with small areas of glacier cover, such as the tropical Andes, will lose more than 80% of their current mass by 2100 (Pörtner et al. 2019). Additionally, the surface air temperature in high mountain regions has increased at an average rate of 0.3 ºC / decade over the past sixty years. There is high confidence that this will continue until the mid-21st century (Hock et al., 2019). For instance, in the Andes, the temperature increased by 0.10 °C / decade with a total increase since 1939 of 0.68°C (Vuille et al., 2008). These temperature changes will alter the hydrological and biogeochemical cycling of mountain regions, affect regional phenomena such as El Niño / Southern Oscillation (ENSO) (Beniston, 2003; Diaz et al., 2003), and modify the size and distribution of glaciers and other ecosystems (Urrutia & Vuille, 2009).

Over the past few decades, several observational studies have found that the Andes have experienced increasing temperatures. In contrast, trends in annual precipitation across the north-tropical (north of 8°S) and south-tropical (8 °S – 27 °S) Andes have not exhibited a homogenous pattern. Climate projections show that the Andes will experience an increasing temperature trend, with the lowest increments (less than 3°C) in extratropical latitudes and the highest increments over the Central Andes (up to 5°C). By contrast, projections of precipitation have high uncertainty (Pabón-Caicedo et al., 2020). In the tropical Andes, increasing temperatures are projected to be higher at higher elevations, about 4°C for 2040 – 2070, for the most extreme scenario, i.e., CMIP5 RCP8.5. Projections also show that precipitation patterns will be highly variable, with marked differences for the eastern and western slopes but with significant uncertainties for certain regions due to the complex topography of the Andes. In this way, climate change is likely to alter the distribution and extent of Andean biomes (Tovar et al., 2022), affecting the area and distribution of glaciers and other ecosystems (Urrutia & Vuille, 2009), such as Andean wetlands (Otto & Gibbons, 2017; Dangles et al., 2017; Polk et al., 2017). Although mean annual rainfall is a critical climatic variable that determines the occurrence of wetlands, these ecosystems can also receive water inputs from glacier melt and underground water sources (Otto & Gibbons, 2017). Additionally, glacier shrinkage in areas with important glacier cover in the Andes will significantly impact landscapes and ecosystems (Madrigal-Martínez et al., 2022). These changes include the formation of new lakes, the fragmentation and attrition of former lakes, changes in the hydrological dynamics in glacier-fed streams and wetlands, the colonization of deglaciated areas, and upward migration of plants (Cuesta et al., 2019). Therefore, it is critical to increase my understanding of the potential impacts of future climate change on vegetation for both conservation efforts and human welfare (Tovar et al., 2022). The Cordillera Blanca, a mountain range located in Peru that contains about 70% of the world's tropical glaciers, has experienced glacier retreat, with a total glacier cover loss of ~800–850 km^2 in 1930, 660–680 km^2 in 1970, and 620 km^2 in 1990 (Georges, 2004). The decline in the Cordillera Blanca's sustained meltwater inflow may have led to soil desiccation and, therefore, wetland degradation, altering their distribution and coverage (Polk et al., 2017).

Climate change is transforming plant communities in mountain regions. Cold-adapted species are declining, while plant species adapted to warm environments are colonizing colder areas (Gottfried et al., 2012; Zhu et al., 2024; Zu et al., 2021). Because temperature decreases with altitude by 5–10 °C/km, temperature increases will reduce the aerial extent of the coolest climatic zones at the mountain peaks and modify vegetation belts. These changes will trigger shifts in the assembly of communities, lead to the formation of novel ecosystems (Williams et al., 2007), and alter ecosystem processes (Gottfried et al., 2012). Nonetheless, the balance of species' positive and negative responses to temperature increases and changes in precipitation patterns will determine their adaptation and survival. However, these responses are also affected by biotic and abiotic factors. For example, increases in plant productivity are enhanced by temperature, but they require optimal soil moisture levels and nutrient availability. Furthermore, different responses of plant species and functional groups to climate change are expected. For instance, grasses will respond better than cushion plants and prostrate plants to increases in temperature since they will compete well for light (Winkler et al., 2019).

Although it is anticipated that the effects of climate change will be significant in the tropical Andes, the extent of these impacts is still not well understood (Tovar et al., 2022). In this context, the main goal of this chapter is to explore the potential ecological impacts of climate change in a mountain landscape in the tropical Andes of Peru. In particular, I explore how projected climate conditions would alter ecosystems' structure and functioning. I used the climate data of three Global Circulation Models (GCM) for the Representative Concentration Pathways (RCP) scenarios 4.5 (an intermediate emissions scenario) and 8.5 (the most extreme emissions scenario) from 2020 to 2070 to capture the ecosystems' potential response to changes in temperature and precipitation, such as changes in herb and bare cover and primary production. My analysis also includes projected atmospheric carbon dioxide (CO_2) enrichment for each RCP. For the analysis, I parametrized the L-Range model, an ecosystem-process model (Boone et al., 2024) to simulate vegetation dynamics and biogeochemical processes, i.e., ecosystems response, under future climate conditions, such as plant growth, plant reproduction, water loss, and nutrient cycling (Boone et al., 2011). To the best of my knowledge, no similar simulation analyses have been performed to explore the potential ecological impacts of climate change in the tropical Peruvian Andes.

2. Study area

The study site is the Arhuaycancha valley of Huascarán National Park (HNP), located in the north-central Andes of Peru (Figure 3.1). HNP was established in 1975, with a delimiting boundary at 4000 m (Young & Lipton, 2006), covers 3400 km^2, and includes the Cordillera Blanca Mountain range (Chimner et al., 2019; Young & Lipton, 2006). The ecological gradients of the Cordillera Blanca influence their use by local communities. People cultivate wheat, barley, and Andean tubercles at lower elevations and intermontane valleys. The upper zones, i.e., areas with an elevation ranging from 3900 to 5000 masl, are used for livestock grazing. However, in some high-elevation valleys, livestock graze freely, i.e., no herders present (Young & Lipton, 2006). Large daily temperature changes and minimal temperature variations throughout the year characterize the climate in the Cordillera Blanca (Kaser & Georges, 1997). The precipitation follows a strong seasonal pattern, with a dry season from May to September and a wet season from October to April, during which about 80% of the annual precipitation occurs (Vuille et al., 2008). Soils in the area are mainly entisols, inceptisols, and histosols. Entisols are young and shallow soils, inceptisols are soils in the early stages of development, and histosols are peat soils with high organic matter and acidity, formed in areas of poor drainage (Polk, 2016).

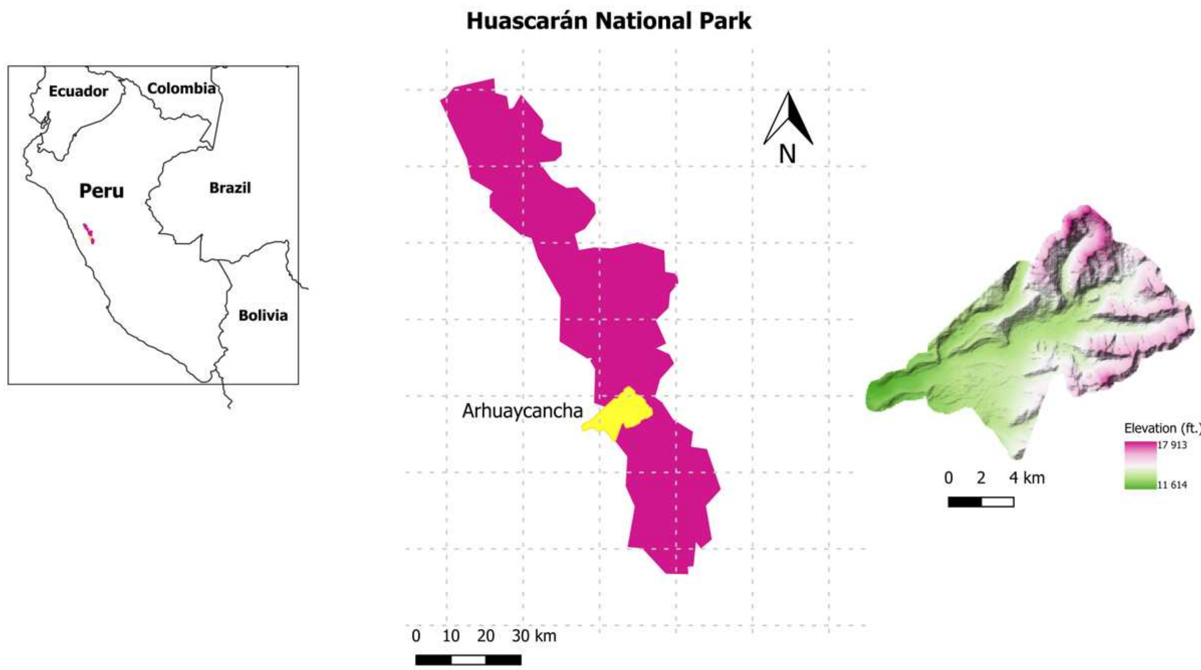

Figure 3.1. *Study area*

The principal characteristic of the park is the presence of tropical glaciers that occupy approximately 14% of its area (Chimner et al., 2019). These glaciers are critical for the functioning of various ecosystems, including wetlands, rangelands, and water bodies. The park's landscape is characterized by patches of wetlands, shrubs, and *Polylepis* sp. forests within a grassland matrix, with some areas under ecological succession due to glacier retreat (Young et al., 2017).

The Arhuaycancha valley is situated around Rio Negro, in the Rúrec catchment, in the province of Recuay, and drains to the Santa River. The elevation of Arhuaycancha valley ranges from 3540 to 5463 masl. The Uruashraju, Yanamarey, and Pucaraju glaciated mountaintops flank Arhuaycancha. Part of the valley lies in HNP, while the other part falls in the lands of the Cordillera Blanca community. The land cover of the Arhuaycancha valley consists of barren areas (56.4%), grasslands (13.4%), graminoid wet meadows (12.6%), peatlands (10.2%), snow/ice (2.4%), woodlands (1.5%), shrublands (1.3%), agricultural lands (1.1%), cushion wet meadows (1.0%), water bodies (0.2%), and developed areas (0.002%) (Chimner et al., 2019). Vegetation in the Arhuaycancha valley is patchy and heterogeneous.

Wetlands are primarily found in flat areas across the watershed. Woodlands and shrublands are mainly situated on mountain slopes. Grasslands are present on both mountain slopes and flat areas throughout the watershed.

3. Methodology

The simulation of ecosystem processes was performed using L-Range, the local version of the global rangeland model G-Range (Boone et al., 2018; Sircely et al., 2019). G-Range is a simulation tool that spatially explicitly represents ecosystems. The foundation of the biogeochemical modeling of G-Range is the CENTURY model (Parton et al., 1993), while other aspects of the ecosystem-process modeling come from the SAVANNA model (Coughenour, 1992). The biogeochemical processes that G-Range simulates are decomposition, N and C cycling, transpiration, primary production, and plant population dynamics for three types of plant functional groups or facets: herbs, shrubs, and trees. The vegetation facets represent the model's hierarchical structure and determine the vegetation cover dynamics. The herb facet includes a vegetation layer of herbs, a layer of herbs under shrubs, and a layer of herbs under trees. The shrub facet comprises a layer of shrubs and a layer of shrubs under trees (Figure 3.2). The tree facet consists only of a layer of trees. The plant parts of the herb facet consist of leaves and fine roots. The shrub and tree facets include those parts plus fine branches, coarse branches, and coarse roots. The L-Range model does not represent the hydrological processes of glaciers and underground water sources, such as meltwater flow and aquifer storage and flow.

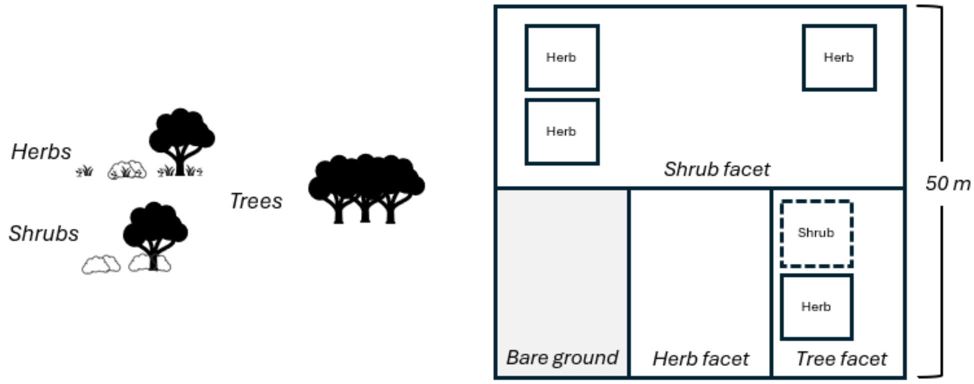

Figure 3.2. *Representation of vegetation layers by facet in L-Range.*

G-Range works with spatial surfaces and a set of soil, climatic, and plant parameters that determine plant growth, and other ecological attributes of the landscape (Boone et al. 2018). G-Range uses landscape cells to estimate biomass production and works with overstory and understory cover of the functional groups. Plant growth is determined by soil nutrients availability, plant reproduction is limited by seed production and soil moisture, and water loss is estimated based on transpiration and evaporation rates (Boone et al., 2011). G-Range's ability to simulate biogeochemical processes and plant dynamics makes it suitable for performing projections of rangeland ecosystems responses to climatic and management scenarios (Boone et al. 2018). G-Range consists of core state variables, plant, climatic, and soil parameters, and "hard-wired" parameters and variables derived from CENTURY and SAVANNA. These variables and parameters are assigned by landscape or grid cells, facets, or plant parts. L-Range simulates the same ecosystem processes as G-Range but on a local scale. For L-Range, the simulation area and resolution are established by the user. Moreover, L-Range can be linked to agent-based models to represent animal behavior and human decision-making and address different scenarios of interests, such as changes in land management, and stocking density (Boone et al., 2024).

3.1 Model parametrization and implementation

Implementing the L-Range model required the parametrization of 54 climatic, edaphic, and plant variables. I also provided L-Range with spatial surfaces that contain landscape information, such as fractional vegetation cover, topographic features, and soil properties. The tree, shrub, and herb fractional cover were obtained from the EarthEnv 1-km dataset (Tuanmu & Jetz, 2014). Soil physical and chemical properties data, e.g., texture, coarse fragments, and soil organic carbon, was derived from the SoilGrids250m database (Hengl et al., 2017). The slope was derived from the Shuttle Radar Topography Mission (SRTM) imagery, which consists of a fine-resolution (30 m) topographic map. The land cover map of the study area was obtained from Chimner et al. (2019). All these layers were resampled to 50 m, i.e., the spatial resolution of my analysis, and were georeferenced to the WGS84 datum, UTM projection Zone 18, using the free open source QGIS Geographic Information System software (version 3.20 Odense, QGIS Development Team, 2021).

Critical variables of L-Range are monthly mean minimum and maximum temperature and monthly precipitation. This data was obtained from the Climatologies at high resolution for the earth's land surface areas (CHELSA version 1.2) dataset. CHELSA provides high resolution (~ 1 km) and long-term (1979, onwards) climate data with global coverage. Climate data from CHELSA are based on a quasi-mechanistical statistical downscaling of the ERA-Interim global circulation model with Global Precipitation Climatology Centre (GPCC) and a Global Historical Climatology Network (GHCN) bias correction (Karger et al., 2017). Additionally, CHELSA data has topographic adjustments based on the surface altitude and orography from the Global Multi-resolution Terrain Elevation Data (*GMTED2010*). I downloaded monthly mean minimum and maximum temperatures (K) and monthly mean precipitation (kg m^{-2}) historical (1970 to 2005) and projected raster data (2006 to 2100) from CHELSA.

Climate projection data came from the RCP4.5 and RCP8.5 pathways of three global circulation models: the Australian Community Climate and Earth System Simulator (ACCESS1.3) model, the Community Earth System Model version 1.0 with Biogeochemistry (CESM1-BGC), and the Euro-Mediterranean Center on Climate Change Climate Model (CMCC-CM).

The scenarios under analysis also included ecosystems' responses to projected atmospheric carbon dioxide (CO_2) enrichment for the RCP 4.5 and RCP 8.5 projections used by the IPCC (Meinshausen et al., 2011). I included the atmospheric CO_2 enrichment projections to analyze vegetation responses to changes in CO_2 concentration. L-Range can estimate plant productivity in response to CO_2 fertilization, which originally was implemented in the CENTURY model by Parton et al., (2001). Changes in plant productivity are calculated using a production correction factor:

$$1 + (CO_2ipr - 1)/(\log_{10}(2) * \log_{10} (CO_2\ concentration/350)$$

Where CO_2ipr is the multiplier on plant production of doubling the atmospheric CO_2 concentration from 350 ppm to 700 ppm and was 1.25. Also, I used 2006 as the baseline year to capture CO_2 enrichment effects and additional corrections to plant productivity respected the CENTURY model (e.g., a correction factor for proportion live material per vegetation layer), and therefore a constant (0.20) was subtracted from the values. Thus, the RCP4.5 values ranged from 0.8 historically to 0.915 in 2070 while the RCP8.5 values spanned from 0.8 to 1.008; for my analysis I used the same curve for all vegetation cover classes.

Using a Python script, I extracted the climate data to a reference region, projected it, resampled it to 1 km, and converted the data units to Celsius for temperature and millimeters for precipitation. Next, I projected the climate data to the UTM projection Zone 18, resampled them to a 50 m resolution, and trimmed them to the two study sites using the projectRaster and crop functions of the “raster” (Hijmans et al., 2015) package in R (version 4.1.1) using RStudio (version 1.4.17.17). All resampling used nearest neighbor methods. The landscape units included the natural vegetation classes from the land cover map developed by Chimner et al. (2019), i.e. grasslands, shrublands, woodlands, cushion wet meadows, graminoid wet meadows, and peatlands.

3.2 Model initialization, calibration, and evaluation

I initialized the L-Range parameters using Boone et al. (2018) values as reference and modified them based on a literature review of studies conducted in high-elevation regions. The calibration of L-Range involved adjusting the various plant facets and soil parameters for the different vegetation cover classes. Some parameters adjusted include the death rate of shoots, leaves, and roots, seed production, herb and wood cover effect on plant establishment, soil drainage affecting anaerobic decomposition, and plant temperature production. The two “hard-wired” parameters of L-Range that were modified were heat accumulation and temperature effect on decomposition.

Since my main goal was to control vegetation dynamics and ecosystem processes, I adjusted the L-Range model parameters until the variables of interest, i.e., Aboveground Net Primary Productivity (gm^2yr^{-1}), soil organic carbon (gm^2yr^{-1}), facet cover (%), and bare cover (%), were similar to estimations from peer-review articles and theses and surfaces derived from MODIS data (Myneni, Knyazikhin, & Park, 2015) (Figure 3.3). I validated the Aboveground Net Primary Productivity using MODIS data from 2000 to 2020 for the different cover classes. I download the MODIS data using the Application for Extracting and Exploring Analysis Ready Samples (AppEEARS TEAM 2022). However, it is important to note that despite significant progress in vegetation mapping and monitoring using remote sensing data over the decades, gaps remain, particularly in degradation assessments. Moreover, accurate estimations of primary production through remote sensing still require ground validation that incorporates site-specific features and detailed in situ data (Abdelmajeed and Juszczak, 2024).

All simulations were performed with a 100-year spin-up simulation from 1970 to 2069. I run the L-Range model for a 100-year spin-up time to allow the model’s state variables to reach an equilibrium. I used the values of the state variables from the final day of the spin-up simulation as the initial values for the simulations. I ran simulations for a 50-year period (2020 – 2070). Due to time constraints, I performed four repetitions for the current climate conditions and the RCP4.5 future climate change scenarios and two repetitions for the RCP8.5 scenario. I created average raster layers to analyze the spatial structural and functioning changes in the ecosystems under analysis, such as changes in facet cover and aboveground net primary production. I calculated the mean value for all repetitions of all climate data models (ACCESS, CMCC, and CESM1) for the RCP 4.5 scenario for 2030 and 2070. I created these layers in QGIS using the raster calculator.

The time required to perform the simulations with the L-Range model was approximately 12 hours per repetition. These simulations took longer because the L-Range model was linked to the land management dynamics and grazing behavior sub-models, which were essential for estimating the biomass consumed and left on the grazing fields, information that is necessary for simulating primary production. Due to time constraints, I reduced the number of repetitions per scenario. I conducted four repetitions per global circulation model for the RCP4.5 scenario and two repetitions for the RCP8.5 scenario. After completing these repetitions, I estimated the coefficient of variation across repetitions and found minimal variations. While performing more repetitions at a faster pace could be achieved using a supercomputer, if such infrastructure is unavailable and simulation time needs to be reduced, one option would be to modify some processes. For instance, instead of modeling livestock movement on an hourly basis and subsequently estimating hourly forage intake, these processes could instead be estimated on a daily or monthly basis.

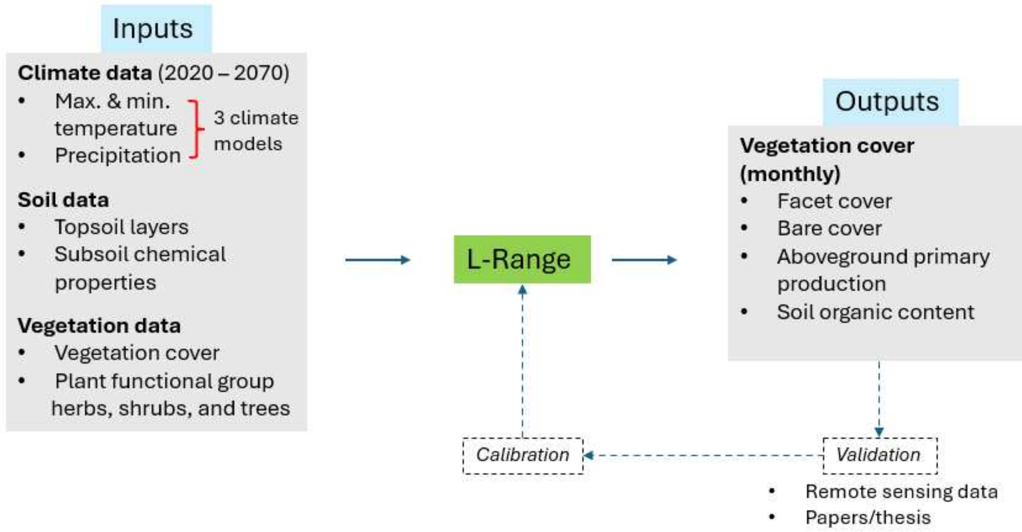

Figure 3.3. *Workflow of the parametrization and validation of L-Range.*

4. Results

I present 50-year simulation results of ecosystems' responses to projected atmospheric carbon dioxide enrichment and temperature and precipitation changes for the 4.5 and 8.5 Representative Concentration Pathways (RCP) of three global circulation models. Additionally, I include simulation results of the "current-climate conditions" scenario, created using historical data (1970 to 2020), as a reference. Since I found minimal variation across repetitions, I present the average results for each scenario to facilitate the analysis.

4.1 Changes in ecosystems productivity

4.1.1. Aboveground Net Primary Production (ANPP)

Woodland ecosystems will respond favorably to future climate conditions (RCP 4.5 and 8.5), i.e., atmospheric carbon dioxide enrichment and temperature increases, becoming the most productive ecosystem. Shrublands will also respond positively, but only to the less extreme scenario (RCP 4.5). However, under the most extreme climatic scenario (RCP 8.5), shrublands productivity will decline from 2050 onwards. On the contrary, all three wetland types are expected to be less productive under future climate conditions (RCP 4.5 and 8.5), with graminoid wet meadows most adversely impacted (Figure 3.4). The ANPP of grasslands, cushion wet meadows, and graminoid wet meadows will fluctuate most over time, regardless of the scenario. Additionally, from 2040 onwards, the three wetland types will exhibit a marked decrease in ANPP of about 50% compared to 2020, regardless of the scenario.

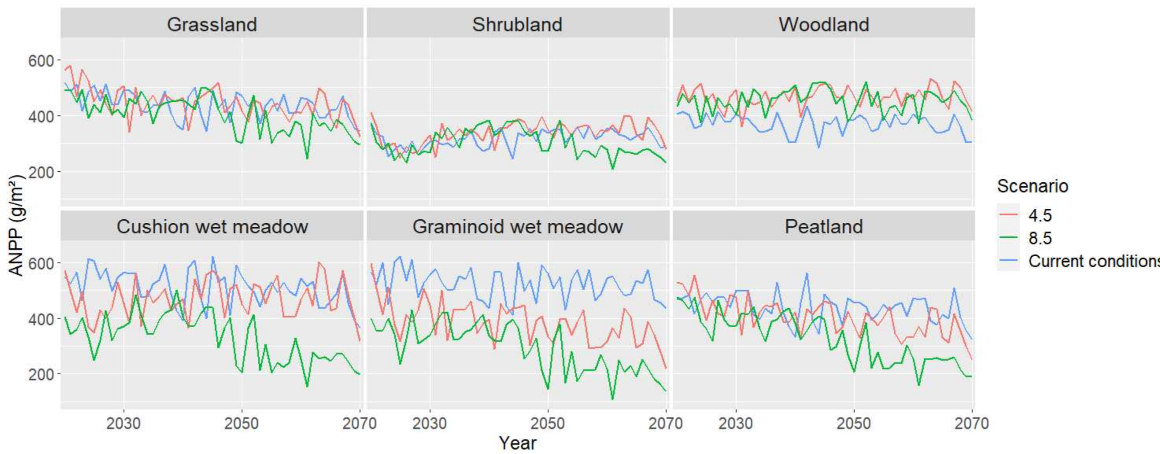

Figure 3.4. *Changes in Aboveground Net Primary Production (ANPP) by cover class and scenario*

4.1.2. Soil organic carbon (SOC)

The SOC of grasslands, shrublands, and woodlands will increase over time across all scenarios, with higher values for both climate projection scenarios than the "Current Conditions" scenario (Figure 3.5). In the case of wetlands, only graminoid wet meadows will have a positive trend on SOC accumulation, with higher values for the "Current Conditions" scenario. Peatlands and cushion wet meadows will exhibit a decreasing SOC accumulation trend over time.

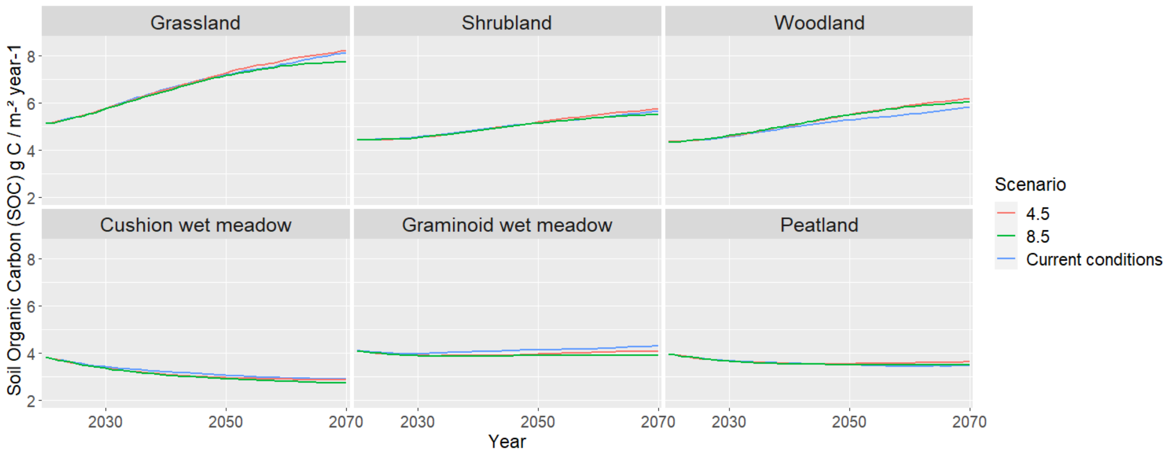

Figure 3.5. *Changes in Soil Organic Carbon (SOC) by cover class and scenario*

4.2 Changes in facet cover

4.2.1 Herb cover

Changes in herb cover (forbs, grasses, and graminoids) did not vary markedly across cover classes (Figure 3.6 and Figure 3.7). Across the three wetland classes, herb cover showed a slightly declining trend under the analyzed scenarios; however, this decline is projected to be minimal. By 2050, the expected decline in herb cover is projected to be 1.5% for graminoid wet meadows and peatlands, and 2% for cushion wet meadows (Figure 3.6). Changes in herb cover for the other cover classes were more variable, particularly in shrublands. The herb cover of grasslands is expected to increase by up to 6.3%, while the herb cover in woodlands is projected to decrease by about 14.8% compared to 2020. Although changes in herb cover for shrublands exhibited a dynamic pattern, the overall range of change, whether increases or decreases, was only about 1.6% (Figure 3.7).

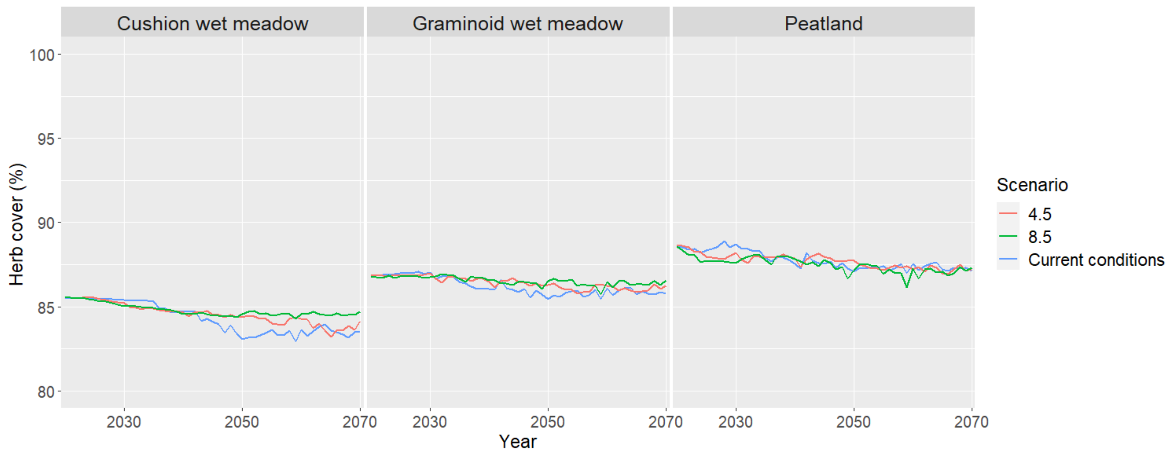

Figure 3.6. *Changes in herb cover (%) for wetlands by scenario*

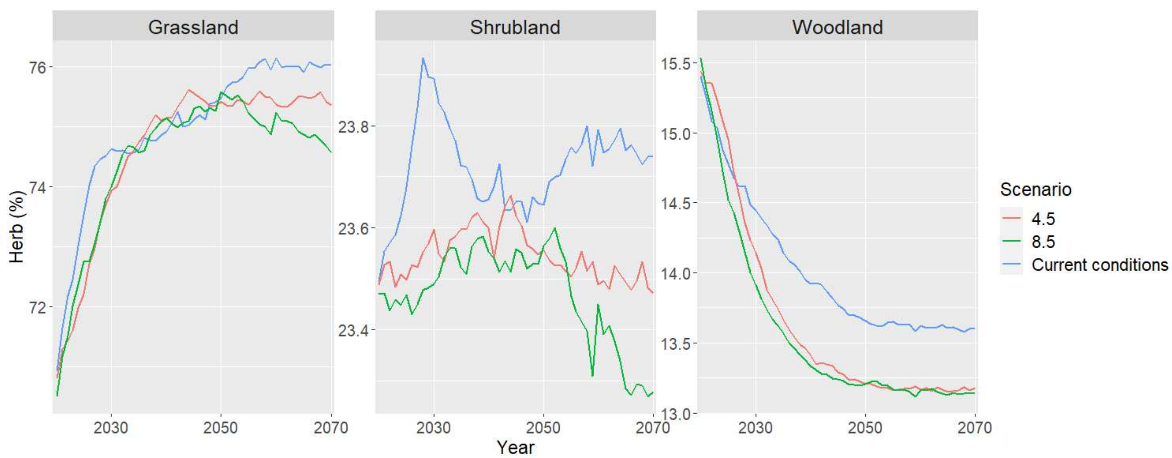

Figure 3.7. *Changes in herb cover (%) for grasslands, shrublands, and woodlands by scenario*

4.2.2 Shrub cover

Changes in shrub cover of grasslands and wetlands were more dynamic compared to other vegetation cover classes (see Figure 3.8 and Appendix B2). In grasslands, shrub cover showed a declining trend, decreasing from 10% to approximately 4% by 2050 across all scenarios analyzed, which represents a reduction of about 50% from its initial value. For wetlands, the shrub cover exhibited a decreasing trend under the RCP4.5 and RCP8.5 scenarios. The reductions in shrub cover by 2050 was 5.6% for cushion wet meadows, 20% for graminoid wet meadows, and 33% for peatlands

(Figure 3.8) compared to initial value. In contrast, the shrub cover of shrublands, and woodlands remained relatively stable across time and scenarios (Appendix B2). Regarding tree cover, slight variations were observed across time for all cover classes analyzed (Appendix B3).

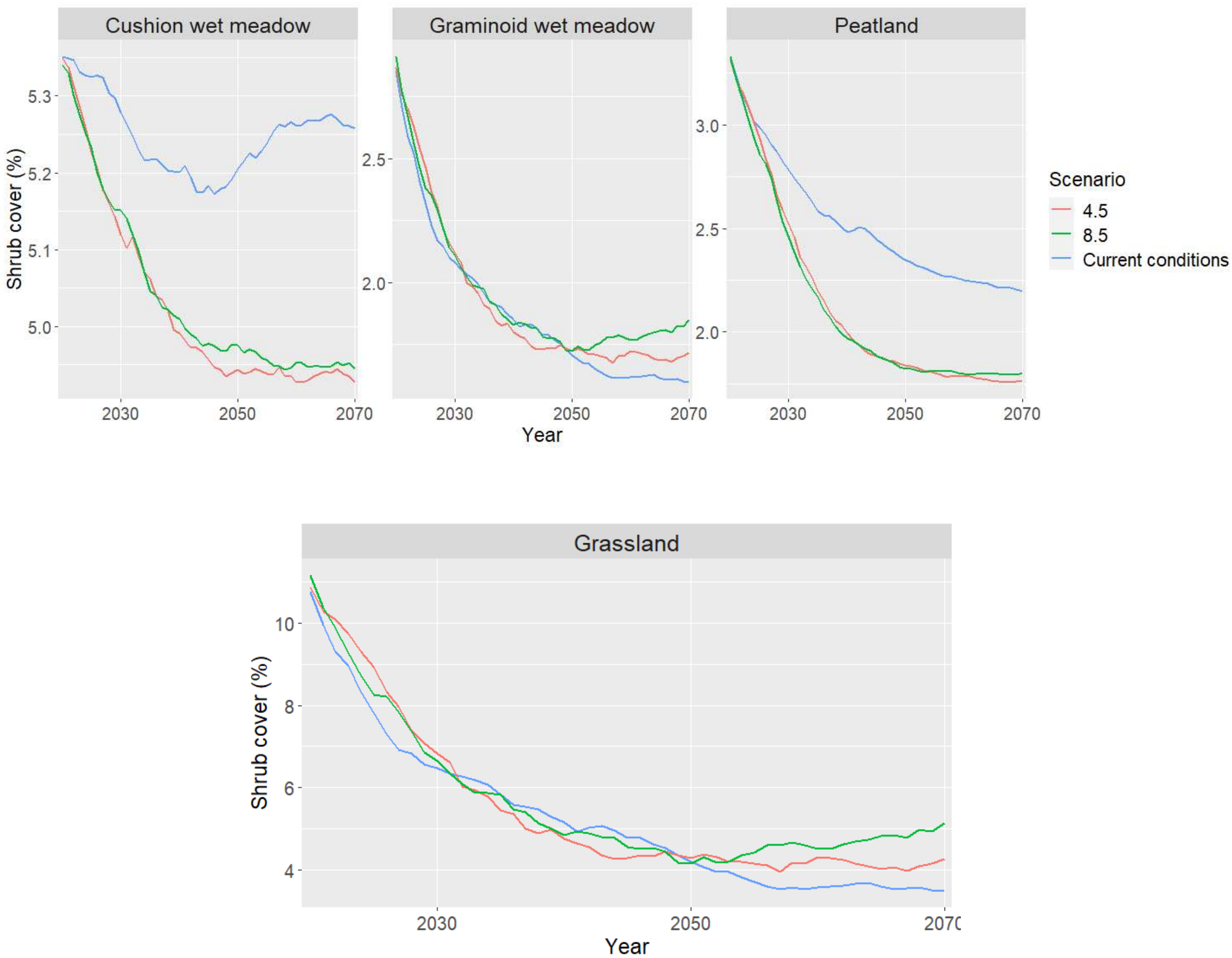

Figure 3.8. *Changes in shrub cover (%) for wetlands and grasslands*

4.3 Changes in bare ground cover

The bare cover across different vegetation classes showed a positive trend in all scenarios, with a marked increase observed in wetlands (see Figure 3.9 and Appendix B4). Changes in the bare cover of grasslands, shrublands, and woodlands were much less variable. The percentage of bare cover in the climate projection scenarios was higher than in the 'Current Conditions' scenario for all classes except cushion wet meadows and graminoid wet meadows, where the percentage was greater under "Current Conditions" scenario (Figure 3.9). By 2050, the bare cover of cushion wet meadows, peatlands, and graminoid wet meadows increased by approximately 66%, 40%, and 20%, respectively, compared to 2020. In contrast, grasslands and shrublands saw a more modest increase of about 14%, while woodlands increased by only 10%.

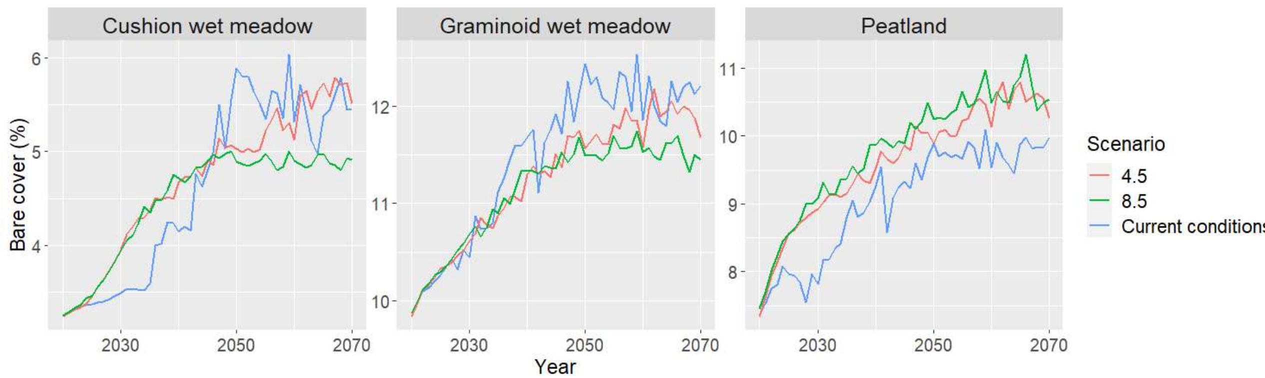

Figure 3.9. *Changes in bare cover (%) for wetlands*

4.4 Spatial changes in ANPP

For the analysis of spatial ANPP changes, I present the difference between the average ANPP from the RCP4.5 scenario and the "Current Conditions" scenario for 2030 and 2070 (Figure 3.10). Flat areas east of the watershed will have higher ANPP (green color) under future climate projections, indicating that the vegetation in this area will become markedly more productive. The cover classes that will benefit from these increases will be shrublands and peatlands. In contrast, wetlands and grasslands in the middle of the watershed will exhibit a reduction in ANPP (fuchsia color).

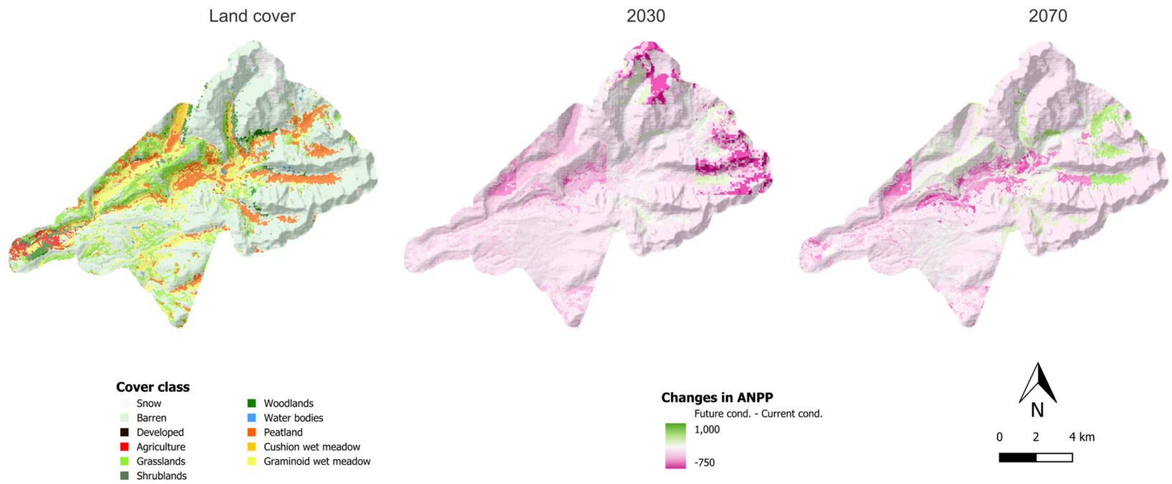

Figure 3.10. *Spatial variation of ANPP for 2030 and 2070*

4.5 Spatial changes in herb and shrub cover

The difference in herb cover between the average RCP 4.5 climate scenario versus the "Current conditions" scenario in the west and the middle zones of the watershed will be positive, indicating more herb cover under future climate conditions (Figure 3.11). The cover classes positively affected by these changes are grasslands, cushion wet meadows, graminoid wet meadows, and peatlands. In contrast, the herb cover in the middle and the low zone of the east part of the watershed will decrease under future climate conditions, affecting grasslands, peatlands, and graminoid wet meadows. Additionally, the herb cover of some patches in barren areas in the lower-east part of the watershed will increase under future climate change conditions.

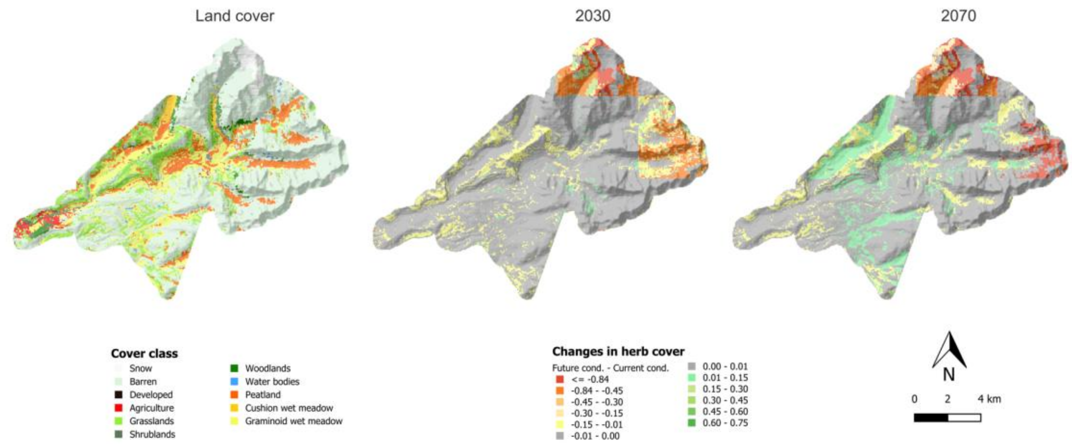

Figure 3.11. *Spatial variation of herb cover for 2030 and 2070*

Under future climate conditions, shrub cover will decrease in the upper northern part of the watershed, especially on mountain slopes. In contrast, shrub cover in the middle of the watershed, where grasslands and graminoid wet meadows are located, will increase (Figure 3.12).

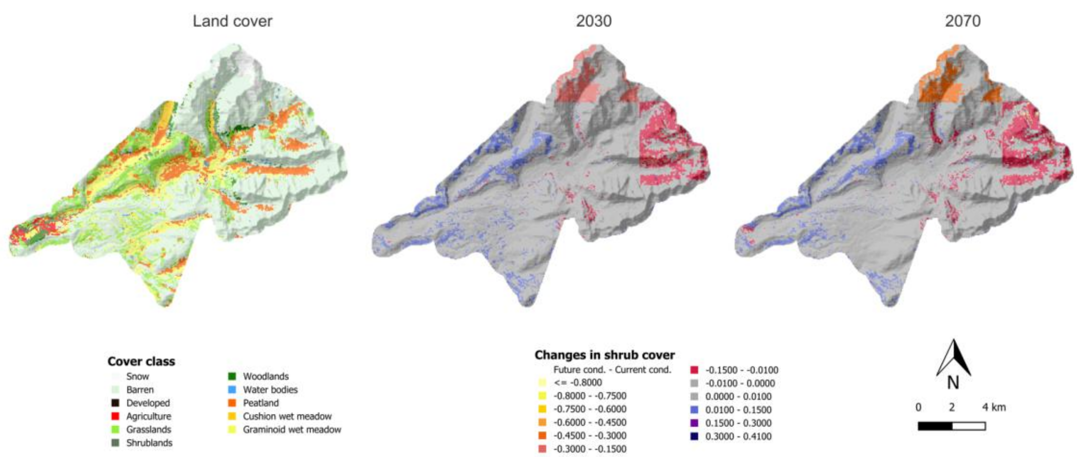

Figure 3.12. *Spatial variation of shrub cover for 2030 and 2070*

4.6 Spatial changes in bare cover

The bare cover will increase under future climate conditions in the watershed's west and middle zones, negatively impacting grasslands, cushion wet meadows, graminoid wet meadows, and peatlands.

Increases in bare cover in these zones will occur in flat areas and on mountain slopes. Moreover, the bare cover in the middle of the watershed will expand. The bare cover of the lower areas on the southeast side of the watershed will decrease under future climate conditions. Conversely, the bare cover in the high-elevation zones in this area will increase under future climate conditions. Similarly, the bare cover in high-elevation zones on the northeast side of the watershed, close to glaciers, will increase (Figure 3.13).

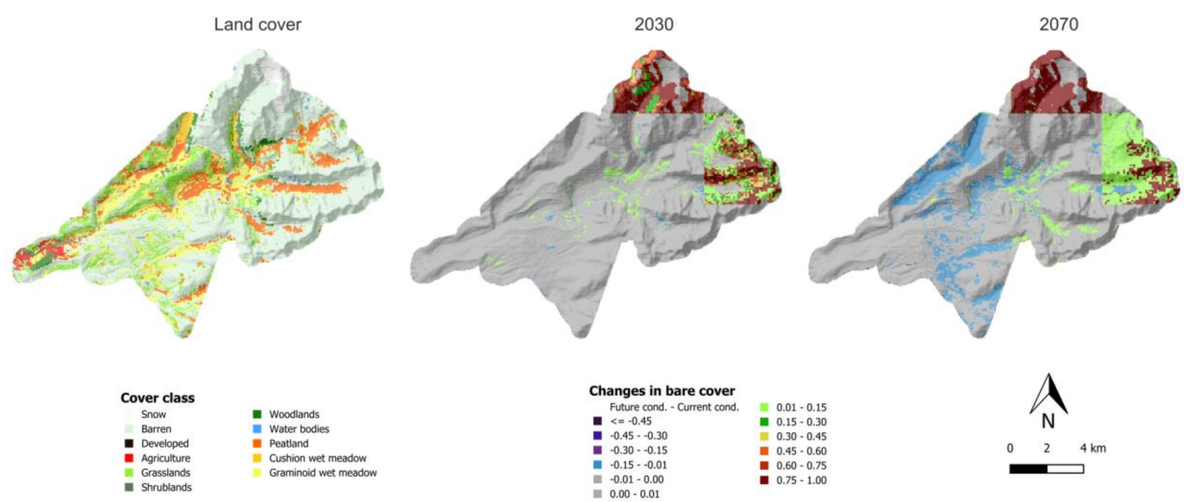

Figure 3.13. *Spatial variation of bare cover for 2030 and 2070*

5. Discussion

Though no similar modeling studies at my level of analysis have been implemented to analyze climate change impacts in the Peruvian Andes, previous studies that used different analytical approaches, such as remote sensing, species distribution models, and field experiments in Andean regions, support my findings. Furthermore, I analyze my findings in relation to other studies conducted in alpine regions around the globe.

5.1 Changes in ANPP

The temperature in the Andes has increased over the past sixty years by about 0.10 °C/decade (Vuille et al., 2008), altering ecosystem processes, functioning, and distributions (Beniston, 2003; Urrutia & Vuille, 2009). Moreover, climate projections reveal that precipitation patterns in the Andes will be highly variable under future climate conditions, with different patterns and distributions for the eastern and western slopes (Tovar et al., 2022). Precipitation patterns and temperature changes affect plant species differently, triggering their range expansion or contraction (Gwate et al., 2023). Temperature increases will reduce the coolest climatic zones at mountain peaks, modify vegetation belts (Williams et al., 2007), and alter species composition. These changes will alter the assembly of communities, create novel ecosystems (Williams et al., 2007), and modify ecosystem processes (Gotfried et al., 2012).

The complex topography and climate of the Andes, with a diversity of biomes, suggest different vulnerabilities and responses of ecosystems to climate change (Young et al., 2011; Tovar et al., 2013). I found that future climate conditions will positively impact woodlands (RCP 4.5 and 8.5) and shrublands (only RCP 4.5), i.e., these ecosystems will become more productive. Nonetheless, under the most extreme climate scenario (RCP 8.5), all ecosystems except for woodlands will be less productive, particularly from 2050 forward. Though no past studies in the Peruvian Andes have estimated future trends in ANPP, Polk et al. (2020) used the Normalized Difference Vegetation Index (NDVI) as a proxy to assess vegetation changes in this region from 2000 to 2017. They found that greening (a positive trend in NDVI, related to increased vegetation) outpaced browning (a negative trend in NDVI, related to decreased vegetation), with 15.1% of the Andean highlands categorized as highest greening and 4.1% as highest browning. These findings indicate that vegetation biomass increased from 2000 to 2017, aligning with my simulation results that indicate that ecosystems will become more productive. Using a similar approach, Choler et al. (2021) found that the uplands of the European Alps undergone increased greening from 2000 to 2020, with high-elevation ecosystems responding favorably to summer warming.

Moreover, areas with sparse vegetation on north-facing slopes that had prolonged snow cover showed the highest responses to warming.

Gao et al. (2016) found that the Net Primary Production of vegetation in alpine ecosystems (>4000 m) in the Qinghai-Tibetan Plateau in Central Asia would significantly increase by 79% and 134% under the RCP4.5 and RCP8.5 scenarios from 2020 to 2080, with variations across space. The authors attribute these changes to a positive response of vegetation to increasing precipitation, temperature, and CO_2 concentrations. Moreover, vegetation found in more favorable hydrothermal conditions, primarily coniferous and broadleaf forests, had the highest Net Primary Production under the RCP8.5. Similarly, Li et al. (2024) found that the Gross Primary Production in the Qinghai-Tibetan Plateau will significantly increase over the 21st century under all future climate scenarios (RCP2.6, 4.5, 7.0, and 8.5), with variations across regions. By 2100, the annual Gross Primary Production is projected to reach about 1011.98 Tg C, 1032.67 Tg C, 1044.35 Tg C, and 1055.50 Tg C for the different scenarios, representing increases of approximately 0.36%, 4.02%, 5.55%, and 5.67% relative to the 2021 Gross Primary Production.

Spatial changes in ANPP will be variable across the watershed. Flat areas in the east-upper part of the watershed, consisting of peatlands, will become more productive. In contrast, wetlands and grasslands in the middle of the watershed will be less productive. Moreover, in general, mountain slopes of the watershed will become more productive over time. These findings can be supported by Polk et al. (2020), who found that greening trends in the Peruvian Andes occurred with major frequency in high-elevation areas (>5000 masl) while browning was dominant in areas below 5000 masl. Nonetheless, it is important to indicate that estimations of ANPP changes also require analyzing the factors that triggered these changes. For instance, the impacts of a grassland becoming more productive at the expense of gaining more shrub cover will differ from those of a case where grassland production is higher due to increased carbon sequestration by herbs. This difference would have ecological and land management implications, such as improving primary production at the ecosystem level and reducing the amount of palatable forage for livestock.

5.2 Changes in herb cover

Changes in herb cover will be minimal, remaining relatively constant across cover classes and scenarios, indicating that climate change will not trigger rapid major changes in herb cover. Tovar et al. (2013) created multiple logistic regression models to determine the distribution of Andean biomes using climate data from the Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model. They found that at the biome level, i.e., not considering plant physiology and species composition, most Andean biomes will remain within the same biome, opposing what is predicted for species. Though gradual changes in species composition will not cause immediate alterations at the biome level, these changes, e.g., alterations in understory vegetation or vertical structure, can alter ecosystem structure functioning (Tovar et al., 2013). For example, soil chemical properties and processes are affected by the quality and quantity of litter inputs (Vivanco et al., 2024).

In a recent study, Cuesta et al. (2023), using information from permanent plots in 45 mountain summits across the high Andes of South America, found that the vegetation in the high Andes is changing, with an average loss of vegetation cover (mean = −0.26% / yr) and a gain in species richness across summits (mean = 0.38 species m^2/yr). The subalpine areas gained vegetation cover while vegetation in the alpine, subnival, and nival areas lost vegetation cover. Species changes were positively associated with minimum air temperature and soil temperature rate of change. At the plant community level, species composition shifted towards species with broader thermal niches.

I also found that the herb cover of wetlands and grasslands varied the most across years compared to the other vegetation classes. The herb cover of wetlands had a declining trend from 2050 onwards, while in the case of grasslands, the herb cover exhibited an increasing trend from the first years of the simulation until it reached stability around 2050. The high variability in the herb cover of wetlands can be associated with alteration in their water inputs. A critical environmental driver determining Andean wetlands' occurrence within a watershed is the mean annual rainfall. However, wetlands can receive water inputs from glacier melt and underground water sources. Projected decreases in mean annual rainfall and increased variability in spatial rainfall patterns might affect the spatial distribution of Andean wetlands (Otto & Gibbons, 2017). Moreover, temperature increases and glacial shrinkage over the next decades will alter the inputs to wetlands from water runoff from melting glaciers, affecting wetlands' hydrological balance and altering their extent and number (Young et al., 2011).

Changes in herb cover in the watershed will not be uniform. Under future climate conditions, the west and middle zones of the watershed will have more herb cover, positively impacting grasslands, cushion wet meadows, graminoid wet meadows, and peatlands. However, future climate conditions will reduce the herb cover of grasslands, peatlands, and graminoid wet meadows in the middle and lower east of the watershed. The location of Andean ecosystems in various landscape settings (valley areas and mountain slopes) and their composition (species taxonomy and physiology) create the conditions for different ecosystem responses to climate change and, therefore, different climate change impacts on them (Young et al., 2011).

5.3 Changes in shrub and bare cover

Shrub cover did not broadly vary across scenarios. The shrub cover of grasslands decreased from 10% to approximately 4% by 2050. The shrub cover of wetlands exhibited a negative trend over time, with reductions of 5.6% for cushion wet meadows, 20% for graminoid wet meadows, and 33% for peatlands. Spatial changes in shrub cover in the watershed will not be uniform. Shrub cover will decrease in the upper northern part of the watershed. However, it will increase on mountain slopes covered by shrublands and woodlands, while decreasing on those covered by grasslands and cushion wet meadows.

There is a global trend of conversion of semi-arid and mesic grasslands to shrub-dominated areas and shrub encroachment of wetlands. These cover changes are associated with warming, the shrub occupation of water-limiting environments (grasslands), and increases in atmospheric CO_2 (Saintilan & Rogers, 2015). Nonetheless, changes in shrub and tree cover in alpine grasslands are constrained by low temperatures, reduced precipitation, and grazing (Snell et al., 2022). In the tropical Andes in South America, natural grasslands above 4000 masl have undergone significant increases in woody vegetation from 2001 to 2014. The woody expansion seemed associated with increased temperature and drier conditions, which could have facilitated shrub encroachment and tree expansion above the treeline (Aide et al., 2019). Temperature increases will exert more pressure on water availability, creating conditions for expanding more drought-tolerant biomes. In contrast, glacier and cryoturbated areas, humid puna, montane shrubland, xeric pre-puna, and evergreen montane forest will undergo upslope displacement of their upper boundary, resulting in a gradual replacement of one biome with another (Tovar et al., 2013).

While studies have identified a global trend of shrub expansion in grasslands and wetlands, this was not observed in the Arhuaycancha Valley. Instead, a slight decline in shrub cover was noted, which can be attributed to various factors. For example, although I parameterized and calibrated the L-Range model to the biophysical conditions of Arhuaycancha, the model was not originally designed for application in alpine regions. Therefore, some processes within the model need to be adjusted to properly simulate alpine ecosystems, such as root growth and decay and seed production. Additionally, the resolution of the data used for model parameterization and the climate scenarios, such as the plant functional group map (1 km) and climate projection data (1 km), may have hindered the L-Range model's ability to capture vegetation responses to changes in climate conditions occurring at much finer scales. It is also important to note that while the L-Range model can simulate changes in vegetation composition (herbs, shrubs, and trees) within specific cover classes (e.g., grasslands, shrublands, and wetlands), it cannot simulate changes in the upper or lower boundaries of these cover classes.

Studies on shrub occurrence in alpine areas have found that shrub expansion is influenced by both climatic conditions and topographical factors. For instance, Bayle et al. (2024) found that topographic factors limiting water availability, such as elevation, slope, and aspect, affect the distribution of mountain Ericaceae-dominated shrublands in the European Alps. Additionally, changes in the upper elevation boundaries of shrublands are influenced by low temperatures.

Similarly, De Toma et al. (2021) found that the distribution of dwarf shrubs from 1960 to 2020 in the Central Apennine region of Italy was strongly affected by fine-scale topography, microclimate, soil features (productive sites vs. poor arid soils), and grazing pressure. De Toma et al. (2021) indicated that dwarf shrubs are mainly associated with harsh environmental conditions and strong resource limitations. Moreover, dwarf shrubs showed poor competitive ability to invade grasslands compared to woody areas.

Also, shrub expansion also depend on the physiological response of shrub species. For instance, Ven et al. (2021) analyzed the temperature range for germination of Australian alpine shrubs. They found that while some shrub species can successfully germinate at high temperatures, others appear to be limited by inherent seed dormancy. The authors indicate that shrub expansion in alpine areas will be associated with conditions that influence seed germination at the microsite scale.

Bare cover increased across all scenarios and cover classes, with marked increases for the three wetland classes. The bare cover areas will expand in flat areas and mountain slopes of the watershed, affecting grasslands, cushion wet meadows, graminoid wet meadows, and peatlands. Lower areas on the southeast side of the watershed will undergo a reduction in bare cover, while the bare cover in high-elevation areas close to glaciers will increase. In the Peruvian Andes, more specifically in Huascarán National Park, Young et al. (2017) found varying land cover changes from 1987 to 2010. From 1987 to 1999, some tropical alpine vegetation areas contracted, creating new barren sites. From 1999 to 2010, the cover of alpine vegetation increased due to plant succession in barren lands and the expansion of grasses and shrubs, mainly on the north and northeast-facing slopes.

Though I found increases in bare cover in areas next to glaciers, the scale of my analysis (50 m) could have hindered detecting ecological changes occurring at a finer scale. For example, glacier retreat creates conditions conducive to ecological succession, as newly exposed barren lands provide substrates that are prone to colonization by forbs and graminoids (Young et al., 2017). However, early plant succession following glacier retreat is not a stochastic process; rather, it is influenced by the local ecological context (Bayle et al., 2023).

5.4 Changes in Soil organic carbon

Although I validated the L-Range model with the best available data for Andean ecosystems, it is noteworthy to indicate thatI am cautious about the model's SOC estimations. The complexity of ecosystems, the limited understanding of soil ecological processes in ecosystems such as peatlands, and the limited information available could affect the model estimations. For example, Chimner et al. (2023) found significant differences in the carbon stocks between peatlands and wet meadows in Huascarán National Park. Carbon stocks in peatlands varied from 278 to 4,740 MgC ha^{-1} with a mean of 1092 MgC ha^{-1} in Huascarán National Park. In contrast, carbon stocks in wet meadows ranged from 3 to 181 MgC ha^{-1} with a mean of 30 MgC ha^{-1}. This broad range of SOC for these wetland types highlights the challenges for the initialization and parametrization of the soil carbon processes module of L-Range.

Moreover, information about SOC is site-specific, especially in areas with highly variable topography, such as the Andes. Therefore, SOC from a different region or quantified at different elevations cannot be directly compared with my estimations. For instance, I only found one study that estimated soil carbon content near the study area. Vivanco et al. (2024) estimated the soil carbon content for *Polylepys sp*. forest in Ulta Valley at Huascarán National Park. They found that through an elevation gradient (3500 and 4500 masl), *Polylepys sp*. forests soils located at intermediate elevations (

~4000 masl) had a thicker soil organic layer and, therefore, higher soil organic carbon stock (154.2 Mg C ha^{-1}), than those located at higher (26.2 Mg C ha^{-1}) and lower elevations (34.8 Mg C ha^{-1}).

Caveats

The heterogeneous nature of the Arhuaycancha landscape, characterized by high variability in vegetation and soil properties, poses a challenge for accurately modeling ecosystem processes. For example, the elevation gradient across the valley results in rapid variations in temperature and humidity. These conditions, along with diverse soil types and properties, are not adequately represented by the L-Range model, reducing its effectiveness in capturing the dynamics of the ecosystems. Furthermore, the accuracy of the L-Range outputs is constrained by the spatial resolution of the input data. Although I used the best available data for model parameterization and validation, the lack of high-resolution data for climate projections, slope, and plant functional groups may have affected the model estimations.

In addition, field studies of vegetation dynamics and ecosystem processes in the Andes, such as aboveground and belowground primary production and nitrogen and carbon cycling, are limited, which hindered model parameterization and calibration. For instance, it was particularly challenging to calibrate soil organic carbon (SOC) accumulation for wetlands. As mentioned in the discussion section, the SOC range in the valley markedly varies across wetland types. For example, Carbon stocks in peatlands ranged from 278 to 4,740 MgC ha^{-1} and from 3 to 181 MgC ha^{-1} for wet meadows (Chimner et al., 2023).

Lastly, because L-Range does not model glacier or hydrological dynamics, the impacts of changes in precipitation, glacier retreat, and groundwater on ecosystem process simulations remain uncertain. Additionally, wildfires were not incorporated into L-Range due to limited data on wildfire occurrences and their triggering factors, such as litter accumulation, moisture content, and wind patterns.

6. Conclusion

The ecological impacts of climate change on Andean ecosystems will be variable across cover classes and scenarios. This variability will also occur at the spatial level. Increases in temperature and changes in precipitation patterns will create the conditions for woodlands and shrublands to become more productive. However, these conditions will not be favorable for wetlands. Nonetheless, the productivity of all cover classes will be negatively impacted under the most extreme climate conditions scenario. Changes in herbs will be minimal. However, the herb cover of wetlands and grasslands will be the most variable across cover classes. Wetlands will undergo a reduction in herb cover from 2050 onwards. The herb cover reduction in wetlands can be associated with the temporal and spatial alteration of water inflows, i.e., precipitation, underground water, and glacier retreat water inputs. Shrub cover changes will also be minimal, with the shrub cover of grasslands being the most variable across cover classes. Under future climate conditions, bare cover will increase in all cover classes. However, this increase will be larger for wetlands. Furthermore, the spatial distribution of bare cover will broadly vary across the watershed. For instance, it will increase in flat areas and some mountain slopes but decrease in low-elevation areas in the basin mouth. In contrast, bare cover will increase in areas close to glaciers. The SOC will increase over time across the area except for peatlands and cushion wet meadows.

I identified the ecological processes, ecosystem attributes, and cover classes that will be more affected by climate change. Moreover, my spatial explicit analysis allowed us to identify the areas where most changes in ecological processes will occur. In this way, my study provides information that can be used as a basis for developing and implementing conservation and restoration strategies. My study represents the first effort to model Peruvian Andean ecosystem responses to future climate conditions.

Recommendations

The lack of information for model parametrization and validation posed challenges to my analysis, highlighting the need for further research. Field experiments can provide valuable information about ecosystem properties and processes. For example, estimations *in situ* of ANPP and SOC for the different cover classes across different elevation gradients and health condition assessments of vegetation will help determine ecosystems' response to climate change. Additionally, remote sensing analysis, e.g., land cover classification, estimation of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI), and landscape analysis, using high-resolution data will provide the information needed to improve model parameterization and validation. Moreover, creating species distribution models will help complement my analysis and better understand how future climate conditions will influence changes in ecosystem composition.

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CHAPTER 4: A SOCIAL-ECOLOGICAL MODELING APPROACH TO EXPLORE THE POTENTIAL IMPACTS OF LAND MANAGEMENT IN HUASCARÁN NATIONAL PARK, PERU

1. Introduction

1.1 Mountain socio-ecological systems

Mountain ecosystems are distributed across all continents and cover about 27% of the world's land surface (Romeo et al., 2020). On a global scale, the freshwater supply to lowlands represents one of the most critical ecosystem services these regions provide (Egan & Prize, 2017). Globally, mountains contribute significantly to the economies of upstream and downstream communities (FAO and UNCCD, 2019) and the maintenance of food systems (Immerzeel et al., 2020). These regions support 1.1 billion people worldwide, about 15% of the global population, with 91% in developing countries (Romeo et al., 2020). Hence the conservation of mountain ecosystems and the sustainable management of the natural resources within them are a global priority (FAO and UNCCD, 2019) critical to achieving the United Nations' Sustainable Development Goals (SDGs) (Immerzeel et al., 2020).

Mountains are social-ecological systems (SESs) characterized by vertical gradients of climate, and cultural and natural diversity (Klein et al., 2019). SESs consist of a complex and dynamic network of agents, e.g., individuals, families, and institutions, under the constant pressure of exogenous and endogenous drivers (Dawson et al., 2010). The components of SESs are dynamic and interact with each other through decisions and management from the social system and the provision of goods and services from the natural system (Klein et al., 2011). Mountain SESs are under pressure from various socioeconomic and environmental factors such as political water conflicts, governance effectiveness, population growth, and climate change (Immerzeel et al., 2020; Klein et al., 2019). In mountain regions, people use rangelands for extensive livestock production. Rangelands present extreme climates, have low productivity, and are primarily managed in common (Reid et al., 2014). Many rangelands that previously were used for livestock production are currently under protection with different levels of use (López-i-Gelats et al., 2016; Reid et al., 2014), which has affected communities and families (Galvin, 2009).

1.2 Agent-based models for SESs analysis

Using simulation models to analyze coupled human-natural systems can serve multiple purposes, such as integrating multidisciplinary views and analytical approaches, analyzing SESs patterns and dynamics, developing conceptual frameworks for data collection, and creating analysis scenarios of interest (Robinson et al., 2007). One approach to analyzing SESs is using simulation models to represent the feedback of various levels of aggregation of the natural and human systems and subsystems, which operate across different scales (Martin & Schlüter, 2015). Different simulation models can represent the components and processes of coupled natural-human systems. For instance, one or more process models can simulate ecosystem responses coupled with an agent-based model (ABM) representing households (Boone & Galvin, 2014).

ABM is a bottom-up simulation approach that captures the emergence of group-level behaviors from decision-making at the individual level (Grimm, 2005). ABMs are simulation models in which the "agents" may be heterogeneous, autonomous, and dynamic entities with adaptive behavior, able to interact with each other and their environment (Abar et al., 2017; McLane et al., 2011). Critical features of ABMs are their ability to represent a variety of behaviors and analyze interactions between and within agent types (Heppenstall et al., 2021). Moreover, researchers can use ABMs to represent systems where agents follow simplified behavioral rules, allowing for the analysis of emergent patterns resulting from agents' interaction with each other and their environment (Moritz et al., 2023). Consequently, ABMs can help represent and study complex systems like SESs since they are composed of dynamic interacting ecosystem components and agents, such as organisms, people, and any other entity that pursues a goal (Abar et al., 2017; Sweety et al., 2022). Moreover, the flexibility of ABMs in establishing spatial and temporal scales makes them suitable for linking them with socio-demographic, ecological, and biophysical models (Filatova et al., 2013).

Some applications of ABMs in the context of SESs aim to provide insight into the sustainable management of natural resources and the formulation of policies. For instance, Müller-Hansen et al. (2019) built an ABM to study the role of cattle ranching intensification and deforestation in the Brazilian Amazon. Another example is the model developed by Bazzana et al. (2022), which aimed to analyze how community networks and environmental externalities influence the adoption of different climate-smart agricultural practices in Ethiopia. Using ABM as a modeling approach allows researchers to analyze pastoral systems and examine their complex dynamics, such as the interaction between households, livestock, and grazing field management. Furthermore, ABMs can be built to model spatially explicit systems, analyze long-term dynamics, and create what-if scenarios of interest, which might be complex, controversial or unethically to explore empirically (Moritz et al., 2023).

1.3 The Cordillera Blanca and the establishment of Huascarán National Park

The Cordillera Blanca is one of the most extensively glacier-covered mountain ranges in the tropics (Ames & Francou, 1995). It is in the Northern Andes of Peru, in the Ancash region. The Cordillera Blanca includes portions of three important basins (Santa, Marañón, and Pativilca). Glaciers on the west side of the Cordillera Blanca drain into the Santa River basin. This basin significantly contributes to the water supply to important cities, such as Huaraz, Chimbote, and Trujillo, and Peru's energy development through hydroelectric plants. Glaciers and rivulets from the eastern flank converge in three main rivers (Rupac, Yanamayo, and Silhuas) that drain to the Marañón basin in the Amazon. The southeast side of the Cordillera Blanca originates from the Pativilca basin, which drains into the Pacific Ocean; along its route, it irrigates large-scale agroindustrial areas such as Barranca, Pativilca, and Paramonga (INAIGEM, 2018). The Cordillera Blanca comprises more than two hundred peaks with elevations higher than 5000 masl and thirty peaks higher than 6000 masl. The Cordillera Blanca has 755 glaciers that extend over 527,62 km^2 (UGRH, 2014). The various ecological gradients of the Cordillera Blanca determine their use by local communities. People grow wheat, barley, potatoes, quinoa, and other Andean tubercles at lower elevations and intermontane areas. The upper zones (3900 to < 5000 masl) are used for raising livestock.

However, in certain high-elevation valleys, animals frequently graze freely without the continuous presence of herders to tend to them (Young & Lipton, 2006). The creation of a park in the Cordillera Blanca was proposed in 1960 by Augusto Guzman Robles, a local senator who presented a bill to the Peruvian congress with the main goal of increasing tourism and revenue to the Ancash region (Barker, 1980; Lipton, 2014). In 1970, after the devastating impacts of the Ancash earthquake, the inter-ministerial emergency relief and recovery committee recommended the creation of a national park in the Cordillera Blanca. In 1975, the decree of the creation of Huascarán National Park (HNP) was approved (Barker, 1980). HNP was established with the main goals of (1) conserving the flora, geology, archeology, and scenery of the Cordillera Blanca, (2) contributing to improving the quality of life of peasant communities, (3) diffusing natural and historical values at regional, national, and international levels, and to (4) stimulate and regulate tourism in the Cordillera Blanca (Barker, 1980). HNP was designated as a Biosphere reserve in 1977 and recognized as World Heritage Site in 1985 by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (Rasmussen et al., 2019).

HNP has an extent of 3400 km^2 and encompasses the Cordillera Blanca Mountain range (Chimner et al., 2019; Young & Lipton, 2006). HNP's boundary is roughly 4000 masl, with the southern section established at approximately 4300 masl. The criteria for selecting this elevation was that higher-elevation areas were considered to have limited agricultural productivity. HNP's buffer zone was defined several years later, in 2002 (Lipton, 2014). HNP is surrounded by 43 agropastoral communities that were settled in the park and its periphery before the park was established (Young et al., 2023). Despite most of HNP's neighboring communities traditionally using lands above 4000 masl for migratory and rotational communal grazing of cattle, sheep, horses, llamas, and alpacas (Barker, 1980;

Lipton, 2014), the 1975 documentation of the park's creation stipulated that grazing in the park was not allowed (Lipton, 2014). Nonetheless, the Park Service permitted grazing activities in the park due to the communities' limited alternatives for accessing their traditional grazing lands (Barker, 1980). By that time, grazing by alpaca and llama, but not cattle or sheep, were permitted in the park. However, in 1977, this restriction was lifted, permitting sheep, cattle, and goats to graze on the park's land since these species did not compete with the vicuña, a South American camelid species considered endangered by that time. Since that year, grazing in the park has been permitted in a limited way (Lipton, 2014). The Park Service also implemented a co-management policy in which user groups of grazing fields were created to monitor and report the number of livestock grazing on the park's lands (Lipton, 2014). Currently, some communities have specific agreements and arrangements with the Park Service that provide them with access rights to grazing areas (Chimner et al., 2020; Young et al., 2023). The number of cattle and sheep grazing in the park is high, with most animals grazing freely. Moreover, livestock presence and their impacts have become the most visible feature of the landscape (Chimner et al., 2020).

HNP comprises sixty peaks with elevations over 5700 masl, with Huascarán the highest peak at 6768 masl. Forty-four deep glacial valleys or quebradas cut across the mountain range from west and east. Most valleys have relatively easy accessibility for hikers, climbers, and livestock from the communities (Byers, 2000). The park's main feature is the presence of tropical glaciers that currently cover about 14% of its area (Chimner et al., 2019) and are critical for the functioning of various ecosystems, such as wetlands, rangelands, and water bodies. However, due to glacier retreat, some areas are experiencing ecological succession (Young et al., 2017), significantly impacting ecosystems and local communities that rely on natural resources. The land cover of the park includes barren areas (48%), snow (14%), vegetation (36%), agricultural and developed areas (< 1%), and water sources (< 1%) (Chimner et al., 2019). The vegetation cover of the park can be classified into five categories. Peatlands (4.5%), poorly drained areas dominated by cushion plants with more than 40 cm of organic soil; wet meadows (4.9%), areas dominated by graminoids and cushion plants with less than 40 cm of organic soil; shrublands (5.8%) covered by woody vegetation shorter than 6 m; woodlands (5.5%) dominated by trees over 6 m; and grasslands (15.7%) (Chimner et al., 2019).

The west side of HNP borders the agricultural valley of the Santa River. This region is densely populated and encompasses relatively modern and prosperous cities such as Huaraz and Caráz and rural villages. However, people living near the park do so under traditional subsistence conditions (Byers, 2000). The park's east side consists of a group of valleys, known as Callejón de Conchucos, that are the headwater of the Marañón River, a major tributary of the Amazon. This region is more isolated and less developed than the park's west area (Byers, 2000). Historically, livelihoods in these areas consist of agriculture and livestock production. Local inhabitants have used for many years the resources in HNP, such as freshwater, rangelands for livestock grazing, medicinal plants, and fuel wood (Byers, 2009). The neighboring communities of HNP, mainly those on the west side of the Cordillera Blanca, provide access points to the park. Residents from those communities often seasonally work as porters, muleteers, cooks, and camp guardians, with these activities represented a crucial source of income (Byers, 2009). HNP has experienced rapid growth in conventional and adventure tourism (mountaineering, trekking, mountain biking, bungee jumping) since the demise of the insurgent group Sendero Luminoso (Shining Path) in the early 1990s (Byers, 2000; Byers, 2009).

HNP is under pressure from various socioeconomic and climatic factors that are significantly impacting the park and its neighboring communities. Socioeconomic pressures include overgrazing of grasslands and wetlands, conflicts with the neighboring communities about land ownership and access, national-level policies that favor resource-extractive activities within the park boundaries, and external pressures advocating for developing mining, hydroelectric, and tourism infrastructure (Byers, 2009). The climatic and ecological challenges HNP face are temperature increase, precipitation patterns changes, reduction of glacier cover, alteration of streams discharge, changes in vegetation cover, and water sources contamination by acid rock drainage.

In this context, the main goal of this chapter is to analyze the potential ecological and economic impacts of land management in a valley of HNP under future climate conditions using an SES modeling approach. The SES framework can help analyze various components of a coupled system, identify its thresholds and tipping points, and generate information for developing policies (Carpenter et al., 2009). The analysis of the natural system required the parametrization of the L-Range model, a localized version of the global rangeland model G-Range (Boone et al., 2018; Sircely et al., 2019). L-Range estimates monthly primary production as a function of precipitation, temperature, and soil and plant variables. I used climate data projections of three global circulation models to analyze ecosystems' potential response to changes in temperature and precipitation patterns, such as shrub encroachment, wetland fragmentation, and changes in primary production. The analysis of the human system involved building the Agent-based model of laNd management Dynamics and Ecosystem Services (ANDES). The ANDES model simulates the dynamics of land and livestock management, livestock foraging behavior, and households' economies. The scenarios under analysis include changes in the access to the park's land, livestock population reduction, and the establishment of rotational grazing systems. I coupled the ANDES and L-Range models to analyze the interactions between the elements and processes of the human and natural systems and, therefore, gain a better understanding of the coupled system's functioning and thresholds. More specifically, the coupled ANDES/L-Range model provides insights into how land management and climate change would impact ecosystems and families' economic well-being.

2. Study area

The study area comprises the valley of Arhuaycancha, located at HNP in the north-central Andes of Peru. The valley is used as grazing lands by the Cordillera Blanca community. Arhuaycancha Valley (UTM coordinates: zone 18 south, 240930 and 8933102) is situated around Rio Negro, a river in the Rúrec catchment, in the province of Recuay that drains to the Santa river. The elevation of the valley ranges from 3540 to 5463 masl. The Uruashraju, Yanamarey, and Pucaraju glaciated mountaintops flank Arhuaycancha Valley. Part of the valley lies in the park and the other part falls in the lands of the Cordillera Blanca community.

Large daily temperature changes and minimal temperature variations throughout the year characterize the climate in the Cordillera Blanca (Kaser & Georges, 1997). The precipitation exhibits strong seasonality (Mourre et al., 2016) and it is characterized by the alternation of a dry (May-September) and a wet season (October to April), in which about 80% of the annual precipitation occurs (Vuille et al., 2008).

The land cover classes of Arhuaycancha valley include barren areas (56.4%), i.e., areas with less than 33% of vegetation cover, dispersed scrubby vegetation, bare rock, and transitional areas, grasslands (13.4%), graminoid wet meadows (12.6%), peatlands (10.2%), snow/ice (2.4%), woodlands (1.5%), shrublands (1.3%), agricultural lands (1.1%), cushion wet meadows (1.0%), water bodies (0.2%), and developed areas (0.002%).

In the Arhuaycancha Valley, acid rock drainage resulting from oxidation and leaching processes associated with glacier retreat has contaminated several water sources. This contamination has led to high concentrations of metals and sulfates, posing risks to human health and ecosystems (Bravo-Zevallos et al., 2024).

2.1 Land and livestock management in Arhuaycancha Valley

Information from this section comes from a report from the Mountain Institute elaborated by Alata and Fuentealba (2018). The report preparation involved implementing of surveys, conducting interviews, and participant observation, and was conducted respecting the ethical procedures for working with human subjects.

The Cordillera Blanca community was created in 1992, has a board of directors, and its administration consists of six committees: (1) Agriculture, (2) Forestry, (3) Peasant Patrols locally known as *rondas campesinas*, (4) Research, (5) User Committee of Communal Grasslands, and (6) User Committee of Rangelands of Arhuaycancha valley. In 2017, the Cordillera Blanca community had 99 members, with 70 active members. The duties of community members include participating in communal work, locally known as *faenas*, and attending communal assemblies.

Some benefits for the community members are free access to the community's grazing and farmlands. Rules for using the community's grazing lands include not exceeding the maximum number of livestock established by the User Committee of Communal Grasslands; otherwise, families with livestock excess must pay a grazing fee. Cattle, sheep, horses, and burros can graze in the community's lands. The board of directors of the community can temporarily change some of these rules. For instance, the directory decided not to implement the payment of the fee for livestock excess for 2017.

The User Committee of Rangelands of Arhuaycancha Valley establishes rules for accessing the grazing lands inside HNP. These rules aim to keep constant or reduce the number of members using the valley's grazing lands and livestock population. Thus, there is no admission for new users. However, a user can transfer his/her land use rights to a direct descendent, e.g., spouse, children, and grandchildren. The number of animals per member grazing in Arhuaycancha Valley should not exceed the maximum number of livestock established by the Park Service. Otherwise, a fee must be paid annually. Cattle and sheep can graze in the park; however, horses, burros, and pigs are not permitted in the park. Nonetheless, some families raise these species in the valley.

2.2 Management arrangements

Land and livestock management schemes of the Cordillera Blanca community are complex and dynamic. In 2017, the number of families using the lands of Arhuaycancha V alley that fall within HNP's boundaries was 17. These families owned an estimated 500 cattle, 3000 sheep, and 100 horses. Land and livestock management involves seasonal rotation among grazing fields and the establishment of management arrangements among families. Twelve of the 17 families share grazing fields. However, different livestock management agreements are set up for the community's and the park's grazing lands. During the wet season (Dec – May), families graze livestock on the community's grasslands, wetlands, and some park lands. During the dry season (Nov – Apr), families move their livestock to the park's grazing areas. Nonetheless, livestock rotation varies depending on the start of the rainy season. In addition, some families move their milking cows and occasionally sheep to Canrey Chico Town in August and September to be fed with crop harvest residues.

Families of the Cordillera Blanca community have established three arrangement schemes for livestock tending: *Turnaje*, *Encargo*, and *Arriendo*. *Turnaje* occurs when livestock owners take a turn for tending animals. Depending on the number of livestock a family has, livestock tending can last from a few days to months. Thus, families with more animals tend livestock for a longer time. *Encargo* involves livestock owners making a monetary payment to the person tending animals, giving them access to agricultural lands, or helping in land cultivation, or a mix of these. The closer the family bond is, e.g., father and children, siblings, the arrangement involves less monetary retribution. The arrangement relies more on money when kinship is more distant. *Arriendo* consists of livestock owners giving the shepherd half of the calves and lambs born yearly. The shepherd also keeps milk from the tended cows. Burros and horses are not part of these arrangements.

The establishment of livestock management agreements varies according to a family's age group. A young family (< 30 years) has an average of 50 sheep, 10 cattle, and 6 horses but also tends livestock of other families. The principal livestock arrangement a young family establishes is *Arriendo*, with the primary goal of incrementing its livestock capital. A consolidated or middle-aged (31 – 60 years) family has an average of 160 sheep, 21 cattle, and 10 horses. This type of family's primary livestock production goal is to keep the number of livestock constant over time. The management agreement they establish is *Turnaje.*An elderly family (>60 years) has an average of 165 sheep, 27 cattle, and 5 horses. Since this type of family needs help to tend their livestock, the agreements they establish are *Turnaje* and *Encargo*.

2.3 Livestock management

Livestock management is different for cattle and sheep. A herd is composed of cattle and sheep tended by one shepherd that lives in a *cancha*. A *cancha* consists of a set of *choza* and corrales that belong to one or more families who have established arrangements for livestock tending. A *choza* is the temporal house where a shepherd and her or his family live. Cattle are not herded, though the shepherd ensures everyday cattle leave the corral, find a grazing area, and return to the corral in the evening around 6 pm. Cattle mainly graze on wetlands and other flat areas. Calves older than four weeks graze with their mother until 7 months. Sheep are herded. In the morning, around 9 am, the shepherd moves animals to a grazing area, mainly grasslands on mountain slopes. Later, around 3 pm, the shepherd moves the sheep to a grazing area near the corrals (about 200 m). Then, around 5 pm, animals are returned to their corrals. Each day the shepherd selects a different grazing area within a grazing field. Occasionally, sheep can graze on wetlands only after cattle have been rotated to a different area. Lambs younger than thirty days stay in the *corrals*. Horses and burros are not herded; they graze freely, mainly in wetlands. It is common to see horses and burros grazing next to cattle. The fenced grazing fields in the community's land are mainly reserved for creole or mix-breed cows; however, occasionally, sheep can use the fields after cattle have grazed on them.

Generally, women are responsible for tending livestock. In contrast, men work in other activities in Canrey Chico Town, such as managing their family's cropland fields and occasional jobs in tourism, timber production, and construction. Nonetheless, when men are not working in the town, they go to the highlands or Puna to help their spouses. In most cases, older children stay in the towns of Canrey Chico, Olleros, or the cities of Huaraz and Recuay for education but go to the Puna during the weekends or holidays.

Income from livestock production comes from selling cattle, sheep, horses, and small-farm animals (e.g., pigs, hens, and guinea pigs), livestock products (i.e., cheese, milk, and wool), and livestock tending. Incomes from agricultural production, an activity that takes place in Canrey Chico, are mainly destined for self-consumption (Alata & Fuentealba, 2018).

3. Methodology

The analysis of the coupled human-natural system required the creation of the Agent-based model of laNd management Dynamics and Ecosystem Services (ANDES) to couple it with L-Range (Boone et al., 2024), an ecosystem process model (Figure 4.1). ANDES is a spatially explicit model of livestock foraging behavior, land and livestock management, and households' economies. L-Range simulates biogeochemical processes and vegetation dynamics, such as monthly primary production, N and C cycling, and plant population dynamics for herbs, shrubs, and trees.

Creating the ANDES model required converting information about livestock social and grazing behavior and livestock energy dynamics from peer-reviewed articles and theses to a programming language (i.e., NetLogo; Wilenski 1999). Similarly, information from the land and livestock management report (Alata & Fuentealba, 2018) was converted into NetLogo programming language. Implementing L-Range required parametrizing soil and plant variables, and using landscape and climatic information, such as vegetation cover, soil properties, maximum and minimum monthly temperature, and monthly precipitation. Climate projection data came from the Representative Concentration Pathway (RCP 4.5) of three global circulation models and were obtained from the Climatologies at High resolution for the Earth's Land Surface Areas (CHELSA version 1.2) (Karger et al. 2017).

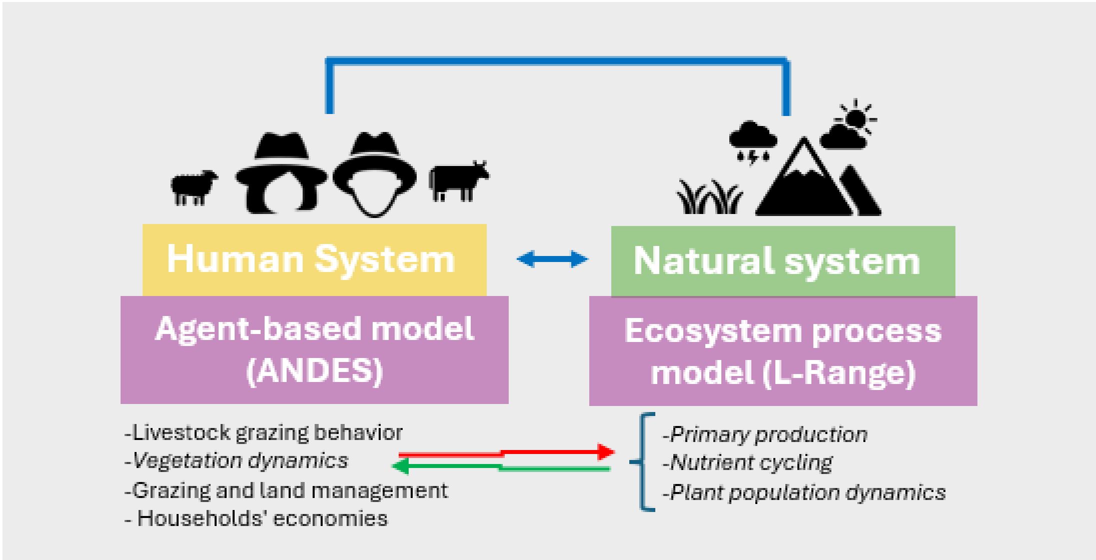

Figure 4.1. *A representation of the social-ecological system approach used in the analysis. ANDES is coupled to the L-Range model via the Vegetation dynamics sub-model (italicized words).*

I described ANDES using the *Overview, Design concepts, and Details* protocol (Grimm et al., 2010), an accepted method for standardizing ABMs descriptions (Table 4.1). The *Overview* section includes the purpose of the model, the agents or entities, and the variables and processes of the system under analysis. The *Design concepts* sections describe the agents' behavior based on theories and hypotheses that underlie the model. This component is used to set the predicted conditions of the agents' behavior and to determine if the modeled processes are random or partly random. The *Details* section defines the initial state of the world to be modeled and other details, i.e., it indicates the number of entities and established parameters of the variables (Grimm et al., 2010).

Table 4.1. *Description of the ANDES model*

Purpose	The ANDES/L-Range coupled model is intended to explore the ecological and economic impacts of climate change and land management in Arhuaycancha Valley in the Andes of Peru. The ANDES model simulates livestock foraging behavior, livestock and land management, and households' economies. ANDES is coupled with L-Range, an ecosystem-process model that estimates biogeochemical processes and vegetation dynamics. The ANDES/L-Range coupled model aims to deepen my understanding of the coupled system's functioning.
Entities, state variables, and scales	The ANDES model consists of four entities: families, cattle, sheep, horses, and patches of land. Families are the only agent types not spatially explicit in the model. – Some examples of state variables of families are age group, livestock sales income, number of animals owned, corrals and grazing fields identification. – Some examples of state variables for livestock are herd identification, behavioral role, body weight, daily biomass consumption, and distance moved. – Some state variables for land patches are land cover class, elevation, slope, biomass availability, the Habitat Suitability Index, corrals, and grazing fields. ANDES simulates livestock grazing behavior and livestock and land management at multiple temporal scales. For example: – The simulation of livestock movement and forage intake occurs hourly. – Grazing field rotation runs monthly or every 45 days, depending on the scenario. – Biomass consumption is estimated monthly, which matches the monthly temporal scale at which the ecosystem-process model (L-Range) operates. – Mortality and livestock sales are performed annually. One time step or tick represents 1 hour. The number of years simulated varies depending on the scenario under analysis. The model's landscape comprises 6.38 km. The grid cells have a resolution of 50 x50 m. One grid cell or pixel represents a feeding site or a grazing area.
Design concepts	<u>Emergence</u> Agents interact with their environment and other agents based on the behavioral rules implemented. Thus, patterns of selection of grazing areas or feeding sites, forage consumption, distance traveled, and proximity to herd neighbors are considered emergent. These patterns are expected to vary as a function of ecological and social factors, e.g., forage availability and grazing behavior role, and produce complex responses. <u>Adaptation</u> Livestock adaptation is determined by the different grazing behavioral rules that maximize forage consumption and reduce energy costs. <u>Sensing and Interaction</u> Sensing and interaction occur in multiple instances. For example, livestock sense their environment at the feeding site level by estimating the Habitat Suitability Index. Interactions among agents, agent types, and their environment are direct and indirect. Leader animals (cattle and horses) interact and sense their environment when determining the most suitable feeding site for grazing. Follower animals interact with leader animals by moving close to their selected feeding site or grazing area. Followers interact with each other when they seek to herd up if they are too far from their neighbors. Sheep interact with their conspecifics by determining the most suitable feeding site for grazing and ensuring they are part of a sub-grazing group. Sheep indirectly interact with cattle by keeping a determined distance from grazing near them. <u>Stochasticity</u> In the model, stochasticity occurs when animals are randomly created, assigned to an owner, and positioned in the landscape. Livestock are randomly placed in already-defined grazing

	fields. The interaction among agents of the same type and agents of different types is random. Stochasticity also occurs in different processes, such as livestock sales, where the animals to be sold are randomly selected. <u>Collectives</u> In the model, each animal agent type (cattle, horses, and sheep) is part of a grazing group, with sheep forming sub-grazing groups. In the case of cattle and horses, each grazing group has a leader who determines the most optimum feeding site. Followers graze in the feeding site established by the leader, but each animal selects its most optimum area to graze within the patch. Sheep form grazing groups based on forage availability, proximity to cattle, and distance to their (conspecific) neighbors.
Sub-models	The ANDES model comprises four sub-models: Vegetation Dynamics, Livestock Grazing Behavior, Grazing and Land Management, and Households' Economies. Each sub-model performs various processes. – Vegetation Dynamics: This sub-model couples the ANDES model to the ecosystem-process model (L-Range). L-Range provides estimates of monthly primary production in eight biomass groups, a proxy of forage availability necessary to estimate livestock consumption. – Livestock Grazing Behavior: This sub-model consists of processes, such as: o Establishing social behavior rules for each livestock species, such as creating grazing groups (cattle, horses, and sheep) and sub-groups (only for sheep). o Estimating the Habitat Suitability Index based on topography and forage availability. The animals or their herders use this index to select the most optimal grazing field area. o Estimating forage consumption, energy, and body weight dynamics. – Land Management: This sub-model consists of decision-making rules for land and livestock management, such as assigning grazing fields and implementing rotation schemes. – Households' Economies: This sub-model includes processes for livestock sales, estimation of incomes from livestock production and tending, and fees for an excess livestock population.
Input data	The ANDES model uses input data from L-Range to represent time-varying processes, e.g., primary production for each vegetation facet and biomass pool. L-Range generates these layers monthly. Other data used include the spatial layers of grazing fields and corrals.

Scenarios under analysis

The scenarios developed include potential management strategies implemented at the family and Park Service levels. Some scenarios are based on current regulations established by the Park Service, but that are not currently implemented, such as exclusive access to the park lands only during the dry season and the payment of a mandatory fee for livestock excess. Additionally, I created scenarios to analyze the ecological and economic implications of a new rotational grazing scheme and implementing stricter policy, i.e., livestock population reduction (Table 4.2 and Figure 4.2). Logistic constraints and the pandemic posed significant challenges to the collaborative development of these scenarios. I simulated each scenario over a 30-year period from 2020 to 2050, with two repetitions per scenario and climate model. Given the minimal variation across these repetitions, I present the average results for each scenario to facilitate analysis.

The time required to perform the simulations using the ANDES/L-Range coupled model was approximately 16 hours per repetition. The simulations for the land management scenarios took longer (~16 hours) compared to those of the L-Range model because the management scenarios required hourly and daily updates of information for the agents (cattle, sheep, and families). The ANDES model simulates hourly processes of livestock grazing behavior and management, such as the daily routine of livestock, which involves animals leaving their corrals in the morning to find an optimum grazing area and returning in the late afternoon. For that reason, only two simulations per scenario were performed.

Table 4.2. *Description of the management scenarios*

Scenario	Short name	Description
Current management	Current management	– Wet season grazing (Nov - Apr): livestock graze in the community's lands and some grazing areas in the park. – Dry season grazing (May - Oct): animals graze only in the park. – This management scheme includes 17 grazing fields (community and park). – Cattle graze in flat areas, while sheep graze only on mountain slopes. – Livestock population: 417 cattle, 2684 sheep, and 87 horses.
Current management + mixed grazing	Mixed grazing	– Grazing field rotation is the same as the "Current management" scenario. – Cattle and sheep graze in the same areas. – Livestock population: 417 cattle, 2684 sheep, and 87 horses.
Current management + livestock population reduction	Population reduction	– Grazing field rotation is the same as the "Current management" scenario. – The livestock population is reduced to the maximum number of animals established by the Park Service and the community[2]. – Livestock population: 302 cattle, 1491 sheep, and 36 horses.
45-day rotation + livestock population reduction	45-day rotation	– The livestock population is reduced. – Herds owned by different families are grouped and assigned to grazing fields. – This management scheme consists of 12 grazing fields, where animals are rotated every 45 days during the year.
Seasonal access + livestock population reduction	Seasonal access	– The livestock population is reduced. – Animals can graze areas in the park (within the park boundaries) only during the dry season. – This new management scheme consists of six grazing fields in the park and six in the community.

[2] *Note: A family is allowed to keep a maximum of 20 cattle and 100 sheep in the park. Horses are not permitted in the park, and only three horses per family are allowed on community lands. In all scenarios, horses graze freely. Fees for excess livestock were estimated only for the 'Current management' and 'Mixed grazing' scenarios. The annual fee for exceeding 20 cattle, 100 sheep, and 3 horses is S/.10.0, S/.5.0, and S/.30.0 per extra animal, respectively. In all scenarios, horses graze freely.*

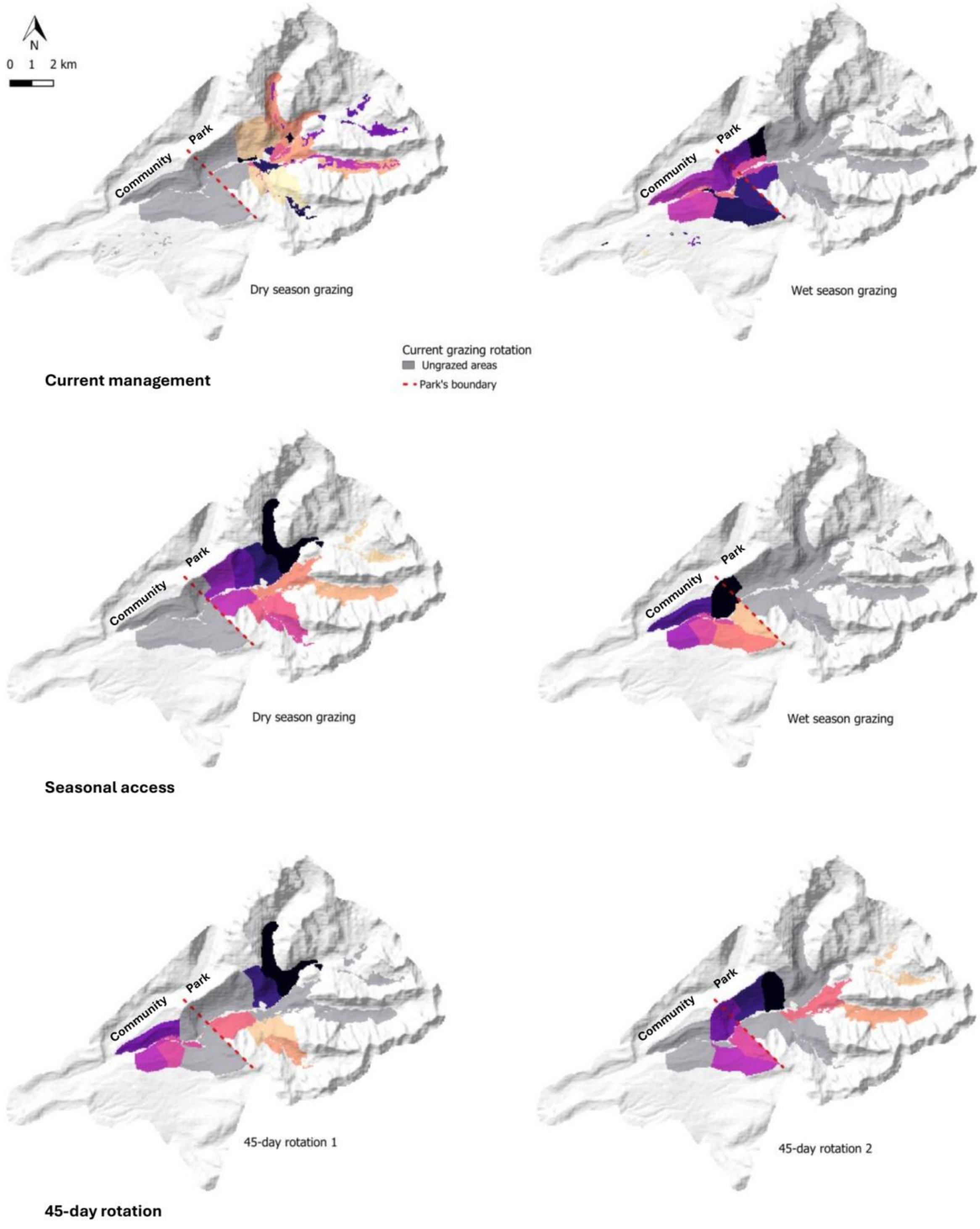

Figure 4.2. *Grazing field rotation for the Current management, Seasonal access, and 45-day rotation scenarios. All grazing fields are shared by various families.*

3.1 Model assessment

The assessment of the ANDES model was done following a pattern-oriented approach (Grimm et al., 2005). I compared the simulated responses of the different processes, such as forage consumption and livestock energy dynamics, with information from peer-reviewed journals and theses. I used information from the land and livestock management report to verify estimations of incomes and livestock population. The validation of the ecosystem process model required comparing outputs, such as net primary production and soil organic carbon, with MODIS data (Myneni, Knyazikhin, & Park, 2015) and information from scientific articles, reports, and theses. The analyses were performed using R v 4.1.1 (statistical analysis), QGIS v 3.20 (spatial analysis), NetLogo v 6.2.0 (agent-based model creation and simulation), and L-Range (ecological simulations).

4. Results and Discussion

4.1 Economic impacts

I implemented new management scenarios such as rotational grazing schemes, mandatory payment of fees for livestock excess, and animal population reduction to examine its ecological and economic impacts. Under all scenarios, the two primary sources of income for elderly and middle-aged families came from the sale of animals and livestock products. In contrast, the primary income sources for young families came from livestock sales and livestock tending (Figure 4.3). Families from all age groups under scenarios without the reduction of livestock population, i.e., “Current management” and “Mixed grazing,” generated the highest incomes. These incomes were approximately 10%, 15%, and 21% higher for young, middle-aged, and elderly families, respectively (Table 4.3), compared to the other scenarios. The findings also show that the reduction in livestock population affected all age groups, mainly middle-aged and elderly families whose incomes from livestock tending and sales decreased by about 17.2 and 23.2%, respectively (Figure 4.3 and Table 4.4). These findings indicate that middle-aged and elderly families will be the most affected by implementing livestock population reduction scenarios, which coincides with the fact that families of these age groups own more livestock and tend to a large number of animals.

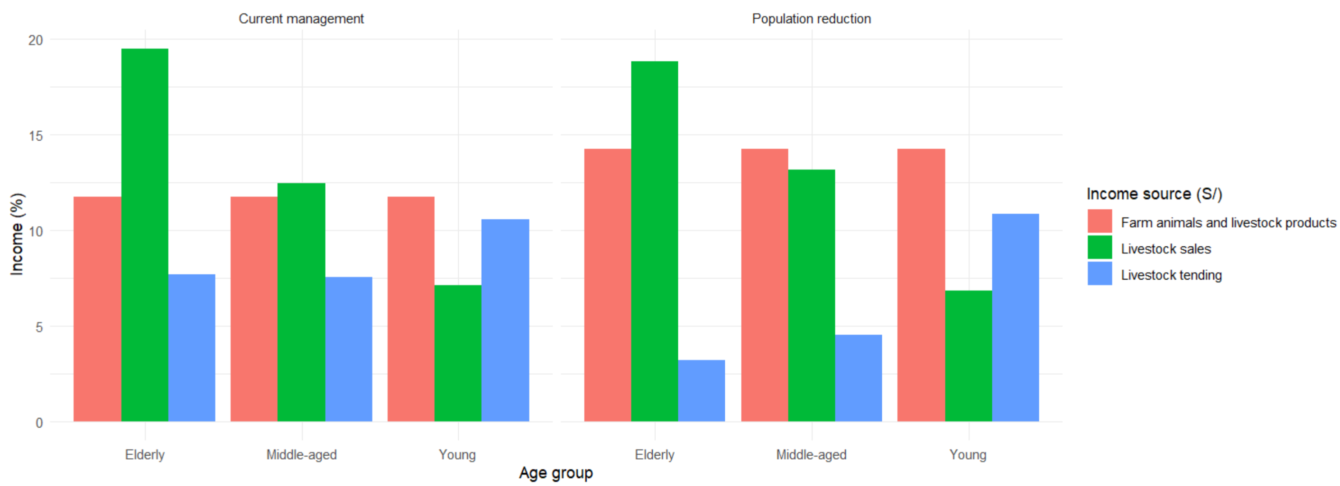

Figure 4.3. *Income distribution (%) of families in the "Current management" and "Population reduction" scenarios.*

Table 4.3. *Total mean annual incomes[3] (S/) from livestock production by age-group*

Scenario	Young	(%)	Middle-aged	(%)	Elderly	(%)
Current management	5365.59	100.00	5756.81	100.00	6949.90	100.00
Mixed grazing	5407.26		5775.14		6965.24	
Population reduction	4838.37		4840.44		5436.12	
Seasonal access	4850.87	~90.00	4835.58	~84.08	5411.47	~78.21
45-day rotation	4842.53		4856.55		5426.51	

Table 4.4. *Income losses (%) due to livestock population reduction*

Age group	Livestock sales Income loss (%)	Livestock tending Income loss (%)	Total (%) income loss
Young	5.16	5.57	10.73
Middle-aged	5.15	12.12	17.27
Elderly	10.29	13.00	23.29

[3] *Note: Average mean annual incomes from the last ten years of the simulations. Peruvian currency: Soles. 1 sol = 0.27 US dollars.*

In my analysis, I examined the scenario of paying a fee for excess livestock. Although the Park Service and the community established a fee structure for exceeding the maximum number of livestock allowed to graze on the park's and communal grazing lands, families with more animals than permitted are not currently paying these fees. I found that families of all age groups must pay a fee for exceeding the number of animals permitted in the community's grazing lands, with elderly families' fees being about 5.7 times higher than those of young and middle-aged families (Table 4.5). Furthermore, I found that only middle-aged and elderly families should pay a fee for exceeding the maximum number of animals grazing in the park. Notably, the fees paid to the community are approximately double those to be paid to the Park Service, suggesting that more animals graze on the community's lands throughout the year than the parks' grazing areas. Moreover, the average fee an elderly family should pay for exceeding the livestock number represents only 1.6% of their income from livestock production. The excess of livestock suggests that, from an individual perspective, having more animals can be seen as an opportunity to increase profits. However, if every family adopts this rationale and adds more animals to their herds, livestock productivity will decline, and grazing lands will be at risk of overuse, ultimately affecting all families.

***Table 4.5**. Fee for livestock excess in the lands of the community and the park*

Age group	Community	Park
Young	18.90	-
Middle-aged	20.30	7.40
Elderly	112.40	52.20

While the analysis of the impacts of land management on grazing behavior and livestock performance is discussed in detail in the next chapter, several findings emphasize their economic impacts and significance to human systems. For instance, higher livestock body condition indices were observed in scenarios that involved a reduction in the livestock population. This suggests that, to increase revenues from livestock production, families need to adjust the number of animals grazing in the fields. Reducing the livestock population will not only enhance forage consumption, leading to better animal condition, but will also lower mortality rates.

Furthermore, the improved performance of animals in scenarios that required a more dynamic grazing fields rotation indicates that optimizing the distribution of livestock across grazing fields is necessary. A better distribution of animals will promote a more uniform use of vegetation across these areas. In this way, changes in livestock management will have positive impacts not only on families' economies but also on vegetation.

As mentioned above, implementing the new management scenarios has economic impacts; however, it also has sociocultural, management, and ecological repercussions. For instance, one of the current livestock agreements among families in the Cordillera Blanca community and introduced above is *Encargo*, a payment or retribution livestock owners make to families that help tend their animals. In the ANDES model, the implementation of *Encargo* consists only of a monetary payment. However, different forms of retribution for livestock tending are currently being established, such as granting families access to agricultural land or assisting them with land cultivation. Therefore, while the economic impacts of these scenarios are evident, their sociocultural repercussions, such as changes in management agreements and the erosion of cultural practices, remain unknown.

Implementing management strategies, such as new rotational grazing schemes and changes in accessibility to grazing lands, requires not only families' willingness to adopt these strategies but also to have the capacity to implement them. This includes having the necessary workforce for livestock management and resources to create new infrastructure, such as corrals. For instance, under the "Mixed Grazing" scenario, families would only need to move sheep to flat areas to graze with cattle. While this change may seem simple, it could entail increased labor for managing livestock, in terms of personnel and time, which may hinder the adoption of this management scheme.

The most controversial scenarios are those that require reducing the livestock population, as this will directly affect families. Implementing these scenarios would involve establishing a retribution mechanism to compensate families for the incomes they will no longer receive. This retribution could be implemented as part of a Payment for Ecosystem Services (PES) mechanism. PES consists of voluntary arrangements between ecosystem services users (e.g., downstream communities) and providers (e.g., agropastoral families). The ecosystem services beneficiaries provide economic incentives to landowners or resource managers to ensure the sustainable management of natural resources and the continuous ecosystem service provision (Muradian, 2013). The development of the PES should include sustainable management practices such as rotational grazing schemes, revegetation, and the protection of riparian areas. Establishing this mechanism should also be in harmony with traditional land and livestock management practices to prevent the loss of traditional knowledge.

Though PES are the most common financial incentives for the sustainable management of natural resources, families of the Cordillera Blanca community, along with local institutions and non-governmental organizations, could develop marketing strategies that can help them add value to their products from the sustainable production of livestock. To achieve this, it is essential not only to consider new sustainable practices but also to identify and acknowledge the role of traditional land and livestock management practices in livestock production.

4.2 Ecological impacts

Livestock grazing management factors, such as the number of animals grazing an area and the frequency of grazing field use, can profoundly impact ecosystems by altering carbon sequestration, vegetation cover, and soil health. My findings reveal that the biomass left in grazing fields under the "Seasonal Access" and "45-Day Rotation" scenarios was much higher, about six times more, compared to other scenarios (Table 4.6). These scenarios required reducing livestock population and establishing grazing field rotations of 2 months and 45 days, respectively. Moreover, the similar amount of live biomass left on grazing fields under the “Population reduction”, “Current management” and “Mixed grazing” scenarios reveals that current grazing management requires adjusting the stocking rate, improving animal distribution, and modifying the frequency of grazing.

Table 4.6. *Total biomass in grazing fields (kg/ha) by management scenario*

Scenario	Total biomass (kg/ha)
Seasonal access	623.16
45-day rotation	592.74
Population reduction	119.45
Mixed grazing	102.54
Current management	101.48

In addition, the biomass consumed varied by scenario and location. For example, under the “Current management” and “Population reduction” scenarios, the biomass consumed was the highest and exhibited a clustered pattern compared to the “45-day rotation” scenario, indicating a more uniform and less intense vegetation use under the new rotational grazing scheme (Figure 4.4). The positive response of vegetation to the rotational grazing schemes aligns with several studies indicating that this grazing method improves plant productivity and use. Rotational grazing involves alternating grazing periods and rest across two or more fields or paddocks, allowing plants to grow and develop deeper roots (Andrae, 2008). Furthermore, by facilitating a more uniform distribution of livestock, rotational grazing enhances vegetation use (Rivero, 2021).

Nevertheless, it is important to note that most studies on the impacts of rotational grazing on vegetation focus on temperate rangelands. The limited research available on grazing impacts on wetland ecosystems has reported mixed results (Sonier et al., 2023). For example, Sonier et al. (2023) found that grazing at different intensities negatively affected species composition; however, livestock exclusion also negatively impacted species diversity and composition. Furthermore, Gisela et al. (2021) found that both short resting/long grazing periods and long resting/short grazing periods in wetlands led to lower diversity and richness compared to ungrazed wetlands, indicating that vegetation recovery requires longer resting periods. Additionally, it is important to consider the effects of grazing on vegetation. For example, Boughton (2021) found that plant survival was higher at the edges compared to the centers in ungrazed wetlands. In contrast, there was no significant difference in plant survival between wetland edges and centers in grazed wetlands.

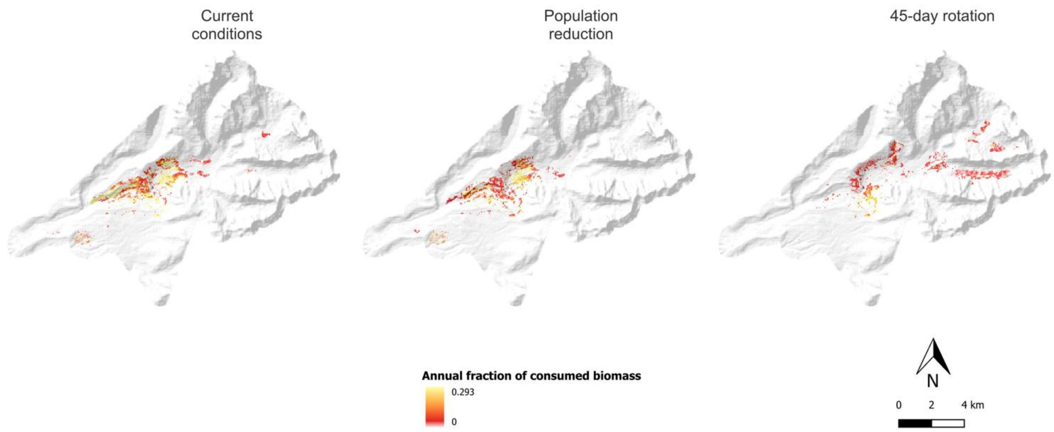

Figure 4.4. *The total fraction of biomass consumed on grazing fields for 2030. Higher values (yellow) indicate less biomass available. Fraction scale: 0 - 1.*

4.3 Factors influencing the implementation of management scenarios

Although the analysis of the social and cultural factors associated with implementing management scenarios is beyond the scope of my study, its inclusion in scenario design and implementation is crucial. For example, migration is a critical factor affecting the continuity of agropastoral activities. The depopulation of the Puna is an issue not only for families of the Cordillera Blanca community but also across the Andes. According to Alata et al. (2018), families of the Cordillera Blanca community are moving to cities for various reasons, which vary by generational group, including job opportunities, access to education, and the demanding work this activity means for older individuals. Puna depopulation breaks the agropastoral system cycle due to the lack of workforce replacement. This disruption results reduced longevity of the agropastoral system that will rely on older individuals for their continuity and affect decision-making processes, such as adopting new practices

(Arzamendia et al., 2021). The Puna's abandonment will have economic and cultural repercussions, including losing traditional knowledge such as herding practices and norms for vegetation and water source use (Arzamendia et al., 2021). In addition, land abandonment will disrupt social systems by altering social practices (Subedi et al., 2021).

Another factor affecting land and livestock management is increasing climate variability. Climate change will have direct impacts not only on ecosystems but also on land management. Agropastoral families in the high Andes of Peru have developed strategies, such as combining on-farm with non-farm activities and livestock production diversification to maximize animal and economic performance while avoiding economic risks, mitigating climate change impacts, and improving living conditions (Radolf et al., 2022). Diversification increases households' resilience by reducing the dependency on only one source of income. For instance, integrating subsistence and market-oriented agriculture, rent of lands, wage labor, and familial bonds is pivotal for household self-sufficiency (López-i-Gelats, et al., 2016; Radolf et al., 2022, and Young & Lipton, 2006).

Nonetheless, livelihood diversification can affect the agropastoral system cycle. For instance, Ponce (2023) found that families' response to increasing climate variability in the Northern and Central Andes of Peru was an increase in diversification into non-farm activities that resulted in more non-farm working hours and more household incomes from these activities. These findings align with Alata and Fuentealba (2018), who found that families of the Cordillera Blanca Community have developed various livelihood strategies, such as raising cattle, sheep, and horses in the Puna and small-farm animals, i.e., pigs, hens, and guinea pigs, in the community. Moreover, some families have expanded their livelihoods by including farming, tourism, and employment in the city.

Changes in seasonal precipitation and forage availability will impact livestock management and production and, consequently, family economies. In response to these changes, agropastoral families may need to adjust their grazing management practices. However, the extent of these adjustments will be constrained by families' willingness to move their animals to different areas (Young et al., 2023).

Additionally, socioeconomic factors such as migration, workforce availability, and implementation costs will play a significant role in adopting new management strategies.

Caveats

To build the ANDES model, I used information from the 2018 Mountain Institute report on land and livestock management of the Cordillera Blanca community. However, this information needs to be updated. A more accurate representation of the socioeconomic system should include not only current management information but also data on livestock population structure and income from lowland activities such as livestock production, construction, farming, and tourism.

The land and livestock management system represented in the ANDES model is specific to the Cordillera Blanca community. Therefore, applying the ANDES model to other communities across Huascarán National Park will require adjustments to land and livestock management and household economy decision rules, as many communities have specific agreements with the Park Service.

Logistical constraints hindered the collaborative design of scenarios. Involving stakeholders, including representatives from the Cordillera Blanca community, Park Service personnel, and local authorities and institutions, could have facilitated the identification and design of the most relevant management scenarios.

5. Conclusion

Implementing new management schemes will have economic, cultural, and ecological implications. Families under the “Population reduction”, “45-day rotation”, and “Seasonal access” scenarios will generate similar incomes; however, these will be lower compared to the “Current management” and “Mixed grazing” scenarios, which did not involve reducing livestock population. In addition, adopting new management schemes will alter cultural practices, such as livestock management agreements and the use of natural resources. The ecological impacts of the new management strategies were also substantial. For instance, the biomass available in grazing fields was much higher in the scenarios with reduced livestock population and new rotational grazing schemes, indicating that livestock number and grazing frequency should be adjusted. The fact that excess livestock fees represent only 3.4% of elderly families' revenues indicates a need to modify the regulation of livestock populations. This could involve increasing fees or enforcing stricter rules, such as reducing the number of animals each family can have on a grazing field. However, any changes should involve dialogue among families, the community, and the Park Service.

Implementing the new management scenarios requires families' willingness to adopt them, and it is subject to various factors, such as collective support, the level of labor needed, and the current social dynamics of the agropastoral system. Scenarios that involve a reduction in livestock population are less likely to be adopted because of their economic impacts and the conditions for their implementation, e.g., developing a compensatory mechanism due to the reduction of incomes from livestock production. Other challenges the establishment of these new management strategies faces are the potential disruption of traditional management practices and the undermining of traditional knowledge. Finally, the disruption of the system's cycle due to migration represents a major hurdle to adopting new management strategies and, more importantly, the continuity of agropastoral activities.

I analyzed the potential economic and ecological impacts of implementing new management practices in the agropastoral social-ecological system. In this way, my study provides critical information that can serve as the basis for developing management strategies that can help increase the resilience of the coupled system. This includes adjusting livestock numbers based on available forage and modifying grazing frequency to improve animal performance while preventing resource overuse.

Recommendations

Future research and collaborative work with stakeholders, e.g., families, communities, the Park Service, and local authorities and institutions, is essential to understand the sociocultural and ecological impacts of implementing new management schemes. I recommend identifying stakeholders' management priorities and needs and co-developing management scenarios. In this way, the scenarios developed will address more relevant land management and conservation challenges and, therefore, have a higher chance of being implemented.

The ANDES model could be enhanced by incorporating updated information on grazing management and household economies. This includes data on livestock population structure, rotation of grazing fields, and income from non-livestock production activities. Additionally, incorporating factors that influence sheepherders' decision-making regarding daily and seasonal livestock movement, such as frost, forage availability, and proximity to water sources, can further enhance the model. Moreover, providing more detailed information on market dynamics, its role in livestock sales, and its impact on household economies and livestock management could enrich the model and foster a better understanding of the agropastoral system.

Traditional knowledge can provide valuable insights into livestock grazing behavior, land and animal management, and the use of natural resources, as well as scenario development. This knowledge can enhance the representation of the socio-ecological system and improve the accuracy and utility of the ANDES model. To achieve this, it is essential to work collaboratively, actively, and closely with the families of the Cordillera Blanca community, ensuring that knowledge generation is participatory.

To effectively implement the ANDES model across Huascarán National Park, it is essential to identify the most representative land and livestock management systems within the park’s surrounding communities. This information will be crucial for adjusting the parameters and values of the current sub-models related to land and livestock management, as well as household economies. However, since the ANDES model was developed based on the management practices of the Cordillera Blanca community, it is likely that new sub-models and processes will be needed to accommodate the diverse land and livestock management practices of neighboring communities around Huascarán National Park.

To successfully communicate the research findings of the coupled ANDES/L-Range model, the first step is to identify stakeholders, such as families from the Cordillera Blanca community, personnel at Huascarán National Park, local authorities, research institutions, and non-governmental organizations. Next, it is essential to work with extensionists and science communication experts to create informational materials that present key information from the ANDES/L-Range model in a simple and straightforward manner tailored to specific audiences.

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CHAPTER 5: THE ROLE OF BIOPHYSICAL AND SOCIAL FACTORS IN GRAZING BEHAVIOR OF LIVESTOCK

1. Introduction

Rangelands, defined as lands with predominant native or naturalized vegetation of grasses, forbs, and shrubs (Briske & Coppock, 2022), comprise about 54% of the global land surface. Approximately 78% of rangelands can be classified as drylands, i.e., areas where the precipitation/potential evapotranspiration ratio ranges from 0.05 to 0.65 (ILRI et al., 2021). Protected areas comprising rangelands extend over 9,438,874 km^2, about 7% of the world's terrestrial surface (ILRI et al. 2021). Globally, 1.7% of rangelands are Key Biodiversity Areas (KBA) (ILRI et al., 2021), i.e., essential areas that contribute substantially to the protection of global species and habitats (IUCN, 2016). Nonetheless, rangelands face accelerated social and ecological changes, such as population growth, unsustainable use of natural resources, land conversion and fragmentation, land governance issues, and increased climate variability (Bedunah & Angerer, 2012; Briske et al., 2020), whose complex and cross-scale interactions have led to rangeland degradation (Sayre et al., 2013).

Approximately 84% of global rangelands are used for livestock production, with livestock-only production systems, i.e., lands that cannot be used for crop production, representing about half (46%) of them (ILRI et al., 2021). Livestock grazing is the primary factor altering the structure and functioning of rangelands (Asner et al., 2004). The expansion of livestock production has led, in many cases, to overgrazing, dryland degradation, rangeland fragmentation, and bush encroachment (Millennium Ecosystem Assessment, 2005), with livestock overstocking and unsustainable livestock management being the leading causes of land degradation (Coughenour, 1991; Harris et al., 2010). Though the degradation of rangelands also depends on factors such as precipitation and nutrient cycling, grazing management has been the focus of research for the past eight decades. Most studies analyzed the effects of grazing systems on vegetation trends, livestock performance, and soil properties in short-term production without considering other factors such as rangeland type, landscape composition, animal type, paddock sizes, and long-term ecosystem sustainability under the assumption that rangelands were systems in equilibrium, i.e., *"the equilibrium paradigm"*(di Virgilio et al., 2019).

The effects of grazing on ecosystems are variable and mainly depend on factors such as herbivore type, grazing pressure and regime, and ecosystem response (Eldridge et al., 2016). The impacts of grazing also depend on the spatial distribution of herbivores in the landscape (Coughenour, 1991). Grazing behavior results from the interaction of abiotic and biotic factors at different spatiotemporal scales (Bailey et al., 1996; Tang and Bennet, 2010). Even though animal distribution is an essential component of livestock management (Senft et al., 1985), determining grazing behavior and their associated environmental factors is challenging. Nonetheless, using simulation models, such as agent-based models (ABMs), represents a convenient approach for analyzing complex processes, such as livestock grazing behavior (Fust & Schlecht, 2017; Gersie, 2020; Jablonski et al., 2020). ABMs consist of a set of autonomous and dynamic agents or entities able to interact with each other and their environment (Abar et al., 2017; McLane et al., 2011). Furthermore, ABM is a bottom-up simulation approach able to capture group-level behaviors that emerge from decision-making at the individual level (Grimm, 2010).

1.1 Spatiotemporal scales of livestock foraging behavior

Foraging from herbivores occurs at different spatial hierarchies and temporal levels (Bailey, 1996 & Senft et al., 1987), making grazing behavior a complex process (Senft et al., 1987). At the lowest hierarchy or the bite level, animals make foraging decisions in about 2 seconds, influenced by nutrient concentration, secondary compounds, and plant morphology and size. At the feeding station level, defined as plants available for consumption without requiring an animal to move its front feet, foraging decisions occur at intervals of 5 to 100 seconds. Decisions at this level are influenced by forage abundance and quality. At the patch level, i.e., a group of feeding stations, grazers move to a new location or feeding station at intervals from 1 to 30 minutes. Forage availability and quality, social interactions, and topography influence decisions at this level. Finally, at the feeding site level, defined as a cluster of patches in the contiguity of an area, herbivores make foraging decisions at intervals ranging from 1 to 4 hours. At this level, decisions are affected by topography, distance to water, forage quality and abundance, and predation risks (Bailey, 1996).

Decisions grazers make at broader spatiotemporal scales can affect and limit foraging behaviors at smaller scales. In contrast, decisions at lower levels can be integrated and used to make higher-level decisions (Bailey, 1996). Foraging goals differ from one scale to another due to the distribution of resources, energetic expenditure, and predation risks. However, foraging decisions are less frequent at broader scales than low levels (Senft et al., 1987). Foraging decisions at the landscape level are affected by differences in nutrient content, forage availability, and time and energy costs of traveling to a different area (Senft et al., 1987). For instance, herbivores may decide whether to graze in an easily accessible area *vs.* a distant zone, which would influence their energy expenditure (Bailey, 1996). Thus, to avoid significant loss of foraging time, herbivores need to use suboptimal habitats or forage sources moving through the landscape to also obtain water and shelter, i.e., herbivores' available time must be used efficiently to satisfy multiple goals (Senft et al., 1987).

Diet selection involves the maximization of forage quantity and quality. However, because most forage available has relatively low nutritional value, the selection for quality is at the cost of quantity (Senft et al., 1987). Herbivores may solve this quality-quantity dilemma by using momentary maximization. This strategy requires grazers to consume the most palatable plants and plant parts in each feeding location until the palatability decreases to some threshold (Staddon, 2016). Thus, the variability in forage quality and quantity in feeding sites influence livestock movement from one feeding site to another, allowing diet mixing (Bailey et al., 2015). The most critical foraging pattern at the landscape level is matching, which consists of selecting plant communities based on the availability of preferred species and nutrient abundance. Landscape matching also involves herds of animals moving slowly toward more productive and high-nutrient-quality communities. At the plant community level, grazers must determine their diet selection, i.e., plants and plant parts that will be consumed, and location selection, i.e., how they move through the plant community (Senft et al., 1987).

1.2 Livestock social behavior and its role in grazing patterns

Though animals can acquire information about the environment from their own perception, they can also obtain information from their conspecifics. The association of animals with their conspecifics provides several advantages, such as protection against predators through communal defense and shared vigilance, and the location of forage sources (Pays et al., 2014). However, sociality can also be disadvantageous due to increased resource competition, disease transmission, and conflicting needs at the individual and group levels (Sueur et al., 2018). Animals make decisions routinely to meet their needs. Two types of decisions can be made in a group: consensus and combined decisions. A consensus decision occurs when animals of a group choose between two or more mutually exclusive actions to reach a consensus. Some examples include the selection of grazing areas after a rest period or the timing for starting certain activities. A combined decision results from individual decisions that affect the whole group without aiming to reach a consensus, e.g., group joining or leaving (Conradt & Roper, 2005).

The movement of animals is a collective behavior that requires the participation of many individuals, and that is determined by shared consensus decisions (Ramseyer et al., 2009; Ramos et al., 2021; Sueur et al., 2018). The movement of a group of animals involves three phases: the pre-departure period, the initiation phase, and the following process. In the pre-departure period, individuals indicate their willingness to depart through increased activity and intentional body movement (Ramos et al., 2021). Several individual features such as age, sex, reproductive status, social relationships, and personality type influence an individual to initiate group movements. If an individual plays a more critical role in a group decision by being more active or having more followers, this individual can be considered the group's leader (Sueur et al. 2018). However, the success of this phase is affected by some individuals, such as the first follower (Ramseyer et al., 2009; Sueur et al., 2018).

1.3 Range and grazing management in the Peruvian Andes

In the Peruvian Andes, rangelands cover approximately 22 million hectares and have a critical role in livestock production. In high-elevation areas, the production of cattle, sheep, and camelids (alpaca, llama, and vicuna) mainly relies on the use of natural vegetation (Flores et al., 2014), while at lower elevations, the diet of livestock also includes cultivated pastures and the supplementation with crop residues. Most livestock raised in the Peruvian Andes are creole animals, adapted to harsh environments, and with low productivity (Flores et al., 2014). In the Peruvian Andes, livestock production is carried out by peasant communities that have different organization schemes and arrangements for managing their resources and distributing work activities, such as communal cooperatives, communal farms, and producer associations (Flores et al., 2007). For many families in these communities, livestock production is a source of economic stability and is closely tied to their social life, tradition, and culture (Flores et al., 2014). Typical characteristics of range and livestock management in these communities include: 1) Individual ownership of livestock and their products by community members, with a small number of animals per family, i.e., an average of 35 to 50 sheep equivalent units. 2) Herds of animals are individually tended on communal grasslands, and 3) Livestock and rangeland management arrangements among families and between each family and the community are very complex (Lozada, 1991).

The range management practice commonly applied in the Peruvian Andes is continuous grazing, in which livestock can access any grazing area at any given time, i.e., there are no rotational schemes of grazing fields. However, some communities have also established deferred rotational and mixed grazing systems. Deferred rotational grazing systems involve the delay of using a grazing field to achieve a specific management objective, such as seedling establishment or ensuring seed production.

While mixed grazing systems, where more than one livestock species with different diet selection and grazing behavior concurrently or sequentially graze a given field, are implemented to optimize resource efficiency and animal productivity (Novoa & Flores, 1991; Quispe et al., 2021). Overgrazing, the limited implementation of soil conservation practices, and the inherent fragility of Andean ecosystems due to a marked precipitation seasonality and steep topography, have contributed to the degradation of rangelands (Lozada, 1991), with overgrazing as a widespread problem in the Peruvian Andes (World Bank, 2007).

In this context, this study aims to analyze the impact of grazing management schemes, such as livestock population reduction and mixed grazing, on forage consumption, grazing behavior, and animal performance in a heterogenous landscape. To perform this analysis, I built the Agent-based model of laNd management Dynamics and Ecosystem Services (ANDES), a spatially explicit agent-based model of livestock foraging behavior, land and livestock management, and households' economies, linked to L-Range (Boone et al., 2018). L-Range is an ecosystem-process model that simulates biogeochemical processes and vegetation dynamics, such as monthly primary production, N and C cycling, and plant population dynamics (herbs, shrubs, and trees) for rangeland ecosystems. The scenarios analyzed include changes in livestock population and the implementation of different grazing systems, such as deferred-rotation and mixed grazing systems.

2. Study area

The study area comprises the Arhuaycancha valley of Huascarán National Park (HNP), located in the north-central Andes of Peru, in the Ancash region. HNP was established in 1975, has an extent of 3400 km^2, and encompasses the Cordillera Blanca mountain range (Chimner et al., 2019; Young & Lipton, 2006). The land cover of the park includes barren areas (48%), glacier cover (14%), natural vegetation (36%), agricultural lands and developed areas (~1%), and water bodies (~ 1%) (Chimner et al., 2019). HNP is surrounded by 43 agropastoral communities (Young et al., 2023) that traditionally used what today are the park lands for migratory and rotational communal grazing of cattle, sheep, horses, llamas, and alpacas (Barker, 1980; Lipton, 2014). However, with the establishment of the park, livestock grazing was banned. Nonetheless, this restriction was lifted in 1977 due to the limited alternatives for communities to access their traditional grazing lands (Barker, 1980). The Park Service also implemented a co-management policy for establishing grazing land user committees to monitor livestock population and grazing areas (Lipton, 2014). Moreover, some communities have established specific agreements with the Park Service to access grazing areas in the park (Chimner et al., 2020).

2.1 Land and livestock management

Families of the Cordillera Blanca community use the lands of the Arhuaycancha Valley for livestock grazing. The community was established in 1992 and has a committee of communal grasslands and a committee of the Arhuaycancha Valley's grasslands users. As of 2017, it had 99 members, with 17 raising livestock in the Arhuaycancha. These families owned about 500 cattle, 3000 sheep, and 100 horses. Out of the 17 families, 12 shared grazing fields. The Cordillera Blanca community has complex land and livestock management schemes. In addition, the community and the Park Service have established different agreements for using the park's lands. During the wet season, from December to May, families use the community's grasslands and wetlands for livestock grazing. Nonetheless, families also use some lands of the Arhuaycancha Valley. During the dry season, from November to April, families move their animals to the park's lands. However, livestock rotation can vary depending on when the rainy season begins. Cattle are not herded, but the shepherd ensures that animals leave their corral daily to graze on wetlands and other flat areas and return to their corrals in the late afternoon. Unlike cattle, sheep are herded. In the morning, the shepherd moves sheep to a grazing area, mainly on a mountain slope, within an established grazing field. Later in the afternoon, the shepherd moves animals to a grazing area near the corrals. Every day, the shepherd selects a different grazing area. Finally, around 17:00, livestock are returned to their corrals. Occasionally, sheep can graze on wetlands, but only after cattle have been rotated to a different field. Horses and burros are not herded, i.e., they graze freely, mainly in wetlands. It is common to see horses and burros grazing alongside cattle (Alata & Fuentealba, 2018).

3. Methodology

I built the Agent-based model of laNd management Dynamics and Ecosystem Services (ANDES) to analyze livestock foraging behavior and their distribution patterns in free-ranging and managed conditions. The ANDES model was coupled with L-Range (Boone et al., 2024), an ecosystem process model that estimates rangeland ecosystems' biogeochemical processes and vegetation dynamics. The coupled ANDES/L-Range model simulates livestock grazing behavior, livestock and land management, biomass production, and households' economies.

L-Range is the local version of G-Range, a global ecosystem-process model of rangelands (Boone et al., 2018). G-Range simulates biogeochemical processes and vegetation dynamics at monthly time steps, such as nitrogen and carbon cycling, transpiration, primary production, and plant population dynamics for three plant functional groups: herbs, shrubs, and trees. Vegetation facets determine the hierarchical structure of the G-Range model. The herb facet includes a vegetation layer of herbs, a layer of herbs under shrubs, and a layer of herbs under trees. The shrub facet consists of a layer of shrubs and a layer of shrubs under trees; the tree facet is only composed of a layer of trees. With respect to plant parts, the herb facet contains leaves and fine roots, while the shrub and tree facets include fine branches, coarse branches, and coarse roots. L-Range estimates monthly biomass for eight vegetation pools: green leaves of herbs, dead leaves of herbs, green leaves of shrubs, green shrub branches, dead leaves of shrubs, green leaves of trees, green tree branches, and dead leaves of trees (Boone et al., 2018; Sircely et al., 2019).

The ANDES application includes four entities: families, cattle, sheep, horses, and patches of land. Some state variables of families include age group, number of animals owned, corrals, and grazing fields. Some state variables of livestock are herd identification, social role (only for cattle and horses), age, body weight, distance moved, and herd neighbors. All agents, except for families, are explicitly represented in the application.

The ANDES model consists of four sub-models: (1) *Vegetation Dynamics*, (2) *Livestock Grazing Behavior*, (3) *Grazing and Land Management,* and (4) *Households Economies*, with each sub-model performing various processes. The ANDES model is linked to L-Range, the ecosystem process model, *via* the *Vegetation Dynamics* and *Livestock Grazing Behavior* sub-models. The *Livestock Grazing Behavior* sub-model consists of five processes (Figure 5.1). Some processes, such as movement rules, have specific rules for cattle, horses, and sheep, while others, such as estimations of energy requirements, are common with specific parameters for each species.

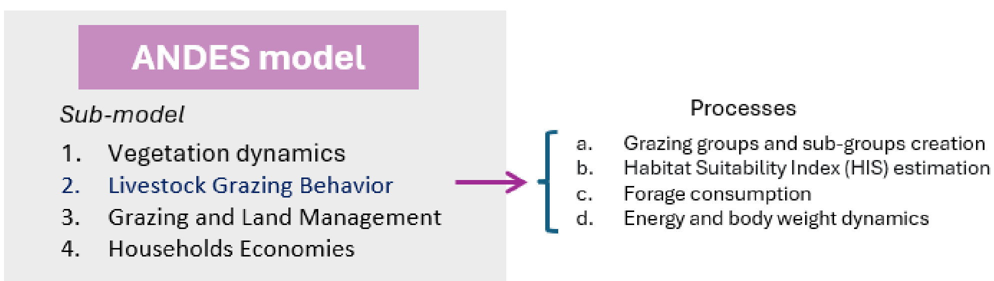

Figure 5.1. *Processes of the Livestock Grazing Behavior sub-model.*

The coupled ANDES/L-Range model performs these processes at various temporal scales. For instance, the *Livestock Grazing Behavior* sub-model runs hourly to simulate animal movement, biomass consumption, and energy and body weight dynamics. These simulations are then aggregated to obtain daily estimations. This sub-model also runs monthly to estimate the fraction of biomass consumed from each vegetation pool and body weight dynamics. The *Grazing and Land Management* sub-model performs monthly simulations, such as the rotation of grazing fields. The temporal scale at which these processes are performed matches the monthly temporal scale at which the ecosystem process model (L-Range) works. Additionally, annual processes such as mortality and livestock sales are performed. Due to the limited information about herds' structure (age and sex), the number of animals lost due to mortality and sales are replaced by "new animals" at the beginning of every year. In this way, the model works with a constant livestock number over the years.

The Arhuaycancha Valley application covers 139.67 km and have a grid cell (pixel) resolution of 50 x50 m. This grid system represents the scale at which the different ecological and grazing behavior processes, e.g., biomass production and consumption, are estimated. Since the primary goal of this chapter is to analyze the role of biophysical and land management factors on livestock grazing behavior, I describe only the ANDES sub-models pertinent to these factors in this section.

a. Vegetation Dynamics sub-model

This sub-model couples the ANDES model to the ecosystem-process model (L-Range). L-Range provides estimates of monthly primary production, a proxy of forage availability for livestock consumption. A more detailed description of the L-Range model can be found in Chapter 2.

b. Livestock Grazing Behavior

Below, I explain in more detail the most relevant processes of the sub-model.

b.1 Grazing groups and sub-groups creation

The first process of this sub-model consists of creating grazing groups (cattle, horses, and sheep) and subgroups (sheep). The creation of grazing groups requires the establishment of livestock hierarchy or ranking. Cattle can be classified as leaders, followers, and independent animals. High-ranking animals are usually leaders. Low-ranking animals are followers or independent animals; however, independent animals do not always follow the group (Sato, 1982). In the sub-model, the percentage established of leaders, followers, and independent cattle were 5, 85, and 10%, respectively (Jablonski, 2018; Sato, 1982). A grazing group or a herd has only one leader. The size of a grazing group is determined by the number of followers within 400 m from a leader.

Horses are social animals that form stable groups, known as bands, that inhabit large geographic areas. Bands that live in the same area form a herd (Krueger et al., 2014; Mills et al., 2005). A band usually consists of 3 to 6 animals (da Cruz et al., 2023; Krueger et al., 2014). Like movement initiation in cattle, high-ranking horses initiate group movement and are followed more often than low-ranking animals (Krueger et al., 2014). In the sub-model, the behavioral roles assigned to horses were leaders and followers. I created grazing groups of 5 animals, with only one leader per group. I set 500 m as the maximum distance between individuals of the same band or grazing group.

Social interaction is critical in altering foraging behavior in highly social animals like sheep (Sibbald et al., 2008). One of the most significant characteristics of social behavior in sheep is their tendency to graze as a group and to gather when disturbed. However, individual responses can alter the strength of this behavior (Sibbald & Hopper, 2003). In the case of sheep, grazing groups and subgroups are created based on the distance between herd neighbors (Sibbald et al., 2008). Animals within a 50 m proximity are part of a grazing group (Dumont & Boissy, 2000); however, sheep prefer to stay within 15 m of their herd neighbors (Sibbald et al., 2008). In the sub-model, multiple groups can graze in the same area (50 x 50 m), with a grazing group consisting of 6 animals. When the number of animals in a grazing group exceeds 6, the group splits into equal-size subgroups (Michelena et al., 2009). Animals within 5 m are considered the nearest neighbors (Sibbald et al., 2008). The maximum distance animals can be separated from each other and still be considered part of a given group is 50 m

b.2 Habitat Suitability Index (HSI) estimation

The second process the Livestock Grazing Behavior sub-model performs is estimating the HSI for each animal species. The HSI for a grazing area, i.e., patches of vegetation in a grazing area, is calculated as a function of slope (all species), forage availability (all species), and the proximity to cattle (only for sheep). The HSI does not include distance to water sources because there is no available data on the water sources livestock use in the study sites. Thus, one assumption in the model is that water is well-distributed across the landscape, and animals do not have a problem accessing it. The slope coefficient follows a linear relationship established in the sub-model and ranges from 0 to 1. For instance, if an animal needs to select between a grazing area with a slope of 15 vs. one with 35 degrees, a smaller value will be assigned to the steeper grazing area than the one in a flat area, with the animals favoring larger numbers. In the sub-model, only leaders (cattle and horses) and independent animals (only cattle) estimate the HSI. To avoid estimating the HSI for the whole landscape, which will increase the demand for computing power, leaders and independent animals calculate the HSI only for a sample of patches within a 600 m radius. Once leaders and independent animals estimate the HIS of a grazing area, they move to the selected area to find the most optimum grazing areas. Followers move to the grazing area or feeding site chosen by the leader and then select their most preferable areas or feeding stations for grazing.

Sheep management in Arhuaycancha consists of herding animals in all vegetation classes except wetlands. Moreover, shepherds prioritize that cattle have access first to the best grazing areas, i.e., wetlands and flat areas. Thus, the HSI estimation for sheep is a function of the slope of a grazing area, vegetation cover class, and the proximity to cattle, with the strength of avoidance represented by a coefficient. The proximity to cattle coefficient prevents sheep from selecting a grazing area if it is less than 500 m from cattle, a distance established to represent the current management sheep and cattle conditions. This coefficient follows a linear relationship established in the sub-model, estimated similarly to the slope coefficient.

b.3 Forage consumption

This process requires information from L-Range, the ecosystem process model, about monthly available biomass from the different biomass pools. Livestock can consume biomass from the eight vegetation pools present in L-Range. However, each species has its own preference for consuming biomass from the different pools. The daily biomass consumed is the sum of forage consumed each hour and depends on an animal's metabolic body weight and forage availability. Since L-Range estimates primary production (forage) monthly, the daily forage consumption is summed to get a monthly estimate. The Vegetation Dynamics sub-model then uses this information to estimate the amount of forage available (not consumed) for the next month.

b.4 Energy and body weight dynamics

This process establishes the daily energetic requirements for basal metabolism, grazing, rumination, and (vertical and horizontal) movement for each species. Then, it calculates the daily energy acquired from forage consumption, which depends on the metabolizable energy of the biomass ingested. I established different metabolizable energy values for each cover class (grasslands, shrublands, wetlands, and woodlands) for the dry and rainy seasons. Nevertheless, I used average energy values at the cover class level due to the limited information on the metabolizable energy of Andean vegetation at the facet level (herbs, shrubs, and trees). Information from daily energy requirements and energy acquired from forage consumption is then used to estimate the energetic budget of an animal for gaining or losing weight. An animal requires 26 MJ of Net Energy/kg Body Weight to gain one kg (Coppock et al., 1986; ARC 1980). Changes in energy budget and body weight are calculated monthly.

c. Grazing and Land Management

Cattle graze from 8:00 to 18:00. In the morning, animals are moved to a grazing field until 15:00. Later, cattle are moved to a grazing area about 200 m near a corral. Finally, cattle return to their corral by 18:00. Sheep graze from 9:00 to 18:00. The morning grazing occurs from 9:00 to 15:00 when animals are moved from their corrals to a grazing area within a grazing field. In the afternoon, around 15:00 sheep are moved to an area 200 m near the corral. Sheep should also be in their corral by 18:00. Horses are not tended; they graze freely in the fields assigned to their owner's family. Different grazing fields are used for the dry and rainy seasons. Two to four families usually share grazing fields. The selection of grazing areas within a grazing field is updated every 4 days for sheep, 3 days for cattle, and 2 days for horses.

Creating the ANDES model required converting information about livestock social and grazing behavior and energy dynamics from peer-reviewed articles and theses to a programming language (e.g., NetLogo; Wilensky, 1999). Similarly, information from the land and livestock management report of the Cordillera Blanca community elaborated by the Mountain Institute (Alata & Fuentealba, 2018), a local non-governmental organization, was converted into a programming language.

3.1 Scenarios under analysis

I designed and implemented management scenarios to analyze their potential impact on livestock grazing behavior and performance. The scenarios under analysis include the current management conditions, a mixed grazing system, a 45-day deferred rotation grazing system, livestock population reduction, and seasonal access to grazing lands in the park (Figure 5.2 and Table 5.1). The management scenarios were created and implemented in the ANDES model. As part of my analysis, I used precipitation and temperature data from three global circulation models for the 4.5 Representative Concentration Pathways (RCP) to simulate ecosystems' responses to climate change in the ecosystem-process model (L-Range). Due to time constraints, I performed two repetitions for each land management scenario and climate model. The number of years simulated for each scenario was 30 (2020 - 2050).

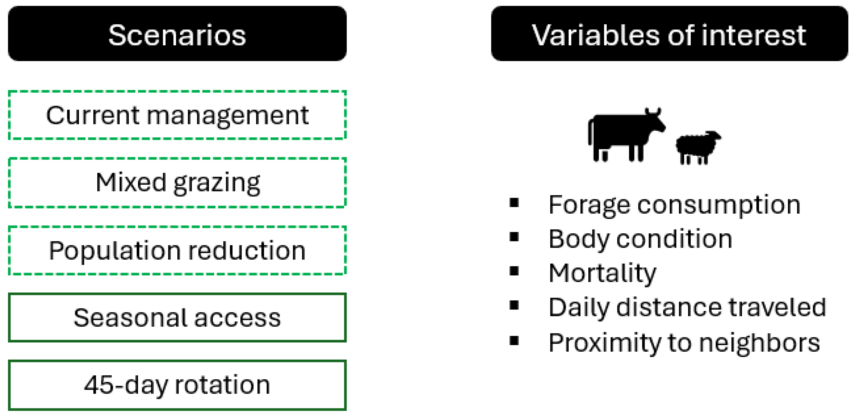

Figure 5.2. *Scenarios under analysis and variables of interest. Note: The dotted lines represent scenarios with no changes in the rotation of grazing fields.*

Table 5.1. *Description of the management scenarios*

Scenario	Short name	Description
Current management	Current management	– During the wet season (Nov - Apr), livestock graze in the community's lands and some grazing areas in the park. – During the dry season (May - Oct), animals graze only in the park. – 17 grazing fields (community and park) are part of this grazing management scheme. – Cattle graze in flat areas (mainly wetlands). – Sheep graze only on mountain slopes. – Livestock population: 417 cattle, 2684 sheep, and 87 horses.
Current management + mixed grazing	Mixed grazing	– The grazing field rotation is the same as the "Current management" scenario. – Cattle and sheep graze in the same areas. – Grazing area selection is based on attributes of the fields, e.g., forage availability and slope. – Livestock population: 417 cattle, 2684 sheep, and 87 horses.
Current management + livestock population reduction	Population reduction	– The grazing field rotation is the same as the "Current management" scenario. – The livestock population is reduced to the maximum number of animals established by the Park Service. – Livestock population: 302 cattle, 1491 sheep, and 36 horses.
45-day rotation + livestock population reduction	45-day rotation	– The livestock population is reduced. – This new management scheme required grouping herds owned by different families and grouping grazing fields (current management).

		– This grazing management scheme consists of 12 grazing fields, where animals are rotated every 45 days during the year.
Seasonal access + livestock population reduction	Seasonal access	– The livestock population is reduced. – Animals can graze areas in the park (within the park boundaries) only during the dry season. – This new management scheme consists of six grazing fields in the park and six in the community.

3.2 Model assessment

The validation of the ANDES model included statistical analysis such as summary statistics of model outputs, time series analysis, the identification of tipping points in the behavior of the sub-models, and the use of extreme values in the model (Grimm & Railsback, 2011). The model was tested through pattern analysis of agents' behavior to analyze its structure and underlying mechanisms (Grimm et al., 2010). For instance, patterns in the fluctuations of body weight and the energetic budget of livestock due to variations in forage availability were compared to empirical outputs from reports, thesis, and peer-review journals. Additionally, sensitivity analysis for the ANDES model was performed by running experimental simulation scenarios. For instance, the analysis of livestock foraging behavior involved creating scenarios where only the number of animals or the amount of available biomass for grazing was shifted. The validation of the L-Range model results required comparing the model outputs, e.g., net primary production and vegetation cover, to historical data and remotely sensed data.

4. Results

I present the average results for each scenario due to the minimal variation across repetitions.

4.1 Changes in daily average forage consumption

Cattle

Animals in the “45-day rotation” scenario have the highest daily forage consumption. Under the “Population reduction” and “Seasonal access” scenarios, forage consumption had an intermediate level

(Figure 5.3). However, cattle consumed about 25% less forage under these two scenarios. The forage consumption of animals under the “Current management” and “Mixed grazing” scenarios was the lowest. Under these scenarios, animals consumed about 50% less forage with respect to the “45-day rotation” scenario. The scenarios with the lowest variability in the total annual forage consumed were the “45-day rotation” and the “Seasonal access”. Daily forage consumption exhibited a negative trend over time in all scenarios. Nonetheless, this trend was very marked for the “Population reduction”, “Current management”, and “Mixed grazing” scenarios.

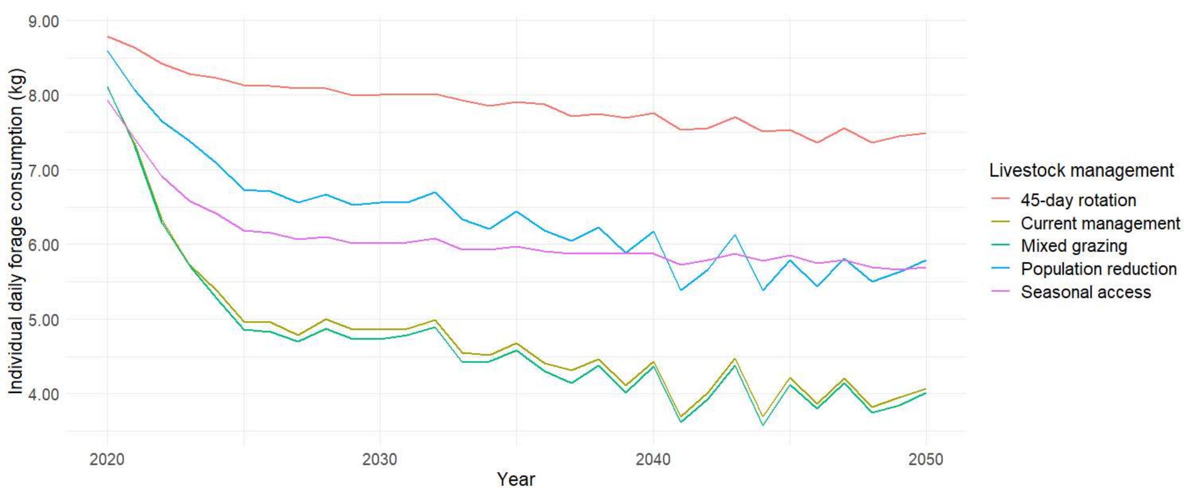

Figure 5.3. *Cattle forage consumption by management scenario – RCP4.5*

Sheep

Animals in the “Population reduction” scenario had the highest daily forage consumption (Figure 5.4). Under the “45-day rotation” and “Seasonal access” scenarios, sheep forage consumption had an intermediate level. Forage consumption in the “Current management” and “Mixed grazing” scenarios was the lowest compared to the other scenarios. The “45-day rotation” scenario had the lowest variability in forage consumption over time. Similarly to my findings for cattle, forage consumption exhibited a negative trend over time for all scenarios, especially for the "Current management" and the "Mixed grazing" scenarios.

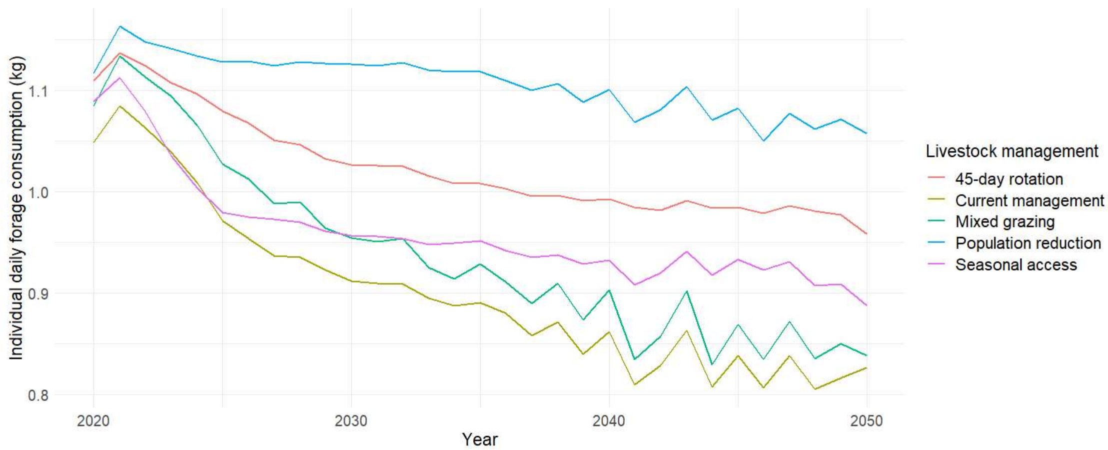

Figure 5.4. *Sheep forage consumption by management scenario – RCP4.5*

4.2 Changes in the daily average distance traveled

Cattle

Animals under the "45-day rotation" scenario traveled the longest distances every day (Figure 5.5). Under the "Seasonal access" scenario, animals also traveled larger distances; however, these distances were about 30% shorter than the "45-day rotation" scenario. The distance traveled for the other scenarios, i.e., "Current management", "Mixed grazing", and "Population reduction", were the shortest. Moreover, these distances did not exhibit much variation between them. Conversely, the distance traveled by cattle in the "45-day rotation" and "Seasonal access" scenarios varied more over time.

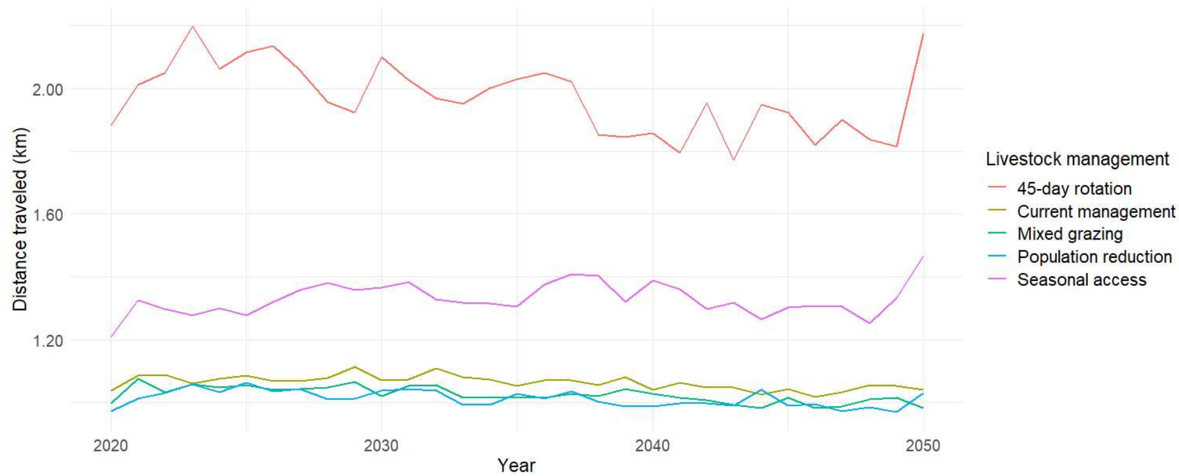

Figure 5. *Daily distance traveled by cattle by management scenario – RCP 4.5*

Sheep

The daily distance traveled by sheep followed the same pattern as cattle. Sheep under the "45-day rotation" scenario traveled the longest distances (Figure 5.6). Under the "Seasonal access" scenario, animals also traveled larger distances; however, these distances were shorter than the "45-day rotation" scenario. These two scenarios showed large variations in sheep's daily distance traveled. The distance traveled for the other scenarios, i.e., "Current management", "Mixed grazing", and "Population reduction", were the shortest, and did not exhibit much variation between them.

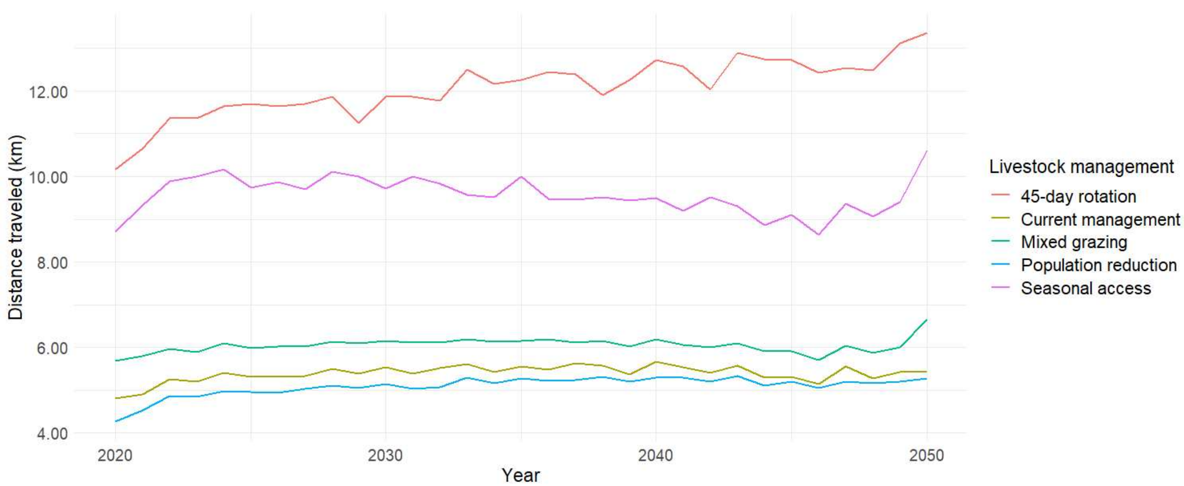

Figure 5.6. *Daily distance traveled by sheep by management scenario – RCP 4.5*

4.3 Changes in the daily average distance to neighbors

Cattle

The daily distance to neighbors followed an opposite pattern than the daily distance traveled (Figure 5.7). The distance to neighbors of animals under the "Population reduction" scenario was the longest (~65 m). The daily distance to neighbors in grazing groups in the "Mixed grazing" and "Current management" scenarios was similar (~55m) but shorter compared to the "Population reduction" scenario. Neighbors in a grazing group under the "45-day rotation" and "Seasonal access" scenarios were much closer to each other, about 30 m. In general, changes in the distance to neighbors did not broadly vary across time for each scenario.

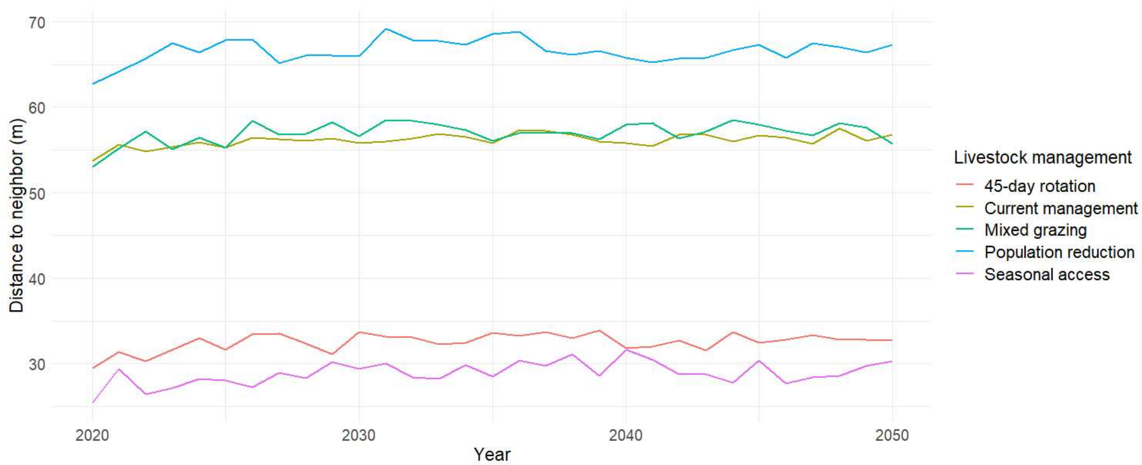

Figure 5. 7. *Daily average distance to neighbors by cattle by management scenario – RCP 4.5*

Sheep

Animals in the "Population reduction" scenario had the longest daily distance to neighbors (~23 m) (Figure 5.8). Conversely, animals in the "Current management" scenario were much closer to each other (~17 m). The daily distance to neighbors was much longer for animals in the "Mixed grazing" scenario than in the "Current management" scenario. Changes in the daily distance to neighbors were very variable across time and scenarios.

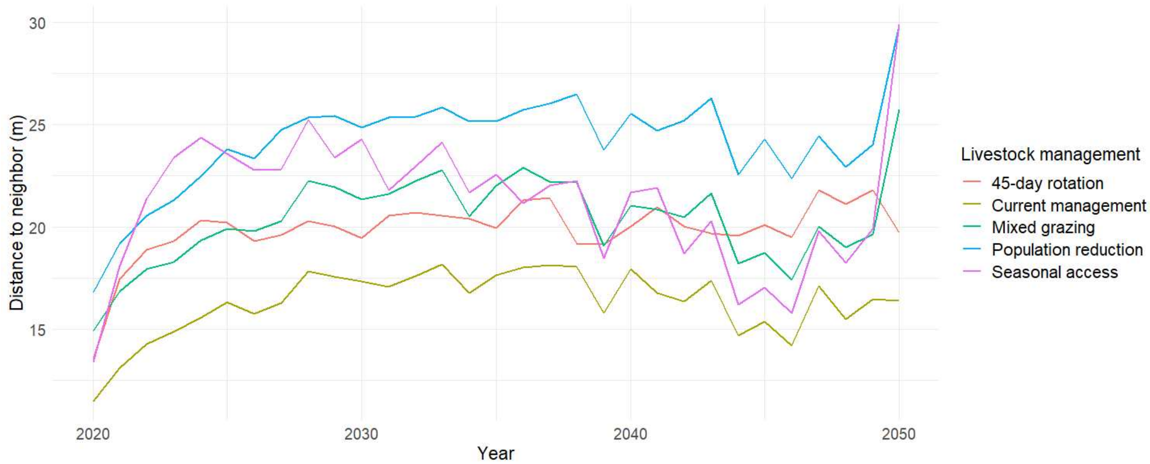

Figure 5.8. *Daily average distance to neighbor by sheep by management scenario – RCP 4.5*

4.4 Changes in body condition index

Cattle

Changes in body condition follow the same pattern as forage consumption. Animals under the "45-day rotation" scenario had the highest body condition index, followed by those under the "Population reduction" scenario (Figure 5.9). The scenarios with the lowest variability in body condition index over time were the "45-day rotation" and "Seasonal access". The body condition index of cattle under the "Seasonal access" scenario was reduced by about 25% compared to those under the "45-day rotation" management scenario. Animals under the "Current management" and "Mixed grazing" scenarios underwent a more extreme reduction of body condition index of about 50% than cattle under the "45-day rotation" scenario. The body condition index of animals in the "Current management", "Mixed grazing", and "Population reduction" scenarios exhibited a negative trend.

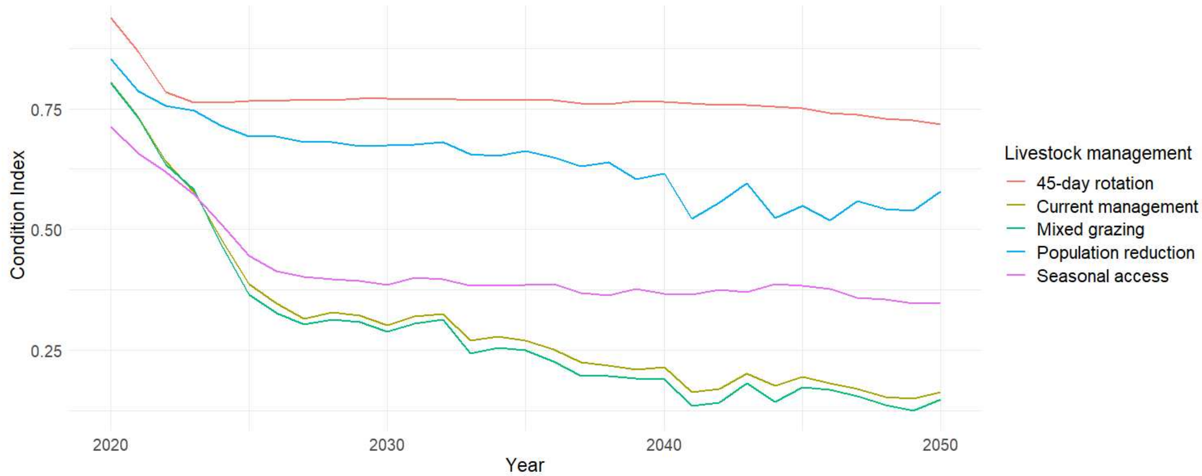

Figure 5.9. *Cattle body condition by management scenario – RCP 4.5*

Sheep

The body condition index of animals under the "Population reduction" scenario was the highest (Figure 5.10). The body condition index was much lower for the other scenarios, for which the index was reduced by about 70%. The "Population reduction" and "Seasonal access" scenarios had the lowest variability in the body condition index over time. The body condition index of all scenarios, except for the "Population reduction" scenario, had a marked negative trend from the beginning of the simulations. However, from all these scenarios, only the condition index of animals in the "Seasonal access" scenario showed a constant trend after year 5 of the simulation.

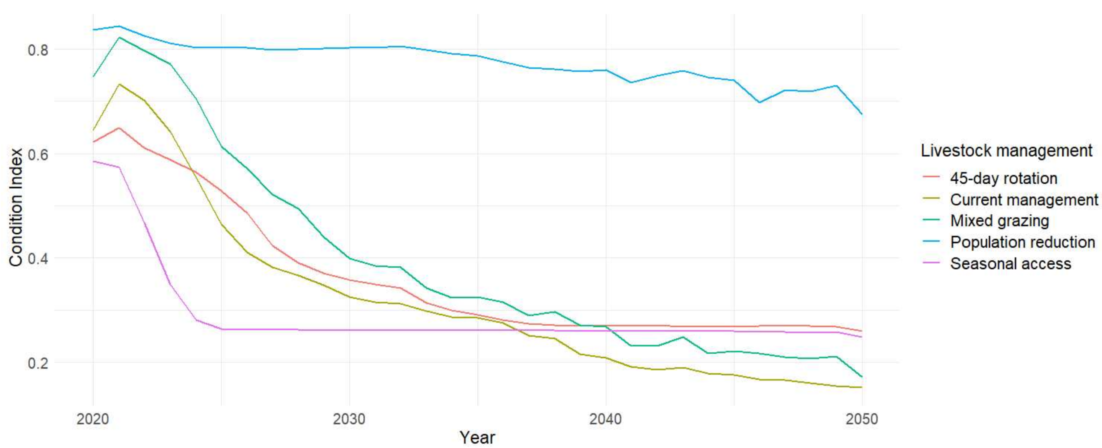

Figure 5.10. *Sheep body condition by management scenario – RCP 4.5*

4.4 Changes in the number of livestock deaths

Cattle

The number of cattle deaths across scenarios followed the same trend as the body condition index. The highest number of deaths occurred under the "Current management" and "Mixed grazing" scenarios (Figure 5.11). The lowest number of deaths occurred under the "45-day rotation" and "Population reduction" scenarios. Under these scenarios, the number of deaths was reduced by about 50%. Nevertheless, the number of deaths varied across years for all scenarios.

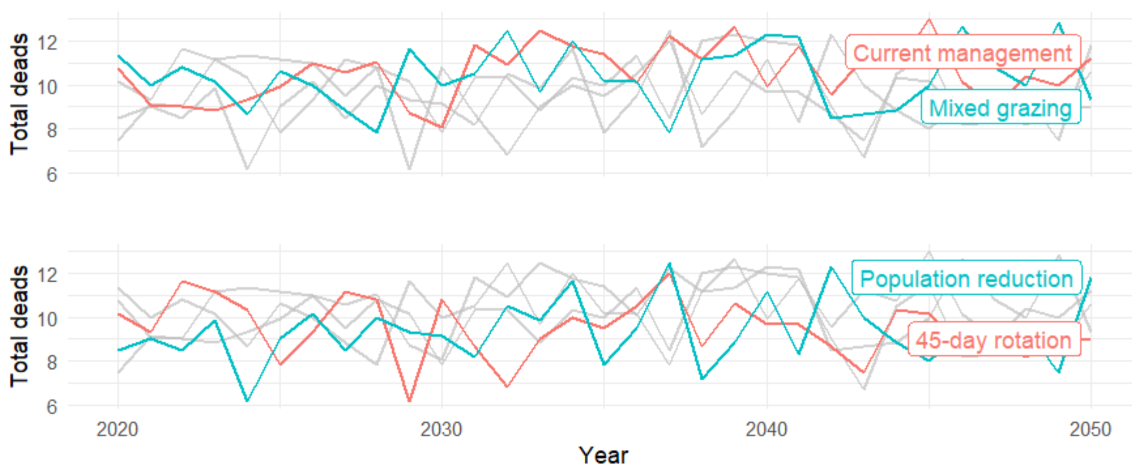

Figure 5.11. Ma*ximum (top plot) and minimum (bottom plot) number of cattle deaths by management scenario – RCP 4.5.*

Sheep

The number of deaths across scenarios followed the same trend as the body condition index. The highest number of deaths occurred under the "Current management" and the "Mixed grazing" scenarios (Figure 5.12), which were 20% higher than the other scenarios. In contrast, the lowest number of deaths occurred under the "Population reduction" scenario. The number of deaths exhibited extensive variation across years for all scenarios.

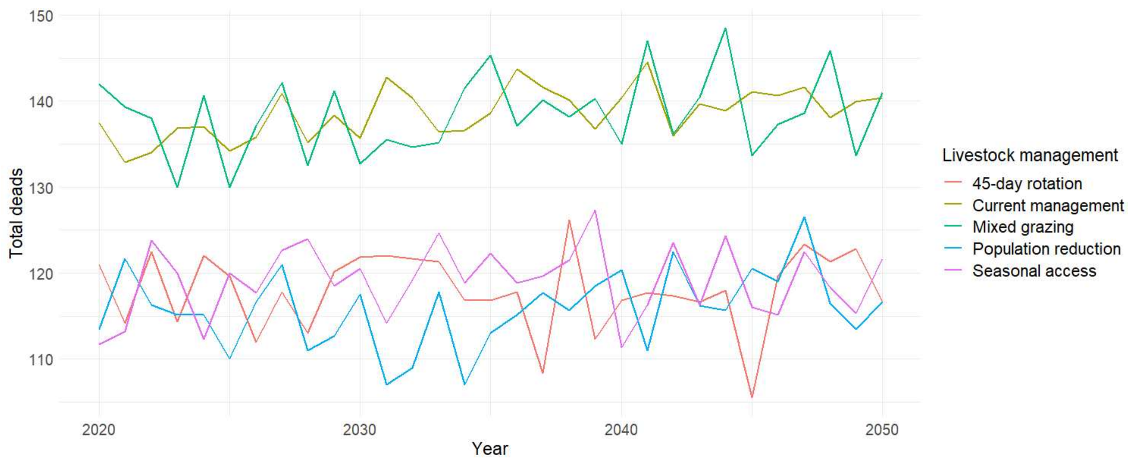

Figure 5.12. *Number of sheep deaths by management scenario – RCP 4.5*

4.5 Changes in grazing behavior and performance of horses

Due to the lack of information about horse management, I did not incorporate specific grazing rules for horses when creating the management scenarios. Moreover, because the horse population is small and should not be allowed to graze in the park, I decided not to focus my analysis on this species. Here, I briefly present the main findings on the impacts of grazing management on horses. Similar to cattle and sheep, horses under the "Population reduction" "Seasonal access", and "45-day rotation" scenarios had the highest body condition (Appendix C). However, the body condition index under all scenarios showed great variability over time, with a marked negative trend for the "Current management" and "Mixed grazing" scenarios. The number of deaths across scenarios followed the same trend as the body condition index. The daily distance traveled by horses did not broadly vary across scenarios. The longest daily distance traveled was under the "Mixed grazing" and "Current management" scenarios. The shortest daily distance traveled was under the "Population reduction" scenario. The longest distance to neighbors (~450 m) was under the "Mixed grazing" scenario. Under the other scenarios, animals in a grazing group were much closer (~130 m).

5. Discussion

5.1 Changes in forage consumption

The highest daily forage consumption for cattle and sheep occurred in different scenarios. Cattle under the "45-day rotation" scenario had the highest forage consumption. In contrast, sheep under the "Population reduction" scenario had the highest forage consumption. These findings suggest that shorter and dynamic grazing management, i.e., the "45-day rotation" scenario, is more beneficial for cattle than sheep. Cattle's favorable response can be related to a more uniform use of forage and a limited grazing selectivity. Rotational grazing systems through a less clustered distribution of livestock promote a more homogenous use of vegetation (Perotti et al., 2018; Rivero, 2021). The less favorable response of sheep to the "45-day rotation" scenario could be associated with competition with cattle, which became less selective under this grazing scheme. Under the scenarios with a reduction in livestock population, the livestock number was reduced by about 28% for cattle, 45% for sheep, and 58% for horses. The highest reduction in sheep population, about 20% more than cattle, can be responsible for sheep's better response to the "Population reduction" scenario than cattle.

The lowest daily forage consumption of cattle and sheep under the scenarios without livestock population reduction suggests that the current demand for forage exceeds the amount of available forage, i.e., the stocking rate exceeds the carrying capacity of the grazing fields. The stocking rate, or the number of animals occupying a particular area over a period of time, affects animal distribution and forage use (Rivero, 2021). Cattle and sheep had intermediate levels of forage consumption in the "Seasonal access" scenario. Under this scenario, the livestock population was reduced, and the area for grazing was significantly limited throughout the year, i.e., animals grazed in the park only during the dry season. These restrictions allow livestock to consume more forage than animals in the "Current management" and "Mixed grazing" scenarios, i.e., scenarios without livestock population reduction. However, the reduced grazing area limited the amount of forage livestock could access throughout the year, which could explain the lower livestock forage consumption in this scenario ("Seasonal access") compared to the "45-day rotation" and "Livestock population reduction" scenarios.

Forage consumption in the "Mixed grazing" and "Current management" scenarios was similar, with sheep responding better than cattle. This better response could be associated with higher forage availability in the "Mixed grazing" scenario compared to the "Current management" scenario, where sheep could only graze on mountain slopes. Moreover, different forage preferences of cattle and sheep could also play a determinant role in forage use. By consuming mid-height or tall grasses, cattle could have facilitated and given sheep access to forbs and legumes (Su et al., 2023). However, the excessive number of animals in this scenario could have affected the positive effect of mixed grazing.

5.2 Changes in average daily distance traveled

Cattle and sheep in the “45-day rotation” scenario traveled the longest daily distances. Cattle and sheep in the “Seasonal access” scenario also traveled larger distances; however, these distances were shorter than the “45-day rotation”. The long distances traveled indicate that animals became less selective and moved more to find more forage resources to meet their daily energy requirements. This finding also reveals that animals under the “45-day rotation” scenario struggle more to find forage than those in the “Seasonal access” scenario.

In contrast, animals under the “Current management”, “Mixed grazing”, and “Population reduction” scenarios traveled the shortest distances, with livestock under the “Population reduction” scenario traveling the least. In the “Current management” and “Mixed grazing”, the short distances traveled could result from competition since the livestock population was not reduced in any of these scenarios. Therefore, animals must consume as much forage as possible before moving to a different area. In contrast, the shortest daily distance animals traveled in the “Population reduction” scenario could result from higher forage availability due to a reduced animal population, making animals not need to travel longer distances to find forage resources.

The heterogeneity of the landscapes in the study area could have created unique conditions, such as dispersed patches of vegetation with high-quality forage or grazing areas with difficult accessibility, that affected livestock grazing behavior and, therefore, the daily distance traveled. The type and quality of vegetation determine the frequency of animal visits, grazing distribution, and resting site selection (Rivero et al., 2021). The distribution of livestock in heterogenous environments like mountain rangelands is often irregular, with abiotic and biotic factors influencing livestock grazing behavior at multiple scales. The importance of biotic factors, such as forage quantity and quality, on livestock selectivity is more relevant at finer scales, such as plants or patches of vegetation. In contrast, abiotic factors, such as topography and water source proximity, are more relevant at larger scales, i.e., landscape level, due to animals' perceptions of their environments (Von Müller et al., 2017). In a recent study, Rivero et al. (2021) performed a literature review of studies that used Global Position Systems collars to analyze the factors influencing grazing selection sites by cattle. They found that stocking rate, the location of shade and water resources, weather conditions, vegetation, and terrain features impact cattle grazing behavior. Baum et al. (2022) found that sheep in mountain landscapes prefer grazing in areas with gentle terrain and higher elevation and take the least resistance path.

Another factor that could influence the daily distance traveled is herding. In the ANDES model, the selection of the most optimum grazing area, *via* the habitat suitability index, was updated at different intervals for each species to speed processing times, potentially impacting grazing behavior, livestock movement, and forage consumption. For instance, if sheep could not find enough forage resources, they had to graze in the same area for four days, the time when the suitability index was updated. In the ANDES model, cattle graze freely in the late afternoon, which gives animals the agency to select their most preferable grazing areas and move more frequently if needed. Raniolo et al. (2022) studied the impacts of herding on grazing patterns of a mixed herd of lactating cows in the Italian Alps

(1957 masl). The management involved herding the animals to a specific area of the pasture in the morning while they were left to graze freely in the afternoon. The herder's choice of pasture area influenced the cows' daily walking distance, vertical movement, and slope preferences. Moreover, the cows preferred grazing on gentler slopes and grassland patches when not herded due to the energetic costs of movement. Though cattle in the ANDES model were not herded, the leader’s decision to find the most optimal grazing area could have impacted the daily distance traveled by animals (followers).

5.3 Changes in distance to neighbors

Cattle and sheep in the “Population reduction” scenario had the longest distances to neighbors, with about ~65 m and ~23 m, respectively. These long distances can result from fewer animals on the landscape, so each one is farther from its neighbors and increases in selectivity, i.e., animals move more to select their most preferred grazing patches, due to higher forage availability. Additionally, social behavior and intrinsic factors, such as animal perception, could also play a role in animal proximity. Forage availability and thermoregulatory needs affect the distance between subgroup members in a cattle herd. If forage is abundant, herds travel in larger groups; however, when forage becomes scarce, herds divide into subgroups (Rivero et al., 2021). Sibbald et al. (2008) found that sheep prefer to graze on the largest patches of vegetation because they perceive them as areas of higher forage resource availability. Besides, larger patches allow sheep to graze at their preferred distance from their group neighbors.

The proximity to neighbors for cattle in the “45-day rotation” and “Seasonal access” scenarios was much closer compared to the other scenarios. Moreover, this distance was reduced by about 45% with respect to the “Population reduction” scenario. This short proximity to neighbors can result from more animals grazing in the same field, which leads to more competition for resources and less time for moving. The distance to the neighbors for sheep in the “Current management” scenario was the shortest, about 25% shorter than in the other scenarios. Since the “Current management” scenario did not imply a livestock population reduction, the short distances can be attributed to competition for limited resources that limited sheep movement.

The proximity to neighbors for cattle in the "Mixed grazing" and the "Current management" scenarios was similar, with animals in the "Mixed grazing" scenario slightly more separated (~3 m) from each other than those in the "Current management" scenario. Sheep in the "Mixed grazing" scenario were much farther (~10 m) from each other than animals under the "Current management" scenario. Under the "Current management" scenario, sheep graze only on mountain slopes. In contrast, under the "Mixed grazing" scenario, sheep were allowed to graze in the same areas as cattle. Thus, this change in grazing management could be responsible for animals walking more to find their most preferred grazing areas. The larger distance to neighbors in the "Mixed grazing" scenario can also be due to increased competition with their conspecifics and the other species (cattle, sheep, and horses), which may cause sheep to move more to find more forage. Additionally, sheep's high variability on the daily distances to neighbors could be caused by social behavior. A sheep would move to a preferred feeding alone or with peers only if it is close to its social group (Dumon & Boissy, 2000).

5.4 Changes in body condition

The body condition of cattle followed the same pattern as forage consumption. Cattle under the "45-day rotation" scenario had the highest body condition index (~0.75), followed by animals under the "Population reduction" (~0.60) and the "Seasonal access" scenarios (~0.40). The body condition index for the other scenarios was much lower (~0.25) and had a marked negative trend. To better understand changes in body condition, it is necessary to analyze other factors such as forage consumption and daily distance traveled. For instance, even though cattle in the "45-day rotation" scenario traveled the longest distances, they could meet their energy requirements and get a high body condition index. However, this was not necessarily the case for cattle under the "Seasonal access" scenario, for which animals also traveled long distances. However, they got an intermediate score on the body condition index. These findings indicate that animal performance under the "45-day rotation" scenario was better than the "Seasonal access" scenario.

The highest body condition index of sheep was for animals under the "Population reduction" scenario. The sheep's body condition for the other scenarios was very low (~0.25) with a negative trend over time, except for animals in the "Seasonal access" scenario, which had a slightly better response. These low scores in sheep's body condition compared to cattle can indicate that forage consumption, in all scenarios, was not enough to meet sheep's daily energy requirements. The low body condition index of sheep under the "45-day rotation" scenario and its negative trend over time can be associated with the longest distances animals traveled daily to meet their energy requirements and with competition. This finding also suggests that the livestock population reduction was not optimal and needs to be adjusted.

5.5 Changes in mortality

The number of deaths across scenarios followed the same trend as the body condition index. However, livestock mortality varied over time for each scenario. The highest number of deaths for cattle and sheep occurred under the "Current management" and "Mixed grazing" scenarios, those that did not imply a reduction in livestock population. The number of cattle deaths under the "45-day rotation" and "Livestock population reduction" scenarios was reduced by up to 50% compared to the "Current management" and "Mixed grazing" scenarios. In contrast, sheep deaths decrease by up to 20%. These findings suggest that lower body condition index had a more negative impact on sheep than cattle, resulting in more deaths. It also indicates an excess of animals under the current management conditions and that forage available is not enough for livestock to meet their energy requirements. Moreover, it reveals that the livestock population should be adjusted, i.e., the number of animals should be even more reduced in all management scenarios to prevent deaths.

Caveats

No model can nor needs to represent all processes, components, and interactions of a system. The lack of information about grazing behavior in heterogeneous mountain landscapes, such as the Peruvian Andes, made the "Livestock Grazing Behavior" sub-model mainly rely on theoretical information for its construction and challenged model validation. Although I used data from field studies conducted in other areas of the Andes of Peru and other Alpine areas worldwide to parametrize and validate the model, I also had to make some assumptions and generalizations.

The processes and variables used to create the "Livestock Grazing Behavior" sub-model of ANDES represent one of many approaches modelers can use to simulate grazing behavior. Therefore, based on users' or modelers' simulation needs, our modeling approach can be more or less convenient. The accuracy of the “Livestock Grazing Behavior” sub-model could have been enhanced with data on livestock structure, including age, sex, physiological state (e.g., pregnant and milking animals), and replacement rates by animal species. Unfortunately, this information was unavailable when I built the model. Furthermore, while I used information from studies on livestock grazing behavior and energy dynamics in mountain areas worldwide to develop the “Livestock Grazing Behavior” sub-model, it remains uncertain how much of this information can be extrapolated to creole and mixed-breed cattle and sheep adapted to Andean conditions.

Additionally, any overestimations or underestimations of forage availability in grazing fields by the L-Range model may have impacted the simulations of the “Livestock Grazing Behavior” sub-model. Furthermore, understanding how shepherds adjust livestock management in response to changes in forage availability and weather conditions (such as frost and precipitation) could enhance the representation of livestock management and grazing behavior throughout the year. Finally, the spatial location of water sources used by livestock, along with water quality parameters, should be incorporated into the sub-model to account for their impact on livestock movement.

6. Conclusion

Livestock grazing behavior and performance were influenced by management scenarios, with some variability for each animal species. Cattle and sheep, under the scenarios of livestock population reduction, consumed the highest amount of forage. Nonetheless, cattle respond more favorably to the short and dynamic grazing rotation scheme, i.e., the "45-day rotation". Competition with their conspecifics and cattle could have been responsible for sheep's lower forage consumption under this scenario. My findings also reveal that the current stocking rate exceeds the carrying capacity of the grazing fields. The daily distance traveled could be associated with livestock management. Animals under the "45-day rotation" scenario traveled the longest daily distances, which can be associated with less competition, and more forage available. Animals in the scenarios with no livestock population reduction traveled the shortest distances every day. Competition and limited forage availability could have reduced animals' selectivity and movement.

The body condition of livestock followed the same pattern as forage consumption. Cattle had higher body condition under all scenarios with livestock population reduction. In contrast, the body condition index of sheep was high only for animals in the "Population reduction" scenario. Variations in cattle' performance can be due to the different management schemes that could affect grazing behavior. Sheep's low performance under all scenarios, except the "Population reduction" scenario, suggests high competition levels even under the new grazing management schemes. My findings also reveal that the stocking rate (cattle and sheep) for the new management scenarios was not optimal. Livestock mortality followed the same trend as body condition. The highest number of deaths occurred under the scenarios that did not imply a reduction in livestock population. This finding also confirms the need for adjusting the carrying capacity across all scenarios to reduce livestock mortality.

As described in Chapter 3, climate change will impact ecosystems differently. Woodlands and shrublands will become more productive, while wetlands will be negatively impacted. Moreover, bare cover will increase for all cover classes, and herb and shrub cover will be variable. These responses of ecosystems to future climate conditions will have significant repercussions on livestock grazing behavior and animal performance.

Overall, I found that grazing management affects forage consumption, grazing behavior, and animal performance. The reduced forage consumption and body condition and the higher number of deaths under the scenarios without the reduction of livestock population indicate that the stocking rate exceeds the carrying capacity of the grazing fields. Moreover, the sub-optimal livestock response under the new management schemes also reveals the need to adjust the stocking rate for these scenarios, not only based on the number of animals allowed by the Park Service or the community but also on the grazing fields' carrying capacity.

Recommendations

This study represents the first effort to model livestock grazing behavior and grazing management in the Peruvian Andes. With my modeling analysis, I was able to determine how different management systems impact livestock grazing behavior and performance and identify data and research gaps and, therefore, opportunities for future research. For example, using Global Position Systems collars to track livestock in real-time can provide information about their location and movement patterns. Using unmanned aerial vehicles or drones can also help determine patterns of grazing use, identify landscape features that hinder or favor livestock movement, and analyze group behavior dynamics. Though using technology is promising for studying grazing behavior, field experiments are equally valuable and needed. For instance, observational studies of livestock forage preferences, forage consumption, and estimations of metabolizable energy of forage and energetic requirements for livestock adapted to the Andean conditions will be beneficial for modeling but, more importantly, for improving livestock management. Finally, designing sustainable grazing management systems requires collaborative work and planning with stakeholders to identify their management challenges, needs, and priorities.

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CHAPTER 6: CONCLUSIONS

What I did and found

This dissertation explores the impacts of socioeconomic and environmental factors on protected areas using big data analysis and agent-based modeling. By adopting a socioecological system approach, I assessed how human and environmental factors affect protected areas, highlighting the role of their biophysical and socioeconomic contexts for their conservation effectiveness and the degree of external pressures they face.

I used novel approaches and techniques to analyze complex social-ecological systems. I used open-source spatial data and performed conditional random forest analyses to quantify landscape changes in protected areas and identify the most important socioeconomic and environmental factors associated with them. I opted for performing conditional random forests over the conventional random forest to reduce potential issues due to the high correlation among variables and obtain more reliable results since variable selection in conditional random forests is based on independent hypothesis testing. Additionally, while most studies of land cover change and degradation in protected areas focus mainly on forests, my analysis includes grasslands, shrublands, and wetlands, providing a more comprehensive understanding of the conservation state of these cover classes and the socioeconomic and biophysical factors driving changes in their landscapes.

For the case study, I used a social-ecological modeling approach to deepen my understanding of how new management scenarios and future climate conditions would impact ecosystems and families' economies in the Andes of Peru. I parametrized an ecosystem-process model (L-Range) to Andean environmental conditions to capture potential ecosystem responses to climate change. Additionally, I built an agent-based model (ANDES) that simulates livestock grazing behavior, land management practices, and household economies. The coupled ANDES/L-Range model represents the first attempt to model a coupled human-natural system in the Peruvian Andes to analyze climate change and land management long-term impacts on ecosystems and households.

My findings indicate that the landscapes of approximately half of the world's protected areas have undergone significant changes between 2000 and 2020, with considerable variation across regions and cover classes. These changes are mainly driven by anthropogenic factors such as agricultural expansion, population density, levels of human development, and the level of regulation governing protected areas. Additionally, the case study on the impacts of climate change and land management on an agropastoral system in the Andes of Peru reveals that climate change impacts on ecosystems will be very variable. Furthermore, implementing new management strategies will lead to economic and ecological repercussions, affecting vegetation, livestock production, and household economies.

The information generated from my analysis has important implications for the sustainable management and conservation of protected areas. Determining the level of fragmentation in protected areas by cover class and regions is critical for assessing their conservation status, effectiveness, and pressure level. Furthermore, identifying key socioeconomic and environmental factors associated with landscape changes provides valuable information for developing integrative policies that balance conservation and sustainable development. The case study increases our understanding of the response of an Andean agropastoral system to changes in future climate conditions and land management and reveals the intertwined nature of the coupled human-environmental system. The response of Andean ecosystems to climate change will vary by cover class, location, and climate scenario. Implementing new management schemes will have economic and ecological impacts on the coupled human-natural system. While management strategies that require a reduction in livestock populations will lead to short-term decreases in family incomes, they will foster, in the long run, positive ecological and livestock performance responses. Adopting new management strategies will hinge on families' willingness and capacity to implement them, as well as the social dynamics of the agropastoral system, which are influenced by factors such as migration and workforce fluctuations.

Additionally, the case study provides insights that can serve as a foundation for developing policies to promote sustainability and increase the resilience of the coupled system. It also has management implications. For example, it is essential to estimate the carrying capacity of grazing lands in the Arhuaycancha Valley to determine forage availability throughout the year. Vegetation assessments should be conducted to identify areas requiring special management, such as degraded zones with minimal vegetation cover that need revegetation. Furthermore, since wetlands are the cover class most likely to be impacted by climate change, they should be prioritized for implementing special management strategies to prevent their degradation. These strategies could include implementing rest periods for vegetation recovery, revegetation, and, if necessary, excluding grazing.

In addition, since livestock performance was highest in scenarios that required a reduction in livestock numbers, the animal population in the Arhuaycancha Valley should be adjusted according to the carrying capacity of the grazing fields. Moreover, implementing a more dynamic rotational grazing scheme could further enhance animal performance. Furthermore, to prevent overuse of vegetation and promote a more uniform distribution of livestock, it will be necessary for cattle and sheep to be herded throughout the day.

Lastly, developing livestock management regulations, such as setting a maximum number of livestock a family can own and changing grazing rotation schemes, requires careful consideration of their socioeconomic impacts. This involves identifying the age groups most likely to be affected by these changes and determining the impact of implementing these strategies on livestock management, including the requirements for personnel, labor, and resources. Furthermore, it is important to offer alternative strategies for families to mitigate any negative impacts on their livelihoods resulting from the implementation of new management schemes.

What I learned

Conducting my research at two different levels of analysis significantly deepened my understanding of the critical role that scale plays in research. While we learned about this in class, experiencing it firsthand is a different matter entirely. Through my local-scale study in the Andes of Peru, I found that fine-scale analyses can also be quite complex. For instance, when developing the sub-model of livestock grazing behavior, I realized the importance of staying focused on the primary modeling research goals. It's easy to get absorbed in intricate details that, in some cases, may not be necessary to model.

From the global-scale analysis, I learned that while this type of analysis often requires making generalizations, it is crucial to consider context-specific variations of explanatory factors. For instance, I grouped protected areas and socioeconomic and biophysical factors by region. This approach allowed me to account for regional variability, such as the differing socioeconomic contexts of protected areas in Latin America and the Caribbean compared to those in North America. Additionally, it enabled me to identify patterns of landscape change across regions.

I used open-source big data for the global analysis, and it was eye-opening to see how much information is available. Before conducting my research, I had never had the opportunity to work with global spatial databases. Through this global analysis, I gained valuable insights into the uses and limitations of these datasets, particularly regarding the importance of using an appropriate projection system to accurately represent the data. In contrast, for the case study in Peru, I encountered difficulties in obtaining climate data and information on vegetation and soil properties specific to the Peruvian Andes. Additionally, finding information on vegetation dynamics in alpine areas worldwide was challenging. It is striking how much open-source data is available, yet some research areas, such as climate change impacts in mountain regions, still have limited information.

What's next?

Implementing the ANDES model across the different valleys of Huascarán National Park will first require identifying the most representative agropastoral systems in the area so that the ANDES sub-models can be updated accordingly. Additionally, it will be necessary to engage with stakeholders, such as representatives from the surrounding communities and park personnel, to identify the most important scenarios for analysis. This approach will enable the ANDES model to address scenarios that are not only more relevant but also more likely to be implemented.

The ANDES model can be applied to agropastoral communities in the Cordillera Negra, a mountain range located west of the Cordillera Blanca. Unlike the Cordillera Blanca, the Cordillera Negra lacks glacier cover. Its highest peaks reach approximately 5,000 meters, and the region is much drier. To implement the ANDES model in the Cordillera Negra, it will be necessary to identify the most representative agropastoral systems and develop scenarios of interest with stakeholders. Additionally, since communities in the Cordillera Negra have already adapted to drier environmental conditions, understanding how these communities have addressed these challenges could be crucial for identifying and designing management scenarios for families in the Cordillera Blanca.

The ANDES model can be scaled up to a broader geographical level, specifically across the Peruvian Andes, by developing specific land and grazing management sub-models based on elevation gradients. To achieve this, it will be necessary to consider the different types of livestock production systems, animal species and breeds, as well as land and livestock management practices across elevation gradients. These applications will include information on livestock production (cattle, sheep, goats, chickens, hens, pigs, and guinea pigs), agricultural activities, and the use of pastures and grasslands according to their respective elevation gradients. Furthermore, these applications will need to incorporate various livestock species and breeds raised at these elevation gradients, such as Brown Swiss cattle in low and middle elevation areas, and mixed-breed or Creole cattle and sheep at higher elevations.

To create a model of livestock production systems in high mountain areas worldwide, it is necessary to identify the most representative production systems in each region. For example, livestock production systems in South America also include the raising of South American camelids, such as llamas and alpacas. At this level of analysis, the scenarios that can be modeled need to be general within regions, such as changes in livestock population and animal species. This approach to scenario development will facilitate comparisons among regions. At this level of analysis, as well as for the local application of the ANDES model, the identification of scenarios of interest with stakeholders, such as policymakers, livestock producers, and researchers across different regions, is crucial to address priority management and information needs.

The L-Range model can also be applied to other areas in the Andes of Peru. Applications at a fine scale, such as specific valleys, with tailored model calibration and validation, will capture ecosystem processes and responses to climate change specific to the area under analysis. In contrast, implementing L-Range across the entire Peruvian Andes will generate information that is applicable only at a broader scale.

APPENDIX

***Appendix Table A1**. IUCN management categories*

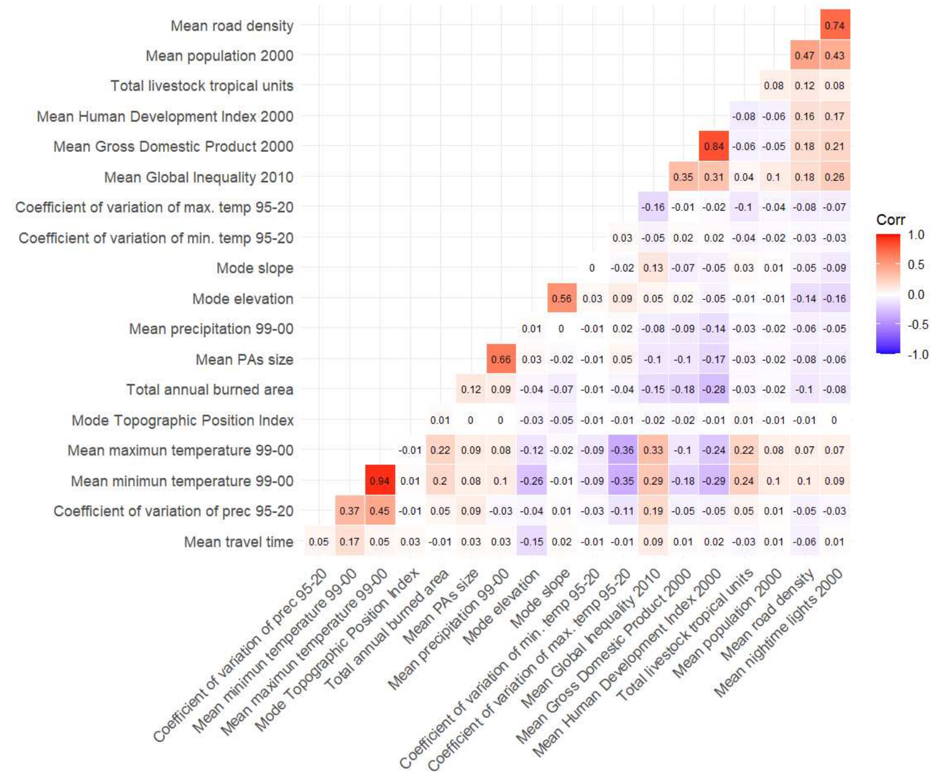
IUCN Category	Description
Ia (Strict nature reserve)	Strictly protected areas set aside to protect biodiversity and also possibly geological/geomorphological features, where human visitation, use and impacts are strictly controlled and limited to ensure protection of the conservation values. Such protected areas can serve as indispensable reference areas for scientific research and monitoring.
Ib (Wilderness area)	Protected areas are usually large unmodified or slightly modified areas, retaining their natural character and influence, without permanent or significant human habitation, which are protected and managed so as to preserve their natural condition.
II (National park)	Protected areas are large natural or near natural areas set aside to protect large-scale ecological processes, along with the complement of species and ecosystems characteristic of the area, which also provide a foundation for environmentally and culturally compatible spiritual, scientific, educational, recreational and visitor opportunities.
III (Natural monument or feature)	Protected areas are set aside to protect a specific natural monument, which can be a landform, sea mount, submarine cavern, geological feature such as a cave or even a living feature such as an ancient grove. They are generally quite small protected areas and often have high visitor value.
IV (Habitat/species management area)	Protected areas aim to protect particular species or habitats and management reflects this priority. Many category IV protected areas will need regular, active interventions to address the requirements of particular species or to maintain habitats, but this is not a requirement of the category.
V (Protected landscape)	A protected area where the interaction of people and nature over time has produced an area of distinct character with significant ecological, biological, cultural and scenic value: and where safeguarding the integrity of this interaction is vital to protecting and sustaining the area and its associated nature conservation and other values.
VI (Protected areas with sustainable use of natural resources)	Protected areas conserve ecosystems and habitats, together with associated cultural values and traditional natural resource management systems. They are generally large, with most of the area in a natural condition, where a proportion is under sustainable natural resource management and where low-level non-industrial use of natural resources compatible with nature conservation is seen as one of the main aims of the area.

Source: Dudley (2008)

Appendix Table A2. Land cover classes

	ESA Land Cover	
Aggregated class	**Original class value**	**Label**
1.Croplands	10, 11, 12	Rainfed cropland
	20	Irrigated cropland
	30	Mosaic cropland (> 50%) / natural vegetation (tree, shrub, herbaceous cover) (< 50%)
	40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (> 50%) / cropland (< 50%)
2. Forests	50	Tree cover, broadleaved, evergreen, closed to open (> 15%)
	60, 61, 62	Tree cover, broadleaved, evergreen, closed to open (>15%)
	70,71,72	Tree cover, needleleaved, evergreen, closed to open (> 15%)
	80,81,82	Tree cover, needleleaved, deciduous, closed to open (> 15%)
	90	Tree cover, mixed leaf type (broadleaved and needleleaved)
	100	Mosaic tree and shrub (> 50%)/herbaceous cover (< 50%)
	110	Mosaic herbaceous cover (> 50%)/tree and shrub (< 50%)
3. Grasslands	130	Grassland
	140	Lichens and mosses
4. Wetlands	160	Tree cover, flooded, fresh or brakish water
	170	Tree cover, flooded, saline water
	180	Shrub or herbaceous cover, flooded, fresh/saline/brakish water
5. Shrublands	120, 121, 122	Shrubland
6. Sparse vegetation	150,151,152,153	Sparse vegetation (tree, shrub, herbaceous cover) < 15%
7. Settlements	190	Urban areas
8. Bare areas	200, 201, 202	Bare areas
9. Water bodies	210	Water bodies
10. Permanent snow and ice	220	Permanent snow and ice

Appendix A3. *Heatmap of the correlation matrix of quantitative socioeconomic and biophysical variables*



Appendix Table A4. *Correlation matrix of qualitative socioeconomic and biophysical variables*

Variables		Correlation	p value
Distance to croplands	Distance to Indigenous Peoples Lands	0.02	0.02
Distance to croplands	Distance to mining areas	0.01	0.25
Distance to croplands	Distance to roads	0.16	0.00
Distance to Indigenous Peoples' Lands	Distance to mining areas	0.04	0.00
Distance to Indigenous Peoples' Lands	Distance to roads	-0.05	0.00
Distance to mining areas	Distance to Indigenous Peoples Lands	0.04	0.00
Distance to mining areas	Distance to roads	0.02	0.11

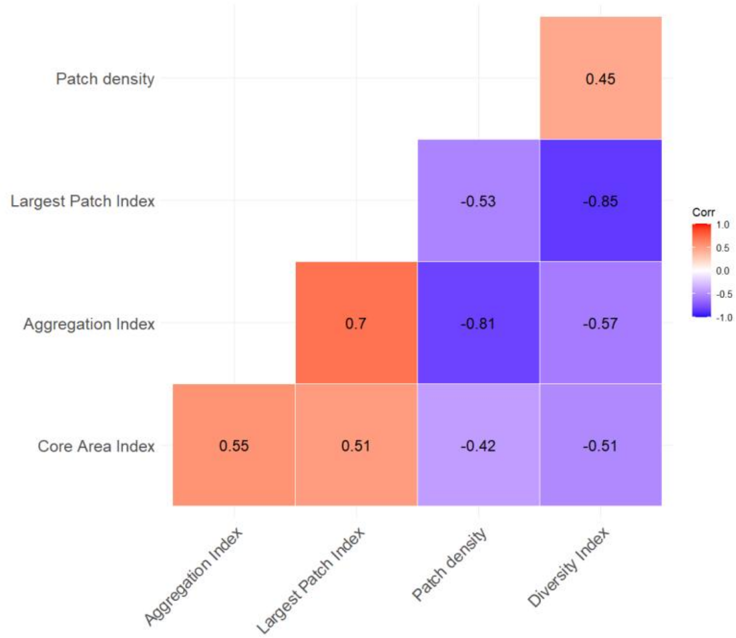
Appendix Table A5. *Socioeconomic and biophysical variables included in the analyses*

Category	Variables	Units	Summarizing value	Temporal resolution	Spatial resolution	Source
Biophysical	Elevation Slope Topographic Position Index	Meters Percentage –	Mode	–	1 km	Amatulli et al., (2018) b
	Average precipitation	mm	Mean annual precipitation	1999-2000 & 2019-2020	1 km	Karger et al., (2017)
	Coefficient of variation of precipitation		Coefficient of variation of annual precipitation	1995-2020		
	Average maximum temperature	°C	Mean maximum temperature	1999-2000 & 2019-2020		
	Coefficient of variation of minimum temperature		Coefficient of variation of minimum temperature	1995-2020		
	Coefficient of variation of maximum temperature		Coefficient of variation of maximum temperature	1995-2020		
Socioeconomic	Annual burnt area inside the PA	Hectares	Sum	2000 & 2015	500 m	Giglio et al., (2018)
	Human Development Index (5km buffer)	–	Mean	2000 & 2015	0.0833	Kummu et al., (2020)

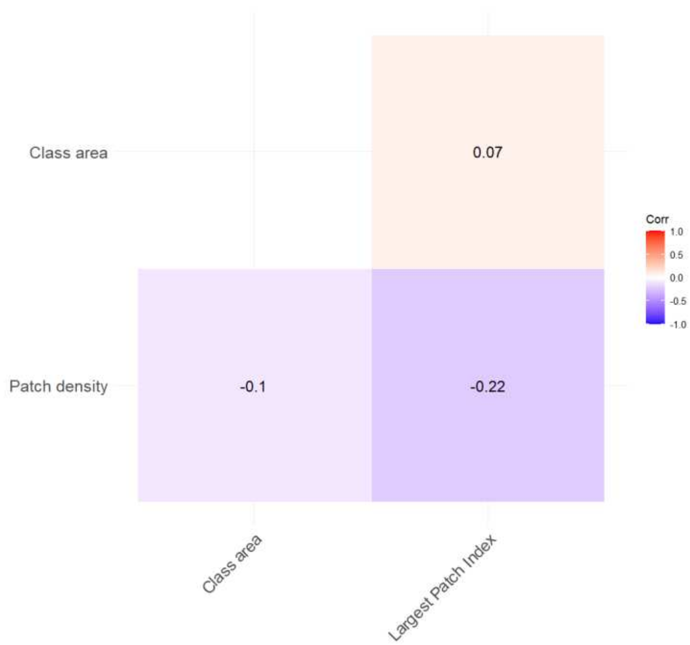
	Gross Domestic Production per capita (purchasing power parity) (5km buffer)	2011 international USD				
	Global Inequality coefficient (5km buffer)	–		2010	1°	Mirza et al., (2021) b
	Population density (5km buffer)	Number of persons per square kilometer		2000 & 2020	0.00833	Warszawski et al., (2017)
	Travel time to nearest city between 5,000 and 10,000 people	Minutes		2015	30 arc sec (1 km)	Nelson et al., (2019) a
	Livestock population (cattle, sheep, goat, horses, buffaloes) in the vicinity of PAs (5 km buffer)	Animal Units (AU) converted to Tropical AU	Mean	2010	0.0833	Gilbert et al., (2010)
	Nighttime lights level in the vicinity of PAs (5km buffer)	Digital Number	Mean	2000 & 2020	0.00833	Li et al., (2020) a
	Road density in the vicinity of PAs (5 km buffer)	km/km2	Mean	2014		Meijer et al., (2018)
	Near distance of PA to Indigenous Peoples Lands (10 km)			2018		Garnett et al., (2018)
	Near distance of PAs to mining areas (10 km)	Km	Classes: 1(0-2.5 km), 2(2.5-5.0 km), 3(5.0-7.5 km), & 4 (7.5-10km)	2017	–	Maus et al. (2022) a
	Near distance of PAs to crop zones (10 km)					Defourny et al. (2017)

	Near distance of PAs to roads (10 km)					Meijer et al., (2018)
PAs design feature	IUCN management category	–	Unique value	–	–	UNEP-WCMC & IUCN (2022)
	Government type	–				
	Size	Square kilometers	Unique value	–	–	

Appendix A6. *Heatmap of the correlation matrix of the landscape level metrics*



Appendix A7. *Heatmap of the correlation matrix of the class level metrics for protected forests*



__Appendix Table A8.__ Description of metrics at the landscape and class level

Description	Level	Definition	Units	Range	Interpretation
Total (class) area (Area and edge metric)	class	The total (class) area sums the area of all patches belonging to class i. It shows if the landscape is e.g. dominated by one class or if all classes are equally present. CA is an absolute measure, making comparisons among landscapes with different total areas difficult	Hectares	CA > 0	Approaches CA > 0 as the patch areas of class i become small. Increases, without limit, as the patch areas of class i become large. CA = TA if only one class is present.
Patch density (Aggregation metric)		It describes the fragmentation of a class, however, does not necessarily contain information about the configuration or composition of the class. In contrast to lsm_c_np it is standardized to the area and comparisons among landscapes with different total area are possible	Number per 100 hectares	1 < PD <= 1e+06	Increases as the landscape gets more patchy. Reaches its maximum if every cell is a different patch.
Largest patch index (Area and Edge metric)		It is the percentage of the landscape covered by the corresponding largest patch of each class i. It is a simple measure of dominance.	Percentage	0 < LPI <= 100	Approaches LPI = 0 when the largest patch is becoming small and equals LPI = 100 when only one patch is present
Total area (Area and edge metric)	landscape	The total (class) area sums the area of all patches in the landscape. It is the area of the observation area.	Hectares	TA > 0	Approaches TA > 0 if the landscape is small and increases, without limit, as the size of the landscape increases.
Aggregation index (Aggregation metric)		It equals the number of like adjacencies divided by the theoretical maximum possible number of like adjacencies for that class summed over each class for the entire landscape. The metric is based on he adjacency matrix and the single-count method.	Percent	0 <= AI <= 100	Equals 0 for maximally disaggregated and 100 for maximally aggregated classes.

Mean of core area index (Core area metric)	The metric summarises the landscape as the mean of the core area index of all patches in the landscape. The core area index is the percentage of core area in relation to patch area. A cell is defined as core area if the cell has no neighbor with a different value than itself (rook's case).	Percent	0 <= CAI_MN <= 100	CAI_MN = 0 when all patches have no core area and approaches CAI_MN = 100 with increasing percentage of core area within patches.
Patch density (Aggregation metric)	It describes the fragmentation the landscape, however, does not necessarily contain information about the configuration or composition of the landscape. In contrast to lsm_l_np it is standardized to the area and comparisons among landscapes with different total area are possible	Number per 100 hectares	0 < PD <= 1e+06	Increases as the landscape gets more patchy. Reaches its maximum if every cell is a different patch.
Largest patch index (Area and Edge metric)	It is the percentage of the landscape covered by the largest patch in the landscape. It is a simple measure of dominance	Percentage	0 < LPI <= 100	Approaches LPI = 0 when the largest patch is becoming small and equals LPI = 100 when only one patch is present
Modified Simpson's diversity index (Diversity metric)	MSIDI is a 'Diversity metric'.	None	MSIDI >= 0	MSIDI = 0 if only one patch is present and increases, without limit, as the amount of patches with equally distributed landscape proportions increases

Source: McGarigal (2015).

Appendix Table A9. *Distribution of PAs by region*

Region	Number of PAs	Percentage (%)
Africa	455	4.00
Western and Central Asia	614	5.40
South-East Asia	412	3.60
Central and Western Europe	2429	21.20
Eastern Europe	2033	17.70
Latin America and the Caribbean	829	7.20
North America	3439	30.00
Oceania	1246	10.90
Total	11457	100.00

Appendix Table A10. Distribution of PAs by topographic features

Elevation range	Number of PAs	Percentage (%)
High altitude	434	3.8
Low elevation	8261	72.1
Medium altitude	2749	24
Very high altitude	13	0.1
Total	11457	100.0

Topographic Position Index range	Number of PAs	Percentage (%)
Flat and middle slope areas (TPI = 0)	1220	10.65
Ridgetops and hilltops (TPI >0)	3750	32.73
Valleys and canyon bottoms (TPI<0)	6487	56.62
Total	11457	100.000

Slope range (%)	Total PAs	Percentage
< 10	9806	85.6
< 20 & 10>	1467	12.8
> 20	184	1.6
Total	11457	100.00

TPI: Topographic Position Index

Appendix Table A11. *Distribution of PAs by regions and IUCN management category*

Region	IUCN management category	Total PAs	PAs by category	Percentage (%)
Africa	Ia	455	15	3.3
	Ib		7	1.54
	II		128	28.13
	III		18	3.96
	IV		188	41.32
	V		15	3.3
	VI		84	18.46
South-East Asia	Ia	412	125	30.34
	Ib		2	0.49
	II		81	19.66
	III		11	2.67
	IV		77	18.69
	V		66	16.02
	VI		50	12.14
Western-Central Asia	Ia	614	31	5.05
	Ib		45	7.33
	II		49	7.98
	III		10	1.63
	IV		231	37.62
	V		196	31.92
	VI		52	8.47
Central and Western Europe	Ia	2429	248	10.21
	Ib		80	3.29
	II		93	3.83
	III		100	4.12
	IV		1359	55.95
	V		498	20.5
	VI		51	2.1
Eastern Europe	Ia	2033	45	2.21
	Ib		7	0.34
	II		26	1.28
	III		729	35.86
	IV		1186	58.34
	V		10	0.49
	VI		30	1.48
Latin America and the Caribbean	Ia	829	93	11.22
	Ib		17	2.05
	II		209	25.21
	III		51	6.15
	IV		141	17.01
	V		95	11.46
	VI		223	26.9
North America	Ia	3439	296	8.61
	Ib		318	9.25

	II		392	11.4
	III		289	8.4
	IV		168	4.89
	V		1903	55.34
	VI		73	2.12
Oceania	Ia	1246	567	45.51
	Ib		3	0.24
	II		150	12.04
	III		314	25.2
	IV		80	6.42
	V		35	2.81
	VI		97	7.78

Appendix Table A12. *Distribution of PAs by cover class and region*

Region	Total	Cover class	Number of PAs by class	% of PAs
Africa	992	Forest	389	39.21
		Grassland	152	15.32
		Shrubland	298	30.04
		Wetland	153	15.42
South-East Asia	733	Forest	378	51.57
		Grassland	25	3.41
		Shrubland	96	13.10
		Wetland	234	31.92
Western-Central Asia	862	Forest	487	56.50
		Grassland	153	17.75
		Shrubland	162	18.79
		Wetland	60	6.96
Central and Western Europe	4005	Forest	2053	51.26
		Grassland	1015	25.34
		Shrubland	322	8.04
		Wetland	615	15.36
Eastern Europe	3222	Forest	1802	55.93
		Grassland	659	20.45
		Shrubland	180	5.59
		Wetland	581	18.03
Latin America and the Caribbean	1871	Forest	759	40.57
		Grassland	356	19.03
		Shrubland	469	25.07
		Wetland	287	15.34
North America	6297	Forest	2806	44.56
		Grassland	1512	24.01
		Shrubland	1026	16.29
		Wetland	953	15.13
Oceania	2429	Forest	1074	44.22
		Grassland	354	14.57
		Shrubland	852	35.08
		Wetland	149	6.13

Note: The number of PAs by cover class exceeds the total PAs (11 457) in the sample because a PA can include multiple cover classes. Thus, the same PA is counted based on its number of classes.

***Appendix Table A13**. Kruskal-Wallis tests results: Differences in landscape-level metrics for global PAs for 2000 and 2020*

Metric	Year	Kruskal-Wallis chi-squared	p-value	Significance
Aggregation index	2000	852.02	< 0.0001	***
	2020	833.12		
Core area index	2000	175.18		
	2020	133.41		
Modified Simpson's diversity index	2000	254.60		
	2020	220.63		
Largest patch index	2000	163.06		
	2020	156.66		
Patch density	2000	1445.21		
	2020	1429.58		

***Appendix Table A14**. Friedman tests results: Differences in landscape-level metrics by regions for 2000 and 2020*

Region	Metric	Friedman chi-squared	p-value	Significance
Africa	Aggregation index	1690.00	<0.0001	***
	Core area index	1477.08		
	Modified Simpson's diversity index	1246.02		
	Largest patch index	1690.00		
	Patch density	1302.16		
South-East Asia	Aggregation index	1468.32		
	Core area index	1238.16		
	Modified Simpson's diversity index	1251.67		
	Largest patch index	1482.00		
	Patch density	983.56		
Western-Central Asia	Aggregation index	2230.95		
	Core area index	1669.44		
	Modified Simpson's diversity index	1696.25		
	Largest patch index	2258.29		
	Patch density	1008.50		
Central and Western Europe	Aggregation index	8702.21		
	Core area index	4204.27		
	Modified Simpson's diversity index	6788.54		
	Largest patch index	8784.29		
	Patch density	1306.72		

Latin America and the Caribbean	Aggregation index	3023.43
	Core area index	2602.58
	Modified Simpson's diversity index	2340.66
	Largest patch index	3023.43
	Patch density	1800.05
Eastern Europe	Aggregation index	7540.00
	Core area index	5029.79
	Modified Simpson's diversity index	6776.12
	Largest patch index	7540.00
	Patch density	2982.56
North America	Aggregation index	12639.71
	Core area index	6361.50
	Modified Simpson's diversity index	9991.89
	Largest patch index	12639.71
	Patch density	2252.37
Oceania	Aggregation index	4499.15
	Core area index	2477.80
	Modified Simpson's diversity index	3550.06
	Largest patch index	4512.86
	Patch density	594.77

Appendix Table A15. *Kruskal-Wallis tests results: Differences in class-level metrics for protected forests, grasslands, shrublands, and wetlands for 2000 and 2020*

Cover class	Metric	Year	Kruskal-Wallis chi-squared	p-value	Significance
Forests	Class area	2000	1263.79	<0.0001	***
		2020	1276.81		
	Largest patch index	2000	213.70		
		2020	192.65		
	Patch density	2000	1322.28		
		2020	1316.18		
Grasslands	Class area	2000	329.42		
		2020	307.22		
	Largest patch index	2000	410.36		
		2020	422.91		
	Patch density	2000	877.54		
		2020	896.57		
Shrublands	Class area	2000	339.82		
		2020	301.44		
	Largest patch index	2000	466.27		
		2020	468.52		
	Patch density	2000	822.65		
		2020	803.73		
Wetlands	Class area	2000	168.69		
		2020	200.57		
	Largest patch index	2000	401.00		
		2020	388.33		
	Patch density	2000	721.26		
		2020	684.36		

Appendix Table A16. *Friedman tests results: Differences in class-level metrics by regions for 2000 and 2020*

Region	Cover class		Friedman chi-squared	p-value	Significance
Africa	Forest	Class area	778.00	< 0.0001	***
		Largest patch index	440.44		
		Patch density	766.05		
	Grassland	Class area	304.00	0.91	n.s
		Largest patch index	0.01		
		Patch density	304.00		
	Shrubland	Class area	596.00	< 0.0001	***
		Largest patch index	24.61		
		Patch density	580.11		

	Wetland	Class area	306.00		
		Largest patch index	40.40		
		Patch density	306.00		
South-East Asia	Forest	Class area	756.00		
		Largest patch index	651.86		
		Patch density	732.19		
	Grassland	Class area	50.00	< 0.0001	***
		Largest patch index	13.52		
		Patch density	50.00		
	Shrubland	Class area	192.00		
		Largest patch index	0.33	0.56	n.s
		Patch density	192.00	< 0.0001	***
	Wetland	Class area	468.00		
		Largest patch index	0.01	0.93	n.s
		Patch density	448.21	< 0.0001	***
Western-Central Asia	Forest	Class area	974.00		
		Largest patch index	541.15		
		Patch density	884.17		
	Grassland	Class area	306.00	< 0.0001	***
		Largest patch index	69.66		
		Patch density	302.01		
	Shrubland	Class area	324.00		
		Largest patch index	0.79	0.37	n.s
		Patch density	312.11		
	Wetland	Class area	120.00		
		Largest patch index	19.20	< 0.0001	***
		Patch density	116.03		
Central and Western Europe	Forest	Class area	4106.00		
		Largest patch index	3760.55		
		Patch density	3226.89		
	Grassland	Class area	2030.00		
		Largest patch index	858.29	< 0.0001	***
		Patch density	1484.58		
	Shrubland	Class area	644.00		
		Largest patch index	140.90		
		Patch density	616.30		
	Wetland	Class area	1230.00		

		Largest patch index	502.27		
		Patch density	1056.59		
Eastern Europe	Forest	Class area	3604.00	< 0.0001	***
		Largest patch index	3234.02		
		Patch density	3237.81		
	Grassland	Class area	1318.00		
		Largest patch index	20.91		
		Patch density	1219.90		
	Shrubland	Class area	360.00		
		Largest patch index	76.54		
		Patch density	360.00		
	Wetland	Class area	1162.00		
		Largest patch index	19.64		
		Patch density	1146.06		
Latin America and the Caribbean	Forest	Class area	1518.00	< 0.0001	***
		Largest patch index	1089.46		
		Patch density	1454.68		
	Grassland	Class area	712.00		
		Largest patch index	10.16		
		Patch density	692.14		
	Shrubland	Class area	938.00		
		Largest patch index	127.63		
		Patch density	918.11		
	Wetland	Class area	574.00		
		Largest patch index	26.79		
		Patch density	554.17		
North America	Forest	Class area	5612.00	< 0.0001	***
		Largest patch index	4929.84		
		Patch density	4479.72		
	Grassland	Class area	3024.00		
		Largest patch index	996.43		
		Patch density	2360.97		
	Shrubland	Class area	2052.00		
		Largest patch index	462.95		
		Patch density	1856.87		
	Wetland	Class area	1906.00		

		Largest patch index	433.02		
		Patch density	1587.47		
Oceania	Forest	Class area	2148.00	< 0.0001	***
		Largest patch index	1763.00		
		Patch density	1825.14		
	Grassland	Class area	708.00		
		Largest patch index	187.67		
		Patch density	532.48		
	Shrubland	Class area	1704.00		
		Largest patch index	1127.35		
		Patch density	1233.86		
	Wetland	Class area	298.00		
		Largest patch index	27.88		
		Patch density	266.86		

Appendix Table A17. *Regional changes in landscape metrics from 2000 to 2020 by cover class*

Protected Forests

Region	Total PAs	PAs (%) with Class Area increment	PAs (%) with Class Area decrement	PAs (%) with constant Class Area	PAs (%) with Largest Patch Index increment	PAs (%) with Largest Patch Index decrement	PAs (%) with constant Largest Patch Index	PAs (%) with Patch Density increment	PAs (%) with Patch Density decrement	PAs (%) with constant Patch Density
Africa	389	57.84	23.14	19.02	50.90	24.42	24.68	33.93	27.51	38.56
South-East Asia	378	39.42	41.80	18.78	37.57	39.68	22.75	31.48	22.75	45.77
Western-Central Asia	487	27.52	25.46	47.02	21.97	22.18	55.85	17.45	13.55	68.99
Central and Western Europe	2053	23.43	21.43	55.14	19.87	18.66	61.47	12.32	10.72	76.96
Eastern Europe	1802	24.14	30.80	45.06	21.70	28.52	49.78	16.81	10.16	73.03
Latin America and Caribbean	759	38.08	33.73	28.19	34.65	31.09	34.26	23.45	20.82	55.73
North America	2806	15.54	29.51	54.95	12.22	25.98	61.80	13.51	7.98	78.51
Oceania	1074	22.81	11.45	65.74	19.46	10.61	69.93	9.96	7.64	82.40

Protected Grasslands

Region	Total PAs	PAs (%) with Class Area increment	PAs (%) with Class Area decrement	PAs (%) with constant Class Area	PAs (%) with Largest Patch Index increment	PAs (%) with Largest Patch Index decrement	PAs (%) with constant Largest Patch Index	PAs (%) with Patch Density increment	PAs (%) with Patch Density decrement	PAs (%) with constant Patch Density
Africa	152	25.00	36.18	38.82	16.45	30.92	52.63	28.95	23.03	48.03
South-East Asia	25	16.00	28.00	56.00	8.00	24.00	68.00	32.00	4.00	64.00
Western-Central Asia	153	35.95	45.10	18.95	28.76	39.22	32.03	43.14	17.65	39.22
Central and Western Europe	1015	12.81	14.09	73.10	6.80	8.67	84.53	10.74	5.71	83.55
Eastern Europe	659	25.95	19.73	54.32	15.78	16.08	68.13	24.13	10.93	64.95
Latin America and the Caribbean	356	29.21	29.78	41.01	15.17	20.22	64.61	31.74	14.61	53.65
North America	1512	18.65	14.29	67.06	9.06	9.66	81.28	16.60	5.69	77.71
Oceania	354	16.38	13.28	70.34	12.15	9.04	78.81	17.80	5.08	77.12

Protected Shrublands

Region	Total PAs	PAs (%) with Class Area increment	PAs (%) with Class Area decrement	PAs (%) with constant Class Area	PAs (%) with Largest Patch Index increment	PAs (%) with Largest Patch Index decrement	PAs (%) with constant Largest Patch Index	PAs (%) with Patch Density increment	PAs (%) with Patch Density decrement	PAs (%) with constant Patch Density
Africa	298	17.45	55.70	26.85	13.42	46.98	39.60	35.23	19.46	45.30
South-East Asia	96	29.17	58.33	12.50	25.00	47.92	27.08	52.08	31.25	16.67
Western-Central Asia	162	16.67	17.28	66.05	6.17	12.96	80.86	17.90	11.11	70.99
Central and Western Europe	322	13.04	25.16	61.80	8.39	17.39	74.22	12.42	7.45	80.12
Eastern Europe	180	51.11	13.89	35.00	34.44	16.11	49.44	49.44	10.56	40.00
Latin America and the Caribbean	469	35.61	34.54	29.85	26.87	29.64	43.50	34.12	20.47	45.42
North America	1026	28.46	17.74	53.80	19.49	13.65	66.86	20.47	10.53	69.01
Oceania	852	9.39	26.06	64.55	7.39	19.60	73.00	11.15	9.27	79.58

Protected Wetlands

Region	Total PAs	PAs (%) with Class Area increment	PAs (%) with Class Area decrement	PAs (%) with constant Class Area	PAs (%) with Largest Patch Index increment	PAs (%) with Largest Patch Index decrement	PAs (%) with constant Largest Patch Index	PAs (%) with Patch Density increment	PAs (%) with Patch Density decrement	PAs (%) with constant Patch Density
Africa	153	31.37	17.65	50.98	24.18	20.26	55.56	33.33	16.34	50.33
South-East Asia	234	30.34	22.65	47.01	20.09	21.79	58.12	31.20	14.53	54.27
Western-Central Asia	60	11.67	11.67	76.67	13.33	25.00	61.67	20.00	21.67	58.33
Central and Western Europe	615	24.23	17.24	58.54	19.84	14.96	65.20	16.26	10.73	73.01
Eastern Europe	581	49.74	16.52	33.73	57.49	37.01	5.51	62.99	34.77	2.24
Latin America and the Caribbean	287	35.19	25.09	39.72	26.83	24.04	49.13	42.86	13.94	43.21
North America	953	14.90	21.93	63.17	21.83	31.06	47.11	30.75	27.18	42.08
Oceania	149	16.11	12.75	71.14	8.72	18.12	73.15	21.48	12.08	66.44

Appendix Table A18. *Variable importance for the 2000 and 2020 global CRF models for landscape-level metrics*

Aggregation index

Year	2000
Mean PA area	0.10838
Mean Human Development Index 2000	0.1013
Distance to croplands	0.09238
IUCN category	0.05645
Mode slope	0.05224

Year	2020
Mean PA area	0.11421
Mean Human Development Index 2015	0.09523
Distance to croplands	0.0781
IUCN category	0.06081
Mode slope	0.05116

Patch density

Year	2000
Mean PA area	0.28012
Mean Human Development Index 2000	0.1
Distance to croplands	0.09265
Mode slope	0.06244
IUCN category	0.04998

Year	2020
Mean PA area	0.28727
Mean Human Development Index 2015	0.09466
Distance to croplands	0.07801
Mode slope	0.06701
IUCN category	0.05035

Core area index

Year	2000
Distance to croplands	0.41383
Mean Human Development Index 2000	0.06817
Mode slope	0.06383
Mean Gross Domestic Product 2000	0.05074
IUCN category	0.04376

Year	2000
Distance to croplands	0.37154
Mode slope	0.0591
Mean Human Development Index 2015	0.05463
Mean Gross Domestic Product 2015	0.04789
IUCN category	0.04464

Largest patch index

Year	2000
Distance to croplands	0.17595
Mode slope	0.05764
IUCN category	0.04157
Mode Topographic Position Index	0.0337
Mean Gross Domestic Product 2000	0.03361

Year	2020
Distance to croplands	0.14982
Mode slope	0.05304
IUCN category	0.04288
Mode Topographic Position Index	0.03816
Mean Gross Domestic Product 2015	0.03063

Modified Simpson's diversity index

Year	2000
Distance to croplands	0.21237
Mode slope	0.06933
Mean maximum temperature 99 00	0.04351
Total livestock tropical units	0.04038
Mode elevation	0.03899

Year	2020
Distance to croplands	0.18178
Mode slope	0.06539
Total livestock tropical units	0.04639
Mode elevation	0.04042
Mode Topographic Position Index	0.03813

Appendix Table A19. *Conditional Random Forest models results for metrics at the cover class level for 2000 and 2020 global PAs*

Cover class	**Landscape metric**	**Root mean square error (RMSE)**		**Coefficient of determination (R^2)**		**Mean absolute error (MAE)**	
		2000	**2020**	**2000**	**2020**	**2000**	**2020**
Forest	Class area	54868.92	53632.21	60.24%	61.82%	5839.09	5691.02
	Patch density	0.3	0.3	46.13%	45.18%	0.18	0.18
	Largest patch index	27.87	28.06	41.65%	40.51%	23.73	23.93
Grassland	Class area	44579.55	43401.75	31.23%	31.70%	5697.62	5720.16
	Patch density	0.33	0.33	46.00%	46.09%	0.2	0.2
	Largest patch index	19.94	19.72	30.00%	30.75%	13.94	13.75
Shrubland	Class area	26959.2	27023.1	38.51%	34.81%	6518.19	6591.29
	Patch density	0.25	0.25	52.88%	53.06%	0.16	0.16
	Largest patch index	22.74	22.43	35.84%	37.63%	17.04	16.79
Wetland	Class area	44011.75	44262.79	9.42%	9.41%	5036.12	5037.35

Patch density	0.25	0.25	47.46%	46.59%	0.14	0.15
Largest patch index	19.429	19.576	32.04%	31.71%	13.1	13.17

__Appendix Table A20.__ Variable importance for the 2000 and 2020 global CRF models for class-level metrics

Protected Forests

Class area

Year	2000
Mean precipitation 99 00	0.59609
Mean PA area	0.35864
Coefficient of variation of prec 95 20	0.02205
Mean Human Development Index 2000	0.01649
Mean road density	0.00793

Year	2020
Mean precipitation 19 20	0.61095
Mean PA area	0.37045
Mean Human Development Index 2015	0.03249
Coefficient of variation of prec 95 20	0.02013
Mean road density	0.00815

Patch density

Year	2000
Mean PA area	0.0733269
Mean Human Development Index 2000	0.0116811
Mean Gross Domestic Product 2000	0.0069521
IUCN category	0.0065099
Mode elevation	0.0050522

Year	2020
Mean PA area	0.075166
Mean Human Development Index 2015	0.011003
IUCN category	0.006918
Mean Gross Domestic Product 2015	0.005467
Mean precipitation 19 20	0.005279

Largest patch index

Year	2000
Mode slope	327.39872
Distance to croplands	200.12014
IUCN category	87.880666
Mean maximum temperature 99 00	82.435973
Mode Topographic Position Index	64.48228

Year	2020
Mode slope	329.9807
Distance to croplands	163.5789
IUCN category	92.17394
Mean maximum temperature 19 20	82.50632
Mode Topographic Position Index	68.10967

Protected Grasslands

Class area

Year	2000
Mean PA area	0.39910
Mean Human Development Index 2000	0.10055
Mean precipitation 99 00	0.09850
Mean maximum temperature 99 00	0.07276
Total annual burned area	0.02871

Year	2020
Mean PA area	0.37302
Mean Human Development Index 2015	0.15070
Mean precipitation 19 20	0.12858
Mean maximum temperature 19 20	0.06740
Mode slope	0.01301

Patch density

Year	2000
Mean PA area	0.0571
Mean Human Development Index 2000	0.0225
Mean Gross Domestic Product 2000	0.00823
Mean road density	0.00658
Total livestock tropical units	0.00636

Year	2020
Mean PA area	0.06066
Mean Human Development Index 2015	0.01289
Mean road density	0.00835
Total livestock tropical units	0.00659
Mean Gross Domestic Product 2015	0.00606

Largest patch index

Year	2000
Total livestock tropical units	82.20827
Mean Gross Domestic Product 2000	45.35376
Mean Human Development Index 2000	37.47053
Mode elevation	33.62418
IUCN category	27.7183

Year	2020
Total livestock tropical units	81.88411
Mean Gross Domestic Product 2015	66.9031
IUCN category	31.86344
Mean Human Development Index 2015	31.09956
Mode elevation	20.48728

Protected Shrublands

Class area

Year	2000
Mean PA area	0.40667
Mean precipitation 99 00	0.18902
Total annual burned area	0.03507
Mode slope	0.02086
Mean maximum temperature 99 00	0.01822

Year	2020
Mean PA area	0.39988
Mean precipitation 19 20	0.16385
Mode slope	0.02055
Mean maximum temperature 19 20	0.01321
Mean Human Development Index 2015	0.01305

Patch density

Year	2000
Mean PA area	0.03901
Mean Human Development Index 2000	0.01440
IUCN category	0.01175
Mean Gross Domestic Product 2000	0.00642
Mean road density	0.00300

Year	2020
Mean PA area	0.03778
Mean Human Development Index 2015	0.01269
IUCN category	0.01041
Mean Gross Domestic Product 2015	0.00640
Mean road density	0.00305

Largest Patch index

Year	2000
Mean maximum temperature 99 00	116.24894
Mean Gross Domestic Product 2000	65.90401
Mean Human Development Index 2000	62.83446
Mode elevation	62.68214
IUCN category	62.52430

Year	2020
Mean maximum temperature 19 20	104.49040
Distance to croplands	71.68868
IUCN category	64.28902
Mean Gross Domestic Product 2015	62.17128
Mode elevation	57.06684

Protected Wetlands

Class area

Year	2000
Mean precipitation 99 00	0.40779
Mean PA area	0.26123
Mean Human Development Index 2000	0.13637
Mean maximum temperature 99 00	0.07603
Mean road density	0.04913

Year	2020
Mean precipitation 19 20	0.32745
Mean PA area	0.25296
Mode slope	0.03465
Mode elevation	0.03161
Distance to roads	0.03023

Patch density

Year	2000
Mean PA area	0.03995
Mean Gross Domestic Product 2000	0.00613
Mean Human Development Index 2000	0.00598
IUCN category	0.00433

Year	2020
Mean PA area	0.04069
Mean Human Development Index 2015	0.00686
IUCN category	0.00500
Distance to roads	0.00447

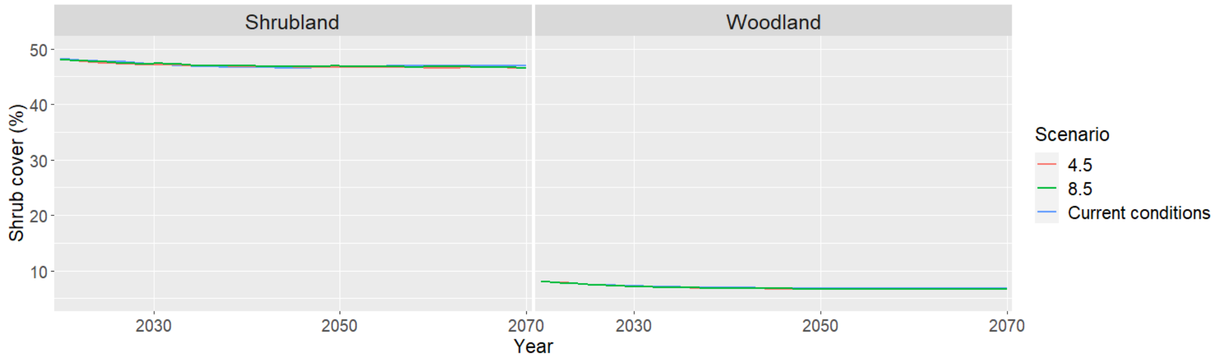
Distance to roads	0.00407	Mean Gross Domestic Product 2015	0.00372

Largest patch index

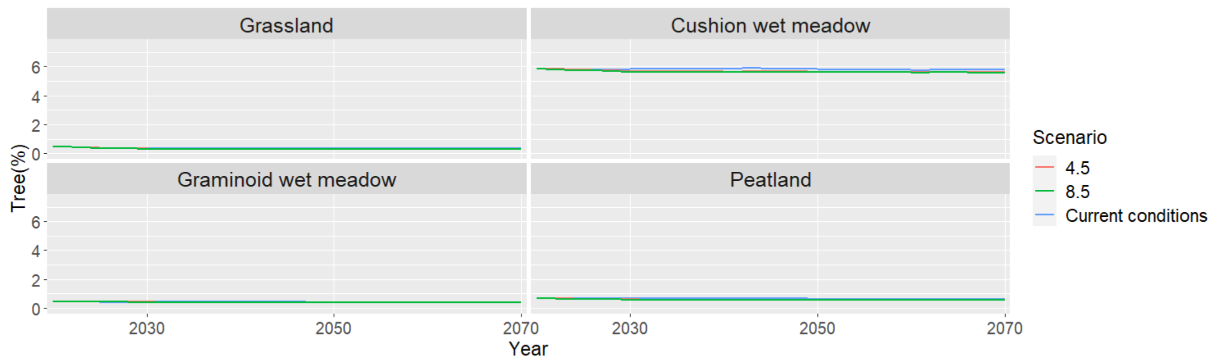
Year	2000
Mode slope	90.62002
Distance to croplands	47.89580
Mean Gross Domestic Product 2000	31.91590
Mode elevation	28.54387
Distance to roads	22.34942

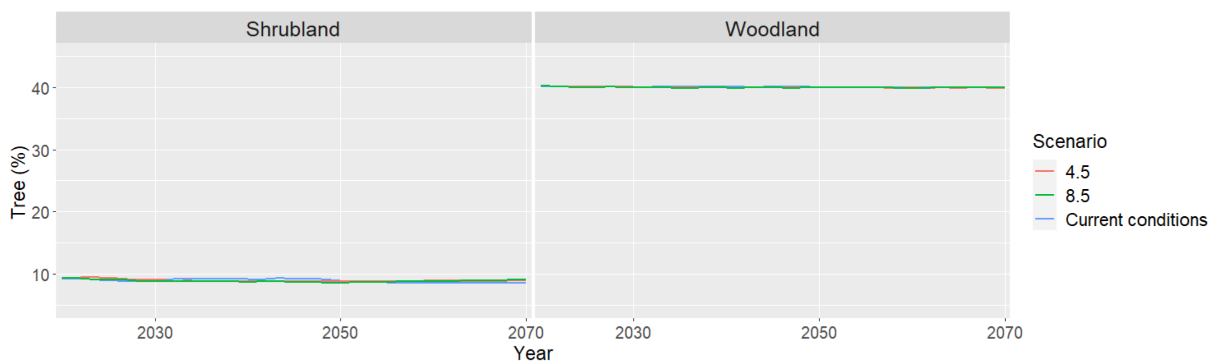
Year	2020
Mode slope	102.27346
Distance to croplands	49.20967
Mode elevation	25.11677
Distance to roads	24.47781
IUCN category	22.48575

Appendix B1. *Changes in shrub cover (%) for shrublands and woodlands*

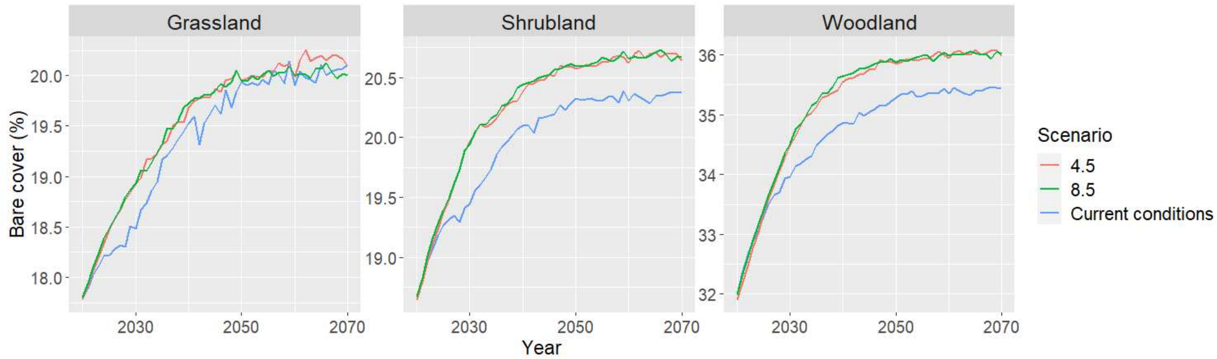


Appendix B2. *Changes in tree cover (%) for all cover classes*

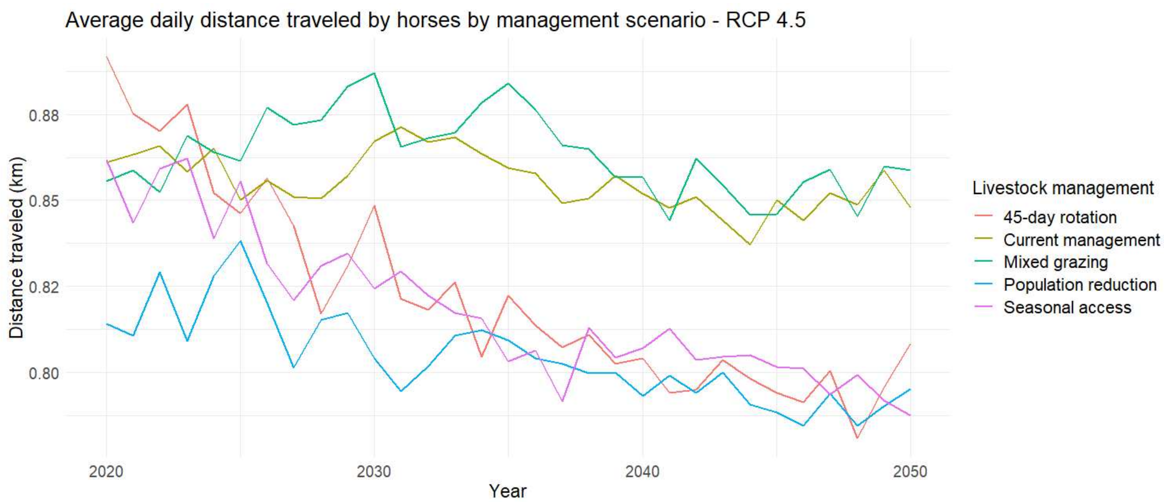


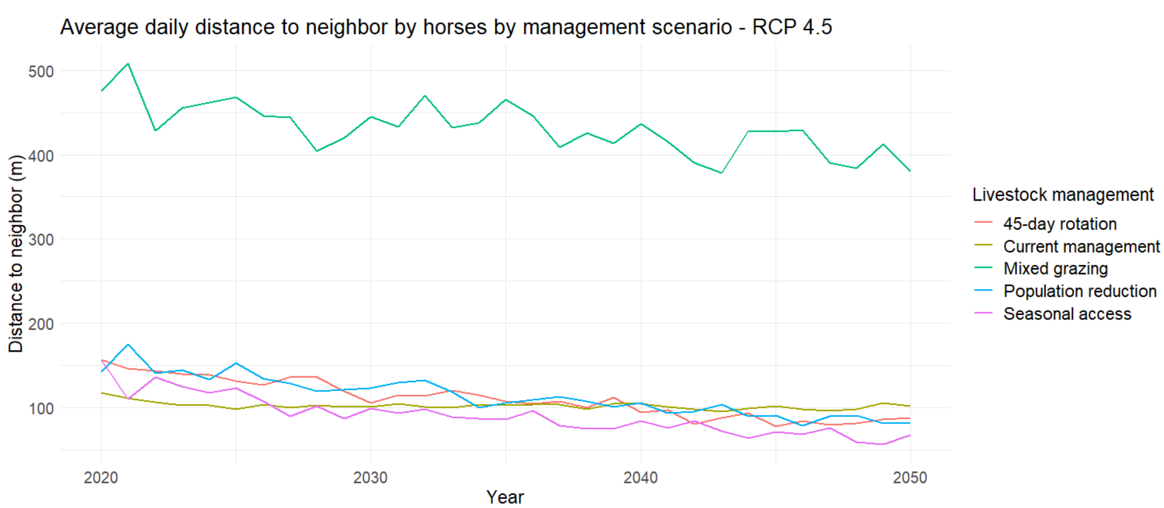


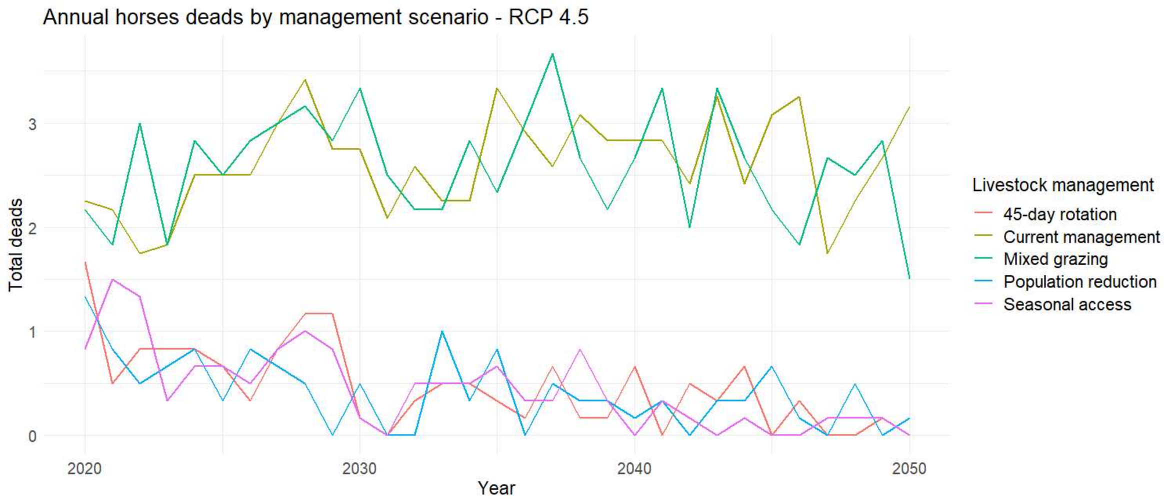
Appendix B3. *Changes in bare cover (%) for grasslands, shrublands, and woodlands*



Appendix C. *Simulation outputs for horses*







Annual horses deads by management scenario - RCP 4.5
Total deads
Year
Livestock management
45-day rotation
Current management
Mixed grazing
Population reduction
Seasonal access