UNDERSTANDING SUSTAINABLE DEVELOPMENT PROGRESS IN A METACOUPLED WORLD

By

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ABSTRACT

With industrialization and human development over the past centuries, one of the primary challenges to humans is the global biodiversity loss at a massively accelerated rate. The United Nations (UN) has adopted the 17 Sustainable Development Goals (SDGs), aiming to provide human welfare and conserve the planet, now and into the future. Two of the SDGs directly address biodiversity conservation and sustainable development – SDG 14 (life below water) and SDG 15 (life on land). Although the UN has issued annual reports on SDGs, the reports do not consistently reveal the progress over time, because of inconsistent methods such as estimation based on different indicators across years. Besides the lack of a consistent assessment of integrated efforts (e.g., SDGs 14 and 15) in biodiversity conservation and sustainable development, the other challenge for conservation science is to identify key drivers for the socioecological changes and achieve environmental and socioeconomic sustainability within and across boundaries. The main objective of this dissertation is to fill the knowledge gaps by providing a consistent assessment of SDGs 14 and 15 over time (Chapter 2), exploring the key drivers for socioecological changes (Chapter 3), and conducting scenario analysis through the metacoupling framework and modeling approaches (Chapter 4). This dissertation would better inform countries to review their sustainable development progress associated with Life below Water and Life on Land and empower decision-makers with support for future conservation planning and sustainable development. The open-source database would contribute to future research in biodiversity conservation, sustainability science, and other disciplines. The methodology used in this study can also be generalized and contribute to the broader scientific community and beyond.

To my dearest parents, grandparents, and myself

ACKNOWLEDGEMENTS

The journey of completing a PhD and writing a dissertation was full of dreams, adventures, challenges, happiness, and achievements, which cannot be completed alone. I am so lucky to have received so much support, company, and enlightenment over the past six years from so many great minds and souls that guided me through the long winters in Michigan and dark nights of my life.

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Second, I would like to thank my advisor, Jack Liu, for being the best model of a diligent, humble, inspiring, and serious scientist. I always appreciate Jack for training my scientific instinct and curiosity, teaching me how to work independently and collaboratively, providing me with the great platform and opportunities in lab, center, and conference to learn and grow, and passing down the scientific passion, joy, and inspiration to me like he received from greatest scholars of previous generations. All these served where I am now and will be carried forward into the future.

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PREFACE

The chapters in this dissertation were conceptualized as individual research projects under the primary theme and common goals. While the chapters principally represent my own work, I use the pronoun *we* throughout the dissertation as an acknowledgement for the contributions of my collaborators. I am deeply honored to work with them and genuinely grateful for their contribution, enlightenment, and guidance along this journey. Without them, none of this would have been possible.

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CHAPTER 1: INTRODUCTION

1.1 Background

With industrialization and human development over the past centuries, one of the primary challenges to humans is the global biodiversity loss at a massively accelerated rate (Mace et al. 2005, Rockström et al. 2009). The United Nations (UN) has called for sustainable development and adopted the 17 Sustainable Development Goals (SDGs), aiming to provide human welfare and conserve the planet, now and into the future. Two of the SDGs take the initiative for an integrative assessment of biodiversity conservation efforts and economic development – SDG 14 (Life below Water) and SDG 15 (Life on Land).

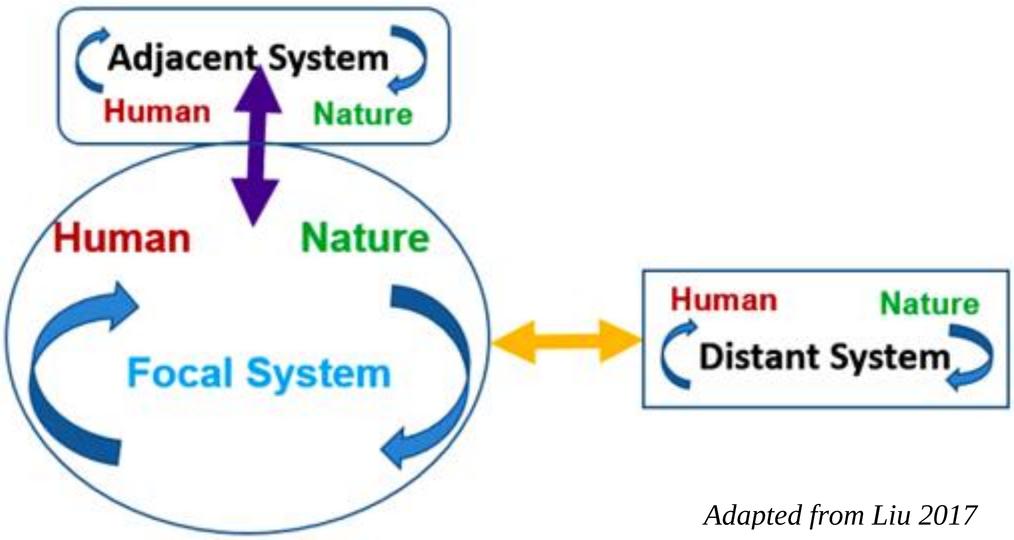
This initiative appears hopeful to fill the current gap of estimating conservation efforts and economic development separately. Although annual reports were produced by the United Nations to inform how sustainable development progress is being made on a global scale, those annual assessments were considered problematic, because the assessed values and indicators selections were inconsistent from one year to the other (Xu et al. 2020). Therefore, this dissertation aims to evaluate global SDGs 14 and 15 progress over time, identify countries that have high and low SDG scores, and explore the drivers for countries' SDGs 14 and 15 score variation.

It is challenging for conservation science to achieve environmental and socioeconomic sustainability within and across boundaries due to the complex system dynamics (interactions among system components, emergent behavior, etc.). To advance the knowledge of complex socio-environmental interactions within and across systems, this dissertation applies the metacoupling framework (Liu 2017) and uses System Dynamics to simulate the complex system interactions and processes.

The outcomes of this dissertation (1) fill the current knowledge gap in the SDGs 14 and 15 assessments at a global scale, (2) identify countries that did better or worse in SDGs 14 and 15, (3) provide potential explanations that drive the SDGs score variation, and (4) discover the impact of endogenous and exogenous environmental and social variables on SDG 15. This dissertation hopes to better inform countries on how to review their sustainable development progress associated with Life below Water and Life on Land and empowers decision-makers with support for future conservation planning and sustainable development. The methodology used in this study can also be generalized and contribute to the broader scientific community and beyond.

1.2 Theoretical framework

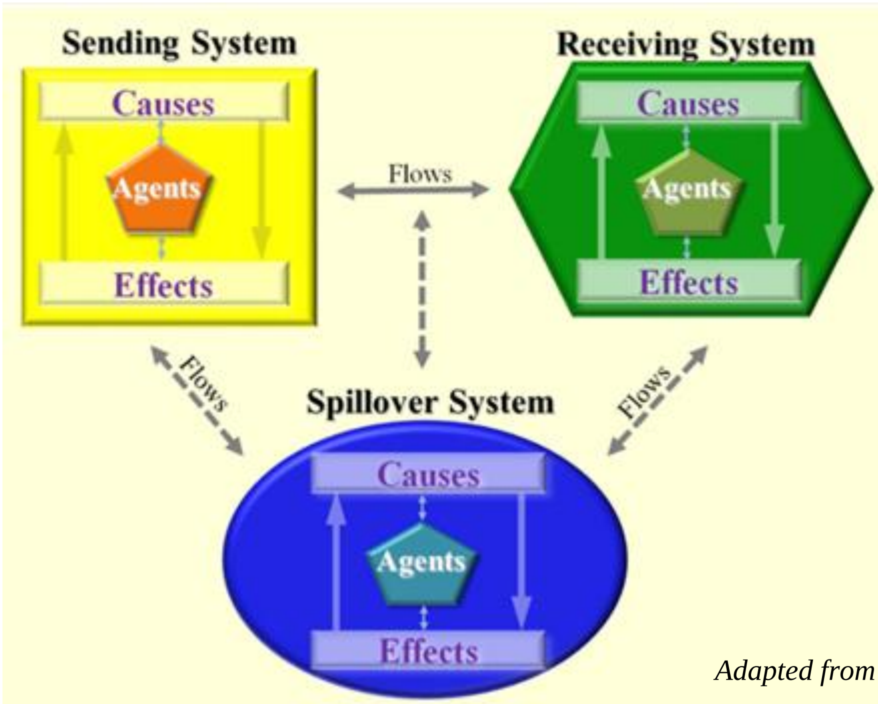
The metacoupling framework (Liu 2017) is a powerful tool for understanding the complex system interactions within and across different scales and borders. Three types of human-nature interactions (couplings) are delineated under the complete metacoupling framework (Figure 1.1): (1) within a coupled system (intracoupling), (2) between distant coupled systems (telecoupling), and (3) between adjacent coupled systems (pericoupling).



Adapted from Liu 2017

Figure 1.1. Three categories of the conceptual metacoupling framework – intracoupling, telecoupling, and pericoupling (Liu, 2017).

Systems can be defined as sending, receiving, and/or spillover systems depending on the directional movement of flows. Within each system, causes, agents, and effects are included for analysis. Between systems, there are direct or indirect flows (e.g., material, money, information).



Adapted from Liu et al. 2013

Figure 1.2. Sending, receiving, spillover systems and major system components under the metacoupling framework (Liu et al., 2013). Within each system, causes and effects are interrelated through agents. Between systems, flows of directional movement (e.g., materials, energy, and information) influence system interactions.

1.3 Objectives and research questions

Chapter 2: Global Decadal Assessment of Life below Water and on Land

Research questions: (1) How had sustainable development in terms of life below water and on land progressed, as measured in SDGs 14 and 15? (2) How did the SDG scores change before and after the adoption of SDGs in 2015? (3) Which countries had high or low SDG scores? (4) Which countries experienced drastic changes (increase or decrease) in SDG scores?

This chapter evaluates countries' SDGs 14 and 15 scores (at goal and target levels) between 2010 and 2020, based on the indicator selection and guidance from the United Nations. I also compare countries' SDG progress before and after 2015 (when SDGs were adopted by United Nations member states).

Chapter 3: Analyzing Global Threats and Opportunities for Life below Water and on Land

Research questions: (1) What drives the sustainable development progress variation among countries, in terms of the SDGs 14 and 15 measurements? (2) How different are the drivers for different groups of countries (e.g., income level, biodiversity hotspot)? (3) Are there any synergies and trade-offs between SDGs and their Targets?

This chapter uses multivariate regressions with regularization techniques to explore the drivers for countries' SDG variation. Several environmental and social variables are used for analysis. The data are either from publicly available databases or from the previous chapter.

Chapter 4: Sustaining Life on Land through a Metacoupling Approach: Simulating Spain's SDG 15 Progress

Research questions: (1) How does the change of forest area impact a country's SDG 15 progress? (2) What parameter has the largest impact on a country's SDG 15 progress?

This chapter frames the interactions among forest, land transformation, population, and SDG 15 with the metacoupling framework, then applies the system dynamics model (SDM) to simulate the stocks (e.g., forest area, population) change over the interactions. The data are either from publicly available databases or from the previous chapters.

CHAPTER 2: GLOBAL DECADAL ASSESSMENT OF LIFE BELOW WATER AND ON LAND

2.1 Abstract

The United Nations (UN) has adopted the 17 Sustainable Development Goals (SDGs), aiming to provide human welfare and conserve the planet, now and into the future. Two of the SDGs directly address biodiversity conservation and sustainable development – SDG 14 (life below water) and SDG 15 (life on land). Although the UN has issued annual reports on SDGs, the reports did not consistently reveal the progress over time, because of inconsistent methods such as estimation based on different indicators across years. Our research examined the dynamics of the same 10 indicators for SDGs 14 and 15 between 2010 and 2020. Results indicate that the overall SDG 14 scores had a small growth between 2010 and 2020, whereas the substantial increase in SDG 15 scores spotlighted the conservation efforts and sustainable use of terrestrial ecosystem services, especially in countries with biodiversity hotspots. Globally, there was more progress in terms of SDG 15 scores during 2015–2020 than during 2010–2015 (before the UN adopted SDGs in 2015). Surprisingly, SDG 14 score had smaller progress during 2015–2020 than during 2010–2015. Special attention should be given to low-income countries lagging in sustainable development performance when implementing the post-2020 global biodiversity framework.

2.2 Summary

In this chapter, I evaluated countries' SDGs 14 and 15 performances between 2010 and 2020, based on the indicator selection and guidance from the United Nations. This delineates how countries did in SDGs 14 and 15 over the past decade, and that through comparisons, which countries did well or poorly. This evaluation step fills the current knowledge gap at a global scale of estimating conservation efforts and economic development separately, and it also provides

significant data for the following chapters. With collaborative efforts, I designed the research, collected raw data, performed data analysis, interpreted the results, and wrote the chapter. This chapter has been published in an open-access journal with details below.

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For the full text of this work, please go to: https://doi.org/10.1016/j.isci.2023.106420

CHAPTER 3: ANALYZING GLOBAL THREATS AND OPPORTUNITIES FOR LIFE BELOW WATER AND ON LAND

3.1 Abstract

Anthropogenic activities have increasingly altered the environment and challenged global socioecological sustainability. Two of the 17 Sustainable Development Goals (SDGs) – SDGs 14 (life below water) and 15 (life on land) - aim to conserve biodiversity and sustainably use natural resources for sustainable development. Countries have achieved significant positive progress in SDGs 14 and 15 in the past decade at different rates. But what drives or impedes countries' SDG progress remains unknown. Here, we identified key factors that directly and indirectly affect countries' SDG 14 (52 countries) and 15 (143 countries) progress between 2010 and 2020. Our results demonstrate mixed expected and unexpected impacts of multiple drivers on SDG progress for countries across different income and biodiversity hotspot groups. Fish Production has the most profound negative impact on SDG 14 progress, and the impact on SDG 15 progress for countries of different income levels and biodiversity hotspot status varied substantially among drivers such as Agricultural Land Percentage, Forestry Import, Forestry Production, Forest Rents in GDP Percentage, and Political Stability. Synergies and trade-offs between SDGs and their Targets call for special attention for policy making to maximize the common benefits of multiple socioecological sustainability goals while minimizing the conflicting interests. Incorporating the significant direct and indirect drivers for SDG progress in future planning is imperative as the deadline for the 2030 agenda approaches.

3.2 Introduction

In 2015, the United Nations Member States adopted 17 Sustainable Development Goals (SDGs) and aimed to address big sustainability challenges globally. Two of the 17 SDGs directly aim to prevent biodiversity loss and buttress sustainable natural resources management: SDG 14 (life below water) – Conserve and sustainably use the oceans, seas and marine resources for sustainable development and SDG 15 (life on land) – Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss. The progress of SDGs 14 and 15 revealed countries' integrated efforts in biodiversity conservation and socioeconomic sustainable development. Countries have achieved significant positive progress in SDGs 14 and 15 between 2010 and 2020 at different paces (Zhang et al., 2023); however, what drives countries' SDG progress and what factors affect the rate of progress remain yet unclear.

Studies have shown the drivers for environmental stress and sustainability from the disciplines of sociology, economics, geography, etc. and interdisciplinary perspectives over past decades (Stern et al., 1992, Dietz and Rosa, 1994, Dietz et al., 2015, Dietz, 2017, Jorgenson et al., 2019). The spirit of SDGs is to achieve both environmental and socioeconomic sustainability; therefore, it is important to investigate socioecological stressors for environment and human well-being. But the literature that explained the drivers for the SDG progress is rather limited, nor does an exhaustive theory exist. Earlier studies have explored the linkage between environmental impact and population, affluence, and technology (Stern et al., 1992, Dietz and Rosa, 1994, Ehrlich and Holdren, 1971), which structured the debate about the effects of population, affluence and technology on the environment and provided a simple and robust framework for broader study references. Recent research has examined additional factors such as social dimensions of economic system, power, social stratification, inequality, and governance impact on global climate change (Jorgenson et al., 2019). The study of direct and indirect drivers (Díaz et al., 2019) further investigates their environmental impacts on terrestrial, freshwater, and marine ecosystems.

Important direct factors include land/sea use change, direct exploitation, climate change, pollution, invasive alien species; indirect factors are grouped into four categories: demographic and sociocultural, economic and technological, institutions and governance, conflicts and epidemics (Díaz et al., 2019). This provides guidelines for research on environmental impact and sheds light on studying the drivers for SDG progress. The metacoupling framework (Liu, 2017) that helps understand environmental and socioeconomic interactions within and across adjacent and distant systems is also useful to identify important natural and social, internal and external variables and map the interactions among them within and across systems (Wu et al., 2021, Chung and Liu, 2022). The metacoupling framework is more general and broader than the world systems framework that has sometimes been used to explain differences across countries in stress placed on the environment (Burns et al., 1994, Burns et al., 2003, Jorgenson and Givens, 2013).

A major barrier to social scientific inquiry into the human–environment relationship is the difficulty in selecting appropriate analytic techniques and models that allow for a precise specification of the functional form of the relationship between driving forces and environmental impacts (York et al., 2003). Although linear regression is a simple, interpretable, and useful tool to estimate the direct and indirect drivers' impact on SDG progress, it is limited by the knowledge of specification and data availability, and the misspecification of regression can lead to biased, inconsistent, inefficient, and misleading predictions (Dewey et al., 2000). To reduce the number of irrelevant variables while balancing the explaining power of the regression model, the Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996) regression is a machine learning process to regulate the number of variables by adding a penalty term to the traditional regression model and shrinking some coefficients towards zero. Studies that used the LASSO regression for variable selection have yielded interpretable models by selecting appropriate variables and reducing the risk of overfitting (Muthukrishnan and Rohini, 2016, Shortreed and Ertefaie, 2017, Wang et al., 2018). LASSO regression is useful as an exploratory method and a parsimonious model, but it may produce spurious conclusions if interpreted causally without care.

The Environmental Kuznets Curve (Kuznets, 2019, Grossman and Krueger 1991) has shown that income differences among countries could lead to different patterns of energy use, economic growth, and the environmental outcomes (Stern, 2004, Leal and Marques, 2022). Earlier research has observed that countries of different income levels and biodiversity hotspot status performed significantly differently in terms of SDG 14 and 15 progress (Zhang et al., 2023). To prevent capturing only the average impact and to draw policy implications that are salient for specific countries, in this article we studied different drivers' impact on SDG progress by allowing interactions of countries' income level and biodiversity hotspot status with other independent variables. In particular, we addressed the following questions: (1) What drives the sustainable development progress variation among countries, in terms of the SDGs 14 and 15 measurements? (2) How different are the drivers for different groups of countries (e.g., income level, biodiversity hotspot)? (3) Are there any synergies and trade-offs between SDGs and their Targets?

We first selected drivers for SDG progress analysis based on the inclusion of relevant direct and indirect drivers (Díaz et al., 2019) with the best available data for the study period between 2010 and 2020: 21 independent variables for SDG 14 among 52 countries/regions and 25 variables for SDG 15 among 143 countries/regions. Then interaction terms were generated based on countries' income level and biodiversity hotspot status, which expanded to 40 independent variables for SDG 14 (19 high-income countries, 33 low-income countries) and 71 for SDG 15 (53 biodiversity-hotspot countries, and 90 non-hotspot countries. See Methods section for details about income level and biodiversity hotspot status classification for SDGs 14 and 15). We utilized the

LASSO technique to reduce the number of irrelevant variables and establish reliable statistical inferences. Besides SDG progress at the Goal level, we regressed the drivers against each SDG Target, and analyzed 3 Targets under SDG 14 and 6 Targets under SDG 15. Finally, we compared the multiple regression results and scrutinized the synergies and trade-offs between SDGs and Targets.

3.3 Methodology

3.3.1 Selection of drivers for SDG score change

The goal of this study is to find drivers for SDGs 14 and 15 score change and analyze their impact as completely as possible. Studies have shown that land/sea use change, direct exploitation, climate change, pollution, and invasive alien species were considered the direct drivers for terrestrial, freshwater, and marine ecosystem change (Díaz et al., 2019, Didham et al., 2005, Nelson, 2005, Nelson et al., 2006). Other indirect drivers that may cause those social and ecosystem changes were categorized as demographic and sociocultural (e.g., population size and growth, age distribution), economic and technological (e.g., economic growth, consumption), institutions and governance (e.g., rule of laws, governance performance), and conflicts and epidemics (Díaz et al., 2019, Didham et al., 2005, Nelson, 2005). Based on the metacoupling framework, we developed a conceptual framework of drivers and effects between natural and human systems to understand the relationship between direct and indirect drivers for SDG progress within and across countries (Figure 3.1). To be inclusive whilst relatable to SDG score change with data limitation, we first included 21 variables for SDG 14 (Control of corruption index, Crops and animals export, Crops and animals import, Fish export, Fish import, Fish production, GDP, Government effectiveness index, Political stability index, Population density, Population growth rate, Total population, Regulatory quality index, Rule of law index, Temperature change, Tourist number, Voice and accountability index, Population ages between 0 and 14, Population ages between 15 and 64, Population ages over 65, GDP per capita), and 25 variables for SDG 15 (Agricultural land percentage of total land area, Agricultural land square kilometer, Control of corruption index, Crops and animals export, Crops and animals import, Forest area in square kilometer, Forest Rents percentage of GDP, Forest export, Forest import, Forestry production, GDP, Government effectiveness index, Political stability index, Air Pollution of PM 2.5, Population density, Population growth rate, Total population, Regulatory quality index, Rule of law index, Temperature change, Voice and accountability index, Population ages between 0 and 14, Population ages between 15 and 64, Population ages over 65, GDP per capita).

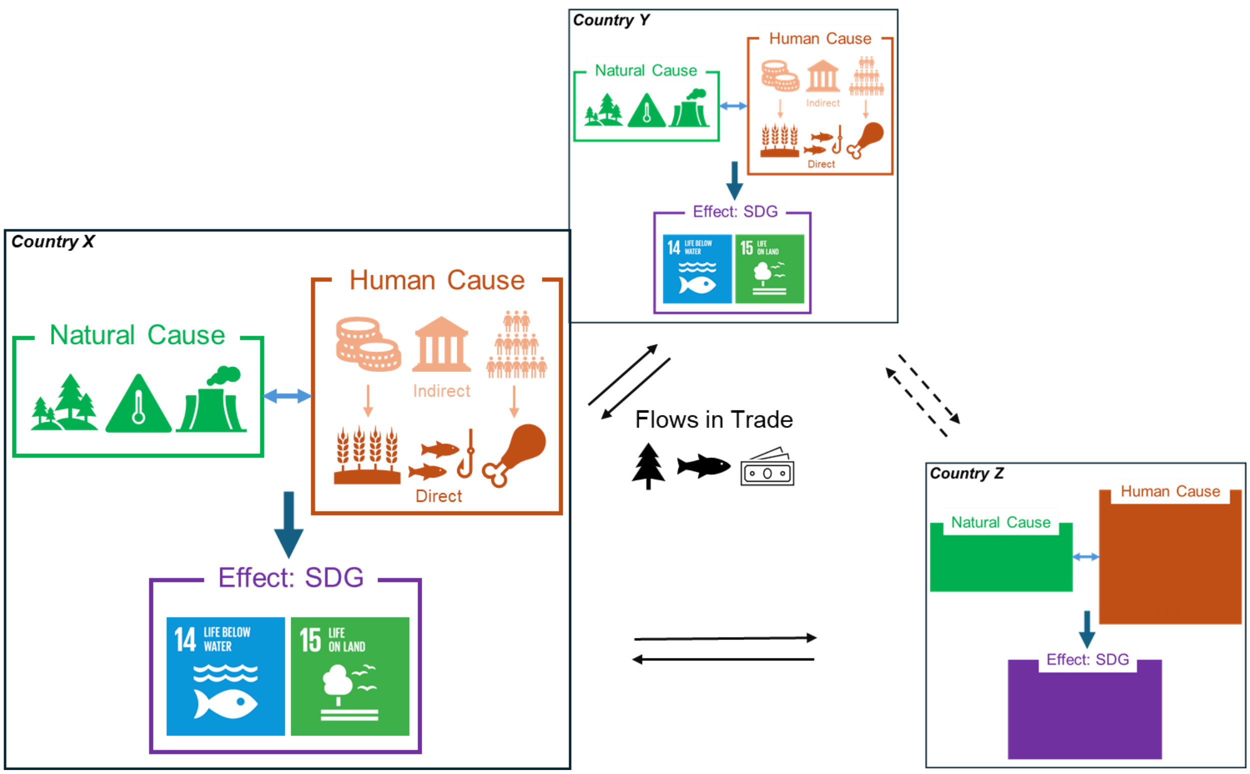
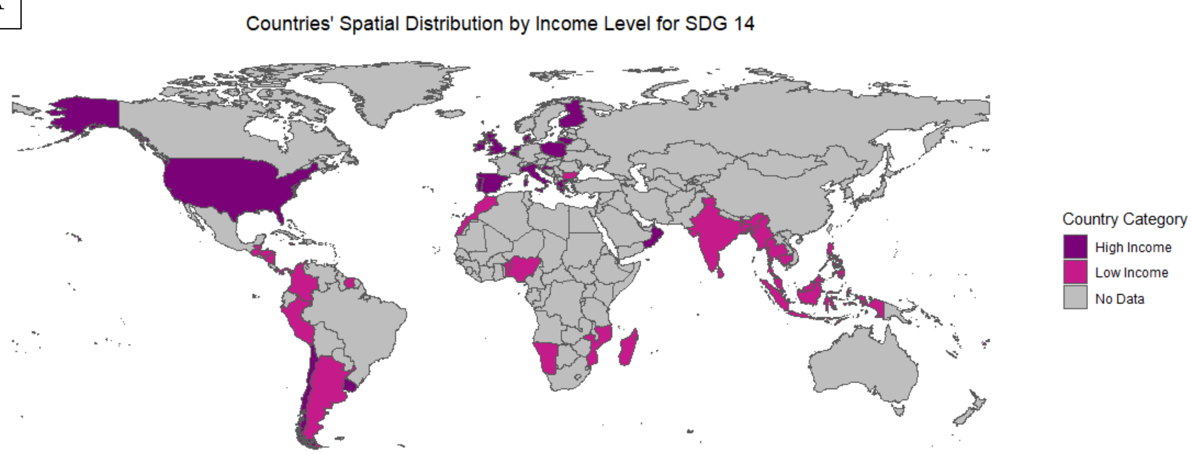


Figure 3.1. Direct and indirect causes of natural and human elements for SDG progress. The internal causes are natural processes and human activities within a country. The effect of the focal country (e.g., country X) could be impacted by its neighboring (country Y) and distant (country Z) countries through trade, which is considered as an external cause.

This study period was between 2010 and 2020, with a coverage of 52 countries/regions for SDG 14 (in 2011, 2013, 2015, 2017, and 2019) and 143 for SGD 15 (annually from 2010 to 2019) analysis (Figure 3.2). We used the SDGs 14 and 15 scores from a published database (Zhang et al., 2023), and we collected the independent variable data from publicly available sources including the World Bank Group (Worldwide Governance Indicators, World Development Indicators), World Health Organization, and United Nations Food and Agriculture Organization (FAO Statistics and Climate).

A



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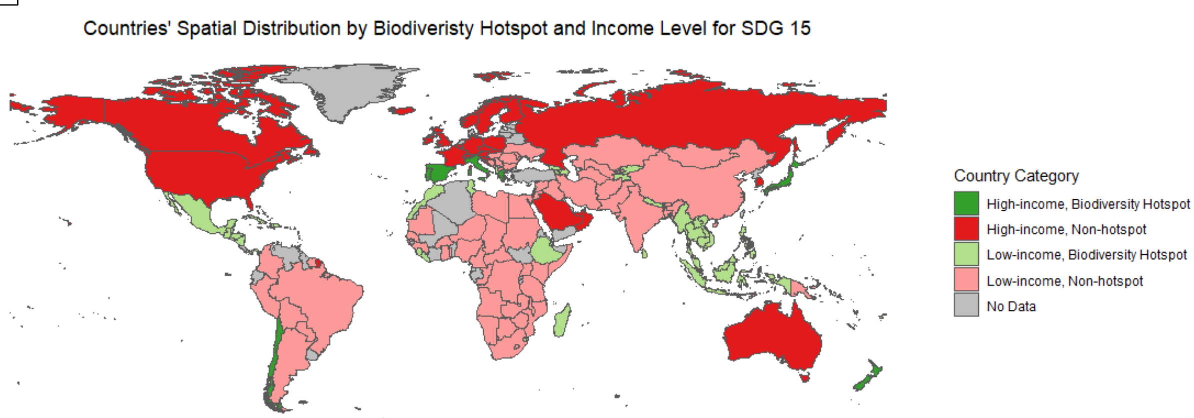


Figure 3.2. Countries' spatial distribution by (A) income level for SDG 14 analysis, (B) income level and biodiversity hotspot status for SDG 15 analysis.

3.3.2 Regression form specification from STIRPAT and empirical observation

We used the ordinary least square regression model to analyze the impact of drivers for SDG score change. To minimize the residual square of error term and make the estimated impact (coefficient) of drivers (independent variable) on SDG score (dependent variable) change comparable, we normalized each independent variable with scale function in R (Becker et al., 1988).

$$X_{scaled} = {(X_{original} - \bar{X})}/{S}$$

Where $X_{original}$ is the original X value, $\bar{X}$ is the sample mean, and S is the sample standard deviation.

We did not use this method to standardize SDG score (dependent variable) because they had been normalized in sourced data (ranging from 0 to 100).

To determine the appropriate specification form of variables included in the model, we plotted each independent variable against SDG 14 and 15 scores (dependent variable) separately (Figures A3.2 and A3.4]. This step provided empirical evidence besides theories of anthropogenic impacts on the environment such as the Stochastic Impacts by Regression Population, Affluence and Technology (STIRPAT) (Dietz and Rosa, 1994, York et al., 2003) of determining the appropriate form (e.g., original form, log form) of each independent variable in the regression. We kept the following variables in the original form: for SDG 14, they are Control of corruption index, Government effectiveness index, Political stability index, Population growth rate, Regulatory quality index, Rule of law index, Temperature change, Voice and accountability index, GDP per capita; and for SDG 15, they are Agricultural land percentage of total land area, Control of corruption index, Forest Rents percentage of GDP, Forest export, Forest import, Forestry production, Government effectiveness index, Political stability index, Population density, Population growth rate, Regulatory quality index, Rule of law index, Temperature change, Voice and accountability index, GDP per capita. We converted the following variables into the log form: for SDG 14, they are Crops and animals export, Crops and animals import, Fish export, Fish import, Fish production, GDP, Population density, Total population, Tourist number, Population ages between 0 and 14, Population ages between 15 and 64, Population ages over 65; for SDG 15, they are Agricultural land square kilometer, Crops and animals export, Crops and animals import, Forest area in square kilometer, GDP, Air Pollution of PM 2.5, Total population, Population ages between 0 and 14, Population ages between 15 and 64, Population ages over 65.

Because some independent variables explained SDG score change differently across income levels and/or biodiversity hotspots, we created additional interaction terms of high-income * independent variable in the regression for SDG 14; for SDG 15, we added biodiversity-hotspot * independent variable interaction terms besides the income level [Supplementary Methods]. The classification of countries into high/low-income and biodiversity/non-biodiversity hotspots (Figure 3.2) was adapted from the sourced SDG 14 and 15 data (Zhang et al., 2023, Chung and Liu, 2022). For SDG 14, countries with more than $12,696 gross national income per capita (World Bank Country and Leading Groups, 2021) were categorized as high-income countries (n=19); otherwise, they were low-income countries (n=33). For SDG 15, countries identified as high biodiversity hotspots in the literature (Zhang et al., 2023, Chung and Liu, 2022) were categorized as biodiversity-hotspot countries (n=53); otherwise, they were non-hotspot countries (n=90) in this study. The addition of interaction terms effectively differentiated the impact of several variables on SDG scores when countries were in different income and biodiversity groups.

3.3.3 LASSO regression model building

With all those interaction terms included in the Ordinary Least Square regression, 40 independent variables were analyzed for SDG 14, and 71 for SDG 15. To reduce the number of irrelevant variables while balancing the explaining power of the regression model, we applied the machine learning regression shrinkage and selection approach via the LASSO regularization technique (Tibshirani,1996) to eliminate those statistically insignificant variables (Figures A3.5 and A3.6). The LASSO regression is intended to balance model simplicity and accuracy, by adding a penalty term to the traditional linear regression model and shrinking some coefficients towards zero. The LASSO regression provides an interpretable model and reduces the risk of overfitting. Studies that used the LASSO regression for variable selection while comparing with other selection approaches have shown the effectiveness in selecting appropriate variables (Muthukrishnan and Rohini, 2016, Shortreed and Ertefaie, 2017, Wang et al., 2018). However, the limitation of the LASSO regression as a variable selector is that when there exist dependence structures among variables (Freijeiro-González et al. 2022), the model did not fully resolve multicollinearity issues in the regression. Therefore, we manually removed all variables with generalized variation inflation factor (GVIF) larger than 5 (Fox and Monette, 1992, O'brien, 2007): we only removed one variable at a time when the variable had the highest GVIF, while we observed the adjusted R-square value change and the GVIFs for other independent variables. After several iterations of eliminating variables, we concluded the final regression model. The coefficient values across different independent variables (shown in Table 3.1 and Table 3.2) were comparable because of data normalization in previous steps.

3.3.4 Regression at Target level

Each SDG has several Targets, and those Targets are closely linked to the SDG and can be used as subgoals to quantify and measure the SDG progress. After we had the regressions for SDGs 14 and 15 at a Goal level, we used the same independent variables to regress against each SDG Target score. This allowed us to detect potential similar and different estimates of variables at a Target level from a Goal level and examine synergies and trade-offs between SDGs and their Targets. For SDG 14, the Targets are 14.1 (By 2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution), 14.5 (By 2020, conserve at least 10 per cent of coastal and marine areas, consistent with national and international law and based on the best available scientific information), and 14.7 (By

2030, increase the economic benefits to small island developing States and least developed countries from the sustainable use of marine resources, including through sustainable management of fisheries, aquaculture and tourism). For SDG 15, the Targets are 15.1 (By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements), 15.4 (By 2030, ensure the conservation of mountain ecosystems, including their biodiversity, in order to enhance their capacity to provide benefits that are essential for sustainable development), 15.5 (Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species), 15.6 (Promote fair and equitable sharing of the benefits arising from the utilization of genetic resources and promote appropriate access to such resources, as internationally agreed), 15.8 (By 2020, introduce measures to prevent the introduction and significantly reduce the impact of invasive alien species on land and water ecosystems and control or eradicate the priority species), and 15.9 (By 2020, integrate ecosystem and biodiversity values into national and local planning, development processes, poverty reduction strategies and accounts). Different Targets were explained differently by those independent variables across income levels and biodiversity hotspot statuses.

3.4 Results

3.4.1 Drivers for SDGs 14 and 15 at a Goal level

After controlling the multicollinearity in the regression, 11 variables are used in the regression for SDG 14 including 1 interaction term. Nine out of the 11 variables are statistically significant with the significance level of $p < 0.05$. Two variables are not significant, one of which is the interaction term (Political Stability * High Income) meaning there is no difference in the effect of Political Stability between high-income and low-income countries for its impact on SDG 14 progress.

The significant variables are relevant to climate change, direct exploitation, institutions and governance, and demographic and sociocultural, economic, and technological pathways (Figure 3.3.A). Among the 9 significant variables, Fish Export (in the log form) has the most important positive role contributing to SDG 14 progress, with the estimate of 0.58, followed by Tourist (in the log form, 0.4) and GDP per Capita (0.23). Fish Production (in the log form) has the most important negative role dragging the SDG 14 progress, with an estimate of -0.51. Many other variables also have negative impacts on SDG 14 progress, such as Fish Import (in the log form, -0.26), Political Stability (-0.25), Population Density (in the log form, -0.18), and Population Growth Rate (-0.12).

Both direct and indirect drivers have impacts on SGD 14 progress, but the average effect that direct drivers have is negative, while the effect of indirect drivers is positive. By summing the coefficient estimates of direct and indirect drivers respectively, the direct sum is -0.36 and the indirect sum is 0.4 (Figure 3.4.A).

A

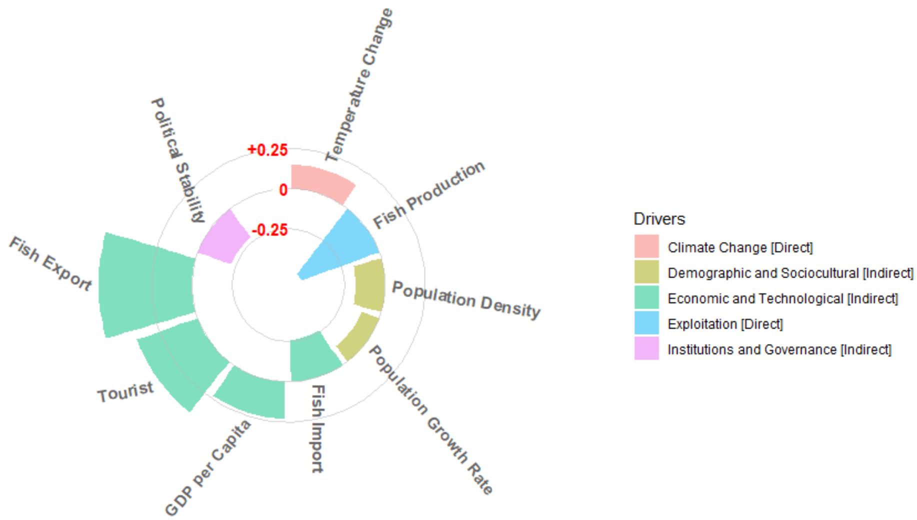
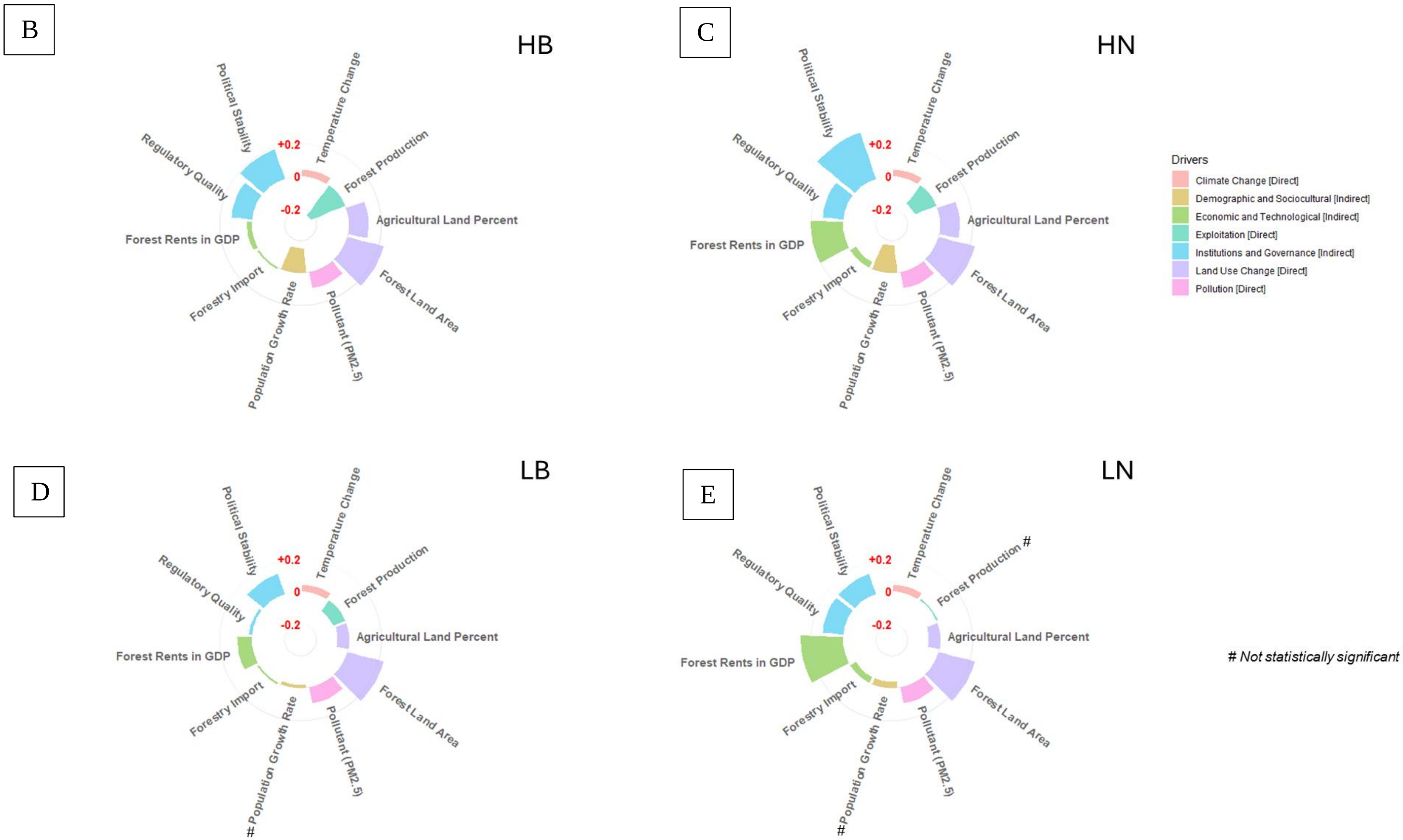


Figure 3.3. Statistically significant drivers' impact on SDGs. (A) Impact on SDG 14 for both high- and low-income countries. (B) Impact on SDG 15 for high-income, biodiversity-hotspot [HB] countries. (C) Impact on SDG 15 for high-income, no-biodiversity-hotspot [HN] countries. (D) Impact on SDG 15 for low-income, biodiversity-hotspot [LB] countries. (E) Impact on SDG 15 for low-income, no-biodiversity-hotspot [LN] countries. (F) Drivers differentiate impact on SDG 15 across country groups.

Figure 3.3 (cont’d)



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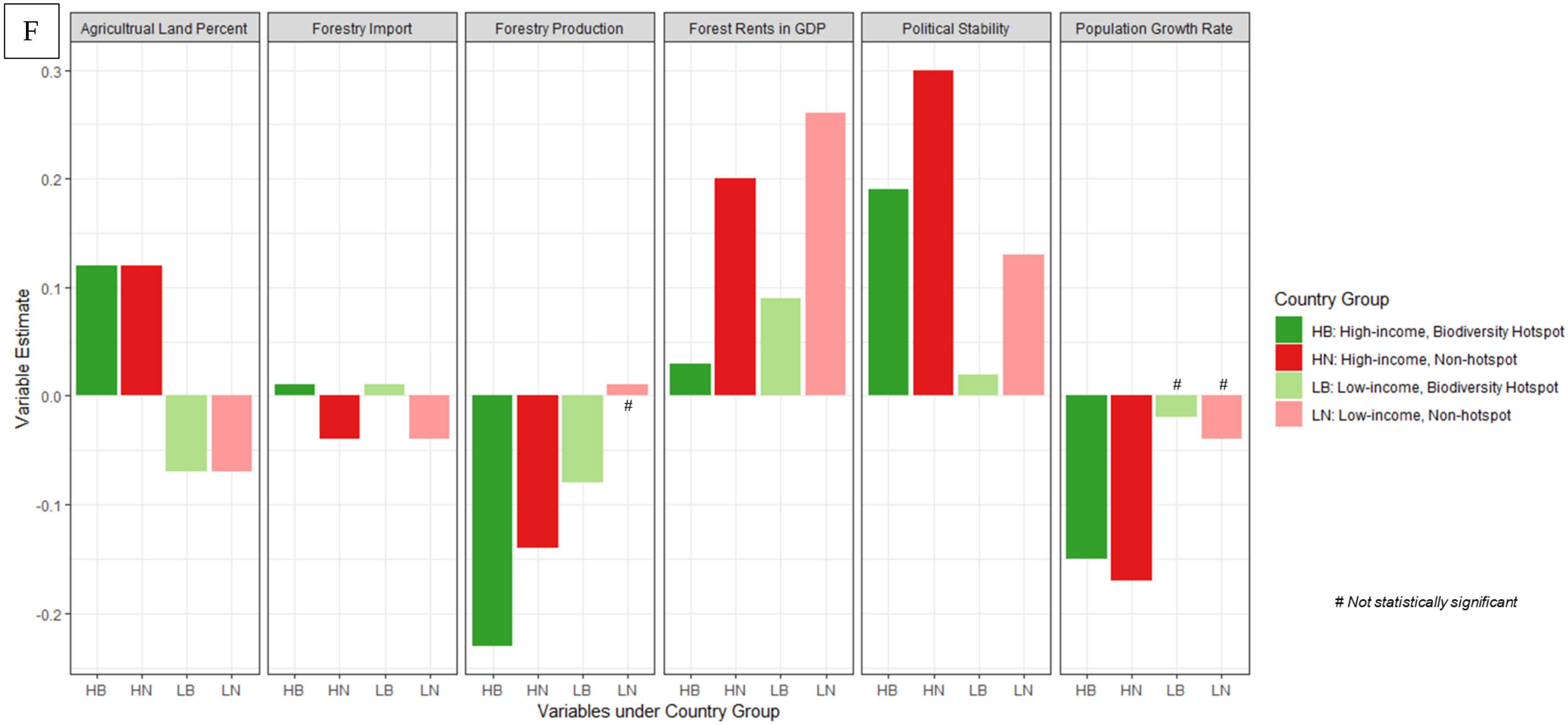
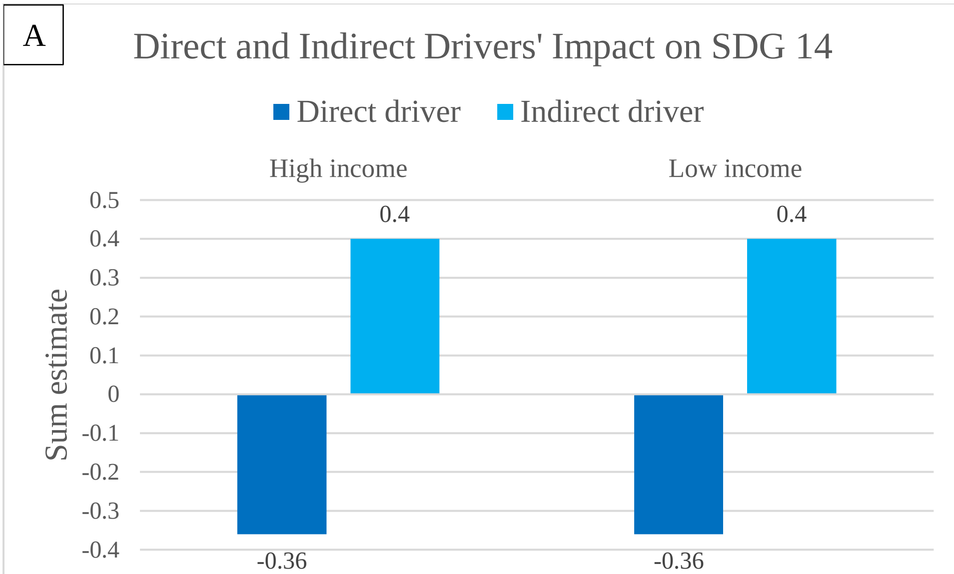




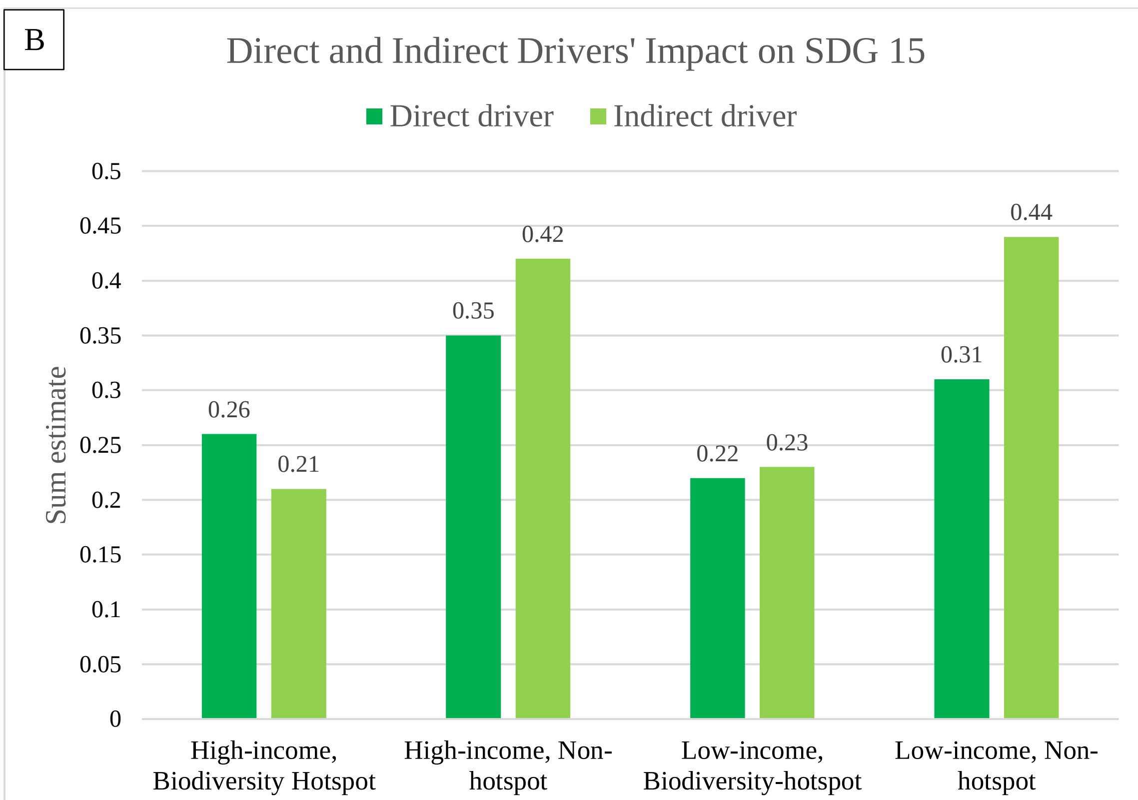


Figure 3.4. Sum estimates of direct and indirect drivers' impact on SDGs. (A) Impact on SDG 14 for both high- and low-income countries. (B) Impact on SDG 15 for countries of different income levels and biodiversity hotspot status.

For SDG 15 regression, 24 variables are analyzed in the model, including 13 interaction terms. Seventeen out of the 24 variables are statistically significant, including 8 primary variables and 9 interaction terms, ranging from direct and indirect driver categories of climate change, land use change, pollution, institutions and governance, and economic and technological pathways.

The differences are significant among high-income vs. low-income, and biodiversity-hotspot vs. non-hotspot countries across different variables (Figures 3.3.B, 3.3.C, 3.3.D, 3.3.E). Specifically, Political Stability has the most important positive impact (with an estimate of 0.3) on SDG 15 progress in high-income, non-hotspot countries (HN), while for low-income, non-hotspot countries (LN), the most important variable for positive impact is Forest Rents Percentage in GDP (0.26). Forest Area has the same estimate (0.23) across all countries, which is deemed as the most important positive factor in both high-income, biodiversity-hotspot (HB) and low-income, biodiversity-hotspot (LB) countries, as well as considered as the second most important positive driver for HN and LN countries. On the contrary, Forestry Production has the most important negative impacts on SDG 15 progress in HB (-0.23), HN (-0.14), and LB (-0.08) countries, followed by Population Growth Rate, which also has profound negative impacts for HN (-0.17) and HB (-0.15) countries.

Some variables have opposite impacts on different country groups. For example, Agricultural Land Percentage has a positive impact (0.12) for SDG 15 progress in HB and HN countries and a negative impact (-0.07) in LB and LN countries; Forestry Import has a positive impact (0.01) in HB and LB countries and a negative impact (-0.04) in HN and LN countries (Figure 3.3.F).

The average effects of both direct and indirect drivers on SGD 15 progress are positive yet they are different across country groups. For HB countries, the direct drivers have more prevailing impacts where the direct impact is summed at 0.26 (to the indirect impact sum estimate of 0.21). However, for other country groups (HN, LB, LN), the indirect drivers play more important roles.

For instance, the sum estimated for HN countries is 0.42 (to the direct impact sum estimate of 0.35) and indirect driver estimates are higher than direct driver estimates for all low-income countries (Figure 3.4.B).

Table 3.1. Regression variable estimates for SDG 14.

Variable name	**Coefficient estimate of**			
	SDG 14	Target 14.1	Target 14.5	Target 14.7
Log of Fish Export	0.58***	-0.18	0.6***	0.27***
Log of Fish Import	-0.26***	0.1	-0.14	-0.43***
Log of Fish Production	-0.51***	0.18	-0.65***	0.25**
GDP per Capita	0.23***	-0.06	0.23***	0.22**
Political Stability	-0.25***	0.12	-0.25***	0.38***
Log of Population Density	-0.18***	0.14**	-0.18***	0.02
Population Growth Rate	-0.12**	0.01	0.1	0.23**
Temperature Change	0.15**	0.16*	0.05	0.15**
Log of Tourist	0.40***	0.1	0.48***	-0.35***

Note: p (<0.1), (<0.05)**, (<0.01)****

Table 3.2. Regression variable estimates for SDG 15.

Variable name	Coefficient estimate of						
	SDG 15	Target 15.1	Target 15.4	Target 15.5	Target 15.6	Target 15.8	Target 15.9
Agricultural Land Percentage	-0.07***	-0.15***	-0.03	-0.05*	-0.07**		-0.04
*Agricultural Land Percentage * High Income (0/1)*	0.19***	0.21***	0.2***	0.11***	0.15***		0.09***
Percentage of Forest Rents in GDP	0.26***	0.4***	0.43***	-0.01	0.17***	0.03*	0.01
*Percentage of Forest Rents in GDP * Biodiversity Hotspot (0/1)*	-0.17***	-0.27***	-0.37***	0.05	-0.07*		-0.04
*Percentage of Forest Rents in GDP * High Income (0/1)*	-0.06**	-0.09***	-0.01	-0.07**	-0.1***	0.1***	-0.03
Forestry Import	-0.04*	-0.08**	-0.12***	-0.08**	-0.04		0.12***
*Forestry Import * Biodiversity Hotspot (0/1)*	0.05**	0	0.05	0.12***	-0.01		0.02
Forestry Production	0.01	-0.19***	0	-0.1***	0.12***	0.05**	-0.03
*Forestry Production * Biodiversity Hotspot (0/1)*	-0.09***	-0.11***	-0.11***	-0.15***	0.03	0.05**	
*Forestry Production * High Income (0/1)*	-0.15***	-0.11***	-0.14***	0.16***	-0.13***	-0.11***	-0.14***
Log of Forest Land Area	0.23***	0.48***	0.14***	-0.13***	0.09***		0.2***
Log of PM2.5	0.1***	0.14***	0.04	0.26***	0.08**	-0.03	0.07
Population Growth Rate	-0.04	-0.31***	-0.19***	0.01	0.16***		0.05*
*Population Growth Rate * Biodiversity Hotspot (0/1)*	0.02	0.14***	0.11***	-0.08**	-0.09***		-0.06*
*Population Growth Rate * High Income (0/1)*	-0.13***	-0.07**	-0.05	-0.11***	-0.11***		-0.02
Political Stability	0.13***	0.22***	0.06	0.15***	0.21***		0.03
*Political Stability * Biodiversity Hotspot (0/1)*	-0.11***	0.01	-0.05	-0.35***	-0.12***		-0.04
*Political Stability * High Income (0/1)*	0.17***	0.07**	0.11***	0.23***			
Regulatory Quality	0.13***						
Temperature Change	0.04**	0	0	0.19***	0.04*	0.02	0.01

Note: p (<0.1), (<0.05)**, (<0.01)***; all variables of interaction terms are italicized.*

3.4.2 Synergies and Trade-offs Between Sustainable Development Goals and Targets

At the Target level, regression estimates showed different impacts. Some variables have the same positive impacts on SDG Targets as they do on SDG progress, while others have the opposite negative impacts. Here, we list some variables that have statistically significant estimates in regressions. For instance, Fish export has both positive impacts on Targets 14.5 and 14.7, with estimates of 0.6 and 0.27 respectively; GDP per capita also has both positive impacts on those Targets (0.23 and 0.22). Fish import has a negative impact (-0.43) on Target 14.7 aligning with the negative impact at the Goal level (-0.26). However, Fish production has a negative impact (-0.65) on Target 14.5, consistent with the negative impact at the Goal level (-0.51) but has a positive impact (0.25) on Target 14.7, opposite to the Goal level estimate. Besides, Population density has the same negative impact (-0.18) on Target 14.5 and SDG 14, but the impact is positive (0.14) on Target 14.1. Tourist has a positive impact (0.48) on Target 14.5 (consistent with a positive impact on SDG 14) and a negative impact (-0.35) on Target 14.7 (Table 3.1).

The same impacts (both positive or negative) among Targets and SDGs are considered synergies, meaning the variable contributes to achieving or preventing the Target and SDG progress at the same time. The same positive impacts are considered positive synergies (win-win), and the same negative impacts are considered negative synergies (lose-lose). For example, GDP per capita has both positive impacts on Targets 14.5 and 14.7, which is a positive synergic effect meaning that GDP per capita helps achieve both Targets 14.5 and 14.7. On the contrary, Fish production has both negative impacts on SDG 14 and Target 14.5, which is a negative synergic effect meaning that Fish production suppresses both SDG 14 and Target 14.5 progress. The opposite impacts (one positive, while other negative, vice versa) among Targets and SDGs are seen as trade-offs (win-lose), meaning the variable buttresses to fulfill one Target/SDG while compromising the other (Zhao et al., 2021, Xing et al., 2024). Both synergies and trade-offs exist in SDGs 14 and 15 among their Targets. From the results above, many trade-offs have been detected among SDG 14 and their Targets.

Most variables in the SDG 15 Target regressions have consistent impacts (both positive or both negative) on SDG 15 and their Targets, so synergies are more prevailing (Table 3.2). Nevertheless, a few trade-offs are noticeable. For example, Forestry Import for non-hotspot countries has negative impacts on SDG 15 (-0.04), Targets 15.1 (-0.08), 15.4 (-0.12) and 15.5 (-0.08), but it has a positive impact (0.12) on Target 15.9. Forestry Import for biodiversity hotspot countries has positive impacts on SDG 15 (0.01) and Target 15.5 (0.04). Forestry Production for LB countries has negative impacts on SDG 15 (-0.08), Targets 15.1 (-0.3), 15.4 (-0.11), and 15.5 (-0.25), but a positive impact on Target 15.8 (0.1). Forestry Production for LN countries has negative impacts on SDG 15 (-0.14), Targets 15.1 (-0.3), 15.4 (-0.14), 15.6 (-0.01), 15.8 (-0.06), and 15.9 (-0.17), but a positive impact on Target 15.5 (0.06). In addition, Forest Land Area has a negative impact (-0.13) on Targets 15.5, while it has all positive impacts on SDG 15 (0.23), Targets 15.1 (0.48), 15.4 (0.14), 15.6 (0.09), and 15.9 (0.2). The synergies and trade-offs among SDGs and their Targets could reveal insights into further actions and policy implications to achieve sustainable development holistically.

3.5 Discussion

Our LASSO regression approach and results identified the key variables and their impact on SDGs 14 and 15 progress among countries of different income levels and biodiversity hotspot status. Fish Production has the most profound negative impact on SDG 14, so does Forestry Production on SDG 15. Forest Area and Forest Rents in GDP Percentage have the most positive impact on SDG 15, while Fish Export, surprisingly, has the most positive correlation with SDG

14. The drivers for SDG progress and their significant levels largely vary among countries of different income and biodiversity hotspot status. Both synergies and trade-offs exist among SDGs and their Targets, highlighting potential challenges for future sustainable planning and opportunities to maximize the common benefits of multiple socioecological sustainability goals while minimizing the conflicting interests.

The mixed expected and unexpected variable estimates on SDG progress are not fully understood. Several variables have either positive or negative effects on SDG progress, aligning with theories and expectations of drivers for environmental change. For example, Fish harvest and human population pressures have negative impacts on SDG 14 progress, which is illustrated by the negative estimates of Fish production, Human population density, and Population growth rate. Economic factors such as GDP per capita have a positive impact on SDG progress. However, fish trade has an interestingly mixed impact when Fish export has a positive estimate and Fish import has a negative outcome, refuting the assumption that SDG 14 scores should be higher when countries import more fish and conserve their domestic fish stocks, and lower SDG 14 scores when countries export more fish and consume their own natural resources. Namely, countries such as Croatia (high-income) and Morocco (low-income) that made great SDG 14 progress report mixed impacts of Fish export (negative for both countries), Fish import (positive for Croatia, negative for Morocco), and Fish production (positive for both countries); other countries such as Finland (high-income) and Tonga (low-income) that had retrogress in SDG 14 also show mixed impacts of Fish export (positive for Finland, negative for Tonga), Fish import (negative for Finland, positive for Tonga), and Fish production (positive for both countries). Possibly, the increase in domestic aquaculture that is highly correlated with Fish production and Fish export reduced the negative exploitation impact and sufficed sustainable fish capture. This might also result from the potential reverse causation when higher global sustainable fisheries standards are imposed, countries with better SDG 14 progress practice more sustainable fishing and hence are likely to have more fish exports. Meanwhile, political stability also has an unexpected negative impact on SDG 14 progress when separating countries by their income levels. This is contradictory to the literature and beyond established knowledge (Feng, 1997, Aisen and Veiga, 2013, Ali, 2019), likely resulting from the limitation of LASSO technique that causal inference was not fully established during the regularization and modeling process.

Due to data limitations, our study does not capture all variables of direct and indirect drivers for SDG progress. The data analyzed in this study include (1) as many variables as possible, (2) as many countries as available, and (3) as long-time span as possible. The panel data and regression analysis can reveal a significant part of the relationship in how different drivers impact SDG 14 and 15 progress as proxy of global socioecological change. However, it requires caution in examining the causal inference. The LASSO technique is useful as an exploratory approach to provide an initial understanding of significant variables that correlate with target-dependent variables while balancing the simplicity of regression models. However, limited causal inference, which is important for theory testing or policy making, is produced due to a lack of explicit pathways and mechanisms identified. For example, it is unlikely that the increased temperature or pollutants would improve SDG progress. These may not be the perfect indicators to choose based on data insufficiency. Other variables, such as fish trade, may involve dual directional causalities, meaning that those variables may have impacts on SDG progress at the same time being affected by SDG progress. Hence, further pathway studies are needed to discover the mechanisms for theory testing or policy recommendations.

For SDG 15 progress, the expected and unexpected impacts are also mixed across variables and vary among different country groups (income level, biodiversity hotspot). Specifically, both Forest land area and Agricultural land percentage have positive impacts on high-income countries, but Agricultural land percentage has a negative impact on low-income countries regardless of biodiversity hotspot difference. Forest land area is truly important for all countries to improve SDG 15 progress, with positive impacts across all country types. The expansion of Agricultural land percentage remains controversial, because agricultural land percentage has a positive impact on SDG 15 progress for high-income countries and a negative impact for low-income countries. Further investigation should focus on potential different mechanisms of how agricultural lands impact countries' SDG 15 progress while considering other hidden factors. For example, agroecosystems that provide habitats for wildlife and enhance biodiversity while achieving food supply goals in highly developed countries with limited land would require exhaustive study and careful design. Besides, Forestry import has positive impacts on both high- and low-income countries when they are biodiversity hotspots. This can be explained by the fact that countries show better sustainability progress by conserving domestic resources through import while transferring environmental costs to other countries (Chung and Liu, 2022, Xu et al., 2020). It is critical and efficient to conserve forest ecosystems in countries with rich biodiversity. But Forestry import has a negative impact on non-hotspot countries. This could be the fact that they rely more on domestic forest consumption and reduce forestry import when biodiversity is not a primary goal to protect local forests and thus countries are not motivated to plant trees. For those countries, it is unlikely that Forestry import will directly impact their SDG 15 progress, but instead, domestic forest consumption could be more significant, calling for closer scrutiny. Additional causal path diagrams with quantitative analysis would be beneficial to enhance the understanding. Forest rent percentage of GDP plays a more important and positive role in non-hotspot countries than that in biodiversity hotspot countries. Considering the concept of forest rent (roundwood harvest times the product of regional prices and a regional rental rate) and determinants to this variable, it could be explained that non-biodiversity countries produce more quantities of forestry products with a lower cost. All these assumptions and explanations need further examination and empirical studies, particularly those that are inconsistent with existing theories or established knowledge.

The indirect drivers are more important than the direct drivers for all countries in SDG 14 progress and non-biodiversity hotspot countries in SDG 15 progress. However, direct drivers have a profound impact on SDG 15 progress for biodiversity hotspot countries. It is critical to examine the hidden factors and associated mechanisms that drive environmental and socioeconomic changes. The integrated metacoupling framework (Liu, 2017, Liu, 2023) has helped to identify important natural and social drivers domestically and internationally for SDG progress in this study, and it would be of great use to further demonstrate interactions among different endogenous (domestic land competition between forest and agriculture, population (Stern et al., 1992, Dietz and Rosa, 1994, Ehrlich and Holdren, 1971, da Silva et al., 2021) and exogenous (tourism, trade (Xu et al., 2020, Zhao et al., 2020)) factors and analyze system feedbacks within and beyond countries, placing the foundation for building complex system dynamics models. Furthermore, understanding the mechanisms that cause SDG 15 progress for biodiversity hotspot countries is urgently needed. Intense land competition between forest and agricultural activities significantly influences countries' SDG 15 progress. Further study could explore the possibility of releasing agricultural land use pressure of those hotspot countries by satisfying domestic agricultural needs through international trade or from countries with less land use competition.

Synergies and trade-offs among SDGs and their Targets should be carefully evaluated and incorporated into decision making. Drivers that promote synergic effects among SDGs and Targets should be emphasized and those creating conflicts should be given special attention. For example, Fish export creates the opportunity to improve Targets 14.5, 14.7 and SDG 14 simultaneously, which could be an effective leverage and promotion for future marine resources management and sustainable development, considering almost half a billion people depend at least partially on small-scale fisheries (Sachs et al., 2022). But key questions on Fish export including the portion of wild capture vs. aquaculture, direct export and re-export, should be cautiously examined prior to implementing policies at a global scale. The trade-offs should be realized to inform policymaking. For instance, Forest Land Area plays such an imperative role in contributing to SDG 15 and most of its Target progress, but attention must be drawn to investigate the mechanism of how it negatively impacts Target 15.5 as a measure of trends in overall extinction risk (Red List Index). The discussion of biodiversity habitat quality versus quantity should be adequately considered in future conservation planning and policy agenda.

3.6 Conclusions

Using a metacoupling framework, we explored the relationship between drivers for SDG progress within and among countries. In particular, we deployed the machine learning based statistical approach (LASSO) to learn the significant variables that impact countries' SDG progress. Our study highlights the expected and unexpected impacts of multiple factors that affect SDG progress for countries at different income levels and biodiversity hotspot statuses. Our results further illustrate the synergies and trade-offs between SDGs and their Targets, calling for careful decision making in the future to maximize the common benefits of multiple socioecological sustainability goals while minimizing the conflicting interests. Our study provides an exploratory example of integrating the metacoupling framework and the LASSO statistical approach, paving the way for more pathway studies.

CHAPTER 4: SUSTAINING LIFE ON LAND THROUGH A METACOUPLING APPROACH: SIMULATING SPAIN'S SDG 15 PROGRESS

4.1 Abstract

Anthropogenic activities such as natural resources harvest, trade, and population growth have substantial impacts on the environment and become a major challenge to socioecological sustainability. Lack of understanding in achieving environmental and socioeconomic sustainability within and across boundaries is a bottleneck in conservation and sustainability science. The metacoupling framework that integrates interactions across multiple scales and borders, together with System Dynamics Model, is a powerful tool to analyze system interactions and simulate responses both qualitatively and quantitatively. We first applied the metacoupling framework to understand the interactions among environmental and socioeconomic variables and their impact on countries' SDG 15 progress. Then we used Spain as an example and developed a System Dynamics Model to explore how SDG 15 progress responded to forest and population change. Our results show that Net Forest Import has the dominant impact on SDG 15 progress, while other variables like Forestry Production, Forest Regeneration Rate, and Human Population also have impact on SDG 15 progress to different extents. SDG 15 progress, resonating with Forest Area variation, is likely to reach the peak in mid 2030s and depreciate in the long run with the increase of forest harvest. Future natural resources management and conservation planning should be aware of and set up the baseline for potential minimum sustainable forest regeneration and maximum sustainable harvest. The modeling outcome not only served such purposes for providing important information to natural resources management but can also be utilized by broader stakeholders for communication with different communities and learning feedback for model refinement.

4.2 Introduction

A major challenge for conservation science is to achieve environmental and socioeconomic sustainability within and across boundaries. Integrated studies of coupled human and natural systems (CHANS, Liu et al., 2007a, Liu et al., 2007b) have generated important findings on complex patterns and processes that studies through a single lens of physical or social sciences cannot obtain. The holistic metacoupling framework (human-nature interactions within a CHANS as well as between adjacent and distant CHANS, Liu, 2017) integrates interactions across multiple scales across borders. This framework could provide a useful conceptual platform for stakeholder coordination and decision-making to achieve conservation and sustainable goals beyond boundaries. However, quantification of the framework is needed to make coordination and decision-making more effective.

System dynamics modeling (SDM) is used to simulate and understand complex system patterns and processes with quantification features (Meadows, 2008). By identifying the stocks and flows, SDM represents the key feedback structures in the system. SDM can also show scenarios based on different policy interventions. For example, different extents of resource consumption would be the specific scenario analysis in the system dynamics model. Through the feedback loops in the system, potential problems and solutions could be found in terms of conservation and sustainable development goals. Besides, SDM could also help identify the delayed effect of policy intervention, which is significant and informative for future planning. Therefore, SDM is an appropriate approach used in this study to evaluate different policy scenarios and analyze potential strategies for achieving sustainable development goals.

We have identified significant variables that impact SDG progress for countries at different income levels and biodiversity hotspot statuses in the previous chapter. However, the mechanisms through which those variables impact SDG progress differ from country to country and therefore remain unknown. Intermediate converters among variable interactions were not fully understood. Here, we first apply the metacoupling framework to delineate the problem (system processes and interactions among forest, land use for anthropogenic activities, governance, economy, and SDG progress), and then use SDM to model the problem by identifying and quantifying the interactions among system components. The modeling outcomes aim to inform future conservation planning, natural resource management, and community sustainable development.

Research questions: (1) How does the change of forest area impact a country's SDG 15 progress? (2) What parameter has the largest impact on a country's SDG 15 progress?

4.3 Methodology

4.3.1 Metacoupling framework

To systematically understand the human-nature interactions within and across multiple scales and borders, metacoupling framework is used to understand the problem of this study. Three types of human-nature interactions (couplings) are delineated under the complete metacoupling framework: (1) within a coupled system (intracoupling), (2) between distant coupled systems (telecoupling), and (3) between adjacent coupled systems (pericoupling). Here, we adopted the metacoupling framework and followed the six general procedures for operationalizing this framework (Liu, 2017) including setting research goal, defining focal system, reviewing literature and conducting additional studies on flows, agents, causes, and effects, identifying couplings and sending, receiving, and spillover systems, conducting further studies on metacoupling components and interrelationship, and publishing and communicating final results. The preliminary system identification and definition (CHANS, metacoupling) can be found in Figure 4.1.

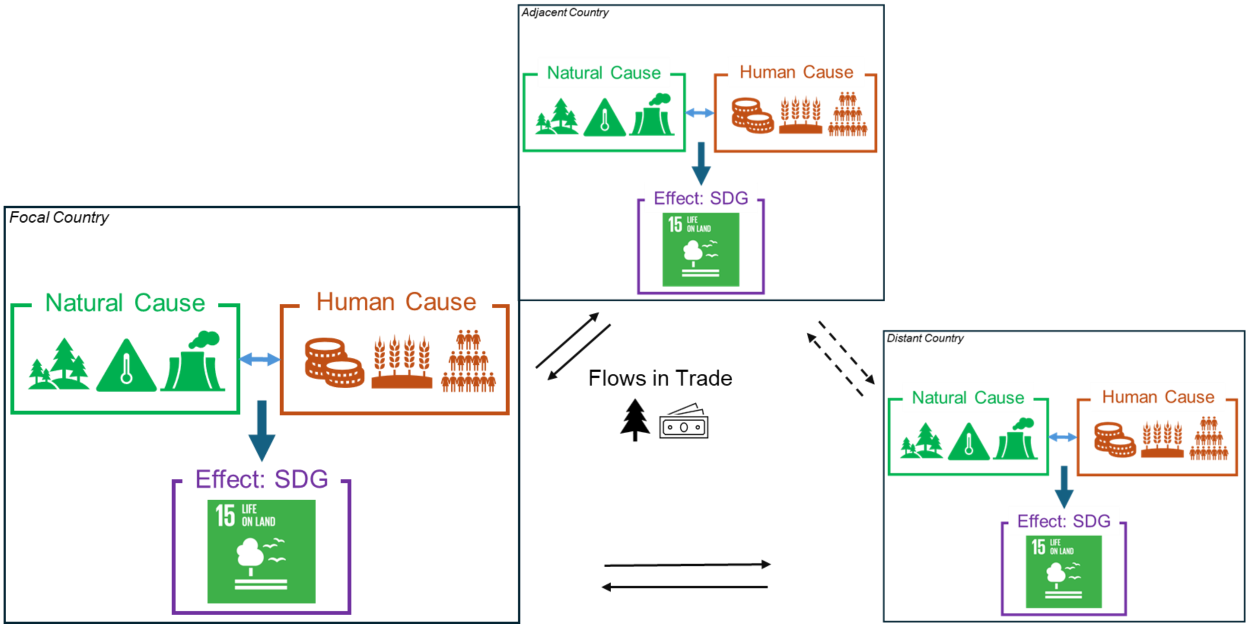


Figure 4.1. Simplified conceptual metacoupling framework: focal country (coupled human and natural system), adjacent country, distant country, and relationships between forest harvest, agricultural land transformation, population, economy development, SDG 15 performance, and international forest trade within the three coupled countries. Components are categorized under human system (brown rectangle) and natural system (green rectangle), including agricultural land, population, economy, forest, temperature, pollution, as causes and SDG 15 progress as effect. The interactions within a coupled human and natural system are shown in light blue arrows. The forestry trade is another component (i.e., flow) between the focal country and adjacent/distant countries. Each country was confined with a black line of rectangle. The interactions between different coupled human and natural systems (e.g., between focal system and distant system) are shown in black arrows (the solid line indicates a direct/observable interaction; the dash line indicates an indirect/unobservable or potential interaction).

4.3.2 Conceptual Framework based on Metacoupling

With the focus on only one country (system), the Casual Loop Diagram below shows the interactions among forest, agriculture, population, economy, governance, and trade. There are two balancing feedback loops (labelled as brown B in Figure 4.2) and five reinforcing feedback loops (labelled as green R in Figure 4.2). The first balancing loop (B1) is that the larger total forest size will provide more forest harvest, but more harvest will lead to a decreasing forest size. The second balancing loop (B2) is that more population will have more population deaths holding the death rate constant, and the more deaths will cause a smaller size of population. Therefore, the population is balanced out through this loop. On the other hand, the reinforcing feedback loops include: R1.

More domestic forest demand will require more forest product, and more forest product will meet more domestic demand; R2. More economic growth (development activities) will boost domestic forest demand, and more domestic demand will satisfy economic needs; R3. More population will create more economy (productivity), and more economy will support larger population; R4. More population will drive more agriculture (activity, products), and more agriculture will support more population; R5. More population will drive more population births holding the birth rate constant, and more population births will contribute to a larger population size.

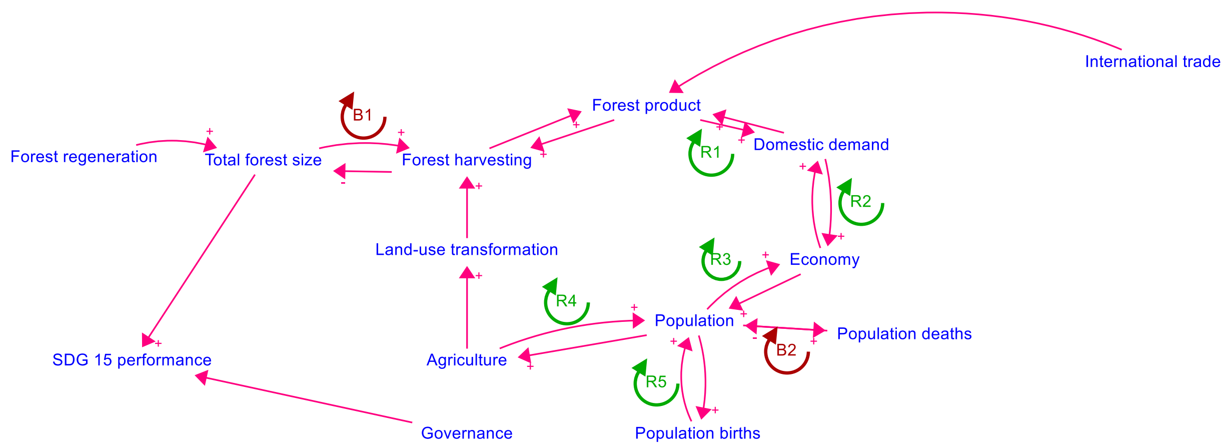


Figure 4.2. Causal loop diagram with feedback loops for the forest system. The system components are in blue text, and the interactions among components are connected through pink arrows. The positive sign shows a positive effect, and the negative sign shows a negative effect. Feedback loops are labelled as unclosed ½ circles with arrows. The brown feedback loops with letter "B" are negative (balancing) feedback loops; the green feedback loops with letter "R" are positive (reinforcing) feedback loops.

4.3.3 System Dynamics Model (SDM)

4.3.3.1 Geographic foci, data sources, and assumptions

This study used Spain as an example, to illustrate the interactions among forest, population, and SDG 15 progress. Spain is one of countries that made tremendous progress in SDG 15 between 2010 and 2020, with scores increasing from 29.74 to 77.31 and ranks emerging from the 60th to the 15th worldwide over those ten years (Zhang et al., 2023). Understanding on how Spain achieved their SDG 15 progress and what variables have large impacts is useful for future conservation and development planning and as a reference for other countries.

Multiple sources of data were used in this study. Population, Population Growth Rate, Forest Area, Forestry Production, and Net Forest Import data were collected through World Bank Group (World Bank Country and Lending Groups, 2021), while Forest Regeneration Rate, Carrying Capacity, and SDG 15 Progress were referred from literature review (Bolin et al., 2000, Instituto Nacional de Estadística, 2022, Zhang et al., 2023). The formula used to define relationships between components in the model were not all available. Several trials were made in calibration and validation processes to best match the real-world data, such as Forestry Production, Net Forest Import, and Population Growth Rate. The other assumption was also made especially for generating the graphical function for Effect of Carrying Capacity on the ratio of Population Growth Rate/Carrying Capacity (the effect increases with the ratio increase at a diminishing rate of return, range from 0 to 1). Namely, when the population approaches the carrying capacity, the effect is more profound leading to a lower population growth rate (Cohen, 1995, Vandermeer, 2010, Meadows et al., 2018).

4.3.3.2 Model description

To simplify the complex system, only limited components and their interactions were included in the model from the causal loop diagram (Figure 4.2). The model simulated the human and natural system interactions (e.g., population, land use change, forest change through production, trade, and regeneration, and SDG progress) from 2000 to 2050 with DT = 1 year. The model was developed with Stella Architect V2.1.5 (ISEE System 2022), with initial settings listed in Table 4.1. The complex system is a coupled human and natural system at a country scale, where there are two major sub-systems: population and forest.

The model has two stocks (Population, and Forest Area), and four flows (Net Growth, Forest Regeneration, Net Forest Harvest, and Land use change). The Net Growth is a bi-flow, meaning it can be an inflow towards or outflow from the stock of Population (contributing to the increase or decrease of the stock) depending on the positive or negative values of Net Growth. Namely, if the Net Growth is positive, there will be more population added towards the stock of Population; if the Net Growth is negative, there will be a removal from Population. The Net Growth is determined by the Population Growth Rate, which is dependent on Effect of Carrying Capacity. The Effect of Carrying Capacity relies on Population and Carrying Capacity. The Carrying Capacity is a user-defined value, and it varies from country to country (for Spain, it is set as 53 million people, Instituto Nacional de Estadística, 2022). Land Use Change is an outflow, meaning that the stock Forest Area may be taken away by Land Use Change depending on both Population and Carrying Capacity. Forest Regeneration is an inflow towards the stock of Forest Area, and it is the multiplication of Forest Area and Forest Regeneration Rate. Forest Harvest is an outflow of Forest Area, which is impacted by Forestry Production and Net Forest Import.

There is one balancing feedback loop (labelled as brown B), one reinforcing feedback loop (labelled as green R), and one mixed (reinforcing and balancing) feedback loop (labelled as yellow R/B in Figure 4.3) in the system. The mixed loop (R1/B1) between Population and Net Growth is dependent on whether Net Growth is positive or negative. If positive (inflow), it is a reinforcing loop because larger population will have more net population growth, which in turn contributes to a larger population size. If negative (outflow), it is a balancing loop because larger population will have less Net Growth, as a source of reducing population size. The balancing loop (B2) is that larger Population, stronger Effect of Carrying Capacity, lower Population Growth Rate, lower Net Growth, smaller Population, in this case, the Population is constrained through this loop. The reinforcing loop (R2) is that more Forest Area, more Forest Regeneration holding the Forest Regeneration Rate constant, contributing to additional Forest Area, in this case, Forest Area is reinforced through the loop.

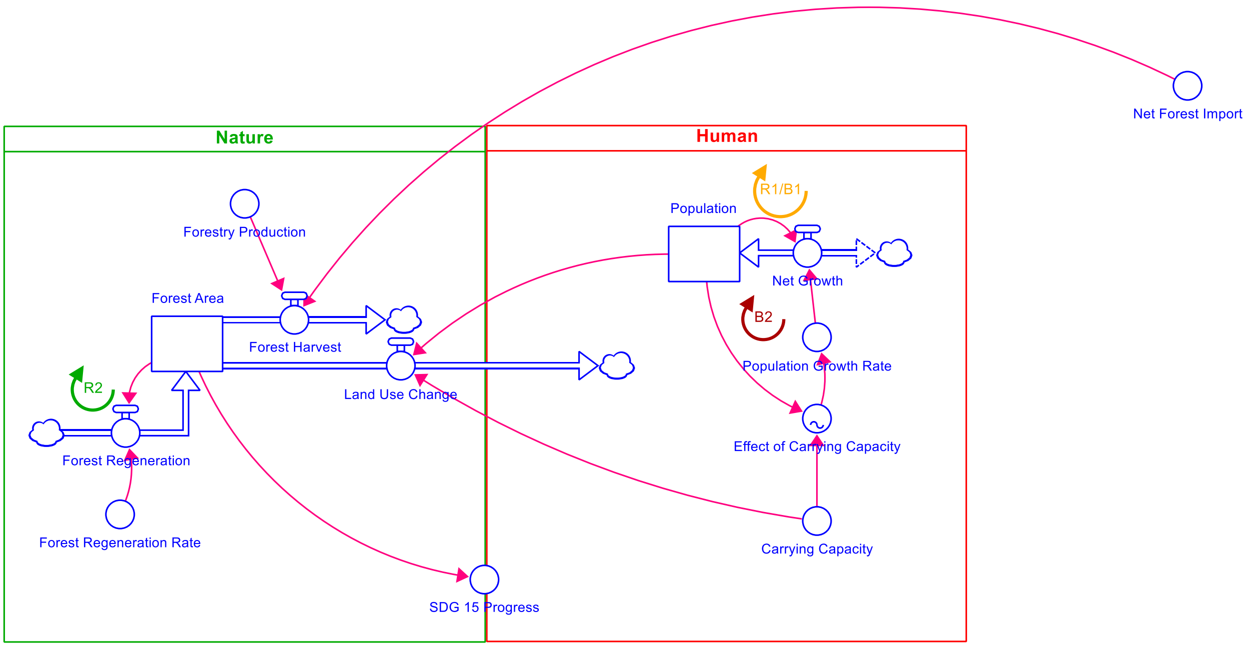


Figure 4.3. System dynamics model with feedback loops for the population and forest system. The system components are in blue text, and the interactions among components are connected through pink arrows. Feedback loops are labelled as unclosed ½ circles with arrows. The brown feedback loops with letter "B" are negative (balancing) feedback loops; the green feedback loops with letter "R" are positive (reinforcing) feedback loops; the yellow feedback loops with letters "R/B" are mixed (both reinforcing and balancing) feedback loops.

Table 4.1. Summary of system components and initial values or formula.

Component	Name	Initial values or formula [unit]
Stock	Population	40,567,864 [person]
	Forest Area	170,939.3 [km^2]
Flow	Net Growth	Population_Growth_Rate/100*Population
	Land Use Change	(Population/Carrying_Capacity)*1000 [km^2]
	Forest Harvest	(Forestry_Production-Net_Forest_Import)/12000 [km^2]
	Forest Regeneration	Forest_Area*Forest_Regeneration_Rate [km^2]
Converter	Population Growth Rate	(1-Effect_of_Carrying_Capacity)*43
	Effect of Carrying Capacity	Population/Carrying_Capacity (in graphical function)
	Carrying Capacity	53000000 [person]
	Forestry Production	98018*(TIME-2000) + 15921000 [m^3]
	Net Forest Import	-266374*(TIME-2000) + 3354634 [m^3]
	Forest Regeneration Rate	0.016
	SDG 15 Progress	0.000528131*Forest_Area - 20.77720428

4.3.3.3 Model calibration and validation

To calibrate the model, I ran the model for 10 years with initial settings (DT=1) and plotted the simulated Population, Forest Area, Forestry Production, and Net Forest Import results against the real-world data from 2000 to 2010. The parameters I changed to fit the model with reality were Forest Harvest, Land Use Change, Population Growth Rate, and Effect of Carrying Capacity in graphical function.

With the final calibrated model, I changed the runtime to 20 years from 2000 to 2020. After exporting simulated data from 2010 to 2020, I validated the model results by plotting them against real-world data. Because SDG 15 Progress data was not available before 2010 and the major data jumps between 2011 and 2012, 2015 and 2016 could mislead the prediction, only data from 2016 to 2020 were used for this variable in the iterative model calibration process to avoid noises.

4.3.3.4 Reference model prediction and sensitivity analysis

The reference model prediction was based on the existing variables and their relationships with no interventions after model validation, between 2020 and 2050. The key variables of interest are Forest Area and SDG 15 Progress. I changed the runtime to 50 years from 2000 to 2050.

The sensitivity analysis was also performed during the same period after model validation. The key variables of interest are Forest Area and SDG 15 Progress. To perform the five runs of sensitivity analysis, Forest Regeneration Rate, Initial Forest Area, Population, Forestry Production, and Net Forest Import were changed one at a time ranging from 10% lower and 10% higher than the baseline values or formula while holding other input variables constant. Sensitivity is estimated by the index of Sx, within the following formula.

$$S_x = \frac{\Delta X}{X} \Big/ \frac{\Delta P}{P}$$

Where *X* is the variable under the original condition, *ΔX* is either the difference of the variable at 10% lower value between the original variable value or the difference of the original variable and the variable at 10% higher value. For example, for Forest Regeneration Rate analysis, X is the Forest Regeneration Rate at the baseline of 0.016; *ΔX* is either the difference between 0.0144 (lower 10%) and 0.016 (baseline) or the difference between 0.016 (baseline) and 0.0176 (higher 10%).

P represents the value of either Forest Area or SDG 15 Progress under the original condition and *ΔP* is the difference in the data value of either Forest Area or SDG 15 Progress between the original and modified conditions. For example, for Forest Regeneration Rate analysis, *P* is either Forest Area or SDG 15 Progress (when Foerst Regeneration Rate is set at 0.016); *ΔP* is either the difference between Forest Area values (when Forest Regeneration Rate is 0.0144 and

0.016; or when Forest Regeneration Rate is 0.016 and 0.0176) or the difference between SDG 15 Progress values under the above conditions.

S_x refers to the change in the Forest Area or SDG 15 Progress due to the change in the following variables at a time (Forest Regeneration Rate, Initial Forest Area, Population, Forestry Production, and Net Forest Import). The larger the value, the more sensitive Forest Area or SDG 15 Progress are to those variables of change.

For Initial Forest Area, the baseline is 170,939.3, lower bound is 153,845.37, and upper bound is 188,033.23. For Population, the baseline is 40,567,864, lower bound is 36,511,077.6, and upper bound is 44,624,650.4. For the formula of Forestry Production and Net Forest Import, a coefficient of 0.9 or 1.1 was multiplied to its original formula to represent the 90% or 110% of variable levels. I ran each of the five sensitivity analyses individually and then exported the changed Forest Area and SDG 15 Progress in separate Excel files. For each sensitivity analysis, two Sx values were produced – one showed the difference between the baseline value and its 10% lower value, the other showed the difference between the baseline value and its 10% higher value. Those Sx values would depict how input variable sensitivity affects the key output variables of interest and show which variable among those five changed variables is more significant to the output variable variation.

Table 4.2. Summary of modified system component values for five runs of sensitivity analysis.

Component	**Name**	**Lower/higher values or formula**
Converter	Forest Regeneration Rate	0.0144, 0.0176
	Forest Area	153,845.37, 188,033.23
	Population	36,511,077.6, 44,624,650.4
	Forestry Production	0.9* (98018*(TIME-2000) + 15921000), 1.1* (98018*(TIME-2000) + 15921000)
	Net Forest Import	0.9* (-266374*(TIME-2000) + 3354634), 1.1* (-266374*(TIME-2000) + 3354634)

4.4 Results

4.4.1 Calibration

The model calibration indicated when Forest Harvest, Land Use Change, Population Growth Rate, and Effect of Carrying Capacity in graphical function were set as current formula summarized in Table 4.1, the model best fit the real-world data from 2000 to 2010 (Table 4.3), especially for the key stocks of interest (Forest Area and Population). Then I plotted the simulated data against the real-world data for Forest Area, Forestry Production, Net Forest Import, and Population, which generated the R^2 values of 0.998, 0.211, 0.606, and 0.987 (Figure 4.5).

Table 4.3. Real-world and modeled data for Forest Area, Population, Forestry Production, and Net Forest Import between 2000 and 2010.

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Real-world Forest Area	170939.3	172390.71	173842.12	175293.5	176744.9	178196.4	179647.8	181099.2	182550.6	184002	185453.4
Modeled Forest Area	170939.3	171861.7002	172758.6346	173630.2	174476.6	175297.9	176094.2	176865.3	177611.2	178331.7	179026.7
Real-world Forestry Production	15921000	16986000	17828000	18135000	18345000	17711000	17323000	16510000	19627374	16060035	21209399
Modeled Forestry Production	15921000	16019018	16117036	16215054	16313072	16411090	16509108	16607126	16705144	16803162	16901180
Real-world Net Forest Import	3354634	3641000	3059000	2871000	2639000	3287000	3325000	3332098	1576000	944904	392626
Modeled Net Forest Import	3354634	3088260	2821886	2555512	2289138	2022764	1756390	1490016	1223642	957268	690894
Real-world Population	40567864	40850412	41431558	42187645	42921895	43653155	44397319	45226803	45954106	46362946	46576897
Modeled Population	40567864	41090352.04	41584035.81	42049673	42488118	42902337	43300841	43683868	44051685	44404589	44742902

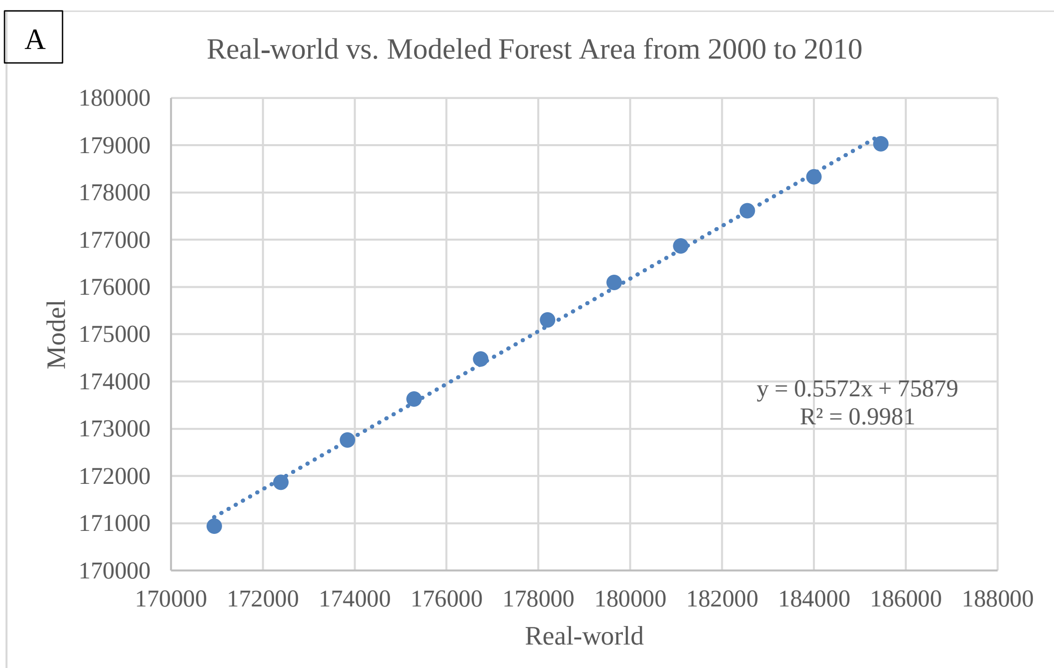
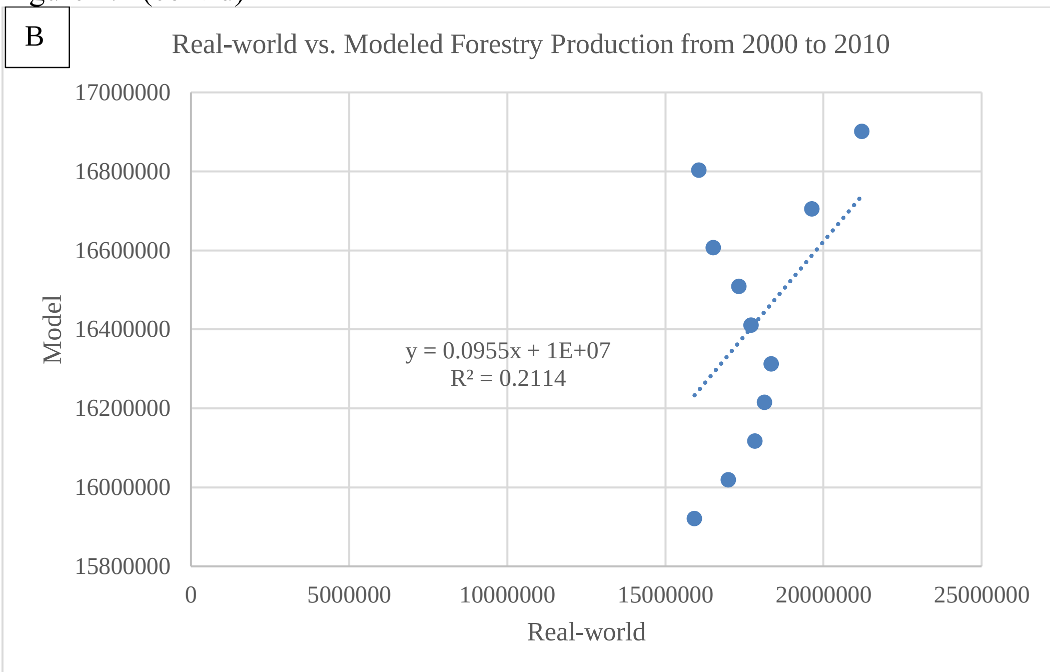
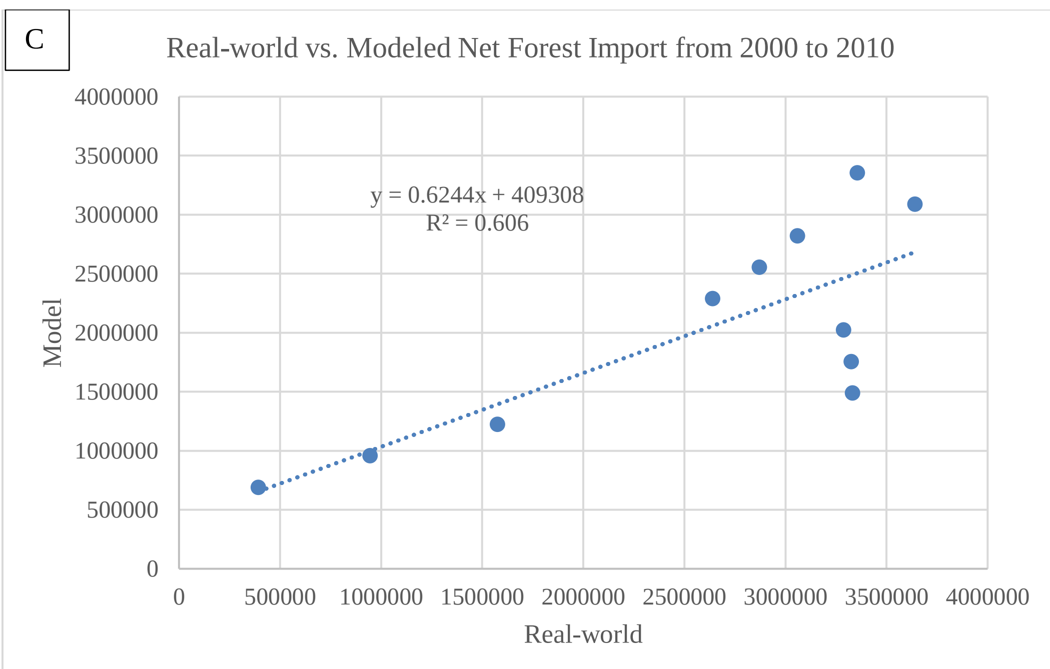


Figure 4.4. Plots of modeled against real-world data for four variables between 2000 and 2010. (A) Forest Area, (B) Forestry Production, (C) Net Forest Import, and (D) Population.

Figure 4.4 (cont'd)





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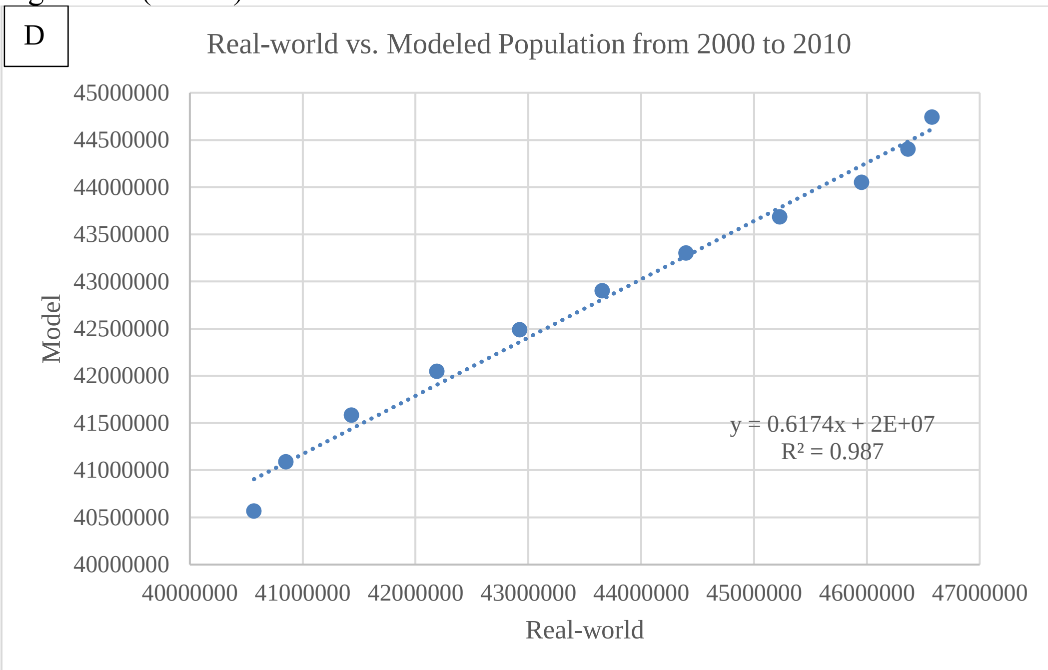


With the initial values or formula of stocks, flows and converters in Table 4.1, the simulation results from 2000 to 2010 are shown in Figure 4.5.

Forest Area constantly increased from 171 to 179 thousand square kilometers, while the three major flows all increased – Forest Regeneration increased from 2.74 to 2.86 thousand square kilometers, Forest Harvest increased from 1.05 to 1.35 thousand square kilometers, and Land Use Change slightly increased from 765 to 844 square kilometers. Forestry Production increased from 15.9 to 16.9 million cubic meters, while Net Forest Import decreased from 3.35 million to 691 thousand cubic meters. Population drastically increased from 40.6 to 44.7 million over 2000 and 2010.

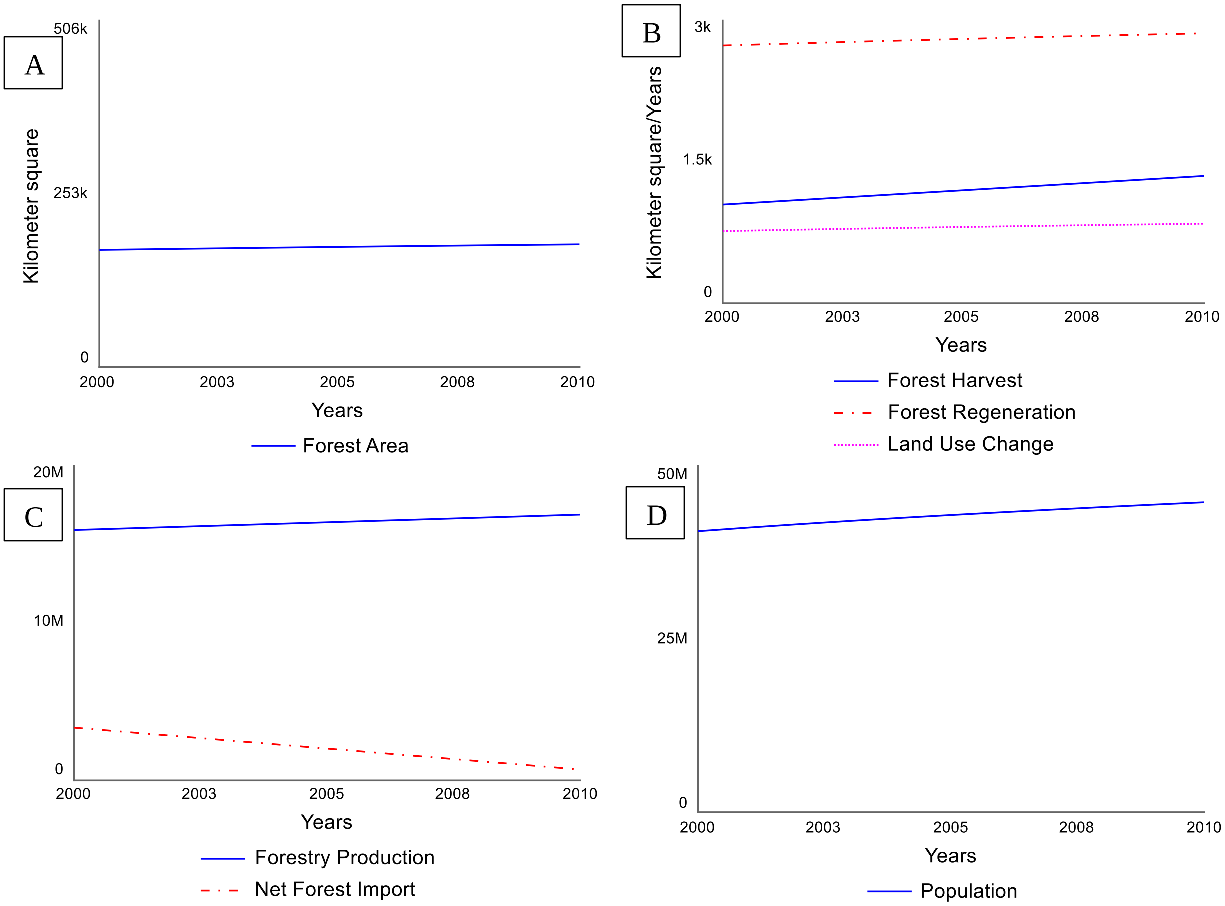


Figure 4.5. Model calibration results. (A) Forest Area, (B) Forest Harvest, Forest Regeneration, Land Use Change, (C) Forestry Production, Net Forest Import, and (D) Population estimates between 2000 and 2010.

4.4.2 Validation

Keeping the initial values and formula set in calibration and increasing the runtime for another 10 years (till 2020), I found the model fit the real-world data well (Table 4.4). Then I plotted the modeled data against the real-world data, which generate the R^2 values of 0.902, 0.004, 0.640, and 0.280 (Figure 4.6).

Table 4.4. Real-world and modeled data for Forest Area, Population, Forestry Production, and Net Forest Import between 2010 and 2020.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Real-world Forest Area	185465.1	185476.8	185488.4	185500.1	185511.8	185552.4	185593	185635.9	185678.8	185721.7
Modeled Forest Area	179696	180339.6	180957.3	181548.9	182114.2	182653.1359	183165.4254	183650.8929	184109.3261	184540.5019
Real-world Forestry Production	19327772	17686795	18994298	20104343	21950361	19171601	19179531	22469782	18635586	17881367
Modeled Forestry Production	16999198	17097216	17195234	17293252	17391270	17489288	17587306	17685324	17783342	17881360
Real-world Net Forest Import	23361	-116431	-625677	-1162310	-1456442	-1621376	-855882	-873275	-1586331	-1972841
Modeled Net Forest Import	424520	158146	-108228	-374602	-640976	-907350	-1173724	-1440098	-1706472	-1972846
Real-world Population	46742697	46773055	46620045	46480882	46444832	46484062	46593236	46797754	47134837	47365655
Modeled Population	45066968	45377147	45673817	45957366	46228191	46486695.51	46733288.81	46968381.02	47192382.69	47405702.71

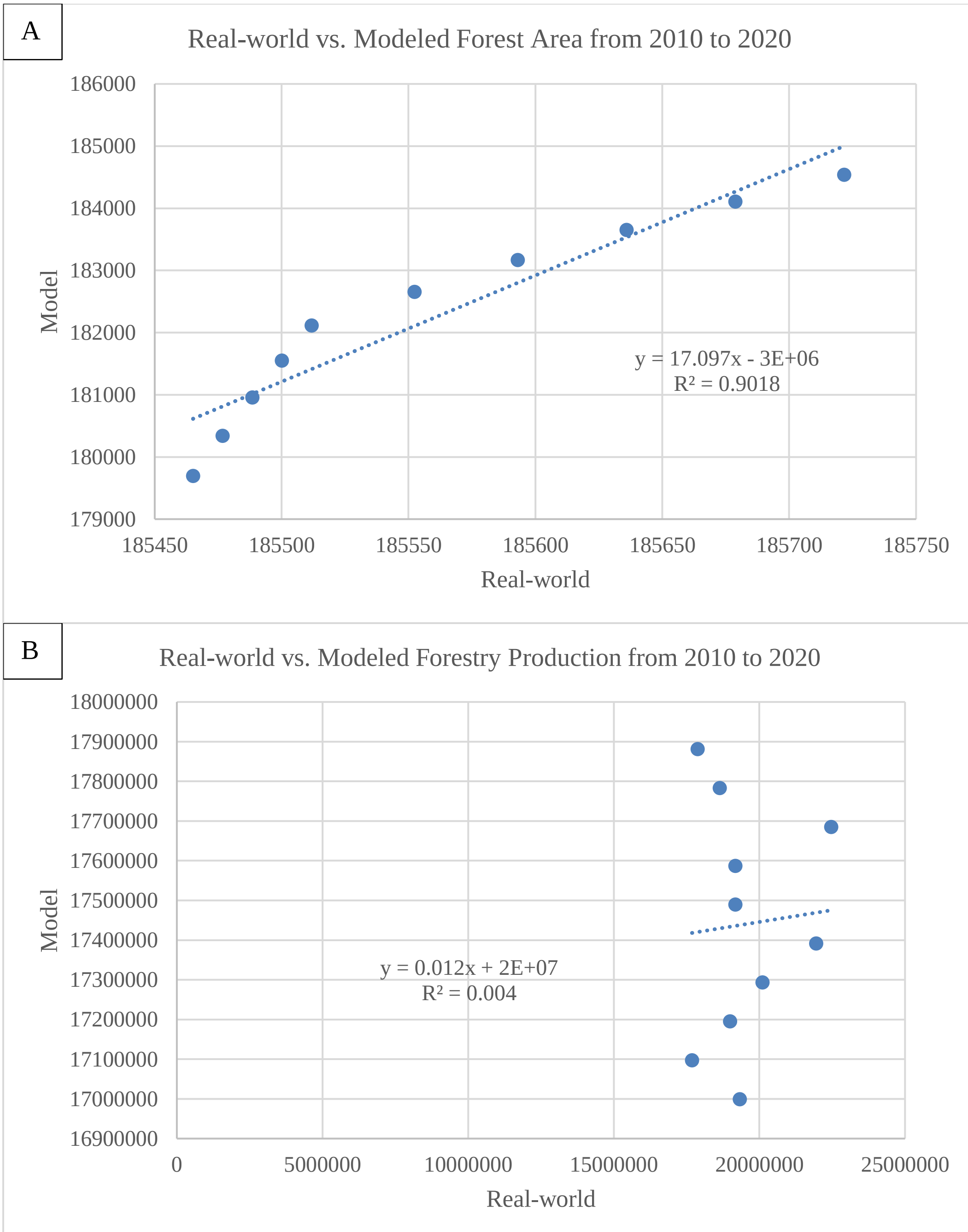
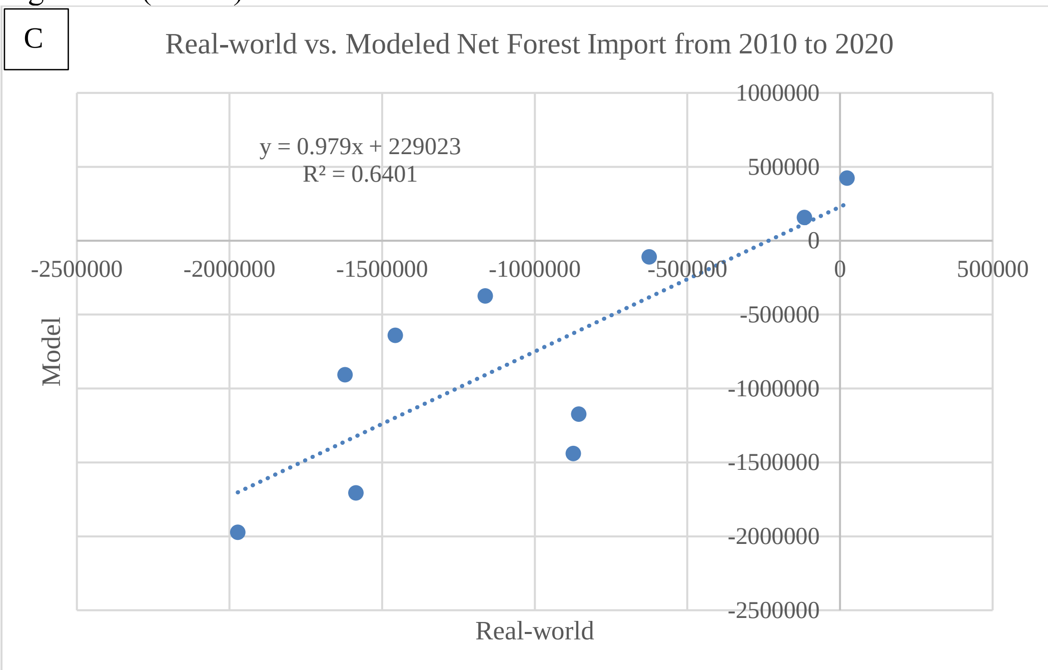
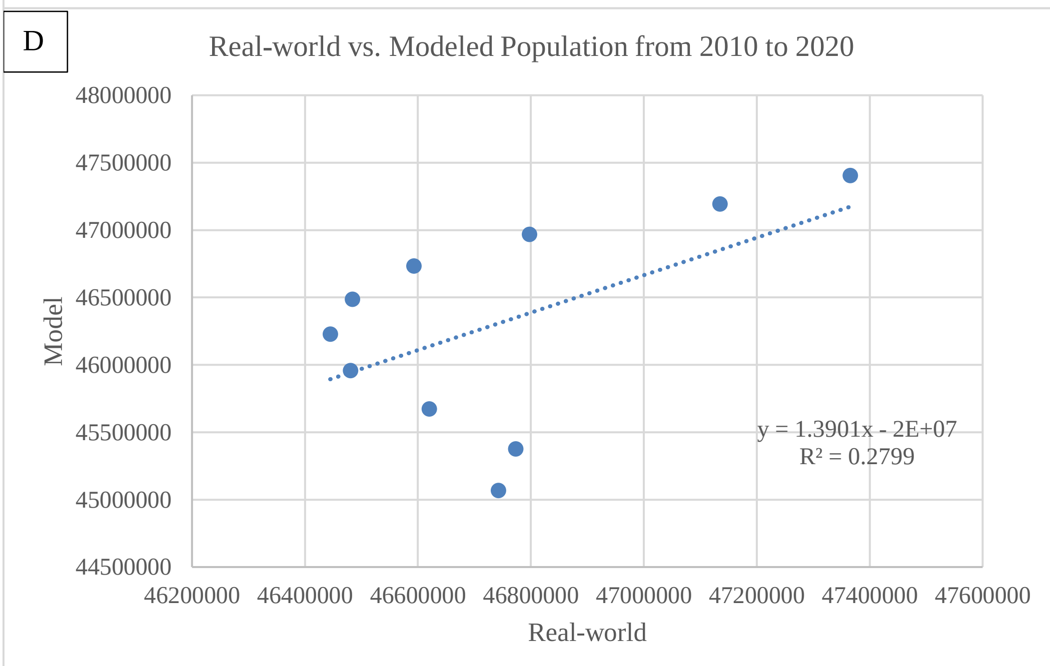


Figure 4.6. Plots of modeled against real-world data for four variables between 2010 and 2020. (A) Forest Area, (B) Forestry Production, (C) Net Forest Import, and (D) Population.

Figure 4.6 (cont'd)





With the initial values or formula of stocks, flows and converters in Table 4.1, the simulation results from 2000 to 2020 are shown in Figure 4.7.

Forest Area kept increasing from 179 to 185 thousand square kilometers, with Forest Regeneration increasing from 2.86 to 2.95 thousand square kilometers. Land Use Change increased from 844 to 894 square kilometers, but Forest Harvest increased at a slower rate from 1.35 to 1.65 thousand square kilometers. This is mainly due to the change in Net Forest Import from 16.9 to -1.97 million cubic meters, while Forest Production increasing from 16.9 to 17.9 million cubic meters. Population increased from 44.7 to 47.4 million between 2010 and 2020.

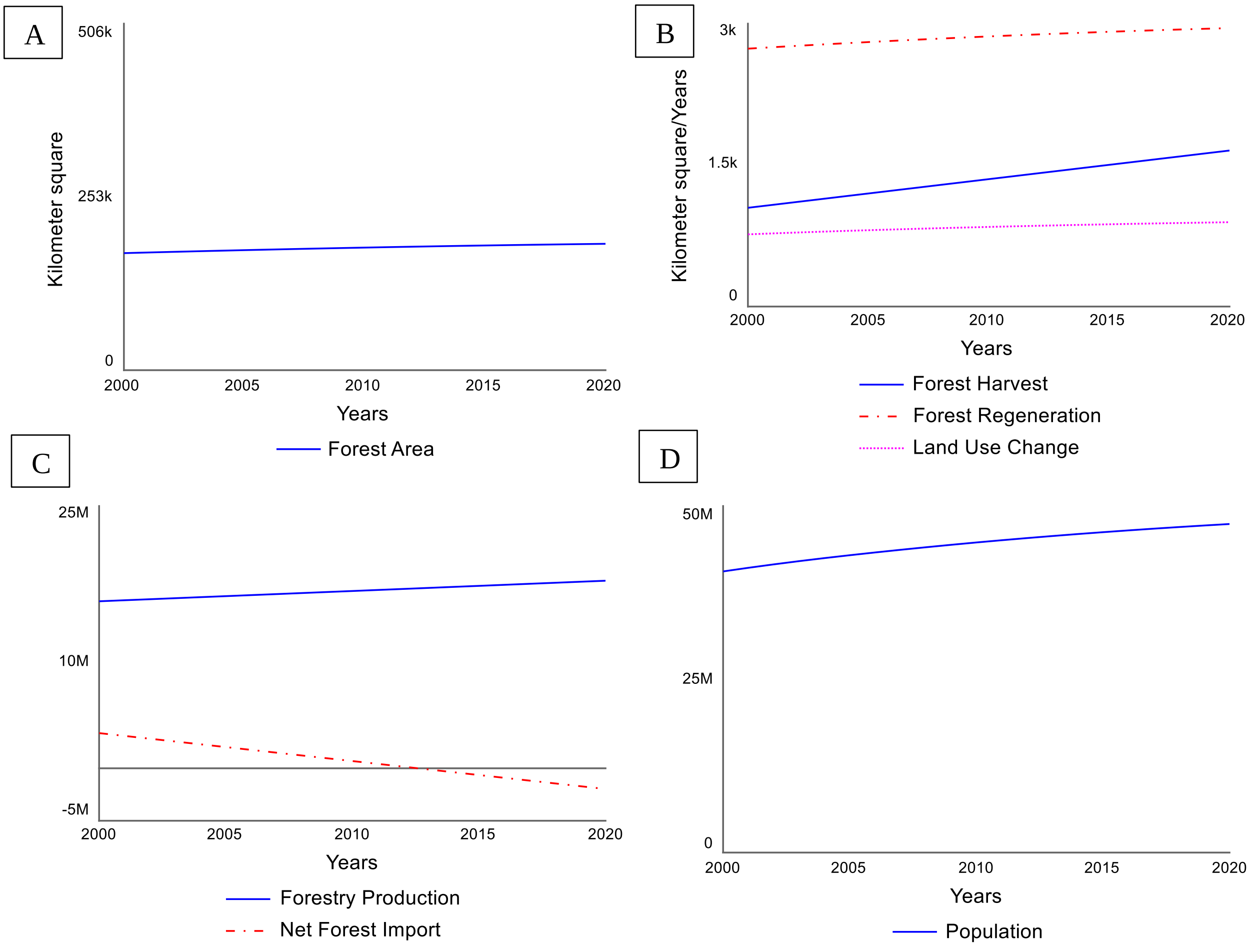


Figure 4.7. Model validation results. (A) Forest Area, (B) Forest Harvest, Forest Regeneration, Land Use Change, (C) Forestry Production, Net Forest Import, and (D) Population estimates between 2000 and 2020.

4.4.3 Reference model prediction and sensitivity analysis

4.4.3.1 Reference model prediction

With the initial values or formula of stocks, flows, and converters in Table 4.1, I ran the reference model between 2000 and 2050. Forest Area constantly increased and reached the peak of 187,549 km^2 in 2034, then slightly decreased to 183,071 km^2 in 2050. SDG 15 Progress followed the same pattern: it reached the peak of 78.27 in 2034 and then slightly dropped to 75.91 by the end of 2050. Land Use Change gradually increased from 765 to 966 km^2 between 2000 and 2050. Forest Regeneration increased and reached the peak of about 3,000 km^2 in 2034 and then decreased to 2,929 km^2 in 2050, while Forest Harvest continuously increased from 1,047 to 2,565 km^2 over those 50 years. This is primarily because Net Forest Import dropped from 3,354,634 to -9,964,066 m^3, which became a net export, while Forest Production kept increasing from 15,921,000 to 20,821,900 m^3 between 2000 and 2050. Population increased from 40,567,864 to 51,196,843, but the growth rate became slower over the years (Figure 4.8).

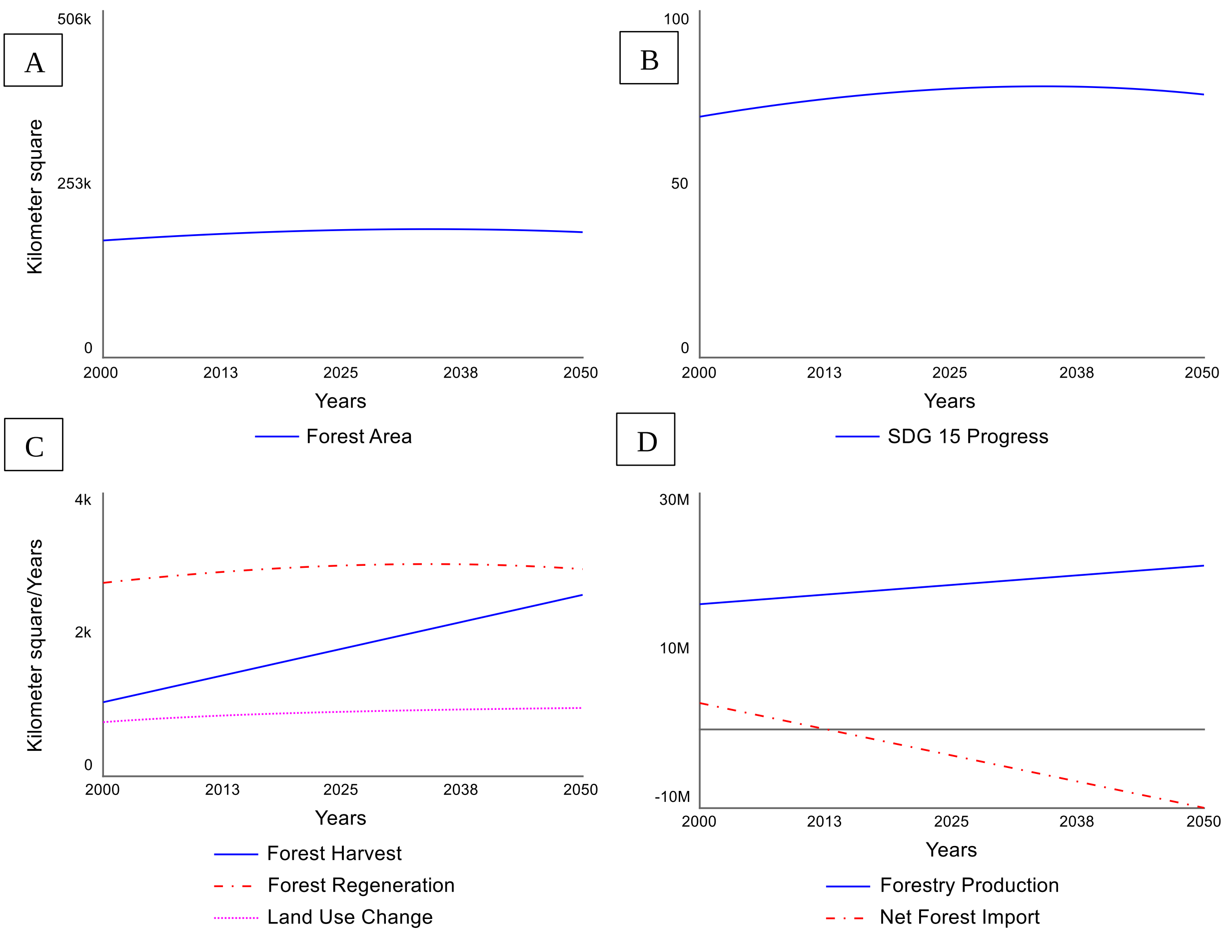
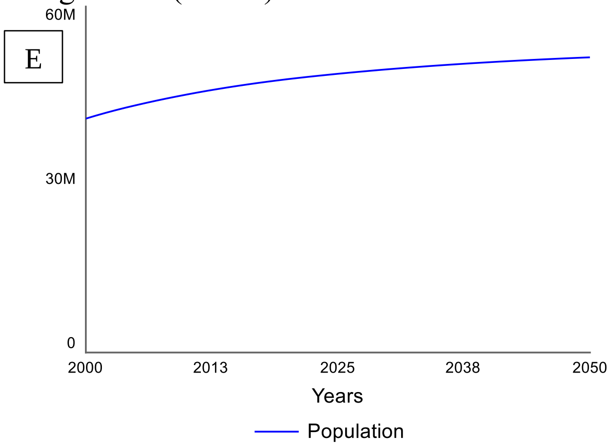


Figure 4.8. Reference model results. (A) Forest Area, (B) SDG 15 Progress, (C) Forest Harvest, Forest Regeneration, Land Use Change, (D) Forestry Production, Net Forest Import, and (E) Population estimates between 2000 and 2050.

Figure 4.8 (cont'd)



4.4.3.2 Sensitivity analysis of Forest Area

Among the five runs of sensitivity analysis by changing one variable at a time, Forest Area is most sensitive to Net Forest Import and least sensitive to Initial Forest Area. Both 10% lower and higher values of Net Forest Import had major impact on Forest Area, with S_x values over 200 at the first few years of study. Although the S_x values dropped down to 80 around 2015, they bounced and peaked over 1700 in 2028. The absolute value of S_x remained as high as 700 in 2029 and shrank to about 10 at the end of 2050. Population and Forestry Production also had a large impact on Forest Area, but their S_x values (absolute) were not as high as Net Forest Import and decreased over time. Forest Regeneration Rate had a smaller impact on Forest Area, with an initial S_x value of 60 and diminishing towards 0 in 2050. Initial Forest Area has the minimal impact on Forest Area, regardless of 10% lower or higher of its baseline.

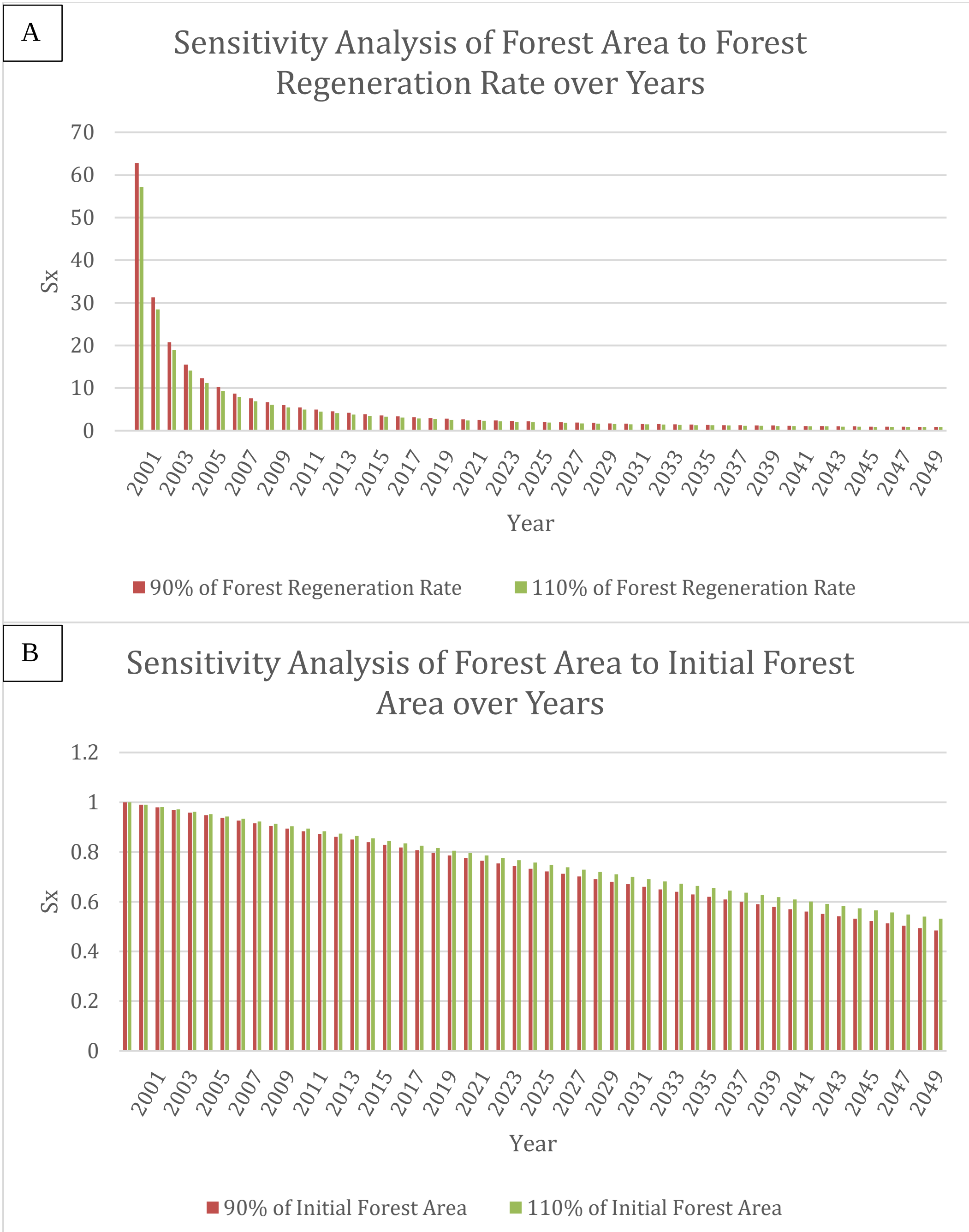


Figure 4.9. Sensitivity estimates of Forest Area to five variables between 2000 and 2050. The lower 10% of baseline value (e.g., 90% of variable) estimate is orange, and the higher 10% of baseline value (e.g., 110% of variable) estimate is in green. (A) Forest Regeneration Rate, (B) Initial Forest Area, (C) Population, (D) Forestry Production, and (E) Net Forest Import.

Figure 4.9 (cont'd)

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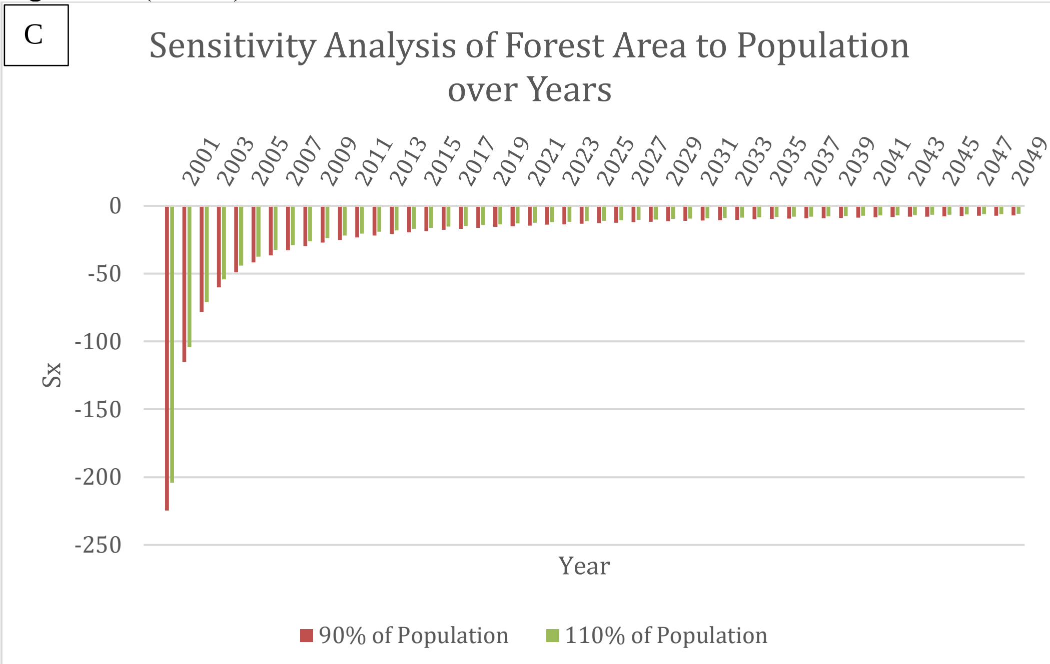

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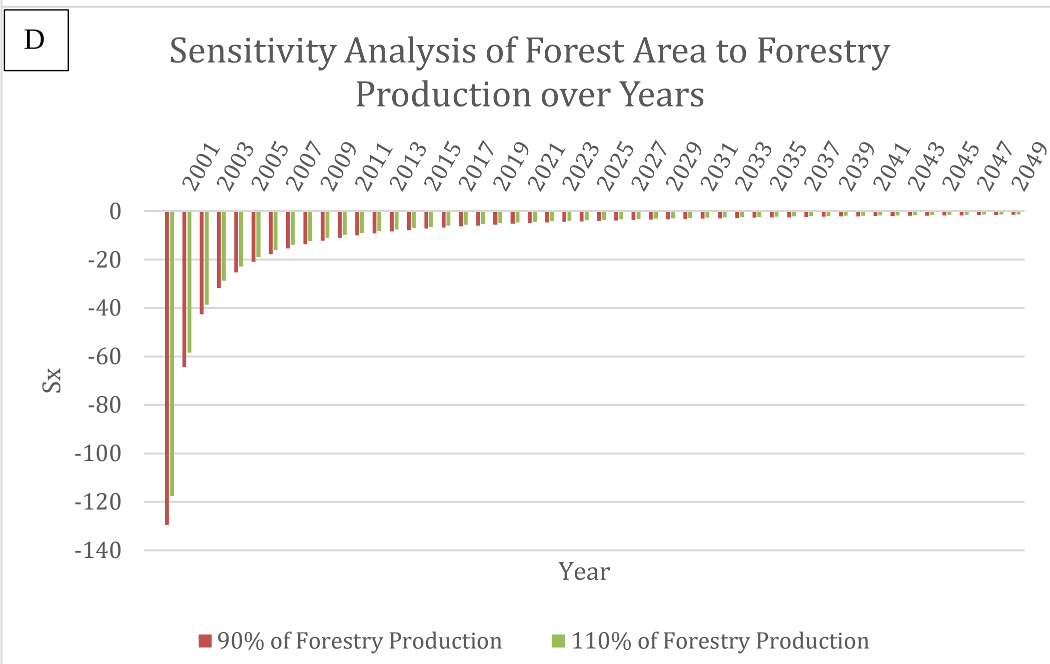

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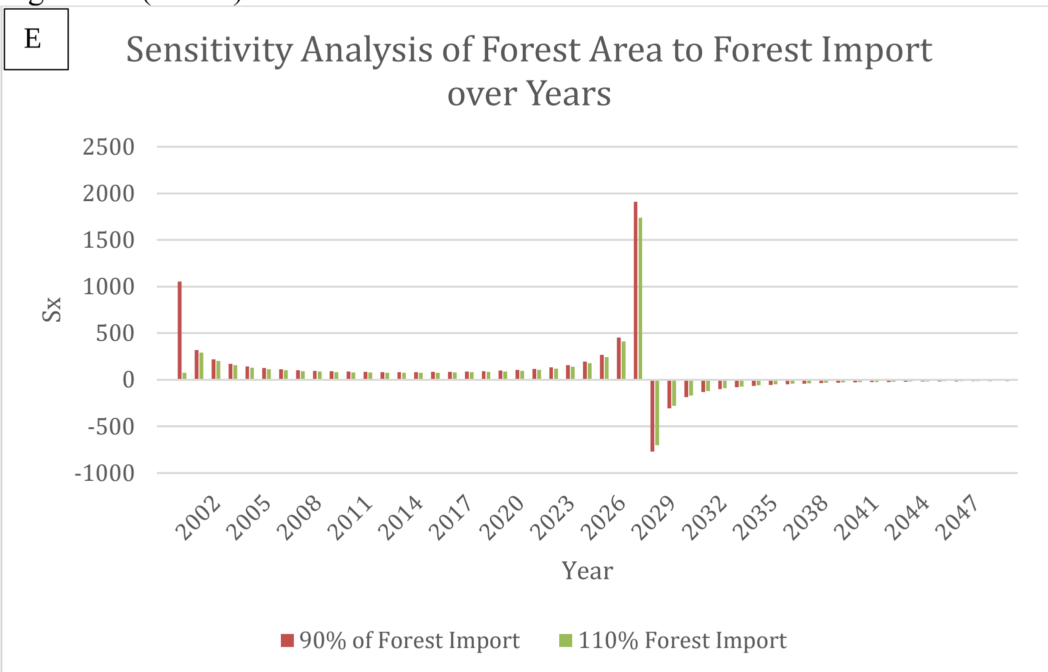


4.4.3.3 Sensitivity analysis of SDG 15 Progress

SDG 15 Progress is also most sensitive to Net Forest Import and least sensitive to Initial Forest Area. SDG 15 Progress is highly sensitive to both 10% lower and higher values of Net Forest Import, with S_x values over 150 for the first four years of study. The S_x values decreased to 60 in 2015, but they immediately increased by 1000 in 2028. The absolute value of S_x stayed as high as 550 in 2029 and eliminated to 9 in 2050. Population and Forestry Production had smaller but still noticeable impact on SDG 15 Progress, with an initial S_x value over 100 and reducing to single digits by the end of 2050. Forest Regeneration Rate had an even smaller impact on SDG 15 Progress, with an initial S_x value of about 50 and dropping to 0 in 2050. Initial Forest Area has the smallest impact on SDG 15 Progress throughout the whole study period between 2000 and 2050.

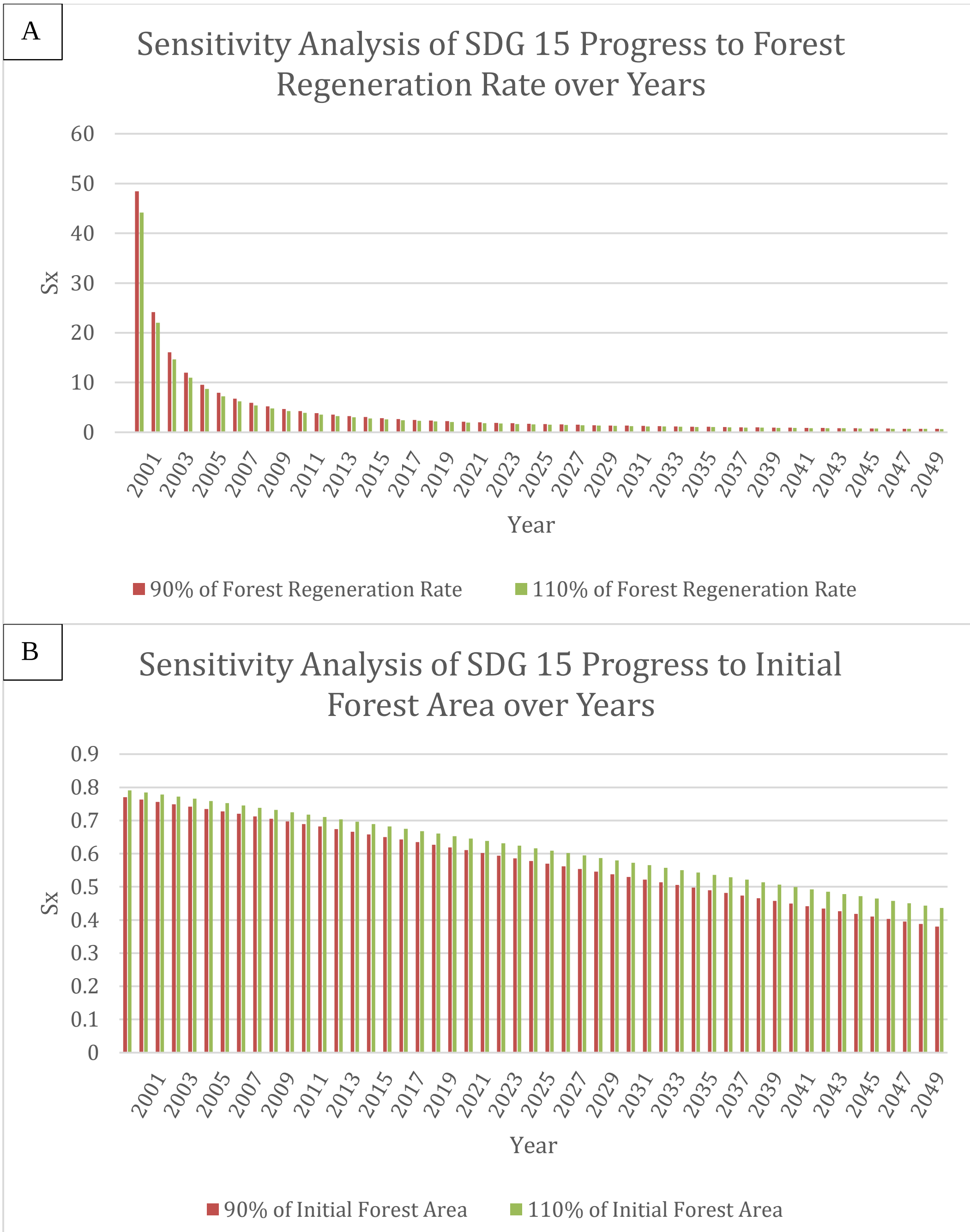
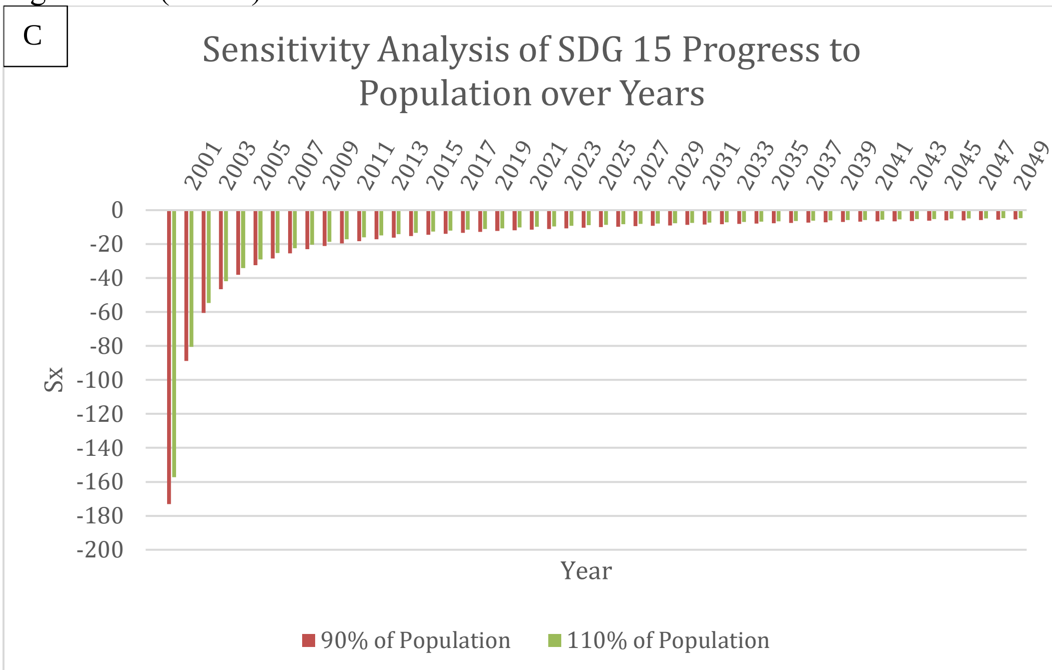


Figure 4.10. Sensitivity estimates of SDG 15 Progress to five variables between 2000 and 2050. The lower 10% of baseline value (e.g., 90% of variable) estimate is orange, and the higher 10% of baseline value (e.g., 110% of variable) estimate is in green. (A) Forest Regeneration Rate, (B) Initial Forest Area, (C) Population, (D) Forestry Production, and (E) Net Forest Import.

Figure 4.10 (cont'd)



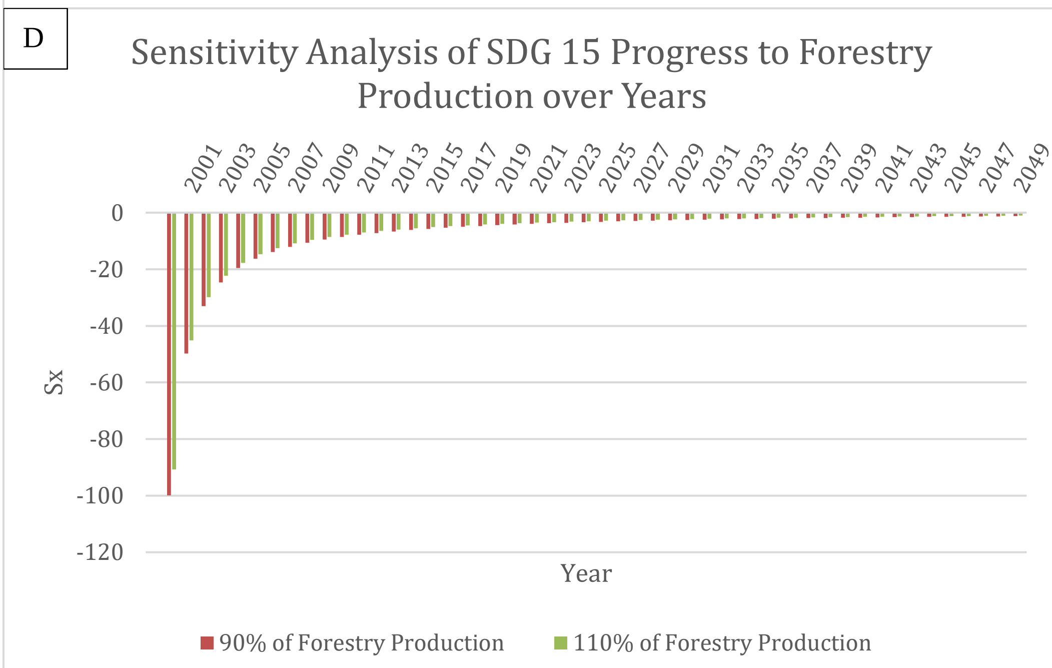
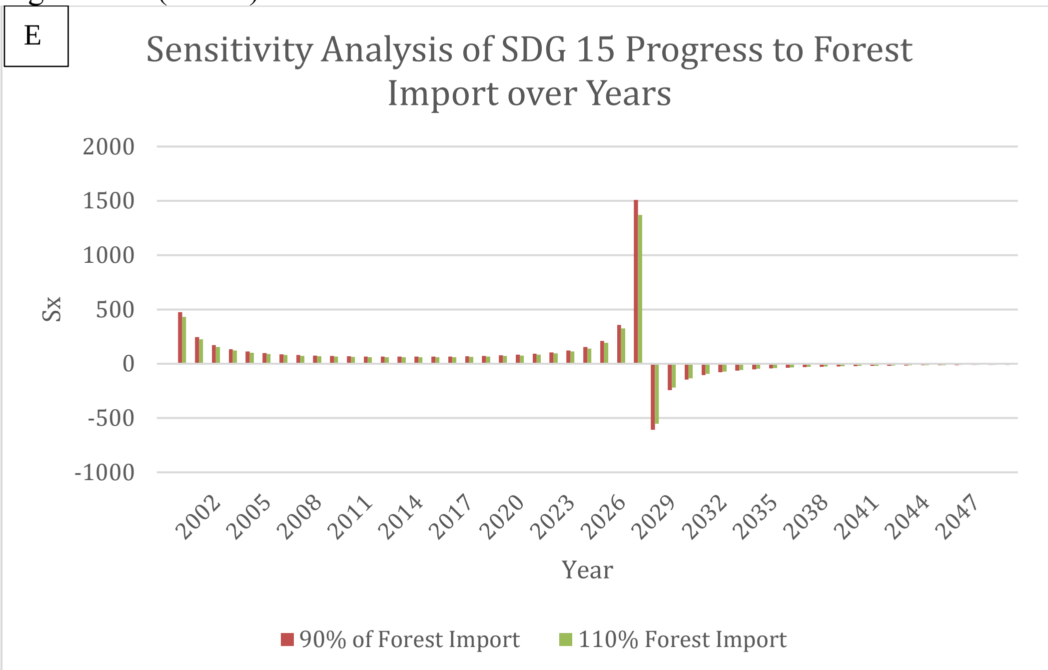


Figure 4.10 (cont'd)



4.5 Discussion

Our model results document how forest, SDG 15 progress, and population interacted within the couple human and natural system using Spain as an example. With the existing data from 2000 and 2010, the model is well calibrated by adjusting the initial values or formula for each parameter. The model fit well with the real-world Forest Area for those years. The calibration method is valid because only the endogenous factors in the model were changed which generates its own system behavior. Further, through the calibration and validation processes, the model well explains the trajectory of Forest Area (key stock of interest) patterns and sufficiently delineates Net Forest Import with real-world data from 2010 to 2020, despite that Forestry Production and Population variables are sparsely fit. The simulation result of SDG 15 Progress between 2020 and 2050 reflects the joint impact of forest and population systems. SDG 15 Progress, resonating with Forest Area dynamics, is likely to gain moderately by 2050 compared to 2000. However, it is noticeable that the peak of SDG 15 Progress would reach in 2034, and that SDG 15 Progress may collapse due to loss of Forest Area and overharvest in the long term.

Forest Area and SDG 15 Progress are sensitive to different parameters to various extents. The Net Forest Import, as a result, has the largest impact on SDG 15 Progress, because the sensitivity index (S_x) has the highest values compared to other variables of change (Population, Forestry Production, Forest Regeneration Rate, and Initial Forest Area) between 2000 and 2050. Many Targets (United Nations, n.d.) under SDG 15 are directly associated with Forest or Protected Area. Adding such Forest Area would have a direct impact on SDG 15 Progress, and such a linear relationship between Forest Area and SDG 15 Progress was defined in the model. The growth of Net Forest Import seems to have a profound impact on Forest stock in Spain. Besides, Forestry Production and Population can also have a large impact on SDG 15 Progress especially during early years when SDG 15 Progress was at a relatively low level. Forest Regeneration Rate has a smaller impact on SDG 15 Progress, but it should not be ignored. This provides potential insights for domestic sustainable forest harvest and international trade. For example, considering population growth and domestic demand for forestry, a baseline for sustainable forest harvest and trade should be set for Spain and the international community, to achieve both domestic and international forest conservation and sustainable development.

Challenges such as lack of data and bounded rationality of picturing system structure existed when building the model. Several assumptions have been made to indicate the limit of this model and under what conditions the model worked. It is difficult to overcome existing limitations in this study such as the underestimation of Forestry Production and simplification of Net Forest Import trend. Our goal is to train the model with best fit to as many variables as possible, but modeled Forest Area (key stock of interest) reliably fit real-world data at the cost of sparsely fit of

Forestry Production with a simple time-dependent function defined in the model. The change of Forestry Production and Net Forest Import are highly dependent on the market (involving both domestic and international supply and demand) which is not necessarily correlated with time or maybe there is a delay in market response reflected in the change at specific years. External variables could also shape the dynamics of markets such as global economy, transportation delays, pandemic (Li et al., 2017, Amrouss et al., 2017, Golar et al., 2020). Another limitation is although Forest Area and Population (stocks) generally fit the real-world data during calibration and validation processes, Forestry Production and Net Forest Import could be under/overestimated, which could add uncertainty for prediction outcomes. To obtain a better and realistic estimate result and represent a more complete system patterns and processes, future study should consider more elements of both natural and human factors including the elasticity of the forestry market, differentiation between neighboring and distant trade partners, domestic and global economy, domestic and international policies' intersections and interactions, and socioecological shocks (e.g., pandemic, natural disaster, climate change) (Frieden and Martin, 2002, Michinaka et al., 2011, Xu et al., 2020, White and Wulfing, 2024). The modeling approach integrating human and natural systems can be generalized and applied to other countries and SDG Progress simulations at different scales.

Despite the limitations, the information offered by the System Dynamics Model in this study would still assist in better adaptive management for Forest management, natural resources policy-making, and sustainable development in the future. To disseminate the modeling results, future work should extend to stakeholder engagement. In this case, by sharing the findings with stakeholders (natural resources management, demographics, and development planning governments, research institutes, associate NGOs, and public communities), obtaining feedback on the model and additional real-world data could help include important parameters and refine the model. The modeling outcomes would also be utilized to facilitate communications among community members, governments and NGOs. Those findings would be informative to stakeholders such as the public and decision makers on land use and management. For instance, the public might have a better understanding of the policy impact – how it would regulate their agricultural and urban land, how it would enhance forest conservation and trade, and whether it would bring them more environmental and economic benefits in a sustainable way. Winning public support is a significant part of conducting sustainable development work. With the outcomes from the model, decision-makers would have more information of benefits and losses at specific time to make cost-effective policies for natural resources management and conservation planning.

CHAPTER 5: SYNTHESIS

This dissertation focuses on the current challenge for conservation science and the knowledge gap in the United Nations' SDGs 14 and 15 assessments on a global scale. Adding to the knowledge of SDG assessment, socioecological driver exploration, and mechanism disentanglement, this dissertation broadly contributes to public research and development. Analyzing environmental and social drivers for SDGs 14 and 15 variations offers helpful information for domestic and international development and decision-making. With operationalizing the metacoupling framework, this dissertation explores complex system dynamics (interactions and processes) and conducts scenario analysis to better inform future conservation planning and natural resources sustainable management. The main conclusions of each chapter are summarized below.

Chapter 2 evaluated countries' SDGs 14 and 15 performances between 2010 and 2020, based on the indicator selection and guidance from the United Nations. This delineates how countries did in SDGs 14 and 15 over the past decade, and that through comparisons, which countries did well or poorly. This evaluation step also provides significant data for the following chapters. Global biodiversity conservation and sustainable development made positive progress, but ocean sustainability progress surprisingly slowed after the United Nation Member States adopted SDGs in 2015. Low-income countries lagged in SDGs 14 and 15 progress, and the gap between low-income and high-income countries became wider over time.

Chapter 3 identified the important direct and indirect socioecological drivers for countries' SDG variation with multivariate regressions. This chapter further sheds light on the understanding of mechanisms that drive SDGs 14 and 15 variations and places the foundation for the following modeling work. Multiple drivers have mixed expected and unexpected impacts on SDG progress for countries across different income and biodiversity hotspot groups. Fish production has the most profound negative impact on SDG 14 progress for all countries, while the positive and negative impact of drivers on SDG 15 progress varies for countries of different income levels and biodiversity statuses. Synergies and trade-offs between SDGs and their Targets call for special attention for policy making to maximize the common benefits of multiple socioecological sustainability goals while minimizing the conflicting interests.

Chapter 4 investigated the drivers for SDG 15 in Spain and framed the interactions among forest, land transformation, population, and SDG 15 with the metacoupling framework. System Dynamics modeling is exercised to simulate the stocks (e.g., forest, population) change over interactions and time. This chapter deepens understanding of drivers for SDG 15 and provides useful policy implications for decision-makers with scenario analysis. SDG 15 progress, associated with forest area, is likely to reach the peak in the mid-2030s and depreciate in the long run as forest harvest increases. Forestry trade and production as well as human population have a major impact on SDG 15 progress. Future natural resources management and conservation planning should be aware of and set up the baseline for potential minimum sustainable forest regeneration and maximum sustainable harvest.

In summary, achieving sustainable development everywhere is the goal that requires every country to actively participate and make enormous efforts. To know where countries stand in SDGs 14 and 15 is the first important step. By understanding the drivers for those SDGs variations, countries would make better-informed and collaborative decisions for future sustainable development and conservation planning. Following sustainable practices in natural resources management and holding socioecological baselines are the cornerstone for a prosperous society and a sustainable planet, now and into the future.

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APPENDIX A SUPPORTING INFORMATION FOR CHAPTER 2

Please see **Supplementary Material** section in: Zhang, Y., Li, Y., & Liu, J. (2023). Global decadal assessment of life below water and on land. *Iscience*, *26*(4). https://doi.org/10.1016/j.isci.2023.106420

The supporting information includes 4 tables in Excel:

Table S1. SDG 14 scores & targets. This spreadsheet contains calculations for SDG 14 scores and target values for all countries between 2011 and 2019, and analysis by country's income level.

Table S2. SDG 15 scores & targets. This spreadsheet contains calculations for SDG 15 scores and target values for all countries between 2010 and 2020, and analysis by country's biodiversity-hotspot and income category.

Table S3. SDG data source. This spreadsheet has a detailed description of SDG, target, indicator, sub-indicator, data characteristics, and sources.

Table S4. Country class/category. This spreadsheet includes the categorized country (by income, and by biodiversity-hotspot and income) information used in SDGs 14 and 15 analyses.

APPENDIX B SUPPORTING INFORMATION FOR CHAPTER 3

Table A3.1. Full regression results for SDG 14.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Log of Fish Export	0.58	0.40, 0.76	**<0.001**	4.3	2.1
Log of Fish import	-0.26	-0.45, -0.07	**0.008**	4.6	2.1
Log of Fish Production	-0.51	-0.70, -0.31	**<0.001**	4.7	2.2
GDP per Capita	0.23	0.06, 0.41	**0.008**	3.8	1.9
Political Stability	-0.25	-0.43, -0.07	**0.007**	4.1	2.0
Political Stability * High Income (0/1)	0.03	-0.13, 0.19	0.68	3.2	1.8
Log of Population Density	-0.18	-0.28, -0.08	**<0.001**	1.3	1.1
Population Growth Rate	-0.12	-0.24, -0.01	**0.035**	1.6	1.3
Temperature Change	0.15	0.03, 0.27	**0.012**	1.7	1.3
Log of Tourist	0.40	0.21, 0.59	**<0.001**	4.5	2.1
Voice and Accountability	0.09	-0.04, 0.23	0.18	2.4	1.6

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.2. Full regression results for Target 14.1.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Log of Fish Export	-0.18	-0.43, 0.07	0.16	4.6	2.1
Log of Fish Import	0.10	-0.16, 0.35	0.45	4.8	2.2
Log of Fish Production	0.18	-0.08, 0.44	0.17	5.0	2.2
GDP per Capita	-0.06	-0.29, 0.17	0.60	3.9	2.0
Political Stability	0.12	-0.12, 0.37	0.33	4.4	2.1
Political Stability * High Income (0/1)	-0.15	-0.39, 0.08	0.20	4.2	2.0
Log of Population Density	0.14	0.00, 0.27	**0.042**	1.3	1.1
Population Growth Rate	0.01	-0.24, 0.25	0.96	4.4	2.1
Population Growth Rate * High Income (0/1)	0.03	-0.19, 0.25	0.80	3.6	1.9
Temperature Change	0.16	-0.03, 0.35	**0.092**	2.6	1.6
Temperature Change * High Income (0/1)	-0.01	-0.26, 0.25	0.96	4.9	2.2
Log of Tourist	0.10	-0.15, 0.35	0.42	4.6	2.1
Voice and Accountability	-0.24	-0.43, -0.06	**0.010**	2.5	1.6

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.3. Full regression results for Target 14.5.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Log of Fish Export	0.60	0.44, 0.77	**<0.001**	4.6	2.1
Log of Fish Import	-0.14	-0.30, 0.03	0.11	4.6	2.1
Log of Fish Production	-0.65	-0.82, -0.48	**<0.001**	5.0	2.2
GDP per Capita	0.23	0.08, 0.38	**0.003**	3.9	2.0
Political Stability	-0.25	-0.41, -0.09	**0.003**	4.4	2.1
Political Stability * High Income (0/1)	0.15	0.01, 0.29	**0.031**	3.2	1.8
Log of Population Density	-0.18	-0.27, -0.09	**<0.001**	1.3	1.1
Population Growth Rate	0.10	-0.06, 0.26	0.23	4.2	2.1
Population Growth Rate * High Income (0/1)	-0.24	-0.39, -0.10	**<0.001**	3.5	1.9
Temperature Change	0.05	-0.05, 0.15	0.36	1.8	1.3
Log of Tourist	0.48	0.32, 0.65	**<0.001**	4.6	2.1
Voice and Accountability	0.15	0.03, 0.27	**0.017**	2.5	1.6

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.4. Full regression results for Target 14.7.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Log of Fish Export	0.27	0.07, 0.47	**0.008**	4.6	2.1
Log of Fish import	-0.43	-0.63, -0.23	**<0.001**	4.6	2.1
Log of Fish Production	0.25	0.04, 0.46	**0.019**	5.0	2.2
GDP per Capita	0.22	0.04, 0.40	**0.019**	3.9	2.0
Political Stability	0.38	0.18, 0.57	**<0.001**	4.4	2.1
Political Stability * High Income (0/1)	-0.28	-0.45, -0.11	**0.001**	3.2	1.8
Log of Population Density	0.02	-0.08, 0.13	0.64	1.3	1.1
Population Growth Rate	0.23	0.04, 0.43	**0.018**	4.2	2.1
Population Growth Rate * High Income (0/1)	-0.29	-0.47, -0.12	**0.001**	3.5	1.9
Temperature Change	0.15	0.03, 0.28	**0.016**	1.8	1.3
Log of Tourist	-0.35	-0.55, -0.15	**<0.001**	4.6	2.1
Voice and Accountability	-0.30	-0.45, -0.16	**<0.001**	2.5	1.6

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.5. Full regression results for SDG 15.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Agricultural Land Percentage	-0.07	-0.11, -0.03	**<0.001**	1.6	1.3
Agricultural Land Percentage * High Income (0/1)	0.19	0.14, 0.24	**<0.001**	2.5	1.6
Percentage of Forest Rents in GDP	0.26	0.20, 0.31	**<0.001**	2.7	1.6
Percentage of Forest Rents in GDP * Biodiversity Hotspot (0/1)	-0.17	-0.23, -0.11	**<0.001**	3.0	1.7
Percentage of Forest Rents in GDP * High Income (0/1)	-0.06	-0.10, -0.01	**0.013**	1.8	1.3
Forestry Import	-0.04	-0.09, 0.01	**0.094**	2.3	1.5
Forestry Import * Biodiversity Hotspot (0/1)	0.05	0.00, 0.10	**0.038**	2.0	1.4
Forestry Production	0.01	-0.04, 0.07	0.59	2.7	1.6
Forestry Production * Biodiversity Hotspot (0/1)	-0.09	-0.14, -0.05	**<0.001**	2.0	1.4
Forestry Production * High Income (0/1)	-0.15	-0.20, -0.11	**<0.001**	1.8	1.4
Log of Forest Land Area	0.23	0.18, 0.28	**<0.001**	2.4	1.5
Log of PM2.5	0.10	0.04, 0.16	**0.001**	3.2	1.8
Political Stability	0.13	0.07, 0.19	**<0.001**	3.3	1.8
Political Stability * Biodiversity Hotspot (0/1)	-0.11	-0.16, -0.06	**<0.001**	2.2	1.5
Political Stability * High Income (0/1)	0.17	0.11, 0.22	**<0.001**	2.5	1.6
Population Density	-0.03	-0.08, 0.02	0.22	2.4	1.6
Population Density * Biodiversity Hotspot (0/1)	-0.02	-0.07, 0.04	0.53	2.9	1.7
Population Density * High Income (0/1)	0.01	-0.05, 0.06	0.80	2.7	1.6
Population Growth Rate	-0.04	-0.10, 0.01	0.15	2.8	1.7
Population Growth Rate * Biodiversity Hotspot (0/1)	0.02	-0.04, 0.07	0.57	2.8	1.7
Population Growth Rate * High Income (0/1)	-0.13	-0.17, -0.08	**<0.001**	2.0	1.4
Regulatory Quality	0.13	0.06, 0.19	**<0.001**	3.6	1.9
Temperature Change	0.04	0.00, 0.08	**0.029**	1.5	1.2
Temperature Change * Biodiversity Hotspot (0/1)	0.03	-0.03, 0.08	0.30	2.7	1.7

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.6. Full regression results for Target 15.1.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Agricultural Land Percentage	-0.15	-0.20, -0.10	**<0.001**	1.6	1.3
Agricultural Land Percentage * High Income (0/1)	0.21	0.14, 0.27	**<0.001**	2.5	1.6
Forest Rents in GDP Percentage	0.40	0.33, 0.47	**<0.001**	2.7	1.6
Forest Rents in GDP Percentage * Biodiversity Hotspot (0/1)	-0.27	-0.34, -0.20	**<0.001**	3.0	1.7
Forest Rents in GDP Percentage * High Income (0/1)	-0.09	-0.15, -0.04	**<0.001**	1.7	1.3
Log of Forest Area	0.48	0.42, 0.55	**<0.001**	2.4	1.5
Forestry Import	-0.08	-0.14, -0.02	**0.015**	2.4	1.5
Forestry Import * Biodiversity Hotspot (0/1)	0.00	-0.06, 0.06	0.96	2.0	1.4
Forestry Production	-0.19	-0.25, -0.12	**<0.001**	2.8	1.7
Forestry Production * Biodiversity Hotspot (0/1)	-0.11	-0.17, -0.06	**<0.001**	2.0	1.4
Forestry Production * High Income (0/1)	-0.11	-0.17, -0.06	**<0.001**	1.8	1.4
Political Stability	0.22	0.14, 0.29	**<0.001**	3.3	1.8
Political Stability * Biodiversity Hotspot (0/1)	0.01	-0.05, 0.07	0.70	2.2	1.5
Political Stability * High Income (0/1)	0.07	0.01, 0.14	**0.025**	2.4	1.6
Log of PM2.5	0.14	0.07, 0.21	**<0.001**	3.2	1.8
Population Density	-0.02	-0.08, 0.05	0.62	2.5	1.6
Population Density * Biodiversity Hotspot (0/1)	0.07	0.00, 0.14	**0.053**	2.9	1.7
Population Density * High Income (0/1)	0.02	-0.04, 0.09	0.46	2.6	1.6
Population Growth Rate	-0.31	-0.37, -0.24	**<0.001**	2.8	1.7
Population Growth Rate * Biodiversity Hotspot (0/1)	0.14	0.07, 0.21	**<0.001**	2.8	1.7
Population Growth Rate * High Income (0/1)	-0.07	-0.13, -0.02	**0.011**	2.0	1.4
Temperature Change	0.00	-0.04, 0.05	0.85	1.5	1.2
Temperature Change * Biodiversity Hotspot (0/1)	0.01	-0.06, 0.07	0.88	2.8	1.7
Voice and Accountability	0.19	0.12, 0.25	**<0.001**	2.5	1.6

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.7. Full regression results for Target 15.4.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Agricultural Land Percentage	-0.03	-0.09, 0.03	0.39	1.6	1.3
Agricultural Land Percentage * High Income (0/1)	0.20	0.13, 0.28	**<0.001**	2.6	1.6
Forest Rents in GDP Percentage	0.43	0.36, 0.51	**<0.001**	2.7	1.6
Forest Rents in GDP Percentage * Biodiversity Hotspot (0/1)	-0.37	-0.45, -0.28	**<0.001**	3.0	1.7
Forest Rents in GDP Percentage * High Income (0/1)	-0.01	-0.07, 0.06	0.80	1.7	1.3
Log of Forest Area	0.14	0.06, 0.21	**<0.001**	2.5	1.6
Forestry Import	-0.12	-0.20, -0.03	**0.008**	3.2	1.8
Forestry Import * Biodiversity Hotspot (0/1)	0.05	-0.02, 0.12	0.18	2.0	1.4
Forestry Production	0.00	-0.08, 0.08	0.92	2.8	1.7
Forestry Production * Biodiversity Hotspot (0/1)	-0.11	-0.18, -0.04	**0.001**	2.0	1.4
Forestry Production * High Income (0/1)	-0.14	-0.22, -0.05	**0.001**	3.0	1.7
Political Stability	0.06	-0.03, 0.14	0.21	3.3	1.8
Political Stability * Biodiversity Hotspot (0/1)	-0.05	-0.12, 0.02	0.20	2.2	1.5
Political Stability * High Income (0/1)	0.11	0.03, 0.18	**0.005**	2.5	1.6
Log of PM2.5	0.04	-0.04, 0.13	0.32	3.3	1.8
Population Density	-0.14	-0.22, -0.07	**<0.001**	2.5	1.6
Population Density * Biodiversity Hotspot (0/1)	0.06	-0.02, 0.14	0.14	2.9	1.7
Population Density * High Income (0/1)	0.02	-0.06, 0.10	0.64	2.6	1.6
Population Growth Rate	-0.19	-0.27, -0.11	**<0.001**	2.8	1.7
Population Growth Rate * Biodiversity Hotspot (0/1)	0.11	0.03, 0.19	**0.006**	2.8	1.7
Population Growth Rate * High Income (0/1)	-0.05	-0.12, 0.01	0.11	2.0	1.4
Temperature Change	0.00	-0.06, 0.06	0.94	1.5	1.2
Temperature Change * Biodiversity Hotspot (0/1)	0.04	-0.04, 0.12	0.30	2.8	1.7
Voice and Accountability	0.16	0.08, 0.24	**<0.001**	2.5	1.6

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.8. Full regression results for Target 15.5.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Agricultural Land Percentage	-0.05	-0.10, 0.00	**0.071**	1.6	1.3
Agricultural Land Percentage * High Income (0/1)	0.11	0.05, 0.18	**<0.001**	2.5	1.6
Forest Rents in GDP Percentage	-0.01	-0.08, 0.05	0.67	2.7	1.6
Forest Rents in GDP Percentage * Biodiversity Hotspot (0/1)	0.05	-0.02, 0.12	0.14	3.0	1.7
Forest Rents in GDP Percentage * High Income (0/1)	-0.07	-0.12, -0.02	**0.011**	1.7	1.3
Log of Forest Area	-0.13	-0.19, -0.07	**<0.001**	2.4	1.5
Forestry Import	-0.08	-0.14, -0.01	**0.016**	2.4	1.5
Forestry Import * Biodiversity Hotspot (0/1)	0.12	0.06, 0.18	**<0.001**	2.0	1.4
Forestry Production	-0.10	-0.17, -0.04	**0.003**	2.8	1.7
Forestry Production * Biodiversity Hotspot (0/1)	-0.15	-0.20, -0.09	**<0.001**	2.0	1.4
Forestry Production * High Income (0/1)	0.16	0.10, 0.21	**<0.001**	1.8	1.4
Political Stability	0.15	0.07, 0.22	**<0.001**	3.3	1.8
Political Stability * Biodiversity Hotspot (0/1)	-0.35	-0.41, -0.29	**<0.001**	2.2	1.5
Political Stability * High Income (0/1)	0.23	0.16, 0.29	**<0.001**	2.4	1.6
Log of PM2.5	0.26	0.19, 0.33	**<0.001**	3.2	1.8
Population Density	-0.24	-0.30, -0.17	**<0.001**	2.5	1.6
Population Density * Biodiversity Hotspot (0/1)	-0.27	-0.33, -0.20	**<0.001**	2.9	1.7
Population Density * High Income (0/1)	0.00	-0.06, 0.07	0.94	2.6	1.6
Population Growth Rate	0.01	-0.06, 0.08	0.79	2.8	1.7
Population Growth Rate * Biodiversity Hotspot (0/1)	-0.08	-0.14, -0.01	**0.025**	2.8	1.7
Population Growth Rate * High Income (0/1)	-0.11	-0.16, -0.05	**<0.001**	2.0	1.4
Temperature Change	0.19	0.15, 0.24	**<0.001**	1.5	1.2
Temperature Change * Biodiversity Hotspot (0/1)	-0.14	-0.21, -0.08	**<0.001**	2.8	1.7
Voice and Accountability	0.03	-0.04, 0.09	0.42	2.5	1.6

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.9. Full regression results for Target 15.6.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Agricultural Land Percentage	-0.07	-0.12, -0.02	**0.010**	1.7	1.3
Agricultural Land Percentage * Biodiversity Hotspot (0/1)	0.08	0.02, 0.15	**0.014**	2.6	1.6
Agricultural Land Percentage * High Income (0/1)	0.15	0.09, 0.21	**<0.001**	2.5	1.6
Forest Rents in GDP Percentage	0.17	0.11, 0.24	**<0.001**	2.7	1.6
Forest Rents in GDP Percentage * Biodiversity Hotspot (0/1)	-0.07	-0.14, 0.00	**0.054**	3.0	1.7
Forest Rents in GDP Percentage * High Income (0/1)	-0.10	-0.15, -0.05	**<0.001**	1.8	1.3
Log of Forest Area	0.09	0.03, 0.15	**0.004**	2.3	1.5
Forestry Import	-0.04	-0.10, 0.03	0.25	2.5	1.6
Forestry Import * Biodiversity Hotspot (0/1)	-0.01	-0.07, 0.04	0.67	1.8	1.4
Forestry Production	0.12	0.05, 0.18	**<0.001**	2.7	1.7
Forestry Production * Biodiversity Hotspot (0/1)	0.03	-0.03, 0.08	0.32	2.0	1.4
Forestry Production * High Income (0/1)	-0.13	-0.18, -0.07	**<0.001**	1.8	1.3
Political Stability	0.21	0.15, 0.28	**<0.001**	3.0	1.7
Political Stability * Biodiversity Hotspot (0/1)	-0.12	-0.18, -0.06	**<0.001**	2.2	1.5
Log of PM2.5	0.08	0.01, 0.16	**0.030**	3.4	1.8
Population Density	0.03	-0.02, 0.08	0.21	1.7	1.3
Population Density * High Income (0/1)	0.05	-0.01, 0.11	0.12	2.4	1.6
Population Growth Rate	0.16	0.10, 0.23	**<0.001**	2.9	1.7
Population Growth Rate * Biodiversity Hotspot (0/1)	-0.09	-0.15, -0.02	**0.011**	2.8	1.7
Population Growth Rate * High Income (0/1)	-0.11	-0.17, -0.05	**<0.001**	2.1	1.5
Temperature Change	0.04	0.00, 0.09	**0.067**	1.4	1.2
Voice and Accountability	0.01	-0.06, 0.09	0.69	3.3	1.8
Voice and Accountability * High Income (0/1)	0.14	0.07, 0.21	**<0.001**	3.4	1.8

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.10. Full regression results for Target 15.8.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Forest Rents in GDP Percentage	0.03	0.00, 0.07	**0.080**	1.3	1.1
Forest Rents in GDP Percentage * High Income (0/1)	0.10	0.06, 0.14	**<0.001**	1.6	1.3
Forestry Export	-0.03	-0.09, 0.03	0.32	4.0	2.0
Forestry Export * Biodiversity Hotspot (0/1)	-0.13	-0.17, -0.08	**<0.001**	2.3	1.5
Forestry Production	0.05	0.01, 0.10	**0.020**	2.3	1.5
Forestry Production * Biodiversity Hotspot (0/1)	0.05	0.01, 0.10	**0.027**	2.3	1.5
Forestry Production * High Income (0/1)	-0.11	-0.16, -0.05	**<0.001**	2.9	1.7
Political Stability	-0.01	-0.07, 0.05	0.76	3.7	1.9
Political Stability * Biodiversity Hotspot (0/1)	0.04	0.00, 0.08	**0.077**	2.0	1.4
Political Stability * High Income (0/1)	0.10	0.05, 0.14	**<0.001**	2.4	1.5
Log of PM2.5	-0.03	-0.08, 0.02	0.23	2.7	1.6
Log of PM2.5 * High Income (0/1)	-0.05	-0.10, -0.01	**0.012**	1.9	1.4
Log of Population aged between 0 and 14	0.12	0.06, 0.17	**<0.001**	3.0	1.7
Temperature Change	0.02	-0.01, 0.06	0.24	1.4	1.2
Temperature Change * Biodiversity Hotspot (0/1)	0.03	0.00, 0.07	**0.080**	1.6	1.3
Voice and Accountability	0.09	0.05, 0.14	**<0.001**	2.1	1.5

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Table A3.11. Full regression results for Target 15.9.

Characteristic	Beta	95% CI[1]	p-value	GVIF[1]	Adjusted GVIF[2,1]
Agricultural Land Percentage	-0.04	-0.08, 0.01	0.11	1.5	1.2
Agricultural Land Percentage * High Income (0/1)	0.09	0.03, 0.15	**0.004**	2.5	1.6
Forest Rents in GDP Percentage	0.01	-0.05, 0.07	0.80	2.7	1.6
Forest Rents in GDP Percentage * Biodiversity Hotspot (0/1)	-0.04	-0.11, 0.02	0.20	2.9	1.7
Forest Rents in GDP Percentage * High Income (0/1)	-0.03	-0.08, 0.02	0.26	1.7	1.3
Log of Forest Area	0.20	0.14, 0.25	**<0.001**	2.2	1.5
Forestry Import	0.12	0.06, 0.18	**<0.001**	2.4	1.6
Forestry Import * Biodiversity Hotspot (0/1)	0.02	-0.03, 0.07	0.38	1.6	1.2
Forestry Production	-0.03	-0.09, 0.03	0.40	2.6	1.6
Forestry Production * High Income (0/1)	-0.14	-0.19, -0.09	**<0.001**	1.7	1.3
Political Stability	0.03	-0.04, 0.09	0.41	3.0	1.7
Political Stability * Biodiversity Hotspot (0/1)	-0.04	-0.09, 0.02	0.19	1.9	1.4
Log of PM2.5	0.07	0.00, 0.14	**0.050**	3.4	1.8
Population Density	0.04	0.00, 0.09	**0.072**	1.7	1.3
Population Density * High Income (0/1)	-0.03	-0.09, 0.03	0.36	2.4	1.6
Population Growth Rate	0.05	-0.01, 0.12	**0.10**	2.9	1.7
Population Growth Rate * Biodiversity Hotspot (0/1)	-0.06	-0.12, 0.01	**0.082**	2.8	1.7
Population Growth Rate * High Income (0/1)	-0.02	-0.07, 0.04	0.58	2.1	1.5
Temperature Change	0.01	-0.03, 0.06	0.65	1.4	1.2
Temperature Change * Biodiversity Hotspot (0/1)	0.11	0.05, 0.17	**<0.001**	2.4	1.6
Voice and Accountability	0.06	0.00, 0.13	**0.064**	3.2	1.8
Voice and Accountability * High Income (0/1)	0.04	-0.02, 0.11	0.21	3.4	1.8

[1] CI = Confidence Interval, GVIF = Generalized Variance Inflation Factor

[2] GVIF^[1/(2*df)]

Supplementary Methods: Raw Data Analysis

1. Raw data preliminary analysis for SDG 14

(1) Drivers' correlation (including all variables)

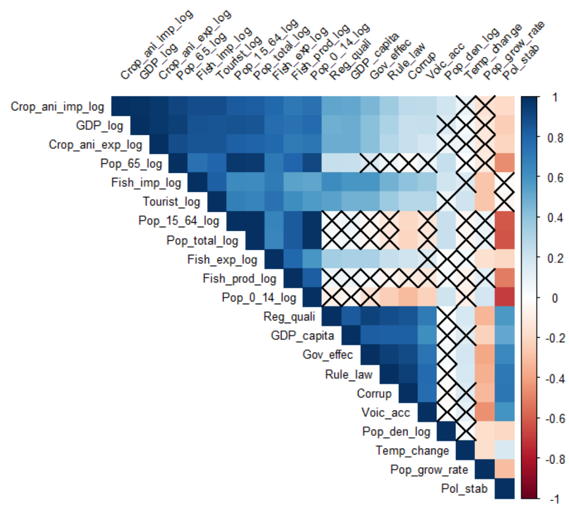


Figure A3.1. Correlation among independent variables for SDG 14.

(2) Form specification analysis

Below, From left to right, there are four plots for SDG 14, and five plots for SDG 15. The first plot is (1) original form vs. SDG, and the second plot (2) uses a nonlinear detection package (nlcor) provided by R (Ranjan and Najari, 2020). Although the second plots produced several piecewise lines that were not convenient to incorporate into one regression, they confirmed whether both plot (1) and plot (2) were the same, then a linear relationship between that independent variable and SDG should be used in the regression. The third plot (3) is log form vs. SDG, which is only shown if the original form plot was non-linear, or the distribution of independent variables is obviously skewed (close to zero because the numeric scale range is large).

The fourth plot (4) is original or log form (depending on whether plot (1) or (3) is a better fit) of independent variable vs. SDG separated by income level. For SDG 15, plot (4) was separated by biodiversity hotspot, and plot (5) was separated by income level. In total, according to the number of independent variables, there are 21 subplots for SDG 14 and 25 subplots for SDG 15.

After this step, we added interaction terms of high-income * independent variable (for SDGs 14 and 15) and biodiversity-hotspot * independent variable (for SDG 15 only, because biodiversity hotspot was based on terrestrial lands, Zhang et al., 2023). The high-income and biodiversity-hotspot were dummy variables, meaning that when a country was a high-income country, the high-income value would be 1 and there would be a coefficient estimate for that independent variable; otherwise, when a country was a low-income country, the high-income value would be 0 and there would not be a coefficient estimate for that independent variable. We only included interaction terms when a major difference between lines was observed in the plots (4) and (5). For instance, if in plot (4) or (5) the lines were significantly different from each other, we generated the interaction terms. For example, when one coefficient is positive, while the other coefficient is negative, we used the interaction terms; if the two lines were paralleled, we considered there was no need to include such interaction terms.

Raw vs. SDG 14	Nonlinear detection	Log vs. SDG 14	Separated raw/log vs. SDG 14

a.

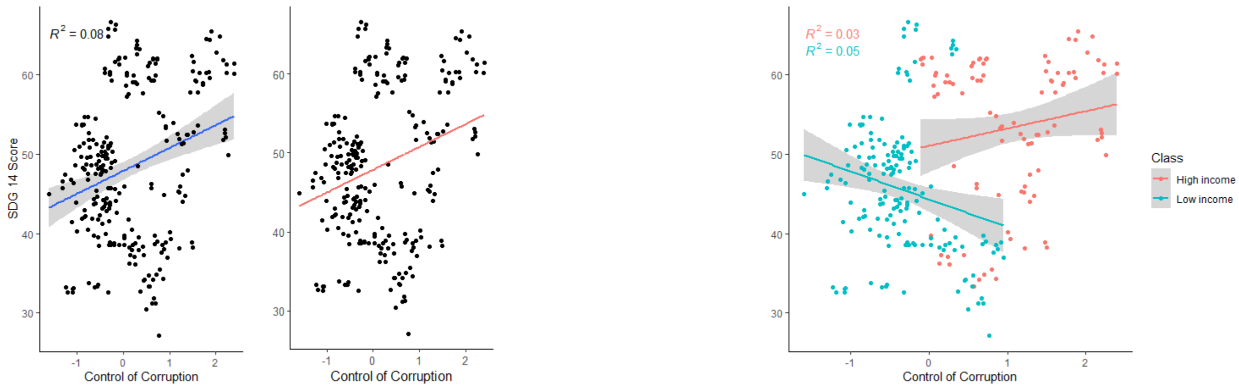
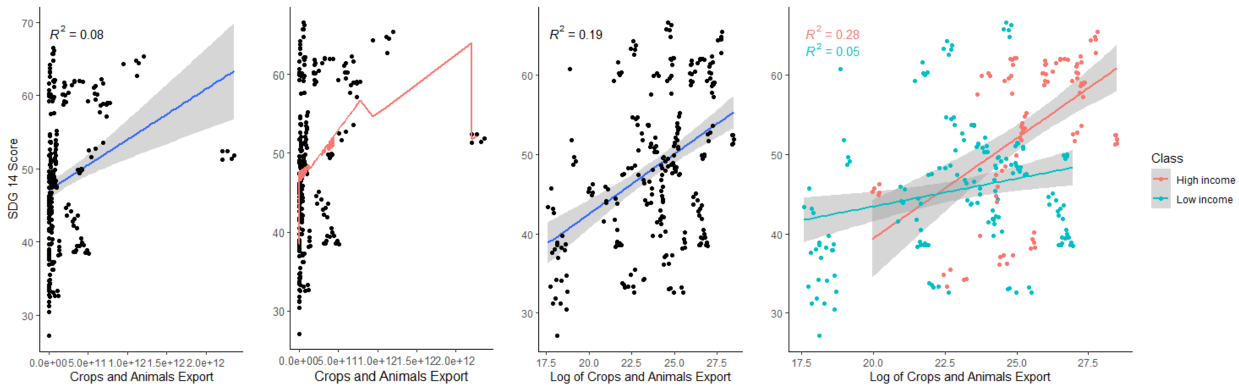


Figure A3.2. Plots of each independent variable vs. SDG 14. From the left to right, the independent variables are in the form of (1) original, (2) with nonlinear detecting result, (3) log, and (4) separated original or log form depending on (1) or (2) by income level. (a) Decision on variable form: Corrupt vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (b) Decision on variable form: log.Crop_ani_exp vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (c) Decision on variable form: log.Crop_ani_imp vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (d) Decision on variable form: log.Fish_exp vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (e) Decision on variable form: log.Fish_imp vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (f) Decision on variable form: log.Fish_prod vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (g) Decision on variable form: log.GDP vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (h) Decision on variable form: GDP_Capita vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (i) Decision on variable form: Gov_effec vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (j) Decision on variable form: Pol_stab vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (k) Decision on variable form: log.Pop_0_14 vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (l) Decision on variable form: log.Pop_15_64 vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (m) Decision on variable form: log.Pop_65 vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (n) Decision on variable form: log.Pop_den vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (o) Decision on variable form: Pop_grow_rate vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (p) Decision on variable form: log.Pop_total vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (q) Decision on variable form: Reg_quali vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (r) Decision on variable form: Rule_law vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (s) Decision on variable form: Temp_change vs. SDG 14 SCORE,

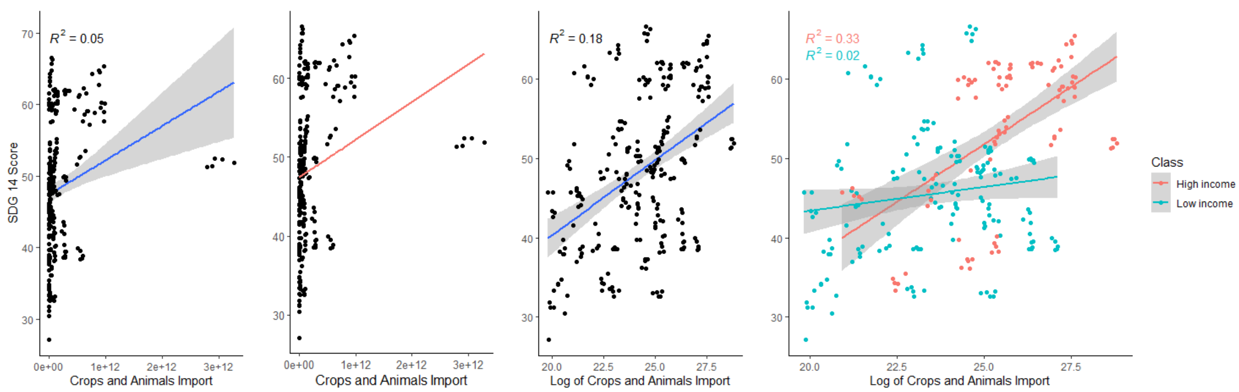
Figure A3.2 (cont'd)

linear form is the best fit based on the plots above and will be used in the overall regression. (t) Decision on variable form: log.Tourist vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (u) Decision on variable form: Voic_acc vs. SDG 14 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression.

b.



c.



d.

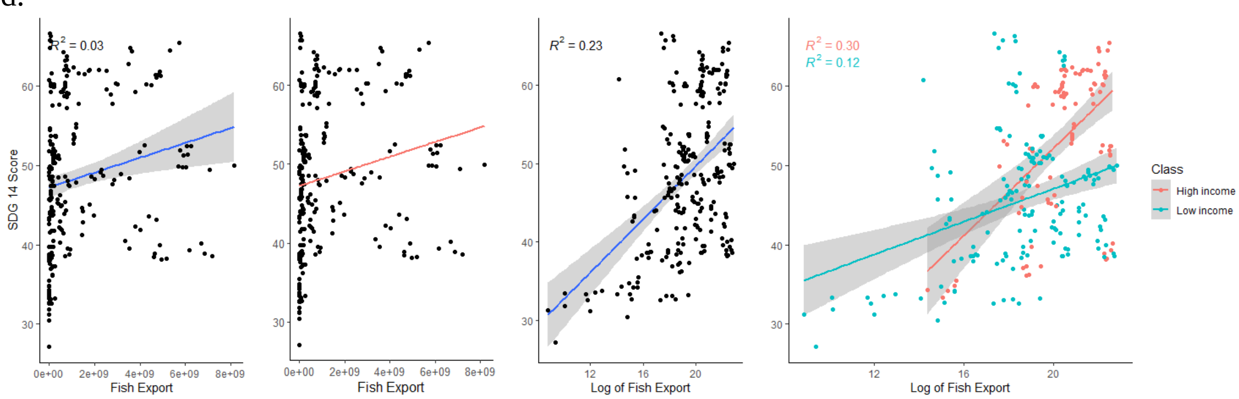
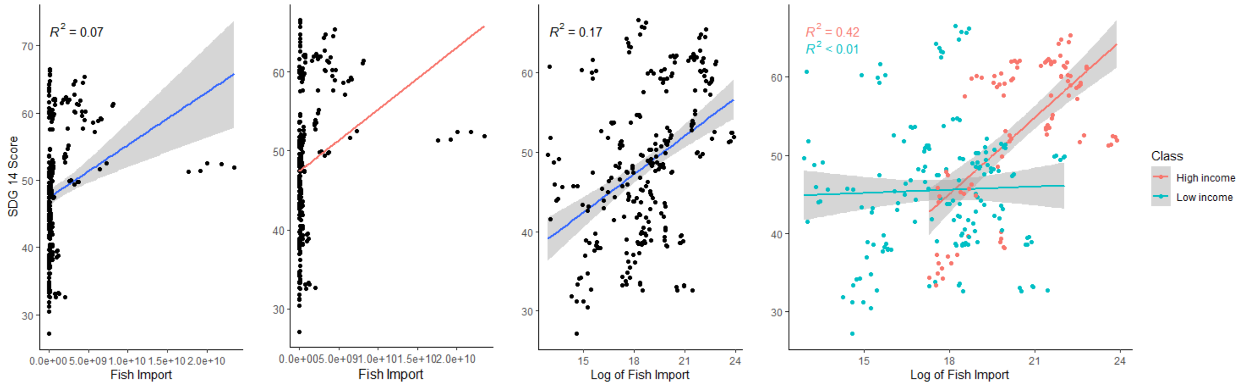
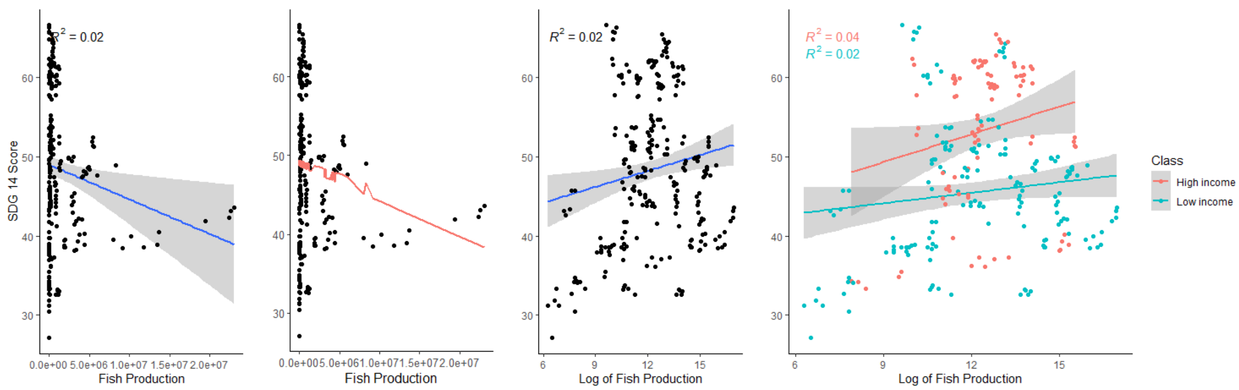


Figure A3.2 (cont'd)

e.



f.



g.

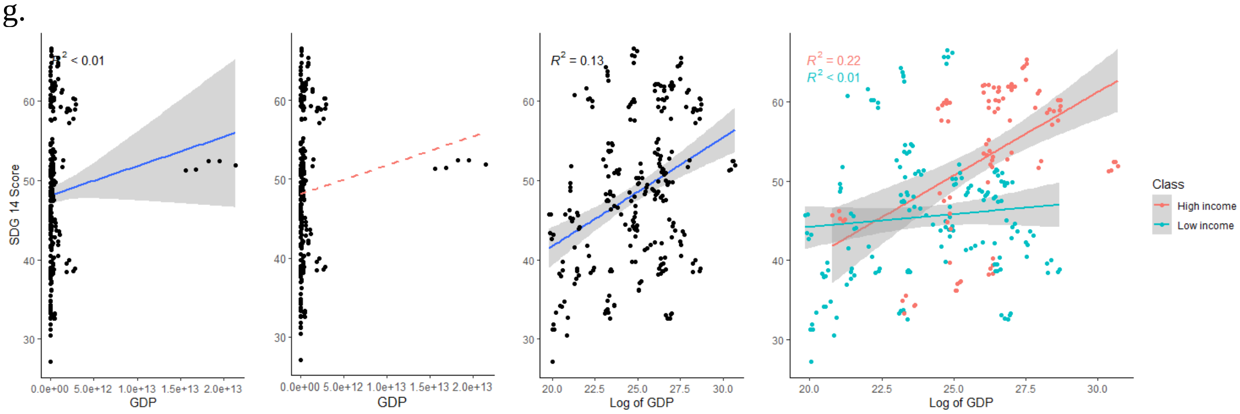
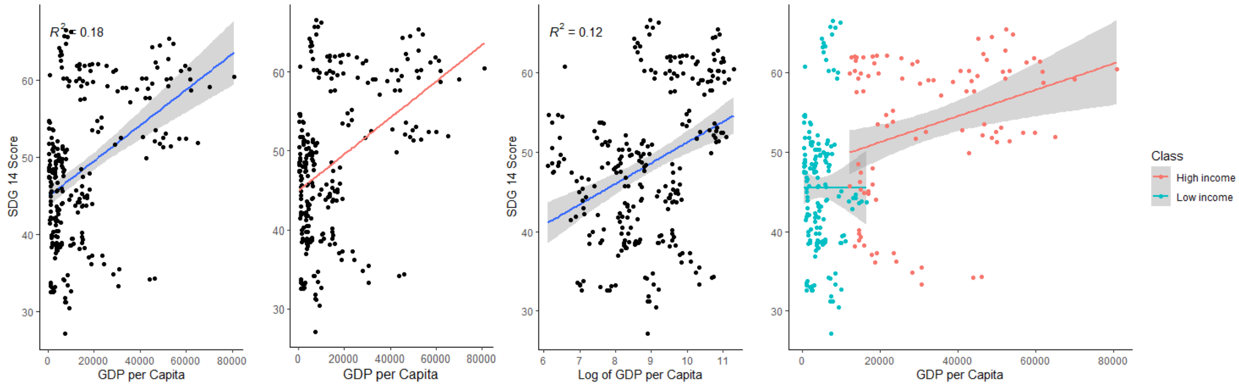
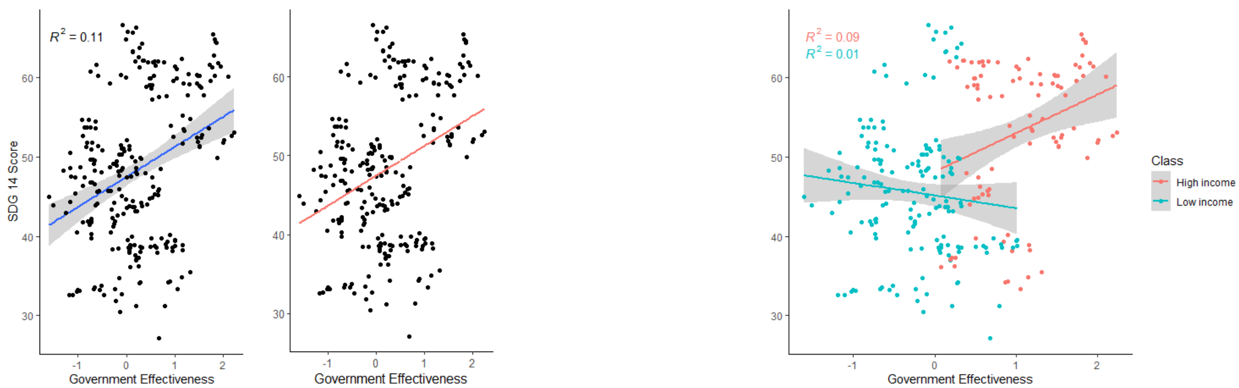


Figure A3.2 (cont'd)

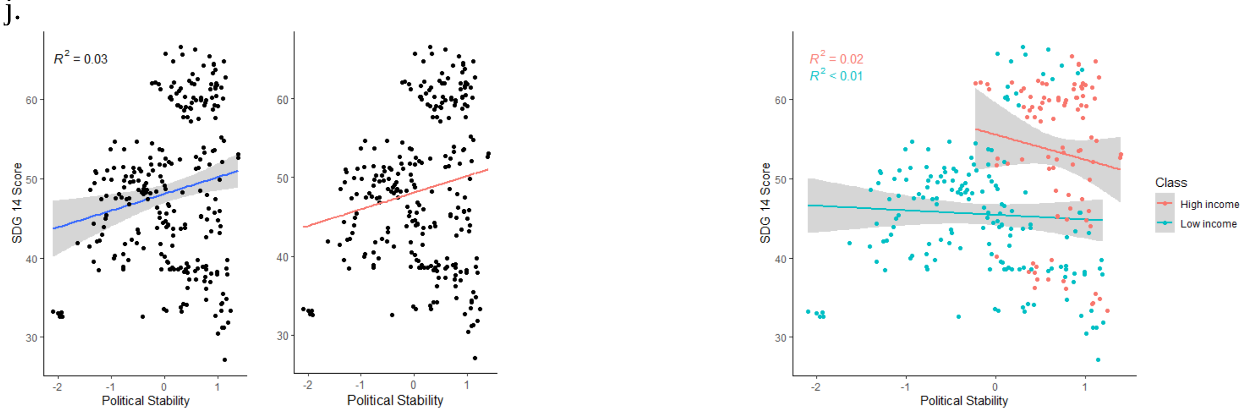
h.



i.



j.



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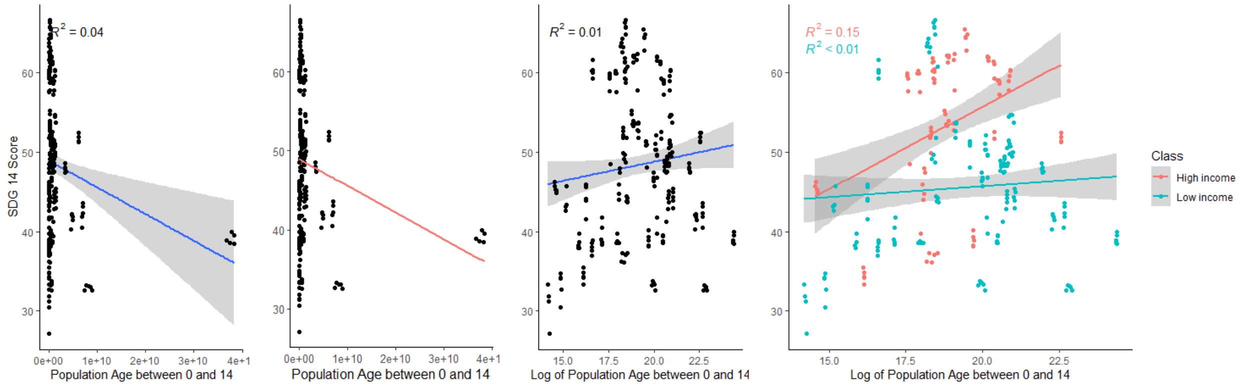

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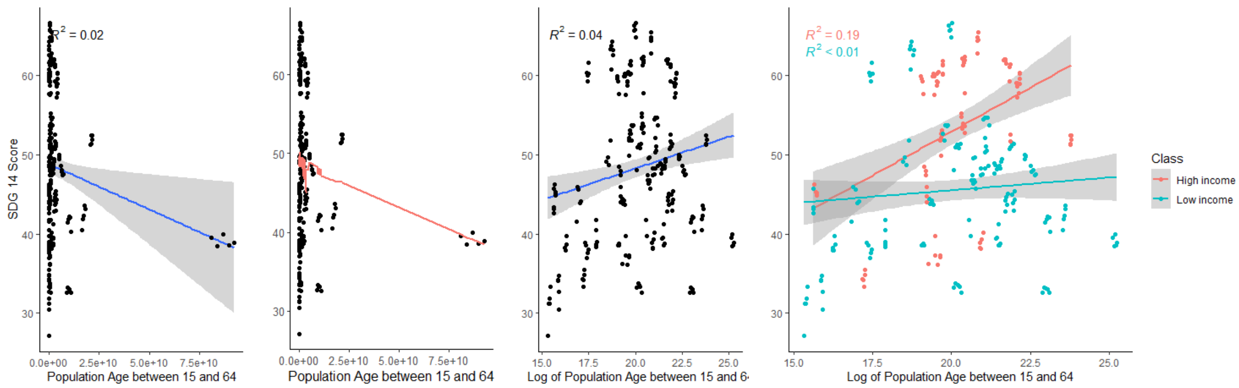

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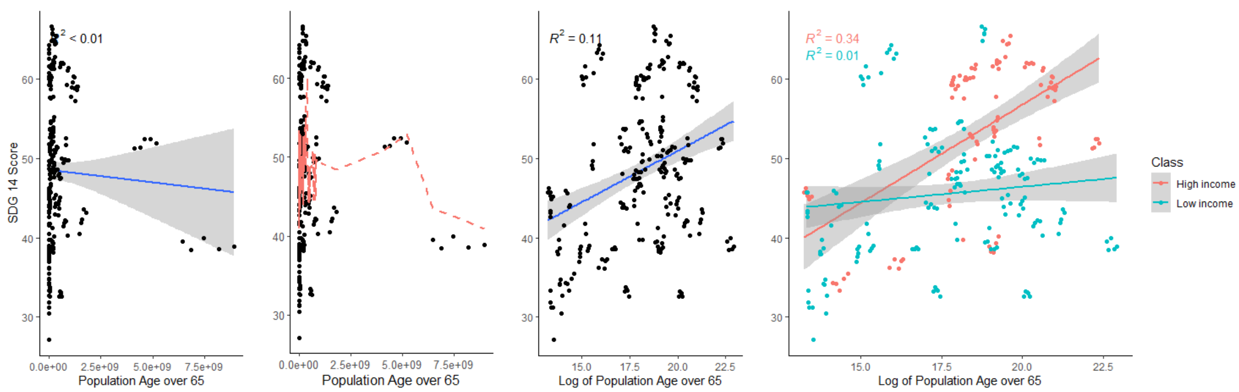

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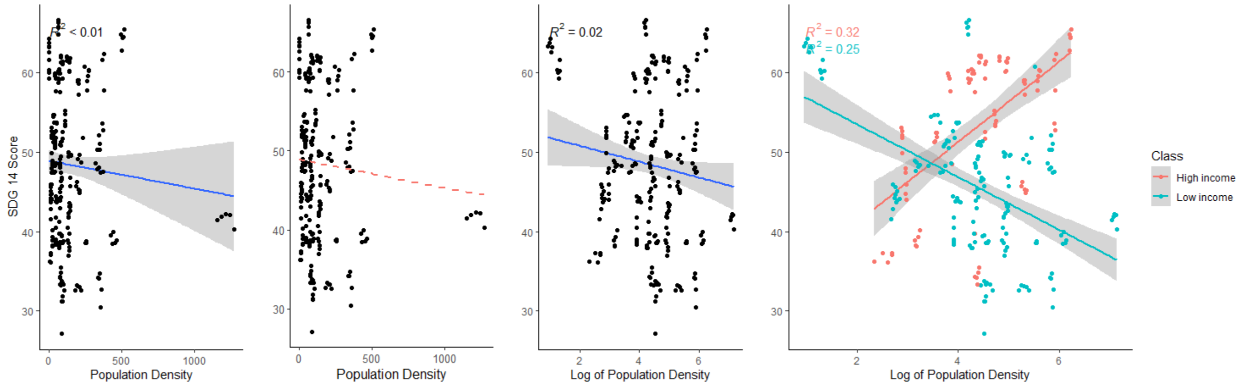

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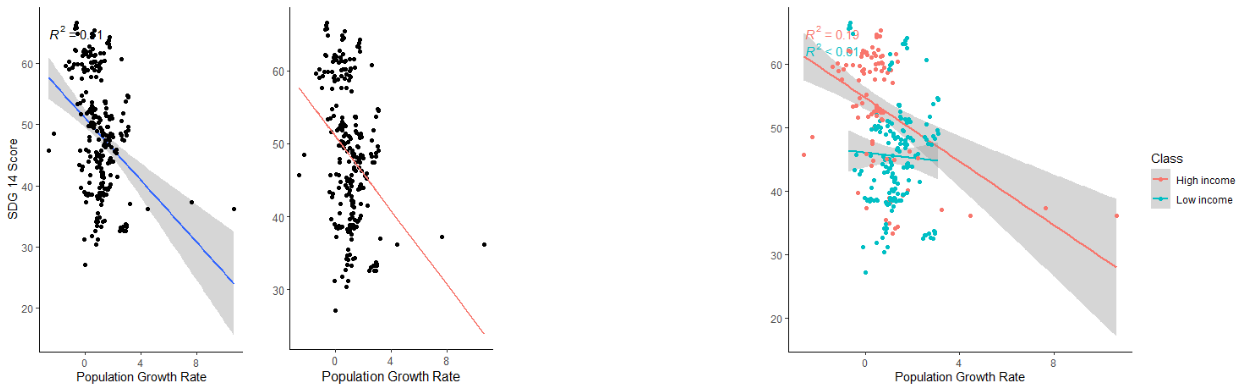

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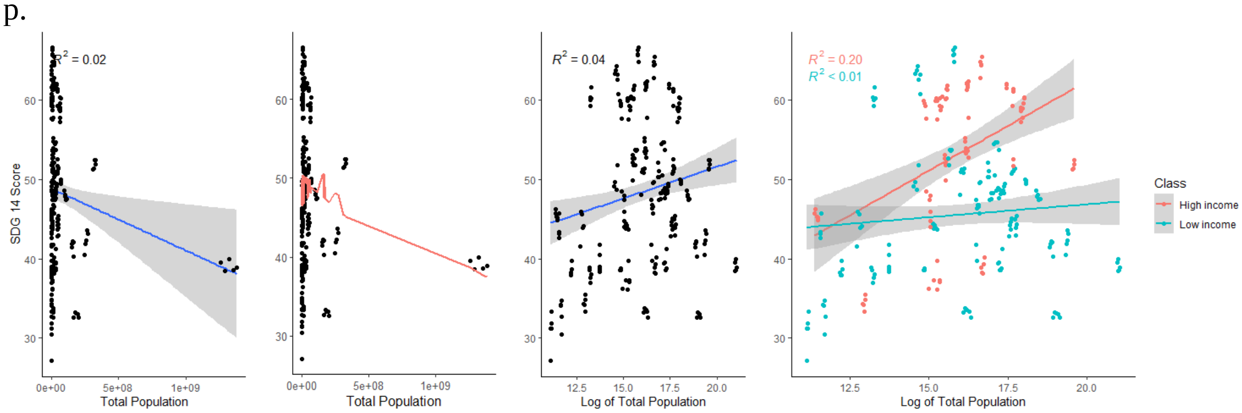

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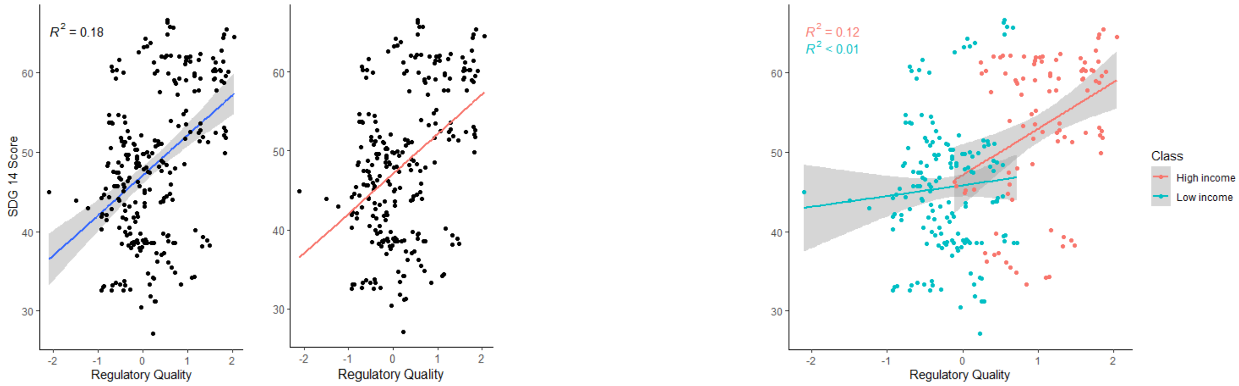

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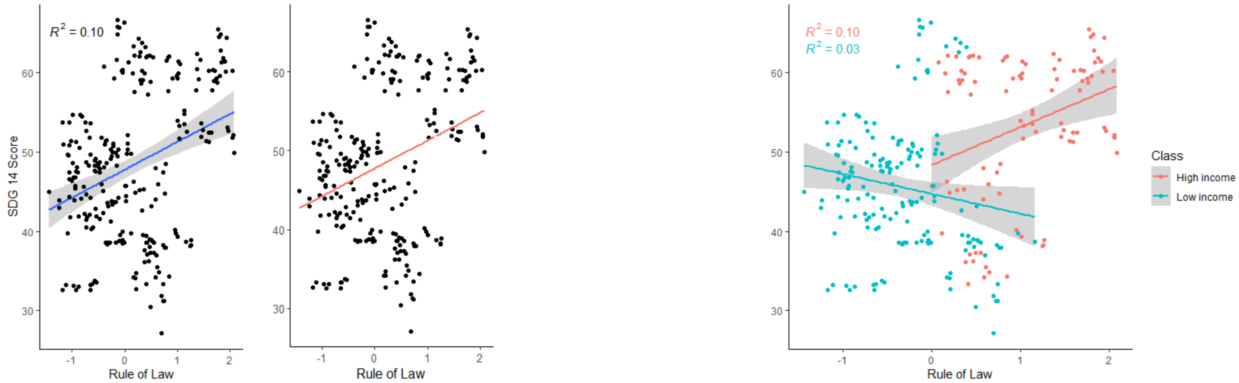

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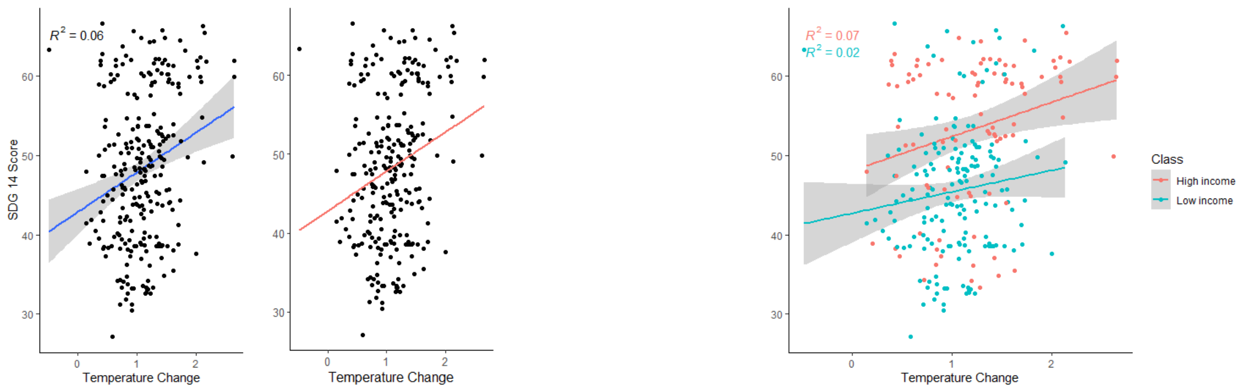

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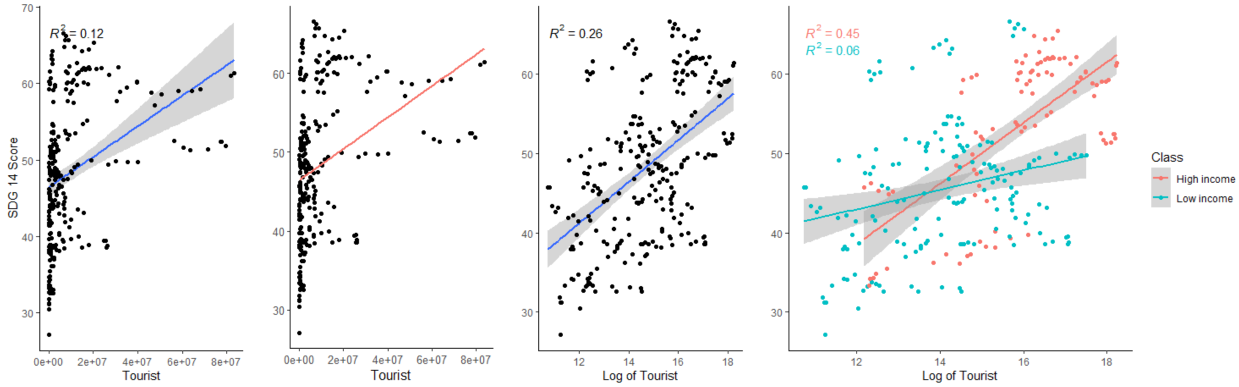

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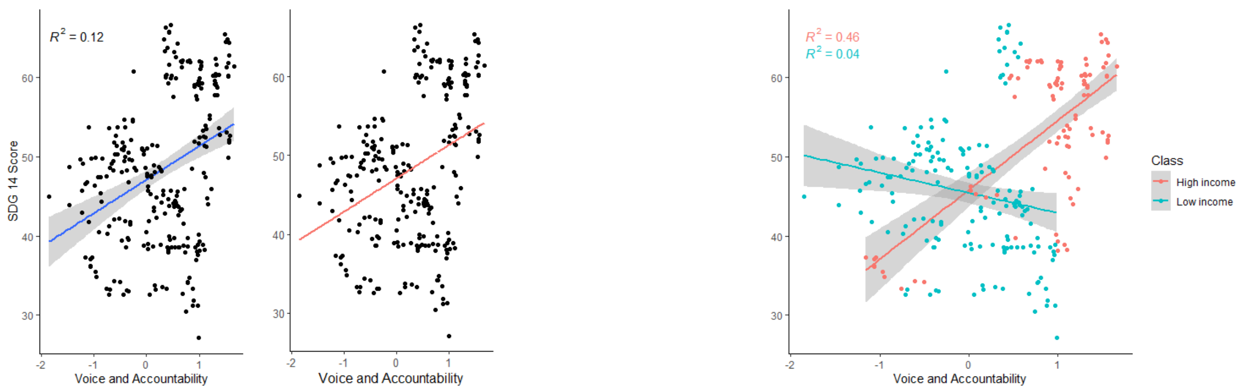


2. Raw data preliminary analysis for SDG 15

(1) Drivers' correlation (including all variables)

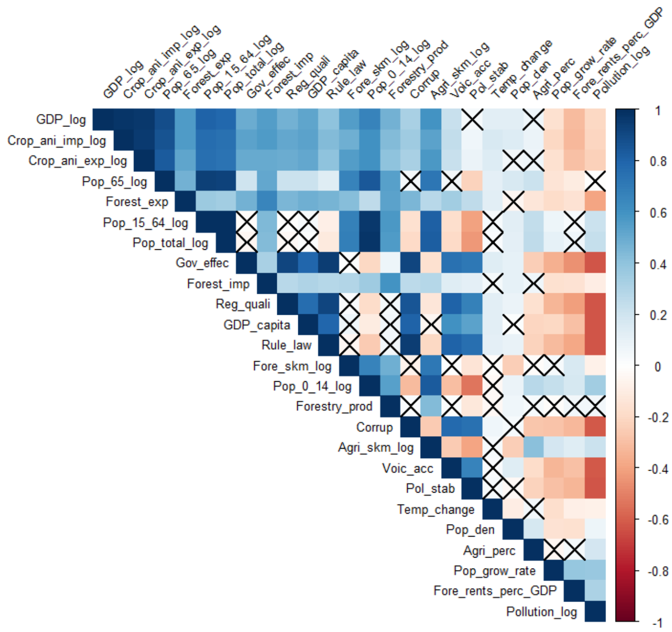


Figure A3.3. Correlation among independent variables for SDG 15.

(2) Form specification analysis

Raw vs. SDG 15	Nonlinear detection	Log vs. SDG 15	Separated hotspot raw/log vs. SDG 15	Separated income raw/log vs. SDG 15

a.

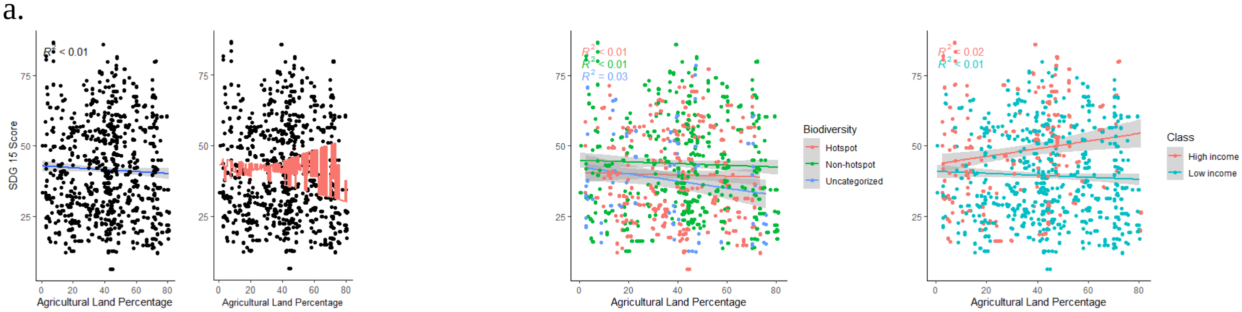


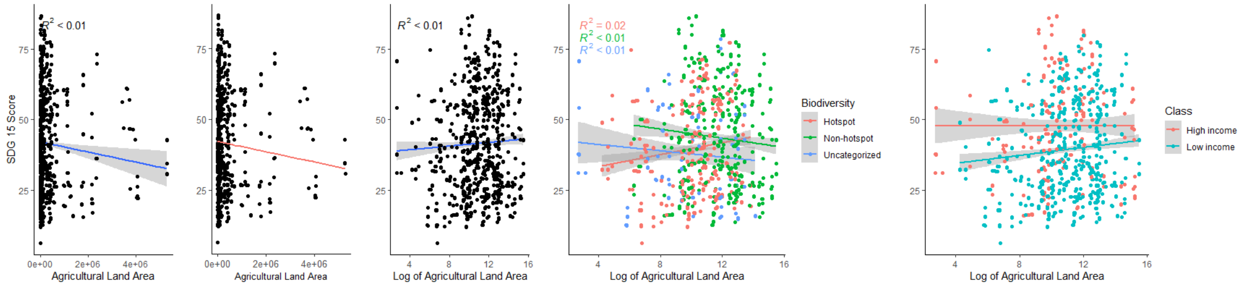
Figure A3.4. Plots of each independent variable vs. SDG 15. From the left to right, the independent variables are in the form of (1) original, (2) with nonlinear detecting result, (3) log, (4) separated original or log form depending on (1) or (2) by biodiversity hotspot status, and (5) separated original or log form depending on (1) or (2) by income level. (a) Decision on variable form: Separate Agri_perc vs. SDG 15 SCORE, linear form is the best fit based on the plots above and

Figure A3.4 (cont'd)

will be used in the overall regression. (b) Decision on variable form: Separate log.Agri_skm vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (c) Decision on variable form: Separate Corrup vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (d) Decision on variable form: Separate log.Crop_ani_exp vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (e) Decision on variable form: Separate log.Crop_ani_imp vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (f) Decision on variable form: Separate Fore_rents_perc_GDP vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (g) Decision on variable form: Separate log.Fore_skm vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (h) Decision on variable form: Separate Forest_exp vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (i) Decision on variable form: Separate Forest_imp vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (j) Decision on variable form: Separate Forestry_prod vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (k) Decision on variable form: Separate log.GDP vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (l) Decision on variable form: Separate GDP_capita vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (m) Decision on variable form: Separate Gov_effec vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (n) Decision on variable form: Separate Pol_stab vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (o) Decision on variable form: Separate log.Pollution vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (p) Decision on variable form: Separate log.Pop_0_14 vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (q) Decision on variable form: Separate log.Pop_15_64 vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (r) Decision on variable form: Separate log.Pop_65 vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (s) Decision on variable form: Separate Pop_den vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (t) Decision on variable form: Separate Pop_grow_rate vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (u) Decision on variable form: Separate log.Pop_total vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (v) Decision on variable form: Separate Reg_quali vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (w) Decision on variable form: Separate Rule_law vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (x) Decision on variable form: Separate Temp_change vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression. (y) Decision on variable form: Separate Voic_acc vs. SDG 15 SCORE, linear form is the best fit based on the plots above and will be used in the overall regression.

Figure A3.4 (cont'd)

b.



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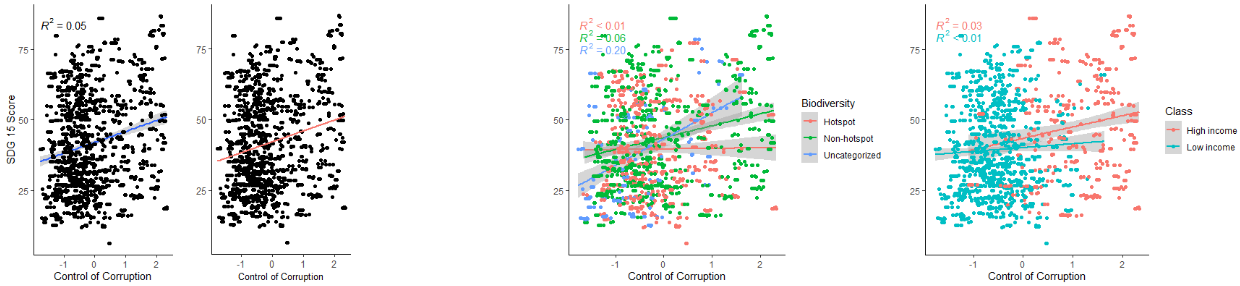

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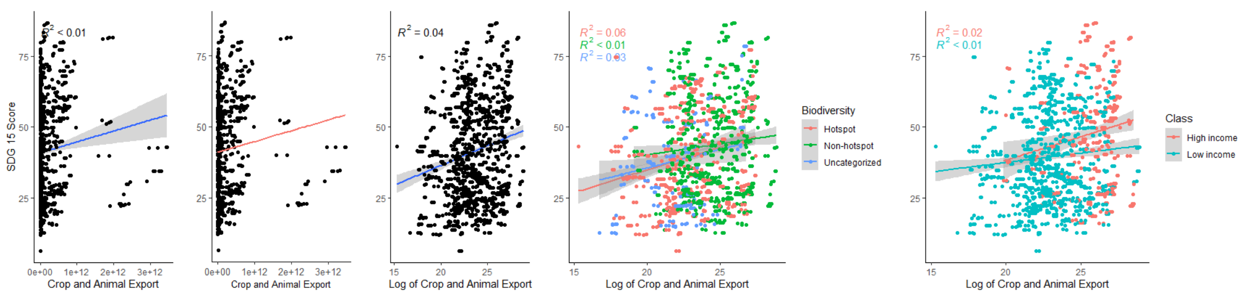

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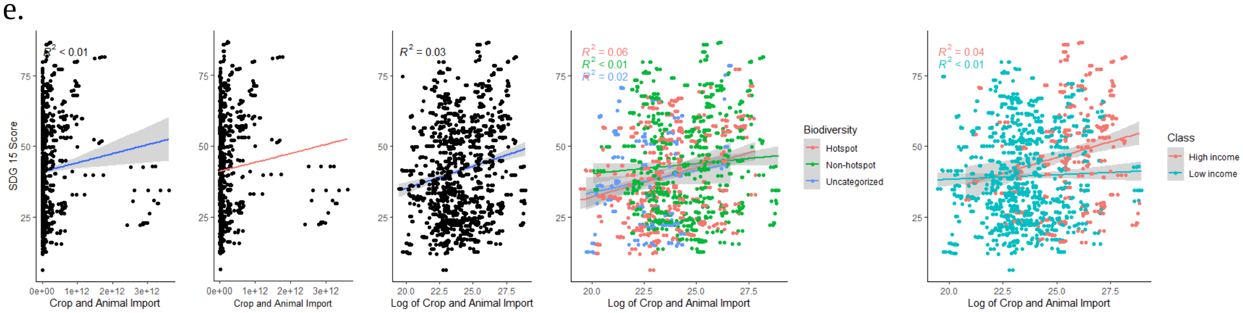

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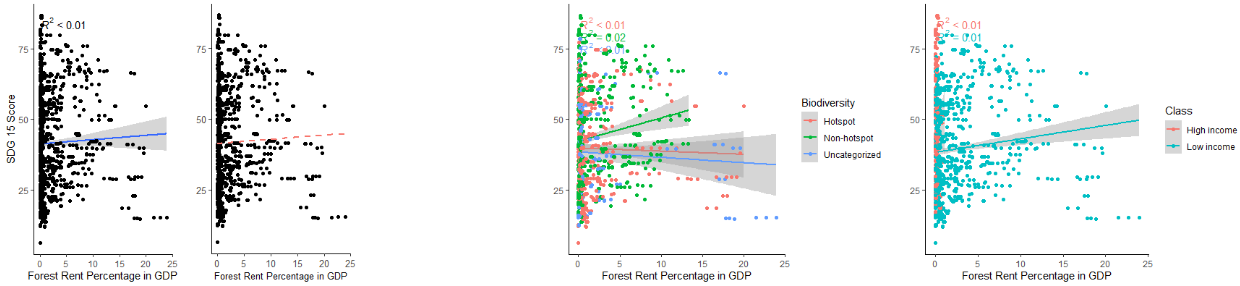

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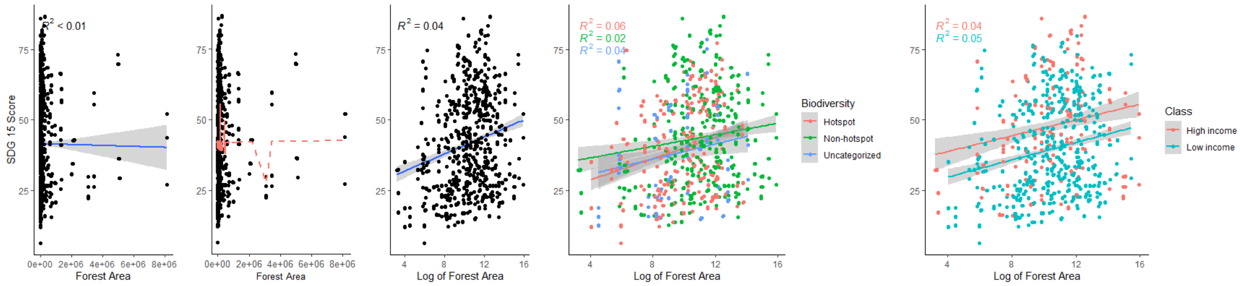

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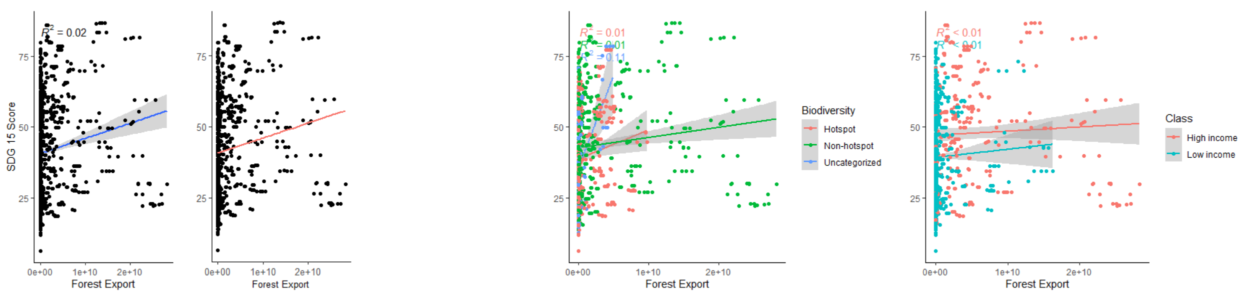

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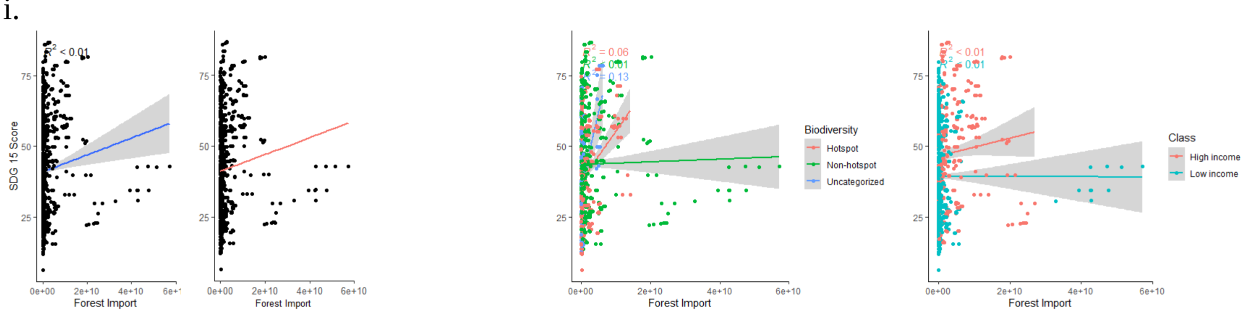

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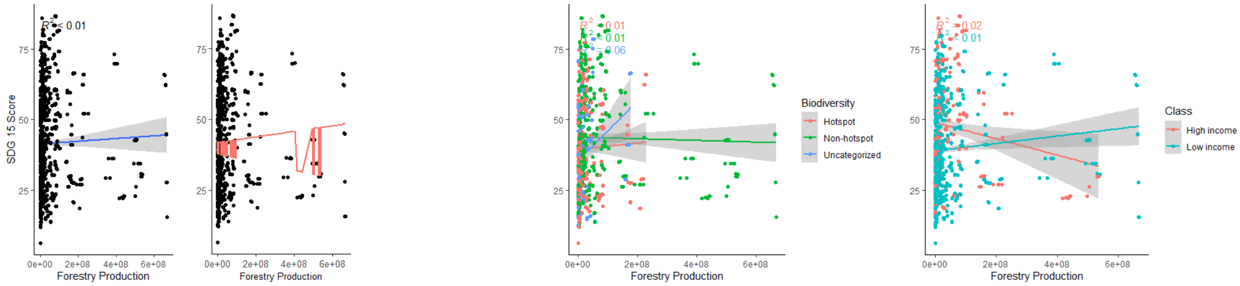

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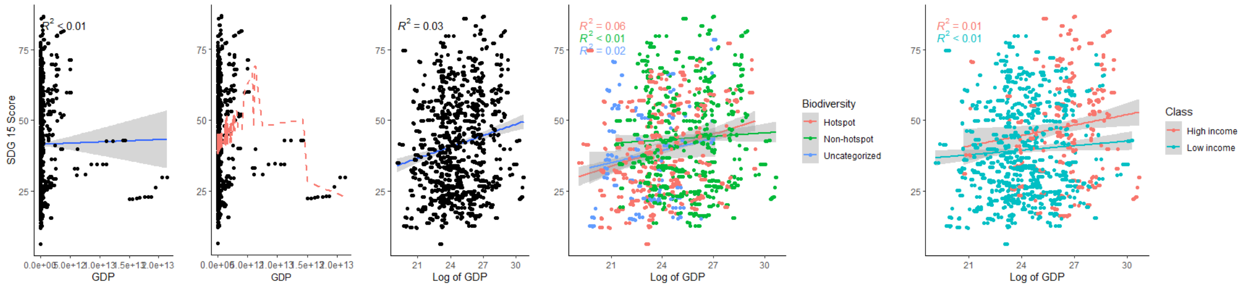

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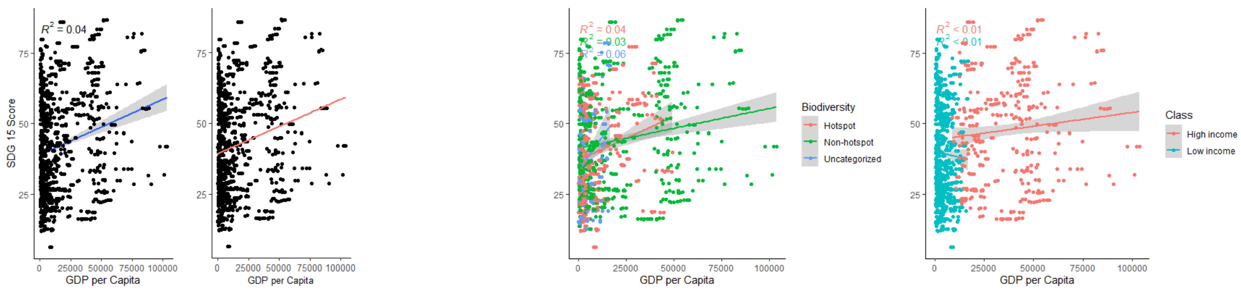

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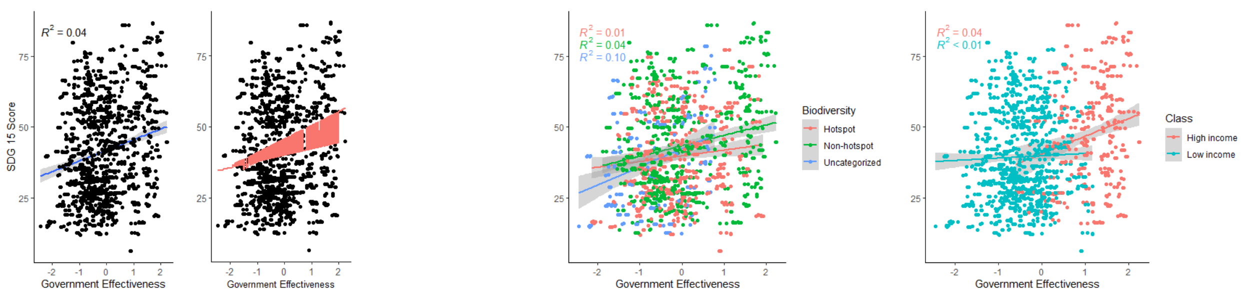

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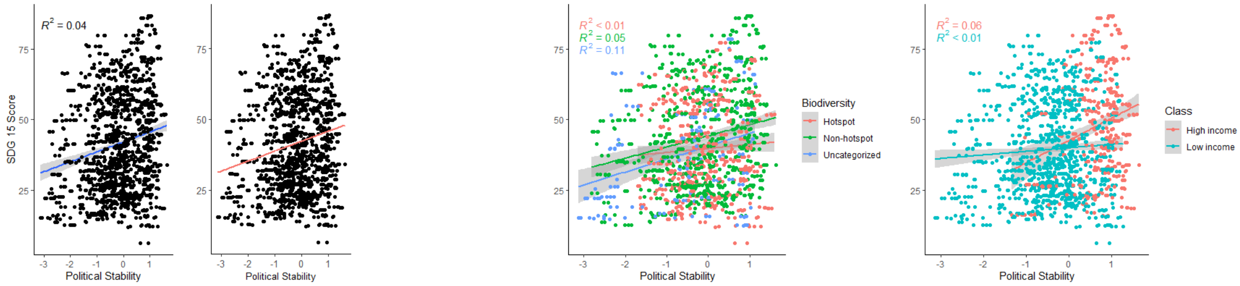

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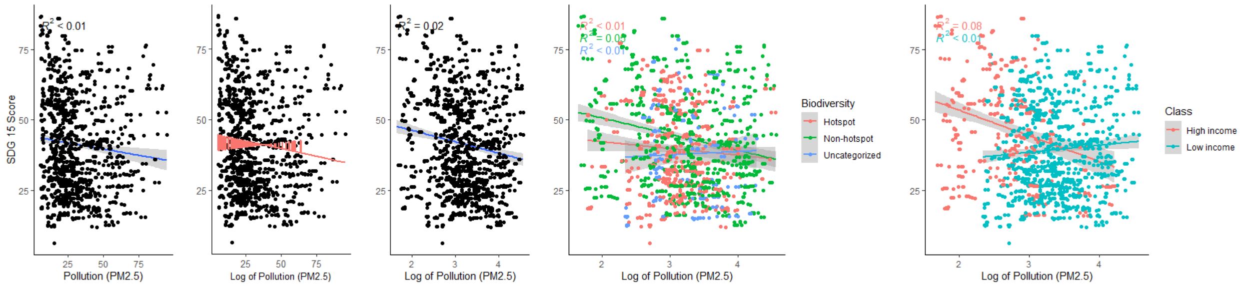

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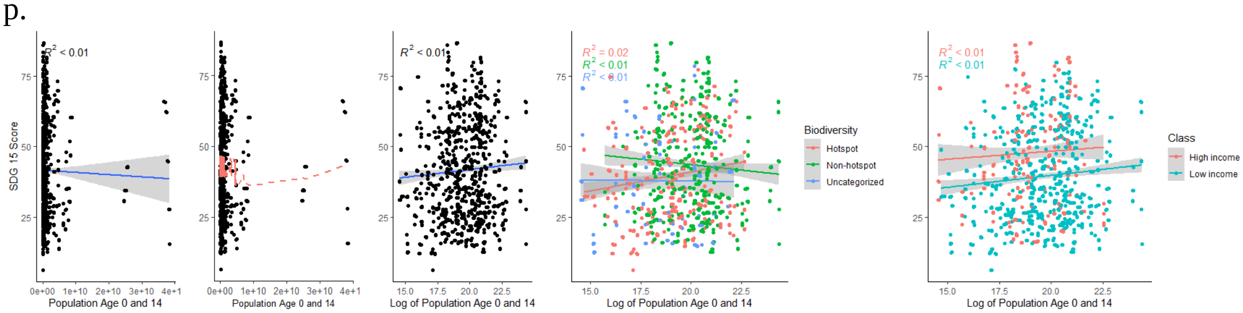

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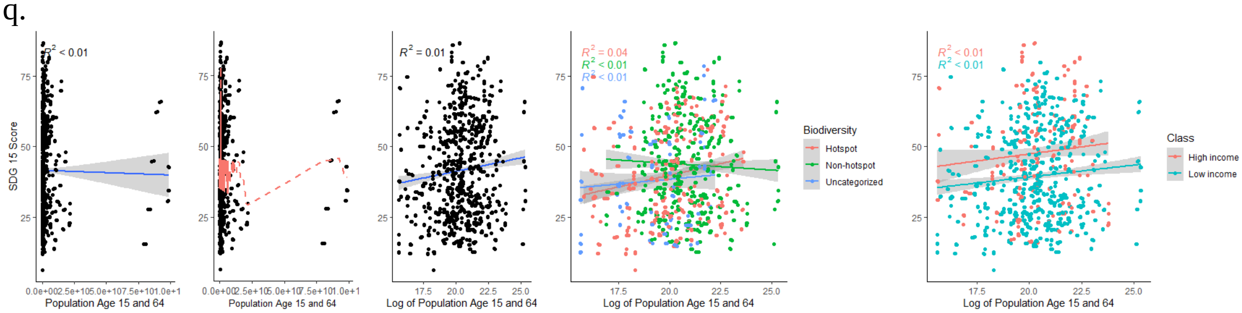

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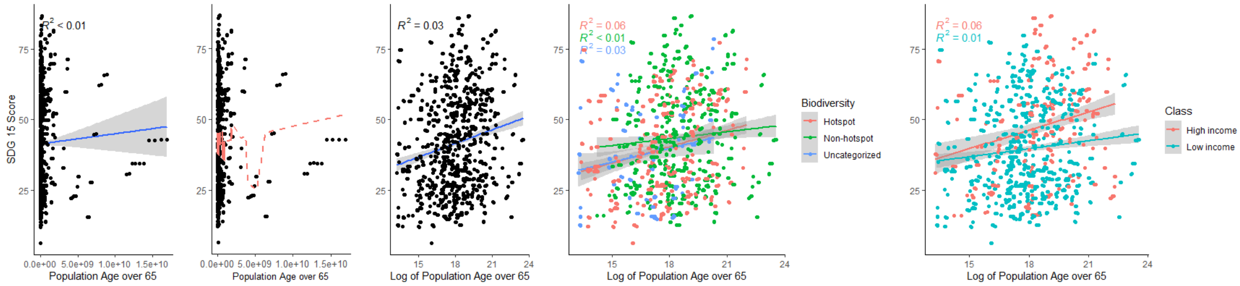

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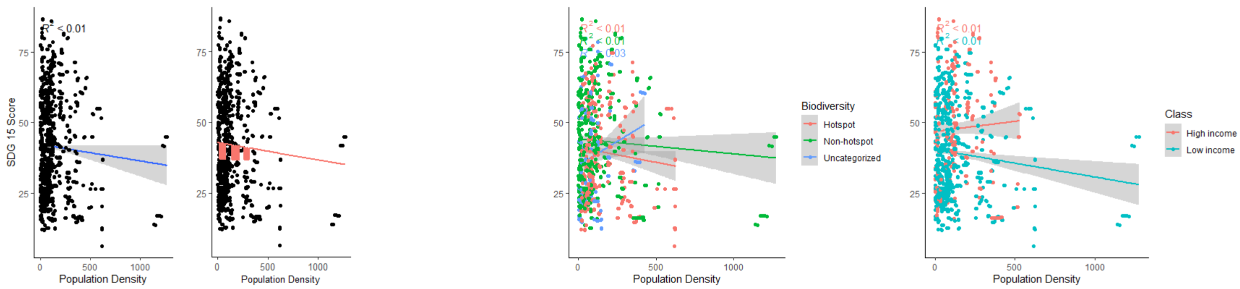

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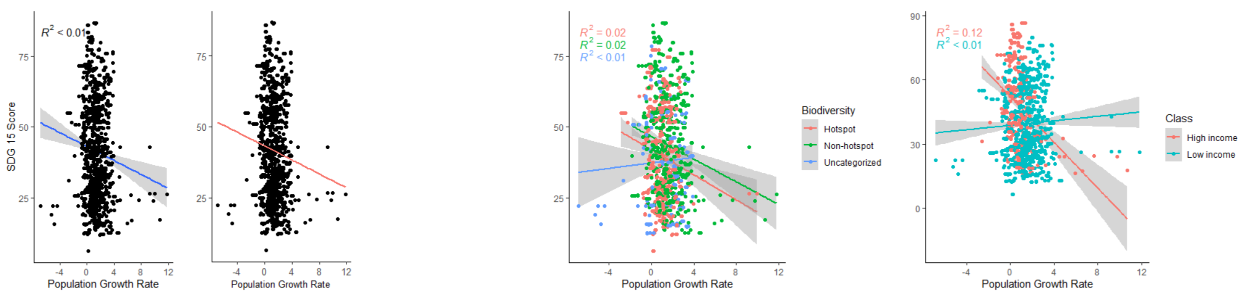

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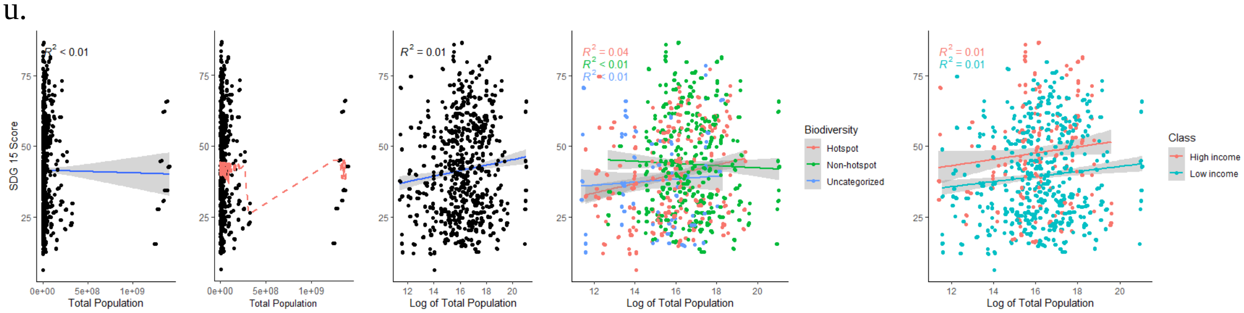

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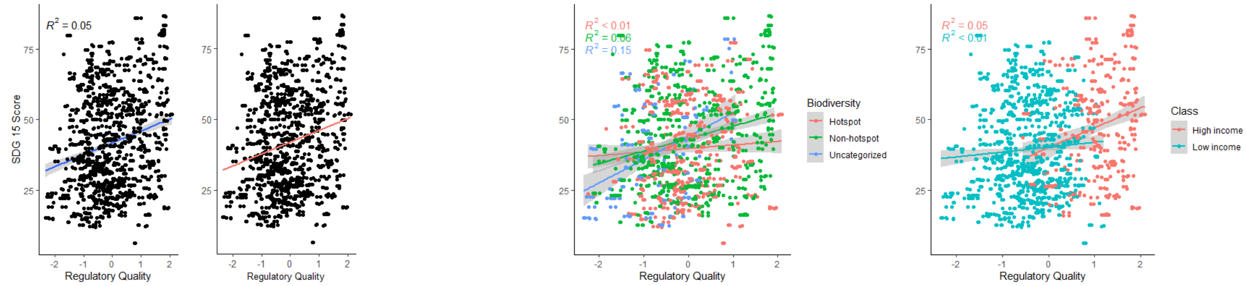

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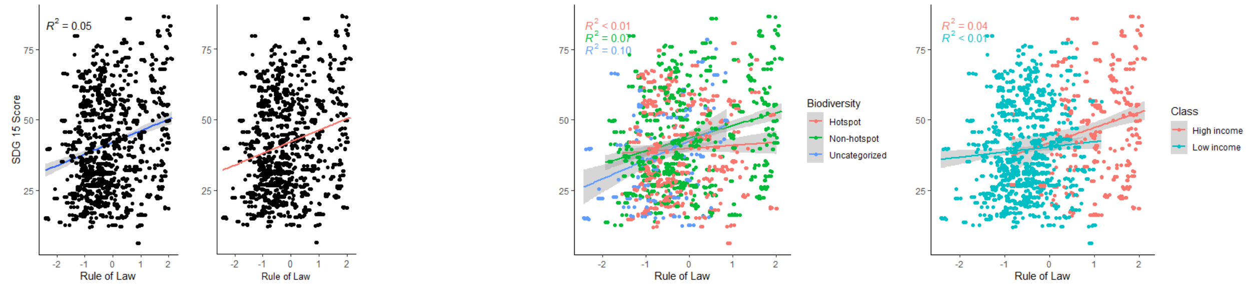

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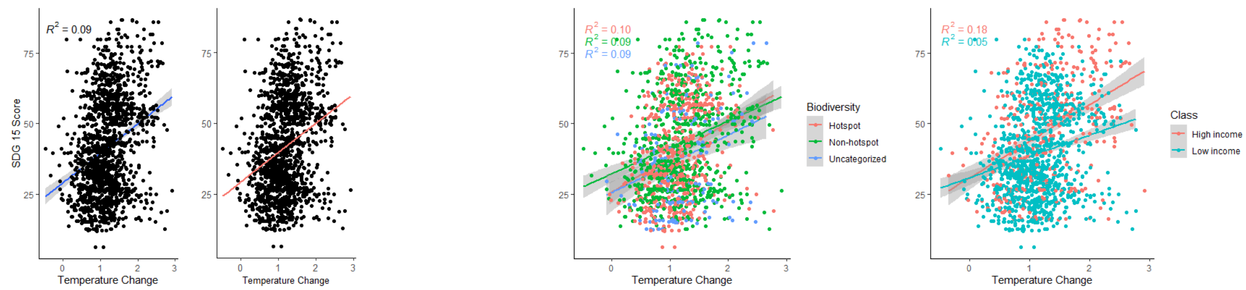

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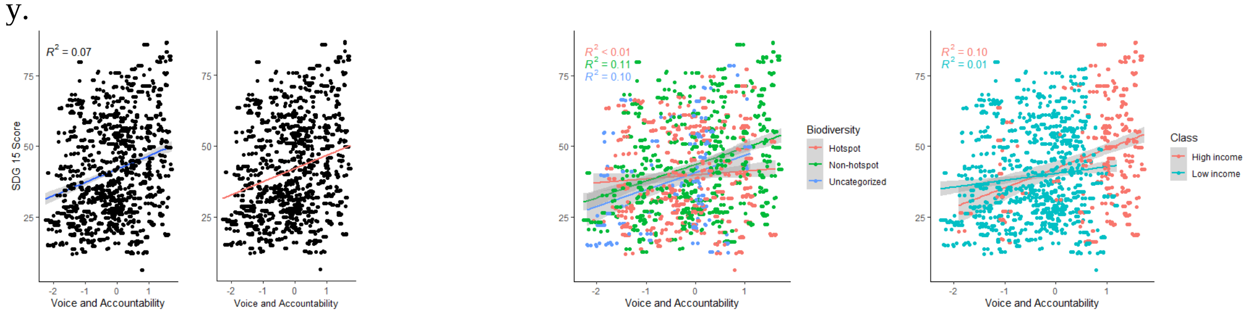


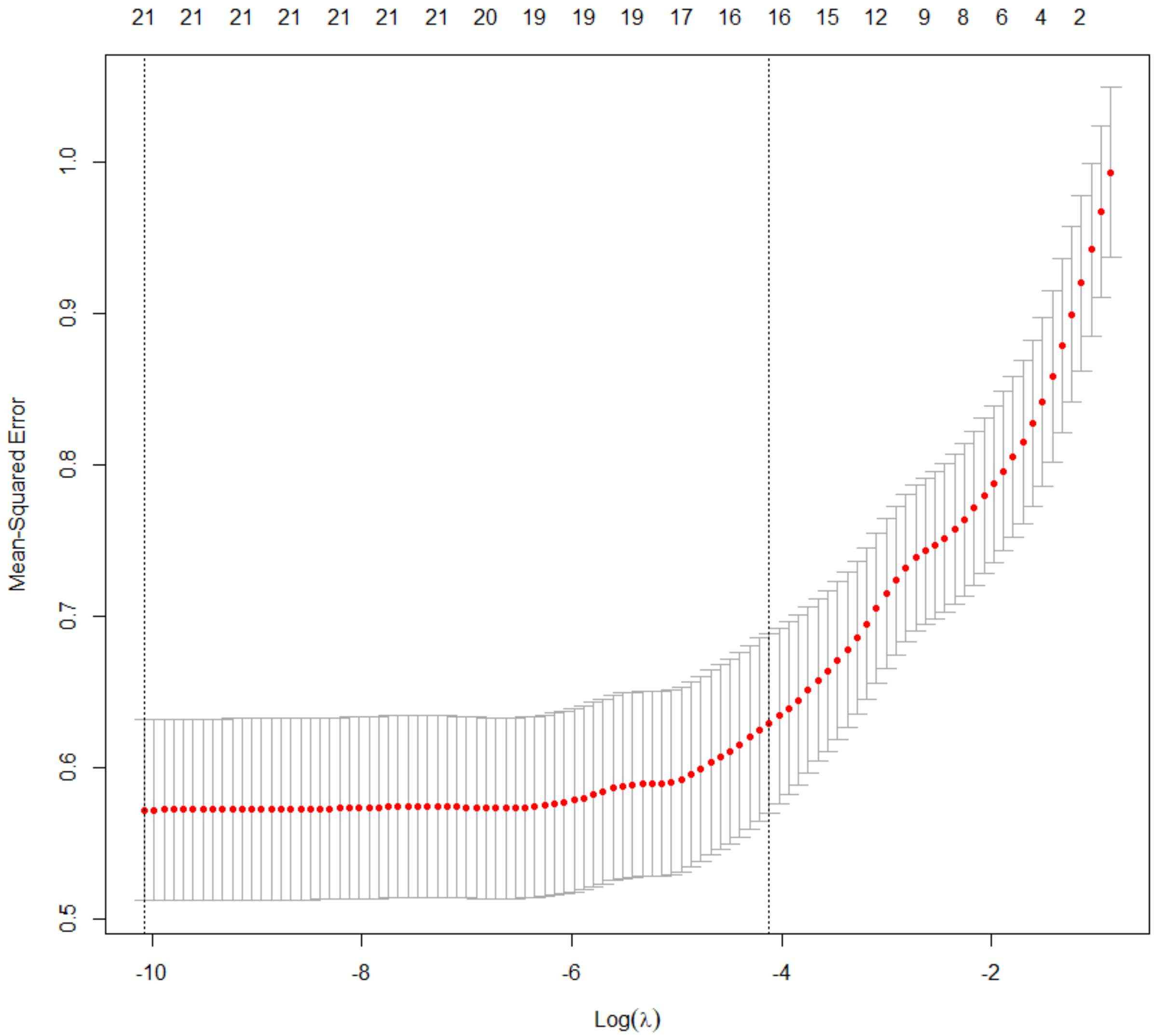
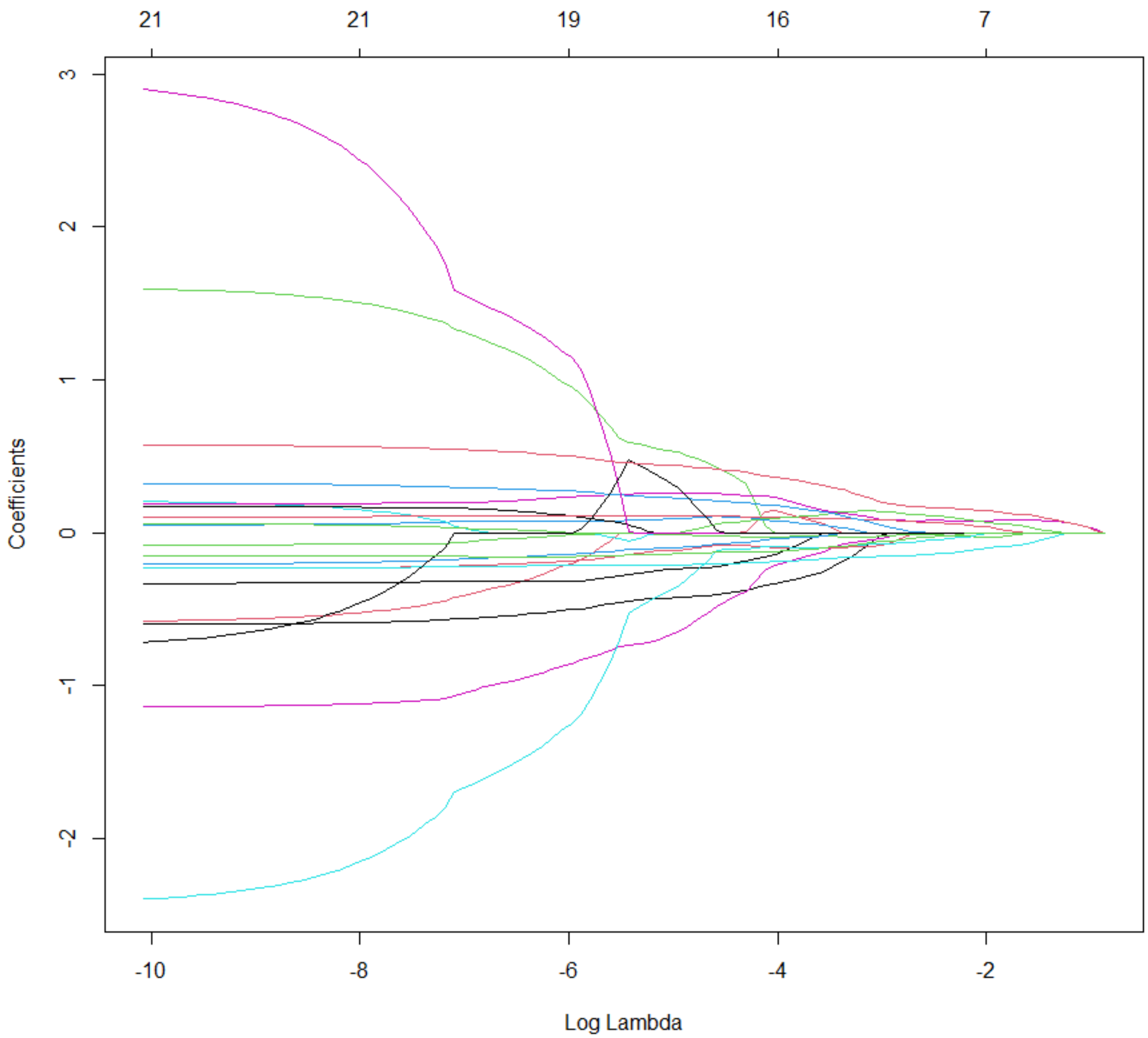


Figure A3.5. LASSO process for SDG 14.

Figure A3.5 (cont'd)



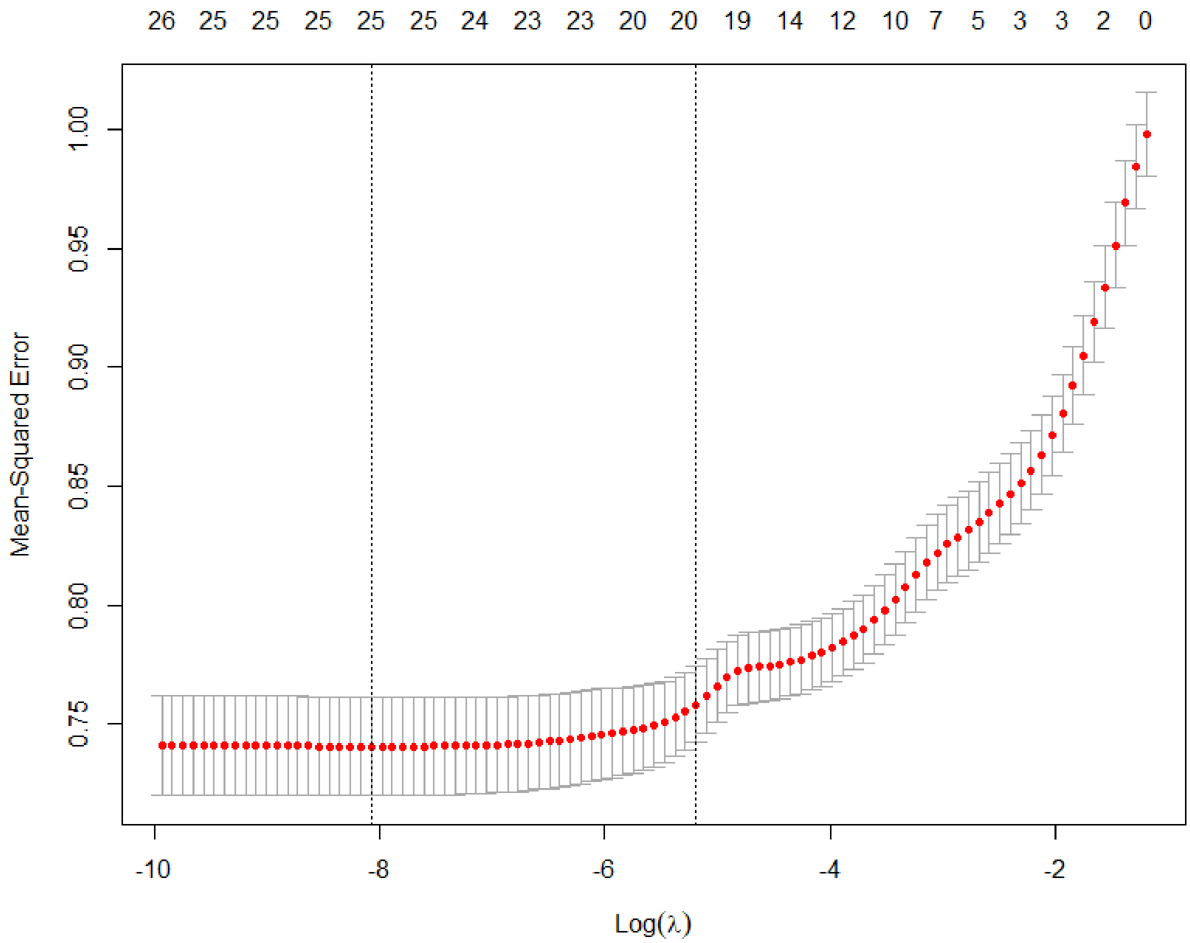
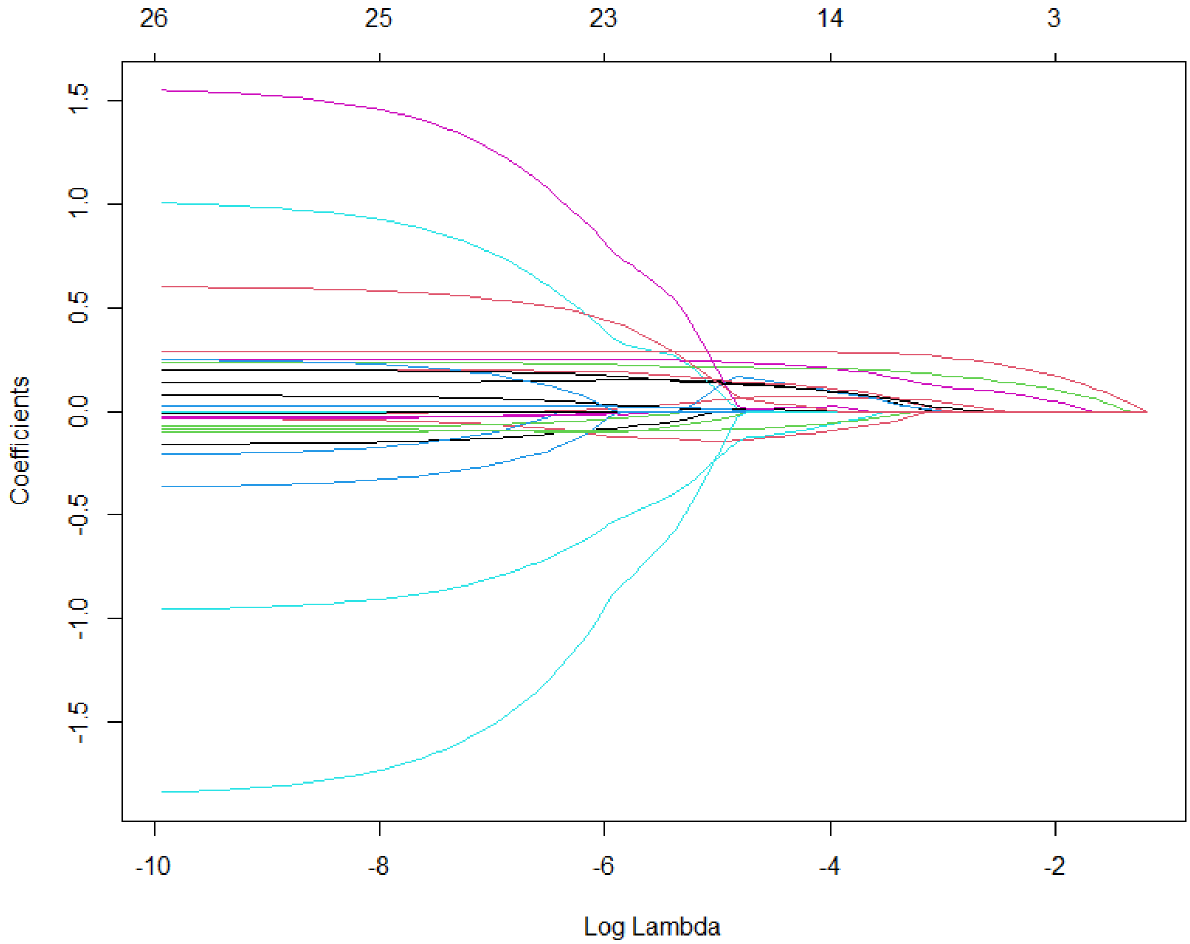


Figure A3.6. LASSO process for SDG 15.

Figure A3.6 (cont'd)



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Ranjan, C., & Najari, V. (2020). Package 'nlcor': Compute Nonlinear Correlations. In:Research Gate. doi:10.13140/RG.2.2.33716.68480.

Zhang, Y., Li, Y., & Liu, J. (2023). Global decadal assessment of life below water and on land. *Iscience*, *26*(4).

APPENDIX C SUPPORTING INFORMATION FOR CHAPTER 4

Table A4.1. Sensitivity Analysis of Forest Area and SDG 15 Progress to Forest Regeneration Rate between 2000 and 2050.

Year	Forest Area	SDG 15 Progress	Estimates under 90% of Forest Regeneration Rate		Sx_90		Estimates under 110% of Forest Regeneration Rate		Sx_110	
			Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress
2000	170939.3	69.50113917	170939.3	69.50113917	#DIV/0!	#DIV/0!	170939.3	69.50113917	#DIV/0!	#DIV/0!
2001	171861.7002	69.98828733	171588.1974	69.84384198	62.8372543	48.45312609	172135.2031	70.13273268	57.21568573	44.13920554
2002	172758.6346	70.46198618	172206.2146	70.17023603	31.273057	24.15148249	173311.9299	70.75419855	28.47598992	22.01207216
2003	173630.2392	70.92230755	172793.4504	70.4803735	20.74959161	16.04816524	174469.6862	71.36564557	18.89443809	14.63394908
2004	174476.6378	71.36931689	173349.9909	70.77429977	15.48636455	11.99449795	175608.6675	71.96717688	14.10247816	10.94314855
2005	175297.9402	71.80307217	173875.907	71.05205237	12.32727496	9.560742822	176729.0563	72.55888893	11.22639758	8.727330522
2006	176094.202	72.22360273	174371.2149	71.3136398	10.2202852	7.936982934	177830.9824	73.1408503	9.308288435	7.249044222
2007	176865.3191	72.63085355	174835.7702	71.55898586	8.714513802	6.776102515	178914.4175	73.71304597	7.937611268	6.192231505
2008	177611.1811	73.02476641	175269.4222	71.78801093	7.584520332	5.904543598	179979.3282	74.27545831	6.909096596	5.398863138
2009	178331.671	73.40527944	175672.0128	72.00063153	6.705059898	5.225884645	181025.6754	74.82806667	6.108705565	4.781144625
2010	179026.6641	73.77232687	176043.3762	72.19676005	6.000985189	4.682272197	182053.4137	75.37084712	5.468014494	4.286398721
2011	179696.0279	74.12583862	176383.338	72.37630439	5.424474783	4.236889883	183062.4909	75.90377208	4.943480642	3.881103006
2012	180339.621	74.4657401	176691.7147	72.53916772	4.94364733	3.86519295	184052.8474	76.42681007	4.506075124	3.542908696
2013	180957.2932	74.79195193	176968.3137	72.68524819	4.536430745	3.550188405	185024.4157	76.93992543	4.135700653	3.256343087
2014	181548.8846	75.10438968	177212.9321	72.81443875	4.187058899	3.279737957	185977.1202	77.44307817	3.818001682	3.010353823
2015	182114.2254	75.40296372	177425.357	72.92662695	3.88396963	3.044939795	186910.8762	77.93622367	3.542450498	2.796835447
2016	182653.1359	75.68757902	177605.365	73.02169473	3.618491012	2.839117189	187825.5904	78.41931262	3.301151024	2.609708508
2017	183165.4254	75.95813501	177752.7216	73.09951834	3.383991292	2.657164065	188721.1602	78.89229077	3.088064817	2.444323685
2018	183650.8929	76.21452543	177867.1815	73.15996813	3.175312174	2.495108719	189597.4733	79.35509888	2.898495067	2.297064537
2019	184109.3261	76.45663824	177948.4878	73.20290855	2.988381083	2.349815306	190454.4078	79.80767255	2.728733539	2.165075702
2020	184540.5019	76.68435552	177996.3726	73.22819797	2.819939732	2.218774883	191291.8319	80.24994218	2.575813439	2.046072633
2021	184944.1855	76.89755336	178010.556	73.23568865	2.667350255	2.099956156	192109.6037	80.68183284	2.437332885	1.938205703
2022	185320.1311	77.09610187	177990.7466	73.22522669	2.528454206	1.991696927	192907.5713	81.10326428	2.311326525	1.839961365
2023	185668.0811	77.27986504	177936.6412	73.19665198	2.401468348	1.892623868	193685.5725	81.51415081	2.196170646	1.750089097
2024	185987.7329	77.44868306	177847.8913	73.14978042	2.284906067	1.801591929	194443.4011	81.91438357	2.090511643	1.667546254
2025	186278.7455	77.60237584	177724.1098	73.08440757	2.177518176	1.7176388	195180.8138	82.30383409	1.993212103	1.591456594
2026	186540.7697	77.74075898	177564.9014	73.00032465	2.078247611	1.639950129	195897.5605	82.68237023	1.903309548	1.5210786
2027	186773.4484	77.86364378	177369.8623	72.89731845	1.986193846	1.567832122	196593.3838	83.04985612	1.819984036	1.455780523
2028	186976.4156	77.97083708	177138.5804	72.77517131	1.900584944	1.500690008	197268.0195	83.40615212	1.742532705	1.395020788
2029	187149.2973	78.06214126	176870.635	72.63366104	1.820755377	1.438010973	197921.1957	83.75111471	1.670349588	1.338332437
2030	187291.7106	78.13735415	176565.5967	72.47256086	1.746128293	1.379350492	198552.6333	84.08459648	1.602909457	1.285310703
2031	187403.264	78.19626895	176223.0273	72.29163934	1.676201215	1.324321323	199162.0456	84.40644604	1.539754807	1.235602973
2032	187483.557	78.23867419	175842.4797	72.09066035	1.610534413	1.27258455	199749.1384	84.71650795	1.48048527	1.188900642
2033	187532.1804	78.26435366	175423.4978	71.86938303	1.548741403	1.223842268	200313.6097	85.01462271	1.424748962	1.144932448
2034	187548.7155	78.27308637	174965.6164	71.62756166	1.490481113	1.177831546	200855.1494	85.30062664	1.372235348	1.10345898
2035	187532.7347	78.26464644	174468.3611	71.36494571	1.4354514	1.134319437	201373.4399	85.57435189	1.322669341	1.064268128
2036	187483.8011	78.2388031	173931.2481	71.08127972	1.383383639	1.093098813	201868.1551	85.83562632	1.275806376	1.027171296
2037	187401.4683	78.19532057	173353.7844	70.77630325	1.334038195	1.053984876	202338.9609	86.0842735	1.231428288	0.992000221
2038	187285.2803	78.13395807	172735.4674	70.44975085	1.287200612	1.016812221	202785.5151	86.32011261	1.189339839	0.958604303
2039	187134.7714	78.05446969	172075.7848	70.10135203	1.242678383	0.981432352	203207.4669	86.54295841	1.149365777	0.92684834
2040	186949.4665	77.95660439	171374.2148	69.73083116	1.200298208	0.947711567	203604.457	86.75262119	1.111348342	0.896610603
2041	186728.8801	77.8401059	170630.2257	69.33790744	1.159903649	0.915529157	203976.1176	86.94890669	1.075145131	0.867781198
2042	186472.5172	77.70471268	169843.2759	68.92229487	1.121353129	0.884775859	204322.0723	87.13161606	1.040627273	0.840260655
2043	186179.8723	77.55015786	169012.8139	68.48370216	1.0845182	0.855352526	204641.9356	87.3005458	1.007677855	0.813958716
2044	185850.43	77.37616917	168138.2782	68.02183273	1.049282053	0.827168978	204935.3134	87.45548772	0.976190562	0.788793294
2045	185483.6644	77.18246889	167219.0969	67.53638461	1.015538226	0.800143007	205201.8024	87.59622885	0.946068502	0.764689561
2046	185079.0392	76.96877378	166254.6881	67.02705041	0.983189477	0.774199511	205440.9903	87.72255139	0.917223185	0.741579163
2047	184636.0075	76.73479502	165244.4593	66.49351726	0.952146808	0.749269738	205652.4555	87.83423267	0.889573625	0.719399531
2048	184154.0118	76.48023814	164187.8077	65.93546679	0.922328604	0.725290626	205835.7668	87.9310451	0.863045562	0.698093279
2049	183632.4837	76.20480299	163084.1198	65.35257502	0.893659878	0.702204222	205990.4841	88.01275605	0.837570774	0.677607676
2050	183070.8439	75.9081836	161932.7716	64.74451234	0.866071614	0.679957174	206116.157	88.07912786	0.813086478	0.657894184

Table A4.2. Sensitivity Analysis of Forest Area and SDG 15 Progress to Initial Forest Area between 2000 and 2050.

Year	Forest Area	SDG 15 Progress	Estimates under 90% of Initial Forest Area		Sx_90		Estimates under 110% of Initial Forest Area		Sx_110	
			Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress
2000	170939.3	69.50113917	153845.37	60.47330482	1	0.769853949	188033.23	78.52897351	1	0.790776317
2001	171861.7002	69.98828733	154494.2674	60.81600763	0.98956306	0.763041356	189229.1331	79.16056702	0.990511873	0.784583051
2002	172758.6346	70.46198618	155113.3228	61.14295001	0.979062521	0.756108088	190403.9464	79.78102235	0.980965928	0.77828008
2003	173630.2392	70.92230755	155702.6024	61.4541668	0.968506006	0.749062666	191557.8759	80.3904483	0.971369097	0.771875151
2004	174476.6378	71.36931689	156262.1588	61.74968589	0.957900788	0.741913249	192691.1167	80.98894789	0.961727989	0.765375681
2005	175297.9402	71.80307217	156792.0296	62.02952708	0.947253791	0.734667631	193803.8508	81.57661727	0.952048901	0.758788755
2006	176094.202	72.22360273	157292.1968	62.29368091	0.936571392	0.727333045	194896.2072	82.15352455	0.942337629	0.75212095
2007	176865.3191	72.63085355	157762.4818	62.54205299	0.925858899	0.719915644	195968.1564	82.71965412	0.932598999	0.745377858
2008	177611.1811	73.02476641	158202.6984	62.77454503	0.915121413	0.712421359	197019.6638	83.27498778	0.922837648	0.738564872
2009	178331.671	73.40527944	158612.6526	62.99105453	0.904363834	0.704855906	198050.6894	83.81950436	0.913058031	0.731687188
2010	179026.6641	73.77232687	158992.1414	63.19147435	0.893590861	0.697224791	199061.1868	84.35317938	0.903264419	0.72474981
2011	179696.0279	74.12583862	159340.9528	63.37569246	0.882807001	0.68953331	200051.103	84.87598478	0.89346091	0.717757554
2012	180339.621	74.4657401	159658.8647	63.54359161	0.872016567	0.681786556	201020.3773	85.3878886	0.883651425	0.710715051
2013	180957.2932	74.79195193	159945.6448	63.69504906	0.861223688	0.673989426	201968.9416	85.8888548	0.873839717	0.703626751
2014	181548.8846	75.10438968	160201.0498	63.82993636	0.850432312	0.66614662	202896.7193	86.37884299	0.864029374	0.696496927
2015	182114.2254	75.40296372	160424.8253	63.94811915	0.839646207	0.658262653	203803.6256	86.85780829	0.854223825	0.689329684
2016	182653.1359	75.68757902	160616.7054	64.04945694	0.828868976	0.650341855	204689.5664	87.3257011	0.844426341	0.682128959
2017	183165.4254	75.95813501	160776.412	64.13380297	0.81810405	0.64238838	205554.4388	87.78246705	0.834640046	0.674898527
2018	183650.8929	76.21452543	160903.6553	64.20100408	0.807354704	0.63440621	206398.1305	88.22804678	0.824867913	0.667642009
2019	184109.3261	76.45663824	160998.1327	64.25090055	0.796624055	0.626399159	207220.5196	88.66237593	0.815112777	0.660362872
2020	184540.5019	76.68435552	161059.5294	64.28332602	0.785915071	0.618370882	208021.4744	89.08538501	0.805377338	0.653064439
2021	184944.1855	76.89755336	161087.5174	64.2981074	0.775230577	0.610324879	208800.8536	89.49699933	0.795664161	0.64574989
2022	185320.1311	77.09610187	161081.7563	64.29506477	0.764573256	0.602264498	209558.5058	89.89713897	0.785975687	0.638422271
2023	185668.0811	77.27986504	161041.8923	64.27401135	0.753945659	0.594192945	210294.2698	90.28571874	0.776314235	0.631084495
2024	185987.7329	77.44868306	160967.5251	64.23473571	0.743350073	0.58611315	211007.9406	90.66263042	0.766681885	0.623739227
2025	186278.7455	77.60237584	160858.2144	64.17700532	0.732788566	0.578027815	211699.2766	91.02774635	0.757080515	0.616388923
2026	186540.7697	77.74075898	160713.5101	64.10058254	0.722263115	0.569939541	212368.0293	91.38093542	0.747511923	0.609035946
2027	186773.4484	77.86364378	160532.9526	64.00522451	0.711775609	0.561850831	213013.9441	91.72206304	0.737977826	0.601682574
2028	186976.4156	77.97083708	160316.0719	63.89068311	0.701327852	0.553764094	213636.7593	92.05099105	0.728479865	0.594330995
2029	187149.2973	78.06214126	160062.3881	63.75670483	0.690921567	0.545681648	214236.2065	92.3675777	0.719019606	0.586983316
2030	187291.7106	78.13735415	159771.4109	63.60303073	0.680558397	0.537605721	214812.0104	92.67167757	0.709598542	0.579641564
2031	187403.264	78.19626895	159442.6395	63.42939635	0.670239908	0.529538455	215363.8885	92.96314154	0.700218098	0.572307686
2032	187483.557	78.23867419	159075.5625	63.23553163	0.659967591	0.521481909	215891.5516	93.24181674	0.690879628	0.564983554
2033	187532.1804	78.26435366	158669.6579	63.02116083	0.649742866	0.513438061	216394.7028	93.5075465	0.681584423	0.557670964
2034	187548.7155	78.27308637	158224.3927	62.78600245	0.639567082	0.505408809	216873.0383	93.76017029	0.672333711	0.550371644
2035	187532.7347	78.26464644	157739.2228	62.52976918	0.629441521	0.497395977	217326.2467	93.99952371	0.663128655	0.543087252
2036	187483.8011	78.2388031	157213.593	62.2521678	0.6193674	0.489401313	217754.0093	94.2254384	0.653970364	0.535819376
2037	187401.4683	78.19532057	156646.9368	61.95289911	0.609345873	0.481426496	218155.9998	94.43774204	0.644859884	0.528569542
2038	187285.2803	78.13395807	156038.6763	61.63165786	0.599378033	0.473473135	218531.8842	94.63625828	0.635798212	0.521339213
2039	187134.7714	78.05446969	155388.2218	61.28813268	0.589464914	0.46554277	218881.3211	94.82080671	0.626786285	0.514129791
2040	186949.4665	77.95660439	154694.972	60.92200599	0.579607493	0.457636878	219203.9609	94.9912028	0.617824993	0.506942617
2041	186728.8801	77.8401059	153958.3138	60.53295393	0.569806692	0.449756875	219499.4465	95.14725788	0.608915175	0.499778977
2042	186472.5172	77.70471268	153177.6218	60.12064627	0.560063382	0.441904113	219767.4126	95.28877909	0.60005762	0.492640103
2043	186179.8723	77.55015786	152352.2586	59.68474639	0.550378379	0.434079887	220007.486	95.41556933	0.591253072	0.48552717
2044	185850.43	77.37616917	151481.5745	59.22491112	0.540752454	0.426285434	220219.2856	95.52742723	0.582502231	0.478441304
2045	185483.6644	77.18246889	150564.9072	58.74079071	0.531186328	0.418521938	220402.4217	95.62414707	0.573805753	0.47138358
2046	185079.0392	76.96877378	149601.5819	58.23202874	0.521680675	0.410790528	220556.4966	95.70551881	0.56516425	0.464355025
2047	184636.0075	76.73479502	148590.9109	57.69826206	0.512236128	0.403092282	220681.1042	95.77132797	0.556578298	0.45735662
2048	184154.0118	76.48023814	147532.1936	57.13912066	0.502853274	0.395428228	220775.8301	95.82135563	0.548048431	0.450389298
2049	183632.4837	76.20480299	146424.7164	56.55422762	0.49353266	0.387799347	220840.2511	95.85537835	0.539575145	0.443453952
2050	183070.8439	75.9081836	145267.7523	55.94319903	0.484274794	0.380206573	220873.9355	95.87316817	0.531158904	0.43655143

Table A4.3. Sensitivity Analysis of Forest Area and SDG 15 Progress to Population between 2000 and 2050.

Year	Forest Area	SDG 15 Progress	Estimates under 90% of Population		Sx_90		Estimates under 110% of Population		Sx_110	
			Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress
2000	170939.3	69.50113917	170939.3	69.50113917	#DIV/0!	#DIV/0!	170939.3	69.50113917	#DIV/0!	#DIV/0!
2001	171861.7002	69.98828733	171938.2434	70.02871213	-224.5292	-173.1320349	171785.1571	69.94786252	-204.026546	-157.3018503
2002	172758.6346	70.46198618	172908.9735	70.54138481	-114.912794	-88.74458073	172607.973	70.38241708	-104.151473	-80.41315138
2003	173630.2392	70.92230755	173851.953	71.03940151	-78.3127614	-60.56871668	173407.6434	70.80474781	-70.8204365	-54.75339885
2004	174476.6378	71.36931689	174767.3112	71.52283057	-60.0249578	-46.49052585	174184.0554	71.2147951	-54.1212265	-41.89747032
2005	175297.9402	71.80307217	175655.1816	71.99174244	-49.0698822	-38.05743974	174937.0872	71.61249454	-44.0716117	-34.16049721
2006	176094.202	72.22360273	176515.6977	72.44620765	-41.7784143	-32.44474632	175666.6074	71.99777677	-37.3477399	-28.98361397
2007	176865.3191	72.63085355	177348.9898	72.88629505	-36.5673004	-28.43345966	176372.475	72.37056732	-32.5333343	-25.27656668
2008	177611.1811	73.02476641	178155.1819	73.31207007	-32.6490691	-25.41727673	177054.539	72.73078645	-28.9160064	-22.49095363
2009	178331.671	73.40527944	178934.3886	73.72359331	-29.58793	-23.06066038	177712.6383	73.07834908	-26.0982886	-20.32079912
2010	179026.6641	73.77232687	179686.7131	74.12091919	-27.1232395	-21.16292348	178346.6014	73.41316467	-23.8409301	-18.58192237
2011	179696.0279	74.12583862	180412.2445	74.50409484	-25.0896188	-19.59672712	178956.2465	73.73513715	-21.9912943	-17.15681864
2012	180339.621	74.4657401	181111.0565	74.87315911	-23.3771483	-18.27743418	179541.3811	74.04416485	-20.4474157	-15.96698961
2013	180957.2932	74.79195193	181783.053	75.22806129	-21.9140345	-17.14981565	180101.8019	74.34014047	-19.1385835	-14.95799732
2014	181548.8846	75.10438968	182428.0988	75.56872996	-20.6489932	-16.17442901	180637.2837	74.62294502	-18.0139935	-14.09072476
2015	182114.2254	75.40296372	183046.0516	75.89508999	-19.5437988	-15.32187336	181147.5402	74.8924273	-17.0354923	-13.33578218
2016	182653.1359	75.68757902	183636.7614	76.20706218	-18.5693764	-14.56978494	181632.2779	75.14843226	-16.1746543	-12.67127282
2017	183165.4254	75.95813501	184200.0701	76.50456296	-17.7032193	-13.90085082	182091.1957	75.39080101	-15.4098748	-12.0805542
2018	183650.8929	76.21452543	184735.8106	76.78750409	-16.9276339	-13.30145968	182523.9854	75.61937068	-14.7244476	-11.55075749
2019	184109.3261	76.45663824	185243.8062	77.05579235	-16.2285196	-12.76076336	182930.3311	75.83397442	-14.1052589	-11.07178133
2020	184540.5019	76.68435552	185723.8709	77.30932936	-15.5945022	-12.2700104	183309.9091	76.03444133	-13.541878	-10.63559166
2021	184944.1855	76.89755336	186175.8079	77.54801131	-15.0163062	-11.82206372	183662.388	76.22059636	-13.0259113	-10.23572412
2022	185320.1311	77.09610187	186599.4102	77.77172883	-14.4862937	-11.41104578	183987.4285	76.39226032	-12.5505345	-9.866923778
2023	185668.0811	77.27986504	186994.4598	77.98036677	-13.9981196	-11.03207348	184284.6832	76.54924977	-12.1101484	-9.524879816
2024	185987.7329	77.44868306	187360.7275	78.17380409	-13.5461369	-10.68079394	184553.7968	76.691377	-11.700395	-9.206242599
2025	186278.7455	77.60237584	187697.9727	78.35191375	-13.1253641	-10.35336232	184794.4056	76.81844997	-11.3178205	-8.908362074
2026	186540.7697	77.74075898	188005.9433	78.51456254	-12.7316502	-10.04657546	185006.1377	76.93027225	-10.9594612	-8.628964365
2027	186773.4484	77.86364378	188284.3752	78.66161109	-12.3615149	-9.757748557	185188.6128	77.02664298	-10.6227603	-8.366087703
2028	186976.4156	77.97083708	188532.9927	78.79291369	-12.0120242	-9.484619311	185341.442	77.1073568	-10.3055005	-8.118031052
2029	187149.2973	78.06214126	188751.5079	78.90831833	-11.6806931	-9.225272653	185464.2278	77.17220384	-10.0057503	-7.883312549
2030	187291.7106	78.13735415	188939.6109	79.00766135	-11.3654763	-8.978134898	185556.5643	77.2209696	-9.72181924	-7.660635686
2031	187403.264	78.19626895	189096.9278	79.09074532	-11.0649623	-8.742127957	185618.0366	77.253435	-9.45222253	-7.448861545
2032	187483.557	78.23867419	189223.0764	79.15736826	-10.7778946	-8.516292492	185648.2208	77.26937621	-9.19565063	-7.246985914
2033	187532.1804	78.26435366	189317.6652	79.20732355	-10.5031518	-8.299772344	185646.6842	77.26856472	-8.95094465	-7.054120262
2034	187548.7155	78.27308637	189380.2942	79.24039986	-10.2397301	-8.09180134	185612.9851	77.25076718	-8.71707568	-6.869475863
2035	187532.7347	78.26464644	189410.5542	79.25638111	-9.98672869	-7.891692091	185546.6725	77.21574542	-8.4931274	-6.692350471
2036	187483.8011	78.2388031	189408.0268	79.25504634	-9.74333736	-7.698826413	185447.2861	77.1632564	-8.27828139	-6.522117061
2037	187401.4683	78.19532057	189372.2845	79.23616968	-9.50882544	-7.512647119	185314.3564	77.09305208	-8.07180475	-6.358214307
2038	187285.2803	78.13395807	189302.8899	79.19952029	-9.2825328	-7.332650949	185147.4043	77.00487948	-7.87303949	-6.200138447
2039	187134.7714	78.05446969	189199.3966	79.14486225	-9.06386175	-7.158382465	184945.9411	76.89848052	-7.68139347	-6.047436345
2040	186949.4665	77.95660439	189061.3481	79.07195455	-8.85227014	-6.98942875	184709.4685	76.77359203	-7.49633267	-5.899699519
2041	186728.8801	77.8401059	188888.2782	78.98055096	-8.64726532	-6.825414794	184437.4785	76.62994568	-7.31737444	-5.756559003
2042	186472.5172	77.70471268	188679.7107	78.87040003	-8.44839886	-6.66599947	184129.4531	76.46726792	-7.14408174	-5.617680886
2043	186179.8723	77.55015786	188435.1596	78.74124498	-8.25526198	-6.510872006	183784.8643	76.28527989	-6.97605809	-5.482762457
2044	185850.43	77.37616917	188154.1283	78.59282364	-8.06748142	-6.359748884	183403.174	76.08369743	-6.81294318	-5.351528825
2045	185483.6644	77.18246889	187836.1102	78.42486841	-7.88471595	-6.212371109	182983.834	75.86223096	-6.65440904	-5.223729983
2046	185079.0392	76.96877378	187480.5881	78.23710617	-7.70665316	-6.068501795	182526.2856	75.62058544	-6.50015668	-5.099138219
2047	184636.0075	76.73479502	187087.0343	78.02925822	-7.53300669	-5.92792403	182029.9596	75.35846031	-6.34991315	-4.977545845
2048	184154.0118	76.48023814	186654.9104	77.80104022	-7.36351375	-5.790438971	181494.2764	75.0755494	-6.20342889	-4.858763197
2049	183632.4837	76.20480299	186183.6673	77.55216213	-7.1979329	-5.655864158	180918.6456	74.77154092	-6.06047548	-4.74261686
2050	183070.8439	75.9081836	185672.7449	77.28232813	-7.03604211	-5.524032	180302.4659	74.44611734	-5.92084355	-4.628948099

Table A4.4. Sensitivity Analysis of Forest Area and SDG 15 Progress to Forestry Production between 2000 and 2050.

Year	Forest Area	SDG 15 Progress	Estimates under 90% of Forestry Production		Sx_90		Estimates under 110% of Forestry Production		Sx_110	
			Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress
2000	170939.3	69.50113917	170939.3	69.50113917	#DIV/0!	NA	170939.3	69.50113917	#DIV/0!	NA
2001	171861.7002	69.98828733	171994.3752	70.05835711	-129.5358223	-99.88370026	171729.0252	69.91821755	-117.6689951	-90.71244934
2002	172758.6346	70.46198618	173026.9242	70.60367824	-64.39258744	-49.72895869	172490.345	70.32029411	-58.44781244	-45.11723316
2003	173630.2392	70.92230755	174037.13	71.13719924	-42.67243798	-33.00374563	173223.3483	70.70741586	-38.702207	-29.91249687
2004	174476.6378	71.36931689	175025.1643	71.65901079	-31.80823973	-24.63611315	173928.1112	71.079623	-28.82566774	-22.30555805
2005	175297.9402	71.80307217	175991.1855	72.1691965	-25.28656823	-19.61166379	174604.6949	71.43694785	-22.89688007	-17.73787662
2006	176094.202	72.22360273	176935.2983	72.66781175	-20.9362708	-16.25892291	175253.1057	71.77939371	-18.94206554	-14.68992993
2007	176865.3191	72.63085355	177857.4488	73.15482802	-17.82683418	-13.86152527	175873.1894	72.10687909	-16.11530335	-12.51047772
2008	177611.1811	73.02476641	178757.5776	73.63021395	-15.49299716	-12.06128719	176464.7846	72.41931887	-13.99363388	-10.87389736
2009	178331.671	73.40527944	179635.6194	74.09393502	-13.6762831	-10.65921516	177027.7226	72.71662387	-12.34207506	-9.599286603
2010	179026.6641	73.77232687	180491.502	74.54595318	-12.22160209	-9.535912318	177561.8262	72.99870055	-11.01963849	-8.578102015
2011	179696.0279	74.12583862	181325.1464	74.9862266	-11.03026151	-8.615396821	178066.9094	73.26545064	-9.936601091	-7.741269814
2012	180339.621	74.4657401	182136.4654	75.41470932	-10.03646295	-7.847013209	178542.7766	73.51677089	-9.033148239	-7.042739338
2013	180957.2932	74.79195193	182925.3639	75.83135107	-9.194654225	-7.195691171	178989.2225	73.75255279	-8.267867359	-6.450628308
2014	181548.8846	75.10438968	183691.738	76.236097	-8.472296068	-6.636379226	179406.0311	73.97268235	-7.611178024	-5.942162895
2015	182114.2254	75.40296372	184435.475	76.62888755	-7.845525458	-6.150705454	179792.9759	74.17703989	-7.041387035	-5.50064129
2016	182653.1359	75.68757902	185156.4526	77.00965821	-7.296445295	-5.724889997	180149.8191	74.36549983	-6.542222828	-5.113536356
2017	183165.4254	75.95813501	185854.5393	77.37833942	-6.81136729	-5.348394527	180476.3115	74.5379306	-6.101243053	-4.771267745
2018	183650.8929	76.21452543	186529.5935	77.73485646	-6.379645504	-5.013021764	180772.1923	74.6941944	-5.70876859	-4.46638343
2019	184109.3261	76.45663824	187181.4637	78.0791293	-5.992873788	-4.712299507	181037.1886	74.83414719	-5.357158124	-4.192999567
2020	184540.5019	76.68435552	187809.9881	78.41107255	-5.644327282	-4.441049359	181271.0156	74.95763848	-5.04029745	-3.946408488
2021	184944.1855	76.89755336	188414.9949	78.73059537	-5.328560754	-4.195078612	181473.3762	75.06451135	-4.753237099	-3.722798745
2022	185320.1311	77.09610187	188996.3015	79.03760144	-5.041119149	-3.970956424	181643.9606	75.15460229	-4.491926446	-3.519051283
2023	185668.0811	77.27986504	189553.7152	79.33198889	-4.778321274	-3.765848012	181782.4469	75.2277412	-4.25301927	-3.332589112
2024	185987.7329	77.44868306	190086.9989	79.61363255	-4.537098387	-3.577389836	181888.4668	75.28373358	-4.03372573	-3.1612635
2025	186278.7455	77.60237584	190595.8784	79.88238756	-4.314871716	-3.403595475	181961.6125	75.32236411	-3.831701477	-3.0032686
2026	186540.7697	77.74075898	191080.0722	80.13810533	-4.109458879	-3.242783793	182001.4673	75.34341263	-3.644962674	-2.857076178
2027	186773.4484	77.86364378	191539.2919	80.38063349	-3.919000872	-3.093522529	182007.6048	75.34665406	-3.471818917	-2.72138411
2028	186976.4156	77.97083708	191973.2417	80.60981584	-3.741903589	-2.954583732	181979.5895	75.33185832	-3.310821478	-2.59507612
2029	187149.2973	78.06214126	192381.6185	80.82549228	-3.576792984	-2.824908628	181916.9762	75.29879025	-3.160720921	-2.477189668
2030	187291.7106	78.13735415	192764.1116	81.02749876	-3.422477805	-2.703579396	181819.3096	75.24720954	-3.020434408	-2.366890359
2031	187403.264	78.19626895	193120.4029	81.21566724	-3.277920417	-2.589796428	181686.1251	75.17687066	-2.889018575	-2.263451293
2032	187483.557	78.23867419	193450.1665	81.3898256	-3.142212628	-2.482859882	181516.9476	75.08752277	-2.765647888	-2.166236251
2033	187532.1804	78.26435366	193753.0687	81.54979764	-3.014556311	-2.382154564	181311.292	74.97890969	-2.649596605	-2.07468597
2034	187548.7155	78.27308637	194028.768	81.69540297	-2.894246868	-2.287137499	181068.663	74.85076976	-2.5402244	-1.988306816
2035	187532.7347	78.26464644	194276.9148	81.82645702	-2.780660231	-2.197327584	180788.5546	74.70283586	-2.436963864	-1.906661442
2036	187483.8011	78.2388031	194497.1517	81.94277095	-2.673241532	-2.112297038	180470.4506	74.53483525	-2.339310509	-1.829360941
2037	187401.4683	78.19532057	194689.1129	82.04415159	-2.57149572	-2.031664163	180113.8237	74.34648956	-2.24681429	-1.756058334
2038	187285.2803	78.13395807	194852.4244	82.13040146	-2.474979709	-1.955087325	179718.1362	74.13751469	-2.159072442	-1.686443024
2039	187134.7714	78.05446969	194986.7039	82.20131863	-2.383295727	-1.882259779	179282.839	73.90762076	-2.07572341	-1.620236167
2040	186949.4665	77.95660439	195091.5607	82.25669675	-2.296085778	-1.812905347	178807.3723	73.65651203	-1.996441598	-1.557186682
2041	186728.8801	77.8401059	195166.5955	82.29632497	-2.213026527	-1.746774669	178291.1647	73.38388684	-1.920933212	-1.497067883
2042	186472.5172	77.70471268	195211.4005	82.31998787	-2.133825469	-1.683642026	177733.6338	73.0894375	-1.848932229	-1.439674571
2043	186179.8723	77.55015786	195225.5591	82.32746545	-2.058217107	-1.62330259	177134.1856	72.77285027	-1.780197373	-1.384820537
2044	185850.43	77.37616917	195208.6459	82.31853307	-1.985960066	-1.565570054	176492.2142	72.43380527	-1.714509155	-1.332336414
2045	185483.6644	77.18246889	195160.2267	82.29296139	-1.9168343	-1.510274577	175807.1022	72.0719764	-1.651667551	-1.282067797
2046	185079.0392	76.96877378	195079.8582	82.25051631	-1.850638824	-1.457260995	175078.2202	71.68703125	-1.591489845	-1.233873631
2047	184636.0075	76.73479502	194967.0882	82.19095898	-1.787189675	-1.406387264	174304.9269	71.27863106	-1.533808807	-1.187624785
2048	184154.0118	76.48023814	194821.4552	82.11404566	-1.726318158	-1.357523094	173486.5685	70.84643063	-1.478471062	-1.143202814
2049	183632.4837	76.20480299	194642.4884	82.01952774	-1.667869265	-1.310548758	172622.4791	70.39007823	-1.425335703	-1.100498869
2050	183070.8439	75.9081836	194429.7077	81.90715165	-1.611700323	-1.265354023	171711.9802	69.90921555	-1.374273031	-1.059412748

Table A4.5. Sensitivity Analysis of Forest Area and SDG 15 Progress to Net Forest Import between 2000 and 2050.

Year	Forest Area	SDG 15 Progress	Estimates under 90% of Net Forest Import		Sx_90		Estimates under 110% of Net Forest Import		Sx_110	
			Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress	Forest Area	SDG 15 Progress
2000	170939.3	69.50113917	170939.3	69.50113917	170939.3	NA	170939.3	69.50113917	170939.3	NA
2001	171861.7002	69.98828733	171833.745	69.97352328	171833.745	474.045193	171889.6555	70.00305138	171889.6555	431.0412042
2002	172758.6346	70.46198618	172704.4965	70.43339418	172704.4965	246.4395574	172812.7727	70.49057817	172812.7727	224.1269197
2003	173630.2392	70.92230755	173551.7192	70.88083871	173551.7192	171.0255413	173708.7591	70.9637764	173708.7591	155.568651
2004	174476.6378	71.36931689	174375.5655	71.31593751	174375.5655	133.7020274	174577.71	71.42269628	174577.71	121.6381881
2005	175297.9402	71.80307217	175176.1746	71.73876401	175176.1746	111.6546854	175419.7058	71.86738034	175419.7058	101.595154
2006	176094.202	72.22360273	175953.6319	72.14936327	175953.6319	97.28465068	176234.7722	72.29784219	176234.7722	88.53150038
2007	176865.3191	72.63085355	176707.8632	72.54769623	176707.8632	87.34149929	177022.775	72.71401088	177022.775	79.49226377
2008	177611.1811	73.02476641	177438.7891	72.93372087	177438.7891	80.20685305	177783.5731	73.11581195	177783.5731	73.00623373
2009	178331.671	73.40527944	178146.3237	73.30739181	178146.3237	74.98933273	178517.0182	73.50316708	178517.0182	68.26302502
2010	179026.6641	73.77232687	178830.3741	73.66866001	178830.3741	71.16288191	179222.9542	73.87599372	179222.9542	64.78444328
2011	179696.0279	74.12583862	179490.8397	74.0174724	179490.8397	68.40308779	179901.216	74.23420483	179901.216	62.27553585
2012	180339.621	74.4657401	180127.6122	74.35377168	180127.6122	66.50601855	180551.6298	74.57770853	180551.6298	60.55092185
2013	180957.2932	74.79195193	180740.5743	74.67749599	180740.5743	65.34562783	181174.012	74.90640786	181174.012	59.49602779
2014	181548.8846	75.10438968	181329.6001	74.98857877	181329.6001	64.85087396	181768.169	75.22020059	181768.169	59.04625262
2015	182114.2254	75.40296372	181894.5541	75.28694849	181894.5541	64.99402144	182333.8967	75.51897894	182333.8967	59.17638659
2016	182653.1359	75.68757902	182435.2913	75.57252854	182435.2913	65.78641033	182870.9805	75.8026295	182870.9805	59.89673734
2017	183165.4254	75.95813501	182951.6566	75.84523706	182951.6566	67.28034641	183379.1943	76.07103296	183379.1943	61.25486151
2018	183650.8929	76.21452543	183443.4848	76.10498678	183443.4848	69.57774596	183858.301	76.32406409	183858.301	63.34340386
2019	184109.3261	76.45663824	183910.6003	76.35168497	183910.6003	72.84826946	184308.052	76.56159151	184308.052	66.31660507
2020	184540.5019	76.68435552	184352.817	76.58523333	184352.817	77.36346291	184728.1867	76.7834777	184728.1867	70.42133587
2021	184944.1855	76.89755336	184769.9381	76.8055279	184769.9381	83.56117348	185118.4329	76.98957882	185118.4329	76.05560962
2022	185320.1311	77.09610187	185161.7559	77.01245901	185161.7559	92.1729638	185478.5063	77.17974472	185478.5063	83.88451906
2023	185668.0811	77.27986504	185528.0518	77.20591125	185528.0518	104.4975055	185808.1103	77.35381884	185808.1103	95.08863378
2024	185987.7329	77.44868306	185868.5629	77.3857457	185868.5629	123.0567645	186106.9029	77.51162043	186106.9029	111.9606799
2025	186278.7455	77.60237584	186182.9883	77.55180349	186182.9883	153.4482337	186374.5027	77.65294818	186374.5027	139.5893302
2026	186540.7697	77.74075898	186471.0197	77.70392184	186471.0197	211.0390592	186610.5197	77.77759612	186610.5197	191.944591
2027	186773.4484	77.86364378	186732.3414	77.84193393	186732.3414	358.6558928	186814.5553	77.88535362	186814.5553	326.1418213
2028	186976.4156	77.97083708	186966.6299	77.96566891	186966.6299	1508.674059	186986.2014	77.97600525	186986.2014	1371.612754
2029	187149.2973	78.06214126	187173.5536	78.07495177	187173.5536	-609.3601273	187125.041	78.04933076	187125.041	-553.87315
2030	187291.7106	78.13735415	187352.7735	78.16960333	187352.7735	-242.2925459	187230.6478	78.10510497	187230.6478	-220.1750349
2031	187403.264	78.19626895	187503.9421	78.24944015	187503.9421	-147.0650777	187302.586	78.14309774	187302.586	-133.6045977
2032	187483.557	78.23867419	187626.704	78.31427451	187626.704	-103.4898758	187340.4101	78.16307387	187340.4101	-93.9907865
2033	187532.1804	78.26435366	187720.6954	78.3639143	187720.6954	-78.6097326	187343.6653	78.16479302	187343.6653	-71.37248726
2034	187548.7155	78.27308637	187785.5443	78.39816303	187785.5443	-62.58009128	187311.8866	78.14800971	187311.8866	-56.80008221
2035	187532.7347	78.26464644	187820.8702	78.41681971	187820.8702	-51.4312698	187244.5993	78.11247317	187244.5993	-46.66479217
2036	187483.8011	78.2388031	187826.2839	78.41967886	187826.2839	-43.25554846	187141.3184	78.05792733	187141.3184	-39.23231585
2037	187401.4683	78.19532057	187801.3877	78.40653041	187801.3877	-37.02257474	187001.5489	77.98411074	187001.5489	-33.56597829
2038	187285.2803	78.13395807	187745.7751	78.37715966	187745.7751	-32.12723999	186824.7854	77.89075648	186824.7854	-29.11567305
2039	187134.7714	78.05446969	187659.0307	78.33134724	187659.0307	-28.19097108	186610.5122	77.77759215	186610.5122	-25.53724733
2040	186949.4665	77.95660439	187540.7301	78.26886905	187540.7301	-24.96491453	186358.2028	77.64433974	186358.2028	-22.60446827
2041	186728.8801	77.8401059	187390.44	78.18949619	187390.44	-22.27884043	186067.3202	77.49071561	186067.3202	-20.16258252
2042	186472.5172	77.70471268	187207.7179	78.09299496	187207.7179	-20.01242832	185737.3165	77.31643041	185737.3165	-18.10220786
2043	186179.8723	77.55015786	186992.1118	77.97912673	186992.1118	-18.07827169	185367.6328	77.12118899	185367.6328	-16.3438835
2044	185850.43	77.37616917	186743.1608	77.84764796	186743.1608	-16.41137873	184957.6993	76.90469039	184957.6993	-14.82852626
2045	185483.6644	77.18246889	186460.394	77.69831008	186460.394	-14.96244768	184506.9348	76.6666277	184506.9348	-13.51131614
2046	185079.0392	76.96877378	186143.3315	77.53085952	186143.3315	-13.6934223	184014.7469	76.40668804	184014.7469	-12.35765661
2047	184636.0075	76.73479502	185791.4832	77.34503755	185791.4832	-12.5744751	183480.5318	76.12455248	183480.5318	-11.34043182
2048	184154.0118	76.48023814	185404.3497	77.14058031	185404.3497	-11.58191027	182903.674	75.81989597	182903.674	-10.43810034
2049	183632.4837	76.20480299	184981.4213	76.91721873	184981.4213	-10.69667598	182283.5462	75.49238724	182283.5462	-9.633341665
2050	183070.8439	75.9081836	184522.1786	76.67467843	184522.1786	-9.903287157	181619.5093	75.14168878	181619.5093	-8.912079244