

FORECASTING VERTEBRATE SPECIES HABITAT SUITABILITY AND ECOREGION TYPES
UNDER FUTURE CLIMATE CHANGE SCENARIOS USING SPECIES DISTRIBUTION
MODELING (SDM)

by

Jaris Emmanuel Veneros Guevara

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of the requirements for the degree

of

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DEDICATION

This thesis is dedicated to my parents Lilia and Elianiles, my brothers Mihajlo and André, my grandma Rosita, who is going to turn 100 years old this August, and to South American ecological leaders who expose their lives to protect our planet.

I feel fortunate to have met some truly exceptional people along the way, though some have sadly passed away due to the SARS-CoV-2 pandemic, but their voice remains here. In memory of some relatives, friends, and colleagues.

Also, with much appreciation for the Andes, my country (Perú), Ecuador, and Colombia.

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VITA

Jaris Emmanuel Veneros Guevara was born on August 30, 1988, in Cajamarca, Peru. He spent his childhood in Cajabamba, a city located in the south of Cajamarca, where he attended kindergartens called 312 and La Pampa before moving on to San Juan Bosco educational center for first grade. From second to sixth grade, he attended 111 School, followed by high school at José Gálvez School. Jaris Veneros went on to study Agronomy Engineering at the National University of Cajamarca from 2006 to 2010, graduating with honors. He pursued a master's degree in Environmental Sciences at the National Agrarian University La Molina in Lima, Peru. Throughout his career, he served as a researcher at the International Potato Center and the University of Wisconsin-Madison, and as a lecturer and researcher at the National University Toribio Rodríguez de Mendoza, National University of Jaén, National University of San Martín, National University of Chota, and National Agrarian University La Molina. He was the recipient of several scholarships and funds sponsored by NASA, Graduate School at Montana State University, Flemish Institute for Technological Research (VITO) - PROBA-V satellite operated by ESA (Belgium), Universidad Católica de Chile (Chile) and in Peru through SEPIA (Seminario Permanente de Investigación Agraria), Ministry of Education and National Council of Science, Technology and Technological Innovation. His areas of interest include Remote Sensing, GIS, Species Distribution Modeling (SDM), and Global Change.

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GLOSSARY or NOMENCLATURE

ccafs: Climate Change, Agriculture, and Food Security

GCM: A General Circulation Model

HFP: Human Footprint

HSMs: Habitat Suitability Models

RCP: A Representative Concentration Pathway

RLI: Red List Index

SDGs: Sustainable Development Goals

SDMs: Species Distribution Models

SSPs: Shared Socioeconomic Pathways

ABSTRACT

Peru, Ecuador, and Colombia have identified a total of 23 threatened species, including mammals, birds, and plants, which are also a part of their reports for SDG 15. These countries are keen to monitor the risk of extinction of these species and ensure their protection. As part of the Life on Land Project, we aim to assist these countries in approximating the IUCN Red List index using species occurrence data, climatic data, and variables such as Human Footprint (HFP) in different climate change scenarios. To achieve this, we conducted a general review of climate drivers and climate change for the three countries and explored climate data to estimate the variation of temperature ($^{\circ}\text{C}$) and annual precipitation (mm) change under current climate conditions and in RCPs-2050 climate change scenarios (2.6, 4.5, and 8.5). Our results indicated that the average annual temperature for 2050, using a baseline of 1970-2000, is expected to increase by over 1°C in some areas and over 4°C in others. For annual precipitation, an increase is also predicted, although few global circulation models show a reduction. We also conducted a median comparison to see the differences between the baseline and the RCPs in 2050, indicating that the medians are different. Density plots were used to illustrate the shift to the right for the temperature case, confirming the anticipated temperature increase by 2050 in the three RCPs. Finally, we used the R package (SDM) to estimate habitat suitability probability for the spectacled bear and the páramo ecoregion. Our findings indicated that climate change impacts their areas with high probability of occurrence to a great extent, and their habitats are also affected by HFP. These methods for exploring climate data and assessing habitat suitability are replicable and can be used with other environmental variables.

CHAPTER ONE

INTRODUCTION TO THESIS

The Anthropocene caused a fast loss of biodiversity due to human impact; terrestrial vertebrates have decreased by 60% since 1970, and there have been far more vertebrate extinctions than expected, at least 100 times more (Gonçalves-Souza et al., 2020; Johnson et al., 2017).

Although South America is known for its abundance of biodiversity, the region is facing significant challenges as natural habitats are being converted to other uses at alarming rates; the analysis of species habitat and ecoregions and their vulnerability to climate change and human activity can identify areas that need management attention for the conservation of biodiversity and valuable goods and services in this region (Jarvis et al., 2010; Sayre et al., 2008). For example, the tropical forest, the most productive and biodiverse terrestrial ecosystems on earth, are more vulnerable to climate change than savannas or grasslands (Jarvis et al., 2010).

Climate change will bring about certain changes in temperature and precipitation patterns in South America. Specifically, there will likely be more summer rainfall in the south-eastern subtropical region, less winter rainfall throughout most of the continent, and decreased rainfall throughout the southern Andes in all seasons (Chou et al., 2014). Also, Peru is one of the 20 countries most vulnerable to climate change due to its geography, diversity of ecosystems and microclimates, and its effects are already perceptible in several regions (Altea, 2020). Climate change in Southern Ecuador is expected to increase precipitation and temperature, leading to more climatic variation that could impact ecosystems and their services (Eguiguren-Velepucha et al., 2016). Also, Colombian glaciers lose between 50 centimeters and one meter in thickness per year;

therefore, falling back between ten and twenty meters per year (Costa-Posada, 2017). Another effects of climate change in Colombia are the significant reductions in water supply, significant alterations in the integrity of high mountain ecosystems, and dramatic losses of biodiversity (Ruiz et al., 2008). Therefore, it is important to know the past, present, and future climate for Peru, Ecuador, and Colombia. The IPCC developed the Representative Concentration Pathways (RCPs), these scenarios include time series of emissions and concentrations of the full set of greenhouse gases (GHGs), aerosols and chemically active gases, as well as land use and land cover (Moss et al., 2010).

Recent experiments showed that climatic changes on the scale of years to decades can change species distributions and abundances and alter biotic interactions (Blois et al., 2013). Climate change will increasingly threaten biodiversity in the future, potentially becoming as significant a threat as land use change by 2070 (Lebreton, 2011). The combined effects of both pressures are expected to lead to a cumulative loss average of 37.9% of species of vertebrate communities in the framework of "business as usual" (Newbold, 2018). Although Species Distribution Models (SDMs) show promise, incorporating multispecies, dispersal, and community interactions is essential; and species behavior change is causing extinctions in vulnerable habitats where migration is necessary for survival, but no routes exist due to habitat fragmentation (Mooney et al., 2009). Modeling species is challenging due to the differing observation timescales of the past and present; however, controlling the time frame for calculating rates of biotic and climate change can help mitigate this issue (Blois et al., 2013).

Species Distribution Models (SDMs) are essential for ecology, evolution, and conservation biology and it is through that SDMs we understand environmental relationships and predict species

distribution in both environmental and geographic space (Fletcher & Fortin, 2019; Guisan et al., 2017; Guisan & Zimmermann, 2000). SDMs are numerical tools used to predict species distribution by combining occurrence or abundance data with environmental estimates. They can be used to predict new sites within the range of environments sampled by the training data or to predict new and unsampled geographic domains in future or past climates (Elith & Leathwick, 2009). Studying habitat distribution under different climate scenarios allows conservators to assess the vulnerability of species and ecosystems to climate change (Ksiksi et al., 2019).

The United Nations General Assembly (UNGA) in 2015 adopted the 17 Sustainable Development Goals (SDGs) to end poverty, protect the planet, and ensure prosperity for all by 2030 (Biermann et al., 2017). The targets for SDG 15, Life on Land, including sustainably managing forests, combating desertification, halting, and reversing land degradation, and halting biodiversity loss (Franco et al., 2020). The integrated nature of the SDG objectives means that progress towards one objective is also linked through complex feedback to other objectives, which imposes demands on science and research to support national implementation (Allen et al., 2019).

Spatial data is essential to implementing and reporting on projects that deliver on the SDGs, including SDG 15 (Kussul et al., 2017). To support Peru, Ecuador and Colombia, the NASA-funded Project called “*Maintaining Life on Land (SDG15) under Scenarios of Land Use and Climate Change in Colombia, Ecuador, and Peru*” arose in 2019.

The United Nations Development Programme (UNDP) is the leading agency in the United Nations (UN) system in assisting governments to integrate the SDGs into their national development plans and policies. The UNDP and the Governments of Peru, Ecuador, and Colombia have joined forces with premier research organizations to support countries to deliver on SDG 15.

One of the components of this NASA-funded Project was Forecasting vertebrate species and ecoregions response to climate and land-use change. To respond to this component, the potential distribution of vertebrate species and ecoregions of importance to the three countries will be analyzed under current climate conditions (Baseline 1970-2000) and under climate change scenarios for the year 2050 (RCPs 2.6, 4.5 and 8.5). Finally, the use of a methodology to estimate occurrence probabilities for species and ecoregions in different climatic ecoregions and human footprint maps to the three countries in the Red List Index (RLI) was examined.

Most climate change assessments focus primarily on species and do not directly estimate how entire ecosystems can change (Ponce-Reyes et al., 2017). The vulnerability of species to climate change has been inferred using species distribution models.

The general objective of this work is to analyze the possible effects of climate change and human footprint (HFP) on priority vertebrate species and ecoregions for Peru, Ecuador, and Colombia in terms of probability of occurrence through the SDMs and to establish a methodology with a pilot species and ecoregion so that decision makers or researchers can replicate with other species or ecoregions and thus contribute to their conservation and management through the voluntary reports of SDG 15.

Finally, this research had five general objectives, a. Synthesize the literature on climate change scenarios and global circulation models and their effects on temperature and precipitation in our area of study. b. Summarize the General Global Circulation Models (GCMs) for temperature and annual precipitation (mm) for Peru, Ecuador and Colombia and their Ecoregions in a context of Climate Change. c. Compare differences for temperature and precipitation between the 2050 RCPs and the baseline (1970-2000). d. Perform a normal distribution analysis of temperature and

precipitation as well as a comparison of medians using non-parametric tests for these two variables at the ecoregion level for the baseline and climate change scenarios and f. Develop a pilot methodology for modeling species and ecoregions using climatic variables and HFP (Human Footprint) for the three countries. After this introduction (Chapter I), the following three chapters are shown below.

Dissertation Outline

Chapter 2, one of the requirements for the modeling of species' habitat and ecoregions is to have standardized information on bioclimatic variables. Thus, a review of climatic data with 10-minutes and 30-second resolutions and General Circulation Models (GCMs) and their changes for temperature and precipitation variables in a baseline (1970-2000) and in three climate change scenarios at the country level (Peru, Ecuador, and Colombia) as well as for three ecoregions Sechura Desert, Páramo y Napo Tropical Forest was made using the R package called GCM compareR and "ccafs" (Climate Change, Agriculture, and Food Security) (Fajardo et al., 2020; Navarro-Racines et al., 2020). Climatic data search is important because the countries lack homogenized data between them as well as with the ecoregion maps. Then, an exploration of the data was done through normality tests and median comparisons using the Anderson-Darling test. To calculate if there are statistically significant changes in medians of the temperature (C°) and the annual precipitation (mm) as well as their spatial change the Kruskal-Wallis Nonparametric Test using the R Package 'palmerpenguins' in the software R-4.2.1 (Gorman, 2022; M. Horst et al., 2022) was performed for the Baseline and the three 2050 RCPs in the three ecoregions.

Chapter 3 focuses on developing a methodology for habitat modeling of a pilot species and ecoregion present in Peru, Ecuador, and Colombia. Here we use the R package called SDM R for

the modeling (Naimi & Araújo, 2016; Naimi & Araujo, 2019). Here we make use of observed data for the occurrence of the spectacled bear as well as the Páramo ecoregion. This data is then curated and validated. Pseudo-absences were generated using a buffer, for the spectacled bear considering the home range of the maximum value recorded in the literature, which is 150 km, and for the Páramo ecoregion a buffer of 100 km was generated. Then the abiotic variables included for the modeling were the 19 Bioclimatic variables (WorldClim), elevation and human footprint (HFP-2009) (Venter et al., 2018). Collinearity analyses were then performed using Pairwise correlation coefficients and Variance Inflation Factor (VIF) value. We also explored which variables could have the greatest effect on the modeling through the getVarImp (Relative Importance) function, Random Forest, and decision trees. Finally, we modeled the pilot species and ecoregion under current climate conditions (1970-2000) and for the three climate change scenarios in 2050 (RCPs 2.6, 4.5 and 8.5). It should be noted that the HFP is important because it helps us to integrate human pressure either in the habitat of our pilot species or in the habitat of the ecoregion.

Chapter 4 focuses on general conclusions from the previous chapters as well as advantages and possible improvements that are expected to be made in the methodology explored in this research to help policy makers for the conservation of species and ecoregions in South America.

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CHAPTER TWO

ASSESSING THE IMPACTS OF CLIMATE CHANGE USING GENERAL CIRCULATION MODELS (GCMs): A STUDY OF TEMPERATURE (°C) AND ANNUAL PRECIPITATION (mm) MEDIANS FOR A BASELINE AND THREE 2050 RCPs IN PERU, ECUADOR, AND COLOMBIA.

Contribution of Authors and Co-Authors

Manuscript in Chapter 2

Author: Jaris E. Veneros G.

Contributions: conceived and designed the analysis, collected data, contributed data or analysis tools, performed the analysis, and wrote the paper.

Co-Author: Andrew Hansen

Contributions: contributed to data analysis, methods, writing improvements, and research and publication funding.

Co-Author: Dave Roberts

Contributions: contributed to data analysis, methods and writing improvements.

Co-Author: Elkin Noguera-Urbano

Contributions: contributed to data analysis, methods and writing improvements.

Co-Author: Patrick Jantz

Contributions: contributed to data analysis, methods and writing improvements.

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Jaris Veneros, Andrew Hansen, Dave Roberts, Elkin Noguera and Patrick Jantz

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Abstract

Climate change is a global concern, and its impact on environmental variables such as temperature and annual precipitation is unknown spatially in the Desert, Andes, and Rainforest Ecoregions for Peru, Ecuador, and Colombia. In this study, we conducted a general review of climate drivers for South America and explored climate data using the GCM compareR package.

Our results showed that all global circulation models demonstrated increases in temperature for Peru, Ecuador, and Colombia. On the other hand, most GCMs showed increases in precipitation. We conducted non-parametric tests (Kruskal-Wallis Test) to assess if the medians of temperature and precipitation in the Sechura Desert, Páramo, and Napo Tropical Forest ecoregions are equal for both the baseline and the climate change scenarios.

We rejected the null hypothesis that the medians are equal for both temperatures and precipitation in the baseline vs 2050 RCPs (2.6, 4.5, and 5.8). A spatial analysis was conducted to visualize the variations in temperature and precipitation between the RCPs versus the baseline, and the spatial variation at the country or ecoregion level can be observed.

In conclusion, climate change is likely to have a significant impact on the environmental variables of temperature and precipitation in South American ecoregions. Our study provides important insights into the potential impacts of climate change on these important ecosystems.

Introduction

The Earth's climate has warmed, and precipitation regimes have changed over the last 100 years (Thuiller, 2007). Alarming consequences of climate change on biodiversity have been suggested. It was mentioned that in the next century, many plants and animals will become extinct (Willis & Bhagwat, 2009). Climate change may have effects on different levels of Biodiversity

such as Genetics, Physiology, Phenology, Dynamics, Distribution, Interspecific Relationships, Community Productivity, Ecosystem Services, and Biome Integrity (Bellard et al., 2012).

Latin America is home to a large concentration of plant and animal species and is estimated to be home to one-third of the world's terrestrial biodiversity (Raven et al., 2020); it was also found that 43% of all tree species on Earth are found in South America and that 40% of the world's undiscovered tree species are found there (Gatti et al., 2022)

The greatest risks of species extinction because of climate change are in South America, Australia, and New Zealand (Urban, 2015). and the risks of species extinction due to climate change are not only expected to increase but to accelerate as global temperatures rise and changes in rainfall patterns (Papalexou & Montanari, 2019).

Climate change is a statistically significant variation in the average state of the climate or its variability, which persists for a prolonged period (decades or more) and its origin may be due to internal natural processes or external factors, such as persistent changes in the atmosphere or land use (Arguez & Vose, 2011; WMO, 2018). These changes have been observed over the past 30 years, patterns of temperature, precipitation, humidity, and other environmental variables influencing flora, fauna, ecosystems, ecoregions, and biomes (Arguez & Vose, 2011; Elsen et al., 2022; Kharin et al., 2013).

Thus, in 1988 the Intergovernmental Panel on Climate Change (IPCC) was created to facilitate comprehensive assessments of climate change, its causes, potential impacts, and response strategies (Agrawala, 1998). The first Assessment Report of the IPCC was completed in 1990, it provided the basis for the United Nations Framework Convention on Climate Change (UNFCCC), which included the 1990 IPCC Scenario A (SA90) and the 1992 IPCC Scenarios (IS92) were used

in the Special Report on Emissions Scenarios (SRES) in 2000, in the Third Assessment Report (TAR) in 2001, and in the Fourth Assessment Report (AR4) in 2007 (Strandsbjerg Tristan Pedersen et al., 2021).

Then the Fifth Assessment Report (AR5) on Climate Change was published between 2013 and 2014 where the IPCC chose to use scenarios developed by the scientific community and four scenarios were elaborated, called Representative Concentration Pathways (RCPs), these represent different GHG emissions trajectories and are named according to the forced radiation they are expected to cause in the atmosphere in 2100 and are measured in W/m^2 and these are RCPs 2.6, 4.5, 6.0, and 8.5 (Riahi et al., 2007; van Vuuren et al., 2017), and the lowest trajectory represents 2 °C above pre-industrial levels and the highest trajectory is 8.5 a global warming of 4.5 °C or more above pre-industrial levels. In 2016 the first publications on Shared Socioeconomic Pathways (SSPs) were launched and thanks to these the IPCC's Sixth Assessment Report (AR6) on climate change was published in 2021 (J. S. T. Pedersen et al., 2020).

As computational systems have advanced, more regional, or local analyses are now possible. For example, there are IPCC climate reference regions for subcontinental analysis of climate model data for South America where they indicate that for RCP 8.5 (2081-2100) a temperature increase of greater than 4 °C is expected compared to 1986-2005 (Kharin et al., 2013).

The proportion of extremely warm DJF days was observed to have at least doubled in recent decades in northern South America; less significant increases were observed in southern South America (Feron et al., 2019). Also, in future projections for 2010-2040 and 2070-2100, general warming is indicated throughout South America (SA) and in all its seasons, as well as more intense precipitation is estimated, but annual precipitation (mm) decreases, as well as delays

in rainy seasons are expected throughout SA compared to the 1960-1990 baseline (Reboita et al., 2014).

Warming is projected over South America (SA) and is of greater amplitude in the ETA Scenario forced by HadGEM2-ES RCP 8.5 (2011-2040, 2041-2070, and 2071-2100), warming begins in central and southeastern Brazil and progresses strongly toward the northern part of the SA and more intense precipitation is expected, but annual precipitation is decreasing compared to the 1961-1990 baseline (Chou et al., 2014).

Ideally, we should have monthly observed temperature and precipitation data for minimum periods of 30 years for Peru, Ecuador, and Colombia and with a resolution of greater than 1 km, but for now we have annual meteorological data ≥ 1 km standardized for these areas, which can help us to understand the effects of the variation of these variables in ecoregions and/or vertebrate species for the areas under study. For instance, the spatiotemporal variability of precipitation and temperature trends (minimum, maximum, and average) was analyzed in 47 stations in the Brazilian Amazon for the period 1973-2013, the results showed that these had an increasing trend of approximately 0.04 °C per year and precipitation did not show a marked trend (Almeida et al., 2017).

In two climate change scenarios (RCPs 4.5 and 8.5), a reduction in precipitation of 2.4 to 11% by 2050 and 2070, respectively, and an increase in average annual temperature from 1.7 °C (HadGEM2-ES 2041-2060) and 3.7 °C (GFDL-CM3 2061-2080) in the Uribia-Guajira area compared to the baseline from 1976 to 2005 (IDEAM) are expected (Ospina et al., 2017).

Evaluating climate data for Peru, Ecuador, and Colombia is difficult because of different interpolation methods, different periods for baselines, the selection of different global circulation

models for climate change studies, and the lack of meteorological stations in their territories. The National Meteorological and Hydrological Services of Peru, Ecuador, and Colombia have few meteorological and hydrological stations in high-altitude areas as well as in Amazonian areas (Condom et al., 2020; Gubler et al., 2020; Navarro-Racines et al., 2020).

Also, analyzing minimum temperatures in the Andes is very complex in terms of error and uncertainty concerning maximum temperatures because of the altitude variation (Navarro-Racines et al., 2020), and before using the SDMs, bioclimatic variables from different databases such as WorldClim must be analyzed. For example, variables derived from temperature and precipitation in our area of interest can provide preliminary information on the ecology of the species under study (Booth, 2022).

For this reason, we explored different databases for bioclimatic variables such as "ccafs" (Climate Change, Agriculture, and Food Security) with 10 minutes resolution and WorldClim (Global Climate Data) with 30 seconds resolution because they are standardized for the three countries (Fick & Hijmans, 2017; Navarro-Racines et al., 2020); in terms of Coordinate Reference Systems (CRS), resolution, and spatial extent.

A literature review and exploratory analysis of changes for two variables, temperature ($^{\circ}\text{C}$), and annual precipitation (mm) for a baseline (1970-2000) and Climate Change Scenarios for 2050 (RCPs 2.6, 4.5, and 8.5) in three countries (Peru, Ecuador, and Colombia) and ecoregions (Sechura Desert, Páramos, and Napo Tropical Forest) were carried out because our research question aims to investigate how the annual mean temperature ($^{\circ}\text{C}$) and annual precipitation (mm) will change between the baseline and the three RCP scenarios (2.6, 4.5, and 8.5) in 2050.

Then, statistical analyses of these environmental variables were then carried out for these representative ecoregions, one from the Coast, one from the Andes, and one from the Tropical Rainforest. The purpose of this analysis was to investigate whether there is any significant difference between the means or medians of temperature and precipitation in the baseline and the 2050-RCPs (2.6, 4.5, and 8.5) within these ecoregions. The study aims to provide insights into the potential impact of climate change on these regions.

Methods

Study Area

In this research, an analysis of climate change at the level of three countries Peru, Ecuador, and Colombia (Figure 2.1a), and in three ecoregions Sechura Desert, Páramo, and Napo Tropical Forest (Figure 2.1b) will be carried out. The Peruvian territory is located between the coordinates 0° and 18° 20' of South Latitude and 68° 30' and 81° 25' of West Longitude, covering an area of 1 285 215 km². Much of the territory comprises the Andes Mountains, which extend from South to North, along the South American Continent. The Cordillera de Los Andes determines different geomorphological units, typical of a continental environment and a marine environment (INGEMMET, 1995).

Then, Ecuador is Located on the west coast and straddles the equator. Ecuador has a total area of about 280 000 km². Ecuador has a wide range of natural formations and climates, from the desert-like southern coast to the snowcapped peaks of the Andes Mountains to the plains of the Amazon River Basin. After that, Ecuador is bounded on the west by the Pacific Ocean, on the north by Colombia, and on the east and south by Peru (Moreno et al., 2018).

Lastly, Colombia is located between latitudes 12° 24' north and 4° 17' south, and longitudes 66° 7' and 79° west and it has an area of 1 141 748 km². Colombia's topography has four general elements: the Andes Mountain system, which is united in a single knot at the border with Ecuador and then divides into three major mountain ranges that extend in a north-south direction and are known as the Cordillera Oriental, the Cordillera Central, and the Cordillera Occidental. The group of high mountains in the northeast of the country, between the Guajira peninsula and the Magdalena River valley, is known as the Sierra Nevada. The Bogotá Sabana is in the central-eastern part of the country, on the western side of the Eastern Cordillera. Finally, the great plains in the southeastern part of the country that extends from the Eastern Cordillera to the east and southeast of the country to the basins of the Orinoco and Amazon rivers, being an area much larger than the mountainous and inhabited sector of the country. The great plains of the Orinoco and Amazon are uninhabited except for the tribes (Bell, 2012).

In addition, these countries have 47 ecoregions according to Resolve 2017, but for climate change studies we will use the Sechura Desert, Páramos like Santa Marta, Northern Andean, Cordillera Central and Cordillera de Mérida (Part of Venezuela) and Napo Tropical Forest ecoregions. The three ecoregions under study are described below (Figures 2.1a and 2.1b) (Dinerstein et al., 2017; Olson et al., 2001).

The Sechura Desert is in the western subtropical part of South America, bordering the Pacific Ocean to the west and extending between 20 and 100 km towards the Andean zone and it is characterized by open shrub and tree stands (Block & Richter, 2000; Schipper J, 2017b). The climate of the ecoregion is warm in summer and humid in winter, with average annual temperatures of 22 °C (Schipper J, 2017b). Precipitation in this ecoregion varies with altitude, from 0 mm/year

to 250 mm/year and this ecoregion is characterized by little vegetation cover, but it can be affected by the El Niño phenomenon (Block & Richter, 2000; Fuentes-Castillo et al., 2020; Guerrero et al., 2013; Schipper J, 2017b).

The Páramo has the richest high mountain flora in the world and has a high degree of endemism (Schipper, 2017); for example, this region is home to the spectacled bear and the Andean tapir, both of which are endangered. The descriptions for the types of páramos used in this research are shown below.

First, the páramos of Santa Marta are the northernmost occurrence of this type of habitat in South America and are in the Sierra Nevada de Santa Marta, an isolated mountain massif that breaks away from the Andes and rises to 5775 masl along the shores of the Caribbean Ocean in northern Colombia. The climate is influenced by northeasterly trade winds and rising humid air currents. Most of the rainfall occurs from May to September, with an estimated rainfall of less than 1800 mm/year; the average annual temperature is 6 °C. The northern part is more rugged and receives more precipitation than the southern part.

Second, the Northern Andean Páramo has a temperature range that goes from below freezing to 30 °C, the upper zone of the ecoregion receives more than 2000 mm/year of precipitation, and it has an average humidity of 80 % because it is in the Intertropical Convergence Zone (ITCZ), this slows tree growth and gives way to a tropical alpine grassland environment.

Third, the Cordillera Central Páramo extends in the vicinity of the Marañón Valley, from the extreme south of Ecuador to the northwest of Peru, and ranges in altitude from 3200 m to about 4500 m. The climate is cold and humid, and temperatures can drop below 0 °C. The typical

landscape is that of treeless vegetation dominated by grass and the shrubby alpine grassland is surrounded by montane cloud forest like the *Polylepis* transition forest.

In the end, the Cordillera de Merida Páramo its altitude ranges from 3000 m to approximately 4000 m and these mountains are the highest peaks of the Andes in northwestern Venezuela. Precipitation ranges between 500-1000 mm/year and in the dry season (December-March) less than 80 mm is accumulated. Snowfall is frequent in the highlands, especially during the wet season, although accumulation is unusual. The mean annual temperature at 4 000 m is 2.8 °C with a daily fluctuation of 6 °C. At lower altitudes, daytime temperatures reach 21 °C but can drop to 0 °C at night.

In the Napo Moist Forests, its topography varies between lowlands and undulating also it has swampy lands by the river systems (Schipper J, 2017a). The climate is humid tropical, with a subtle dry season. The average annual temperature is 26 °C and can range from 12 to 38 °C. This ecoregion receives the highest annual rainfall in the Amazon, with up to 4000 mm in the west and 2500-3000 mm in the east. Three main vegetation types occur in this rainforest ecoregion: terra firme forest, várzea forest, and igapó swamp forest, but they are tall, evergreen tropical rainforests. These forests are among the richest in biodiversity of species in the entire Amazon basin, and are among the most diverse in the world, with 219 species of mammals and 649 bird species recorded. This ecoregion is also an evolutionary and dispersal center for neotropical butterflies with high endemism.

Summary of the GCMs for Climate Change

The R package called GCM compareR and "ccafs" (Climate Change, Agriculture, and Food Security) was used (Figure 2.2) (Fajardo et al., 2020; Navarro-Racines et al., 2020) to access the

Global Circulation Models (GCMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5) for the RCPs 2.6, 4.5 and 8.5 - 2050 and it allowed us to access data for 19 bioclimatic variables, these environmental variables were derived from monthly temperature and precipitation (Fajardo et al., 2020). By having temperature (°C) and annual precipitation (mm) data we could infer dry or rainy scenarios as well as analyze ensembles for different scenarios from published climate databases such as WorldClim, CHELSA, or CGIAR (Fajardo et al., 2020; Fick & Hijmans, 2017; Nñez et al., 2009; Poggio et al., 2018).

On the other hand, different climate change studies were analyzed for the three countries, especially changes in temperature (°C) and annual precipitation (mm) for different climate change scenarios up to 2050, as well as their effects on ecoregions.

From some research, temperature, and precipitation maps for climate change RCPs scenarios for 2050 were rebuilt using the ArcGis ver. 10.7 georeferencing tools in the three countries (García et al., 2021). In this way, more detailed climate information was extracted based on their coordinate system, and an overlay of our study areas with the rebuilt maps was then performed to have a clearer spatial interpretation.

Exploratory analysis for temperature and precipitation analysis

For the analysis of temperature (°C) and annual precipitation (mm) for 2050 under the RCP 2.6, 4.5, and 8.5 scenarios, 25 GCMs were used at the country level, and 26, 24, and 25 GCMs were used for ecoregions such as the Sechura Desert, Páramo, and Napo Moist Forest, respectively. The ensembles for the RCPs (2.6, 4.5, and 8.5) were made different GCMs for each RCP from the GCM Downscaled Data Portal of “ccafs: (CCAFS-CLIMATE) (http://ccafs-climate.org/data_spatial_downscaling/). Also, it should be noted that the number of GCMs varies

depending on their availability for each country or ecoregion and its resolution is 10 minutes ~ 18.5 km at the equator.

Statistical analysis: comparison medians at the ecoregion level

First, exploratory analyses of the temperature (°C) and annual precipitation (mm) medians were performed using the R package "ggridges" (Thrun et al., 2020). This package allows us to analyze the normality of temperature (°C) and annual precipitation (mm) in the three ecoregions under study.

The evaluation of the normal or non-normal distribution of the data for these variables for baseline and RCPs allowed us to select the parametric and nonparametric tests for the comparison of means or medians correspondingly (Ramsey & Schafer, 2013). The R package called "nor.test" was also used to analyze the normality analyses of the temperature and precipitation data for the baseline and the three climate change scenarios. The Anderson-Darling test, QQ plots, and histograms were used from this package (Gross & Ligges, 2022).

The statistical analysis of medians comparisons for temperature (C°) and precipitation (mm) for the baseline (1970-2000) and the RCPs 2050 climate change scenarios ensembles (2.6, 4.5, and 8.5) was performed using the Kruskal-Wallis Nonparametric Test using the R Package 'palmerpenguins' in the software R-4.2.1 (Gorman, 2022; M. Horst et al., 2022) in the Sechura Desert, Páramo, and Napo Moist Forest ecoregions.

The ensembles for the RCPs (2.6, 4.5, and 8.5) were made using 14 GCMs for each RCP from the WorldClim Database (https://www.WorldClim.org/data/v1.4/cmip5_30s.html) with a resolution of 30 seconds ~ 1 km at the equator. These GCMs were BCC-CSM1-1, CCSM4, CNRM-CM5, GFDL-CM3, GISS-E2-R, HadGEM2-AO, HadGEM2-ES, IPSL-CM5A-LR,

MIROC5, MIROC-ESM, MIROC-ESM-CHEM, MRI-CGCM3, MPI-ESM-LR and NorESM1-M (For their names and origin, see Table S2.2). The Kruskal-Wallis is a nonparametric statistical test that assesses the differences among three or more independently sampled groups on a single, non-normally distributed continuous variable for non-normally distributed data (Gooch, 2011; Siegel, 1957).

Results

Drivers of climate in South America

To comprehend the climate, we must define meteorology and climatology. Meteorology is the study of the atmosphere and the phenomena within it on scales ranging from minutes to weeks and it focuses on atmospheric variables and Climatology is the study of climates or long-term average atmospheric conditions over a place (Coleman, 2015; Reboita et al., 2022).

The weather is essentially the behavior of the atmosphere during the present time (Coleman, 2015; Lazaridis, 2011). The variables to characterize the weather for a particular place and time are usually temperature, precipitation, relative humidity (RH), cloud cover, wind speed, wind direction, and atmospheric pressure; and climate is the state of the atmosphere based on the record of observation and internationally accepted 30-year averages or climate in a wider sense is the state, including a statistical description, of the climate system (Arguez & Vose, 2011; Coleman, 2015; Hulme, 2020).

Also, the climate of South America is very complex beyond the elements and factors of climate. The Andes Mountain range is the longest in the world (Boschman, 2021; Espinoza et al., 2020; Schellart, 2017) and extends from 11°N to 53°S, this mountain range crosses seven countries

and is characterized by a great variety of ecosystems, and they are related to the climatic contrast on its east and west sides, as well as throughout its latitudinal extent (Espinoza et al., 2020).

The Sechura Desert or the Atacama-Sechura Desert is one of the driest and oldest deserts on Earth (Guerrero et al., 2013). The formation of deserts such as the Sechura and Atacama (hyperarid) is due to these factors (Guerrero et al., 2013; Rundel et al., 1991): a. subtropical atmospheric subsidence; b. the Humboldt current, which runs from south to north and is cold, preventing precipitation in the coastal regions; and (3) the rain shadow effect of the Andes Mountains, which stops moist air from reaching the Pacific coast. A classification of aridity was made according to annual precipitation and is as follows: mesic > 250 mm/y, semiarid < 250 mm/y, arid < 50 mm/y, and hyperarid ≤ 5 mm/y (Figure 2.3) (Guerrero et al., 2013). But we could not analyze the climate drivers of these deserts on their own because they are also due to the relationship they have with other ecoregions.

The hydroclimatic relationship between the Coast, Andes, and tropical forests has these factors (Espinoza et al., 2020):

- a. The large-scale mean atmospheric circulation that characterizes the hydroclimate of the Andes: at latitudes 5°S , trans-Andean flow is predominant, producing a complex rainfall regime over northern Peru, Ecuador, and Colombia. During the austral summer, when the mature phase of the South American Monsoon System (SAMS) occurs, the mountains of the southern tropical Andes between latitudes $8\text{-}27^{\circ}\text{S}$ act as a topographic barrier to the warm and humid flow from the Amazon region; these flows are crucial for the advection of moisture into the tropical Andes; however, studies suggest that land use change in the southern and southeastern Amazon basin has reduced their ability to regulate low flows.

- b. The regular cycles of precipitation: the latitudinal presence of the ITCZ (Intertropical Convergence Zone), westerly winds, the complex Andean orography, as well as local circulations and temperature gradients, are the main factors that explain the regular precipitation cycles over the Andes. Finally, Low-Level Jets (LLJs) are observed on the two sides of the Andes and at different latitudes, which are induced by mechanical blocking of incident flow and/or diabatic heating on mountain gradients and these are important because they transport moisture over large meridional distances, except in the case of jets west of the Andes in subtropical latitudes as seen in Figure 2.4.

Changes in atmospheric pressure or altitude cause changes in wind direction, and this also influences the climate of South America. According to (Espinoza et al., 2020), the following results were obtained in Figure 2.5; additionally, moisture advection from the Amazon region is predominant during the austral summer (Figure 2.5 a, b, c, and d). However, at latitudes of 5°S, where the altitude of the mountains is lower, trans-Andean flows are predominant throughout the year, producing a complex rainfall regime over this region. One of the rainiest places on Earth (Lloró; 5°30'N, 76°32'W) is located along the Pacific coast of Colombia, with an annual precipitation of 13 000 mm, due to the dynamics of the low-level Chocó jet enhanced by atmosphere-ocean-land surface interactions (Espinoza et al., 2020; Sierra et al., 2021; Yepes et al., 2019).

Climate change review, exploration, and statistical analysis

General Circulation Models (GCMs) help to understand the impacts of climate change on our planet. This section presents two parts, the first is a review of the literature on the expected

effects of climate change in our study areas and the second is an exploratory review of GCMs at 10 minutes resolution and statistical analysis of temperature (°C) and annual precipitation (mm) for the RCPs 2.6, 4.5 and 8.5 for the Sechura Desert, Páramo, and Napo Moist Forest at 30 seconds resolution.

Climate change and its scenarios

In the history of our planet, it has been demonstrated that climate change could have natural as well as anthropogenic origins, so this research will analyze climate change events during the Anthropocene, using a baseline from 1970 to 2000, as well as its projections for the RCPs 2050 scenarios (Representative Concentration Pathways).

Climate change refers to a statistically significant variation in the mean state of the climate or in its variability that persists over an extended period, usually decades or longer (WMO, 2018). Furthermore, climate change may be due to internal natural processes or external forcings, or to persistent anthropogenic changes in the composition of the atmosphere or land use. Article 1 of the United Nations Framework Convention on Climate Change (UNFCCC) defines climate change as "a change of climate which is attributed directly or indirectly to human activity that changes the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable periods" (IPCC, 2000; UN, 1992; WMO, 2018, 2022).

According to (Stuart Chapin et al., 2012), the climate on our planet is a dynamic system and in different millennia we have had glacial periods (Figure 2.6) and sea level changes, caused mainly by the distribution of solar energy and atmospheric composition. In other ways, continental drift, mountain formation, and erosion have modified atmospheric and oceanic circulation patterns over longer time scales. Solar radiation has increased by 30% over the last four billion years as the

sun matured, but there are also predictable variations in the earth's orbit that influence the amount of solar radiation our planet receives at different times and latitudes such as eccentricity, tilt, and precession. The periodicities of these orbital parameters are approximately 100 000, 41 000, and 23 000 years. The interactions between these Milankovitch cycles of solar input correlate with glacial and interglacial cycles. Analysis of these cycles indicates that the Earth would not naturally enter another ice age for at least 30 000 years, so natural cycles of solar input will not substantially compensate for human-induced climate warming.

The Anthropocene began around 1750 with the onset of the industrial revolution and is characterized by human domination of the biosphere (Figure 2.6) (Stuart Chapin et al., 2012). Anthropogenic emissions of greenhouse gases have increased since the pre-industrial era, largely, because of economic and population growth (He & Silliman, 2019; Stuart Chapin et al., 2012). As a result, atmospheric concentrations of carbon dioxide, methane, and nitrous oxide have reached levels unparalleled in at least the last 800000 years. The effects of emissions, as well as other anthropogenic factors, have been detected throughout the climate system and are likely to have been the dominant cause of the warming observed since the second half of the 20th century (IPCC, 2014b, 2014a; Salinger, 2005).

The estimated human contribution to global warming is shown in Figure 2.7 (IPCC, 2014a, 2014b), this figure is for the period 1951-2010, the land temperature has increased by about 0.6°C seen in the black bar whiskers with an uncertainty interval of 5% to 95%, due to greenhouse gases or homogeneously mixed, other anthropogenic forcings (including the cooling effect of aerosols and the effect of land use changes), combined anthropogenic forcings, natural forcings, and natural

internal variability (which is the element of climate variability that arises spontaneously in the climate system, even in the absence of forcings).

Climate scientists mentioned that global mean temperature and atmospheric carbon concentrations began to take on importance between the 1970s and 1980s, which gave climate change a global object to be studied on a global scale as well as its periodic assessments; thus, in 1990 the Intergovernmental Panel on Climate Change (IPCC) has been fundamental to the construction of a global ontology of climate change (Livingston et al., 2018). The IPCC was established by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP-UN) to assess scientific, technical, and socio-economic information for understanding the risk of human-induced climate change (IPCC, 2012, 2014b). The 1994 IPCC assessment of the IS92 scenarios concluded that the scenarios were innovative and groundbreaking for that date, both regionally and globally; however, improvements should be made due to new global meteorological data, greenhouse gas data, as well as changing clean air policies adopted by some countries were having an effect (IPCC, 2021). The IPCC has produced four generations of emissions scenarios (J. T. S. Pedersen et al., 2022). Three were developed under its leadership: the 1990 Scientific Assessment (SA90), the 1992 IPCC Scenarios (IS92), and the Special Report on Emission Scenarios (SRES). The fourth comprises the Representative Concentration Pathways (RCPs) and the Shared Socioeconomic Pathways (SSPs), which served as the basis for Phases 5 and 6 of the Climate Model Intercomparison Project (CMIP5/CMIP6). The RCPs have been used in the scenario-based literature informing the IPCC Fifth Assessment Report (AR5), while the SSP/RCP combination will be used for the IPCC Sixth Assessment Report

(AR6). CMIP6 selected the SSP/RCP combinations to be highlighted in AR6 (Figure 2.8) (J. S. T. Pedersen et al., 2020).

On the other hand, as mentioned above, in this research we will analyze and use the RCP scenarios in South America. The RCPs are a set of four pathways developed by the IPCC and published in 2014 (AR5) and they were developed based on the concentration trajectory of greenhouse gases in the atmosphere (IPCC, 2014a). The four RCPs cover the range of radiative forcing values for the year 2100 and they are 2.6, 4.5, 6.0, and 8.5 W/m² (Chou et al., 2014; IPCC, 2014b; J. T. S. Pedersen et al., 2022).

For the development of the RCPs, seven steps were considered seven steps within three groups; for example, Integrated Assessment Models (IAMs), Processing and Completion, and RCP repository (Figure 2.9), where the RCPs are based on scenarios published in the existing literature in terms of emissions and concentrations, they provide information on all components of radiative forcing that are needed as input for climate and atmospheric chemistry modeling such as greenhouse gas emissions and land use, and this data was harmonized over the base year for emissions and land use for historical and future period analyses (2100) (van Vuuren et al., 2011).

The RCPs should not be interpreted as forecasts or absolute limits, nor should they be viewed as prescriptive policies (Carlsen et al., 2017; van Vuuren et al., 2011). The RCPs describe a set of possible developments in emissions and land use, based on consistent scenarios representative of the current literature (van Vuuren et al., 2011). The RCPs scenarios encompass time series of emissions and concentrations of the full range of greenhouse gases and aerosols and chemically active gases, as well as land use and land cover. The word "representative" means that each concentration trajectory provides one of many possible scenarios that would lead to specific

radiative forcing characteristics. The word trajectory emphasizes that only long-term concentration levels are of interest, but also indicates the path followed over time to arrive at the outcome in question (Riahi et al., 2017; van Vuuren et al., 2017). Representative concentration trajectories generally refer to the part of the concentration trajectory up to the year 2100, for which models have been used to model the concentration trajectory 2100, for which the integrated assessment models have generated the corresponding emissions scenarios (IPCC, 2014b, 2014a).

- RCP 2.6: Trajectory in which radiative forcing peaks at about 3 W/m^2 before 2100 and then decreases (the corresponding extended concentration trajectory under the assumption of constant emissions after 2100).
- RCP 4.5 and RCP6.0: Two intermediate stabilization trajectories in which radiative forcing stabilizes at about 4.5 W/m^2 and 6.0 W/m^2 after 2100 (the corresponding extended concentration trajectory under the assumption that concentrations are constant after 2150).
- RCP 8.5: High trajectory for which radiative forcing reaches values $>8.5 \text{ W/m}^2$ in 2100 and continues to increase for a time lag (the corresponding extended concentration trajectory assuming constant emissions after 2100 and constant concentrations after 2250).

Climate change review in ecoregions

In South America (SA), the effects of climate change on temperature and precipitation for 2050-2080 were analyzed with a baseline from 1980 to 2005; the results showed that for the austral summer (DJF) and winter (JJA), there will be an increase in the frequency and intensity of extreme daily rainfall events over the southeast and extreme north of South America; furthermore, in the Amazon during DJF, there is a statistically significant increase in the number of consecutive dry days and a decrease in the number of consecutive wet days (Reboita et al., 2022). In addition,

deforestation, fires, and deaths associated with extreme weather conditions such as droughts, have generated the Amazon forests are threatened to become a savannah (Stark et al., 2020), as a result, studies of climate change in this type of Biome are urgently needed.

Some dynamic vegetation models have been used, and the results of the projections show that some areas of tropical rainforest in the Amazon region are replaced by deciduous forests and grasslands in the RCP 4.5 scenario and only by grasslands in the RCP 8.5 scenario at the end of this century; however, a reduction of the Amazon biome can generate a positive feedback of the temperature increase and affect the regional hydrological cycle (Lyra et al., 2016). Also, warming is projected throughout South America, with greater amplitude in the Eta scenario forced by HadGEM2-ES RCP 8.5 based on the baseline period, 1961-1990, and three-time slices 2011-2040, 2041-2070 and 2071-2100, and for the two emission scenarios RCP 4.5 and RCP 8.5 and precipitation in DJF, there will be the greatest reduction from NO to CS regions, an area generally occupied by the South Atlantic Convergence Zone (SACZ) (Chou et al., 2014). Other research related to the formation of savannas for future climates (RCP 8.5) in the Amazon and Northern Brazil where it is stated that there is a possible increase in the aridity of 33.8% and 36.9% (UNEP index) and 4.6% and 13.9% (Budyko index) respectively, by the end of the 21st century (Fernandez et al., 2019). Otherwise, preserving the Amazon is of great importance for the hydrological cycle, for example, the fraction of the mean annual precipitation that has been transpired by trees in the Amazon basin can be as high as 50% (blue color on the right side of the Andes Mountains, highlands of Peru) (Figure 2.10) (Espinoza et al., 2020; Staal et al., 2018). More studies are needed to understand the hydrological relationship between the Andes and the Amazon rainforest in the context of climate change.

In general, climate change studies and analyses of temperature and precipitation for the Sechura, Páramos, and Napo ecoregions are very scarce (Table S2.1), and studies are usually presented for all South America.

In scenarios of climate change (2035-2065 RCP 8.5 - 1 km of resolution), the Sechura desert is expected in most of the zones, there will be no changes that will affect its biome, however, in some zones, there may be an increase in vertical structure as well as in humidity compared to 1981-2010 climate data (Table S2.1) (Zevallos & Lavado-Casimiro, 2022). Also, in the northern zone of the Sechura Desert by 2100 (26 GCMs from CMIP5 in the four RCPs scenarios with a resolution of $1^\circ \times 1^\circ$), the temperature is expected to increase by over 1.5 °C and the annual precipitation from 50 to over 150 mm/year relative to the pre-industrial period (1861-1890) (Torres et al., 2022).

In Peru, Ecuador, Colombia, and Venezuela for the A1B 2010-2039 and A1B 2040-2069 scenarios, the páramo shows a loss of potential and remaining area concerning the year 2000 (Tovar et al., 2013). In the potential areas, part of the páramo will be replaced by forest biomes, but the páramo appears to be more affected by land use change than by climate change. Projections suggest that the páramo shows an upward shift and an average loss of 31.4% is projected for the potential distribution, but only 25% for the remnant areas (A1B, 2010-2039) (Table S2.1) (Josse et al., 2009; Tovar et al., 2013). In this way, Páramos located at the highest elevations, are the most at risk due to the lack of upland areas for migration (Tovar et al., 2013). Also, Páramos have soils with high organic matter content as well as high humidity, which conditions their presence (Hofstede & Llambí, 2020; Tovar et al., 2013).

Then, the Tropical forests are threatened by deforestation, fragmentation, land use change, and climate change in South America (Morris, 2010). However, vegetation also regulates climate, so it was found that exposure to heat stress due to deforestation was comparable to the effect of climate change under RCP 8.5 (2073-2100) compared to a historical period (1980-2010) in the Napo ecoregion (Alves de Oliveira et al., 2021), and increases in its mean annual temperature and annual precipitation for 2030, 2050 and 2080; for example, the RCP 8.5 (5 km resolution) for 2080 shows an increase in average temperature for this ecoregion of 4.2 °C and 349 mm in annual precipitation compared to a 1981 to 2010 baseline (Table S2.1) (Beltrán-Tolosa et al., 2020).

Temperature and precipitation: exploratory and statistical analysis

For the analysis of temperature and precipitation for 2050 under the RCP 2.6, 4.5, and 8.5 scenarios, 25 GCMs were used at the country level, and 26, 24, and 25 GCMs (10 minutes of resolution) were used for ecoregions such as the Sechura Desert, Páramo, and Napo Moist Forest, respectively; it should be noted that the number of GCMs varies depending on their availability for each country or ecoregion. For details of the GCMs such as the average temperature and precipitation values for the baseline and their names and origins, see these tables in the supplementary data (Tables S2.2, S2.3, S2.4, S2.5, and S2.6).

Table 2.1 shows the changes in average annual temperatures (°C) for the three countries and three ecoregions. The second column shows annual average temperatures for the baseline (1970-2000) for these areas. The temperature variations for RCPs 2.6, 4.5, and 8.5 are shown below, where the minimum and maximum values of the differences between the mean temperatures of the set of GCMs for 2050 of the three RCPs relative to the baseline were selected.

These differences in minimum values, maximum values, and ensembles all have positive signs, so it is expected that the annual mean temperature will increase in all study areas and all scenarios.

In addition, Table 2.2 below shows the changes in annual precipitation (mm) for the three countries and the three ecoregions. The second column shows the average annual precipitation from 1970 to 2000 for these zones. The annual precipitation changes for RCPs 2.6, 4.5, and 8.5 are shown below, where the differences between the annual precipitation of the 2050 RCPs with the baseline indicate that annual precipitation will increase (where the sign is positive) in all study zones and all scenarios; however, some GCMs have negative signs, which indicate that there is a reduction in the annual precipitation by 2050 in the three RCPs. Then, the GCMs indicating the greatest reduction in precipitation (negative sign), as well as the GCMs indicating the greatest increase in precipitation (positive sign), were selected for these RCPs. Finally, all ensembles for the three RCPs indicated that annual precipitation would increase by 2050.

The spatial variation of the differences of the 25 GCMs (10 minutes resolution) for the temperature (°C) vs. annual precipitation (mm) variables for the three countries for the three RCPs vs. the baseline are shown in Figures 2.11, 2.12, 2.13, 2.14, 2.15 and 2.16. Figures S2.1, S2.2, and S2.3 show the annual precipitation (mm) versus temperature (°C) variables in the three countries for the three RCPs 2050. These figures help us to identify the GCMs with low annual precipitation and low temperature or high annual precipitation and high temperature or low annual precipitation and high temperature or high annual precipitation and low temperature as well as their proximity to the ensembles.

Four tables are shown below, two for temperature (°C) ensembles (Tables 2.3 and 2.4) and the others for precipitation (mm) (Tables 2.4 and 2.5) for the baseline and the 2050-RCPs in the three ecoregions (1 km resolution). These ensembles were constructed from 14 GCMs.

The minimum temperatures of the Sechura Desert are below zero degrees and are at a higher altitude. Likewise, their minimum temperatures remain below zero for all three RCPs in 2050 concerning the baseline. On the other hand, for maximum temperatures, there is an increase from 1.82 °C, 2.17 °C, and 2.55 °C for RCPs 2.6, 4.5, and 8.5 in 2050 concerning the baseline. Furthermore, the minimum temperatures in the Páramo decrease only for RCP 2.6 by 0.31 °C but not for RCPs 4.5 and 8.5 compared to the baseline. Otherwise, maximum temperatures increase from 1.21 °C to 1.93 °C in 2050 at the baseline. Average temperatures increase from 1.24 °C, 1.63 °C, and 2.11 °C for RCPs 2.6, 4.5, and 8.5 in 2050 from 1970-2000. Lastly, the minimum temperatures of the Napo increased for the three RCPs by 0.73 °C, 1.16 °C, and 1.65 °C compared to the baseline. Otherwise, maximum temperatures increase from 1.44 °C to 2.44 °C in 2050 compared to the baseline. Average temperatures increase from 1.59 °C, 2.02 °C, and 2.56 °C for RCPs 2.6, 4.5, and 8.5 in 2050 compared to 1970-2000.

The standard deviations for the temperature values for the baseline and the three climate change scenarios 2050 RCPs were also analyzed for each ecoregion, where the Sechura Desert has the highest deviations compared to the Páramo and Napo (Tables 2.3 and 2.4), possibly due to the large variation in altitude of this ecoregion.

The annual precipitation was also analyzed for the 1970-2000 and the three 2050-RCPs in the three ecoregions (Tables 2.5 and 2.6). The Sechura desert presented the lowest annual precipitation with 183.72 mm (minimum precipitation of 0 and maximum of 1194 mm). For the

three climate change scenarios, there will also be zero precipitation values, but there will be an increase in the maximum annual precipitation compared to 1970-2000. The páramo has an annual precipitation of 1151.41 mm with a minimum of 262.00 mm and a maximum of 3169.00 mm for 1970-2000. The climate change scenarios for 2050-RCPs show increases in both the average annual precipitation and its minimum and maximum values concerning the baseline. Ultimately, Napo has an annual precipitation of 2977.45 mm with a minimum precipitation of 1630.00 mm and a maximum of 4778.00 mm. The annual precipitation for this ecoregion does not increase for the scenario 2.6 but it does for scenarios 4.5 and 8.5. On the other hand, the minimum and maximum precipitation for the three climate change scenarios increase, the maximum precipitation presents an increase of over 469.5 mm per year. On the other hand, the minimum and maximum precipitation for the three climate change scenarios (RCPs 2.6, 4.5, and 8.5) increased, the minimum precipitation presented an increase of over 210.21 mm and the maximum precipitation presented an increase of over 469.5 mm per year.

The standard deviation for annual precipitation in the Sechura desert for 1970-2000 is 225.50 and the standard deviations for RCPs 2.6, 4.5, and 8.5 in 2050 are above this value. For the Páramo the standard deviation is 329.50 in its baseline and for the three RCPs, their standard deviations are above this value. Lastly, the standard deviation of the Napo for the baseline is 493.47 and this decreases for RCPs 2.6, 4.5, and 8.5 in 2050 and these are their values of 471.72, 476.07, and 479.75 respectively.

The spatial variation of the differences of the ensembles made for temperature (°C) and annual precipitation (mm) for RCPs 2.6, 4.5, and 8.5 by 2050 from the 14 GCMs vs. the baseline (1 km resolution) for the three ecoregions are shown in Figures 2.17, 2.18 and 2.19. For the Sechura

desert in the three RCPs, temperatures with maximums of over 6.10 (°C) were observed for the central-southern part, while annual precipitation (mm) decreases for the coastal part but increases for the areas near the Andes Mountains. Also, in the Páramo ecoregion for the three RCPs, increases in mean annual temperature with maximums of over 10 (°C) were noted; in terms of precipitation, a decrease in annual precipitation is observed for the páramos of Peru, Ecuador, and Venezuela in most areas. In the Napo, there are pronounced temperature increases in the eastern part (maximum temperatures above 2.71 °C) and a decrease in temperature in the western part, and for annual precipitation, there is a decrease in the central part of this ecoregion and an increase in the northern and southwestern part.

Sechura Ecoregion

The distribution of temperature (°C) and precipitation (mm) for 1970-2000 and three climate change scenarios for the Sechura (Desert) ecoregion respectively are shown in Figures 2.20 and 2.21, showing the non-normal distribution of the data. In the case of temperature, there is a bimodal distribution (Figure 2.20), and in the case of precipitation, there is a skewed right distribution (mean > median) (Figure 2.21). Q-Q plots, histograms, and boxplots for temperature and precipitation for the baseline (1970-2000) and the three RCPs 2.6, 4.5, and 8.5 for 2050 in the Sechura ecoregion were analyzed and suggest that there are serious violations of normality assumptions (Skewed) and several atypical values for low temperatures and high precipitation (Figures S2.4, S2.5 and S2.6).

The Anderson-Darling normality test was performed for the temperature (°C) (Table S2.7) and precipitation data (mm) (Table S2.8) for this ecoregion, there is very strong evidence to reject the null hypothesis that the data follow a normal distribution for the baseline and the three RCPs

in 2050. Therefore, the alternative hypothesis that temperature (p-value= 3.7×10^{-24}) and precipitation (p-value= 3.7×10^{-24}) for the Sechura ecoregion that is not following a normal distribution is accepted.

In Figure S2.6, the median temperature (°C) obtained for this ecoregion in the baseline period (1970-2000) was 17.22 °C. After that, the medians of temperature (°C) for the RCPs 2050 (2.6, 4.5, and 8.5) were calculated, which show an increase in units; these medians were 18.22 °C, 18.69 °C, and 19.17 °C, respectively. On the other hand, precipitation (mm) medians were calculated for the baseline and the RCPs (2.6, 4.5, and 8.5) for 2050 (Figure S2.6). These medians were 64 mm; 56.93 mm; 57.71 mm and 58.57 mm respectively. The three RCPs medians for precipitation are lower than the median precipitation for the baseline.

Kruskal-Wallis test for Temperature (°C) in the Sechura Ecoregion: In Figures 2.22 and 2.23, pairwise comparisons were made for temperature (°C) and precipitation (mm) for the baseline and the three climate change scenarios for 2050 in this ecoregion.

The Kruskal-Wallis test (Table S2.13) and Figure 2.22 showed that there is very strong (or convincing) (p-value < 0.001) evidence against the null hypothesis that the median for temperature (C°) between the baseline and the three RCPs 2050 (2.6; 4.5 and 8.5) are equal and in favor that there is at least one pair of differences among the four medians in the Sechura Ecoregion.

That is, we reject $H_0: M_{1970-2000} = M_{26} = M_{45} = M_{85}$ in favor of $H_1: M_i \neq M_j$ for some $i \neq j$ where i, j represent the temperature (C°) for the baseline and the three RCPs scenarios 1970-2000, 26, 45 and 8.5.

Kruskal-Wallis test for precipitation (mm) in the Sechura Ecoregion: The Kruskal-Wallis test and Figure 2.23 and table S2.14 showed that there is very strong (or convincing) (p-value < 0.001) evidence against the null hypothesis that the median for precipitation (mm) between the baseline and the three RCPs 2050 (2.6; 4.5 and 8.5) are equal and in favor that there is at least one pair of differences among the four medians in the Sechura Ecoregion.

That is, we reject $H_0: M_{1970-2000} = M_{26} = M_{45} = M_{85}$ in favor of $H_1: M_i \neq M_j$ for some $i \neq j$ where i, j represent the precipitation (mm) for the baseline and the three RCPs scenarios 1970-2000, 26, 45 and 8.5.

Páramo Ecoregion

The distribution of temperature (°C) and precipitation for 1970-2000 and three climate change scenarios for the Páramo ecoregion respectively are shown in Figures 2.24 and 2.25. In the case of temperature, there is a normal distribution (Figure 2.24) for the baseline and the three RCPs, and in the case of precipitation, there is a Skewed Right distribution of the data for the baseline, and bimodal distribution for the RCPs 2.6, 4.5 and 8.5 (Figure 2.25).

Q-Q plots, histograms, and boxplots for temperature (°C) and precipitation (mm) for the baseline (1970-2000), and the three RCPs 2.6, 4.5, and 8.5 for 2050 in the Páramo ecoregion were analyzed and suggest that there are serious violations of normality assumptions (Skewed) and several atypical values for low and high temperatures (Baseline and RCPs). These atypical values are also observed for annual precipitation, for example in the baseline we have these values for both low and high precipitation and in the RCPs only for high precipitation (Figures S2.7, S2.8, and S2.9).

The Anderson-Darling normality test was performed for the temperature (°C) (Table S2.9)

and annual precipitation (mm) (Table S2.10) for this ecoregion. There is very strong evidence to reject that the data for temperature (p-value= 3.7×10^{-24}) and annual precipitation (p-value= 3.7×10^{-24}) follow a normal distribution for the baseline and the three RCPs in 2050. So, the alternative hypothesis is accepted that the temperature and precipitation for the Páramo ecoregion that is not following a normal distribution.

The median temperature (°C) obtained for this ecoregion in the baseline period (1970-2000) was 7.80 °C. After that, the medians of temperature (°C) for the RCPs 2050 (2.6, 4.5, and 8.5) were calculated (Figure S2.9), which show an increase in units; these medians were 9.01 °C, 9.39 °C, and 9.88 °C, respectively. On the other hand, precipitation (mm) medians were calculated for the baseline and the RCPs (2.6, 4.5, and 8.5) for 2050, these medians were 1073.00 mm; 1153.50 mm; 1166.53 mm, and 1176.64 mm respectively (Figure S2.9). The three RCPs medians for precipitation are lower than the median precipitation for the baseline.

Kruskal-Wallis test for Temperature (°C) in the Páramo Ecoregion: In Figures 2.26 and 2.27, pairwise comparisons were made for temperature (°C) and precipitation (mm) for the baseline and the three climate change scenarios for 2050 in this ecoregion.

The Kruskal-Wallis test and Figure 2.26 and Table S2.15 showed that there is very strong (or convincing) (p-value < 0.001) evidence against the null hypothesis that the median for temperature (C°) between the baseline and the three RCPs 2050 (2.6; 4.5 and 8.5) are equal and in favor that there is at least one pair of differences among the four medians in the Páramo Ecoregion.

That is, we reject $H_0: M_{1970-2000} = M_{26} = M_{45} = M_{85}$ in favor of $H_1: M_i \neq M_j$ for some $i \neq j$ where i, j represent the temperature (C°) for the baseline and the three RCPs scenarios 1970-2000,

26, 45 and 8.5.

Kruskal-Wallis test for precipitation (mm) in the Páramo Ecoregion: The Kruskal-Wallis test and Figure 2.27 and Table S2.16 showed that there is very strong (or convincing) (p-value < 0.001) evidence against the null hypothesis that the median for precipitation (mm) between the baseline and the three RCPs 2050 (2.6; 4.5 and 8.5) are equal and in favor that there is at least one pair of differences among the four medians in the Sechura Ecoregion.

That is, we reject $H_0: M_{1970-2000} = M_{26} = M_{45} = M_{85}$ in favor of $H_1: M_i \neq M_j$ for some $i \neq j$ where i, j represent the precipitation (mm) for the baseline and the three RCPs scenarios 1970-2000, 26, 45 and 8.5.

Napo Ecoregion

The distribution of temperature (°C) and precipitation for 1970-2000 and three climate change scenarios for the Napo ecoregion respectively are shown in Figures 2.28 and 2.29. In the case of temperature, there is a Skewed Left distribution (Figure 2.28) for the baseline and the three RCPs, and in the case of precipitation there is a Multimodal distribution of the data for the baseline, and for the RCPs 2.6, 4.5 and 8.5 (Figure 2.29).

Q-Q plots, histograms, and boxplots for temperature and precipitation for the baseline (1970-2000) and the three RCPs 2.6, 4.5, and 8.5 for 2050 in the Sechura ecoregion were analyzed and suggest that there are serious violations of normality assumptions (Skewed) and several atypical values for low temperatures and high precipitation (Figures S2.10, S2.11 and S2.12).

The Anderson-Darling normality test was performed for the temperature (Table S2.11) and precipitation data (Table S2.12) for this ecoregion, there is very strong evidence to reject that the

data follow a normal distribution for the baseline and the three RCPs in 2050. Therefore, the alternative hypothesis is accepted that temperature (p-value= 3.7×10^{-24}) and precipitation (p-value= 3.7×10^{-24}) for the Napo ecoregion that is not following a normal distribution.

The median temperature (°C) obtained for this ecoregion in the baseline period (1970-2000) was 25.66 °C. After that, the medians of temperature (°C) for the RCPs 2050 (2.6, 4.5, and 8.5) were calculated, which show an increase in units; these medians were 27.35 °C, 27.29 °C, and 28.34 °C, respectively (Figure S2.12). On the other hand, precipitation (mm) medians were calculated for the baseline and the RCPs (2.6, 4.5, and 8.5) for 2050, these medians were 2972.00 mm; 2823.14 mm; 2901.29 mm, and 2905.21 mm respectively (Figure S2.12). The three RCPs medians for precipitation are lower than the median precipitation for the baseline.

Kruskal-Wallis test for Temperature (°C) in the Napo Ecoregion: In Figures 2.30 and 2.31, pairwise comparisons were made for temperature (°C) and precipitation (mm) for the baseline and the three climate change scenarios for 2050 in this ecoregion.

The Kruskal-Wallis test and Figure 2.30 showed that there is very strong (or convincing) (p-value < 0.001) evidence against the null hypothesis that the median for temperature (C°) between the baseline and the three RCPs 2050 (2.6; 4.5 and 8.5) are equal and in favor that there is at least one pair of differences among the four medians in the Napo Ecoregion (Table S2.17). That is, we reject $H_0: M_{1970-2000} = M_{26} = M_{45} = M_{85}$ in favor of $H_1: M_i \neq M_j$ for some $i \neq j$ where i, j represent the temperature (C°) for the baseline and the three RCPs scenarios 1970-2000, 26, 45 and 8.5.

Kruskal-Wallis test for precipitation (mm) in the Napo Ecoregion: The Kruskal-Wallis test and Figure 2.31 and Table S2.18 showed that there is very strong (or convincing) (p-value < 0.001) evidence against the null hypothesis that the median for precipitation (mm) between the baseline and the three RCPs 2050 (2.6; 4.5 and 8.5) are equal and in favor that there is at least one pair of differences among the four medians in the Napo Ecoregion.

That is, we reject $H_0: M_{1970-2000} = M_{26} = M_{45} = M_{85}$ in favor of $H_1: M_i \neq M_j$ for some $i \neq j$ where i, j represent the precipitation (mm) for the baseline and the three RCPs scenarios 1970-2000, 26, 45 and 8.5.

Lastly, we have the density plots that indicate where the data are most dense or likely, i.e., these plots allow us to visualize where the average annual temperature and annual precipitation data for the baseline (1970-2000) and the three RCPs for 2050 (2.6, 4.5 and 8.5) are most dense (Figures S2.13, S2.14 and S2.15).

In general, the temperature density curves for the three RCPs in the three ecoregions compared to the baseline are shifted to the right which means that they show increases in mean annual temperatures and the low temperatures and high temperatures increase their value. On the other hand, in the case of precipitation, there is a slight increase in annual precipitation for high values for the Sechura desert in the three RCPs compared to the baseline (Figure S2.13). Also, for the Páramo ecoregion, there is a decrease in density or probability for annual precipitation near or at 1000 mm for RCPs 2.6, 4.5, and 8.5 in 2050 compared to the baseline, but a slight increase in the density or probability of precipitation near or at 2500 mm is observed (Figure S2.14). Then, for the Napo ecoregion for the three RCPs in 2050 compared to the baseline, there is a decrease in precipitation density near or at values of 2300 mm and 3200 mm, but there is an increase for

precipitation density at values of 2700 mm up to 2900 mm (Figure S2.15).

Discussion

The analysis of changes in temperature and precipitation for the baseline (1970-200) and for the 2050 RCPs (2.6, 4.5, and 8.5) are important before using SDM models for species or ecoregions in the three countries, as mentioned by (Booth, 2022).

Analyzing climate change using variables such as temperature (C°) and annual precipitation (mm) in three bordering countries from official data published by their National Meteorological and Hydrological Services is a bit complex. The Andean and Amazonian zones are poorly instrumented, and the number of stations varies greatly from one country to another (Campozano et al., 2020; Condom et al., 2020; Newell et al., 2022), making it very difficult to make climate change projections jointly for the three countries. For regional Climate Change studies, standardized climate data is needed in terms of temporal and spatial resolution (extent, resolution, and Coordinate Reference Systems); for which data from Climate Change, Agriculture, and Food Security (“ccafs”) and WorldClim (CMIP5) were used (Fick & Hijmans, 2017; Navarro-Racines et al., 2020).

Some evidence considered overwhelming of climate change estimates that global temperature is projected to increase by up to 4 °C by 2100 (Thuiller, 2007), with alterations in precipitation patterns. However, in our research some GCMs (10 minutes resolution) (Tables S2.3 and S2.6.) such as GFDL.CM3, shows already an increase in the average temperature for Peru, Ecuador, and Colombia above 4 °C for RCPs 4.5 and 8.5 in 2050, and the GCM named IPSL.CM5A.LR also shows an increase in the average temperature above 4 °C in the NAPO ecoregion for the RCP 8.5-2050.

Also, investigations show a reduction in precipitation under SRES (Special Report on Emissions Scenarios) climate change scenarios in the tropics and an increase in precipitation in the southeastern part of South America (Chou et al., 2014); but this research provides an analysis at the ecoregion level as well as the spatial distribution of precipitation for a baseline (1970-2000) and for three RCPs in 2050. It is also necessary to further investigate the change in rainfall intensities in scenarios of climate change and to see what effects these have on the changes in the annual precipitation value for each study zone.

Understanding changes in climate variability and extremes is challenged by the interactions between changes in mean and variability (Meehl et al., 2000). The IPCC presents three assumptions for temperature changes in climate change environments with a normal distribution (Easterling et al., 2012; Folland et al., 2002; Haywood & Schulz, 2007; Kodra & Ganguly, 2014; Lewis & King, 2017; Olsen, 2015; Thornton et al., 2014). An increase in the mean leads to new temperature records, but a change in the mean implies no change in variability and the range between the warmest and coldest temperatures does not change. An increase in variability without a change in the mean implies an increase in the probability of hot and cold extremes, as well as in the absolute value of the extremes, and finally, an increase in the mean and variability is also possible, which affects the probability of hot and cold extremes, with more frequent hot events with more extreme high temperatures and fewer cold events. In contrast, in our research we have temperature data without normal distribution, but when analyzing the temperature density plots for the baseline and the three RCPs in 2050 for the three ecoregions. A shift to the right is observed for the RCPs, which implies that we will have warmer temperatures concerning the baseline (Figures S2.13, S2.14, and S2.15).

In the case of annual precipitation, it is more complex to analyze in terms of density plots because in no ecoregion do we have a normal distribution for this variable. In the Páramo Ecoregion (Figure S2.14) there is a decrease in annual precipitation close to 1000 mm and an increase in annual precipitation to values close to 2000 and 2300 mm. So, in the case of precipitation, for example, changes in total mean precipitation may be accompanied by other changes such as the frequency of precipitation or the shape of the distribution including its variability, i.e. more in-depth studies such as Intensity-Duration-Frequency of rainfall in climate change environments should be done (Das et al., 2022; Pendergrass & Hartmann, 2014; Sun et al., 2019). Nonetheless, in our research at least we have minimum, maximum, and average values of annual precipitation which helps us to infer the change in cumulative precipitation for the baseline and the three climate change scenarios at the ecoregion or country level.

Finally, no transformation of the data was performed to achieve a normal distribution for the following reason: the transformation of the data must be done carefully so that the transformed data continue to represent the same physical processes as the original data (WMO, 2018). Likewise, our research question was to keep the original temperature (°C) and annual precipitation (mm) data for interpretation, both for the baseline and for the climate change scenarios.

Conclusions

A general review of changes in temperature (°C) and annual precipitation (mm) at the country and ecoregion level was made, which will help us to understand the variables derived from these, such as Bioclim variables, and to understand the possible effects of these variables on the distribution of species and ecoregions in environments of climate change.

The findings of this study reveal a consistent trend across all General Circulation Models

(GCMs) used, indicating a projected rise in annual average temperatures by 2050 at both the country and ecoregion levels. Additionally, a majority of the GCMs suggest an increase in annual precipitation during the same period, but a more local and intensity-duration-frequency (IDF) analysis is needed.

Finally, the comparison of medians was important in the statistical analysis part because it allowed us to compare the central tendencies of two or more data sets. The median is a measure of central tendency that represents the average value of a set of data when ordered in ascending or descending order (Prasad, 2022; Ramsey & Schafer, 2013). In many cases, the mean is used as a measure of central tendency, however, the extreme values of the data set strongly influence the mean (Ramsey & Schafer, 2013). In contrast, the median is not affected by outliers, making it a more robust measure of central tendency. Comparing medians helped us to establish whether there are significant differences between two or more data sets. In the context of climate change, comparing the median of temperature (°C) or annual precipitation (mm) values over two different periods can help us assess whether a significant change has occurred.

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Tables

Table 2.1 Average annual temperature (°C) differences for 2050 RCPs and baseline (1970-2000) (10 minutes).

Countries and ecoregions	Baseline T °C	RCP2.6			RCP 4.5			RCP 8.5		
		Min value	Max value	Ensemble	Min value	Max value	Ensemble	Min value	Max value	Ensemble
Peru, Ecuador, and Colombia	21.7	1.0	2.8	1.6	1.0	3.4	1.9	1.5	4.2	2.7
Sechura Desert (Deserts & Xeric Shrublands)	15.0	1.0	2.4	1.6	0.9	3.0	1.9	2.1	3.7	2.7
Páramo (Montane Grasslands & Shrublands)	7.5	0.9	2.4	1.5	1.1	3.0	1.8	1.7	3.8	2.6
Napo moist forests (Tropical & Subtropical Moist Broadleaf Forests)	25.7	0.9	3.3	1.6	1.0	4.0	2.0	1.7	4.9	2.8

Table 2.2 Annual precipitation (mm) differences for 2050 RCPs and baseline (1970-2000) (10 minutes).

Countries and ecoregions	Baseline mm	RCP2.6			RCP 4.5			RCP 8.5		
		Min value	Max value	Ensemble	Min value	Max value	Ensemble	Min value	Max value	Ensemble
Peru, Ecuador, and Colombia	2068.7	-117.5	144.9	48.5	-160.6	219.0	64.5	-210.4	279.2	71.4
Sechura Desert (Deserts & Xeric Shrublands)	190.3	-11.6	196.1	49.1	-13.2	237.3	64.3	-3.5	286.3	81.8
Páramo (Montane Grasslands & Shrublands)	1206.5	-98.8	241.0	73.9	-87.0	70.9	93.3	-50.2	165.2	96.2
Napo moist forests (Tropical & Subtropical Moist Broadleaf Forests)	2825.1	-233.7	195.3	5.0	-415.2	381.9	30.7	-487.7	472.7	40.5

Table 2.3 Average annual temperature (°C) for the baseline (1970-2000) and 2050 RCP 2.6 (1 km).

Ecoregions	Baseline (1970-2000)				RCP2.6			
	\bar{x}	Min value	Max value	Std Dev.	\bar{x}	Min value	Max value	Std Dev.
Sechura Desert (Deserts & Xeric Shrublands)	15.22	-3.47	23.11	5.36	16.35	-3.46	24.93	5.35
Páramo (Montane Grasslands & Shrublands)	8.00	-4.35	24.58	2.68	9.24	-4.66	25.79	2.82
Napo moist forests (Tropical & Subtropical Moist Broadleaf Forests)	25.64	17.88	27.13	0.75	27.23	18.61	28.53	0.73

Table 2.4 Average annual temperature (°C) for the 2050 RCPs 4.5 and 8.5 (1 km).

Ecoregions	RCP 4.5				RCP 8.5			
	\bar{x}	Min value	Max value	Std Dev.	\bar{x}	Min value	Max value	Std Dev.
Sechura Desert (Deserts & Xeric Shrublands)	16.81	-2.89	25.28	5.32	17.3	-2.39	25.66	5.31
Páramo (Montane Grasslands & Shrublands)	9.63	-4.25	26.13	2.82	10.11	-3.86	26.51	2.84
Napo moist forests (Tropical & Subtropical Moist Broadleaf Forests)	27.66	19.04	28.99	0.77	28.2	19.53	29.57	0.78

Table 2.5 Annual precipitation (mm) for the baseline (1970-2000) and RCP 2.6 (1 km).

Ecoregions	Baseline (1970-2000)				RCP2.6			
	Annual pp	Min value	Max value	Std Dev.	Annual pp	Min value	Max value	Std Dev.
Sechura Desert (Deserts & Xeric Shrublands)	183.72	0.00	1194.00	225.50	207.12	0.00	1773.36	279.42
Páramo (Montane Grasslands & Shrublands)	1151.41	262.00	3169.00	329.50	1301.34	302.93	3645.21	495.85
Napo moist forests (Tropical & Subtropical Moist Broadleaf Forests)	2977.45	1630.00	4778.00	493.47	2854.40	1840.21	5247.50	471.72

Table 2.6 Annual precipitation (mm) for the RCPs 4.5 and 8.5 (1 km).

Ecoregions	RCP 4.5				RCP 8.5			
	Annual pp	Min value	Max value	Std Dev.	Annual pp	Min value	Max value	Std Dev.
Sechura Desert (Deserts & Xeric Shrublands)	209.95	0.00	1787.21	283.29	214.50	0.00	1841.86	290.47
Páramo (Montane Grasslands & Shrublands)	1307.97	307.50	3635.50	491.39	1311.11	319.43	3658.71	484.57
Napo moist forests (Tropical & Subtropical Moist Broadleaf Forests)	2938.57	1867.07	5336.86	476.07	2940.21	1866.00	5371.64	479.75

Figures

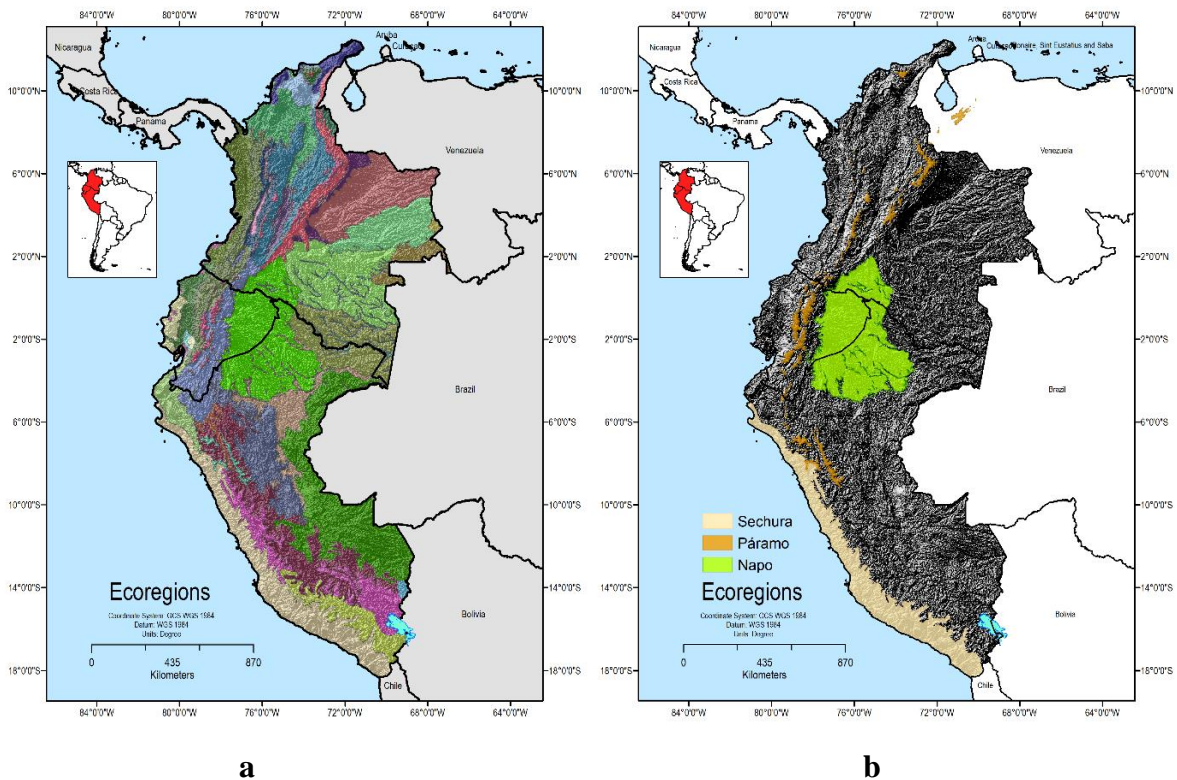


Figure 2.1. a. Peru, Ecuador, and Colombia with their Ecoregions b. Ecoregions under study Sechura Desert, Páramos, and Napo Tropical Forest ecoregions.

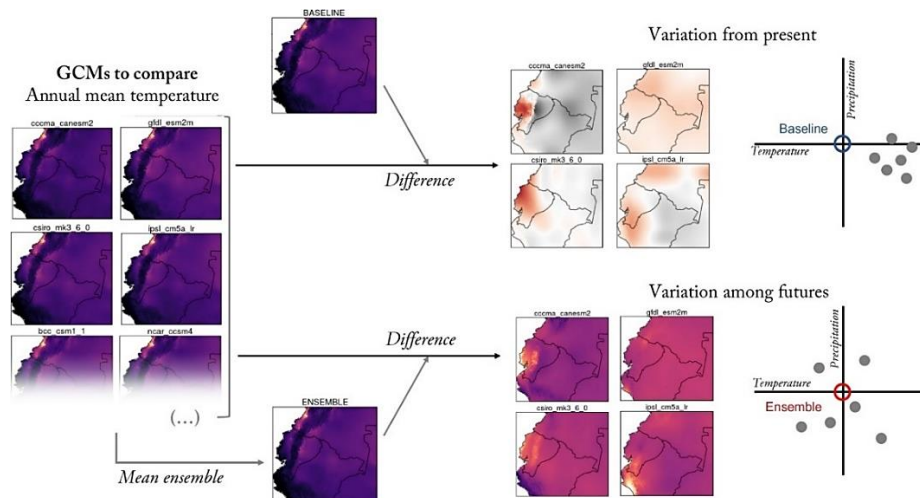


Figure 2.2. CompareR GCM for R (Fajardo et al., 2020).

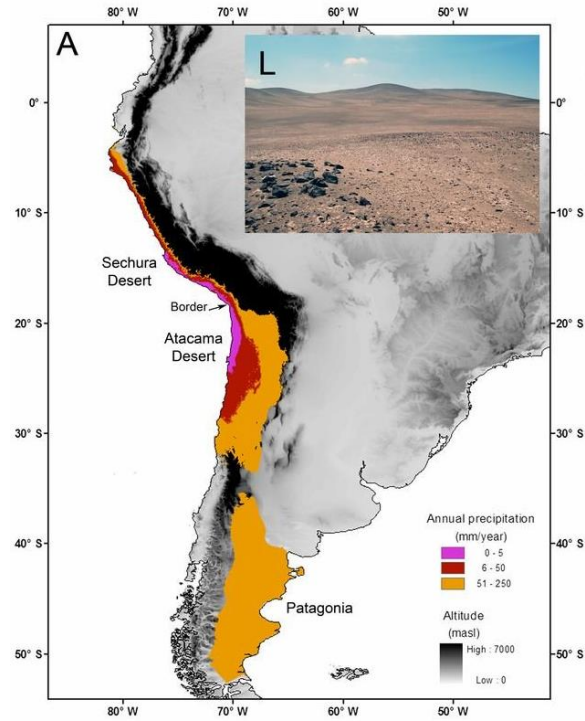


Figure 2.3. Aridity classification based on annual rainfall for the Sechura Desert (Guerrero et al., 2013).

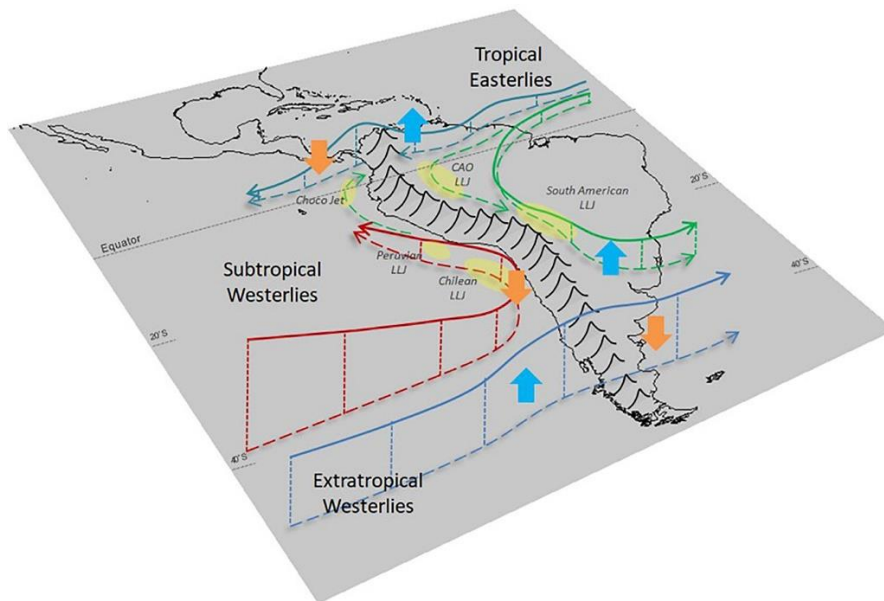


Figure 2.4. South America and its main LLJs on both sides of the Andes Mountains (Espinoza et al., 2020).

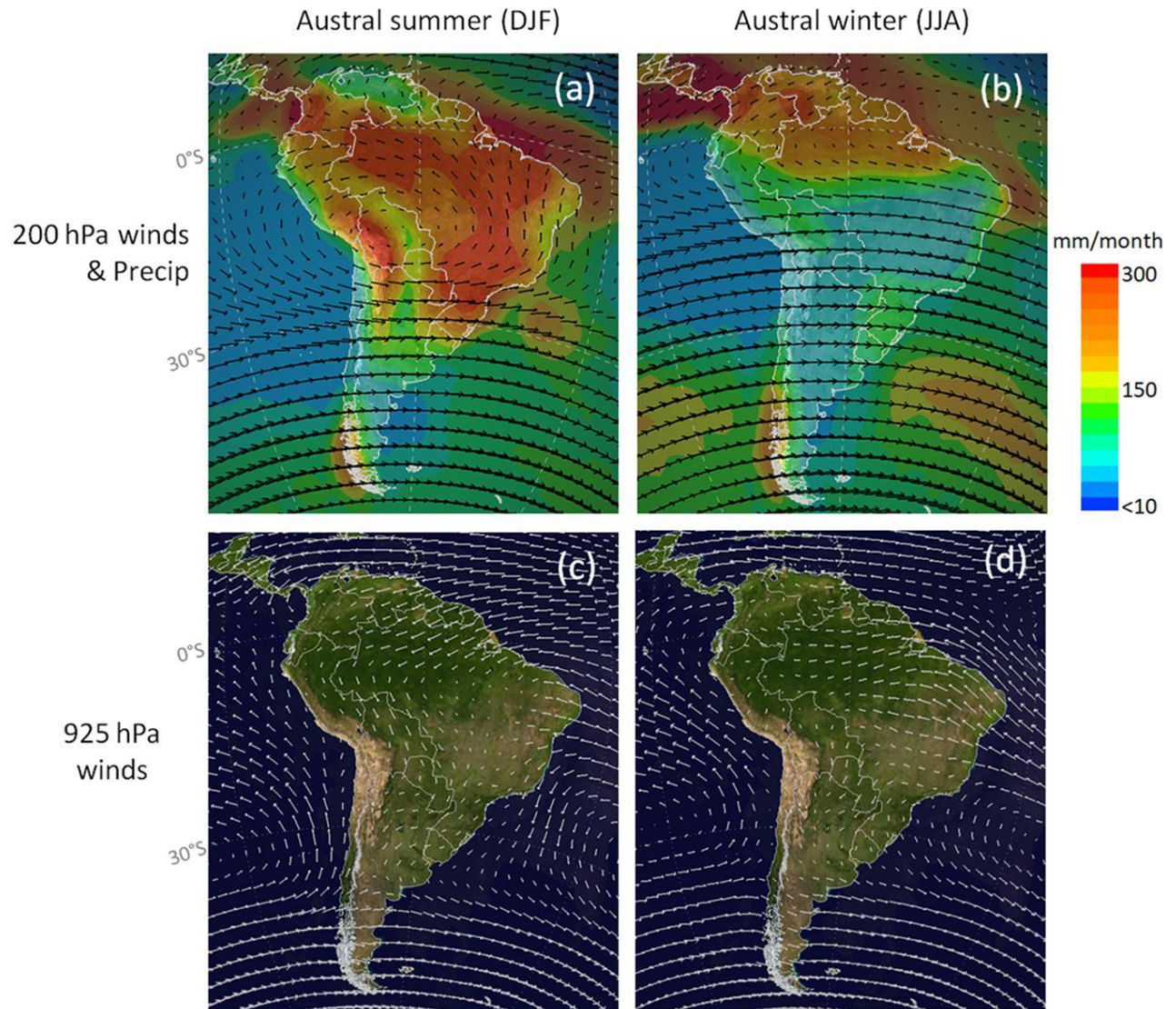


Figure 2.5. a,b Long-term mean (1981-2020) winds at 200 hPa (arrows) and precipitation (shades) and c,d Long-term mean (1981-2020) winds at 925 hPa (arrows) over blue marble (Data from NCEP/NCAR reanalysis) (Espinoza et al., 2020).

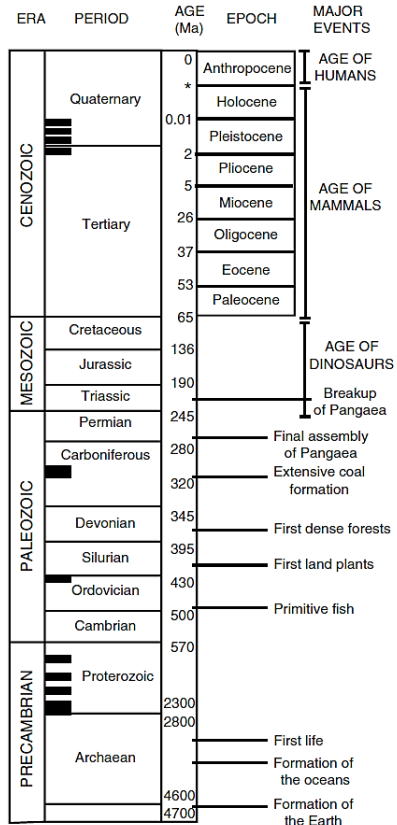


Figure 2.6. Geologic periods of Earth's history, showing major glacial events in dark bars and ecological events that strongly influenced ecosystem processes. Data are in units of millions of years (Ma) (Stuart Chapin et al., 2012).

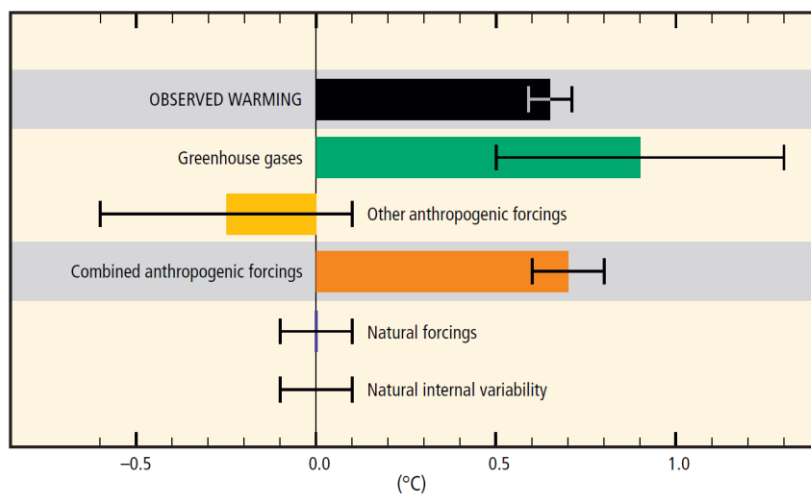


Figure 2.7. Contributions to the observed change in surface temperature from 1951 to 2010 (IPCC a, 2014).

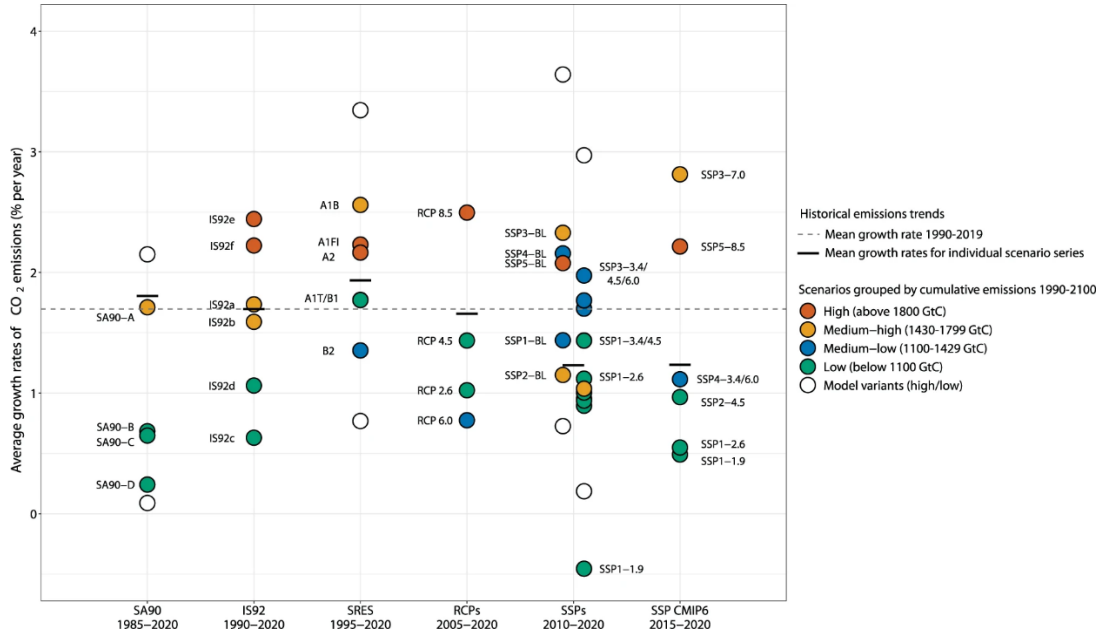


Figure 2.8. Climate Change Scenarios concerning the amounts of CO₂ (Pedersen et al., 2020).

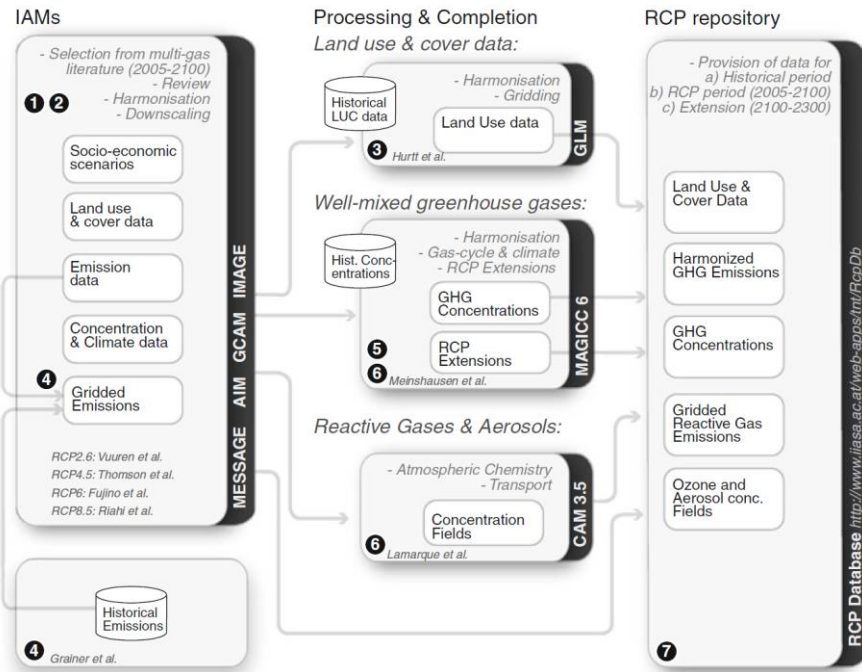


Figure 2.9. RCPs development process (van Vuuren et al., 2011).

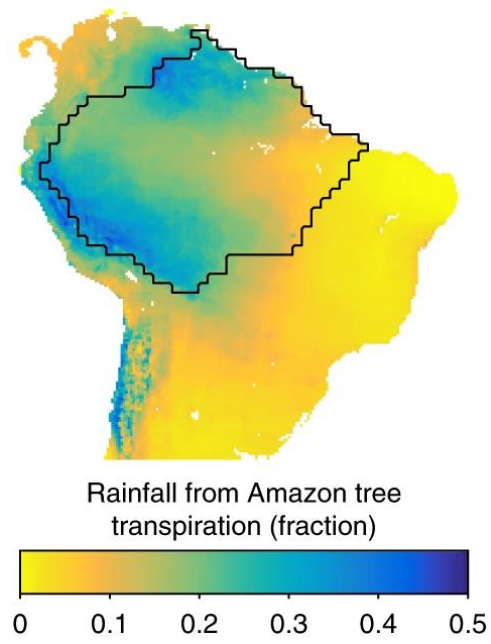


Figure 2.10. Fraction of mean annual rainfall that has been transpired by trees in the Amazon basin (Staal et al., 2018).

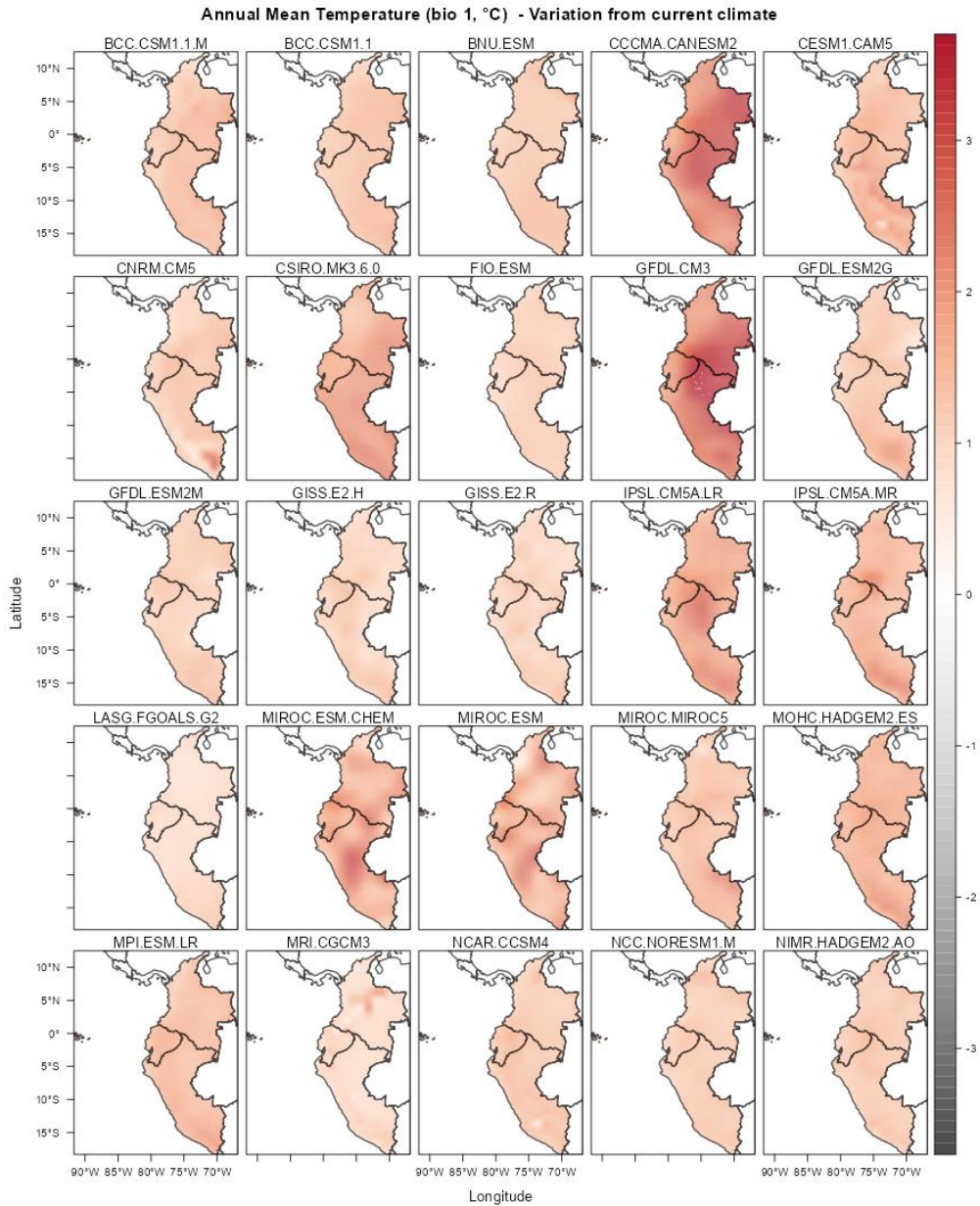


Figure 2.11. Differences for temperature (°C) for the RCP 2.6-2050 and the baseline (1970-2000).

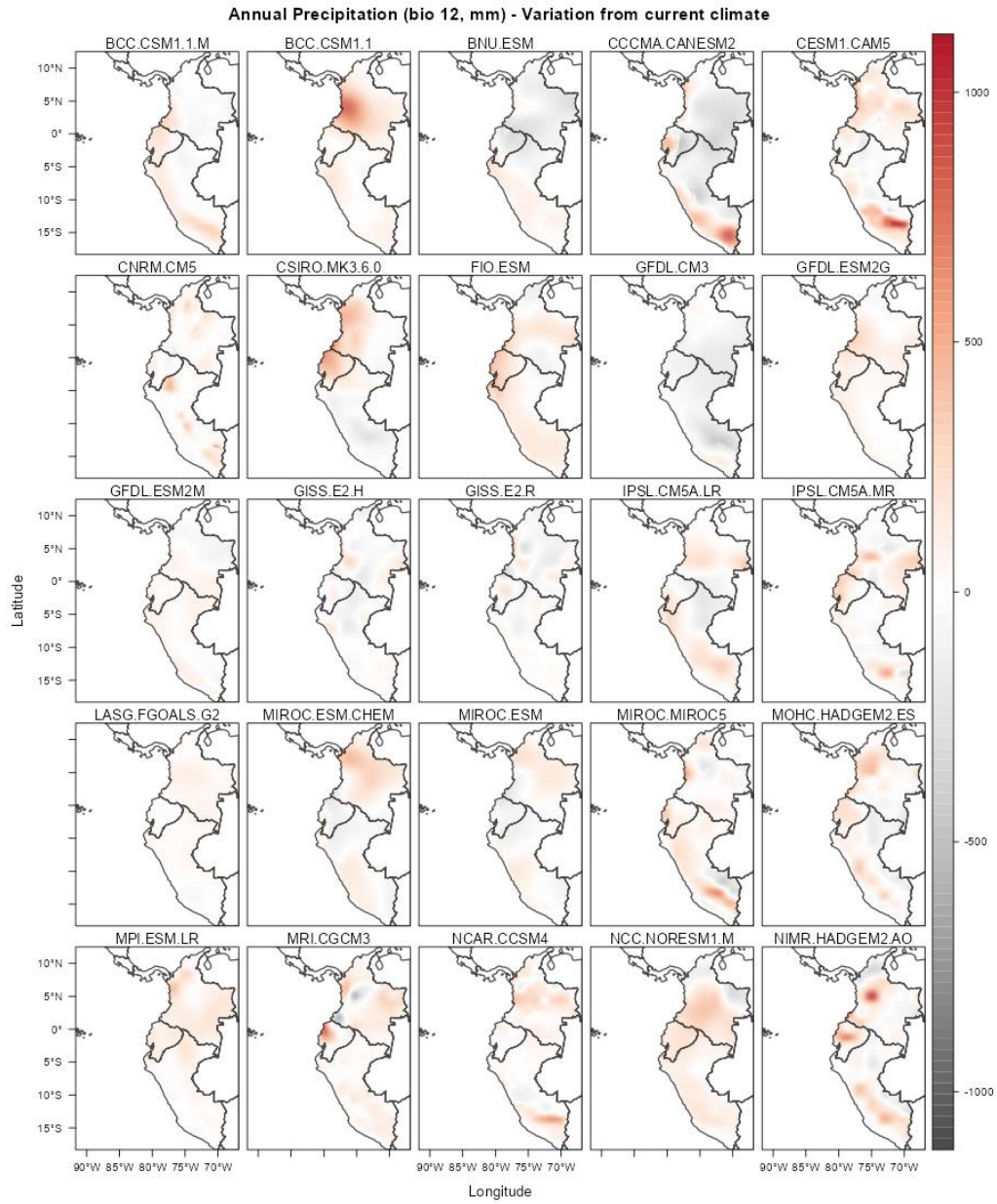


Figure 2.12. Differences for annual precipitation (mm) for the RCP 2.6-2050 and the baseline (1970-2000).

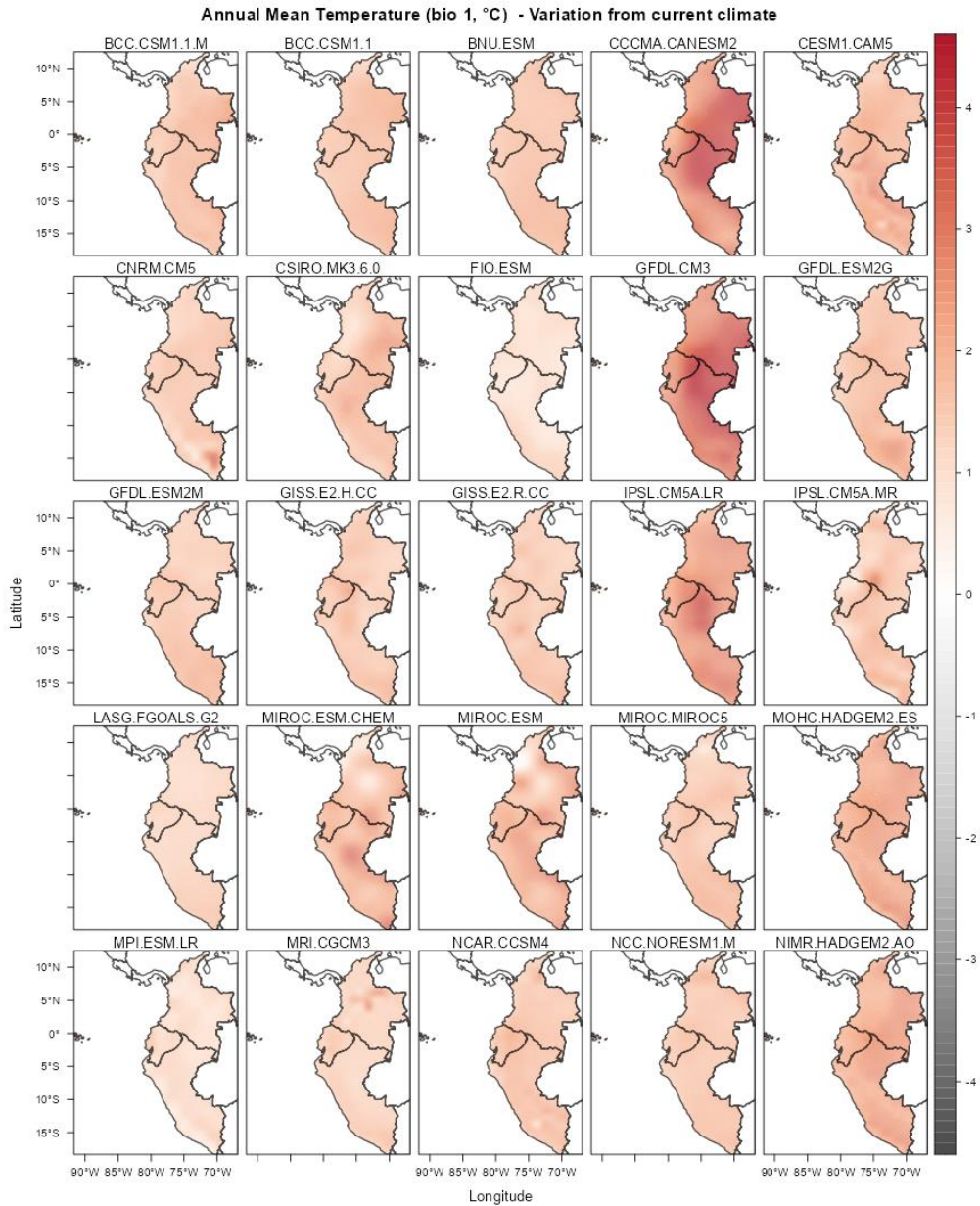


Figure 2.13. Differences for temperature (°C) for the RCP 4.5-2050 and the baseline (1970-2000).

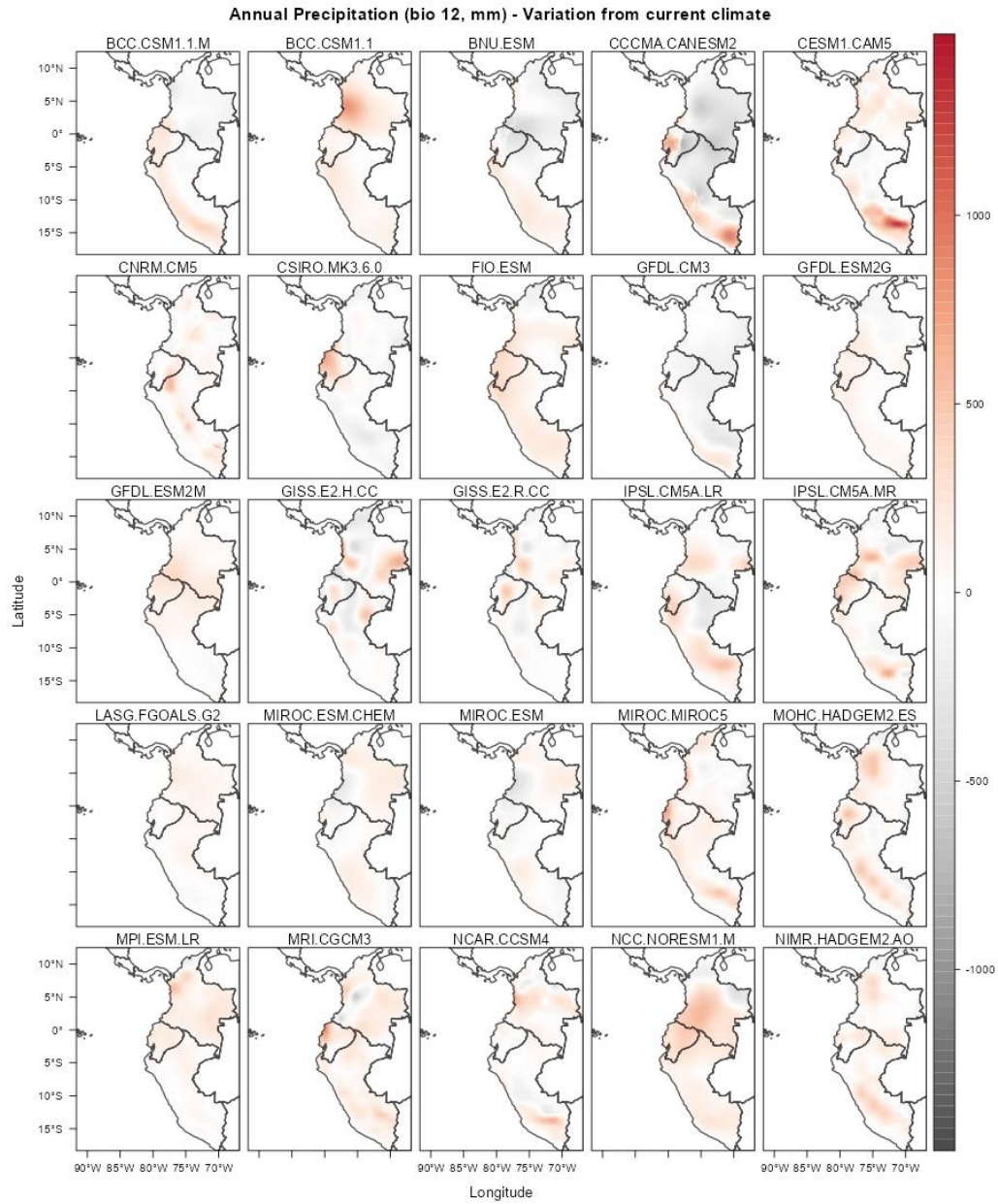


Figure 2.14. Differences for annual precipitation (mm) for the RCP 4.5-2050 and the baseline (1970-2000).

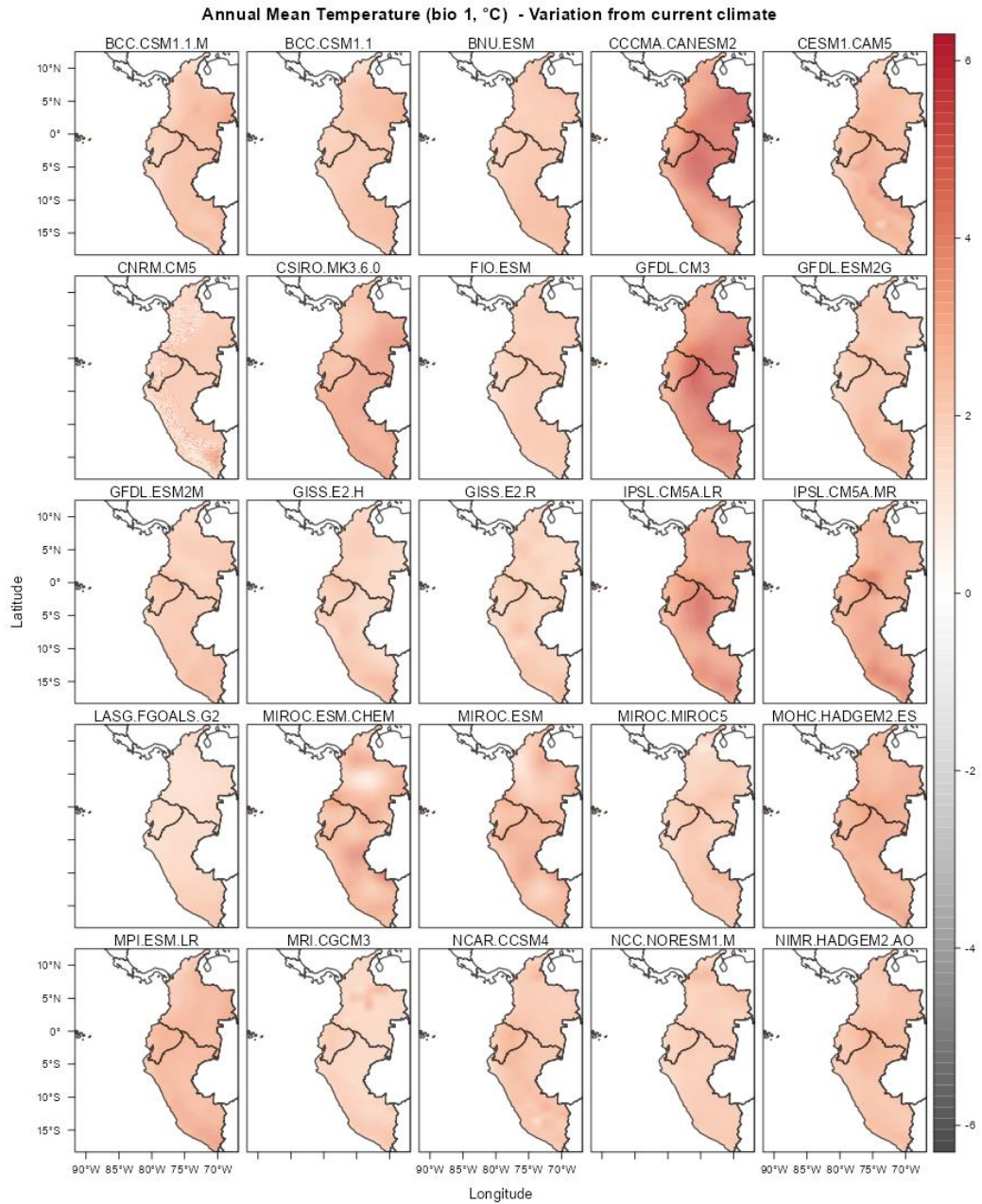


Figure 2.15. Differences for temperature (°C) for the RCP 8.5-2050 and the baseline (1970-2000).

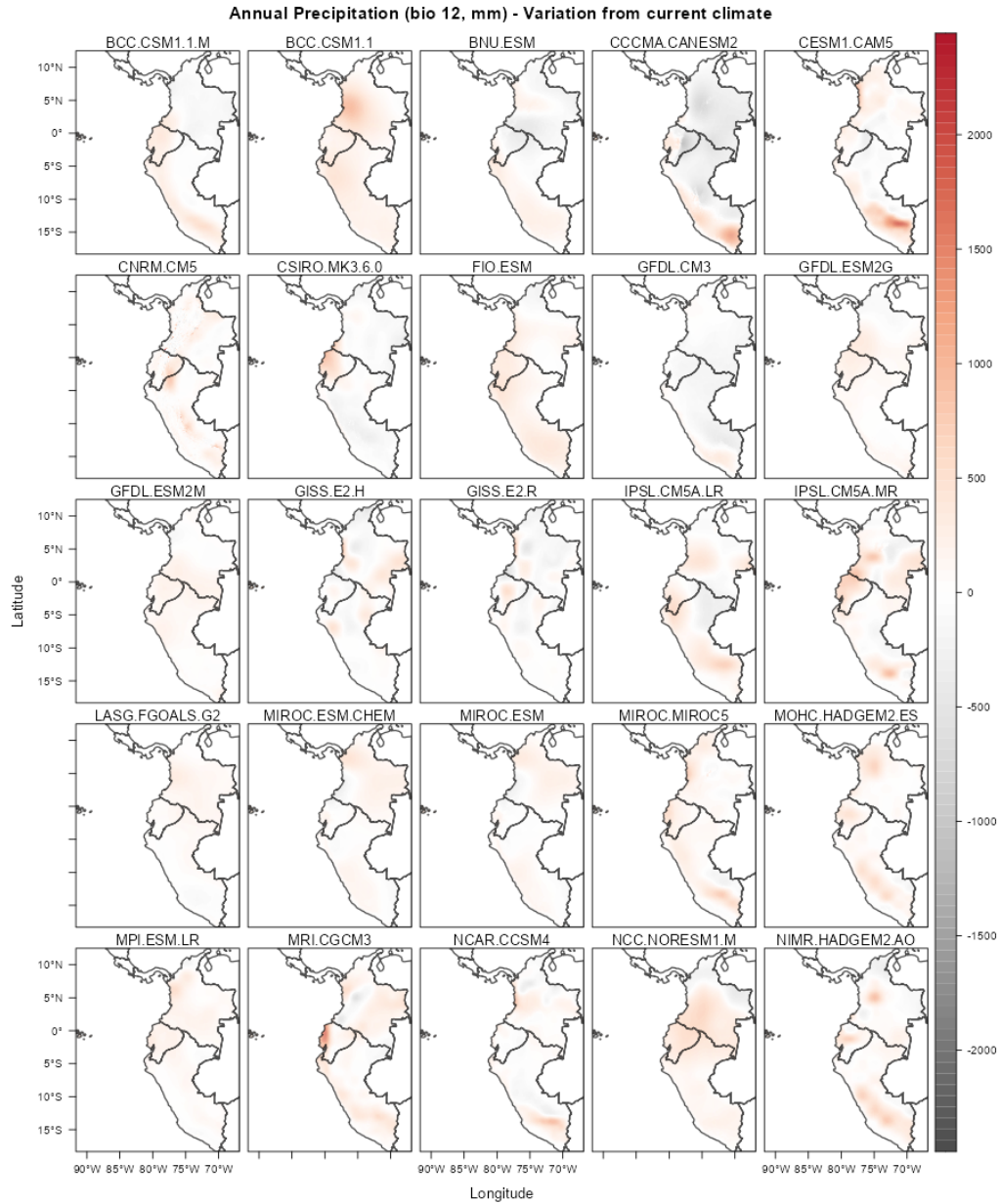


Figure 2.16. Differences for annual precipitation (mm) for the RCP 8.5-2050 and the baseline (1970-2000).

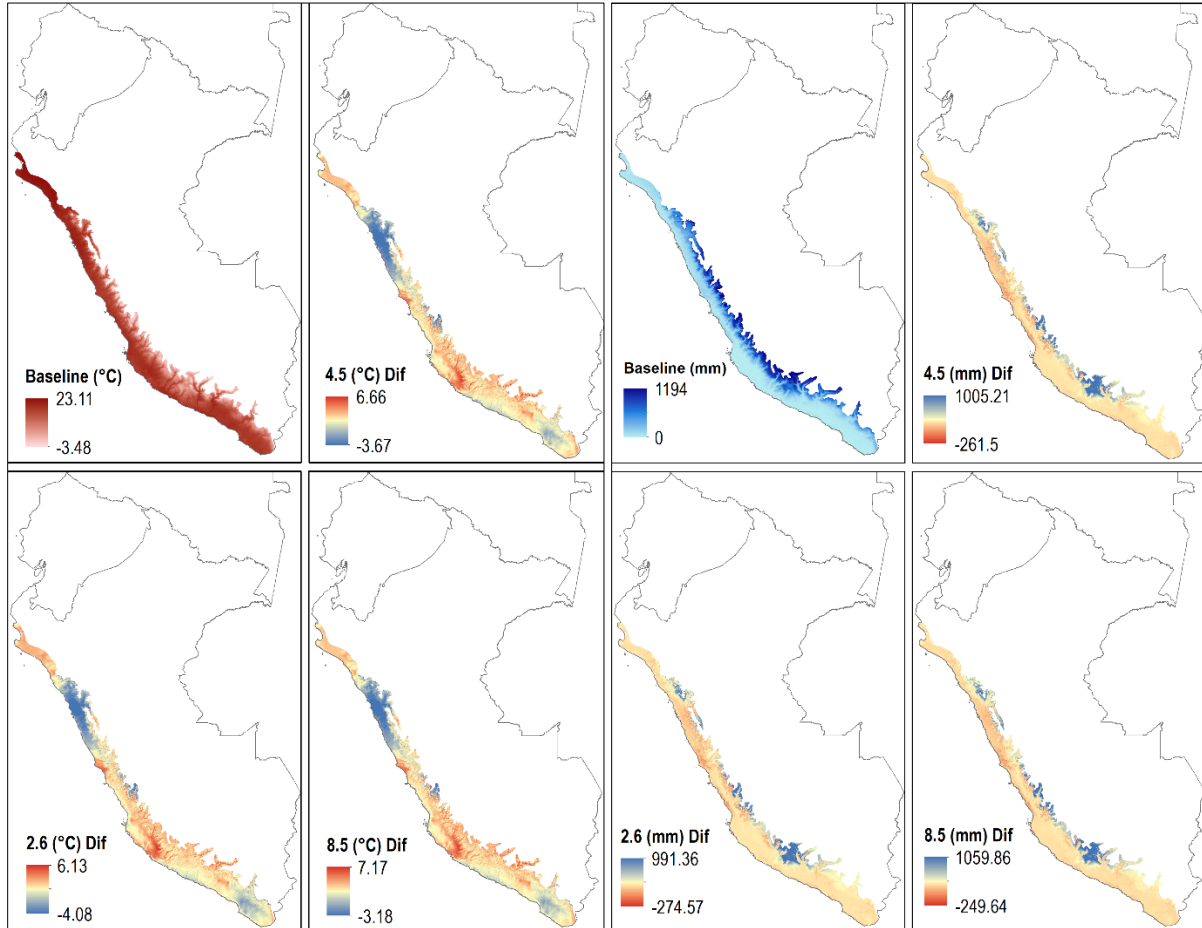


Figure 2.17. Differences for temperature (°C) and annual precipitation (mm) for the RCPs 2.6, 4.5 and 8.5 for 2050 vs the baseline (1970-2000) in the Sechura ecoregion (1 km).

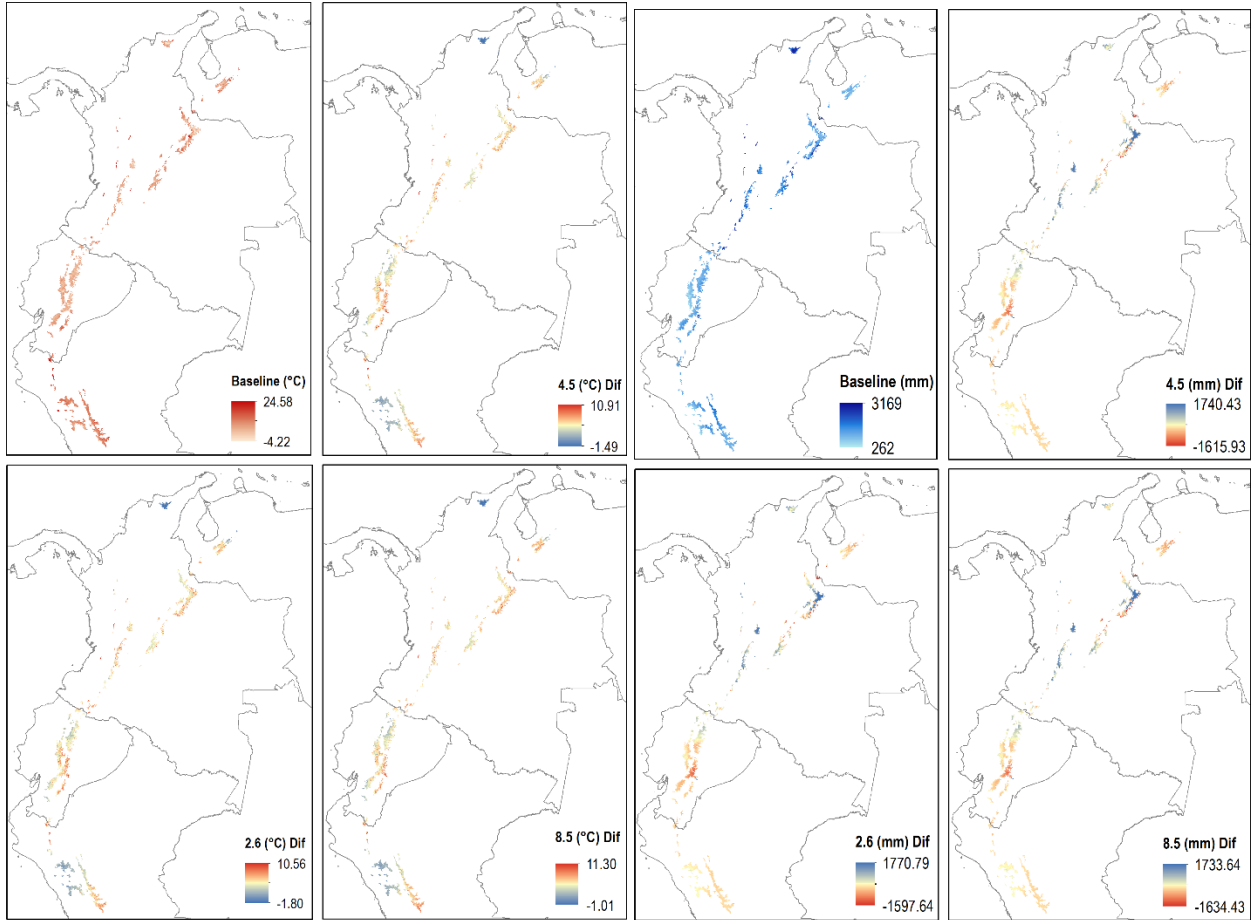


Figure 2.18. Differences for temperature (°C) and annual precipitation (mm) for the RCPs 2.6, 4.5 and 8.5 for 2050 vs the baseline (1970-2000) in the Páramo ecoregion (1 km).

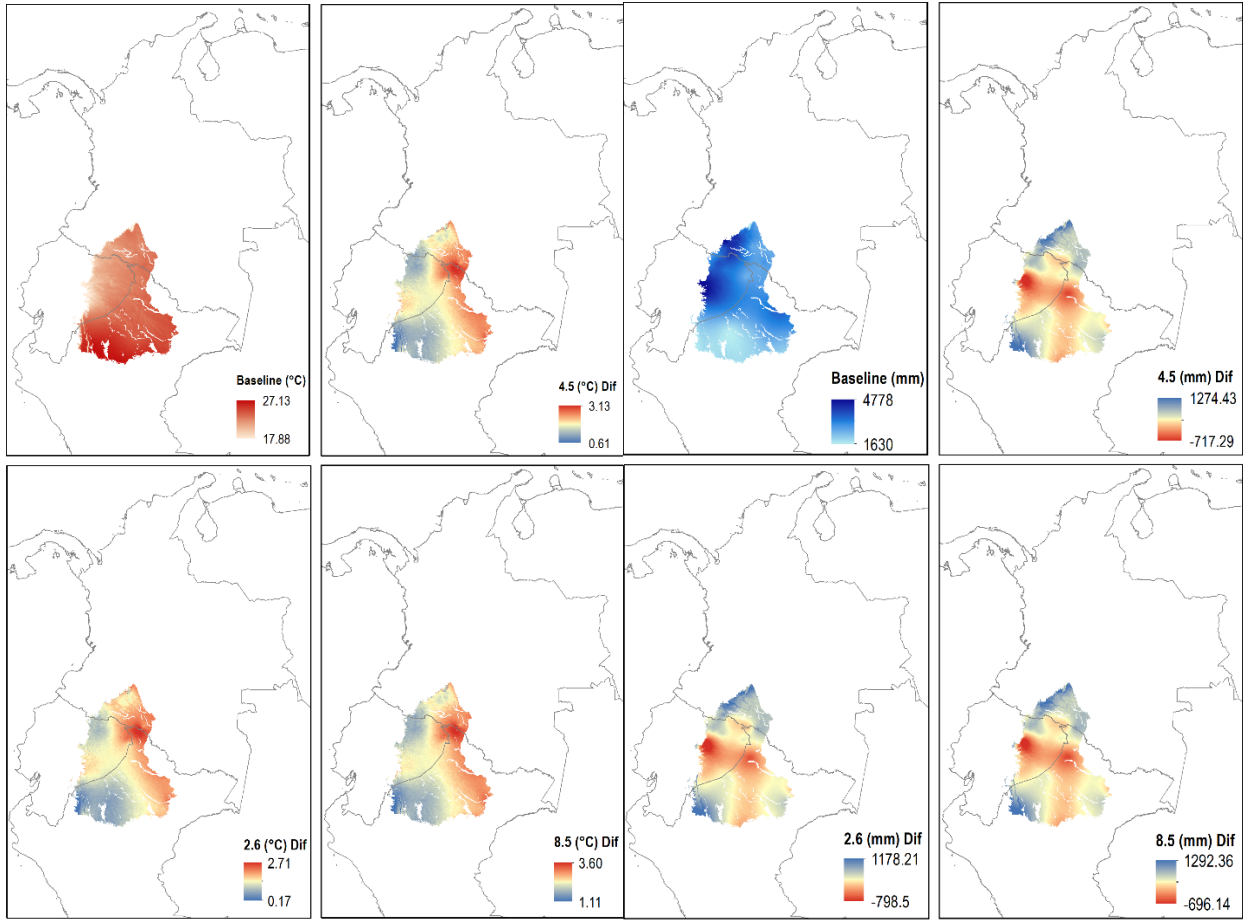


Figure 2.19. Differences for temperature (°C) and annual precipitation (mm) for the RCPs 2.6, 4.5 and 8.5 for 2050 vs the baseline (1970-2000) in the Napo ecoregion (1 km).

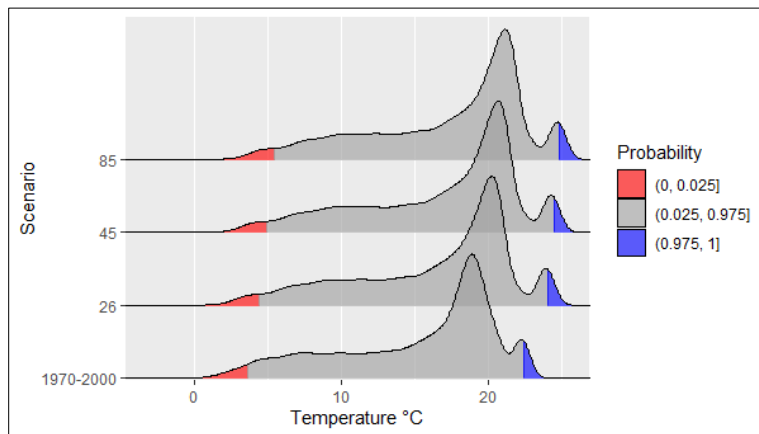


Figure 2.20. Distribution of temperature (°C) for 1970-2000 and three climate change scenarios for the Sechura (Desert) ecoregion.

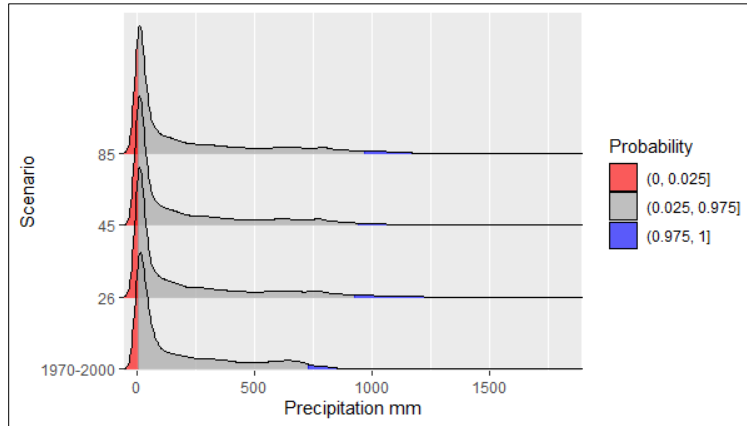


Figure 2.21. Distribution of precipitation (mm) for 1970-2000 and three climate change scenarios for the Sechura (Desert) ecoregion.

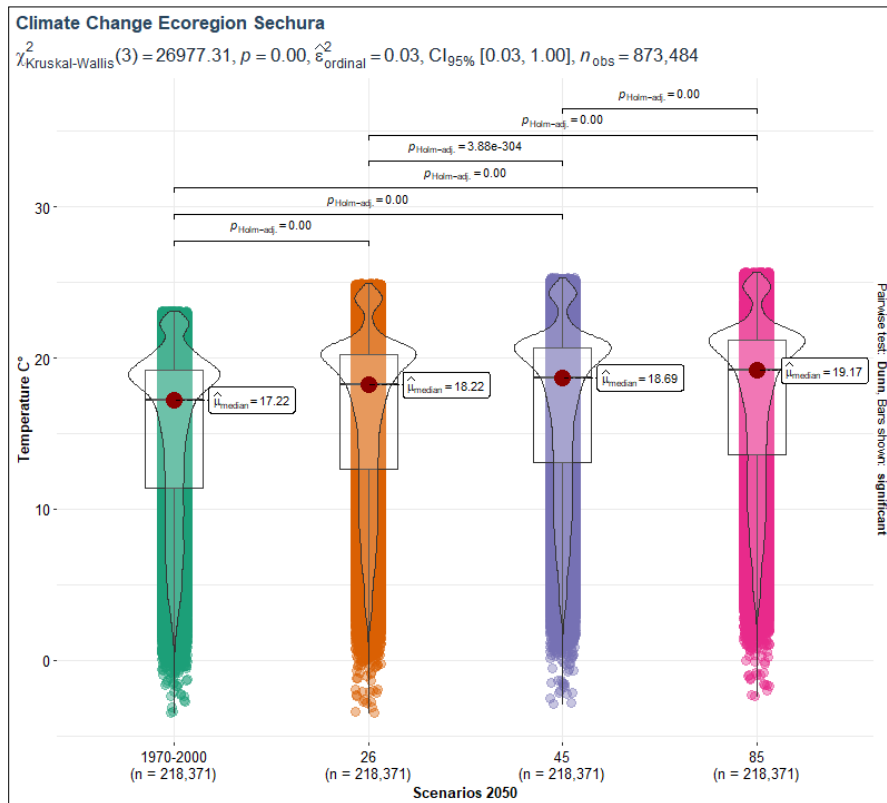


Figure 2.22. Comparison of temperature medians (°C) for 1970-2000 and three climate change scenarios for the Sechura (Desert) ecoregion.

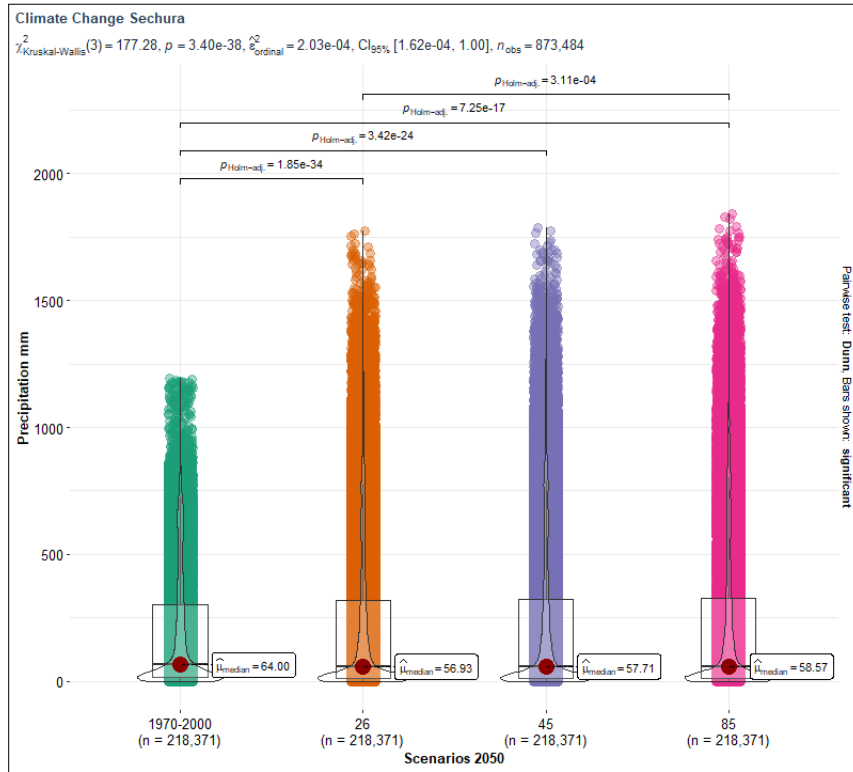


Figure 2.23. Comparison of precipitation medians (mm) for 1970-2000 and three climate change scenarios for the Sechura (Desert) ecoregion.

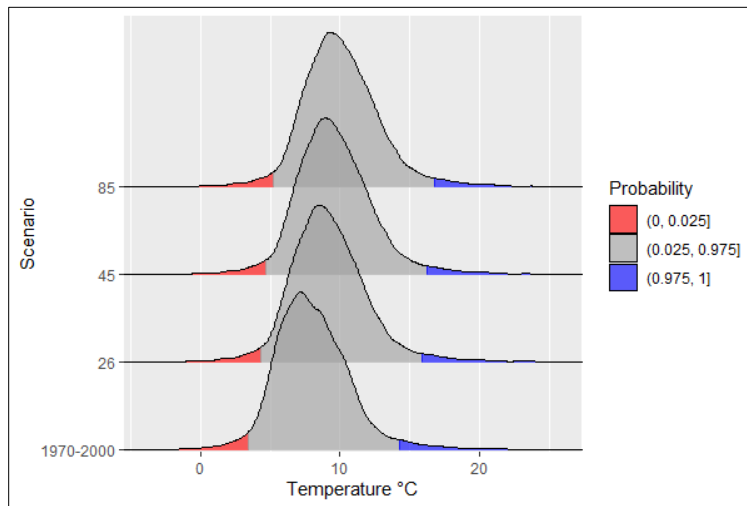


Figure 2.24. Distribution of temperature (°C) for 1970-2000 and three climate change scenarios for the Páramo ecoregion.

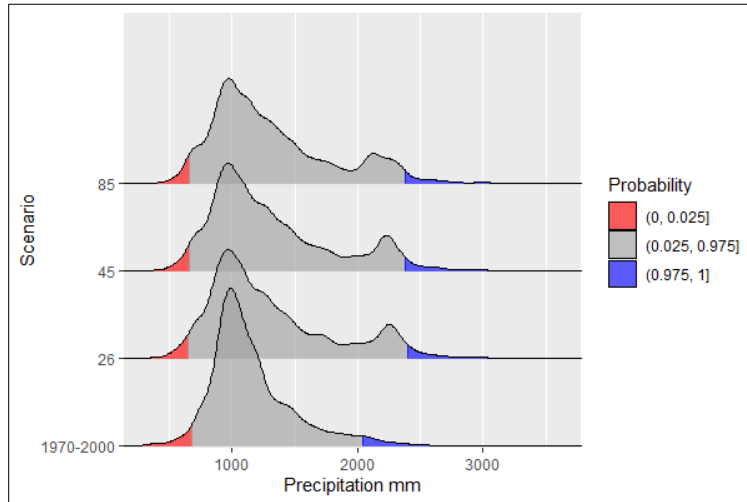


Figure 2.25. Distribution of precipitation (mm) for 1970-2000 and three climate change scenarios for the Páramo ecoregion.

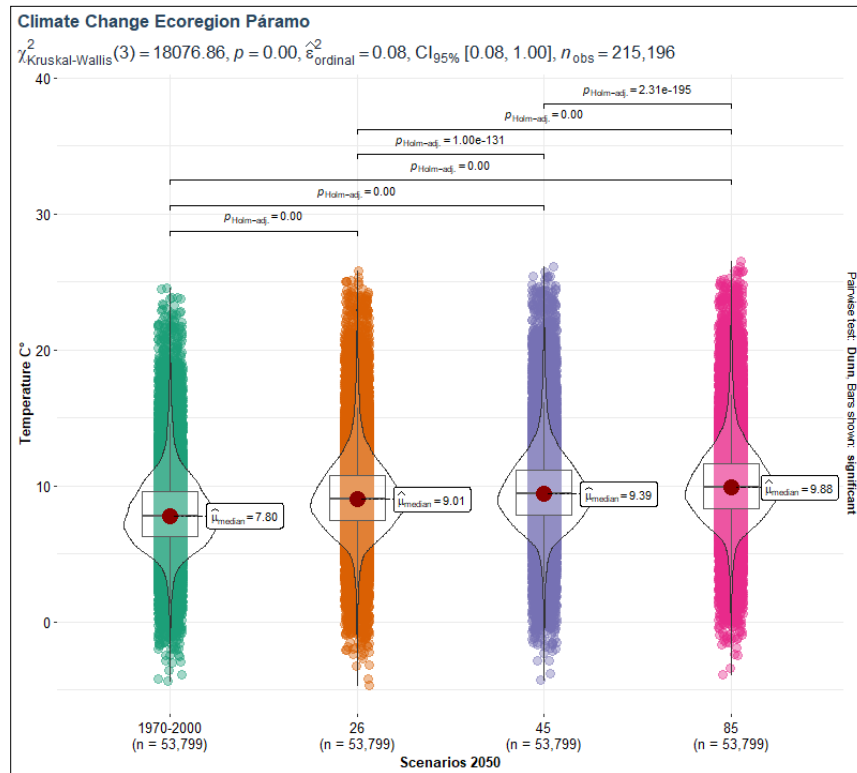


Figure 2.26. Comparison of temperature medians (°C) for 1970-2000 and three climate change scenarios for the Páramo ecoregion.

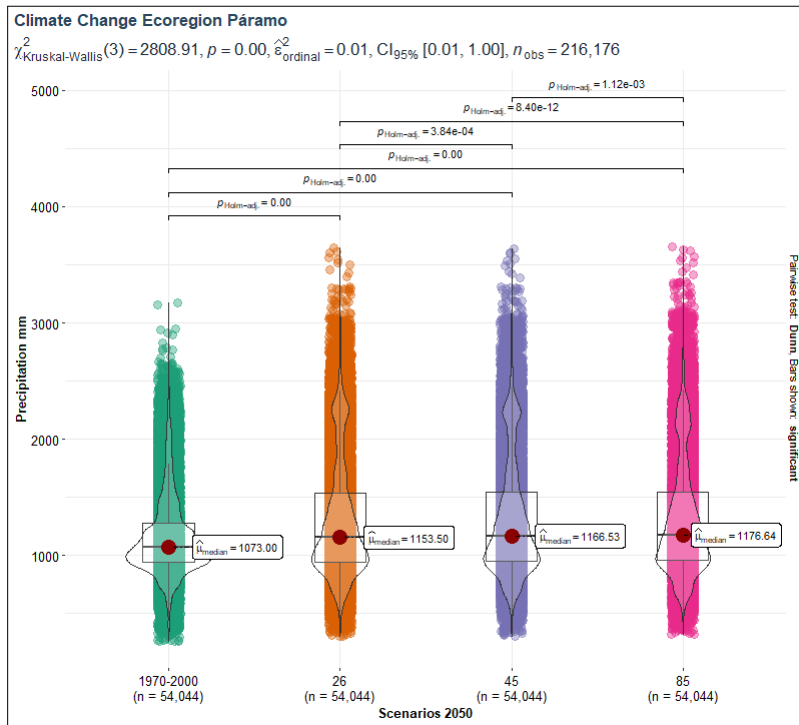


Figure 2.27. Comparison of precipitation medians (mm) for 1970-2000 and three climate change scenarios for the Páramo ecoregion.

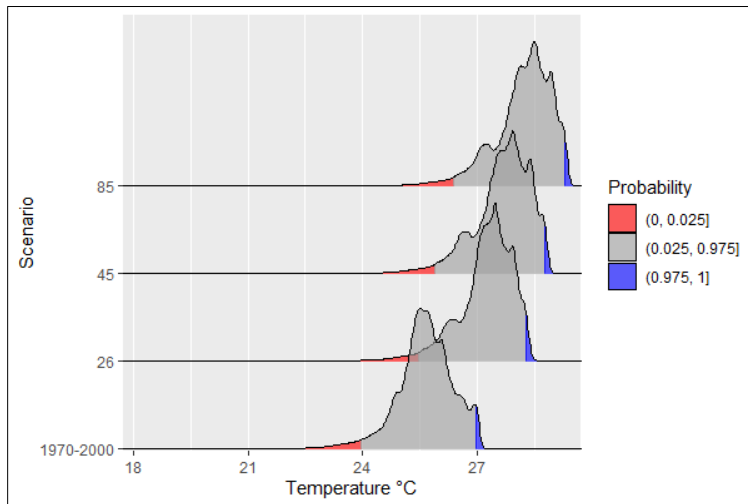


Figure 2.28. Distribution of temperature (°C) for 1970-2000 and three climate change scenarios for the Napo ecoregion.

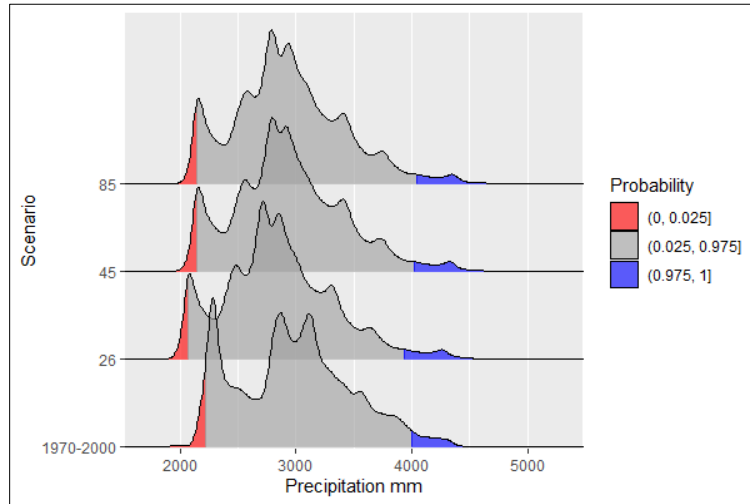


Figure 2.29. Distribution of precipitation (mm) for 1970-2000 and three climate change scenarios for the Napo ecoregion.

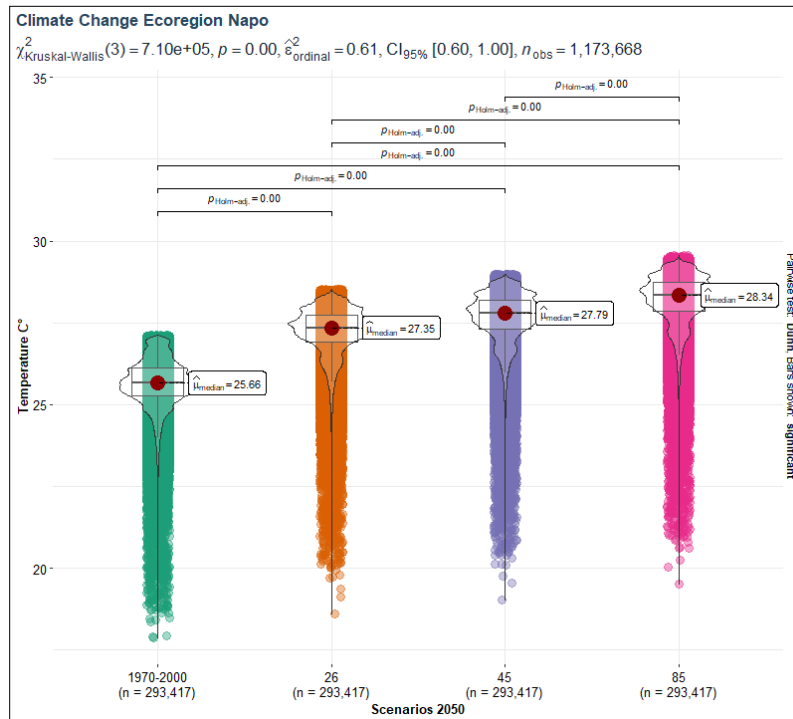


Figure 2.30. Comparison of temperature medians (°C) for 1970-2000 and three climate change scenarios for the Napo ecoregion.

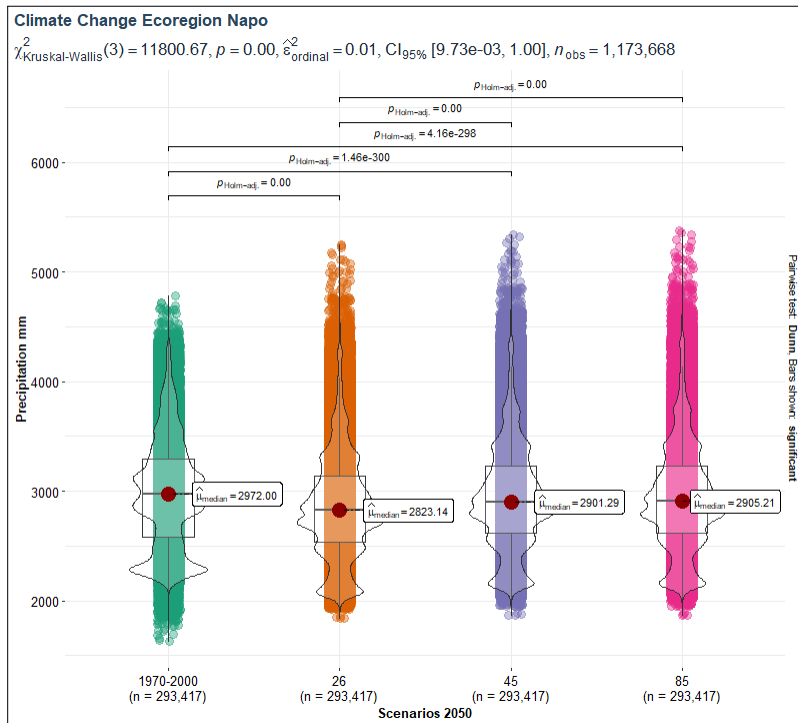


Figure 2.31. Comparison of precipitation medians (mm) for 1970-2000 and three climate change scenarios for the Napo ecoregion.

CHAPTER THREE

FORECASTING THE POTENTIAL HABITAT FOR THE SPECTACLED BEAR AND THE
PÁRAMO ECOREGION FOR CURRENT CONDITIONS AND CLIMATE CHANGE
SCENARIOS IN 2050

Contribution of Authors and Co-Authors

Manuscript in Chapter 3

Author: Jaris E. Veneros G.

Contributions: conceived and designed the analysis, collected data, contributed data or analysis tools, performed the analysis, and wrote the paper.

Co-Author: Andrew Hansen

Contributions: contributed to data analysis, methods, writing improvements, and research and publication funding.

Co-Author: Dave Roberts

Contributions: contributed to data analysis, performed the analysis, methods and writing improvements.

Co-Author: Elkin Noguera-Urbano

Contributions: contributed to data analysis, methods and writing improvements.

Co-Author: Patrick Jantz

Contributions: contributed to data analysis, methods and writing improvements.

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Jaris Veneros, Andrew Hansen, Dave Roberts, Elkin Noguera and Patrick Jantz

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Abstract

Peru, Ecuador, and Colombia selected the Spectacled bear and the Páramo ecoregion as their pilot species and ecoregion to establish a method for forecasting their habitat suitability based on environmental factors for reporting on the Sustainable Development Goals (SDG) 15. We used the SDM R package to model the habitat suitability of this species and the ecoregion. For the spectacled bear, we used 1192 occurrence records and 1000 pseudo-absences, and for the Páramo, we used 50147 occurrence records and 10000 pseudo-absences. We used 19 Bioclim variables, elevation, and Human Footprint in the modeling.

The habitat suitability modeling showed a potential decline in the spectacled bear's habitat in two RCPs in the high category of occurrence, while for the Páramo ecoregion, there was a decrease in all RCPs in the high category of probability of occurrence too. We found that Random Forest performed better than other models within the SDM. The variables of importance in the modeling were assessed in the case of the spectacled bear: altitude for current conditions, but in the RCPs, the bio6 (Min Temperature of Coldest Month) was found. For the Páramos, the most important variable was elevation for both current conditions and for the RCPs 2050.

Introduction

There is a biodiversity crisis and the defaunation of the Anthropocene is likely to intensify in the future if scenarios of further habitat destruction are considered (Gonçalves-Souza et al., 2020). Studying habitat distribution under different climate scenarios allows conservationists and policy makers to assess the vulnerability of species and ecoregions to climate change (Eigenbrod et al., 2015; Foden et al., 2019). In our Life on Land Project will support three countries, Peru,

Ecuador, and Colombia in the development of a procedure through Habitat Suitability Models (HSMs) or Species Distribution Models (SDMs) to have an approximation to this Red List Index based on species and ecoregions occurrences. Suitable habitat is an area within an otherwise inhospitable matrix in which a species can potentially or does occur (DeLong & Gibson, 2012). The suitable habitats are studied employing species distribution models (SDMs), also called bioclimatic envelope models, ecological niche models, and habitat suitability models, which allow us to see the relationship between the geographical presence of species and environmental variables (Guisan and Zimmermann, 2000; Naimi and Araújo, 2016).

The Red List Index (RLI) is an indicator called 15.5.1, this indicator in turn is part of Target 15.5 and this target belongs to SDG 15. Thus, this index tracks the global risk of species extinction (Raimondo et al., 2023). Peru, Ecuador, and Colombia through the Life on Land Project selected priority species for conservation through the SDG 15. Thus, a table of 23 species selected by these countries is shown (Table 3.1) to study the probability of their occurrence in current climate conditions and in scenarios of climate change combined with the Human Footprint.

The spectacled bear and the Páramo ecoregion were selected as pilots for the development of a methodology to estimate their probability of occurrence with abiotic variables. Also, both are found in the three countries and the feeding habits of spectacled bears have been reported in many cases within the páramos, hence the importance of modeling the habitat of the spectacled bear and this ecoregion (Herrera et al., 1994; Kattan et al., 2004; Suarez, 2008).

The spectacled bear or Andean bear is the only bear species living in South America and is listed as Vulnerable on the IUCN Red List of Threatened Species and it is estimated that there are around 2500 to 10000 (02 February 2016) (Velez-Liendo & García-Rangel, 2018).

Tremarctos ornatus (F.G. Cuvier, 1825) is called Spectacled bear because most individuals have white markings around the eyes, and it is a unique representative mark for each one and its presence has been recorded especially in the Andean zone from western Venezuela to southern Bolivia, but it may also inhabit areas or habitats such as desert scrublands, páramos, grasslands and cloud forests (Castellanos, 2011; Del Moral Sachetti & Lameda Camacaro, 2011; Falconi et al., 2022; García-Rangel, 2012; Vela-Vargas et al., 2021). This bear is endangered due to the destruction of its habitat by activities such as agricultural expansion, grazing, mining, oil exploration and road construction, which induced habitat loss and fragmentation (Goldstein et al., 2006; Morrell et al., 2021). Thus, bears have been forced to seek other sources of food, which may include crops or livestock; these activities may increase the likelihood of human-bear contact and conflict and could lead to hunting (Albarracín & Aliaga-Rossel, 2018; Can et al., 2014).

On the other hand, the Páramos are found above the tropical montane forest biome (~3000 m a.s.l.) and below the cryosphere (~5000 m a.s.l.) (Correa et al., 2020). In the Resolve Geoportal in the world, we have four Páramos as ecoregions and these are: Cordillera Central Páramo (Peru and Ecuador), Northern Andean Páramo (Ecuador and Colombia), Santa Marta Páramo (Colombia) and Cordillera de Merida Páramo (Venezuela), finally we will only study the first three (Schipper, 2017). Páramos are a tropical alpine biome in the northern Andes (between 11°N and 8°S) and, to a lesser extent, in parts of Central America and dominated by grasslands, rosettes and shrubs but they are difficult to map due to natural and human-induced disturbances (Correa et al., 2020). The páramos are very important for the amount of water they provide and for their participation in the hydrological cycle, they also help in the storage of carbon but are very vulnerable to human activities (Buytaert et al., 2006; Correa et al., 2020; INGEAG, 2019).

The Life on Land Project is currently creating updated layers for the Human Footprint, and the research team intends to integrate other factors such as climatic variables into its methodology. This will allow cooperating countries, including Peru, Ecuador, and Colombia, to replicate the research using their own selected variables specific to the species and ecoregions of their respective countries. The level of the HFP (Venter et al., 2016; Williams, Venter, Allan, et al., 2020; Williams, Venter, Rehbein, et al., 2020), can give us an idea of the fragmentation of the habitat of species and ecoregions, as well as within the methodology used in this research, we can analyze how much each abiotic variable is affected in the modeling and this approach will also help these countries meet their voluntary reporting requirements for Sustainable Development Goal 15.

Methods

Study Area

Our study area is Peru, Ecuador and Colombia and the observations of spectacled bears in natural conditions within their territory from 1970 onwards. Our study also includes the Páramos within these three countries such as Cordillera Central Páramo, Northern Andean Páramo and Santa Martha Páramo (Figure 3.1) (Dinerstein et al., 2017b).

Habitat suitability modeling

Habitat suitability modeling (HSM) is a method of estimating the suitability of a site for a species or species concerning environmental conditions; furthermore, the HSMs are empirical methods that relate field observations of species to predictor environmental variables, based on a combination of statistically or theoretically derived response curves that reflect their ecological

requirements of the species and ecoregion under study (Guisan et al., 2017a; Kellner et al., 1992; Rowden et al., 2017), and their results are measured in the probability of occurrence from 0 to 1 or 0 using four levels for their potential probability such as the spectacled bear (no potential <0.20, low 0.21-0.40, moderate 0.41-0.60 and high >0.61) (Falconi et al., 2022; Mori et al., 2020). And using four levels for the Páramo ecoregion: 0-0.46, 0.47-0.64, 0.65-0.81 and 0.82-1 (Valencia et al., 2020).

To support countries in their reporting for SDG 15, Indicator 15.5.1 Red List Index, Peru, Ecuador, and Colombia selected vertebrates, plants, and ecoregions to protect and conserve (Table 3.1). Therefore, the spectacled bear and the Páramo ecoregion were designated because they are found in the three countries, and they were our pilot species and ecoregion to establish our HSM approach. For the modeling of the suitable habitat for the spectacled bear and the probability of occurrence of the Páramo, the SDM R package (Naimi & Araújo, 2016; Naimi & Araujo, 2019) was used.

The first requirement for modeling our pilot species was to have records of occurrence with geographic coordinates in decimal degrees (WGS 1984) for the period named baseline (1970-2000) or until 2022. As a result, we used data from the Global Biodiversity Information Facility (GBIF) (Pender et al., 2019), museums, or other research to extract the georeferences of these species following the recommendations for the processing of our data table with the records of our species (García et al., 2022; Scheldeman & van Zonneveld, 2011). A total of 1192 occurrence records were used for this species in Peru, Ecuador, and Colombia (Figure 3.2). The spectacled bear occurrence data were curated with maps elaborated by the Instituto Humboldt of Colombia in its BioModelos portal (Instituto Alexander von Humboldt, 2023), and for Ecuador by the

Pontificia Universidad Católica del Ecuador in its portal called Ecuadorian Mammals (Castellanos & Boada, 2022). Also, for the Páramo ecoregion, a total of 50147 occurrence records were generated every 1 km as points of occurrence in ArcGis ver. 10.7 using the 2017 Ecoregions maps from Resolve: Cordillera Central Páramo, Northern Andean Páramo and Santa Martha Páramo (Dinerstein et al., 2017). For the generation of pseudo-absences in the case of spectacled bear, 1000 were generated and with a buffer of 150 km at random around the occurrences (Falconi et al., 2022). For the Páramo ecoregion we generated 10000 pseudo-absences (Barbet-Massin et al., 2012) with a buffer of 100 km around the shape of this ecoregion. For the AUC within the SDM in R package the gRandom method was used, it randomly selected sub-absences partitions of the data and fits a model to each partition to estimate the test AUC (Naimi & Araújo, 2016). This process provides a less biased model performance estimate than a single partitioning of the data into training and test subsets.

The second requirement is to have the environmental variables, in this case, the 19 bioclimatic variables of Worldclim and the elevation (masl) variable were used (Fick & Hijmans, 2017; Poggio et al., 2018). The bioclimatic variables were for the periods: baseline (1970-2000) and for the RCPs 2.6, 4.5, and 8.5 for the year 2050 (CMIP5 - HadGEM2-ES). Additionally, the Human Footprint (HFP) ver.3, 2018 Release (2009) variable was used and this variable ranges from 0 to 50 where; no pressure, mean HFP = 0; low pressure, HFP =1–2; moderate pressure, HFP =3–5; high pressure, HFP = 6–11; and very high pressure, HFP =12–50 (Venter et al., 2016, 2018), this HFP-2009 was used until the other HFPs are developed for future scenarios.

The HFP had to be resampled due to the different Coordinate Reference System (CRS), resolution, and spatial extent than the WorldClim variables in R 4.2.3 and ArcGis 10.7. Finally, all 21 variables have a resolution of approximately 1 km² (Table 3.2).

Once all the environmental variables were listed, a collinearity analysis was performed based on their Pairwise correlation coefficients and Variance Inflation Factor (VIF) value, and variables with a correlation coefficient greater than 0.7 and a VIF greater than 10 were discarded to avoid collinearity problems in the models for the spectacled bear and the Páramo (Naimi & Araújo, 2016; Naimi & Araujo, 2019). Therefore, after a collinearity analysis for the spectacled bear of the 21 variables for the baseline (1970-2000) we used these variables: bio13, bio14, bio15, bio18, bio19, bio3, bio4, bio7, elevation and HFP and for the RCPs – 2050 (2.6, 4.5 and 8.5) these variables: bio13, bio14, bio15, bio18, bio19, bio2, bio3, bio4, bio6 and HFP were used (From Table S3.1 to S3.4). The same analysis was then carried out for the Páramo ecoregion, using the following variables for the baseline (1970-2000): bio13, bio14, bio15, bio18, bio19, bio3, bio4, bio7, elevation and HFP and for the RCPs – 2050 (2.6, 4.5 and 8.5) these variables: bio13, bio14, bio15, bio18, bio19, bio2, bio3, bio4, elevation and HFP (From Table S3.5 to S3.8).

Third, we selected species modeling methods based on the type of data we had (Presence). In the case of the spectacled bear and Páramo ecoregion, we only obtained presence data, so the models to be used in the R SDM package were Generalized Linear Model (GLM), Maximum entropy (MaxEnt), Boosted Regression Trees (BRT), Random Forests (RF), Functional Data Analysis (FDA) (Naimi & Araujo, 2019). These models were then evaluated in terms of their Area Under the Receiver Operating Characteristic Curve (AUC), Correlation coefficient (COR), True Skill Statistic (TSS), and Deviance to see which of these models performed best in estimating the

potential distribution for the spectacled bear and the Páramo ecoregion. The interpretations for each of our statistics are shown as follows. The AUC is widely used to evaluate models in species distribution and its values have the following interpretation: less than 0.7 is sub-optimal performance, 0.70 – 0.80 is good performance, greater than 0.8 is excellent performance and a value of 1 means a perfect classifier (Dormann et al., 2008; Draelos, 2019; Naimi & Araujo, 2019; Wunderlich et al., 2022; Zhang et al., 2018).

Then, the Pearson Correlation Coefficient (COR) measures the strength and direction of the linear relationship between the predicted probability of presence and presence-absence test data and it ranges from -1 to 1. Where -1 means a perfect negative correlation, 0 means no correlation, and 1 means a perfect positive correlation, so a correlation coefficient between 0.00 and 0.10 is considered Negligible, between 0.10 and 0.39 is weak, between 0.40 and 0.69 is moderate, between 0.70 and 0.89 is strong, and between 0.90 and 1.00 is very strong (Schober & Schwarte, 2018). However, correlation does not imply causation, and the coefficient may not capture other types of relationships (Naimi & Araújo, 2016b; Schober & Schwarte, 2018).

The True Skill Statistics (TSS) was used also to measure the performance models when predictions are expressed as presence or absence maps (Allouche et al., 2006). The TSS values are classified as > 0.8 (good to excellent), 0.6–0.8 (useful), and 0.2–0.6 (poor) for the model performance (Samal et al., 2022; Shabani et al., 2016). Lastly, a high Deviance indicates a high variance in variable importance across runs, so low deviance indicates a good fit between the model and the data (Aguirre-Gutiérrez et al., 2013; Crase et al., 2012; Naimi & Araújo, 2016).

In short, the consideration for selecting the best model was that the values of the AUC, COR, and TSS should be closest to 1, otherwise for Deviance, it should be the lowest value (Azrag

et al., 2022; Kiser et al., 2022; Marsh et al., 2023; Naimi & Araújo, 2016a; Seid & Bekele, 2023; Torabian et al., 2018). Thus, RF was the model with better performance than the others in terms of AUC, COR, TSS, and Deviance for the four scenarios (1970-2000) and the three RCPs 2050 for both the modeling of the spectacled bear and the Páramo ecoregion (From Table S3.1 to S3.8).

To get the relative importance of the variables, the “getVarImp” function of the SDM package for R was used (Naimi & Araujo, 2019). Also, Random Forest and Decision Trees from the libraries in R “randomForest” and “tree” were used separately from the SDM package to find which variable has the greatest influence on the modeling of spectacled bear and Páramo for the baseline and RCPs in 2050 (Fukuda et al., 2013; Smith & Santos, 2020) (From Figures S3.1 to S3.24).

After that, a calibration plot of the predicted probability of occurrence for the best model for the baseline will be developed. This plot allows the assessment of whether the probabilities of occurrence in the model match the observed probabilities of species occurrence for current conditions. After selecting the optimal model, a calibration plot of the predicted baseline occurrence probability for the bear and Páramo modeling. This plot allows us to evaluate whether the probabilities of occurrence in the model match the observed probabilities of species occurrence (Gomes et al., 2018; Phillips & Elith, 2010).

Finally, an analysis is made with the ArcGis 10.7 tool called map algebra to evaluate the changes in potential areas (km²) for the spectacled bear and the Páramo ecoregion between the RCPs for 2050 versus the baseline (1970-2000).

Results

Spectacled bear and Páramo ecoregion

The potential areas for spectacled bear habitat (Figures 3.3, 3.4, 3.5 and 3.6) and the difference in area between the 2050 RCPs and the baseline (1970-2000) were calculated in km² (Table 3.3). Table 3.3 shows a reduction in bear habitat for the two RCPs (2.6 and 8.5) for the high category (> 0.61 High) and an increase in area for the RCP 4.5 in 2050. Also, there is a reduction of its potential area in RCPs 2.6 and 4.5 for the moderate (0.41 – 0.60) and no potential (<0.20) categories. Finally, the non-potential areas increase their areas for all three RCPs in 2050.

Although our climate data is for the years 1970-2000 (baseline) and our HFP is for the year 2009, it is valid to make this analysis of how this HFP is affecting the potential habitat of the spectacled bear because the baseline climate data can be used in a range of 30 years. Therefore, it was found that the HFP with very high pressure (HFP =12–50) is affecting approximately 63 514.69 km² which represents 18.57% of the total potential habitat of this species for the high category of probability of occurrence (> 0.61), as well as the other categories of potential habitat (Table 3.4) and (Figure 3.7).

Next, the potential areas for the Páramo ecoregion (Figures 3.8, 3.9, 3.10 and 3.11) and their area difference between the 2050 RCPs and the baseline (1970-2000) were calculated in km² (Table 3.5). The potential areas of the Páramo were made using the 2017 Ecoregions maps from Resolve as masks. Areas with high potential (> 0.61 High) and low potential (0.21 - 0.40 Low) occurrence for the páramo decrease for all three RCPs in 2050 compared to the baseline (1970-2000). Moderate potential and no potential zones also increase by 2050 in all three RCPs (Table 3.5). Next, it was observed that areas with high potential (> 0.61 High) of occurrence for the

páramo and human footprint with very high pressure (HFP =12–50) represent 21.50% (9 189.02 km²) of the total areas with high probability of occurrence of the páramo (Table 3.6 and Figure 3.12).

Following, an analysis was made of the relative importance of the variables for the baseline (1970-2000) and the three 2050 RCPs (2.6, 4.5, and 8.5) for the spectacled bear and the Páramo. This analysis can be used to evaluate which variables are most important in predicting spectacled bear and Páramo distribution in the three countries and can help guide decisions about which variables to include or exclude from a model as well as conservation efforts. It can also be used to identify variables that may be interacting with each other and to help identify potential areas for future research. In the case of the spectacled bear, the most important variable for the baseline (1970-2000) was the elevation (masl) with 50% over the other variables (Figure S3.1), and for the 2050 RCPs (2.6, 4.5, and 8.5) was the variable bio 6 with around 50% over the other variables for these three scenarios (Min Temperature of Coldest Month °C) according to “getVarImp function”, Random Forest and Decision Trees (Figures from S3.1 to S3.8). The elevation (masl) may no longer be the most important variable by 2050 due to the increase in average temperature over spectacled bear habitat of more than 1 °C. For the modeling of the Páramo ecoregion, the most important variable for the baseline (1970-2000) and the three RCPs for 2050 (2.6, 4.5 and 8.5) was the elevation (masl) by around 70% over the other variables for these three scenarios, according to the three techniques mentioned above (Figures from S3.13 to S3.24).

Random Forest (RF) was the best-performing technique compared to the other models GLM, MaxEnt, BRT and FDA based on its AUC, COR, TSS, and Deviance for modeling spectacled bear habitat and the Páramo ecoregion (From Table S3.1 to S3.8), then the ROC

analysis (Receiver Operating Characteristic) for the RF (Subsampling and Bootstrap) for the baseline (1970 - 2000) and the three 2050 climate change scenarios are presented in Figure 3.13 and Figure 3.14. All AUC values for the spectacled bear and Páramo ecoregion modeling with RF for the baseline and the three RCPs in 2050 showed an AUC greater than 0.7, which is considered a good model (Valavi et al., 2022).

The probabilities predicted by the RF model for the spectacled bear and the páramo ecoregion for the baseline and whether they match the observed probabilities of species or ecoregion presence are shown in Figures 3.15 and 3.16. The observed proportion of presence sites vs the predicted probabilities by the RF model for the spectacled bear and Páramo ecoregion were 0.822 and 0.925 correspondingly (Grouped into bins or quantiles). These values indicate that RF has a high ability to estimate the occurrence for the bear and the Páramo in the baseline.

It is also necessary to indicate that the HFP (2009) was used for the baseline as well as for future scenarios to see the possible impact on the habitat of the spectacled bear or the Páramo Ecoregion. In the baseline (1970-2000) conditions, it was observed that there are groups of occurrences for the bear that are surrounded by areas of HFP with very high pressure, which may represent a danger for this species in the three countries due to the fragmentation of its habitat (Figure 3.7). Also, in areas with very high HFP pressure (2009) and areas with Páramo potential for baseline shows that Ecuador (4 040.30 Km²) has the largest affected area than Colombia (3 443.05 Km²) and Peru (1 813.51 Km²).

Finally, this analysis of the potential habitat of the spectacled bear (pilot species) and the Páramo ecoregion under current climate conditions and climate change conditions for 2050 (RCPs 2.6, 4.5 and 8.5) helped to establish the methodology for the other species and ecoregions selected

by Peru, Ecuador, and Colombia, and all this information will also go to the repository of the UN Biodiversity Lab for use in its SDG 15 reports.

Discussion

In ecology, SDMs and HSMs are commonly used to predict where a species is likely to be found based on environmental factors. To do this, researchers often use pseudoabsences to represent areas where the species is not expected to be found but where data is unavailable (Fournier et al., 2017). For example, a buffer distance of 150 km is used to generate these pseudoabsences and exclude certain areas for the Andean bear (Falconi et al., 2022) and this value was used in our research. However, when studying the spectacled bear, it's important to consider the size of their home range (Sillero et al., 2021), which can vary based on the terrain of the area being studied. For example, theoretical sizes and home range estimates for spectacled bears have been developed by various authors, depending on whether they are males or females, age, study technique, time of observation and seasons of the year (García-Rangel, 2012). In Ecuador's Intag region, the largest home range value ever recorded for this species was reported for male bears (3) with radiotelemetry; this home range was 150 km², while the home range for females (5) was 34 km² (Castellanos, 2011; Castellanos et al., 2016; García-Rangel, 2012; Rodríguez et al., 2019; Yerena & Torres, 1994). Also, to account for this variability, researchers may need to use different buffer distances or exclusion criteria depending on the specific characteristics of the ecoregions or geographic areas studied.

It is critical to consider whether to use a planar or geodetic buffer, and how distances around points are calculated. For our research, we opted for a geodetic buffer because we needed to consider the Coordinate System of the Spectacled bear and the Páramo ecoregion. Geodesic

buffers calculate distances based on the shape of the earth's surface, which is not a perfect sphere, but an ellipsoid. This means that distances can vary depending on the location on the earth's surface and the direction of measurement (Flater, 2011). In contrast, planar buffers assume that the earth's surface is flat and calculates distances in a straight line, planar buffers are appropriate for small areas where the curvature of the earth is not considered, but for larger areas, Geodesic buffers are usually more accurate (Senay et al., 2013). It's important to consider that the probability of occurrence in SDMs or HSMs can be affected by the size of the pixels used to represent the environmental variables. Therefore, it's recommended to be cautious when interpreting the probabilities of occurrence generated by these models, as they can be influenced by the scale at which the data is measured. If several pseudo-absences are framed in the same pixel without considering the total area covered by a group of pixels, it could lead to an over or under representation of certain areas in the model. This could result in inaccurate predictions of species occurrence or habitat suitability. Therefore, it's important to carefully select the pixel size and ensure that pseudo-absences are distributed appropriately across the study area to minimize potential bias in the model.

It is worth noting that the ecoregion maps used in our research only recognize five Páramo Ecoregions across Peru, Ecuador, Colombia, and Venezuela (Dinerstein et al., 2017). However, it is important to recognize that different classifications and sub-classifications for Páramos may exist in other ecosystem maps or in other countries. This can lead to discrepancies in mapping and managing these unique ecosystems, but the products of this work allow you to make analyses at the ecosystem or ecoregion level. It is also necessary to indicate that the HFP (2009) was used for the baseline as well as for future scenarios to see the possible impact on the habitat of the spectacled

bear and Páramos. For example, in the baseline conditions, it was observed that there are groups of records for the bear that are isolated, surrounded by areas of HFP in very high pressure, which may represent a danger for this species in the three countries due to the fragmentation of its habitat.

Finally, in our research, although it is true that the other GLM models, MaxEnt, BRT and FDA obtained results we obtained for modeling the spectacled bear and the Páramo Ecoregion in statistics such as AUC, COR, TSS, and Deviance; RF apparently will not identify other suitable habitats outside the home range (Sillero et al., 2021).

Conclusion

The study aimed to assess the occurrence probabilities of spectacled bears and the state of the Páramo ecoregion across three countries. This was achieved by calculating the probabilities on a scale of 0-1 or in categories. The results showed that potential high-category bear areas decrease for RCPs 2.6 and 8.5, when compared to the baseline. This reduction in potential bear habitat is a cause for concern as it may have a significant impact on the bear population's survival and distribution. Additionally, human activities were found to have a considerable impact on the bear's habitat suitability. In particular, the study found that human activities affect 63 514.69 km² of the bear's habitat suitability in the current climate conditions. This result highlights the urgent need to address human activities that threaten the bear's habitat and survival. Moreover, the Páramos, a high-altitude biogeographic region that is home to unique and endemic flora and fauna, experiences a decrease in area for all RCPs in 2050 compared to the baseline. The study also found that human activities (HFP) affect the Páramos in current climate conditions, reducing the ecoregion's area by 9 189.02 km². It is worth noting that the study recommends the use of an updated PFH to improve the accuracy of the results. Finally, the study compared the performance

of different models such as GLM models, MaxEnt, BRT, FDA, and Random Forest. The study found that Random Forest outperforms the other models in predicting the occurrence probabilities of spectacled bears and the Páramo ecoregion. This finding has significant implications for future research and conservation efforts as it can help identify key areas for conservation and guide the development of effective conservation strategies.

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Tables

Table 3.1. Selected Species for Peru, Colombia, and Ecuador.

PERU		
	Scientific name	Common name
1	Birds	<i>Penelope albipennis</i> <i>the white-winged guan</i>
2		<i>Oreonax flavicauda - Lagothrix flavicauda</i> <i>yellow-tailed woolly monkey</i>
3		<i>Panthera onca</i> <i>jaguar</i>
4	Mammals	<i>Pecari tajacu</i> <i>peccary</i>
5		<i>Tapirus pinchaque</i> <i>the mountain tapir</i>
6		<i>Tayassu pecari</i> <i>the white-lipped peccary</i>
7		<i>Tremarctos ornatus</i> <i>Andean bear or spectacled bear</i>
COLOMBIA		
1		<i>Crax alberti</i> <i>blue-billed curassow or blue-knobbed curassow</i>
2	Birds	<i>Panthera onca</i> <i>jaguar</i>
3		<i>Ateles hybridus</i> <i>brown spider monkey or variegated spider monkey</i>
4	Mammals	<i>Tapirus pinchaque</i> <i>the mountain tapir</i>
5		<i>Tremarctos ornatus</i> <i>andean bear or spectacled bear</i>
6		<i>Bassaricyon neblina</i> <i>olinguito</i>
7	Plants	<i>Cattleya trianae</i> <i>National flower from Colombia</i>
8		<i>Ceroxylon quindiuense</i> <i>wax palm</i>
ECUADOR		
1		<i>Ateles belzebuth</i> <i>white-bellied spider monkey</i>
2		<i>Ateles fusciceps</i> <i>black-headed spider monkey</i>
3		<i>Tapirus pinchaque</i> <i>the mountain tapir</i>
4	Mammals	<i>Tayassu pecari</i> <i>the white-lipped peccary</i>
6		<i>Reithrodontomys soederstroemi</i> <i>Söderström's harvestmouse</i>
7		<i>Thomasomys silvestris</i> <i>ucucha thomasomys</i>
8		<i>Thomasomys erro</i> <i>wandering thomasomys</i>

Table 3.2. Bioclimatic and Human Footprint Variables.

Variable	Units
BIO1 = Annual Mean Temperature	(°C)
BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))	(°C)
BIO3 = Isothermality (BIO2/BIO7) (×100)	-
BIO4 = Temperature Seasonality (standard deviation ×100)	-
BIO5 = Max Temperature of Warmest Month	(°C)
BIO6 = Min Temperature of Coldest Month	(°C)
BIO7 = Temperature Annual Range (BIO5-BIO6)	(°C)
BIO8 = Mean Temperature of Wettest Quarter	(°C)
BIO9 = Mean Temperature of Driest Quarter	(°C)
BIO10 = Mean Temperature of Warmest Quarter	(°C)
BIO11 = Mean Temperature of Coldest Quarter	(°C)
BIO12 = Annual Precipitation	(mm)
BIO13 = Precipitation of Wettest Month	(mm)
BIO14 = Precipitation of Driest Month	(mm)
BIO15 = Precipitation Seasonality (Coefficient of Variation)	-
BIO16 = Precipitation of Wettest Quarter	(mm)
BIO17 = Precipitation of Driest Quarter	(mm)
BIO18 = Precipitation of Warmest Quarter	(mm)
BIO19 = Precipitation of Coldest Quarter	(mm)
Elevation (30 Seconds)	masl
Human Footprint (HFP) - 2009	-

Table 3.3. Potential areas (km²) for the spectacled bear habitat and difference in areas between 2050 RCPs and baseline (1970-2000).

Potential Habitat	1970-2000 (C) km ²	2.6 km ²	4.5 km ²	8.5 km ²	2.6-C km ²	4.5-C km ²	8.5-C km ²
<0.20 No potential	1876999.11	1917109.95	1921944.23	1904105.31	40110.84	44945.13	27106.20
0.21 – 0.40 Low	251712.04	232114.81	233443.59	251990.12	-19597.24	-18268.45	278.08
0.41 – 0.60 Moderate	222773.09	217694.96	189914.53	230890.41	-5078.13	-32858.57	8117.31
> 0.61 High	342060.05	326624.58	348241.94	306558.46	-15435.48	6181.89	-35501.59

Table 3.4. Potential areas (km²) for spectacled bear habitat at baseline (1970-2000) with very high pressure of HFP.

Potential Habitat	1970-2000 (C) km ²
<0.20 No potential	251382.45
0.21 – 0.40 Low	57801.35
0.41 – 0.60 Moderate	65577.44
> 0.61 High	63514.69

Table 3.5. Potential areas (km²) for the Páramo ecoregion and difference in areas between 2050 RCPs and baseline (1970-2000).

Potential Habitat	1970-2000 (C) km ²	2.6 km ²	4.5 km ²	8.5 km ²	2.6-C km ²	4.5-C km ²	8.5-C km ²
<0.20 No potential	23.10	31.66	32.51	31.66	8.56	9.41	8.56
0.21 – 0.40 Low	154.87	125.78	114.65	110.38	-29.09	-40.21	-44.49
0.41 – 0.60 Moderate	289.20	388.45	392.73	422.68	99.25	103.53	133.48
> 0.61 High	42721.36	42642.64	42648.63	42623.82	-78.72	-72.73	-97.54

Table 3.6. Potential areas (km²) for the Páramo ecoregion at baseline (1970-2000) with very high pressure of HFP.

Potential Habitat	1970-2000 (C) km ²
<0.20 No potential	5.44
0.21 – 0.40 Low	30.81
0.41 – 0.60 Moderate	71.60
> 0.61 High	9189.02

Figures

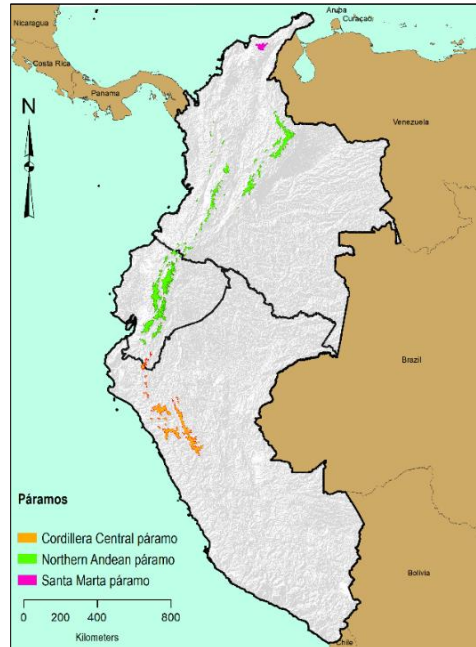


Figure 3.1. Study area: Cordillera Central Páramo, Northern Andean Páramo and Santa Martha Páramo.

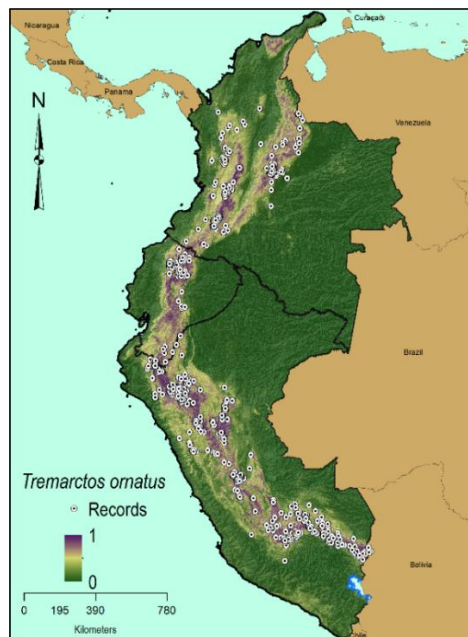


Figure 3.2. Map of the observed distribution of the spectacled bear in Peru, Ecuador, and Colombia.

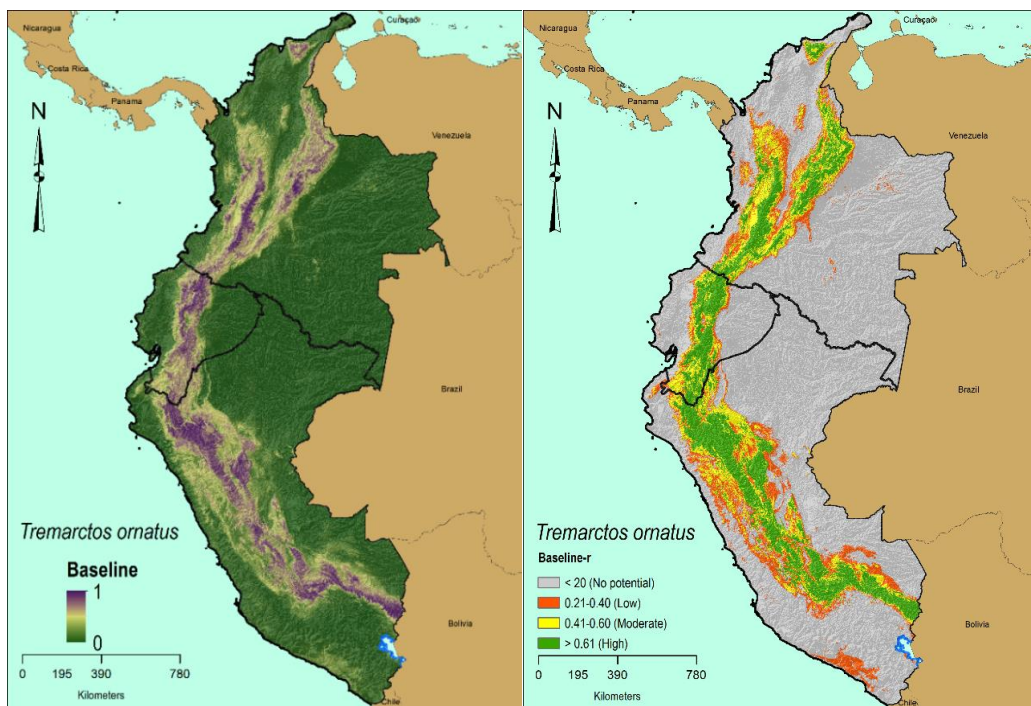


Figure 3.3. Map of the potential distribution of the spectacled bear (Baseline 1970-2000) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

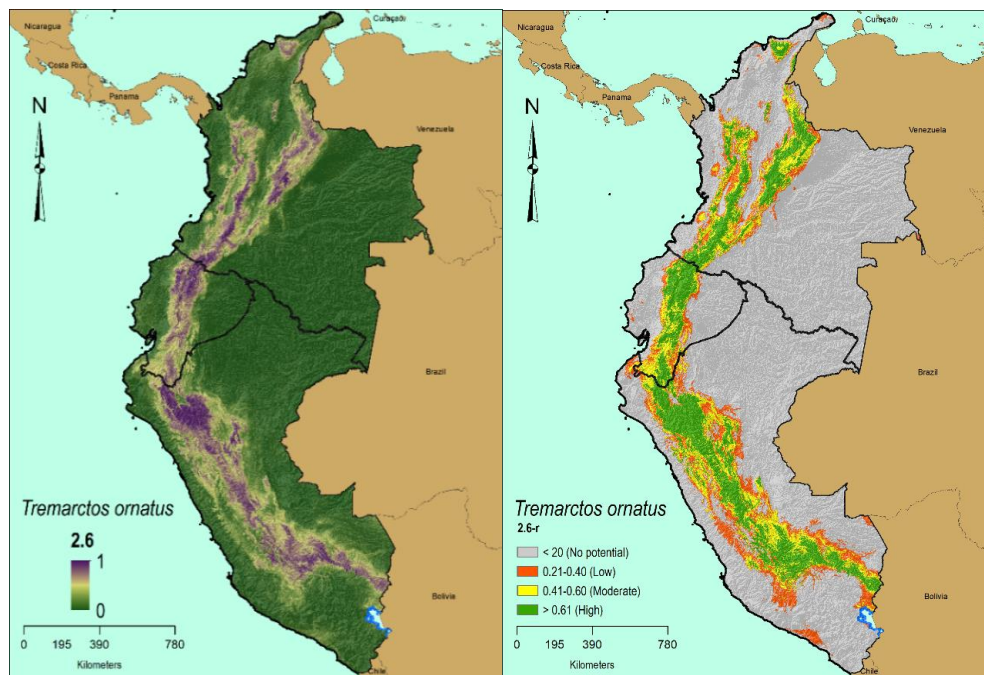


Figure 3.4. Map of the potential distribution of the spectacled bear (RCP 2.6-2050) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

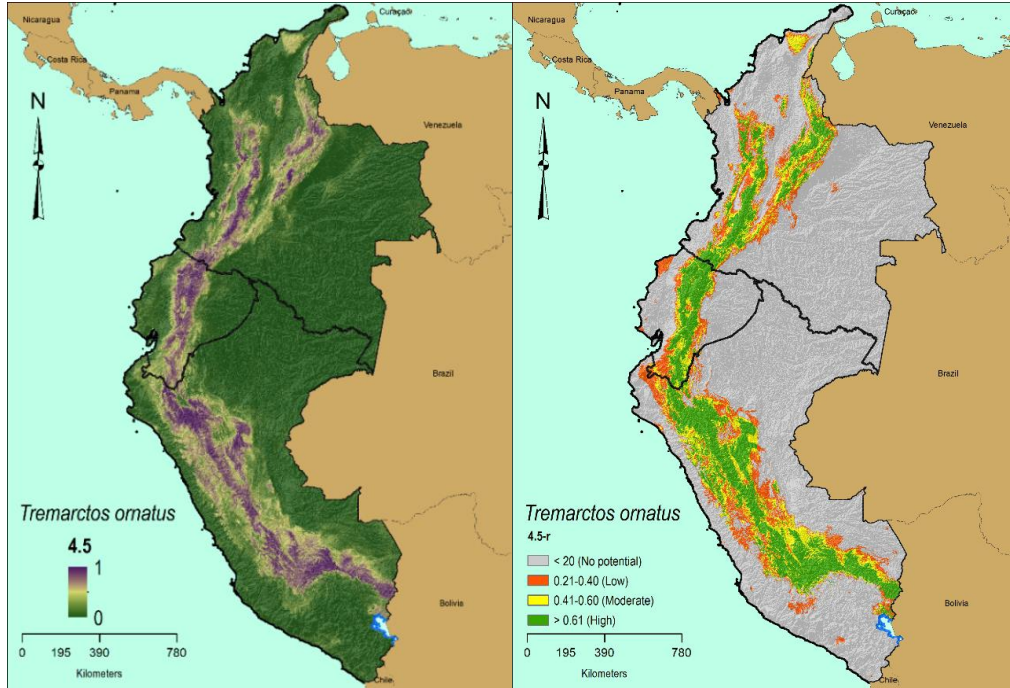


Figure 3.5. Map of the potential distribution of the spectacled bear (RCP 4.5-2050) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

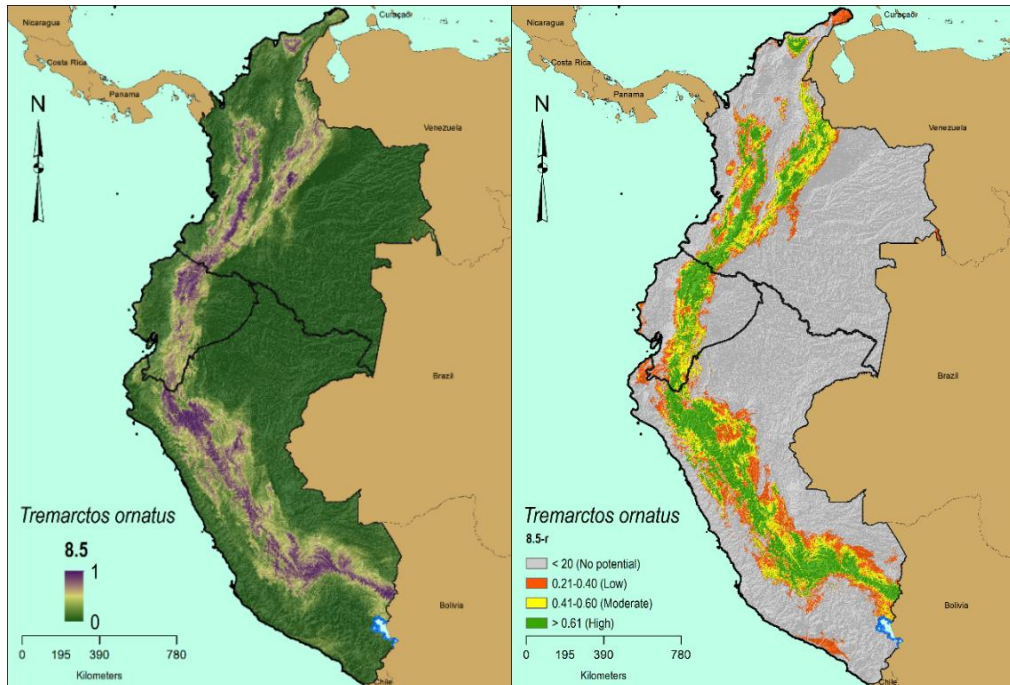


Figure 3.6. Map of the potential distribution of the spectacled bear (RCP 8.5-2050) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

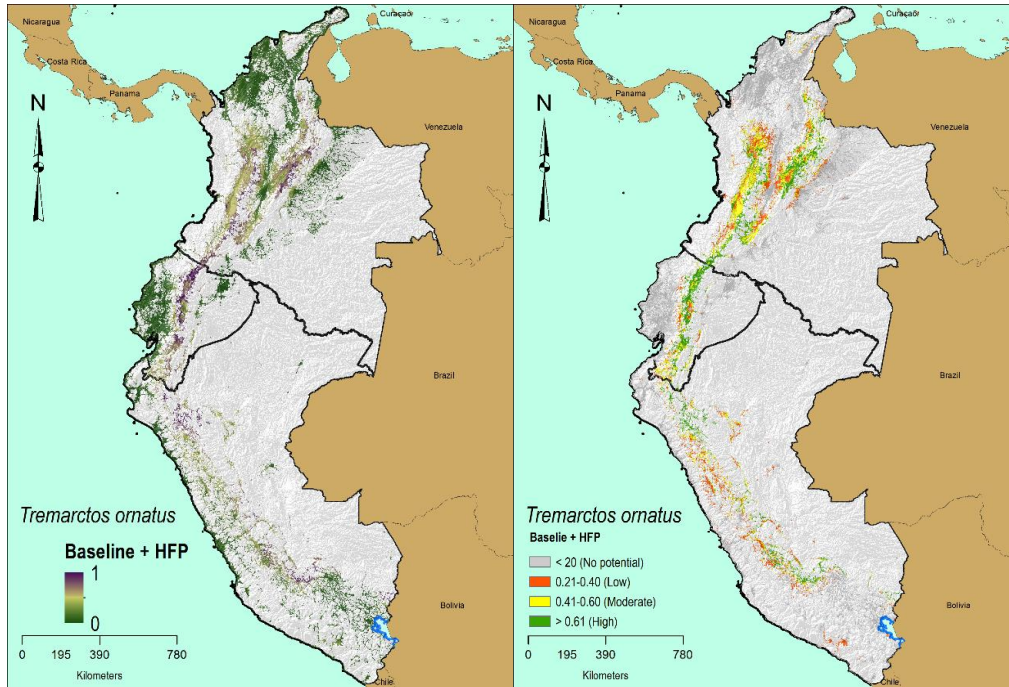


Figure 3.7. Map of the potential distribution of the spectacled bear a. Left: probability from 0 to 1 and b. Right: Probability in categories. Both are in areas with a HFP (12-50) for the baseline (1970-2000).

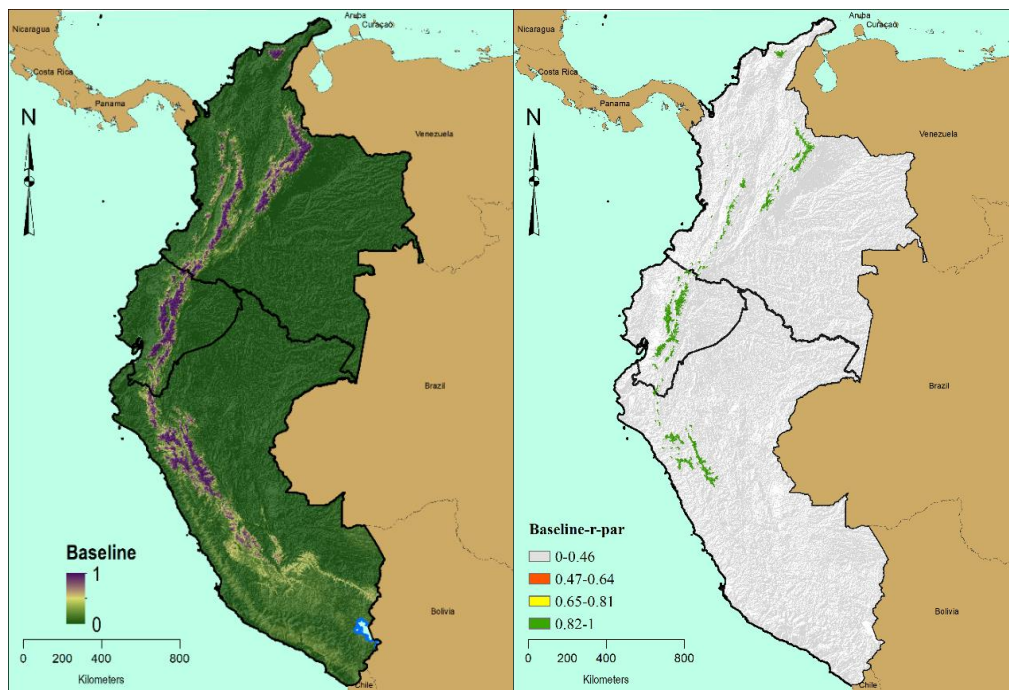


Figure 3.8. Map of the potential distribution of the Páramo ecoregion (Baseline 1970-2000) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

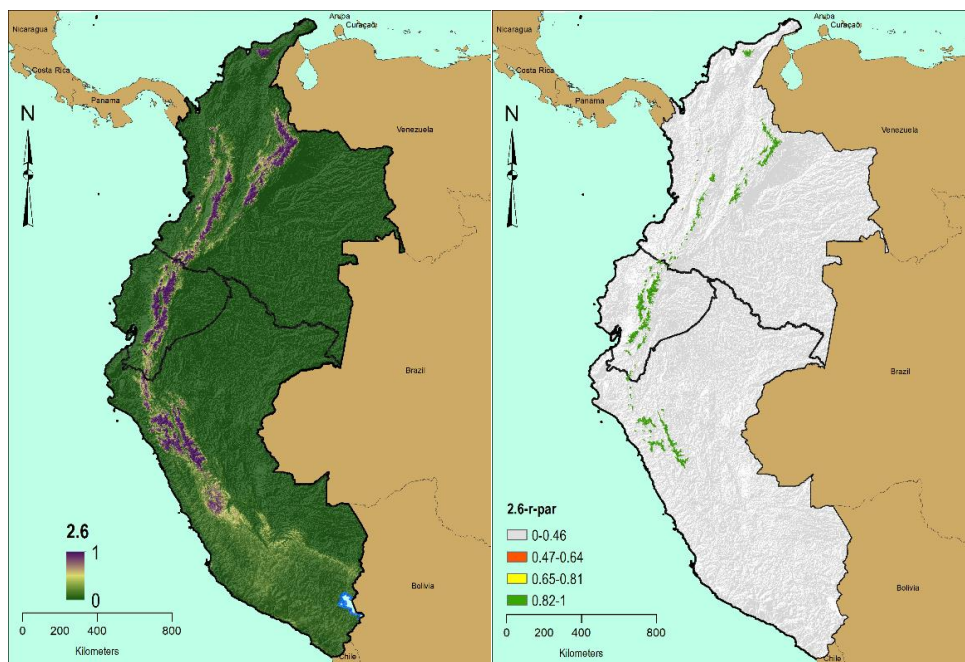


Figure 3.9. Map of the potential distribution of the Páramo ecoregion (RCP 2.6-2050) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

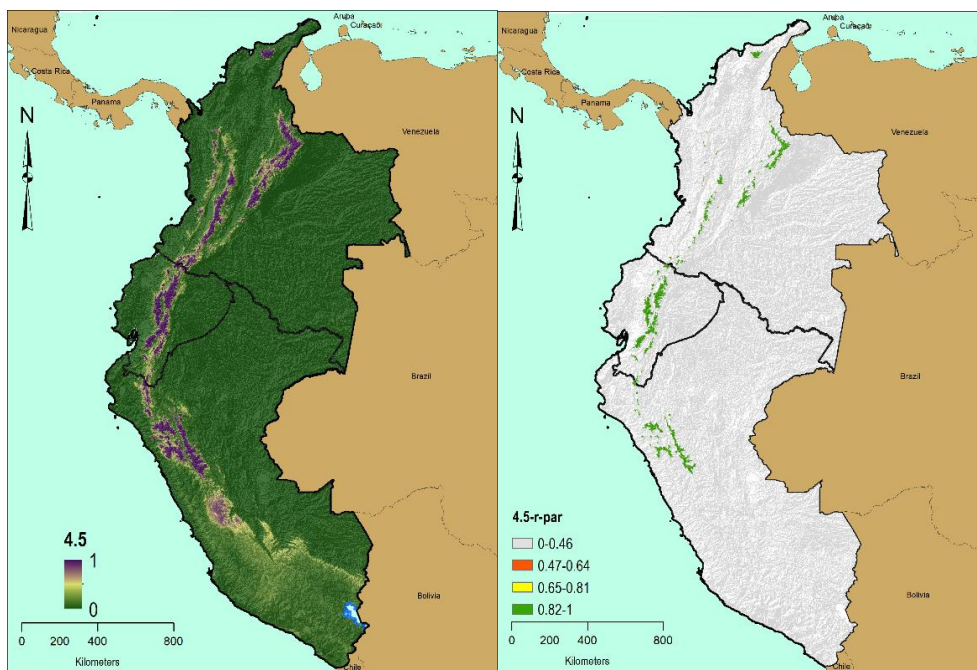


Figure 3.10. Map of the potential distribution of the Páramo ecoregion (RCP 4.5-2050) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

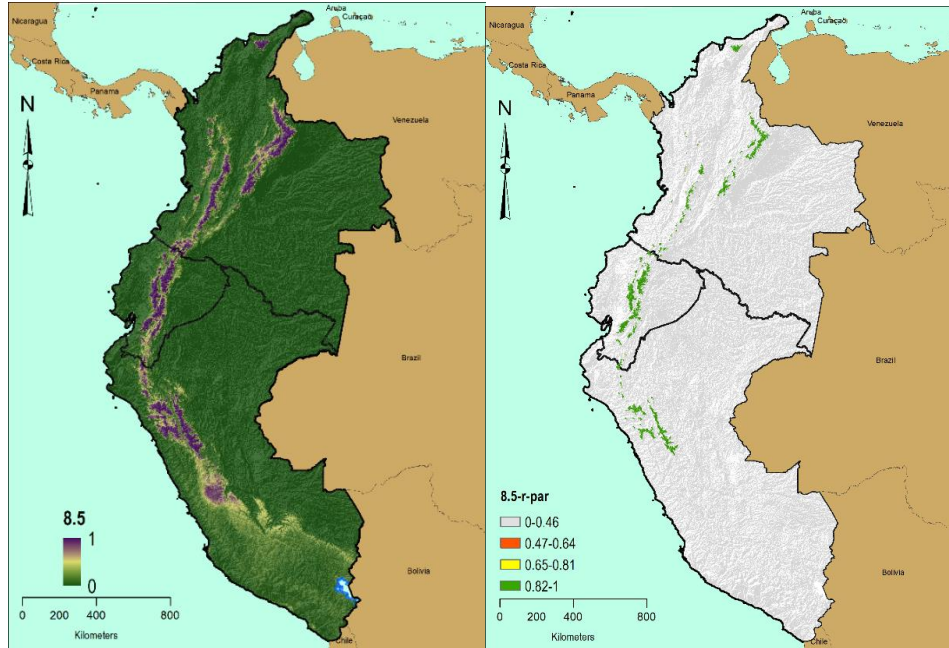


Figure 3.11. Map of the potential distribution of the Páramo ecoregion (RCP 8.5-2050) a. Left: probability from 0 to 1 and b. Right: Probability in categories.

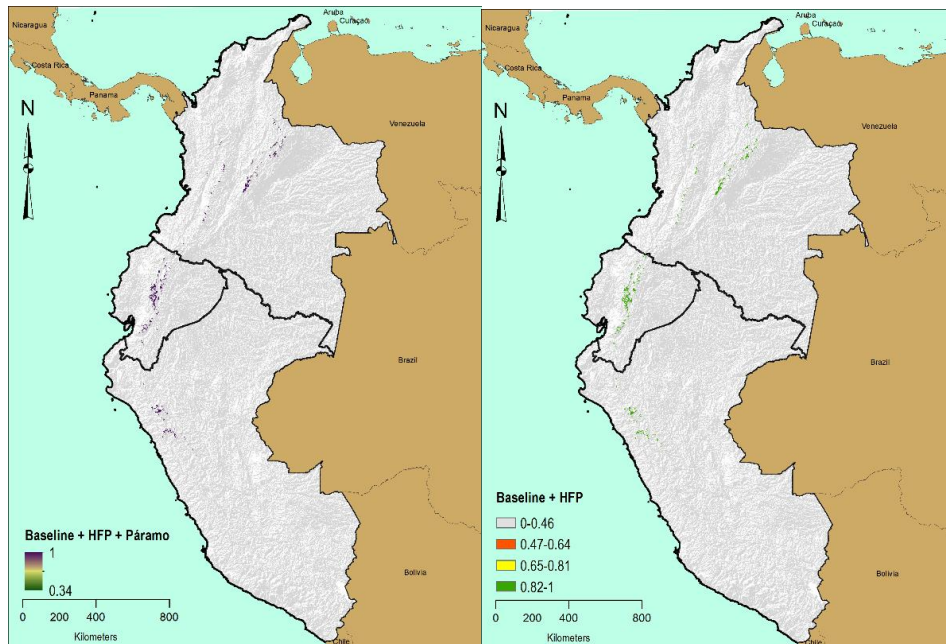
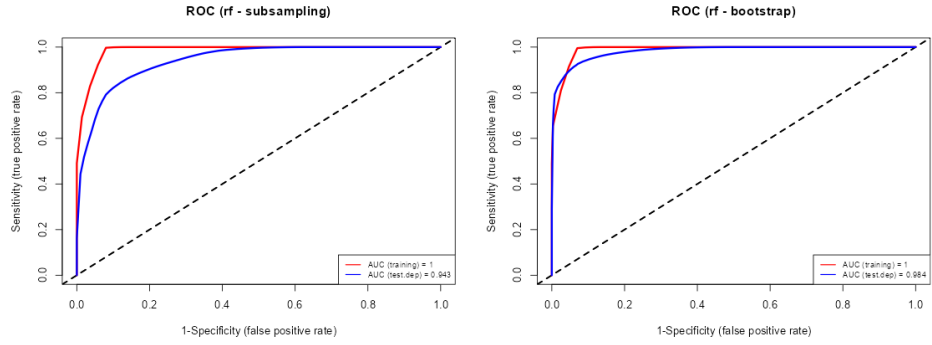
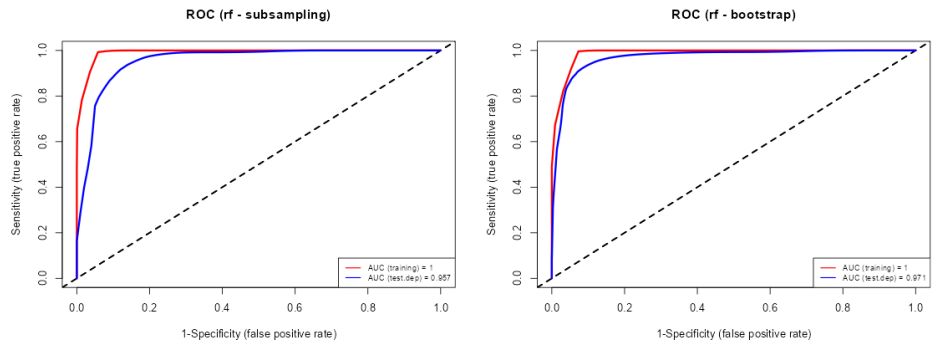


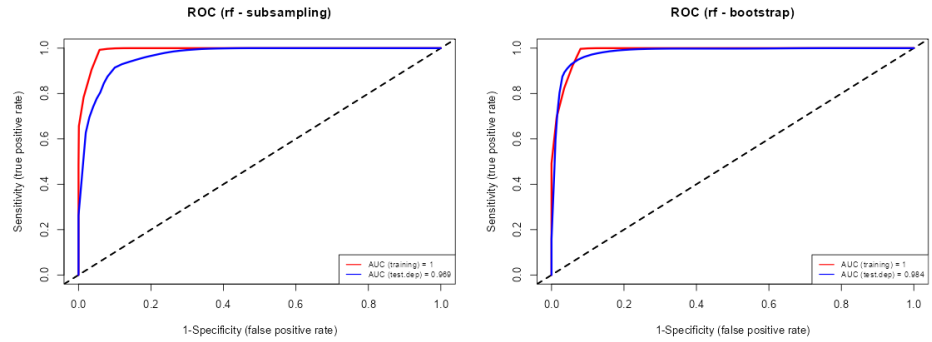
Figure 3.12. Map of the potential distribution of the Páramo ecoregion a. Left: probability from 0 to 1 and b. Right: Probability in categories. Both are in areas with a HFP (12-50) for the baseline (1970-2000).



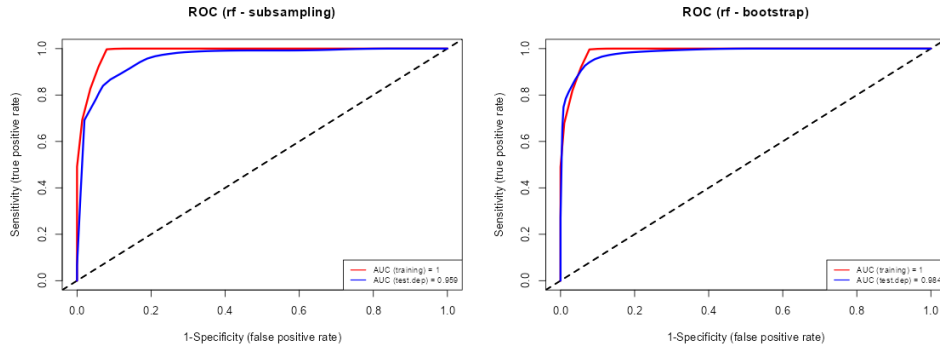
a.



b.



c.



d.

Figure 3.13. ROC analysis (Receiver Operating Characteristic) for the RF (Subsampling and Bootstrap) for the for the spectacled bear (a: Baseline, b: RCP 2.6 c: RCP 4.5 and d: RCP 8.5)

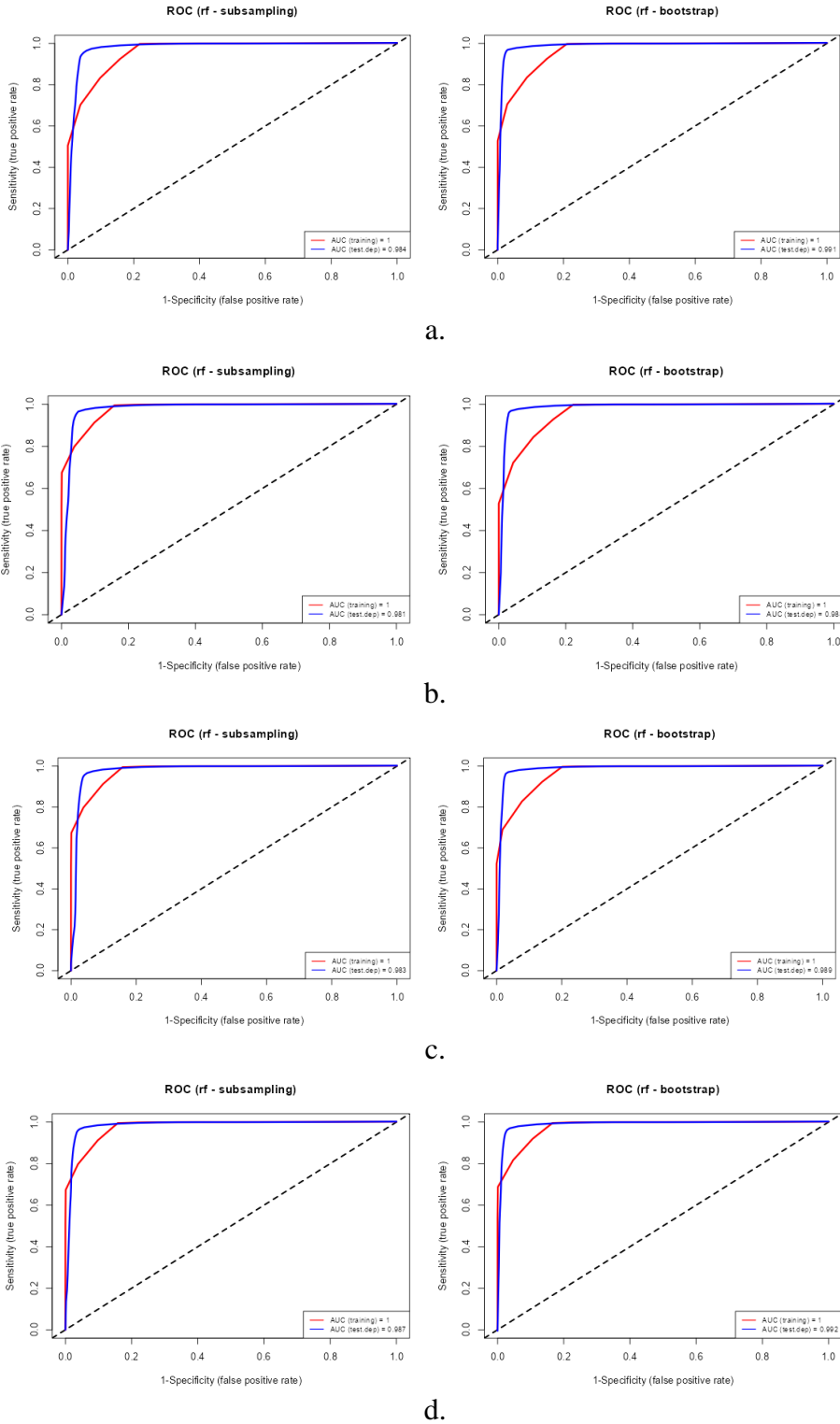


Figure 3.14. ROC analysis (Receiver Operating Characteristic) for the RF (Subsampling and Bootstrap) for the for the Páramo Ecoregion (a: Baseline, b: RCP 2.6 c: RCP 4.5 and d: RCP 8.5).

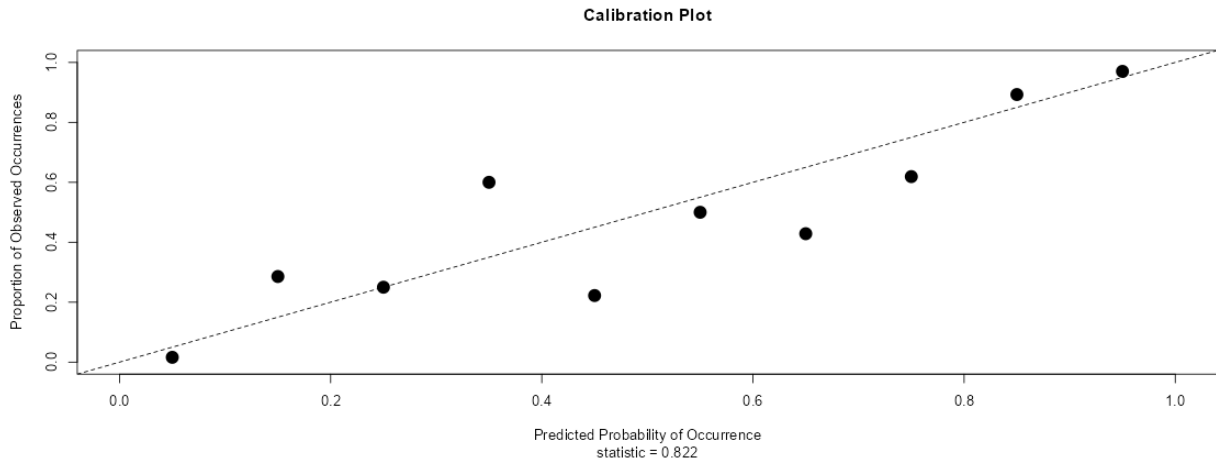


Figure 3.15. Probability predicted by the RF model for the spectacled bear (0.822) (Baseline).

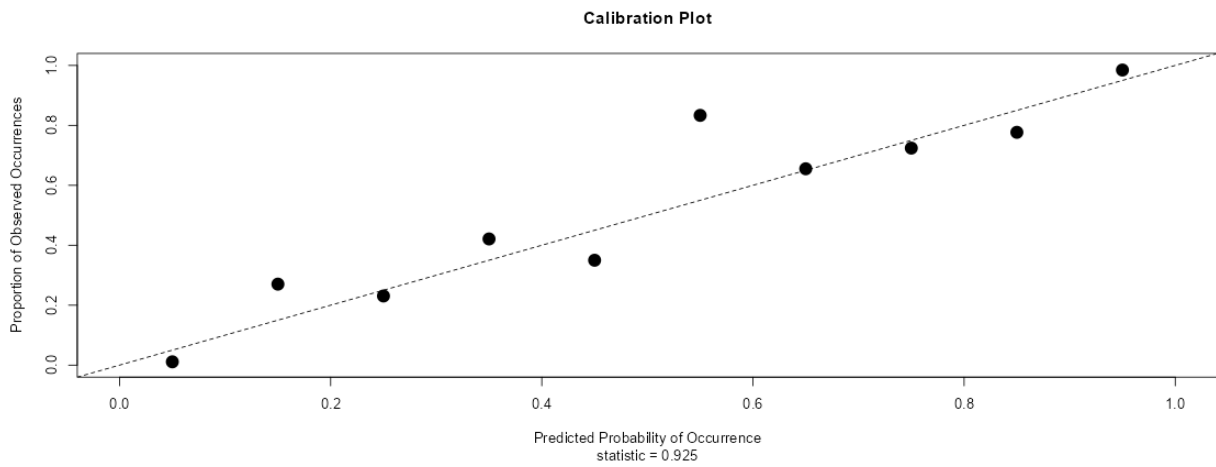


Figure 3.16. Probability predicted by the RF model for the Páramo ecoregion (0.925) (Baseline).

CHAPTER IV

GENERAL CONCLUSIONS

In this research a review of South American climate drivers as well as standardized data at different resolutions were developed with different GCMs. This standardized climate data allowed us to understand the effects of climate change and its effects on temperature (°C) and annual precipitation (mm) variations in Peru, Ecuador, and Colombia and three ecoregions, Sechura Desert, Páramo, and Napo Tropical Forest. The climatic data with an approximate resolution of 10 minutes of resolution (~ 18.5 km at the equator) helped us to have an overview of the changes in the patterns of these environmental variables in numerical values and spatially.

The climate data with an approximate spatial resolution of 30 seconds (~1 km at the equator) helped us to make a comparison of medians with a non-parametric test (Kruskal-Wallis) between the Baseline (1970-2000) and the 2050 RCPs (2.6, 4.5 and 8.5) for three ecoregions where the null hypothesis that at least one median for either temperature or precipitation is the same for the baseline or the RCPs in 2050 was rejected. Density plots also help to evaluate areas with similar records for these variables between the baseline and RCPs.

A process for modeling species and ecoregions habitat for different climate change conditions was then established, as well as including the HFP using a pilot species and a pilot ecoregion. Potential or suitable habitat areas for spectacled bear and páramo were quantified as well as their variation between the baseline and 2050 RCPs. The generation of pseudo-absences for other species will be a criterion for other researchers who will consider the home range of each species. No research has been reported for the generation of pseudo-absences for ecoregions,

however further testing of both buffer distance and number of pseudo-absences for areas at ecoregion scales is recommended. Finally, climate change affects biodiversity, but it should be noted that HFP is important because it helps us integrate human pressure on both our pilot species habitat and ecoregion habitat. It is expected that the combination of these four chapters will help us understand what is known about climate change and Human Footprint (HFP) in these three countries, estimate their effects of on vertebrate species and ecoregions and its ecological implications through SDMs. This methodology is replicable so that countries can use it to make a vulnerability analysis for the probability of occurrence (categories for each species) or non-occurrence of the list of species under study or ecoregions and report their SDG 15 reports as well as establish conservation plans and programs at the national or transboundary level in different climate change scenarios.

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APPENDICES

APPENDIX A

SUPPLEMENTAL TABLES AND FIGURES FOR CHAPTER 2

Table S2.1 Summary of climate change effects on temperature and precipitation for the three ecoregions: Sechura Desert, Páramo, and Napo.

Ecoregion	Base map	Scenarios	Method	Results	Reference
Sechura Desert	National Level	Baseline (1981-2010) Baseline (1970-2000) A1B (2010–2039) A1B (2040–2069)	Georeferenced localities from WorldClim database. Logistic regressions: an ensemble of 8 global climate models – 1 km of resolution.	Increase in vertical structure and Moisture. Based on WorldClim baseline (1970-2000) there are three ranges for precipitation: 0-5 mm/y, 6-50 mm/y and 51-250 mm/y (1970-2000) from WorldClim. Also, there are four habitats based on annual precipitation (mesic >250 mm/y, semiarid <250 mm/y, arid <50 mm/y, and hyperarid ≤5mm/y).	(Guerrero et al., 2013; Tovar et al., 2013; Zevallos & Lavado-Casimiro, 2022)
Páramo	Tropical Andean biomes from Nature Serve (Páramo)	Baseline (1981-2010) Baseline (1970-2000) A1B (2010–2039) A1B (2040–2069)	Georeferenced localities from WorldClim database Logistic regressions: an ensemble of 8 global climate models – 1 km of resolution.	For the A1B 2010-2039 and A1B 2040-2069 scenarios, the páramo shows a loss of surface area (potential and remnant) compared to the year 2000. In the potential areas, part of the páramo grasslands will be replaced by forest biomes but páramo grasslands seem to be more affected by land use change than by climate change. A median loss of 31.4% is projected for the potential	(Josse et al., 2009; Tovar et al., 2013).

				<p>distribution, but it is only 25% for the remaining areas (A1B, 2010–2039).</p> <p>Projections suggest the páramo shows an upslope displacement of its surface area for this scenario (A1B 2040–2069) compared to its lower limit for the year 2000.</p>
Napo Moist Forest	National Level Biome	<p>Current climate (1981 to 2010) was made using data from the National Meteorological Services of Colombia (IDEAM), Peru (SENAMHI), Brazil (INMET), and Ecuador (INAMHI), and data from global weather station networks, including the Global Historical Climatological Network (GHCN) and Global Surface Summary of the Day 2030, 2050 and 2080 RCPs (2.6, 4.5 and 8.5).</p>	<p>ANUSPLIN version 4.3. Sixteen GCMs were downscaled - CMIP5 - 5 km (Delta method)</p>	<p>2030 Annual mean temperature (°C) / Annual precipitation (mm) RCP 2.6: 1.1 / 90 RCP 4.5: 1.3 / 136 RCP 8.5: 1.3 / 89</p> <p>2050 Annual mean temperature (°C) / Annual precipitation (mm) RCP 2.6: 1.2 / 136 RCP 4.5: 1.7 / 136 RCP 8.5: 2.2 / 146</p> <p>2080 Annual mean temperature (°C) / Annual precipitation (mm) RCP 2.6: 1.4 / 51 RCP 4.5: 2.4 / 131 RCP 8.5: 4.2 / 349</p>

Table S2.2. CMIP5 Global Climate Models (Navarro-Racines et al., 2020).

#	GCMs	Institute
1	BCC-CSM1.1	Beijing Climate Center, China Meteorological Administration
2	BCC-CSM1.1(m)	
3	BNU-ESM	Beijing Normal University
4	CCCMA-CanESM2	Canadian Centre for Climate Modelling and Analysis National Science Foundation, Department of Energy, National Center for Atmospheric Research
5	CESM1-BGC	
6	CESM1-CAM5	
7	CNRM-CM5	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique
8	CSIRO-ACCESS1.0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia Queensland Climate Change Centre of Excellence and Commonwealth Scientific and Industrial Research Organization
9	CSIRO-ACCESS1.3	
10	CSIRO-Mk3.6.0	
11	EC-EARTH	European Centre for Medium-Range Weather Forecasts (ECMWF)
12	FIO-ESM	The First Institute of Oceanography, State Oceanic Administration, China
13	GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory
14	GFDL-ESM2G	
15	GFDL-ESM2M	
16	GISS-E2H	NASA Goddard Institute for Space Studies USA
17	GISS-E2HCC	
18	GISS-E2R	
19	GISS-E2RCC	
20	INM-CM4	Institute of Numerical Mathematics of the Russian Academy of Sciences
21	IPSL-CM5A-LR	Institut Pierre Simon Laplace
22	IPSL-CM5A-MR	
23	IPSL-CM5B-LR	
24	LASG-FGOALS-G2	Institute of Atmospheric Physics (LASG) and Tsinghua University (CESS)
25	MIROC-ESM	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology
26	MIROC-ESM-CHEM	
27	MIROC-MIROC5	
28	MOHC-HadGEM2-CC	UK Met Office Hadley Centre
29	MOHC-HadGEM2-ES	
30	MPI-ESM-LR	Max Planck Institute for Meteorology
31	MPI-ESM-MR	
32	MRI-CGCM3	Meteorological Research Institute
33	NCAR-CCSM4	US National Centre for Atmospheric Research
34	NCC-NorESM1-M	Norwegian Climate Centre
35	NIMR-HADGEM2-AO	National Institute of Meteorological Research and Korea Meteorological Administration

Table S2.3. GCMs used at the country level.

GCMs / RCPs	Temperature bio1 (°C) - 2050			Precipitation bio12 (mm) - 2050		
	2.6	4.5	8.5	2.6	4.5	8.5
BASELINE	0	0	0	0	0	0
BCC.CSM1.1	1.4258	1.8560	2.4258	103.6509	99.6192	291.1318
BCC.CSM1.1.M	1.6104	2.0062	2.6855	-20.8775	-30.6166	6.0237
BNU.ESM	1.3282	1.8296	2.4220	-226.7497	-279.9051	-280.5389
CCCMA.CANESM2	2.9507	3.7510	4.7213	-233.6825	-415.2464	-487.7075
CESM1.CAM5	1.7711	2.2656	3.1258	-72.4058	-92.4361	-168.1871
CNRM.CM5	1.5215	1.7876	2.4079	52.9802	170.6311	225.6047
CSIRO.MK3.6.0	1.9248	1.8336	3.1059	167.1291	44.2213	34.3175
ENSEMBLE	1.6332	1.9876	2.7803	5.0200	30.6839	40.4837
FIO.ESM	1.2453	0.9779	2.2963	58.2372	156.4203	208.8986
GFDL.CM3	3.3411	4.0137	4.8586	-165.6337	-169.7036	-211.8142
GFDL.ESM2G	1.3580	1.9040	2.4531	93.3676	93.0211	180.2029
GFDL.ESM2M	1.2705	1.7212	2.3924	46.3742	215.3004	181.4796
GISS.E2.H.CC	1.3364	1.9267	2.1810	-98.5705	-94.2925	-17.0422
GISS.E2.R	1.1874	1.6430	2.1755	-20.4717	12.5823	-9.5876
IPSL.CM5A.LR	2.3767	3.1656	4.1809	-123.8511	-93.3742	-106.9631
IPSL.CM5A.MR	1.8228	1.9393	3.4681	-26.8155	17.5916	63.2437
LASG.FGOALS.G2	0.9360	1.2895	1.7478	32.2912	84.1502	122.3386
MIROC.ESM	1.7590	2.1495	2.8489	-89.3386	-77.5178	-11.9684
MIROC.ESM.CHEM	1.8489	1.9758	2.6920	-55.7589	-27.7497	31.3860
MIROC.MIROC5	1.4953	1.6963	2.3296	69.4084	119.6377	108.0711
MOHC.HADGEM2.ES	1.8109	2.3877	3.2253	-22.6904	48.9433	60.8906
MPI.ESM.LR	1.6360	1.2074	3.0542	141.2899	132.9315	137.2398
MRI.CGCM3	0.9955	1.3615	1.9040	64.6772	202.9065	129.1199
NCAR.CCSM4	1.4191	1.8719	2.6572	20.5165	33.2543	-19.0725
NCC.NORESM1.M	1.2646	1.6569	2.1830	195.3439	381.9368	472.7220
NIMR.HADGEM2.AO	1.3997	2.3946	2.7783	59.3584	110.9354	89.5112

Table S2.4. GCMs used at the Sechura ecoregion level.

GCMs / RCPs	Temperature bio1 (°C) - 2050			Precipitation bio12 (mm) - 2050		
	2.6	4.5	8.5	2.6	4.5	8.5
BASELINE	0	0	0	0	0	0
BCC.CSM1.1	1.3915	1.7901	2.3960	74.6559	101.5207	193.2667
BCC.CSM1.1.M	1.4679	1.7868	2.4852	82.1658	134.7964	144.4775
BNU.ESM	1.3930	1.8668	2.5514	55.4955	109.0342	136.3712
CCCMA.CANESM2	2.2434	2.6717	3.4863	196.1495	237.3171	286.2505
CESM1.CAM5	1.6207	2.0955	2.3256	84.2829	129.2396	147.4865
CNRM.CM5	1.1222	1.4380	2.7634	15.7676	12.1387	38.8468
CSIRO.MK3.6.0	2.2216	1.5775	3.4088	-11.6090	-13.2144	1.8811
ENSEMBLE	1.5586	1.8958	2.6727	49.1495	64.2615	81.8250
FIO.ESM	1.1791	1.3274	2.1526	113.9946	117.4703	179.8216
GFDL.CM3	2.4182	3.0180	3.6919	52.2468	113.6883	127.2198
GFDL.ESM2G	1.5007	2.0000	2.6142	71.3459	68.1856	98.4018
GFDL.ESM2M	1.3625	1.9162	2.4996	61.2198	36.9063	72.2270
GISS.E2.H	1.2407	1.7825	2.3443	3.7189	16.1063	17.6432
GISS.E2.R	1.2023	1.7299	2.2768	5.5369	11.4378	13.2342
IPSL.CM5A.LR	1.9950	1.7623	3.4685	59.3622	65.3063	81.7189
IPSL.CM5A.MR	1.8286	1.4032	3.3890	27.2811	48.7099	58.6649
LASG.FGOALS.G2	1.0899	1.5173	2.1130	9.0829	15.2505	2.6234
MIROC.ESM	1.7114	2.1052	2.7314	54.6000	64.4631	98.6793
MIROC.ESM.CHEM	1.7441	2.1634	2.8995	68.0937	74.6739	80.8937
MIROC.MIROC5	1.5586	1.9020	2.3840	36.6054	67.1676	63.7081
MOHC.HADGEM2.ES	1.8067	2.1906	2.9827	25.7604	43.6703	48.9153
MPI.ESM.LR	1.7272	2.2467	2.9959	-3.4523	47.3153	45.0505
MPI.ESM.MR	1.7692	0.9144	3.1047	13.6685	0.8108	-3.5495
MRI.CGCM3	1.0321	1.5220	2.2303	38.7748	77.9838	134.2450
NCAR.CCSM4	1.3650	1.7431	2.4209	43.9964	54.5045	75.9550
NCC.NORESM1.M	1.2831	1.6966	2.1953	82.1459	103.8468	86.0613
NIMR.HADGEM2.AO	1.2494	2.2240	2.5420	16.9964	35.9658	75.9658

Table S2.5. GCMs used at the Páramo ecoregion level.

GCMs / RCPs	Temperature bio1 (°C)			Precipitation bio12 (mm)		
	2.6	4.5	8.5	2.6	4.5	8.5
BASELINE	0	0	0	0	0	0
BCC.CSM1.1	1.3735	1.7969	2.3857	137.6837	199.6429	327.4898
BCC.CSM1.1.M	1.3449	1.6735	2.3571	115.1735	130.9490	168.3980
BNU.ESM	1.3173	1.7633	2.3663	-98.8367	-87.0102	-50.2143
CCCMA.CANESM2	2.4051	2.9041	3.7929	-29.9184	-7.5510	-134.8061
CNRM.CM5	1.2418	1.5449	1.8000	19.0816	18.5714	49.3673
CSIRO.MK3.6.0	1.8429	1.6531	2.8939	184.7347	129.8469	115.7653
ENSEMBLE	1.5312	1.8412	2.6027	73.9203	93.2610	96.1990
FIO.ESM	1.1582	1.0888	2.1857	196.2449	209.0714	231.4082
GFDL.CM3	2.3735	3.0051	3.6969	-65.8673	-50.5510	-84.3163
GFDL.ESM2G	1.3520	1.8469	2.4010	92.2959	73.7347	123.1429
GFDL.ESM2M	1.2959	1.6673	2.2888	19.3776	148.0408	147.7041
GISS.E2.H	1.1755	1.6694	2.1857	33.0102	58.4184	32.0816
GISS.E2.R	1.1153	1.5398	2.0755	12.7857	119.7857	80.7755
IPSL.CM5A.LR	1.9367	2.5571	3.4041	77.7041	141.1429	209.5306
IPSL.CM5A.MR	1.7327	1.5020	3.2276	100.3469	175.7653	273.6429
LASG.FGOALS.G2	0.9163	1.2837	1.7357	34.1429	52.1122	63.6837
MIROC.ESM	1.9224	2.1673	2.8429	0.1122	-37.7449	45.2857
MIROC.ESM.CHEM	1.9286	1.9306	2.6857	32.9286	7.3163	51.7653
MIROC.MIROC5	1.3929	1.6561	2.1143	87.2959	114.3265	198.6429
MOHC.HADGEM2.ES	1.7541	2.3224	3.0214	184.4796	253.9388	243.9592
MPI.ESM.LR	1.6724	1.1673	2.9816	57.5816	97.6837	95.5306
MRI.CGCM3	1.1694	1.6418	2.2480	69.0510	96.7653	97.5714
NCAR.CCSM4	1.4398	1.8429	2.5724	60.2857	48.2755	-0.2755
NCC.NORESM1.M	1.2745	1.6776	2.2122	190.4796	285.1020	281.2959
NIMR.HADGEM2.AO	1.3041	2.2480	2.5786	241.0204	70.8571	165.2449

Table S2.6. GCMs used at the Napo ecoregion level.

GCMs / RCPs	Temperature bio1 (°C) - 2050			Precipitation bio12 (mm) - 2050		
	2.6	4.5	8.5	2.6	4.5	8.5
BASELINE	0	0	0	0	0	0
BCC.CSM1.1	1.4258	1.8560	2.4258	103.6509	99.6192	291.1318
BCC.CSM1.1.M	1.6104	2.0062	2.6855	-20.8775	-30.6166	6.0237
BNU.ESM	1.3282	1.8296	2.4220	-226.7497	-279.9051	-280.5389
CCCMA.CANESM2	2.9507	3.7510	4.7213	-233.6825	-415.2464	-487.7075
CESM1.CAM5	1.7711	2.2656	3.1258	-72.4058	-92.4361	-168.1871
CNRM.CM5	1.5215	1.7876	2.4079	52.9802	170.6311	225.6047
CSIRO.MK3.6.0	1.9248	1.8336	3.1059	167.1291	44.2213	34.3175
ENSEMBLE	1.6332	1.9876	2.7803	5.0200	30.6839	40.4837
FIO.ESM	1.2453	0.9779	2.2963	58.2372	156.4203	208.8986
GFDL.CM3	3.3411	4.0137	4.8586	-165.6337	-169.7036	-211.8142
GFDL.ESM2G	1.3580	1.9040	2.4531	93.3676	93.0211	180.2029
GFDL.ESM2M	1.2705	1.7212	2.3924	46.3742	215.3004	181.4796
GISS.E2.H.CC	1.3364	1.9267	2.1810	-98.5705	-94.2925	-17.0422
GISS.E2.R	1.1874	1.6430	2.1755	-20.4717	12.5823	-9.5876
IPSL.CM5A.LR	2.3767	3.1656	4.1809	-123.8511	-93.3742	-106.9631
IPSL.CM5A.MR	1.8228	1.9393	3.4681	-26.8155	17.5916	63.2437
LASG.FGOALS.G2	0.9360	1.2895	1.7478	32.2912	84.1502	122.3386
MIROC.ESM	1.7590	2.1495	2.8489	-89.3386	-77.5178	-11.9684
MIROC.ESM.CHEM	1.8489	1.9758	2.6920	-55.7589	-27.7497	31.3860
MIROC.MIROC5	1.4953	1.6963	2.3296	69.4084	119.6377	108.0711
MOHC.HADGEM2.ES	1.8109	2.3877	3.2253	-22.6904	48.9433	60.8906
MPI.ESM.LR	1.6360	1.2074	3.0542	141.2899	132.9315	137.2398
MRI.CGCM3	0.9955	1.3615	1.9040	64.6772	202.9065	129.1199
NCAR.CCSM4	1.4191	1.8719	2.6572	20.5165	33.2543	-19.0725
NCC.NORESM1.M	1.2646	1.6569	2.1830	195.3439	381.9368	472.7220
NIMR.HADGEM2.AO	1.3997	2.3946	2.7783	59.3584	110.9354	89.5112

Table S2.7. Sechura Temperature: Anderson-Darling Normality Test (alpha = 0.05).

	Level	Statistic	p.value	Normality
1	1970-2000	7543.17	3.70E-24	Reject
2	26	6747.25	3.70E-24	Reject
3	45	6920.95	3.70E-24	Reject
4	85	6944.71	3.70E-24	Reject

Table S2.8. Sechura Precipitation: Anderson-Darling Normality Test ($\alpha = 0.05$).

	Level	Statistic	p.value	Normality
1	1970-2000	18829.6	3.7E-24	Reject
2	26	21371.9	3.7E-24	Reject
3	45	21365.9	3.7E-24	Reject
4	85	21452.9	3.7E-24	Reject

Table S2.9. Páramo Temperature: Anderson-Darling Normality Test ($\alpha = 0.05$).

	Level	Statistic	p.value	Normality
1	1970-2000	275.73	3.7E-24	Reject
2	26	347.303	3.7E-24	Reject
3	45	342.764	3.7E-24	Reject
4	85	334.439	3.7E-24	Reject

Table S2.10. Páramo Precipitation: Anderson-Darling Normality Test ($\alpha = 0.05$).

	Level	Statistic	p.value	Normality
1	1970-2000	1459.71	3.7E-24	Reject
2	26	1812.624	3.7E-24	Reject
3	45	1689.895	3.7E-24	Reject
4	85	1530.427	3.7E-24	Reject

Table S2.11. Napo Temperature: Anderson-Darling Normality Test ($\alpha = 0.05$).

	Level	Statistic	p.value	Normality
1	1970-2000	1485.53	3.7E-24	Reject
2	26	4869.66	3.7E-24	Reject
3	45	4111.94	3.7E-24	Reject
4	85	4648.83	3.7E-24	Reject

Table S2.12. Napo Precipitation: Anderson-Darling Normality Test ($\alpha = 0.05$).

	Level	Statistic	p.value	Normality
1	1970-2000	1564.38	3.7E-24	Reject
2	26	1139.97	3.7E-24	Reject
3	45	1117.29	3.7E-24	Reject
4	85	1185.25	3.7E-24	Reject

Table S2.13. Kruskal-Wallis test (Multiple comparison) for temperature (C°) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Sechura ecoregion.

Kruskal-Wallis test				
data: t and group				
Kruskal-Wallis chi-squared = 873483, df = 3, p-value < 2.2e-16				
> kruskalmc(t, group, probs = .05)				
Multiple comparison test after Kruskal-Wallis				
p.value: 0.05				
Comparisons	obs.dif	critical.dif	difference	
1970-2000-26	218371	2013.257	TRUE	
1970-2000-45	436742	2013.257	TRUE	
1970-2000-85	655113	2013.257	TRUE	
26-45	218371	2013.257	TRUE	
26-85	436742	2013.257	TRUE	
45-85	218371	2013.257	TRUE	

Table S2.14. Kruskal-Wallis test (Multiple comparison) for annual precipitation (mm) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Sechura ecoregion.

Kruskal-Wallis test				
data: p and group				
Kruskal-Wallis chi-squared = 873483, df = 3, p-value < 2.2e-16				
> kruskalmc(p, group, probs = .05)				
Multiple comparison test after Kruskal-Wallis				
p.value: 0.05				
Comparisons	obs.dif	critical.dif	difference	
1970-2000-26	218371	2013.257	TRUE	
1970-2000-45	436742	2013.257	TRUE	
1970-2000-85	655113	2013.257	TRUE	
26-45	218371	2013.257	TRUE	
26-85	436742	2013.257	TRUE	
45-85	218371	2013.257	TRUE	

Table S2.15. Kruskal-Wallis test (Multiple comparison) for temperature (C°) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Páramo ecoregion.

Kruskal-Wallis test			
data: t and group			
Kruskal-Wallis chi-squared = 215195, df = 3, p-value < 2.2e-16			
> kruskalmc(t, group, probs = .05)			
Multiple comparison test after Kruskal-Wallis			
p.value: 0.05			
Comparisons	obs.dif	critical.dif	difference
1970-2000-26	53799	999.286	TRUE
1970-2000-45	107598	999.286	TRUE
1970-2000-85	161397	999.286	TRUE
26-45	53799	999.286	TRUE
26-85	107598	999.286	TRUE
45-85	53799	999.286	TRUE

Table S2.16. Kruskal-Wallis test (Multiple comparison) for annual precipitation (mm) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Páramo ecoregion.

Kruskal-Wallis test			
data: p and group			
Kruskal-Wallis chi-squared = 216175, df = 3, p-value < 2.2e-16			
> kruskalmc(p, group, probs = .05)			
Multiple comparison test after Kruskal-Wallis			
p.value: 0.05			
Comparisons	obs.dif	critical.dif	difference
1970-2000-26	54044	1001.558	TRUE
1970-2000-45	108088	1001.558	TRUE
1970-2000-85	162132	1001.558	TRUE
26-45	54044	1001.558	TRUE
26-85	108088	1001.558	TRUE
45-85	54044	1001.558	TRUE

Table S2.17. Kruskal-Wallis test (Multiple comparison) for temperature (C°) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Napo ecoregion.

Kruskal-Wallis test			
data: t and group			
Kruskal-Wallis chi-squared = 1173667, df = 3, p-value < 2.2e-16			
> kruskalmc(t, group, probs = .05)			
Multiple comparison test after Kruskal-Wallis			
p.value: 0.05			
Comparisons	obs.dif	critical.dif	difference
1970-2000-26	293417	2333.7	TRUE
1970-2000-45	586834	2333.7	TRUE
1970-2000-85	880251	2333.7	TRUE
26-45	293417	2333.7	TRUE
26-85	586834	2333.7	TRUE
45-85	293417	2333.7	TRUE

Table S2.18. Kruskal-Wallis test (Multiple comparison) for annual precipitation (mm) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Napo ecoregion.

Kruskal-Wallis test			
data: p and group			
Kruskal-Wallis chi-squared = 1173667, df = 3, p-value < 2.2e-16			
> kruskalmc(p, group, probs = .05)			
Multiple comparison test after Kruskal-Wallis			
p.value: 0.05			
Comparisons	obs.dif	critical.dif	difference
1970-2000-26	293417	2333.7	TRUE
1970-2000-45	586834	2333.7	TRUE
1970-2000-85	880251	2333.7	TRUE
26-45	293417	2333.7	TRUE
26-85	586834	2333.7	TRUE
45-85	293417	2333.7	TRUE

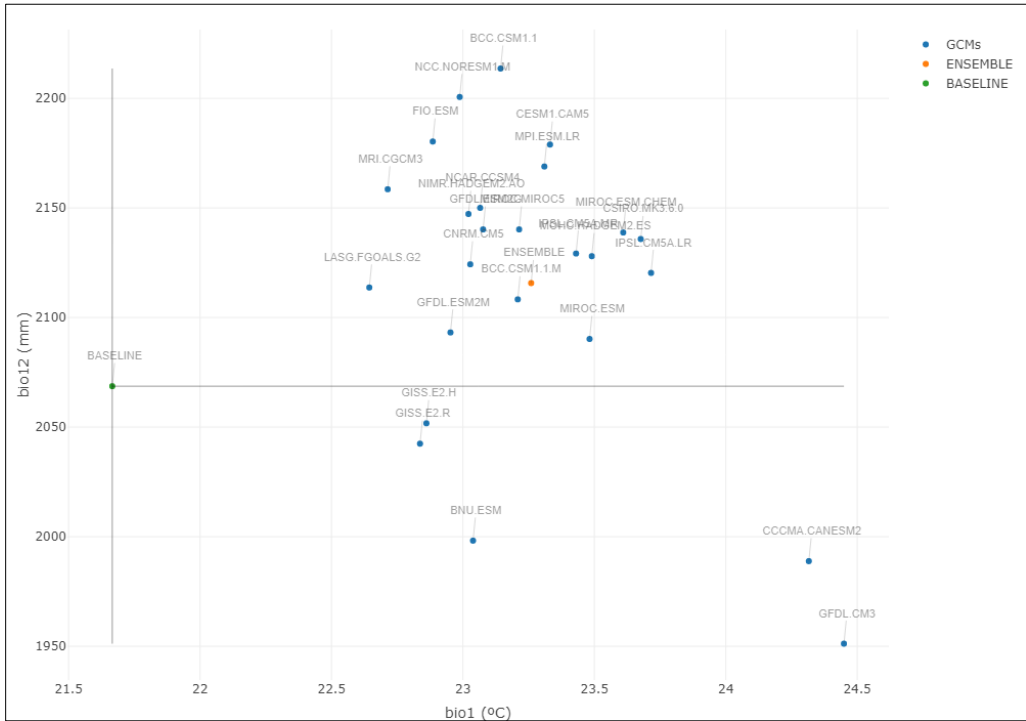


Figure S2.1. GCMs for the annual precipitation (mm) vs. temperature (°C) variables for the three countries for RCP 2.6.

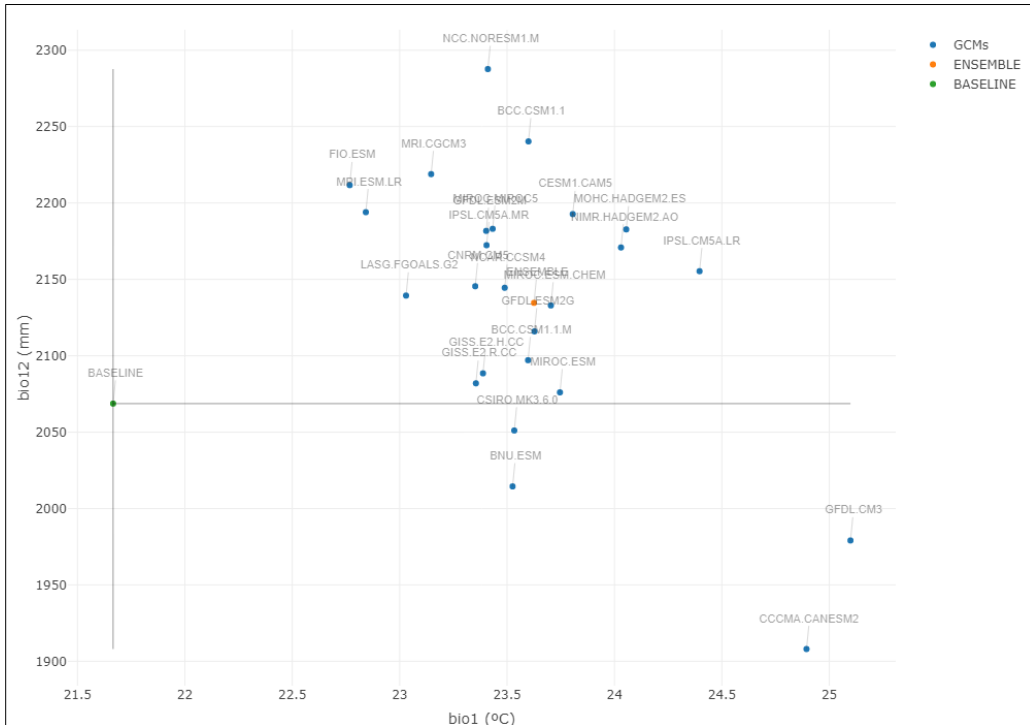


Figure S2.2. GCMs for the annual precipitation (mm) vs. temperature (°C) variables for the three countries for RCP 4.5.

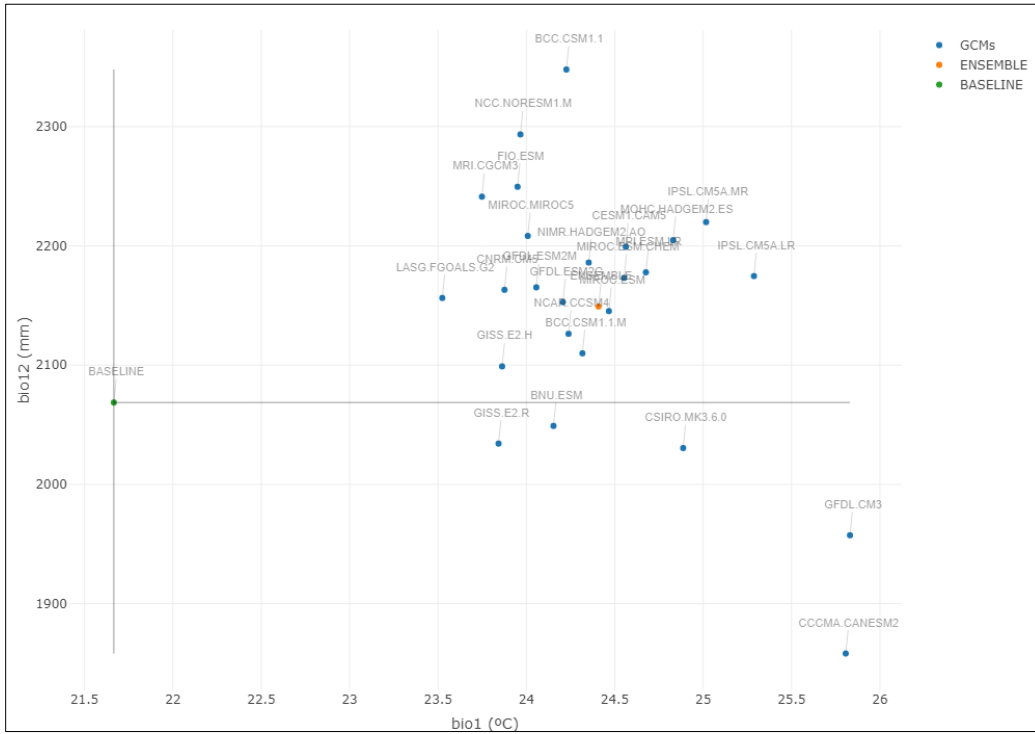


Figure S2.3. GCMs for the annual precipitation (mm) vs. temperature (°C) variables for the three countries for RCP 8.5.

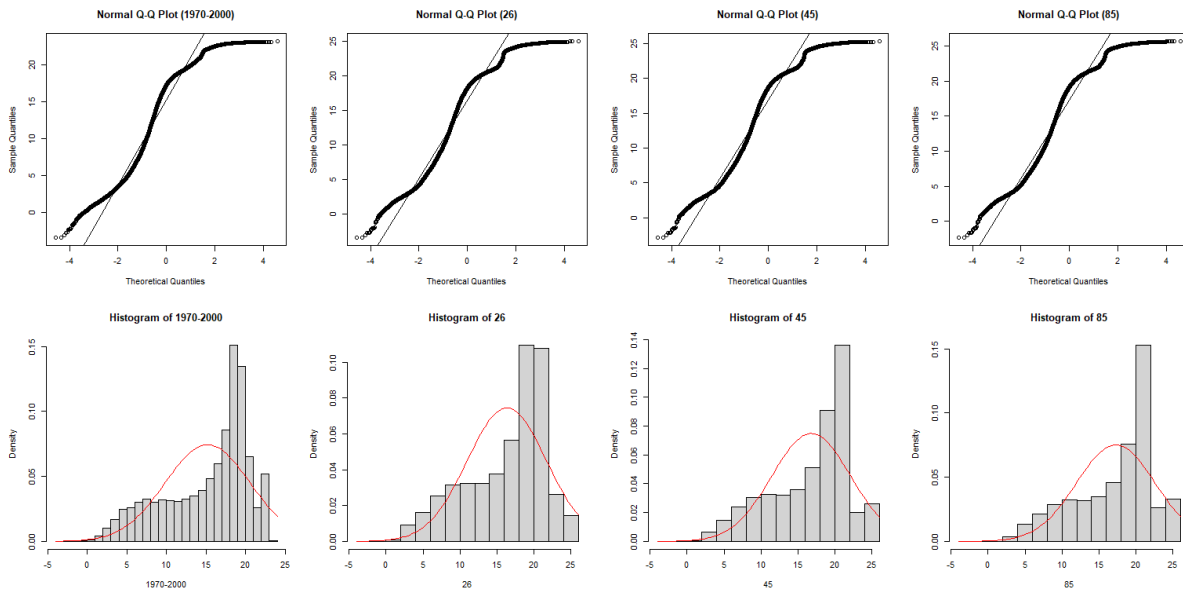


Figure S2.4. Q-Q plots and histograms for temperature (°C) in the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Secura ecoregion.

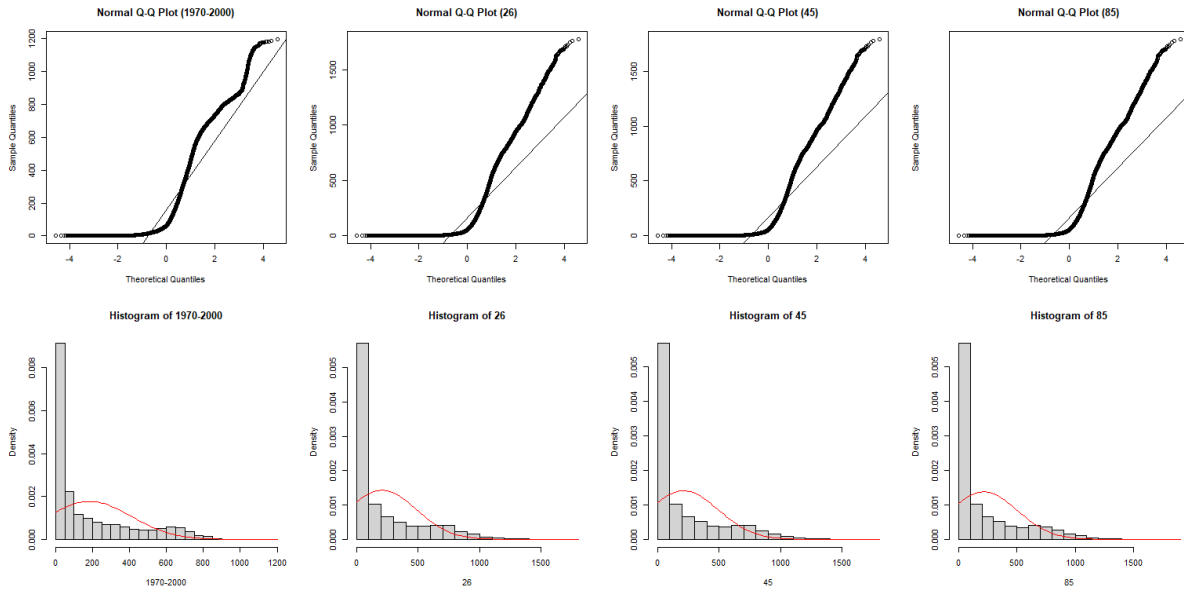


Figure S2.5. Q-Q plots and histograms for precipitation (mm) in the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Sechura ecoregion.

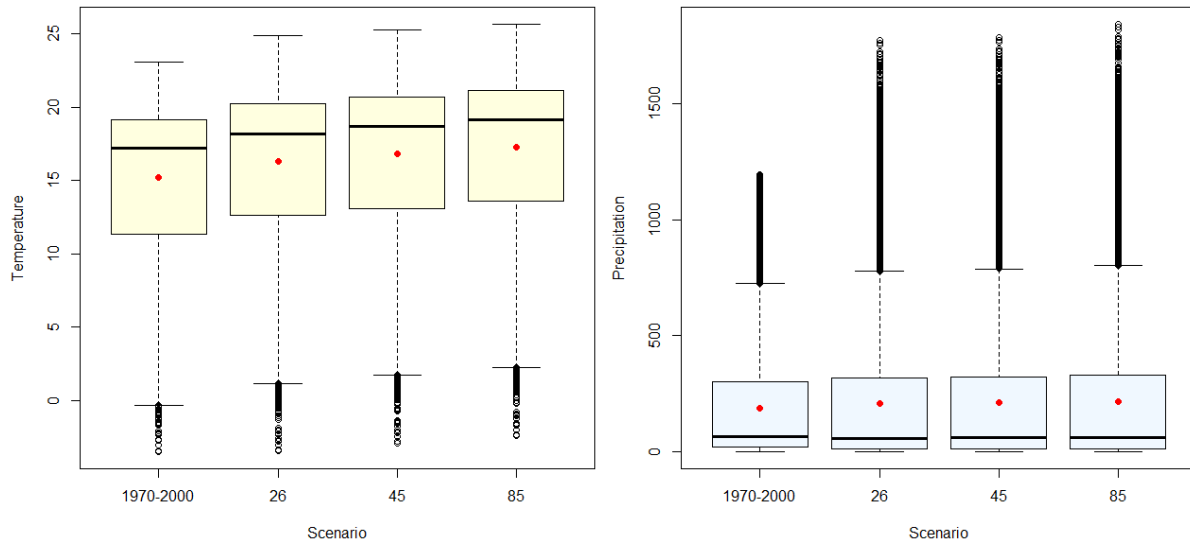


Figure S2.6. Boxplots for temperature (°C) (left) and precipitation (mm) (right) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Sechura ecoregion.

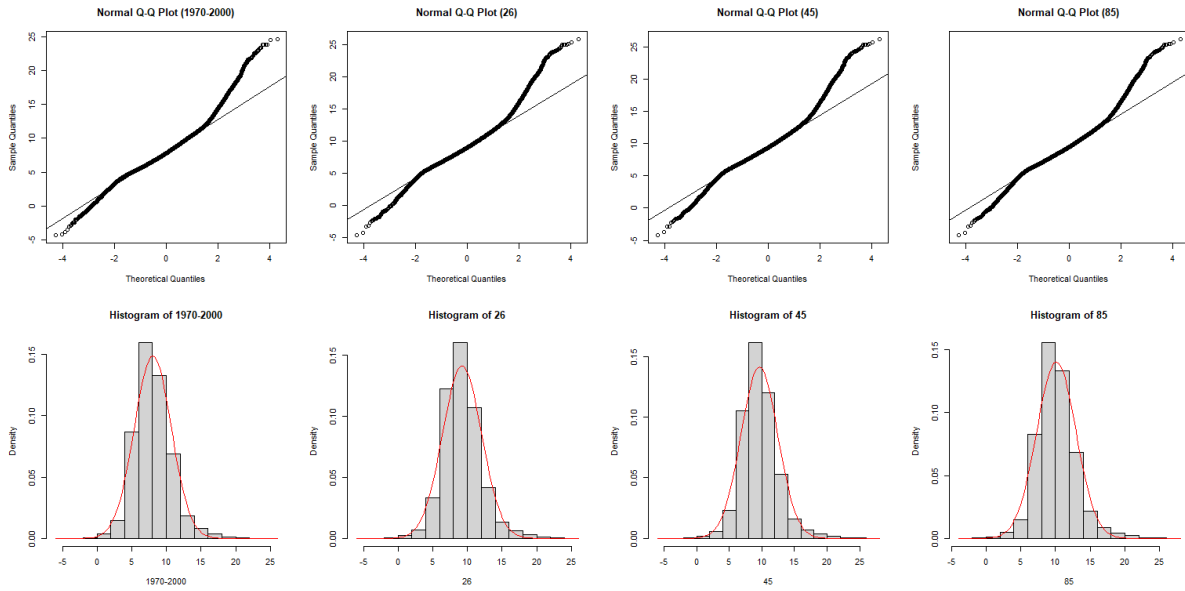


Figure S2.7. Q-Q plots and histograms for temperature (°C) in the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Páramo ecoregion.

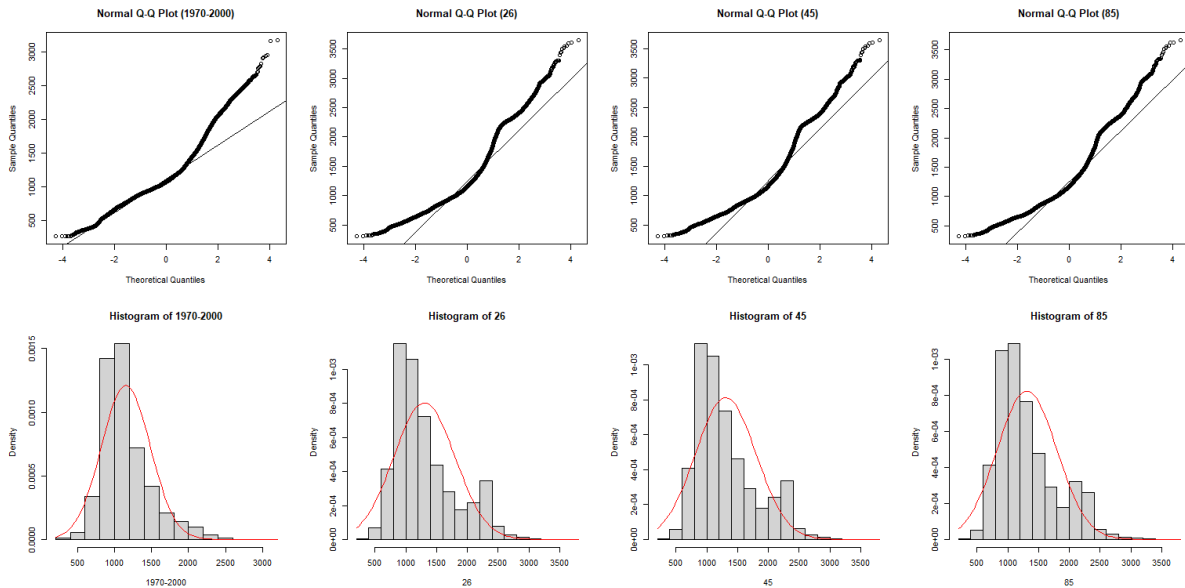


Figure S2.8. Q-Q plots and histograms for precipitation (mm) in the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Páramo ecoregion.

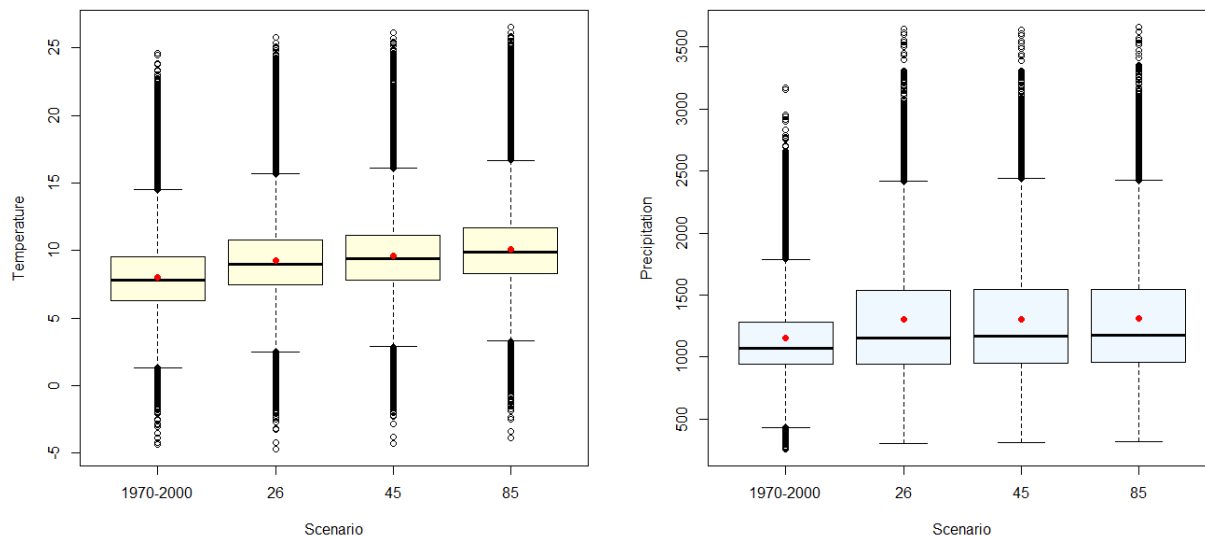


Figure S2.9. Boxplots for temperature ($^{\circ}\text{C}$) (left) and precipitation (mm) (right) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Páramo ecoregion.

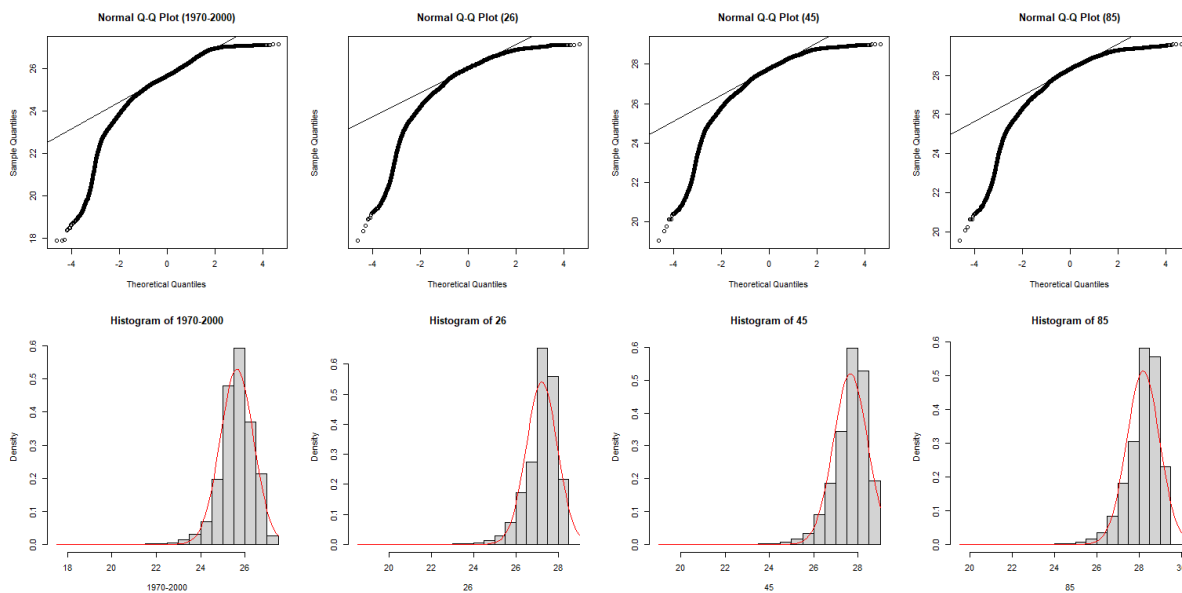


Figure S2.10. Q-Q plots and histograms for temperature ($^{\circ}\text{C}$) in the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Napo ecoregion.

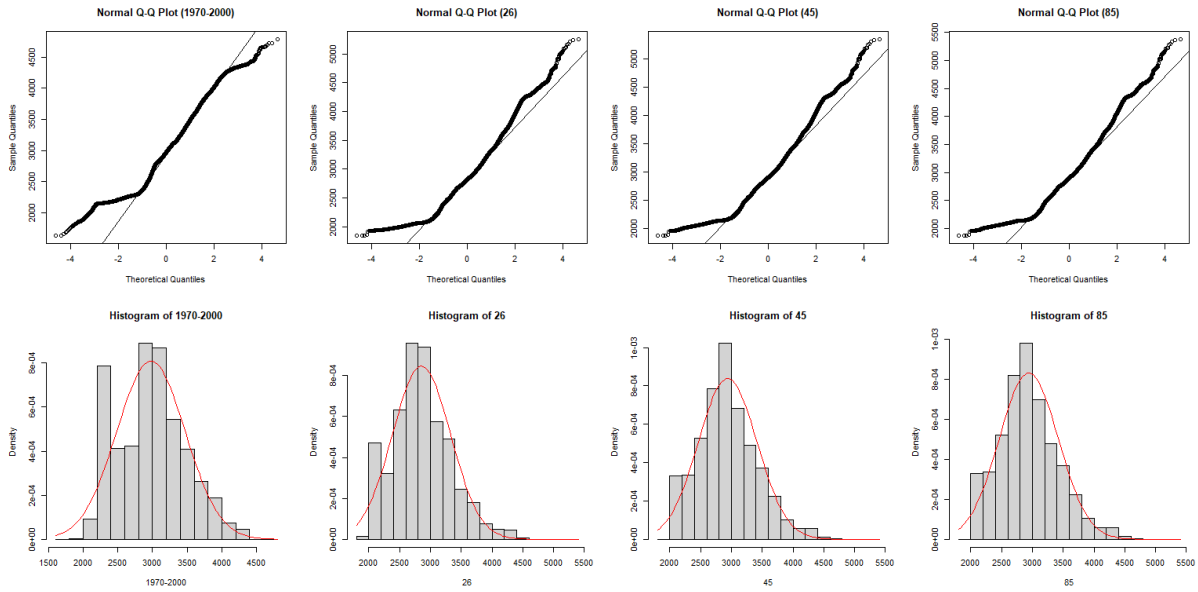


Figure S2.11. Q-Q plots and histograms for precipitation (mm) in the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Napo ecoregion.

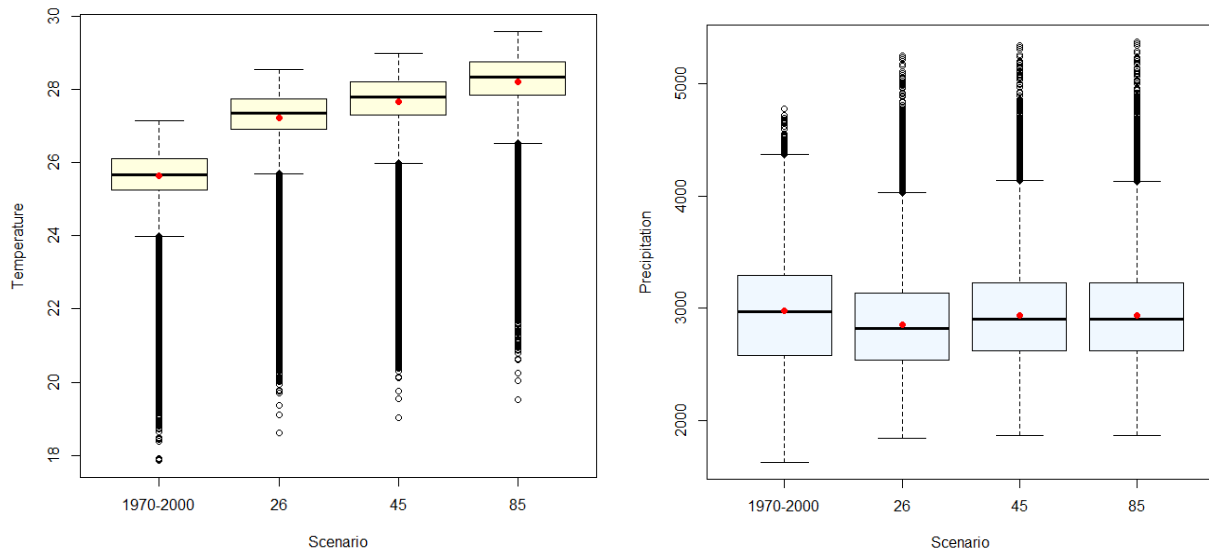


Figure S2.12. Boxplots for temperature (°C) (left) and precipitation (mm) (right) for the baseline (1970-2000) and the three RCPs 2.6, 4.5 and 8.5 for 2050 in the Napo ecoregion.

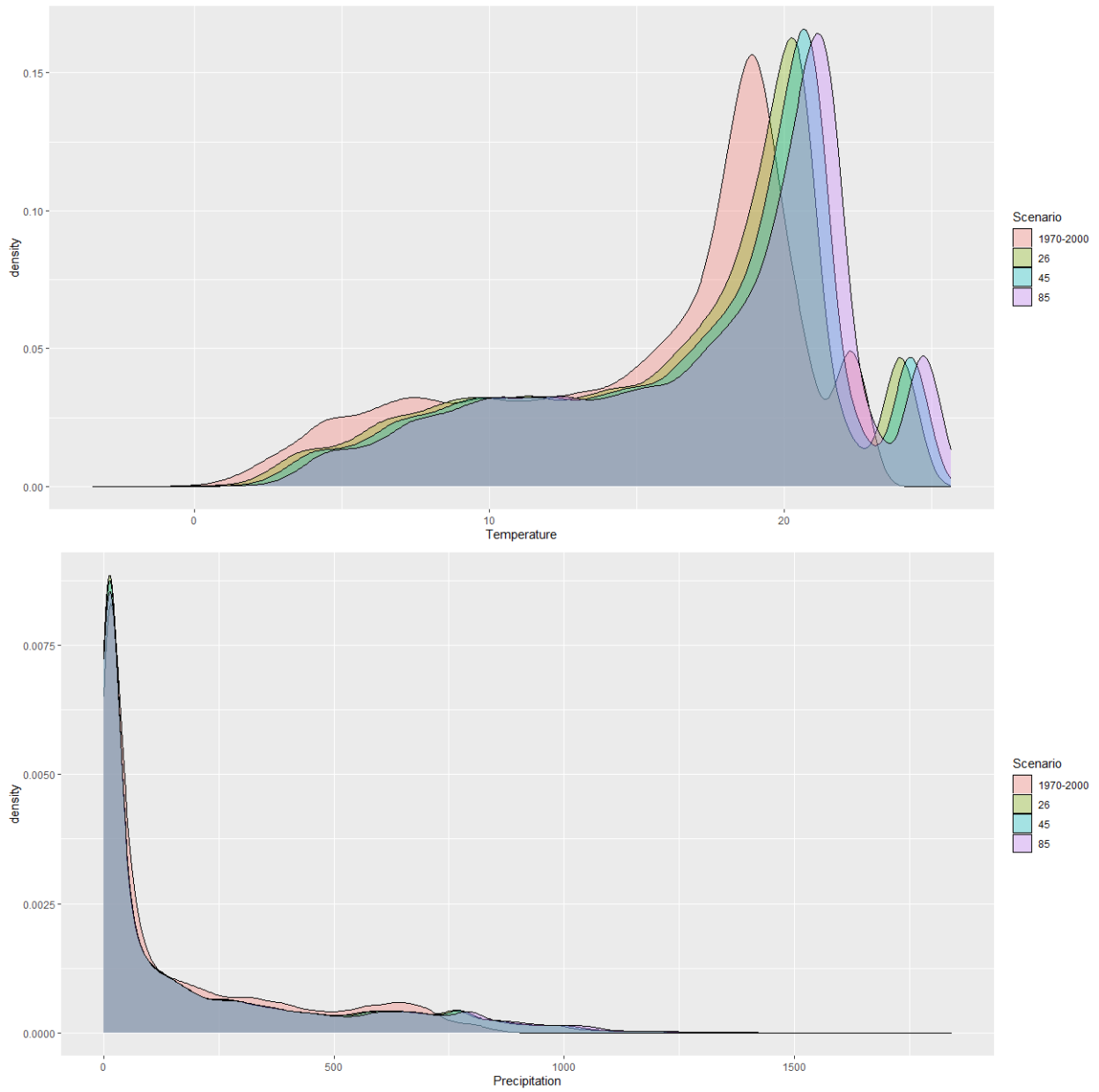


Figure S2.13. Density plots for temperature (°C) and annual precipitation (mm) for the 1970-2000 baseline and the three 2050 RCPs 2.6, 4.5 and 8.5 for the Sechura Desert.

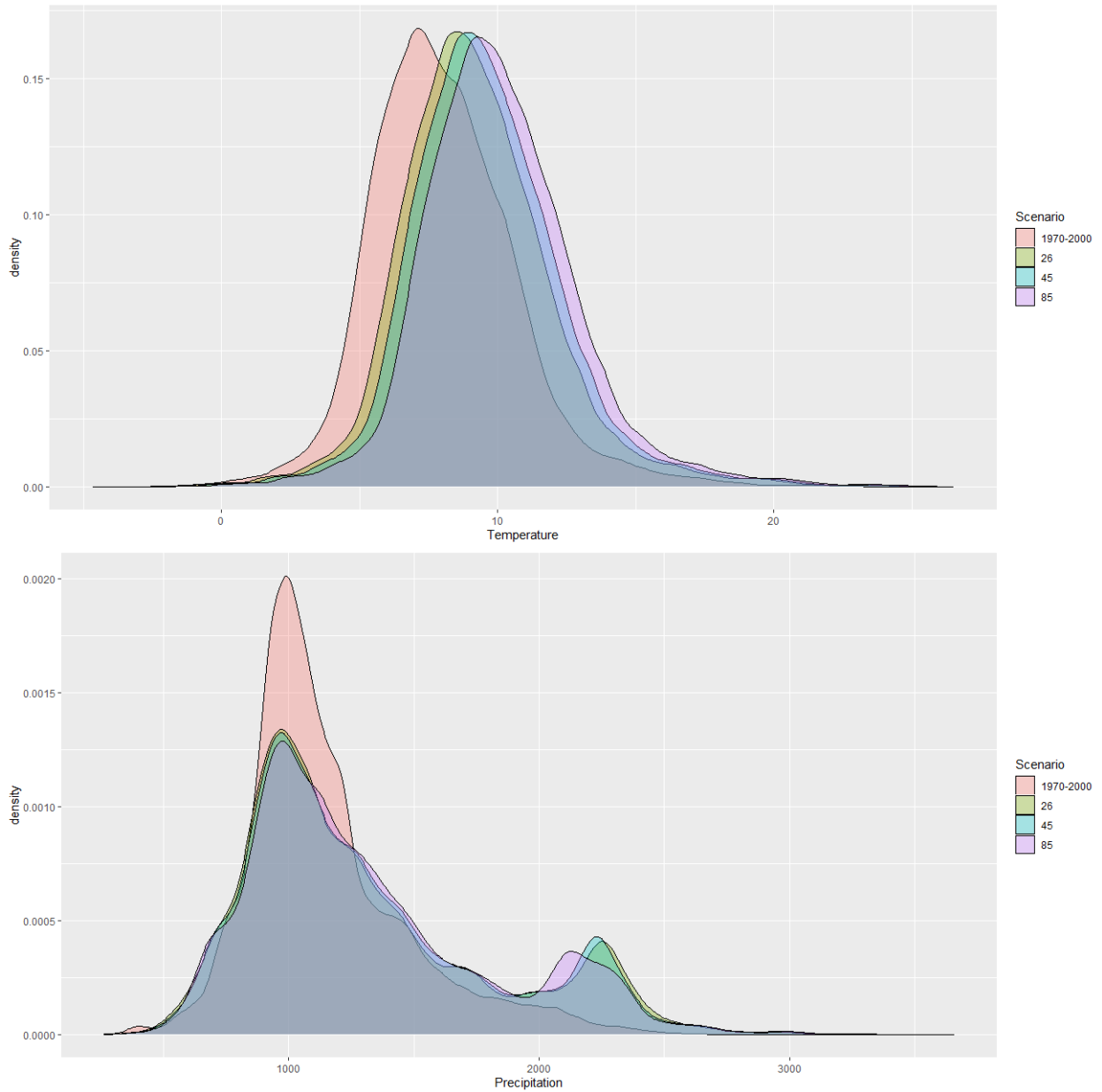


Figure S2.14. Density plots for temperature (°C) and annual precipitation (mm) for the 1970-2000 baseline and the three 2050 RCPs 2.6, 4.5 and 8.5 for the Páramo.

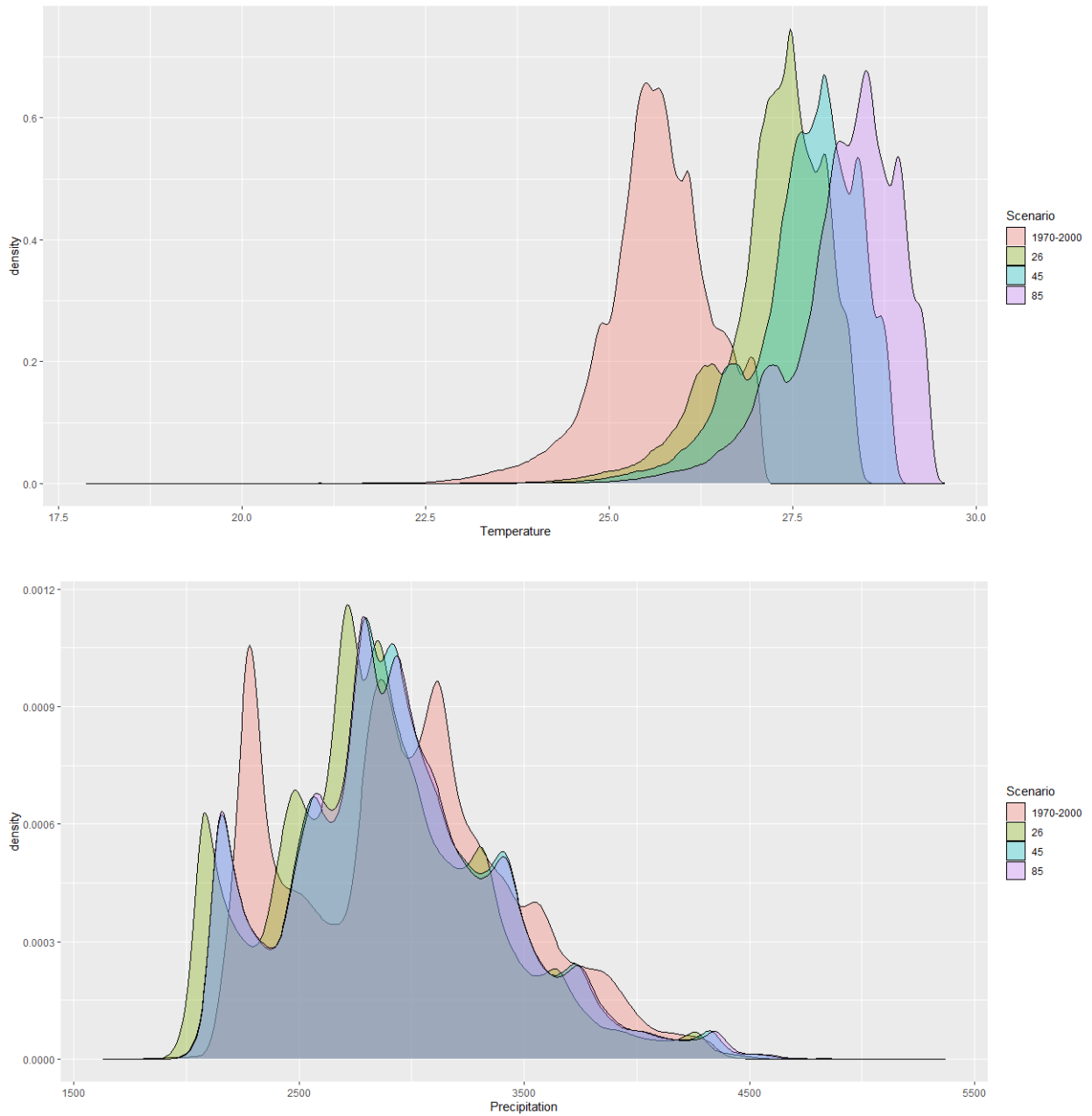


Figure S2.15. Density plots for temperature (°C) and annual precipitation (mm) for the 1970-2000 baseline and the three 2050 RCPs 2.6, 4.5 and 8.5 for the Napo.

APPENDIX B

SUPPLEMENTAL TABLES AND FIGURES FOR CHAPTER 3

Table S3.1 Model Mean performance for the spectacled bear (baseline) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance

glm	:	0.86		0.66		0.66		0.92
maxent	:	0.92		0.74		0.71		0.81
brt	:	0.91		0.74		0.7		0.87
rf	:	0.96		0.83		0.81		0.48
fda	:	0.86		0.65		0.63		0.94

11 variables from the 21 input variables have collinearity problem:

bio5 bio11 bio1 bio10 bio6 bio2 bio8 bio9 bio16 bio17 bio12

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (bio19 ~ bio15): 0.008531107

max correlation (bio7 ~ bio4): 0.7534253

----- VIFs of the remained variables -----

	Variables	VIF
1	bio13	8.123606
2	bio14	7.290143
3	bio15	4.301814
4	bio18	4.297511
5	bio19	6.167758
6	bio3	3.786327
7	bio4	5.178352
8	bio7	5.420382
9	elev	1.859150
10	HFPL	1.221135

Table S3.2. Model Mean performance for the spectacled bear (RCP 2.6) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance

glm	:	0.87		0.68		0.69		0.88
maxent	:	0.91		0.73		0.7		0.85
brt	:	0.9		0.73		0.71		0.88
rf	:	0.96		0.86		0.84		0.47
fda	:	0.85		0.66		0.66		0.92

11 variables from the 21 input variables have collinearity problem:

bio5 bio11 bio1 bio10 bio7 bio9 bio8 bio16 bio17 bio12 elev

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (bio3 ~ bio2): 0.01021654

max correlation (bio18 ~ bio13): 0.8039624

----- VIFs of the remained variables -----

	Variables	VIF
1	bio13	7.455093
2	bio14	6.138331
3	bio15	5.950620
4	bio18	4.030637
5	bio19	5.338846
6	bio2	6.027592
7	bio3	4.121786
8	bio4	6.834590
9	bio6	1.666195
10	HFPL	1.150856

Table S3.3. Model Mean performance for the spectacled bear (RCP 4.5) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance
glm	:	0.87		0.69		0.69		0.89
maxent	:	0.92		0.77		0.73		0.77
brt	:	0.92		0.76		0.75		0.86
rf	:	0.98		0.88		0.87		0.4
fda	:	0.85		0.67		0.68		0.92

11 variables from the 21 input variables have collinearity problem:

bio5 bio11 bio1 bio10 bio7 bio9 bio8 bio16 bio17 elev bio12

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (bio15 ~ bio13): 0.001919466

max correlation (bio2 ~ bio19): -0.7616819

----- VIFs of the remained variables -----

	Variables	VIF
1	bio13	6.587542
2	bio14	5.946828
3	bio15	5.384586
4	bio18	3.457398
5	bio19	5.378554
6	bio2	5.805121
7	bio3	5.164472
8	bio4	7.941285
9	bio6	1.620745
10	HFPL	1.146155

Table S3.4. Model Mean performance for the spectacled bear (RCP 8.5) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance
glm	:	0.85		0.66		0.66		0.93
maxent	:	0.9		0.73		0.69		0.84
brt	:	0.9		0.74		0.7		0.89
rf	:	0.97		0.86		0.84		0.44
fda	:	0.83		0.64		0.63		0.97

11 variables from the 21 input variables have collinearity problem:

bio5 bio11 bio1 bio10 bio7 bio9 bio8 bio16 elev bio12 bio17

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (bio4 ~ bio18): 0.02745786

max correlation (bio18 ~ bio13): 0.7792883

----- VIFs of the remained variables -----

Variables	VIF
1 bio13	7.273928
2 bio14	6.396272
3 bio15	5.343866
4 bio18	3.509488
5 bio19	5.097230
6 bio2	5.723828
7 bio3	5.720737
8 bio4	7.364159
9 bio6	1.692291
10 HFPL	1.150334

Table S3.5. Model Mean performance for the Páramo (baseline) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance

glm	:	0.98		0.91		0.89		0.19
maxent	:	0.97		0.91		0.89		0.82
brt	:	0.97		0.91		0.9		0.35
rf	:	0.99		0.96		0.94		0.11
fda	:	0.97		0.9		0.88		0.48

12 variables from the 21 input variables have collinearity problem:

bio5 bio1 bio11 bio2 bio10 bio6 bio8 bio16 bio9 bio17 bio12 bio15

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (HFPL ~ bio19): -0.0007031895

max correlation (bio7 ~ bio19): -0.6531652

----- VIFs of the remained variables -----

	Variables	VIF
1	bio13	4.273681
2	bio14	2.893106
3	bio18	2.678720
4	bio19	4.336138
5	bio3	3.406332
6	bio4	2.135936
7	bio7	2.251089
8	elev	1.337777
9	HFPL	1.048017

Table S3.6. Model Mean performance for the Páramo (2.6) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance
glm	:	0.97		0.91		0.89		0.2
maxent	:	0.98		0.91		0.89		0.81
brt	:	0.97		0.92		0.9		0.35
rf	:	0.98		0.96		0.95		0.11
fda	:	0.97		0.9		0.89		0.46

11 variables from the 21 input variables have collinearity problem:

bio5 bio11 bio1 bio7 bio10 bio6 bio16 bio8 bio17 bio12 bio9

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (HFPL ~ bio14): -0.01175494

max correlation (bio15 ~ bio14): -0.7506265

----- VIFs of the remained variables -----

	Variables	VIF
1	bio13	7.688562
2	bio14	8.297999
3	bio15	9.387632
4	bio18	2.811522
5	bio19	5.131476
6	bio2	4.122824
7	bio3	2.805719
8	bio4	3.024212
9	elev	1.131320
10	HFPL	1.118382

Table S3.7. Model Mean performance for the Páramo (4.5) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance
glm	:	0.98		0.91		0.89		0.19
maxent	:	0.98		0.91		0.89		0.82
brt	:	0.97		0.91		0.9		0.34
rf	:	0.99		0.96		0.95		0.11
fda	:	0.97		0.9		0.89		0.45

11 variables from the 21 input variables have collinearity problem:

bio5 bio11 bio1 bio7 bio10 bio6 bio16 bio8 bio17 bio12 bio9

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (HFPL ~ bio14): 0.005328383

max correlation (bio4 ~ bio3): -0.7291163

----- VIFs of the remained variables -----

	Variables	VIF
1	bio13	8.052857
2	bio14	7.797299
3	bio15	7.990109
4	bio18	2.803044
5	bio19	5.497189
6	bio2	3.752892
7	bio3	2.743437
8	bio4	2.918318
9	elev	1.224608
10	HFPL	1.121746

Table S3.8. Model Mean performance for the Páramo (8.5) using the test dataset (generated by partitioning) and collinearity analysis of variables (VIF).

methods	:	AUC		COR		TSS		Deviance
glm	:	0.98		0.92		0.89		0.18
maxent	:	0.98		0.92		0.9		0.81
brt	:	0.98		0.92		0.9		0.34
rf	:	0.99		0.96		0.95		0.1
fda	:	0.97		0.91		0.89		0.41

11 variables from the 21 input variables have collinearity problem:

bio5 bio11 bio10 bio7 bio1 bio6 bio16 bio8 bio17 bio12 bio9

After excluding the collinear variables, the linear correlation coefficients ranges between:

min correlation (HFPL ~ bio14): -0.001639866

max correlation (bio4 ~ bio3): -0.810439

----- VIFs of the remained variables -----

Variables	VIF
1 bio13	8.287111
2 bio14	8.271138
3 bio15	8.929230
4 bio18	2.938955
5 bio19	6.120522
6 bio2	3.574268
7 bio3	3.835978
8 bio4	3.561866
9 elev	1.256125
10 HFPL	1.121957

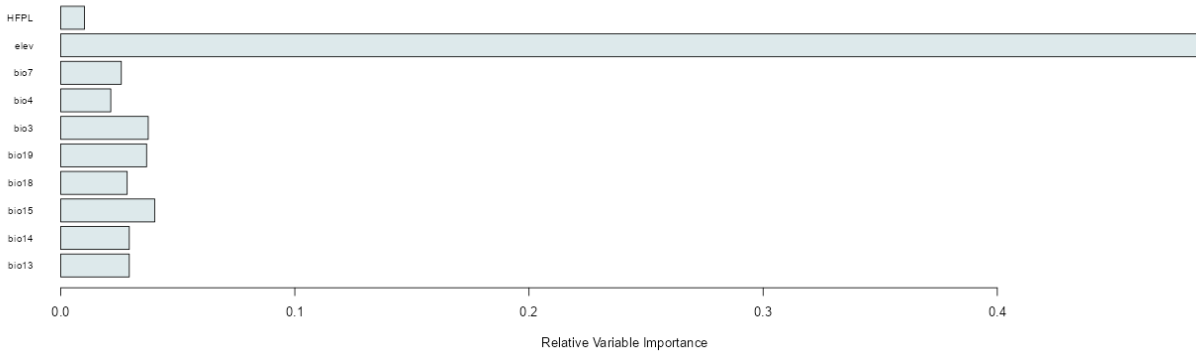


Figure S3.1. Relative importance of the variables, using the `getVarImp` function of the `SDM` package for R for the spectacled bear at the baseline (1970-2000).

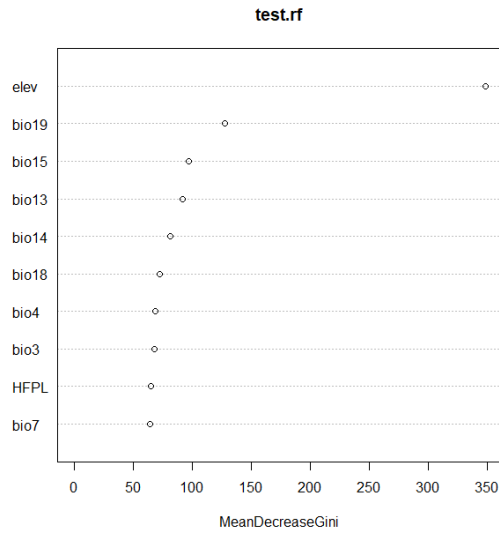


Figure S3.2. Relative importance of the variables, using Random Forest for the spectacled bear at the baseline (1970-2000).

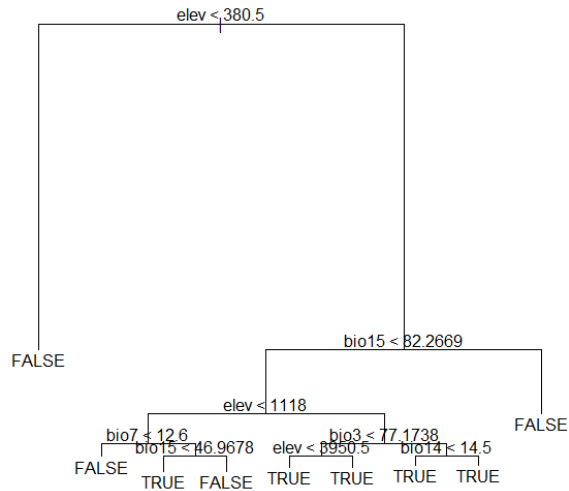


Figure S3.3. Relative importance of the variables, using Decision Trees for the spectacled bear at the baseline (1970-2000).

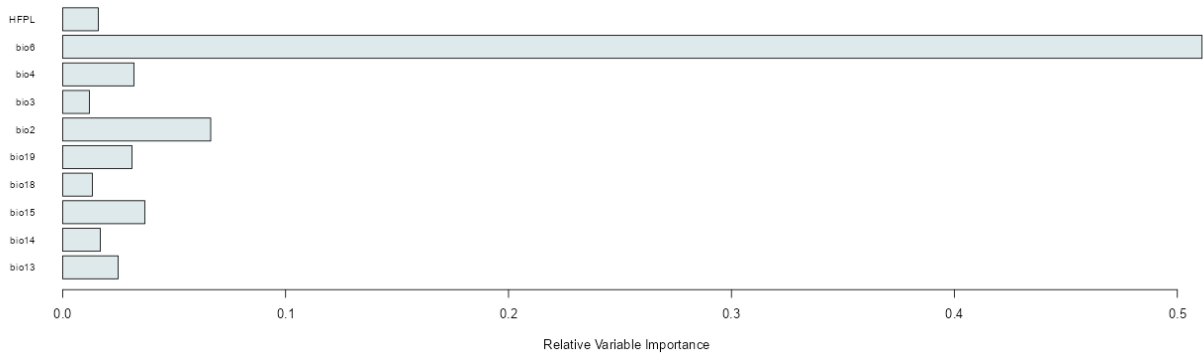


Figure S3.4. Relative importance of the variables, using the getVarImp function of the SDM package for R for the spectacled bear in the RCP 2.6.

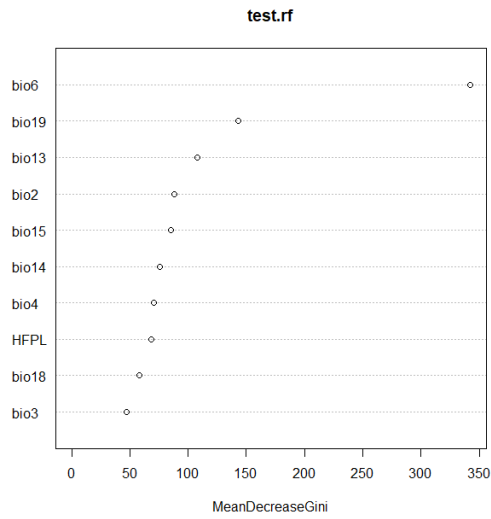


Figure S3.5. Relative importance of the variables, using Random Forest for the spectacled bear in the RCP 2.6.

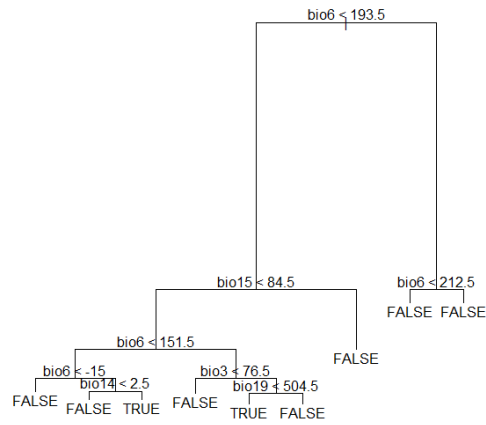


Figure S3.6. Relative importance of the variables, using Decision Trees for the spectacled bear in the RCP 2.6.

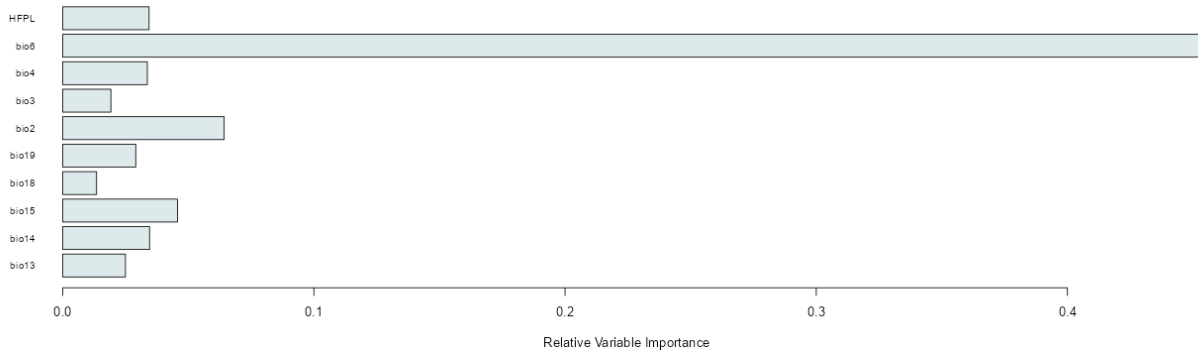


Figure S3.7. Relative importance of the variables, using the getVarImp function of the SDM package for R for the spectacled bear in the RCP 4.5.

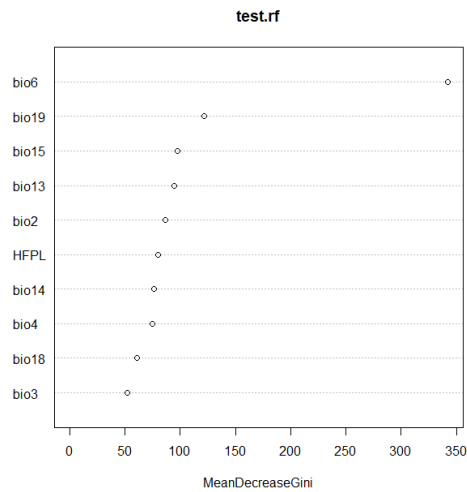


Figure S3.8. Relative importance of the variables, using Random Forest for the spectacled bear in the RCP 4.5.

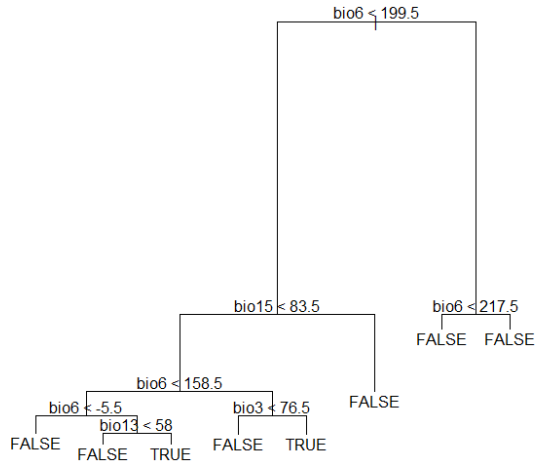


Figure S3.9. Relative importance of the variables, using Decision Trees for the spectacled bear in the RCP 4.5.

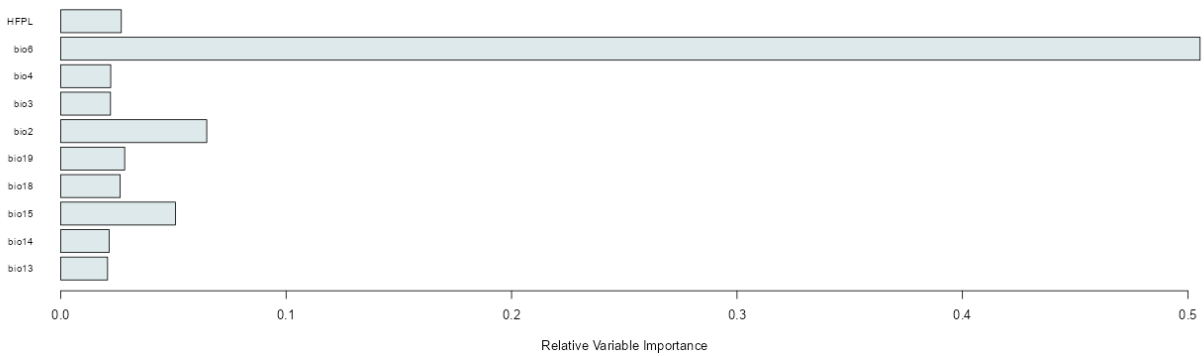


Figure S3.10. Relative importance of the variables, using the getVarImp function of the SDM package for R for the spectacled bear in the RCP 8.5.

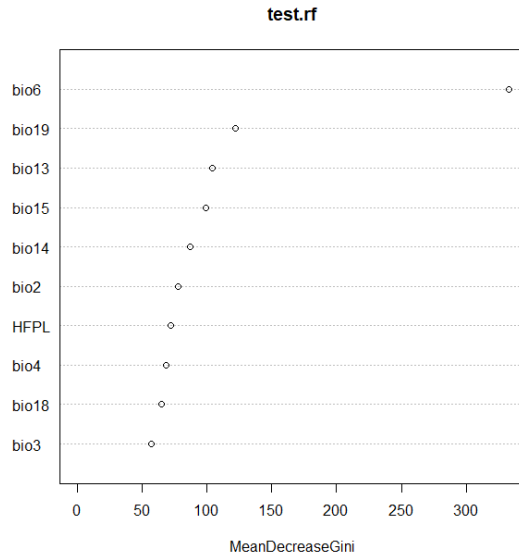


Figure S3.11. Relative importance of the variables, using Random Forest for the spectacled bear in the RCP 8.5.

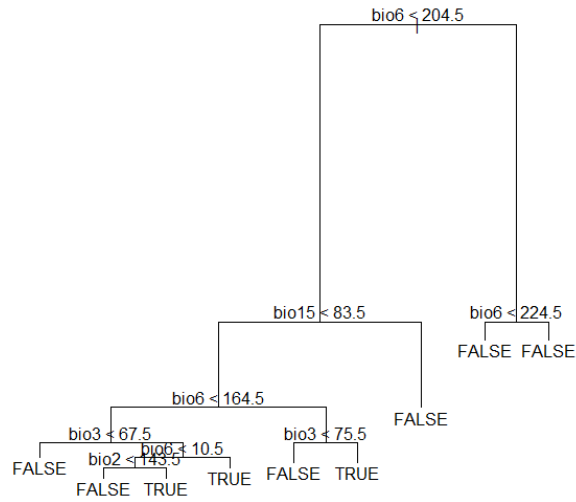


Figure S3.12. Relative importance of the variables, using Decision Trees for the spectacled bear in the RCP 8.5.

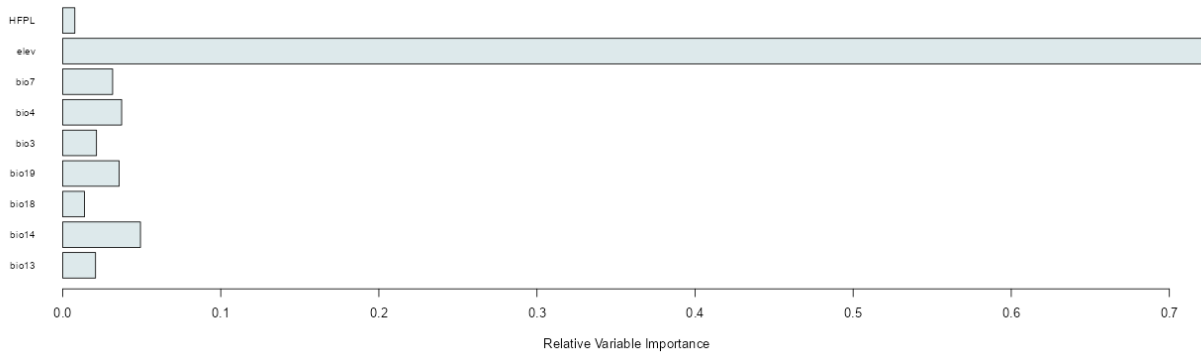


Figure S3.13. Relative importance of the variables, using the `getVarImp` function of the `SDM` package for R for the Páramo at the baseline (1970-2000).

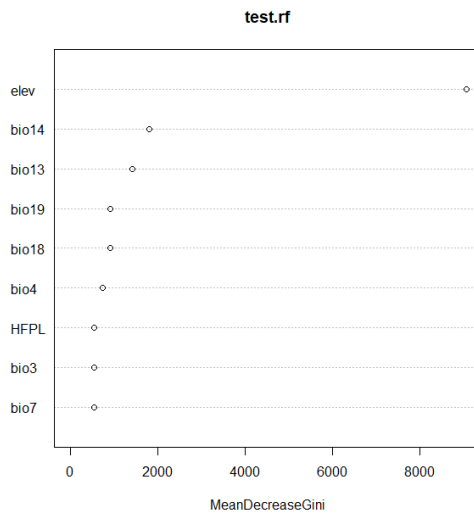


Figure S3.14. Relative importance of the variables, using Random Forest for the Páramo at the baseline (1970-2000).

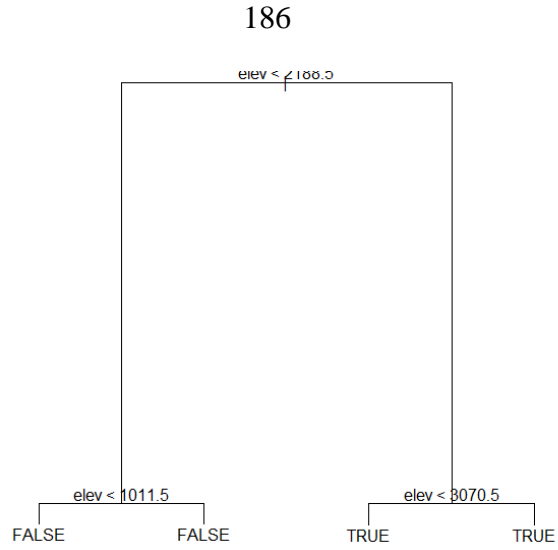


Figure S3.15. Relative importance of the variables, using Decision Trees for the Páramo at the baseline (1970-2000).

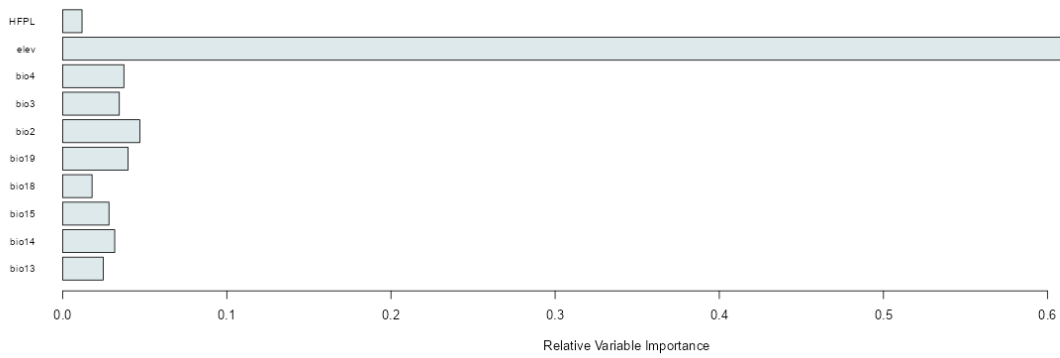


Figure S3.16. Relative importance of the variables, using the getVarImp function of the SDM package for R for the Páramo in the RCP 2.6.

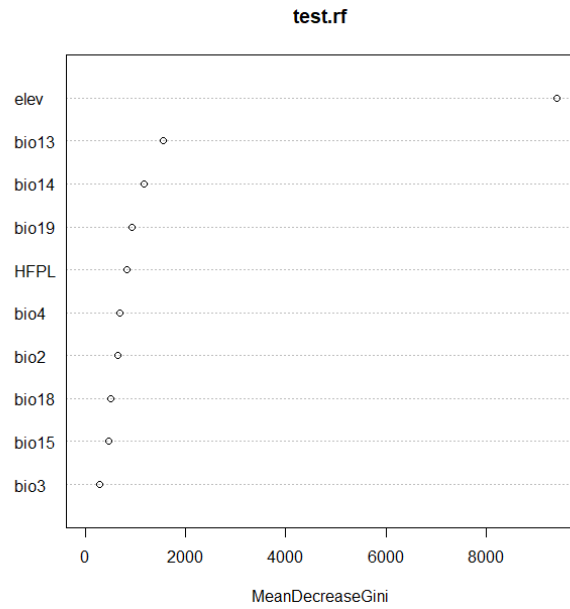


Figure S3.17. Relative importance of the variables, using Random Forest for the Páramo in the RCP 2.6.

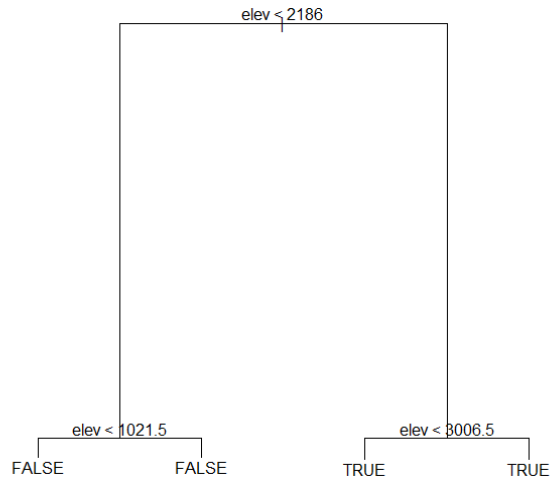


Figure S3.18. Relative importance of the variables, using Decision Trees for the Páramo in the RCP 2.6.

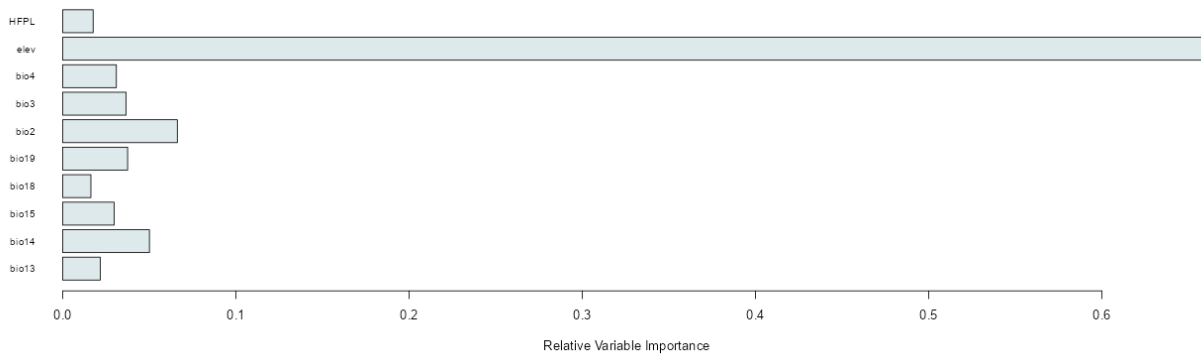


Figure S3.19. Relative importance of the variables, using the `getVarImp` function of the `SDM` package for R for the Páramo in the RCP 4.5.

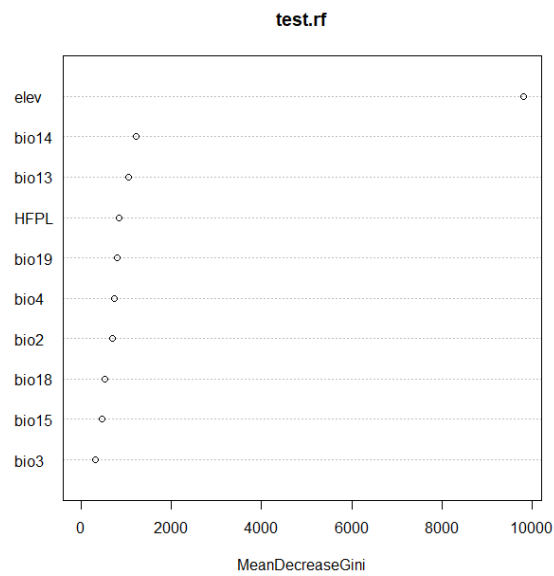


Figure S3.20. Relative importance of the variables, using Random Forest for the Páramo in the RCP 4.5.

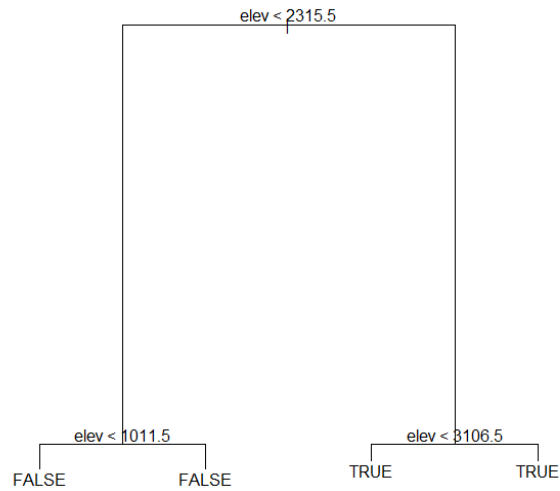


Figure S3.21. Relative importance of the variables, using Decision Trees for the Páramo in the RCP 4.5.

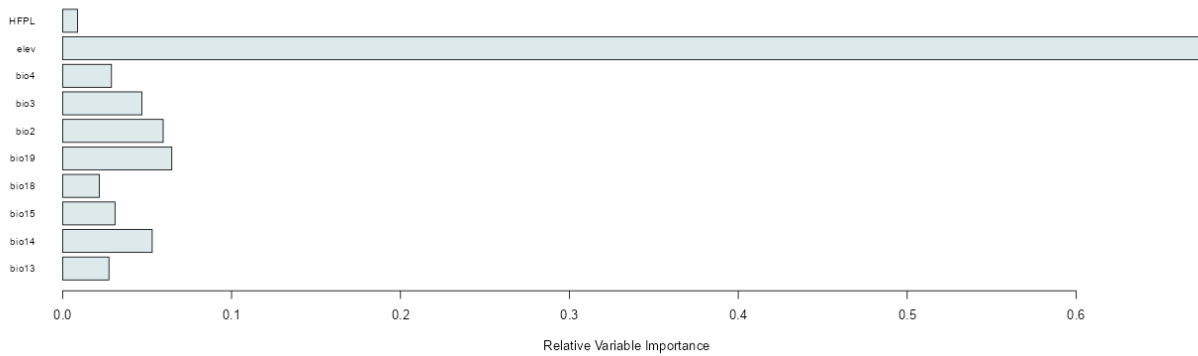


Figure S3.22. Relative importance of the variables, using the getVarImp function of the SDM package for R for the Páramo in the RCP 8.5.

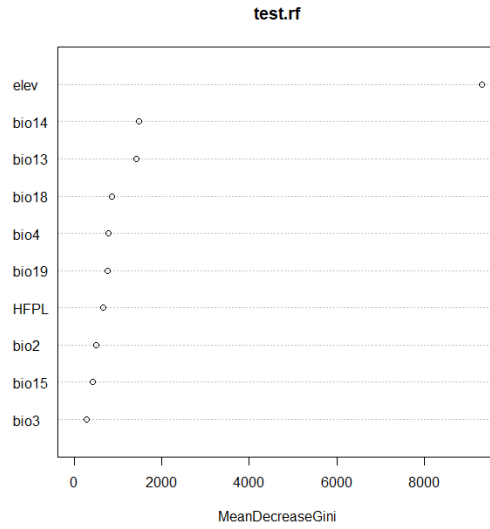


Figure S3.23. Relative importance of the variables, using Random Forest for the Páramo in the RCP 8.5.

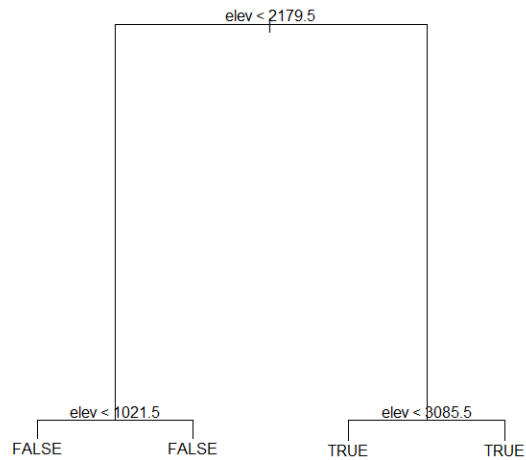


Figure S3.24. Relative importance of the variables, using Decision Trees for the Páramo in the RCP 8.5.