University of Zurich[UZH]

Department of Banking and Finance

Centre of Competence for Sustainable Finance

Economic and Financial Drivers of Forest Cover Change

Master Thesis in Business and Finance

Jérôme Gretener

Full Text Version

CCSF Thesis Series no. 40 (2023)

July 2023

CCSF Thesis Series (formerly CSP/CMF Thesis Series)

Economic and Financial Drivers of Forest Cover Change
Master Thesis in Banking and Finance

Jérôme Gretener
Advisor: Isabelle Jiani Zheng
Professor: Professor Dr. Marc Chesney

Full Text Version
CCSF Thesis Series no. 40 (2022)

Zurich: University of Zurich, Department for Banking and Finance / Center of Competence for Sustainable Finance, Plattenstrasse 14, 8032 Zurich, Switzerland

Abstract

Forest cover loss, be it due to forest fires, deforestation or other reasons, plays a key role within ongoing debates concerning topics such as global warming, climate change, or the loss of biodiversity. An improved understanding of general underlying economic and financial factors and their effect on forest cover loss could help to increase the effectivity and sustainability of efforts in this field.

This thesis aims to provide an overview and summary of existing literature, while additionally exploring the effects of different economic and financial drivers (FDI, GDP, trade) on selected forest and biodiversity related variables. Tropical primary rainforests are of great importance, especially due to their key role regarding biodiversity and carbon storage. Due to this reason and the superior availability of existing literature along with large media, social and political interest, emphasis was put on South America. Data from almost all South American countries was collected, and basic regression was performed.

There were marginally to highly significant effects of especially GDP on all investigated forest and biodiversity variables. Previous studies have strived to find explanations for the relationship between economic drivers (for example GDP) and environmental variables. However, it is challenging to find satisfying explanations for the observed trends, which can sometimes be inconclusive or contradictive. One of the reasons seems to be the quality of the available data. Working with forest and biodiversity related data revealed that data availability and quality is a major concern. Even though data accuracy seems to improve steadily, knowledge and data concerning both forest and biodiversity related topics is incomplete. Improved reporting, data availability, accuracy and comparability is needed to construct more complex and realistic models on forest cover and biodiversity change in future studies.

Table of Contents

Abstract I
List of Figures III
List of Tables III
1 Introduction 1
2 Literature Review 3
2.1 Overview of the Status of Forest Cover Change 3
2.1.1 Trends and Recent Developments 3
2.1.2 Important Factors and Definitions 6
2.1.3 Importance and Implications of Forest Cover Change 8
2.1.4 Forest Cover Change and Biodiversity 13
2.2 Economic and Financial Drivers of Forest Cover and Biodiversity Change 15
2.2.1 Gross Domestic Product 16
2.2.2 International Trade 18
2.2.3 Foreign Direct Investment 20
2.2.4 Grants, Other Finance Sources and Initiatives 20
3 Methodology and Data 24
3.1 Overview and Selection of the Data 24
3.1.1 Dependent and Independent Variables 24
3.1.2 Selection of Countries Included in the Analysis 30
3.2 Data Quality and Discrepancies Between Datasets 31
3.3 Statistical Analysis 33
3.4 Expected Model Outcomes 35
4 Results 38
4.1 Forest and Biodiversity Indicators Over Time 38
4.2 Economic and financial drivers over time 42
4.3 Forest and Biodiversity Indicator Models 45
4.3.1 'Forest Area Net Change FRA' Linear Model 46
4.3.2 'Deforestation FRA' Random Effect Model 48
4.3.3 'Deforestation GFW' Linear Model 49
4.3.4 'BII' Linear Model 50
5 Discussion 54
5.1 Conclusion and Further Research 59
References 62
Appendix 69

List of Figures

Figure 1 Relative Forest Area Net Change in Different South American Countries 39
Figure 2 Deforestation as a Percentage of Forest Extent in Different South American Countries 40
Figure 3 Tree Cover Loss as a Percentage of Forest Extent in Different South American Countries....................41
Figure 4 Biodiversity Intactness Index in Different South American Countries....................42
Figure 5 FDI (% GDP) in Different South American Countries 43
Figure 6 GDP per Capita (Current US$) in Different South American Countries 44
Figure 7 Trade (% GDP) in Different South American Countries 45
Figure 8 'Forest Area Net Change FRA' in relation to 'FDI (% GDP)' 47
Figure 9 'Forest Area Net Change FRA' in relation to 'FDI (% GDP)' on a Country Level 47
Figure 10 'Deforestation FRA' in Relation to 'GDP per Capita' 48
Figure 11 'Deforestation FRA' in Relation to 'GDP per Capita' on a Country Level 49
Figure 12 'Deforestation GFW' in Relation to 'GDP per Capita' 50
Figure 13 'Deforestation GFW' in Relation to 'GDP per Capita' on a Country Level 50
Figure 14 'Biodiversity Intactness Index' in Relation to 'GDP per Capita' 51
Figure 15 'Biodiversity Intactness Index' in Relation to 'GDP per Capita' 52
Figure 16 'Biodiversity Intactness Index' in Relation to 'Trade (% GDP)' 53
Figure 17 'Biodiversity Intactness Index' in Relation to 'Trade (% GDP)' 53

List of Tables

Table 1 Definitions of Variables in the FRA Dataset 26
Table 2 Effects of the Drivers on the Forest and Biodiversity Indicators....................46

1 Introduction

In recent years, awareness and reporting on forest related topics, mainly on deforestation and biodiversity has grown. As some regions encounter their worst-ever forest fire seasons, headlines on forest cover loss are omnipresent amongst news-outlets. Forest cover loss, be it due to forest fires, deforestation or other reasons plays a key role within ongoing debates concerning topics such as global warming, climate change, or biodiversity loss (Alroy, 2017; Ewers, 2006; FAO, 2020b; Watson et al., 2018). While different initiatives help to paint an ever-improving picture of the state of the world's forests, substantial reporting and information gaps remain (Busch, 2015; Harris et al., 2016; Holmgren, 2015a, 2015b; Pearce, 2018).

Even though many of the negative implications and effects of deforestation and forest cover loss in general are well known, finding effective measures to tackle the issues at hand seems complex. An improved understanding of more general underlying factors and their effect on forest cover loss could help to increase the effectivity and sustainability of efforts in this field. Complexity is a persistent factor when talking about forests and their importance. Forests themselves are highly complex systems that provide habitat to not only plant and animal species. They are of great relevance to the economy, society, politics, etc.

An increasing variety of literature examines different effects of forest cover loss (Alroy, 2017; Ewers, 2006; Kinda & Thiombiano, 2021). Existing studies often conclude with estimates of economic damage suffered through forest cover loss, or they try to estimate the cost of regaining what was lost. Considerations of how current economic mechanisms and principles promote forest cover loss are often left out of sight. To address this possible gap, the aim of this thesis is to provide an adequate overview of the topic, current data, challenges and shortcomings in reporting and point out possible areas of interest for future research.

This thesis aims to provide an overview and summary of existing literature while additionally exploring different influences (drivers) on key variables. Exploring the relationship between the underlying variables and the analysed drivers may help to put the specific topic of forest and biodiversity loss into context with broader environmental concerns and economical structures. This will help to comprehensively introduce the field and highlight important linkages, potential shortfalls of current approaches, and new ideas.

Despite different issues, mainly related to data availability and quality, basic regression analysis was performed. Different models, each focusing on specific forest cover or biodiversity related variables were constructed to examine possible underlying effects induced by different drivers.

The drivers, which were examined as part of this thesis, were chosen considering previous literature and other factors, which will further be elaborated. This resulted in a variety of possible indications, which will be discussed. Lastly, the implications derived from these results will be contextualised to highlight potential areas of interest for future research projects and further emphasize the need for ongoing efforts to improve data quality and availability along with the need for stringent reporting standards that would allow for future initiatives to be monitored more effectively and stringently. This could lead to more sustainable results in the long term.

2 Literature Review

2.1 Overview of the Status of Forest Cover Change

2.1.1 Trends and Recent Developments

According to the Food and Agriculture Organization of the United Nations (FAO), the global rate of net loss in forests amounted to 4.7 million ha per year from 2010 to 2020 (FAO, 2020a; Ritchie & Roser, 2021). Although, the forest area is globally still decreasing, the net rate of forest cover loss has slowed from 7.8 million ha per year from 1990-2000 to 5.2 million ha per year from 2000-2010 to the aforementioned 4.7 million ha from 2010-2020 (FAO, 2020a). While net forest loss rates in South America were lower in the last decade compared to the ones before, net forest loss rates in Africa increased steadily over the last three decades (FAO, 2020a). Asia and Europe saw a positive net change in each of the last three decades, nevertheless, the rates of net gain in the last decade were substantially lower than in the one before (FAO, 2020a). North and Central America and the Oceania region show net forest change rates that are either slightly negative or slightly positive for the last three decades (FAO, 2020a).

In contrast to the perception of many, deforestation is not a 'modern' phenomenon. Deforestation has occurred for thousands of years. As the rate of deforestation has increased and the reporting on nature related topics has become more prominent, more and more people have been made aware of the issues that are introduced with high deforestation rates. Ritchie and Roser (2021) analyse how the earth's land surface covered by forests has changed in the last 10'000 years, respectively since the last great ice age. They mention that of the earth's total land surface of 14.9 billion ha, roughly 71% is habitable. Deserts, dunes, glaciers, etc. cover the remaining 29%. Forests covered 57% of the habitable land surface 10'000 years ago, which is roughly 6 billion ha. In 2018, the surface covered by forests decreased to 38% or approximately 4 billion ha (FAO, 2020a; Ritchie & Roser, 2021). Ritchie and Roser (2021) illustrate, that the third of the world's forests that have been lost in the last 10'000 years, (around 2 billion ha) is about twice the size of the United States. The authors further note that deforestation has rapidly accelerated since 1900. In the years since 1900, the same forest area has been lost as in the 9'000 years prior. Finally, Ritchie and Roser (2021) illustrate that the surface covered by urban and built-up land only represents 1% of the earth's habitable surface, whereas a much larger part is consumed by agriculture and food production, 15% for growing crops and 31% for grazing land. There are different reasons as to why forest area gets cleared.

Forest management could for example be focused on the production of wood products (especially in plantations, etc.). In other instances, forest area gets cleared to make room for agricultural expansion. According to the FAO (2020b), the production of wood and non-wood forest products plays an important role, approximately 30% of all forests are managed primarily for these purposes. The FAO (2020a) states in the FRA 2020 report that in 2019, with the assumption of a global population size of 7.79 billion people, there was roughly 0.52 ha of forest area per person. Of the approximately four billion ha of forest, around 45% of the area is classified as tropical forest, 27% as boreal forest, 16% as temperate forest and 11% as subtropical forest (FAO, 2020a). Five countries, Russia (815 million ha), Brazil (497 million ha), Canada (347 million ha), the US (310 million ha) and China (220 million ha), made up for 54% of global forest area in 2020 (FAO, 2020a).

Reporting and measurement of forest related data is a complex topic. Exact numbers differ between data sources, nevertheless, the observed trends are largely persistent. Two of the more prominent publishers of forest related data are Global Forest Watch and the UN FAO (FAO, 2023; Global Forest Watch, 2023a). Data from both sources was used for this thesis. Frequently mentioned concerns regarding data quality and comparability will be discussed as part of the subsequent chapters.

According to data by Global Forest Watch, 11.1 million ha of tree cover in the tropics were lost in 2021 (Weisse & Goldman, 2022). The article by Weisse and Goldman (2022) is directly related to latest GFW data and was published on the GFW website. Especially concerning is the loss of tropical primary rainforest, of which 3.75 million ha were lost in 2021 and 4.12 million ha were lost in 2022 (Global Forest Watch, 2023a; Weisse & Goldman, 2022). Forest loss and deforestation is a major concern in global warming discussions. Limiting deforestation and reducing forest cover loss should be a key priority in addressing these global issues (Pearce, 2018). Tropical primary rainforests are of great importance, especially due to their key role regarding biodiversity and carbon storage. Weisse and Goldman (2022) state that in 2021 the loss of tropical primary forest accounted for 2.5 GT of carbon dioxide emissions, this is comparable to India’s fossil fuel emissions for one year. Primary forest loss rates were mostly consistent over the last two decades with a slight increase in recent years (Global Forest Watch, 2023a; Weisse & Goldman, 2022). Weisse and Goldman (2022) further mention substantial tree cover loss in boreal forests, especially in Russia due to fires in 2021.

Regarding the lost forest area in 2021, the largest area by far was lost in Brazil with more than 1.5 million ha, followed by the Democratic Republic of the Congo with nearly 0.5 million ha

(Weisse & Goldman, 2022). Generally, it is important to distinguish between absolute and relative measures, for example the lost area in ha and the lost area as a percentage of a nations forest cover. Regarding country level specific trends, the percentage of forest cover lost (relative measure) is an interesting measure to compare different countries and the development over time within a country. On a global scale, especially when regarding topics such as climate change or biodiversity loss, the total area (absolute measure) is of interest, especially when whole ecosystems that often span across multiple countries are affected.

Weisse and Goldman (2022) further elaborate on some country specific trends and observations. Although the focus of this thesis is on South American countries, recent developments in other countries are of great interest. New initiatives and policy changes adapted by specific countries could show pathways to ameliorate the situation and motivate other countries to adapt. Indonesia is mentioned as a positive example for improvements in forest management, as the rate of primary forest loss in Indonesia has been declining for five years. The rate fell by 25% when comparing the numbers of 2021 with 2020. Furthermore, Indonesia is on track to reduce emissions across the forest and land-use sector according to an updated national climate plan which aims to transform these sectors to a net carbon sink by 2030. Indonesia gained questionable notoriety through its palm oil industry linked to widespread deforestation. According to Weisse and Goldman (2022), deforestation linked to palm oil in 2021 was at its lowest in 20 years. Projects and initiatives through corporate commitments and government programs started to materialise. In Indonesia and Malaysia, 83% of the palm oil refining capacity is adhering to the No Deforestation, No Peat and No Exploitation (NDPE) commitment, additionally, 80% of Indonesia's pulp and paper industry adhere to this commitment as well. Certification requirements according to the Roundtable on Sustainable Palm Oil (RSPO) where tightened in 2018 and now prohibit deforestation and the clearing of peatland. The Indonesian government increased efforts to tackle forest loss through installing a permanent moratorium on primary forest and peatland conversion and new efforts to protect and restore mangroves and peatland (Weisse & Goldman, 2022). Along with stringent monitoring and enforcement of the new policies, these efforts seem to pay off.

Overall, Brazil is the country with the most primary rainforest and also the country with the highest loss of primary rainforest (FAO, 2020b; Global Forest Watch, 2023a; Weisse & Goldman, 2022). In 2021, more than 40% of tropical primary forest loss was located in Brazil, amounting to 1.5 million ha (Weisse & Goldman, 2022). Primary forest loss rates in Brazil are consistently on a high level. Fluctuations across years are partly due to the spread of out-of-control forest fires. Weisse and Goldman (2022) mention that non-fire losses in Brazil are often linked to agricultural expansion, these losses increased by 9% from 2020 to 2021, marking the highest level of clear-cut deforestation in the Amazon rainforest since 2006. In 2020, there was an area of at least 1.11 billion ha of primary forest remaining according to the FAO (2020a). 'Primary forest' describes forest composed of native species in areas with no visible signs of human activity and where ecological processes are mostly intact (FAO, 2020a). Around 61% of the world's remaining primary forest is located in Brazil, Canada and Russia (FAO, 2020a).

In addition to the main focus on South America and therefore tropical forests, developments in other climate domains with different types of forest are of interest as well. In 2021, boreal forests suffered a substantial increase in forest loss compared to 2020, resulting in a 29% increase in the rate of loss (Weisse & Goldman, 2022). Weisse and Goldman (2022) attest this trend to the effects of climate change, which leads to hotter and drier conditions that result in more fires and additional damage caused by insects. However, it is important to mention, that forest loss in boreal forests rarely leads to permanent deforestation. A large part of this increase originates from the worst fire season Russia has ever experienced since 2001, when record-keeping began. In 2021, more than 6.5 million ha of tree cover was lost to fires in Russia alone (Weisse & Goldman, 2022). These large-scale fires combined with the melting of permafrost for example in Siberia are especially concerning. The melting of permafrost leads to the additional release of carbon dioxide and methane that has been stored in the frozen ground. This leads to a vicious circle, where forest fires and melting permafrost reinforce each other. Forest loss due to fire is not only a pressing issue in Russia but globally. The area that is lost to fire varies significantly between years. In 2015, approximately 98 million ha of forest were disturbed by fire, most of it in tropical forests. In 2015 about four percent of the total tropical forest area was lost to fire (FAO, 2020a). In 2015 for example, severe losses were recorded in Africa and South America. However, as mentioned earlier, in recent years, forest fires were responsible for enormous losses in Europe and Russia as well (FAO, 2020a). Next to fire, forest loss due to diseases, insects or extreme weather events were responsible for damages on a forest area of approximately 40 million ha in 2015 (FAO, 2020a).

2.1.2 Important Factors and Definitions

In order to better understand and compare forest related data, it is crucial to understand the applied definitions behind frequently used terms. Additionally, there are further factors that are of relevance in the context of this thesis.

Forest loss is often mentioned when discussing the topic of deforestation. However, it is important to distinguish between different frequently used terms. 'Net forest loss' or 'forest area net change' for example consider the surface that was lost due to deforestation and add gains in forest cover (afforestation, natural forest expansion, etc.). 'Deforestation' on the other hand, as defined by the FAO for example, describes the permanent conversion of forest area to other land uses (both human-induced or not) (FAO, 2020a). Hence, the FAO for example estimates that between 2015 and 2020, approximately 10 million ha of forest was subject to deforestation, annually (FAO, 2020a; Ritchie & Roser, 2021). For the reader it is often difficult to find exact definitions of the terms used in news publications for example. For the most part of this thesis, deforestation, forest loss, or forest cover loss refer to data that does not account for forest cover gains. Where applicable, the terms net forest loss, or forest area net change are used, these terms capture growing forest extent as well. In the empirical part of this thesis, the exact definitions that were considered while compiling the dataset for the regression analysis will be elaborated.

'Forest growing stock' is a different measure to describe the size, or volume, of forests. According to the FAO (2020a), the global growing stock of trees was 557 billion m^3 in 2020, which compared to 560 billion m^3 in 1990 marks a slight decrease, mainly caused by the net decrease in global forest area. However, growing stock per unit area is increasing in all regions and on a global level, from 132 m^3 per ha in 1990 to 137 m^3 per ha in 2020 (FAO, 2020a). Generally, tropical forests in South and Central America as well as in West and Central Africa show the highest forest growing stock per unit area. The FAO (2020a) translates this into a further measurement and mentions that a total of 606 GT of living biomass is contained in the world's forests, which includes both, biomass above and below ground. On top of that, forests contain a mass of 59 GT of dead wood (FAO, 2020a). Again, since 1990, total biomass has decreased slightly while biomass per unit area has seen a slight increase (FAO, 2020a). Forest growing stock and biomass are useful measures to visualise and monitor the development of forests, especially when looking at forest sustainability, biodiversity and carbon stock.

Apart from the mentioned variables, there are 'soft' factors that are difficult to capture in empirical models. Nevertheless, understanding some of these additional factors will help to better comprehend the indirect effects and interlinkages of changes in forest area. Forest ownership is one of the topics that are often left out of sight when analysing deforestation or forest cover change. The owner of a forest area is in some way responsible and often has personal interest in what is happening to his possession. In 2015, 73% of global forest area was publicly owned, 22% privately owned and the remainder in unknown or other, mainly disputed, ownership (FAO, 2020a). Private ownership of forest area has increased since 1990 (FAO, 2020a). While the share of publicly owned forest area managed by private businesses, organisations and indigenous and tribal communities has increased since 1990, most of the publicly owned forest area globally stays under public administration management with 83% (FAO, 2020a). Forest management approaches also differ vastly between regions. While in Europe, 96% of the forest area is subject to forest management plans, this share is much lower in Africa with 24% and South America with 17% (FAO, 2020a). The absence of forest management plans could be one of many factors that influence permanent forest cover loss / deforestation.

Next to the classification of forest area according to climatic domains, there are additional ways to classify forests. Looking at the total forest area globally in 2020, 93% (3.75 billion ha) is classified as naturally regenerating forest and 7% (290 million ha) as planted forest (3% plantation and 4% other planted forest) (FAO, 2020a). Forest plantations, which account for around 3% of global forest area, are generally subject to intensive forest management. They are composed of regularly spaced trees of often one or two species and are most of the time established with productive purposes in mind (FAO, 2020a). In contrast, other planted forests often are not exhaustively managed and were planted with ecosystem restoration intents or soil and water protection efforts in mind (FAO, 2020a). Depending on the region, the share of plantation forests in planted forests varies strongly (99% of planted forests in South America, 6% of planted forest in Europe) (FAO, 2020a). Plantation forests can consist of native and introduced species. The proportion of these different species drastically varies, for example with native species accounting for more than 95% of plantation forest in North and Central America, whereas the opposite is true for South America (more than 95% introduced species) and Europe (nearly 80% introduced species) (FAO, 2020a). The differences between planted and naturally regenerating forests may have possible implications for biodiversity, resistance to damage caused by fire or insects, etc.

2.1.3 Importance and Implications of Forest Cover Change

When talking about deforestation, tree cover loss, climate change or the loss of biodiversity, the tropics are often focused on. Understanding why the tropics, and especially tropical primary rainforests are of great importance regarding these topics is crucial. According to Weisse and Goldman (2022), Global Forest Watch for example strongly focuses on tropical forest loss. Deforestation in terms of permanent destruction of forest cover by humans happens in the tropics in more than 96% of the cases. In comparison, primary causes of forest loss in temperate and boreal forests are forestry and wildfires. Forest loss due to forestry and wildfires in these areas are mostly temporary disturbances and are mostly compensated by regrowth (Weisse & Goldman, 2022).

As previously mentioned, forests play a crucial role when it comes to carbon stock and moderation of carbon dioxide concentration. Living biomass with 44% and soil organic matter with 45% account for the largest part of forest carbon, the remaining part is contained within dead wood (4%) and litter (6%) (FAO, 2020a). While total carbon stock in forests decreased slightly from 668 GT to 662 GT between 1990 and 2020, carbon density increased from 159 tonnes per ha to 163 tonnes per ha (FAO, 2020a). The role that forests play regarding the storage and moderation of carbon dioxide is one of many reasons why the topic of forest cover change / deforestation deserves increased attention.

Forests play an important role in a plethora of different ways. Forest protection can therefore be driven by different motives. Protected areas, national parks and nature reserves are of great importance to preserve forests and ecosystems that are especially valuable, and to protect biodiversity and vulnerable species. According to FAO (2020a) FRA estimates, 726 million ha of forest was located in protected areas in 2020 worldwide. With 31%, South America is the world region with the highest share of protected forest area. Since 1990, protected forest area has increased by 191 million ha, however, the annual increase rate has decelerated between 2010 and 2020. A total forest area of 424 million ha globally was designated mainly for biodiversity conservation in 2020 (FAO, 2020a). This area increased by 111 million ha since 1990, with the largest part designated from 2000 to 2010 and decreasing additional designation across the last ten years (FAO, 2020a). In addition, the FAO (2020a) estimates, that in 2020, 398 million ha of forest was primarily designated with soil and water protection in mind, this area increased by 119 million ha since 1990 with a noticeable increase in recent years. Lastly, a forest area of approximately 186 million ha globally was allocated for social services in 2020, this includes purposes such as recreation, education, research, tourism, or the conservation of spiritual and cultural sites (FAO, 2020a). The area designated to social services has steadily increased since 2010 (FAO, 2020a).

There are different types of forest cover loss / change that can occur. The application of different definitions and thresholds of what is considered a ‘loss’ or a ‘change’ is cause for major confusion and differences between data sources. Different possible ways in which tree cover loss / change can occur will be briefly introduced. The following explanations are based on information applicable to data by Global Forest Watch for illustrative purposes. Definitions of ‘temporary’ and ‘permanent’ forest cover change for example are different for FAO FRA data.

The exact definitions used to compile the dataset will be elaborated along with further information on the used data. Differences between GFW and FRA definitions will become relevant again when discussing the results of the empirical analysis.

Analysing the direct causes of tree cover loss may help to identify areas of particular interest. When looking solely at tree cover loss, without taking tree cover gains in account, Global Forest Watch and the World Resources Institute identify five main underlying causes; Wildfire, urbanisation, shifting agriculture, forestry and commodity-driven deforestation (Global Forest Watch, 2023a; World Resources Institute, 2023). However, tree cover loss has different implications depending on the type of forest, the region and the underlying cause. The World Resources Institute (2023) notes that, although forestry is for example associated with 135 million ha of (mostly temporary) forest cover loss between 2001 and 2021, most of this loss occurred within managed forests and tree plantations. In these settings, regrowth is likely, either through reforestation / planting of trees or through natural regeneration. On the other hand, commodity-driven deforestation, cause for 117 million ha of tree cover loss between 2001 and 2021, likely results in permanent alteration of the area towards commodity production purposes like mining, agriculture or the production of oil and gas (World Resources Institute, 2023). Approximately 91 million ha of forest were lost to wildfire between 2001 and 2021 (World Resources Institute, 2023). The institute classifies this as a temporary loss through the burning of vegetation without any agricultural or human activity afterwards. Tree cover loss due to forest fires impacts carbon emissions, human health, ecosystems and biodiversity. Assessing trends in forest loss due to fire is difficult, as fire seasons fluctuate strongly depending on weather patterns (Weisse & Goldman, 2022). It is of great importance to differentiate between forest loss caused by fire and other causes, for example logging or agricultural interests, in order to better understand trends and dynamics. Due to shifting agriculture, 88 million ha of mostly temporary tree cover loss occurred between 2001 and 2021 (World Resources Institute, 2023). This involves the agriculture practice of clearing forest area for agricultural purposes for some years and then letting trees regrow in the area, this practice is common across smallholder farming operations. With 3 million ha of permanent tree cover loss to allow for human settlements, urbanisation is a comparably small cause of tree cover loss (World Resources Institute, 2023).

While in boreal and temperate regions, nearly all of the tree cover loss is associated with forestry or wildfires, tropical regions lose tree cover primarily due to agriculture. The World Resources Institute estimates that since 2000 about two-thirds of tree cover loss is of temporary nature, mostly linked to fire and wood harvesting, while one-third of tree cover loss is likely to be permanent due to agriculture and urbanisation (World Resources Institute, 2023). Forest cover loss in tropical forests and forest cover loss in temperate and boreal forests each accounted for roughly 50% of total forest cover loss since 2000 (World Resources Institute, 2023). However, most of the 215 million ha of tree cover loss that occurred in tropical forests since 2000 was permanent. Therefore, close to 97% of global deforestation that was permanent occurred in the tropics. Of further concern is the steady increase in tree cover loss occurring in the tropics since 2000. In stark contrast to the permanent nature of tree cover loss in the tropics, nearly 97% of tree cover loss in temperate and boreal forests was related to temporary drivers with a high chance of the regrowth of tree cover. Estimates show that 99% of wildfire, and 66% of forestry related tree cover loss in temperate and boreal forests since 2000 occurred in Canada, the US or Russia (World Resources Institute, 2023). Further, the institute notes that the condition and ecological value of a regrown forest depends heavily on responsible forestry practices with long enough forestry cycles. Of the 3 million ha of forest cover loss due to urbanisation between 2001 and 2021, two million ha were lost in the United States, Canada is ranking second regarding tree cover loss due to urbanisation with nearly twenty times less area lost (World Resources Institute, 2023).

With new and improved technology that became available to monitor forest status in recent years, additional and especially more exact ways to analyse the status of forest cover and to collect data were established. Based on satellite imagery and additional remote sensing technologies, the understanding of causes of forest cover change has improved (Seymour, 2023). Seymour (2023) mentions that this is of great importance, especially for understanding the trend regarding devastating forest cover loss in the tropics. As mentioned before, the largest part of permanent deforestation in the 21st century occurs in the tropics. The possibility to gather data with these new technologies for the last twenty years allows for a more in-depth analysis of deforestation in the tropics. Most of tropical forest loss is directly linked to increased commercial agriculture activity that comes along with the construction of new roads and infrastructure, etc. Seymour (2023) stresses the overall importance of tropical rainforests. Besides their previously explained crucial role in storing carbon within the vegetation and the soil, they are home to a plethora of different animal and plant species that function within a complex ecosystem. In addition, forests are fundamental in terms of the economic and social wellbeing of a nation / economy. Forests impact broader topics such as rainfall, hydropower, water supply or agriculture. Lastly, forests are of great importance for some indigenous and local communities. Oftentimes, their culture and daily life are heavily dependent on the intactness of the forests they life in (FAO, 2020b; Seymour, 2023).

In relation, and in addition to traditional protection efforts, Seymour (2023) proposes several ways to combat the loss of tropical forest. Much of forest loss is caused by illegal activities, often in protected and especially vulnerable areas. By increasing law enforcement efforts and controls, forest lost due to illegal logging could possibly be reduced. The aforementioned protection efforts for example are only effective when they are stringently enforced and monitored. Timber from illegal logging activities as well as commodities produced on cleared areas often enter regular trading markets and therefore would be subject to international and government regulations (Seymour, 2023). The influence of the political climate in nations on both law enforcement and subsequently the reduction of, for example, illegal logging became apparent in Brazil. After 2004, new public policy measures as well as private actions were introduced, which led to the decrease of deforestation rates for ten years. With changes in Brazil's administration, this trend seemingly came to a halt. However, Seymour (2023) also points out that fighting deforestation is not a trivial task and that appropriate measures vary from place to place. She uses the Congo Basin as an example, where a lot of the deforestation is caused by extremely poor people, who perform small-scale clearing to earn some money. In these settings, increased law enforcement would have to be accompanied by additional welfare efforts in order to protect basic human rights. Reducing the dependence on wood-based fuels through development finance for clean energy sources would be a viable option.

Seymour (2023) mentions that creating protected areas while respecting indigenous communities' rights and interests may help to reduce deforestation in these areas. She mentions that there are successful examples in the Amazon where protected land in indigenous hands suffers of a 50% lower rate of deforestation in comparison to land not in control of indigenous communities. The acceptance of protection measures by locals seems to be a crucial element that determines the success and sustainability of such endeavours. In addition, government and official programs that incentivise forest protection should be funded appropriately in order to provide adequate financial incentives. In general, easy access and understanding of current data and information helps to develop a better awareness regarding the topic. According to a study by Slough et al. (2021), the provision of forest monitoring tools to an indigenous community in Peru along with additional training, caused deforestation to drop by 52% in the first year and 21% in the year after.

Although there are strong connections between many of the economic causes of deforestation and global finance, trade flows and markets, Seymour (2023) stresses the fact that most policies, etc. are local. Besides a lack of financial funds to pursue stronger law enforcement, the political will is often non-existent in particularly concerned countries. In addition, government officials and representatives often lack the knowledge and motivation to attract investments in green technology or carbon finance. Seymour (2023) states that there is a clear relationship between the global demand for commodities and forest loss. Markets fail to internalise the true value of forests and forests are undervalued in economic systems (FAO, 2022; Seymour, 2023). There are many different stakeholders with individual interests which need to be considered when talking about solutions and new approaches concerning this topic. Often, local officials and citizens have little interest to change their practice. Engaging in new or adhering to existing international or global initiatives therefore is often not in their best interest. Simply restricting the import of deforestation linked products may not be the ideal solution, as this might induce adverse reaction by impacted countries and locals. Consumer country initiatives need to include incentives for leaders and other stakeholders.

Illegal deforestation is a huge business, however, capturing the true dimensions of the issue is difficult. In recent years, the topic has gained more and more consumer interest and awareness. A plethora of NGOs, media research projects and other organisations investigate recent trends and try to uncover the extent of the issue (Earthsight, 2023; ICIJ, 2023; NDR, 2023). According to the FAO (2022), forests play a key role in keeping the economy and society running. Around 1% of global employment is in the forestry sector (approximately 33 million people), with the sector contributing US$ 1.52 trillion to the world domestic GSP in 2015 (FAO, 2022). In addition to the importance of forests regarding biodiversity, climate, etc., forests provide essential goods. The FAO (2022) estimates that around one third of the world's population uses wood for cooking and that even more people rely on forest-based products for their own use or for generating income, for example through forest grown fruit, etc.

2.1.4 Forest Cover Change and Biodiversity

Biodiversity describes the variety of life and how different forms of life interact with each other. It includes all species, genes, populations, and ecosystems. Basically, it defines the world as we know it. The exploitation of natural resources is concomitant with land-use change and is cause to a devastating loss of biodiversity and the destruction and deterioration of ecosystems, especially over the past 50 years (Newbold et al., 2016; WWF, 2022). According to the latest calculations and estimates of the WWF (2022), 1% to 2.5% of fish, birds, reptiles, mammals and amphibians have gone extinct, and one million animals and plants are at risk of extinction. At the same time a decrease of population abundance and genetic diversity is occurring and the loss of climatically determined habitats of species further threatens their existence (WWF, 2022). In the case of unhindered continuation of climate change, prospects for biodiversity intactness drastically worsen (WWF, 2022). Next to the frequently discussed persistent and emerging challenges related to climate change, the interlinkages between climate change, environmental deterioration and biodiversity become increasingly evident. According to the WWF (2022), the climate and biodiversity crises are clearly linked. Therefore, efforts need to address all aspects of these areas. Land-use change is identified as the predominant driver of biodiversity loss, this also relates to deforestation / tree cover loss induced land-use changes, which are elucidated as part of this thesis (Newbold et al., 2016; WWF, 2022). The impact of climate change on biodiversity loss likely plays an increasingly important role (WWF, 2022). A report published in 2020 by the Natural History Museum and Vivid Economics assessed that the cost to stabilise biodiversity intactness will increase rapidly if action is not taken immediately (Vivid Economics & Natural History Museum, 2020).

Tropical forests are of particular significance in regard to biodiversity as they are the habitat of an abundance of species. Even though tropical forests cover less than one tenth of global land surface, they provide habitat to more than two thirds of global biodiversity (Giam, 2017). Within regions covered by tropical forest, there are subregions that are of even greater importance. According to Karger at al. (2021), tropical cloud forests for example are an example for extraordinarily species- and endemism-rich ecosystems. Ongoing deforestation and therefore habitat destruction in tropical forests will likely lead to a mass extinction of species (Alroy, 2017; Giam, 2017). Measuring and predicting the extent of possible affected species is complex. Alroy (2017) for example states that estimates may miss species that were never included in the examined sampling pools. Extinction might happen at such a speed that part of it is not recognised within current reporting (Alroy, 2017). Additionally, species may have gone extinct even within seemingly pristine forest areas that were not yet subject to habitat destruction, due to impacts from invasive species, hunting, diseases, rising temperatures or pollution (Alroy, 2017). A different approach is for example utilised in Chile, where the government subsidises afforestation efforts since 1931 (Heilmayr et al., 2020). Initial versions of the Chilean Forest Law aimed to incentivise local timber production and boost afforestation by tax exemptions (Heilmayr et al., 2020). Since 1974, Chile promotes afforestation via two main incentives. Afforested land is permanently protected from expropriation and in addition, 75% of afforestation costs along with further support for plantation management is covered by subsidies (Heilmayr et al., 2020). While this approach may seem desirable at first glance, it comes with inherent risks and problems. Regulation which prohibits the afforestation of originally forested areas to be subsidised, is often not enforced, partially due to lacking financial abilities (Heilmayr et al., 2020). This led to several cases where forest owners and companies circumvented regulations by temporarily converting primary forest to different land uses. Heilmayr et al. (2020) found that in regard to biodiversity, the subsidies are likely to have accelerated biodiversity loss even further. This is mainly due to the fact that plantation forests expand into / or replace more biodiverse forests (Heilmayr et al., 2020). The subsidies are estimated to be responsible for a 3.76% biodiversity loss due to habitat loss in Chile between 1986 and 2011 (Heilmayr et al., 2020). Although the initial intention behind the implementation of subsidy policies in Chile may seem honourable, consequent enforcement of restrictions would be necessary to reduce the risk of negative impacts on biodiversity. The conversion of pristine native forests to plantation forests is especially concerning (Heilmayr et al., 2020).

One of the frequently postulated measures to thwart biodiversity loss to some extent is the preservation and protection of remaining natural vegetation (for example primary forest) to protect these remaining ecosystems (Karger et al., 2021; Newbold et al., 2016; Paiva et al., 2020; WWF, 2022). These efforts are directly linked to the abatement of deforestation in these protected areas in order to protect biodiversity. However, as previously mentioned, protected areas need to be stringently enforced and monitored. Increased efforts not only to enlarge the amount of protected area but especially to enforce the protection are of crucial importance (Karger et al., 2021; Vivid Economics & Natural History Museum, 2020). According to a British report published in 2020, making improvements to more effectively enforce protected areas is the most cost-effective way to slow down biodiversity loss (Vivid Economics & Natural History Museum, 2020). The enforcement and monitoring of these areas are difficult in many cases. New technology and wider availability of monitoring tools, such as remote sensing mapping, for example through projects like GFW, allow for new possibilities to better enforce protection (Paiva et al., 2020). In addition, efforts to restore nature as far as possible are of great necessity (Newbold et al., 2016). Failing to act in a timely manner will lead to greater biodiversity loss and therefore a cascade of subsequently induced issues and newly arising challenges, for example linked to increasing costs of food and material production, etc. (Vivid Economics & Natural History Museum, 2020).

2.2 Economic and Financial Drivers of Forest Cover and Biodiversity Change

There is a wide array of drivers that impact forest cover change. In order to better understand the intention behind the choice of drivers which will be analysed, a short explanation of the role of each driver will allow to gain an overview. The usage of the term ‘driver’ in this thesis differs from other literature that often refers to specific drivers of forest cover and biodiversity change (agricultural expansion, urbanisation, etc.). There is a plethora of underlying drivers that are frequently mentioned in existing literature as being the cause for deforestation. Tsurumi and Managi (2014) for example mention four main factors that are often referred to: Expanding pasture and cropland by converting forest, harvesting of log, an increase in fuel wood demand and urbanisation / infrastructure development. In a more general way, these factors refer to demographic factors, economic interests, politics and trade (Tsurumi & Managi, 2014). In this thesis, 'drivers' relate to general economic and financial terms. As explained before, the intention is to examine how changes in underlying economic and financial variables, or 'drivers', affect forest cover and biodiversity.

2.2.1 Gross Domestic Product

The first and possibly most general driver that will be elaborated is gross domestic product (GDP). GDP and GDP per capita are affected by a large variety of economic, social, political, etc. factors. For context, some of these factors, especially the ones that are of relevance for South America, will be highlighted.

Agriculture is typically mentioned to be the primary driver of forest cover change and deforestation (Miyamoto, 2020). However, it is important to take wider societal and economic variables into account. Miyamoto (2020) for example identifies poverty as the chief underlying cause while agricultural rent acts as the chief proximate cause. Miyamoto (2020) proposes a logical explanation for deforestation consisting of three conditions, poverty, agricultural rent, and the scarcity of forest in the area. In the case, where high poverty and agricultural rent are present and the forest cover is high, deforestation will happen. If however, at least one of the three conditions is not prevalent, deforestation is less likely to occur. From a logical standpoint, Miyamoto (2020) coherently proposes that with the validity of a logical equation, the contrapositive would also be true. Therefore, with the removal of at least one of the three factors, deforestation will be slowed. While policies on forest use restrictions and lowering agricultural rent are common, they may negatively impact the economic wellbeing of the country and locals, therefore creating backlash and opposition (Miyamoto, 2020). Approaching from a different angle and reducing poverty in order to slow deforestation allows for new initiatives that maintain high agricultural rents. Miyamoto (2020) mentions that this proposition is based on empirical evidence from Malaysia, further research is needed to prove the validity in Africa and South America. In conclusion, reducing poverty through different means may sustainably slow deforestation while mitigating some of the problems that come with other policy approaches.

In many countries, especially developing countries, the extraction of natural resources / natural capital through mining, and extracting oil and gas are important contributors to the economy. Extractive industries not only have a substantial impact on the economy, but they also play an important social and political role. According to Kinda and Thiombiano (2021), extractive industries significantly impact the life of approximately 3.5 billion people in 81 countries. Besides the benefits, extractive industries are often causing greenhouse gas emissions and other pollution while impacting biodiversity.

The natural capital of a country is the combination of its natural resources, land, and ecosystems (World Bank, 2021). It provides the basis for everything else that is needed for human existence in the area. Natural capital can be non-renewable (fossil fuels and minerals) or renewable (agricultural land, forests, protected areas, fisheries, and mangroves) (World Bank, 2021). Extractive industries not only deplete the non-renewable natural capital stock of a country but also destroy or degrade other natural capital (forests, biodiversity, etc.). Mineral and gas extraction for example were found to significantly impact forest cover loss (Kinda & Thiombiano, 2021). Depending on the taxation of achieved rents and how the government allocates these rents, the effect can be mitigated or worsened. If the government uses additional funds to create protected areas and fund other projects to slow forest cover loss, this may make up for some or most of the damage. If, however, these economic rents are used to fund additional agriculture or infrastructure, this even worsens the trend. Kinda and Thiombiano (2021) therefore stress the need for appropriate tax regimes and public spending to mitigate adverse environmental impact.

In general, it seems likely that the state of the economy in a specific country or region is linked to the likeliness and extent of forest cover change. Ewers (2006) analysed global deforestation patterns and augmented previous analysis. A lot of previous literature adhered to the assumption that deforestation rates and per-capita income are related, and that the relationship follows the form of the Environmental Kuznets Curve (inverted U shape) (Dietz & Adger, 2003; Ewers, 2006; Pradhan et al., 2022; Tsurumi & Managi, 2014). The theory behind the Environmental Kuznets Curve states that nations in an early economic development stage rely heavily on environmental capital to accelerate economic growth. Following this theory, growing income consequently expedites environmental degradation. After a certain level of economic development is reached, natural capital becomes less relevant to the economy. At the same time, the wealth of individuals increases and the urge for environmental conservation and improvement grows. Subsequently, rates of environmental degradation diminish with further increases in income. Ewers (2006) argues that evidence for the applicability of this theory in the context of deforestation is ambiguous. At the time of publication, Ewers (2006) found both research that empirically supported the theory and literature that refuted its applicability. A newer study by Tsurumi and Managi (2014) reviewed the evidence for the applicability for the EKC theory with regards to deforestation again and found that, at the time of the publication of their study, there was no evidence to argue for a robust EKC relationship with regards to deforestation. There are current studies mentioning that the research on the applicability of the EKC theory is still inconclusive, most of them refute the applicability of the EKC with regards to deforestation and biodiversity loss (Dietz & Adger, 2003; Pradhan et al., 2022; Tsurumi & Managi, 2014).

Ewers (2006) suggests, following the work of Rudel et al. (2005), to focus on 'forest transition' rather than the shape of the relationship of deforestation and wealth. The concept of forest transition focuses on the turning point at which forest cover recovery begins and forest cover loss is ceased (Ewers, 2006; Rudel et al., 2005). Ewers (2006) shows that there are indications for a relationship between forest cover change and the level of economic development. Nations with advanced economic development are more likely to bolster afforestation, for example through investing in plantations. Poor nations rely on deforestation to boost economic growth while not having the resources to invest in environmental protection and reforestation efforts. Ewers (2006) concludes that economic compensation through more developed nations for abstaining from deforestation in poorer nations may help to ameliorate the situation.

Growing populations are sometimes considered as a factor that drives both GDP and deforestation. There are different studies analysing the relationship between demographic factors and deforestation which draw contradictive conclusions. According to Tsurumi and Managi (2014), there is no robust evidence supporting the relationship between deforestation and demographic factors with studies both supporting and denouncing the hypothesis, at the time of publication of their study.

The impact of political institution on deforestation is ambiguous and studies concerning the topic need to be compared with caution (Tsurumi & Managi, 2014).

2.2.2 International Trade

Both, the forestry industry itself and agriculture as one of the main drivers are heavily linked to international trade. Pendrill et al. (2019) for example analysed the relationship between international trade and emissions due to deforestation. According to their models, international trade was the driver of between 29 and 39 percent of deforestation-related emissions (Pendrill et al., 2019). In the context of their research, they state that around 15% of the total carbon emissions linked to food consumption in EU countries is deforestation related (Pendrill et al., 2019).

A study by Tsurumi and Managi (2014) looked at the impact of trade openness with regard to deforestation. The study used annual deforestation rate data covering 142 countries in the timeframe from 1990 to 2003. As other studies in the field, the reasoning mainly is based on the effects of deforestation on greenhouse gas emissions. Unlike previous studies that did not manage to clarify the effects of trade openness and deforestation, Tsurumi and Managi (2014) reach new insights through consideration of newer data and model adjustments. Within the empirical analysis, they additionally considered three effects, the scale, technique and the composition effect. While the scale effect assesses the impact of increased production (measured by GDP for example), the technique effect relates to the influence of income on deforestation (Tsurumi & Managi, 2014). As mentioned before concerning the EKC theory, the idea behind this is that the emphasis on environmental regulations is growing with an increase in income and demand for environmental consciousness. The impact of the composition of the economic output, for example a country's industry structure, which is related to both trade openness and a country's comparative advantage, is captured within the composition effect (Tsurumi & Managi, 2014). Deforestation might be affected through the impact of trade openness as it potentially increases production and income, relating both to the scale and technique effect (Tsurumi & Managi, 2014). An increase in trade openness relates to a negative composition effect. Country specific comparative advantages further affect this effect. Comparative advantages are affected for example by the stringency of environmental regulations, trade openness and factor endowment. The availability of capital and labour further determines the effect. The forestry sector is relatively labour intensive, therefore, countries with low capital-labour ratios are likely to have a comparative advantage (Tsurumi & Managi, 2014). Tsurumi and Managi (2014) base their analysis on the UN FAO FRA 2010, whereas this thesis is based on a more recent FRA dataset.

While discussing the impact of an increase in trade intensity on deforestation, the authors noticed a stark contrast between OECD and non-OECD countries (Tsurumi & Managi, 2014). While an increase in trade openness decelerates deforestation in developed countries, the same is not the case for developing countries (Tsurumi & Managi, 2014). This could be traced back to the controlling role of the composition effect, which indicates that in developed countries, capital-labour as well as environmental-regulation effects are negatively related to deforestation, with the exact opposite being the case in developing countries. In order to address future increases in trade openness in developing countries, incentives to protect forests in developing countries are of great importance.

2.2.3 Foreign Direct Investment

Foreign direct investment (FDI) may be one of the factors that bolster economic growth (Lokonon & Mounirou, 2019; Pradhan et al., 2022). However, as mentioned before, economic growth and therefore FDI might also be related to changes in environmental quality and deforestation (Lokonon & Mounirou, 2019; Muhammad et al., 2021). Lokonon and Mounirou (2019) for example analysed the effects of FDI on deforestation in 35 countries in the Sub-Saharan Africa region. Their calculations showed mixed outcomes depending on the country, therefore no general conclusion was drawn. However, it is mentioned that FDI inflows are of importance for countries in the region and that efforts to attract additional FDI investments should be accompanied by measures to control deforestation (Lokonon & Mounirou, 2019; Pradhan et al., 2022). In a more general approach, Muhammad et al. (2021) found that FDI accelerates environmental degradation in developing and BRICS countries, while the opposite is the case for developed countries. While Pradhan et al. (2022) acknowledge the necessity of FDI inflows for economic development and the benefits that come along with FDI investments, they also put emphasis on the negative effects and risks that arise from increased economic activity. More economic activity usually increases energy and fuel consumption along with the expansion of industries necessitating additional infrastructure and causing emissions and pollution (Pradhan et al., 2022). To mitigate these negative effects, reduce emissions and pollution, it is suggested that FDI investments are made in line with the promotion of environmentally friendly technology and processes both for sourcing energy and resources, and for the processes themselves (Pradhan et al., 2022).

2.2.4 Grants, Other Finance Sources and Initiatives

There is an array of additional sources that are important in financing initiatives for nature and biodiversity conservation, reforestation and other environmental programs. Grants and financing provided by governments, NGOs, foundations and companies for example are likely to play an increasingly important role in financing these efforts. Research specifically addressing grants and other finance sources in the context of forest cover change and biodiversity is scarce, although it seems that interest has increased in recent years. Data on grants and other finance sources for forest cover and biodiversity programs is not available to the extent needed for the empirical part of this thesis. The datasets that could be found often were incomplete, did not cover the desired countries or otherwise were of questionable reliability. Therefore, instead of including a variable for the driver of ‘grants and other finance sources’, a short theoretical overview will be provided. In addition to some remarks on the scale and importance of grants and other finance sources, a brief introduction to the topic of multi stakeholder initiatives in the field of the forestry industry might help to better understand the intentions and origin of related programs.

Among the plethora of different organisations that provide grants and other financial backing for different environmental causes, there are many foundations and companies that concentrate their efforts on small regions or very specific fields of interest. In the fields of forestry and biodiversity related efforts, there are different NGOs, foundations and companies that engage in conservation efforts by providing grants, expertise and other resources (Global Forest Watch, 2023b; IKEA, 2023a; Sustainable Forestry Initiative, 2023; Velux Foundation, 2023; WWF, 2023).

GFW for example has its own program called ‘Small Grants Fund’ that they use to award grants from US$ 10’000 to US$ 40’000 and support initiatives with technical support and their know-how, especially in utilising the GFW tools to monitor forest cover change (Global Forest Watch, 2023b). The World Wide Fund For Nature (WWF) maintains a program called after the founder of the WWF, which provides grants to individuals and organisations since 1994. So far, more than 3’600 grants were awarded (WWF, 2023). According to the WWF (2023), thanks to these efforts, more than two million trees were planted on an area of damaged tropical forest and wetlands larger than 1’000 ha. In addition, 17’000 community members were trained as part of their reforestation and restoration practices (WWF, 2023).

Next to GFW, which mainly engages in forest cover related monitoring and reporting, there are organisations, often multi stakeholder initiatives (MSIs), that are known for their product labels such as the Sustainable Forestry Initiative (SFI) (2023). Most of these MSIs try to alleviate the negative impacts of the forestry industry by certifying companies along the supply chain for sustainable forestry practices. MSIs are often funded by donations and fees generated from certified products. Although MSIs play an increasingly important and popular role in different industries, their efficacy and legitimacy is heavily debated (Arenas et al., 2020; Bowler et al., 2017; Moog et al., 2015; Okereke & Stacewicz, 2018). Due to the way some of these MSIs are set up, there are severe conflicts of interest between different stages of the certification process. Often, external service providers are responsible for the certification. An often-reported conflict of interest is that these providers are paid for by the companies they certify, so they have little incentive to not give out certifications (Moog et al., 2015). While many of the early MSIs in the sector initially strived for stringent standards, they often had to attenuate their standards in order not to lose the race for market dominance (Arenas et al., 2020; Moog et al., 2015). In the last two decades, new certification schemes, many of them launched by industry associations, competed for a share of the certification market. The main competitor in Europe is the Pan-European Forest Certification (PEFC) program, in the US, the SFI label grew rapidly. Many of these newer MSIs are criticised for not aiming for high standards but rather rely on status-quo industry practices (Moog et al., 2015). Since the founding of the Forest Stewardship Council (FSC), around fifty certification schemes targeting the forestry sector emerged, and they are competing for market share (Moog et al., 2015). This large number of existing certification schemes and labels along with (to the customer) often unclear and untransparent standards makes it difficult for customers to navigate the certification landscape in their effort to make environmentally conscious product choices.

There seems to be a growing number of companies that invest in environmental programs. Arguably, many of these efforts may be motivated by marketing and publicity interests, rather than the sole purpose of doing good. Companies and organisations rely on different means to engage in such activities. Many, especially large companies founded their own foundations or teams for these causes (IKEA Foundation, 2023; Nestlé, 2023; Velux Foundation, 2023). IKEA (2023a, 2023b) heavily invests in partnerships, for example with the FSC. Nestlé created a 'Forest Positive External Advisory Council' to help them achieve the goal of deforestation-free supply chains and forest and landscape conservation and restoration (Nestlé, 2023). One of the largest window fabrication companies, VELUX, maintains a forestry program through their own VELUX Foundation to invest in the implementation of sustainable forest management practices to promote biodiversity, carbon emission reduction and still ensure the supply of forestry products (Velux Foundation, 2023). As these often globally active and industry leading corporations are well known, they are suitable targets for "name and shame" campaigns initiated by organisations. IKEA, for example, had to face a surprisingly large number of scandals over recent years despite the measures and marketing campaigns to promote the sustainability of IKEA's business model (Cain, 2022; Earthsight, 2020, 2021).

Company foundations along with funds provided by private foundations and individuals in a philanthropic manner are an additional source of financing for conservation and restoration / reforestation efforts. Most philanthropic campaigns target biodiversity as a topic, which in terms also affects forest conservation and reforestation efforts. Philanthropic capital plays an important and fast changing role in biodiversity conservation according to a recent paper by Beer (2023). With their growing contribution towards closing the 'biodiversity financing gap', which is estimated to annually amount to between 300 to 824 billion US$, they aim to provide the missing funding for the difference between what national governments and additional sources provide for financing the complete cost for meeting global biodiversity conservation goals (Beer, 2023). According to Beer (2023), a five billion US$ pledge through a project called ‘Protecting Our Planet Challenge’ made by nine philanthropic foundations is the largest project to date. Along with Jeff Bezos and others, the Swiss entrepreneur Hansjörg Wyss followed up an earlier pledge of one billion US$ to the program with an additional 500 million US$ through his Wyss Foundation (Beer, 2023). It is mentioned that although philanthropic pledges are not sufficient for closing the gap, they play an important role in attracting further private capital for the cause (Beer, 2023). Despite the potential benefits of philanthropic pledges, Beer (2023) raises concerns on the growing influence of donors on state governance.

3 Methodology and Data

3.1 Overview and Selection of the Data

The empirical part of this thesis is based on a dataset that aggregates data from a variety of sources in order to efficiently run regression analysis and make comparisons. In a first step, forest and biodiversity data for South American countries was aggregated and extended with data on the covered economic and financial drivers. When analysing data on forests, forest cover change and biodiversity, it is crucial to understand what precisely falls under the applied definitions and how the data is measured and reported. Generally, data is collected either via remote sensing / satellite-based technology, or via the collection and aggregation of empirical data from country statistics, literature and estimates (FAO, 2020b; Harris et al., 2016). The data used for the creation of the dependent variables will be described first, this includes forest data from the UN FAO FRA and GFW, as well as the Biodiversity Intactness Index. The data on which the drivers are based will be described afterwards. Within this subchapter, a short rationale is given to allow for better understanding of the origin and selection of the data. Further, the different variables are briefly explained.

3.1.1 Dependent and Independent Variables

As mentioned earlier, there are a few different organisations and projects that collect, analyse and report forest related data. In context of the data analysis conducted as a part of this thesis, several data sources were evaluated. During this process, it became apparent, that the scope, availability, quality and applicability of the available data varies significantly across datasets, countries, indicators and time (further discussed in Chapter 3.2). Due to different reasons explained throughout the thesis, data from the FAO FRA 2020, GFW and the BII was used (FAO, 2020b; Global Forest Watch, 2023a; Natural History Museum, 2022).

One of the main variables of interest in the regression model is forest cover change. In order to obtain comparable data, the underlying variable desirably had to be a relative measure rather than an absolute one. It would make little sense to simply compare forest cover change in hectares between different countries, as substantial differences in the size and forest extent of different countries would not allow for a comparison. For example, it is evident that forest cover loss or forest cover change in absolute numbers in Brazil (country area of ≈ 850 million ha and forest extent of ≈ 500 million ha in 2010) would be much larger than in Uruguay (country area of ≈ 18 million ha and forest extent of ≈ 2.1 million ha in 2010) (Global Forest Watch, 2023a). Therefore, forest cover change should be brought into context with the forest extent of the individual country. As a result, a percentage change in forest cover in relation to the countries' forest extent is calculated. However, to calculate these relative values, there is a need for reliable data on forest extent in each given year. The approach that was chosen to obtain the final values that are used as the dependent variables in the regression analysis differs slightly between the GFW and the FRA based calculations.

GFW Forest Data

The datasets available from GFW contain country-specific data on tree cover loss per year for the years between 2001 and 2020 at different thresholds in hectares. The different thresholds relate to the different percentages of canopy cover. GFW generally refers to tree cover instead of forest, tree cover is defined by said thresholds. As the 30% threshold is used by default by GFW for all their statistics, this threshold was chosen for this thesis (Global Forest Watch, 2023a). In addition, a variable for forest cover extent in the year 2000, forest cover extent in 2010 and forest cover gain from 2000-2012 is included in the dataset. According to GFW (2023a), the underlying methodology in gathering and processing the data has changed between the two time periods 2000-2010 and 2010-2020, which limits the comparability of the corresponding data. While processing the data, different approaches were tried to obtain relative percentages. For the final analysis, the data was augmented by an estimation of yearly tree cover gain in addition to the provided values for tree cover loss. This estimation was based on the provided value for tree cover gain between 2000 and 2012. Then, starting from the provided forest cover extent in 2000, a new, yearly forest cover extent was calculated by deducting the loss and adding the estimated gain in order to then set the loss in relation to the corresponding yearly extent. While comparing the value obtained via this approach with the provided value for forest cover extent in 2010, it became apparent that changes in methodology made by GFW and the quality of the estimated gain indicator in specific cases significantly changed the basis of the underlying extent. This led to inaccurate estimates in some cases. GFW specifically advises against own calculations for net cover change as data quality and availability are sometimes poor (Harris et al., 2016). GFW indicates that the provision of yearly net change data is something they are working on (Weisse et al., 2022). However, as this data is not available yet, the chosen approach was the best possible solution at hand.

GFW provides a number of different datasets, mostly comparing the status of 2000 with the status of 2020. As these datasets do not contain yearly values, they were not suitable for an in-depth analysis. In addition, the absolute numbers of forest cover extent and even country surface vary between datasets. As GFW bases the calculations on different raw data sources and models, varying between the displayed maps and graphs, this makes sense. GFW is continuously improving the provided datasets as part of the efforts made to make the data and reporting more reliable and comparable.

FRA Forest Data

Considering the described issues with the GFW datasets, a comparison to the data provided by the Food and Agriculture Organization (FAO) of the United Nations made sense. The UN FAO regularly publishes the Global Forest Resources Assessment (FRA), the latest, detailed version was published in 2020. Unlike the GFW dataset, the FRA assesses the state of the world's forests in fixed intervals. The accessible dataset covers the periods 1990 to 2000, 2000 to 2010, 2010 to 2015 and then, depending on the variables, either consolidated values for 2015 to 2020 or individual values for the years from 2015 to 2020. The measurement methods used for the FRA are consistently updated. As with the GFW data, there may be some inaccuracies when comparing between different reporting periods. However, the FRA dataset contains all desired variables and values for the given period for all of the countries covered within this thesis. Adding certain variables from other datasets is therefore not necessary, which likely improves the quality of the comparison. There is an ongoing debate on the accuracy and consistency within FRA data (as well as other data sources). Furthermore, the values obtained from the two different FRA and GFW datasets are in many cases vastly different. These issues will be discussed in more detail in Chapter 3.2.

The FAO (2022), which conducts the FRA, defines forest as a combination of physical / biophysical criteria and information on the predominant use of the land. Forests therefore are defined by a threshold of 10% canopy cover, a minimum size of 0.5 ha and a minimum vegetation height of 5 m (FAO, 2020a). Areas that are tree-covered but used for agricultural purposes or located in an urban area are excluded. Oil-palm plantations, orchards and urban parks are therefore not regarded as forest area. Other types of planted forests, rubber plantations for example, are, however, included under FRA definitions. The FRA dataset provides values for the variables that are shortly defined below (Table 1).

Table 1

Definitions of Variables in the FRA Dataset

Forest expansion (1000 ha/year)	This variable captures the area that is transformed from non-forest to forest land use. Hence, forest expansion implies the expansion of forest covered area on land that previously was assigned to different land use.

…of which afforestation (1000 ha/year)	As a sub-category of forest expansion, this variable records the part of forest expansion that was achieved through planting and seeding on previously non-forest use land.
…of which natural expansion (1000 ha/year)	Also a sub-category of forest expansion, this variable captures the expansion through natural succession on previously non-forest land. As an example, the UN mentions forest succession on land that was previously used for agricultural interests.
Deforestation (1000 ha/year)	Deforestation describes the conversion of forest land to other land uses (non-forest), independent on whether the conversion was prompted by human action or not.
Forest area net change (1000 ha/year)	Describes the forest area difference from one FRA reference year to another. This variable can describe a gain in forest area if it is positive, a loss in forest area if it is negative, or no change in forest area if it is zero.
Reforestation	Depicts forest re-establishment by the means of planting or seeding on forest use land. It is important to note, that this does not imply a change in land use (therefore does not influence the variables above). The variable includes planting and seeding of both forest covered areas and momentarily unstocked forest land. It also includes coppice of originally planted and seeded trees.
Forest (1000 ha)	In order to obtain comparable, relative forest cover change values, Forest (1000 ha) is used as a base to calculate forest cover net change as a percentage of total forest cover in a given country. The percentage is not provided by the UN FRA. However, due to the availability of all datapoints from the same source, it can presumably be correctly calculated for all covered countries. UN FRA defines forests as follows: “Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.” (FAO, 2020c, sec. 1a). Within the FRA definitions, some explanatory notes are provided concerning the forest variable (FAO, 2020c). Both, the presence of trees as well as the absence of differing predominant land uses define forest. In addition, the UN

	states, that the possibility for trees to reach a height of at least five meters 'in situ' needs to be given. Areas covered by young trees below the threshold of 5 m and 10% canopy cover but that are expected to reach the threshold are included. Momentarily unstocked areas that were clear cut for forest management reasons or that are unstocked due to natural disasters that are anticipated to be restored within five years are included as well. The forest variable further includes some areas within a forest without tree cover (e.g. forest roads, infrastructure, etc.), which will not be further discussed here. The variable specifically excludes tree stands that are part of agricultural production systems (fruit tree or oil-palm plantations, olive orchards and agroforestry techniques where crops are grown beneath trees). FRA definitions exclude certain agroforestry systems from this exemption, for example the "Taungya" system, where only during the first years of forest rotation crops are grown beneath tree cover.

Note. These descriptions are based on the FAO FRA 2020 definitions (FAO, 2020c).

Biodiversity Data

As a baseline measure for biodiversity in the regression models, the 'Biodiversity Intactness Index' (BII) was used. According to the Natural History Museum (2023a, 2023b), the BII conflates alterations in ecological communities, respectively local terrestrial biodiversity in relation to human pressures. The BII represents an estimate of the percentage of the remaining original number of species and their prevalence in different areas despite human influence (Natural History Museum, 2023a). By averaging the BII across specified areas, for example at a global, country, or regional level, the remaining biodiversity in said area is represented. The underlying data for BII calculations is collected via the PREDICTS (Projecting Responses of Ecological Diversity in Changing Terrestrial Systems) project based on ecological studies conducted globally. In contrast to other indicators, which mostly reflect data on birds and mammals, the BII additionally considers plants, fungi and insects and is based on data comprising more than 58'000 species (Natural History Museum, 2023a, 2023a). By establishing a baseline representing the number and diversity of species present at undisturbed or near-undisturbed sites and comparing biodiversity at high human activity sites to this baseline, these studies provide the foundation of the indicator (Natural History Museum, 2023a). Differences across areas, species groups and sampling methods cause variation, which is considered in the statistical analysis leading to the BII. Two models are the basis from which the BII is derived. One model considers the influence of human activity on the total abundance of species in any area. The other one assesses a site's ecological community similarity in relation to near-undisturbed sites. Information on the presence of original species and dominant species is contained within the second model, which describes compositional similarity. In a further step, the models get merged with maps showing human pressures, for example, land use changes and intensification, population growth and landscape changes. As a result, new maps that show the effect of human pressures on abundance and compositional similarity are obtained. Ultimately, the BII is derived from a combination of these two maps. As mentioned previously, the BII represents the share of original ecological community remaining across a specified area as a percentage. According to the Natural History Museum (2023a), based on the assumption that the relationship existing between human activity and biodiversity is stable, biodiversity projections can be made into the future and in retrospect by stacking multiple years human driver data.

Economic and Financial Drivers

To capture foreign direct investment, the World Bank indicator for 'Foreign direct investment, net inflows (% of GDP)' was chosen. This indicator has been used in literature which conducted data analysis with a similar scope (Lokonon & Mounirou, 2019; Muhammad et al., 2021; Pradhan et al., 2022). The definition of the indicator by the World Bank is as follows (World Bank, 2023a, sec. Details):

> "Foreign direct investment are the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. It is the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors, and is divided by GDP."

Gross domestic product (GDP) generally is a measure of the economic output of an economy. GDP is commonly used to measure and compare the economic activity of countries which to some extent allows to describe and compare economic development levels. According to van den Bergh (2009), the real GDP per capita, adjusted for inflation (current US$) is widely utilised as the main indicator for positioning the economy of a country in relation to other countries and / or over time. Although GDP is not intended to be used as a measure of social welfare or standard of living, it is regularly employed for this cause (Aitken, 2019; van den Bergh, 2009). The appropriate use, the benefits, and the shortcomings of GDP as an indicator are cause for an ongoing theoretical debate (Aitken, 2019; van den Bergh, 2009). While there are issues regarding the capturing of welfare related topics, GDP per capita still allows to compare economies in terms of their output on a general level. Due to the fact, that the indicator is widely used, data on GDP per capita is easily accessible and available for the desired time periods and countries. The accuracy of the data in certain countries leaves room for discussion. As GDP per capita is only one of the underlying drivers included in the model, it might be useful as a general guideline.

GDP per capita (current US$) data was obtained from the World Bank database (World Bank, 2023b). The World Bank (2023b, sec. Details) defines GDP per capita (current US$) as follows:

> "GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars."

As an indicator for a broad measurement of trade activity, trade as a percentage of GDP was employed. The data was obtained from the World Bank database (World Bank, 2023c). According to the World Bank definition, the indicator is based on the sum of exports and imports regarding both, goods, and services in relation to GDP (World Bank, 2023c).

3.1.2 Selection of Countries Included in the Analysis

A thorough review of existing literature provided some insight into the models and methods that are most commonly used. Some of the approaches are similar to the one that was chosen for this thesis. However, in the context of this thesis, the choice of data and the corresponding model was guided by the availability of said data as well as the selection of an approach with adequate complexity. In order not to exceed the format of a master thesis, a choice of countries and variables as explained in this section had to be made. Based on superior availability of existing literature and the commonly larger media, social and political interest and coverage, emphasis was put on regions with tropical forest. Considering this, a clear focus on South America was deemed the most expedient approach. After analysing relevant literature, it became apparent that there is a plethora of additional effects, which exceed the variables of interest included in the model. Country- and continent-based trends and circumstances are likely to have a substantial effect on the influence of different drivers. These effects would subsequently need to be accounted for on a country and continent level, which would result in an increasingly complex model and dataset that would exceed the scope of this thesis. Although it is most probable that there are significant country level effects within South America, the continent-centred approach seemed to be the best possible solution. An interesting approach for future research could be to conduct analysis for different groupings of countries and regions and compare the observed trends.

3.2 Data Quality and Discrepancies Between Datasets

Some of the main challenges include standard statistical issues such as for example the absence of adequate control groups, circular analysis, heteroscedasticity or omitted variables bias. In addition, the aforementioned concerns regarding data quality and comparability are cause for some uncertainty. During the process of reviewing the different data sources and assembling the main dataset, some of these issues were addressed and attempted to control for.

Measurement methods, especially in the field of remote sensing, continuously evolve and become more precise. The comparison of current data with older data is therefore not always possible or reasonable.

The two main underlying areas of interest, forest cover, respectively forest cover change, loss, or gain, and biodiversity are represented by different variables. This allows for additional comparison of the results to gain some information on whether the relationships and effects resulting from the linear models are somewhat plausible.

Although data availability, accessibility and accuracy are steadily improving, there are major differences and discrepancies between data sources and reports. With the choice of the Forest Resource Assessment and Global Forest Watch as data sources, the likely most prominent projects were incorporated (FAO, 2020b; Global Forest Watch, 2023a). The reliability and accuracy of these two data sources are part of an ongoing debate (Busch, 2015; Harris et al., 2016; Holmgren, 2015a, 2015b; Pearce, 2018). Harris et al. (2016) and Holmgren (2015a) mention reporting discrepancies, for example, that in the same year, the headline for the 2015 FRA implied that global deforestation slowed down, while GFW stated that global annual tree cover loss remained at a high level. The underlying differences in comparing the two data sources are diverse and not intuitively apparent at a first glance. It is crucial to understand that both sources play a valuable role in assessing the development and intactness of global forests.

However, as Harris et al. (2016) state, the two projects vary considerably regarding their scope, purpose and approach. The differences begin with diverging definitions of what is considered as forest (as explained in Chapter 3.1). While the FRA adopts a definition based on a combination of biophysical and land use criteria, GFW relies solely on biophysical criteria to measure tree cover (Harris et al., 2016). A further key difference, which was cause to extensive literature research and data revision in the context of this thesis, is the largely different approach to the aggregation of monitoring data for global forest change statistics. While, as previously stated, FRA provides data on forest area net change, considering both forest area gain and loss, GFW publishes data for gross tree cover loss and gross tree cover gain (Harris et al., 2016). Loss data in the GFW dataset is updated frequently, gain data, however, is only updated for larger timespans as forest growth is a gradual process and not clearly measurable in short timespans (Harris et al., 2016). Data collection and origin differs as well. GFW data is based on remote sensing, satellite-based methods. Thanks to this approach, the GFW data is independent, transparent and allows for consistent comparison across the globe. On the other hand, FRA data is a compilation of government statistics and therefore relies on self-reported sources by different countries (Busch, 2015; Harris et al., 2016). This approach leads to some consistency concerns as it includes different sources that use varying methods, which, despite guidelines provided by the FAO likely leads to countries applying their own adaption of definitions (Busch, 2015; Harris et al., 2016).

Additionally, past data points are often corrected / changed from the FRA in one measurement period to the next (Busch, 2015). In some extreme cases, this leads to inconsistent results, where consecutive FRAs contradict previous findings. Busch (2015) found data inconsistencies, where, for example, in the 2015 FRA retroactive claims were made suggesting that between the 2010 and 2015 estimate more than 50% of the allegedly lost forest area was non-existent in the first place. In light of these issues, Busch (2015) questions the validity of statements made within these reports, especially concerning the analysis of ‘changes in changes’ from one reporting period to another. Further uncertainty is induced as country statistics used within the FRA are updated in different frequencies (Busch, 2015; Harris et al., 2016). Especially in developing countries, less frequent updates are common, which in some cases may lead to a discrepancy between reporting quality for temperate, boreal and tropical forests. For the FRA, the FAO completes gaps in the data with estimates and literature-based approaches (Busch, 2015; Harris et al., 2016). At the same time, the satellite data-based approach employed by GFW allows for consistent and regular data gathering across years and regions. Harris et al. (2016) point out a further difference, which is, although not of great relevance for this thesis, the fact that FRA data is available at a country / national scale, while GFW provides data on a pixel scale. By aggregating these pixels, country / national borders can be depicted, but in addition, larger or smaller areas can be defined, even allowing users to define own areas of interest for monitoring, for example national parks or indigenous territory (Harris et al., 2016).

The state of the world's forests and the topic of deforestation is at the heart of different controversial debates. While some critics argue that the FRAs way to report based on net forest change results in an overly optimistic analysis of the trends, others claim the opposite for GFW data. There is an argument to be made for both sides. Net forest change from FRA statistics allow for the "compensation" of, for example, a loss of ancient natural forests with a high value for biodiversity with tree plantation monoculture expansion (Harris et al., 2016). On the other hand, GFW data does not differentiate between temporary and permanent tree cover loss in natural forests or tree plantations, and until now largely ignores tree cover gain (Harris et al., 2016). In the end, both approaches and data sources have their benefits and limitations depending on the application. Limitations concerning the accuracy of data have different causes. Therefore, a combination and comparison of trends and data from both sources is likely the best way to get the best possible overview, hence the choice to include both within this thesis.

Enhanced global efforts to limit deforestation and initiate reforestation campaigns are inevitably necessary (Pearce, 2018). Fortunately, as Pearce (2018) mentions, nature will eventually regenerate to some extent on its own if given the chance. Transparency regarding the reporting and measurement issues at hand is crucial. Holmgren (2015b) emphasises that institutions and individuals reporting on forests should openly point out discrepancies and ambiguities in their results and data. A combination of different reporting approaches and standards along with an increase in funding is necessary to further enhance the accuracy of forest-related reporting (Holmgren, 2015b). Especially when it comes to monitoring the progress and advances in connection to political commitments and programs, reliable and transparent reporting standards are a key instrument in achieving sustainable improvements. This becomes clear when the issue is considered with for example the SDGs in mind.

3.3 Statistical Analysis

Linear models for panel data were performed using the plm R package, version 2.6-3 (Croissant & Millo, 2008) to test the effect of chosen drivers ('FDI, 'GDP', 'Trade') on 'Forest area net change FRA' (NFRA), 'Deforestation FRA' (DFRA), 'Deforestation GFW' (DGFW) and 'Biodiversity Intactness Index' (BII). A second model for biodiversity included NFRA, DFRA and DGFW as independent variables in addition to the economic and financial drivers to check for an effect of these forest cover and deforestation related variables on biodiversity intactness.

The variables 'Country' and 'Year' were specified as indices for the panel linear models to account for a panel effect.

The general framework for the models can be depicted as follows:

$$\text{Forest area net change FRA} = \alpha_{it} + \beta_1 FDI_{it} + \beta_2 GDP_{it} + \beta_3 Trade_{it} + \varepsilon_{it}$$

$$\text{Deforestation FRA} = \alpha_{it} + \beta_1 FDI_{it} + \beta_2 GDP_{it} + \beta_3 Trade_{it} + \varepsilon_{it}$$

$$\text{Deforestation GFW} = \alpha_{it} + \beta_1 FDI_{it} + \beta_2 GDP_{it} + \beta_3 Trade_{it} + \varepsilon_{it}$$

$$\text{Biodiversity model 1} = \alpha_{it} + \beta_1 FDI_{it} + \beta_2 GDP_{it} + \beta_3 Trade_{it} + \varepsilon_{it}$$

$$\text{Biodiversity model 2} = \alpha_{it} + \beta_1 NFRA_{it} + \beta_2 DFRA_{it} + \beta_3 DGFW_{it} + \beta_4 FDI_{it} + \beta_5 GDP_{it} + \beta_6 Trade_{it} + \varepsilon_{it}$$

where $i = 1, 2, ..., n$ is the country; $t = 1, 2, ..., t$ is the year; α_{it} is the intercept, β are the parameters associated with the drivers, and ε_{it} is the residual. The dependent and independent (drivers) variables are described as follows: 'Forest area net change FRA' is based on the data provided by the FAO as part of the 2020 FRA (FAO, 2023). Specifically, it sets the value 'Forest area net change (1000 ha / year)' in relation to 'Forest (1000 ha)'. As 'Forest (1000 ha)' is only provided for certain years in which a FRA was published, the gap years were filled with calculated values, which are based on the last provided yearly value adjusted for the following years forest area net change value. 'Deforestation FRA' is based on the same FRA 2020 dataset, but in contrast to NFRA, 'Deforestation (1000 ha / year)' was set in relation to 'Forest (1000 ha)'. 'Deforestation GFW' is based on the provided value for tree cover loss (in ha at a threshold of 30% canopy cover) in relation to the previously explained value for forest extent (Global Forest Watch, 2023a). 'Biodiversity' uses the Biodiversity Intactness Index (BII) as a baseline and therefore relates to the provided BII for the included countries in the examined timespan (Natural History Museum, 2022). 'FDI', 'GDP' and 'Trade' relate to data provided by the World Bank, specifically the dataset for 'Foreign direct investment, net inflows (% of GDP)' with the WB WDI indicator code 'BX.KLT.DINV.WD.GD.ZS' (World Bank, 2023a); 'GDP per capita (current US$)' with the indicator code 'NY.GDP.PCAP.CD' (World Bank, 2023b) and 'Trade (% of GDP)' from the dataset with the indicator code 'NE.TRD.GNFS.ZS' (World Bank, 2023c).

To obtain a balanced dataset for the linear models, missing values were excluded and only countries that included values for each year were included in the model. The analysis initially included all sovereign states of South America. For the final analysis, Venezuela, Suriname and Guyana were excluded due to gaps in the available data.

The timespan for which data for all variables was available is 2001 to 2019. Therefore, the analysis only examined this time period.

Multiple models were performed using various estimation methods (fixed effects, random effects, pooling OLS) and the best model was chosen for each of the independent variables (NFRA; DFRA; DGFW, and BII). All chosen models were tested for time-fixed effects and pooling by conducting Lagrange Multiplier Tests of the respective models. Breusch-Pagan LM tests and Pesaran CD tests were conducted to check for cross-sectional dependence. Cross-sectional dependence can be a problem in macro panels containing long time series, as is the case here. In addition, Breusch-Godfrey/Wooldridge tests were done to check for serial correlation in the panel models. All models showed cross-sectional dependence as well as serial correlation. This was not investigated further and accepted as a property of the data at hand, as by definition, models with individual effects have serially correlated composite errors. Problems of the data are further discussed in Chapter 3.2. Finally, Breusch-Pagan test were performed to check for Heteroskedasticity. Heteroskedasticity was found in all models and controlled for by using robust covariance matrix estimation.

The data was analysed using R-Studio, Version 2023.03.0+386 (R Core Team, 2022). All the graphs were made using the ggplot2 package, version 3.4.1 (Wickham, 2016). Statistical significance was specified at $p < 0.05$.

3.4 Expected Model Outcomes

The decision to include four (five when considering the two versions of the BII model) different models, three focusing on forest related topics and an additional one for biodiversity intactness is in alignment with the initial scope of this thesis. While the three forest related models allow for an overview of some differences between FRA and GFW data with different adjustments, the last model covers biodiversity intactness, which is linked to changes in forest cover and deforestation. Each model includes the drivers FDI, GDP and Trade as described in the previous chapters. As part of the literature review, possible implications for the impact of each driver were elucidated. Highlighting the hypotheses and possible outcomes of each of the four models might contribute towards a better understanding of the results and discussion section of this thesis.

Previous findings, which were presented as part of the literature review, indicate that there are often no universally applicable theories on how different drivers impact forest cover change, deforestation, or biodiversity intactness. There is a vast array of different interlinkages that affect the impact of the assessed drivers. Controlling for these different effects, which are often country / region specific and are difficult to capture in a statistical manner is one of the main challenges. Addressing these shortcomings within the simple regression analysis performed as part of this thesis was not feasible. For future research in this direction, the models could be expanded indefinitely by adjusting the dataset and adding control variables for example. In line with the decision to focus on South America, comparing the effects between different South American countries still provides some insight that could help to identify areas of interest in future research. However, recapitulating the possible effects that each driver could have within the individual models might contribute to a better comprehensibility of the following chapters.

FDI (% GDP)

As suggested by previous studies, FDI is likely to affect economic growth and therefore may also be linked to environmental and forest cover change (Lokonon & Mounirou, 2019; Muhammad et al., 2021; Pradhan et al., 2022). However, the extent to which FDI impacts forest cover change and environmental changes remains ambiguous. While a study by Lokonon and Mounirou (2019) found varying results for different countries in the Sub-Saharan Africa region, the authors still point out the need for accompanying measures to control for deforestation along with new FDI flows. A recent study by Muhammad et al. (2021), however, concluded that there is a significant relationship between FDI and environmental degradation. Their research showed that FDI accelerates environmental degradation in BRICS and developing countries and decelerates it in developed countries (Muhammad et al., 2021). Therefore the expectation is that FDI might have a significant impact on the examined environmental variables, especially forest area net change and biodiversity intactness.

GDP per Capita

Previous studies suggested that the relationship between GDP / GDP per capita and forest cover change presents itself in the form of the Environmental Kuznets Curve, as described in Chapter

2.2 (Ewers, 2006; Tsurumi & Managi, 2014). However, the applicability of the EKC theory to describe the impact of changes in GDP, or generally the economy of a country, on deforestation has been questioned in more recent publications (Pradhan et al., 2022). Although the relationship between GDP and economic development of a nation and forest cover change seems to be present, capturing it in a theoretical or statistical manner appears to be challenging. GDP was included in the models due to previously elaborated reasons. Nevertheless, it is crucial to understand that there are many effects affecting GDP that may interfere. An increase or decrease of GDP can occur due to a large variety of reasons. An increase of GDP due to increased activity in the forestry sector impacts forest cover change differently than an increase of GDP due to changes in other industries. From a logical standpoint, the mechanism captured within the EKC theory seems comprehensible. Although the extent and the direction of the expected effect of changes in GDP in all four models remains difficult to predict, a significant effect should be observable.

Trade (% GDP)

The impact of changes in trade openness for example was assessed in a study by Tsurumi and Managi (2014). It was found that the effect of a change in trade openness differs depending on a country's development level (Tsurumi & Managi, 2014). Therefore, the expectation is that the effect is not uniform for all countries included in the model. Especially due to the relatively short time period examined, it remains questionable if the overall effect will be of statistical significance. For a very basic assessment of the state of a country's economy, one could refer to GDP per capita as an indicator. With this in mind, it can be expected, that countries with high GDP per capita show a different relationship, than ones with low GDP per capita.

4 Results

The main empirical goal of this thesis is to analyse the effect of different drivers on forest cover change, deforestation and biodiversity intactness through basic regression analysis. Two variables were created based on FRA data. The first variable 'Forest area net change FRA' captures forest area net change (1000ha / year) in relation to forest extent (1000ha). The second variable 'Deforestation FRA' captures deforestation (1000ha / year) in relation to forest extent (1000ha). The choice to utilise two different variables is based on the theoretical idea that assessing both the impact of different drivers on forest area net change (forest area increase minus deforestation) and on deforestation provides valuable insights to spot general trends and derive possible implications for future policies, conservation and reforestation efforts, etc. As a second measure for deforestation, a model based on GFW forest cover loss data ('Deforestation GFW') was built in addition to the FRA models. Lastly, a model assessing the impact of the different driver on the BII was performed.

In the first part of this chapter, the development of forest and biodiversity indicators over time will be presented, followed by the economic and financial drivers over time. In the four subsequent subchapters, the results of the models for the forest and biodiversity variables 'Forest area net change FRA', 'Deforestation FRA', 'Deforestation GFW' and 'Biodiversity Intactness Index' are shown. These models provide some insight into possible interactions between the drivers and the underlying variables.

4.1 Forest and Biodiversity Indicators Over Time

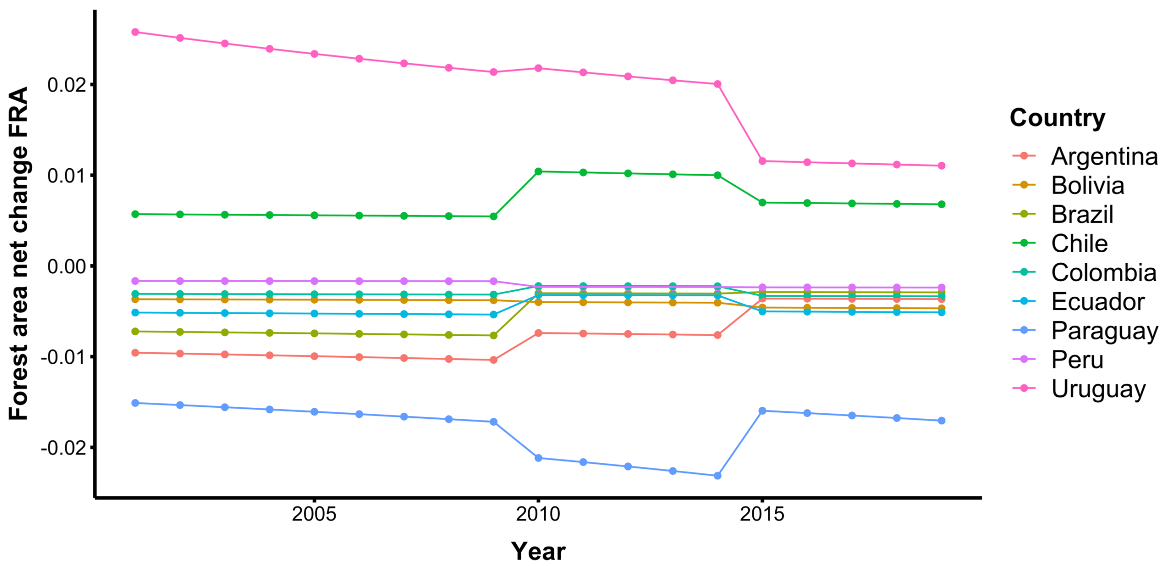
Based on individual figures, the development of the four forest and biodiversity related variables will be introduced. The different figures illustrate the development of these previously introduced indicators for a selection of countries in South America over the time period between 2001 – 2019.

Forest Area Net Change FRA

Figure 1 shows the relative change of forest area for a selection of South American countries from 2001 to 2019 on the basis of UN FAO FRA 2020 data. A negative value for 'Forest area net change' means that the forest area or extent in a country diminished in a certain year, whereas a positive value indicates that the forest extent increased. In the studied time period, Uruguay and Chile were the only countries to experience a net increase in forest area, although this increase became constantly smaller in Uruguay (Figure 1). In Argentina, Bolivia, Brazil, Columbia, Ecuador and Peru forest area net change is relatively constant and slightly negative, meaning that the forest area slightly decreases every year. In Paraguay, the decrease in forest area tends to become larger with every year (Figure 1). This is in concordance with the fact that the values for deforestation tend to increase in most years in Paraguay (Figure 2). At the peak in 2014, Paraguay lost almost 2.5% of its forest area (Figure 1).

Figure 1

Relative Forest Area Net Change in Different South American Countries



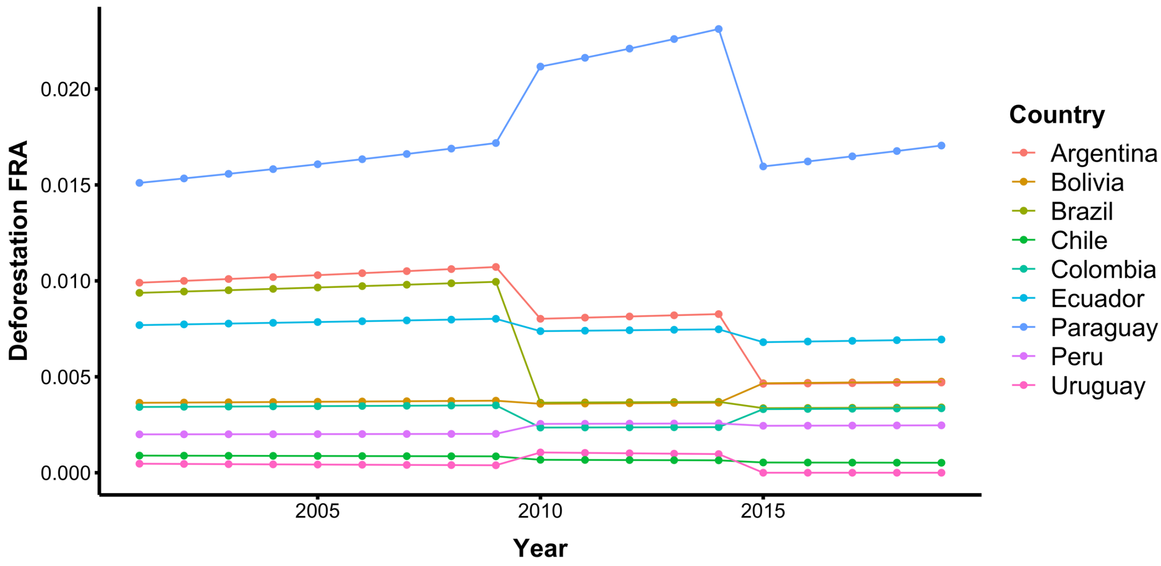
Note. Own representation based on FRA 2020 data and own calculations (FAO, 2023).

Deforestation FRA

Based on the FRA 2020 dataset that includes data based on previous FRAs, which represent different timespans, deforestation as a percentage of net forest extent was calculated. The calculated values for the years 2001 to 2019 can be seen in Figure 2. Paraguay experienced the highest values for deforestation with substantial fluctuations over time (Figure 2). Argentina, Brazil, and Ecuador show relatively high deforestation values as well, compared to the other countries, especially when looking at earlier reporting periods. The values for Bolivia, Chile, Columbia, Peru and Uruguay indicate low and relatively stable levels of deforestation remaining below 5%.

Figure 2

Deforestation as a Percentage of Forest Extent in Different South American Countries



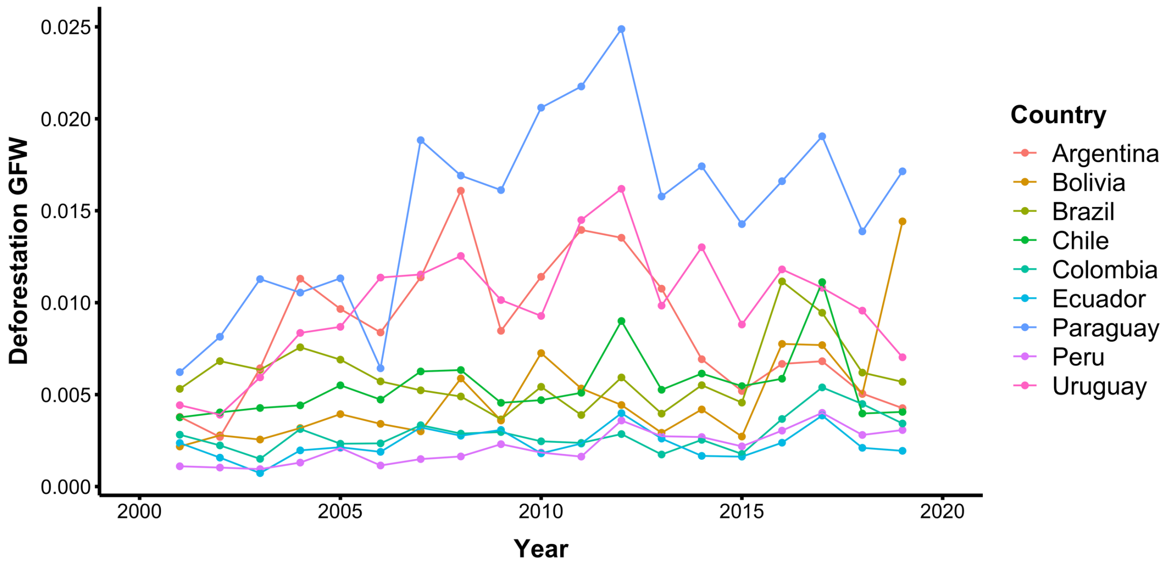
Note. Own representation based on FRA 2020 data and own calculations (FAO, 2023).

Deforestation GFW

Figure 3 shows the calculated values for forest cover loss as a percentage of forest extent based on GFW data for the period of 2001 to 2019. Many countries, such as Paraguay, Uruguay, or Argentina experience high levels and strong fluctuations of tree cover loss relative to their total forest cover extent from year to year (Figure 3). The highest value that the calculated deforestation based on GFW data reached was ca. 2.5% in Paraguay in 2012. Paraguay also showed the strongest fluctuations of relative tree cover loss, where tree cover loss was almost five times as high in some years compared to others. There were some larger fluctuations in Argentina, Brazil, Bolivia, Chile, and Uruguay as well, especially in recent years. Columbia, Ecuador, and Peru maintain low and steady levels of relative tree cover loss per year below 0.5% of their total forest extent.

Figure 3

Tree Cover Loss as a Percentage of Forest Extent in Different South American Countries



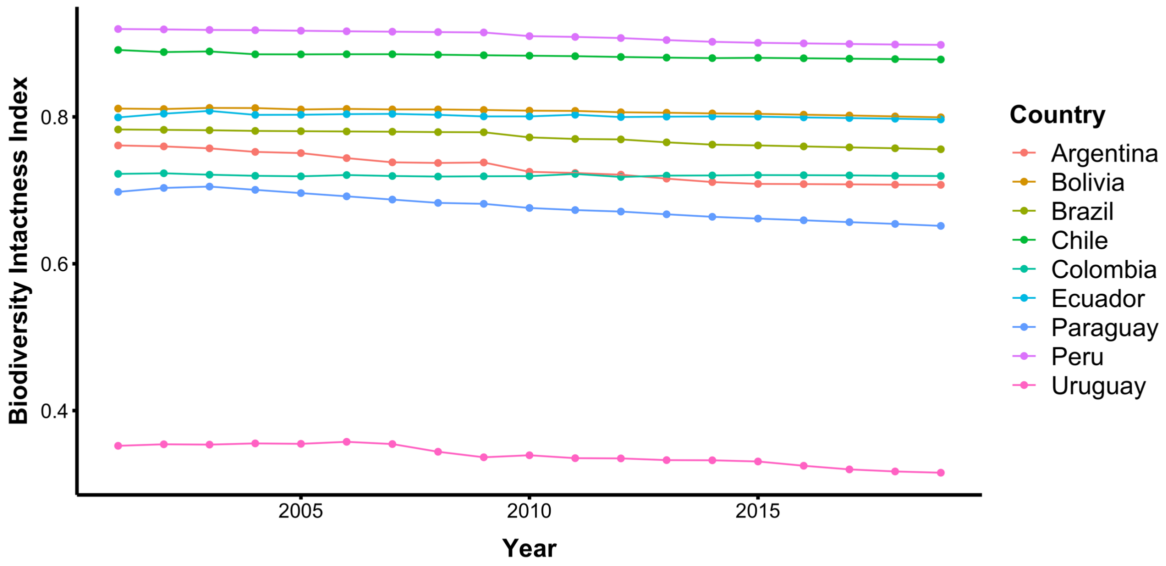
Note. Own representation based on GFW data and own calculations (Global Forest Watch, 2023a).

BII

Figure 4 shows the development of the 'Biodiversity Intactness Index' for the years 2001 to 2019 for the South American countries included in the model. Biodiversity intactness slowly decreases in all countries between 2001 and 2019, except for Colombia, where biodiversity intactness stays relatively constant. The highest BII values are reported in Peru and Chile, where more than 80% of the original biodiversity is still intact. The country with the lowest BII is Uruguay with less than 40% of the original biodiversity still intact. In Argentina, Bolivia, Brazil, Colombia, Ecuador and Paraguay between 60% and 80% of the original biodiversity remains intact.

Figure 4

Biodiversity Intactness Index in Different South American Countries



Note. Own representation of the Biodiversity Intactness Index (Natural History Museum, 2022).

4.2 Economic and financial drivers over time

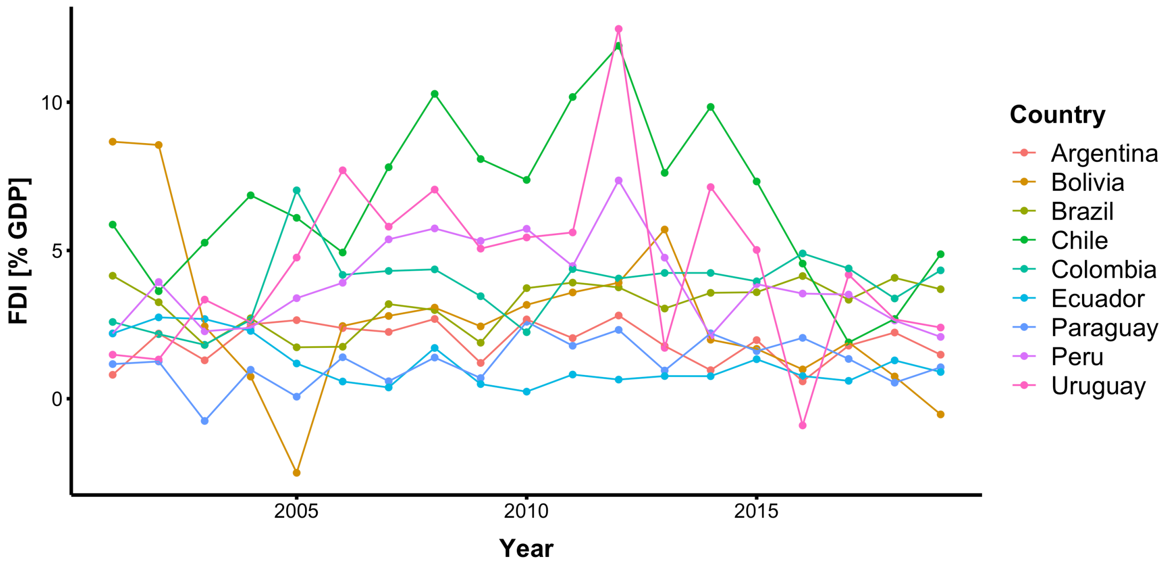
The development of three economic and financial drivers that are part of the performed models will briefly be presented with the help of the corresponding figures.

FDI (% GDP)

Figure 5 illustrates the development of FDI net inflows as a percentage of GDP per year for the South American countries that were included in the models. For better readability, figures and tables will refer to FDI (% GDP) instead of the full name used in the World Bank database (World Bank, 2023a). Some countries, for example, Bolivia, Chile, and Uruguay experienced substantial fluctuations regarding FDI (% GDP). At the same time, countries such as Brazil or Ecuador maintained relatively steady levels of FDI (% GDP).

Figure 5

FDI (% GDP) in Different South American Countries



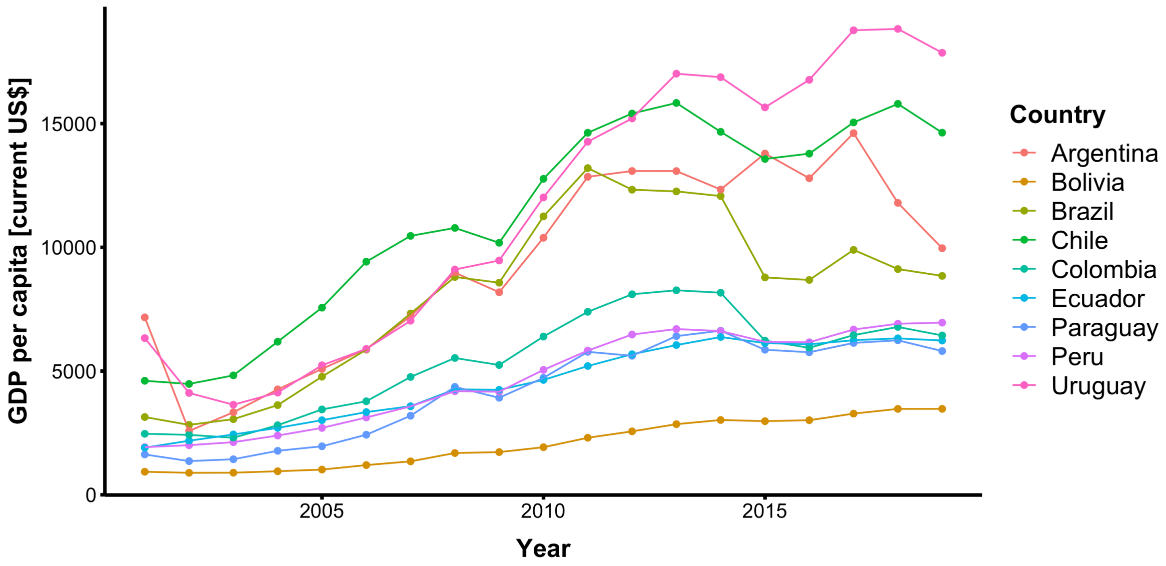
Note. Own representation based on World Bank data (World Bank, 2023a).

GDP per Capita

The development of GDP per capita (current US$) for the South American countries included in the model for the years 2001 to 2019 is presented in Figure 6. GDP per capita overall increased in all countries since 2001, implying similar trends across South America for the considered time period. Uruguay, Chile, Argentina and Bolivia overall have a higher GDP per capita compared to other countries. In comparison, GDP per capita in Bolivia is the lowest across the included South American countries. In Peru, Colombia, Ecuador, and Paraguay, the development of GDP per capita was similar during the last years. The fluctuation was largest for the four countries with the highest values. As can be seen in Figure 6, there are substantial differences in values for GDP per capita when comparing the different countries.

Figure 6

GDP per Capita (Current US$) in Different South American Countries



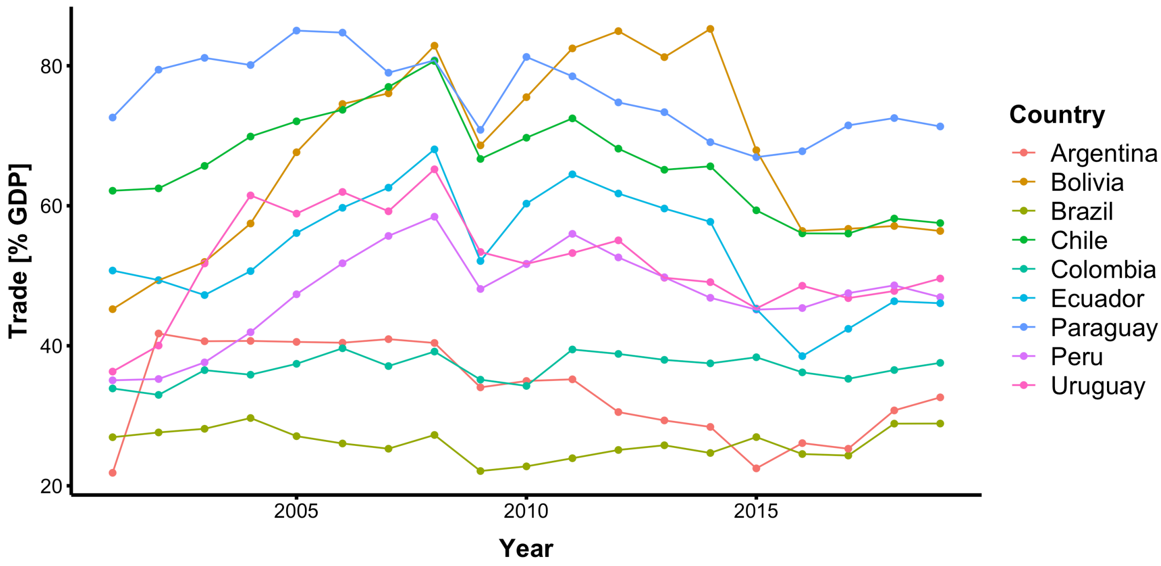
Note. Own representation based on World Bank data (World Bank, 2023b).

Trade (% GDP)

The development of Trade (% GDP) is shown in Figure 7 for the same South American countries between 2001 and 2019. For some countries, the values vary substantially over the studied time period. In Bolivia and Uruguay for example, the fluctuations, especially the increase in the first years, are rather substantial. Overall, the importance of trade, presented as a percentage of GDP, varies significantly between South American countries with values ranging from ca. 30% to around 70% in 2019.

Figure 7

Trade (% GDP) in Different South American Countries



Note. Own representation based on World Bank data (World Bank, 2023c).

4.3 Forest and Biodiversity Indicator Models

Different models were analysed in order to examine the effect of the different drivers on the four forest and biodiversity related variables. Analysis of each of the models revealed different significant effects. An overview of the main results is provided in Table 2. For better readability, the detailed results for all models are included in the Appendix of this thesis. In the following subchapters, significant effects observed for each model will be illustrated by corresponding figures for better comprehensibility. As the effects and their scales often vary across the different observed countries, figures that plot the data for all observed countries will be included in addition to country specific figures. All figures provided are own representations based on the previously explained data sources.

Table 2

Effects of the Drivers on the Forest and Biodiversity Indicators

Drivers	Forest Area Net Change FRA	Deforestation FRA	Deforestation GFW	BII
FDI [% GDP]	2.37e-4 * **(0.029)**	-1.45e-05 (0.745)	1.77e-04 (0.390)	2.33e-04 (0.344)
GDP per Capita [current US$]	-1.06e-7 **.** (0.087)	-1.40e-07 *** (**< 0.001**)	2.66e-07 ** (**0.002**)	-2.55e-06 *** (**< 0.001**)
Trade [% GDP]	-2.07e-5 (0.451)	1.54e-05 (0.250)	4.13e-05 (0.236)	1.69e-04 ** (**0.006**)

Note. Estimates for the coefficients are indicated and p-values are written below the estimates in brackets. Statistical significance is specified at p < 0.05. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

4.3.1 'Forest Area Net Change FRA' Linear Model

Detailed results of the random effect model for the effect of the drivers (FDI, GDP, Trade) on 'Forest area net change FRA' can be found in Table A1. The linear model revealed a positive significant effect of 'FDI (% GDP)' on 'Forest area net change' ($z = 2.18$, $p = 0.029$). On average, 'FDI (% GDP)' has a positive effect on 'Forest area net change'. This implies that the higher 'FDI (% GDP)' is, the less forest cover decreases or the more it increases. Figure 8 shows a plot of all datapoints for the included countries. It is clearly visible, that there are only two countries, Chile and Uruguay that show positive values for 'Forest area net change'. However, as can be seen in Figure 9, the effect of 'FDI (% GDP)' on 'Forest area net change' varies depending on the country and on whether forest area sees a net increase or decrease. For countries with positive values for 'Forest area net change' (forest area is increasing from year to year), the effect of 'FDI (% GDP)' on 'Forest area net change' is clearly positive as can be seen for Chile and Uruguay in Figure 9. In Bolivia and Brazil there is also a positive correlation between an increase of 'FDI (% GDP)' and 'Forest area net change' (Figure 9). However, 'Forest area net change' is negative for Bolivia and Brazil, meaning that there is a loss of forest area from year to year. The observed correlation implies that this loss is smaller when 'FDI (% GDP)' increases. The opposite trend, namely a negative effect of 'FDI (% GDP)' on forest area net change, can be seen in Argentina, Ecuador and Paraguay (Figure 9). The effects in Columbia and Peru are not conclusive.

Lastly, there seems to be a slight negative correlation between 'GDP per capita' and 'Forest area net change' indicating that higher 'GDP per capita' values relate to lower 'Forest area net change' and vice versa. However, this effect is only marginally statistically significant ($p < 0.087$), thus no figures are included.

Figure 8

'Forest Area Net Change FRA' in relation to 'FDI (% GDP)'

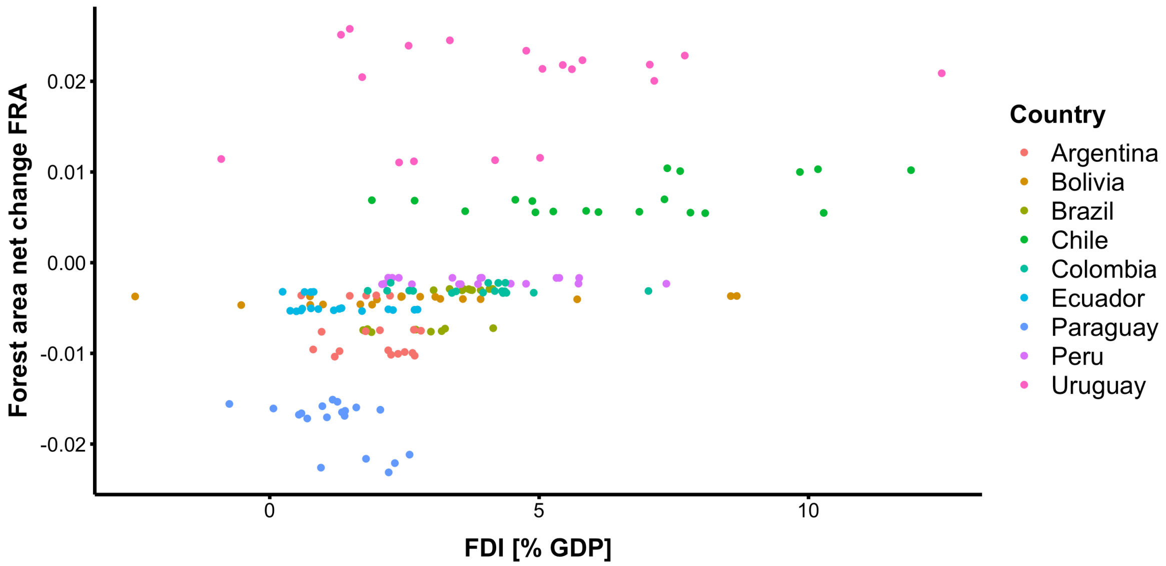
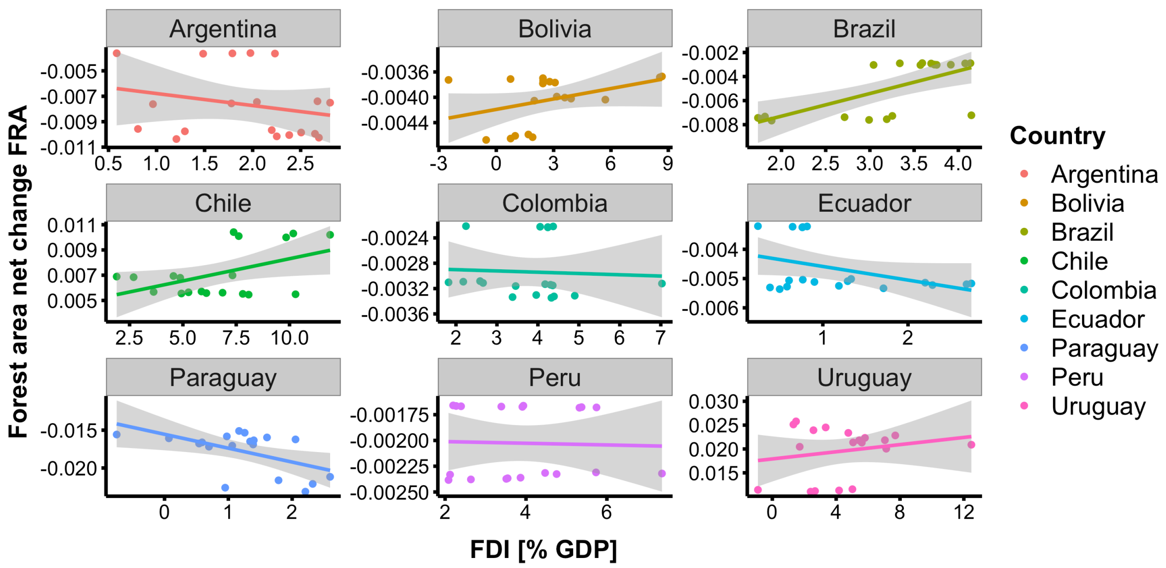


Figure 9

'Forest Area Net Change FRA' in relation to 'FDI (% GDP)' on a Country Level



Note. Note the different scales on the y-axis for the different countries.

4.3.2 'Deforestation FRA' Random Effect Model

The detailed results of the random effect model for the effect of the drivers (FDI, GDP, Trade) on 'Deforestation FRA' can be found in Table A2. The model analysis revealed a significant negative effect of 'GDP per capita' ($z = -3.78$, $p < 0.001$) on 'Deforestation FRA'. Implying that less deforestation occurs when 'GDP per capita' increases. Figure 10 provides an overview of the values of all included countries in South America. It can be seen that there are substantial differences between the deforestation rates across countries. The relationship is again dependent on the country as can be seen in Figure 11. It tends to be negative in Argentina, Brazil, Chile, Colombia, and Ecuador and positive in Bolivia, Paraguay and Peru, for the remaining countries, the trend is inconclusive.

Figure 10

'Deforestation FRA' in Relation to 'GDP per Capita'

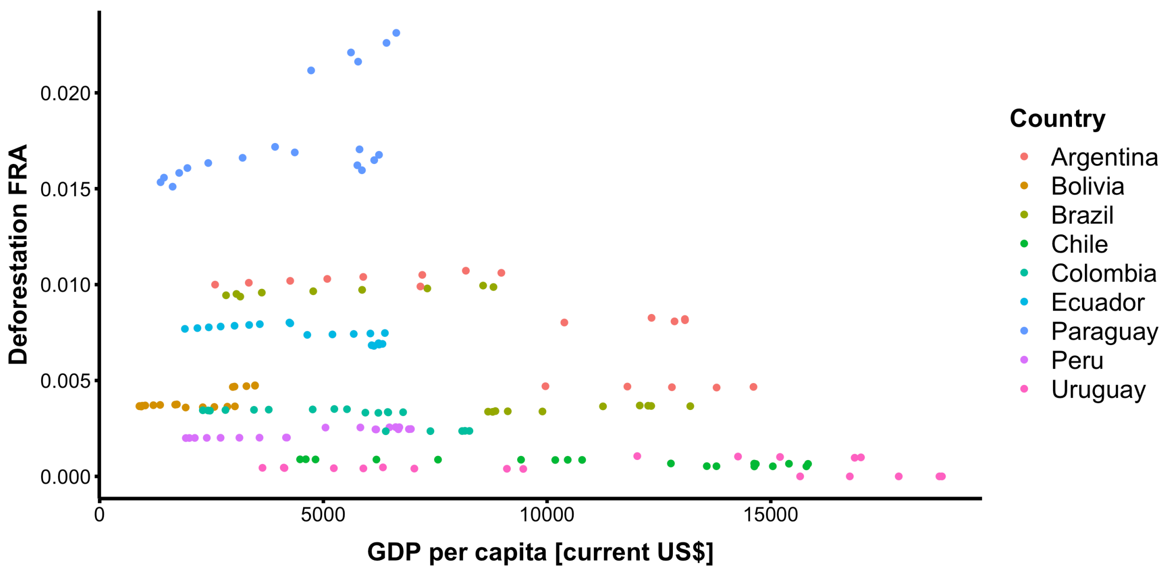
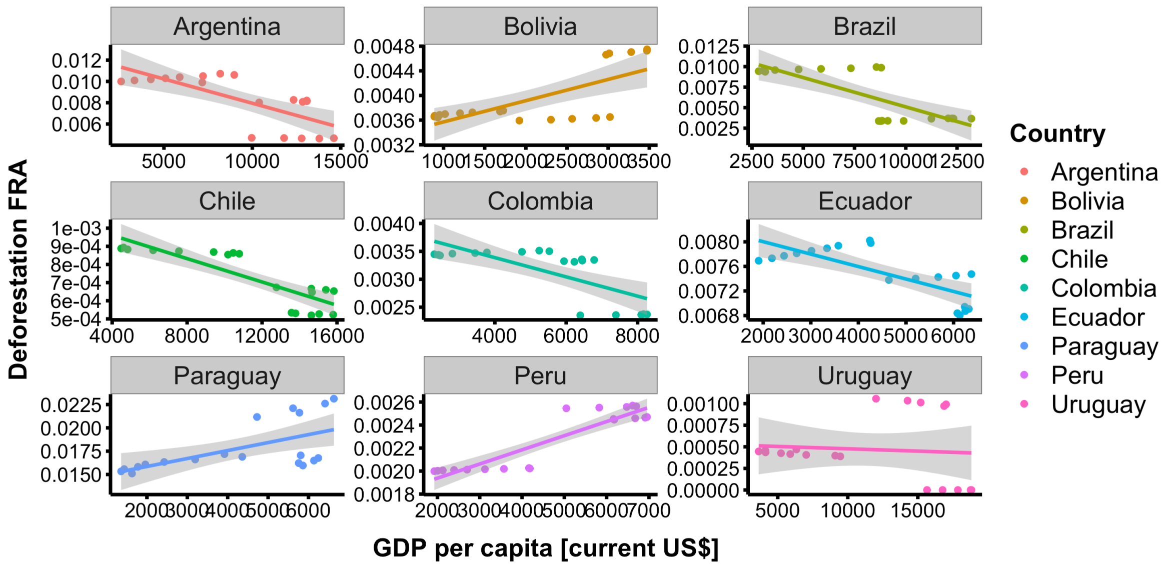


Figure 11

'Deforestation FRA' in Relation to 'GDP per Capita' on a Country Level



Note. Note the different scales on the y-axis for the different countries.

4.3.3 'Deforestation GFW' Linear Model

To analyse the relationship between the different drivers and the forest cover loss / deforestation variable that is based on GFW data, a fixed effect model was analysed. The detailed results of the fixed effect model for the effect of the drivers (FDI, GDP, Trade) on 'Deforestation GFW' can be found in Table A3. The fixed effect linear model revealed a significant positive effect of 'GDP per capita' on 'Deforestation GFW' ($z = 3.14$, $p = 0.002$), meaning that with a higher GDP, more forest is lost to deforestation. In Figure 12, the datapoints for all included countries are visible. Figure 13 shows the results for individual countries, some country-dependent variation is visible. In addition to the country-dependent differences in the GDP-forest loss relationship, the trends are also different than the ones found between the FRA forest loss data and the drivers, this will further be discussed in the following chapter.

Figure 12

'Deforestation GFW' in Relation to 'GDP per Capita'

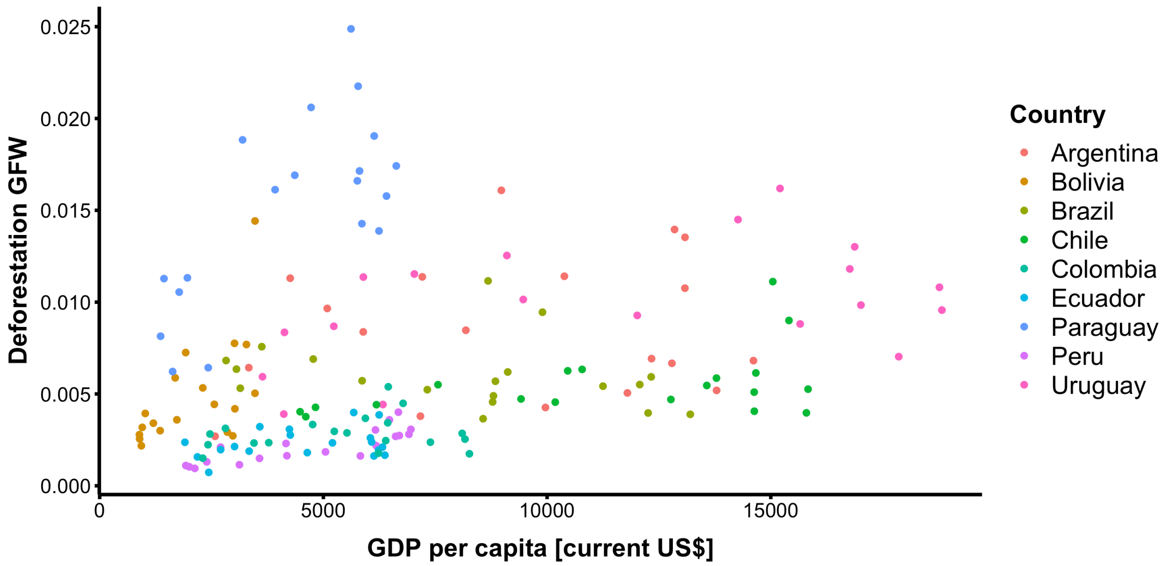
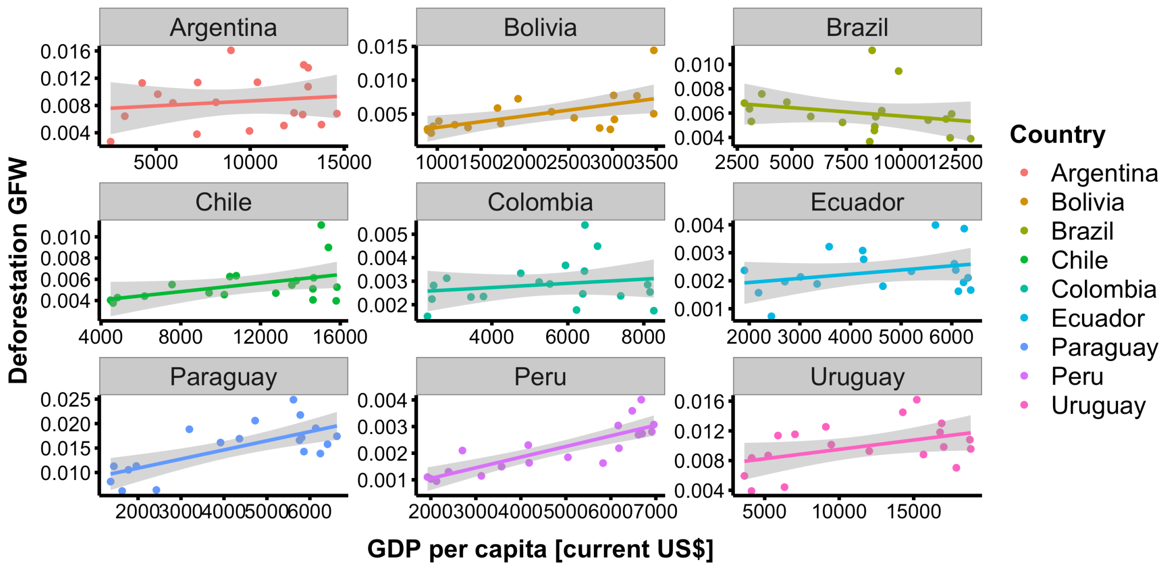


Figure 13

'Deforestation GFW' in Relation to 'GDP per Capita' on a Country Level



Note. Note the different scales on the y-axis for the different countries.

4.3.4 'BII' Linear Model

In order to examine the impact of the different drivers on the Biodiversity Intactness Index, a random effect model was analysed. In a first attempt, the different forest related variables were included in the model in addition to the three drivers. The results of this preliminary model ('Biodiversity model 2') with the additionally included variables can be found in Table A4. Considerations regarding the observed effects of the forest related variables on the 'BII' will be elaborated in the following chapters. However, in order to obtain better comparability and comprehensibility with the previously presented models, the BII model was also performed with the initial selection of drivers ('Biodiversity model 1'). Detailed results of the random effect model for the effect of the drivers (FDI, GDP, Trade) on the 'BII' can be found in Table A5. The results of this analysis were also included in the previous overview of all models (Table 2). Overall, both analyses led to the same observed significant effects.

The analysis showed that there is a significant negative effect of 'GDP per capita' on the 'BII' ($z = -13.99$, $p < 0.001$). Accordingly, this would indicate that increasing values for 'GDP per capita' lead to lower biodiversity intactness (Figure 14 and Figure 15). This trend is consistent in all countries. Biodiversity intactness across the observed countries varies to some extent with a distinct gap between Uruguay and the other countries (Figure 14). While regarding the results and the scale plotted in Figure 15, it is important to consider the relatively small range in which the values are situated for some countries, indicating that the 'BII' is relatively stable across the observed time period.

Figure 14

'Biodiversity Intactness Index' in Relation to 'GDP per Capita'

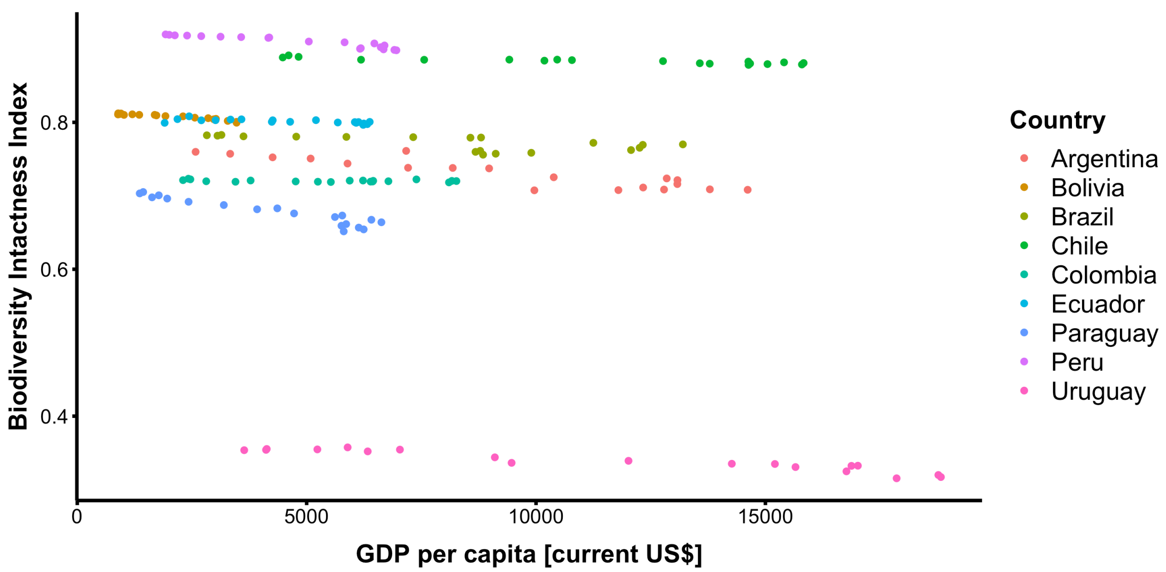
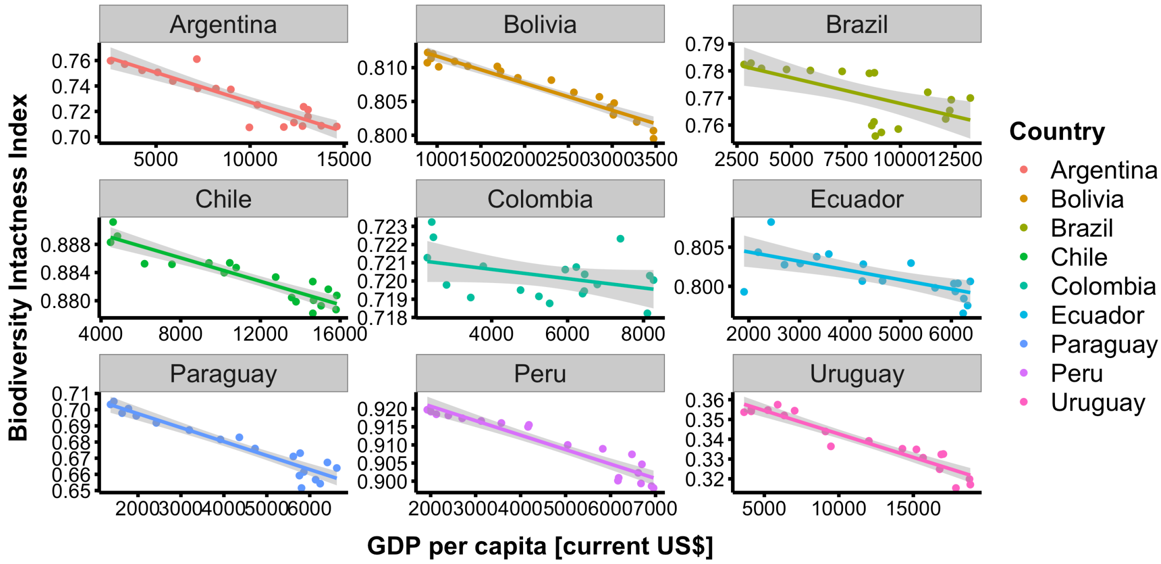


Figure 15

'Biodiversity Intactness Index' in Relation to 'GDP per Capita'



Note. Note the different scales on the y-axis for the different countries.

Finally, the analysis showed a significant positive effect of 'Trade (% GDP)' on biodiversity intactness, with more biodiversity being intact for higher values of trade in relation to GDP ($z = 2.74$, $p = 0.006$). An overview of the corresponding data for the included countries can be found in Figure 16. Again, Uruguay is noticeably sequestered from the other countries due to its low BII (Figure 16). There is some country-specific variation, which can be seen in Figure 17. Due to relatively small changes in the BII values in the regarded time period, the scale of the plots in Figure 17 should again be cautiously considered. Especially for intermediate values of trade, the effect of trade on biodiversity intactness can also be negative in some cases (e.g. Columbia, Peru).

Figure 16

'Biodiversity Intactness Index' in Relation to 'Trade (% GDP)'

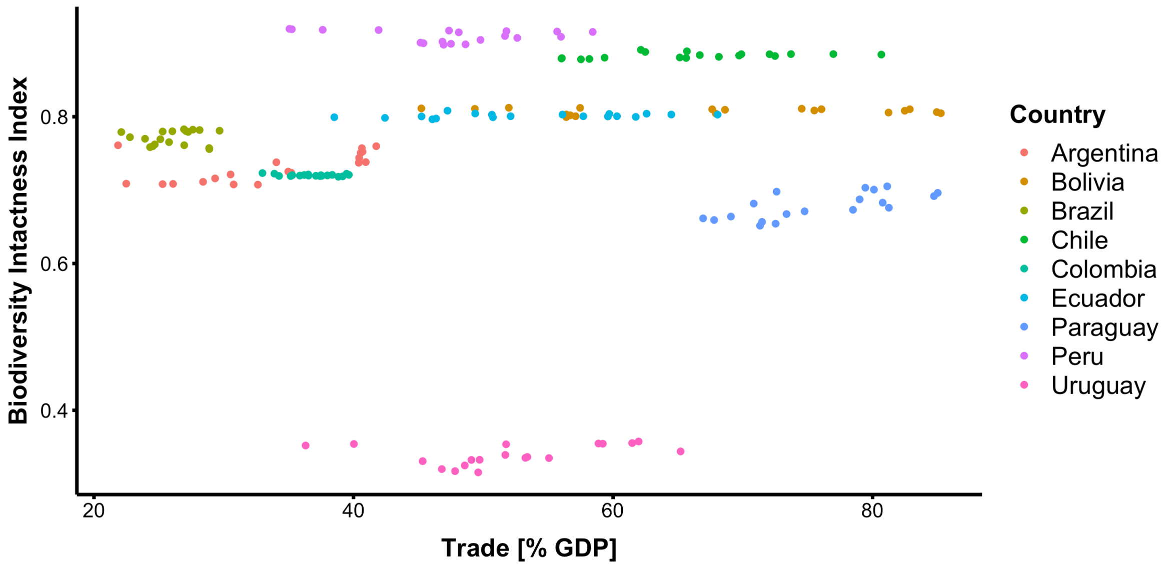
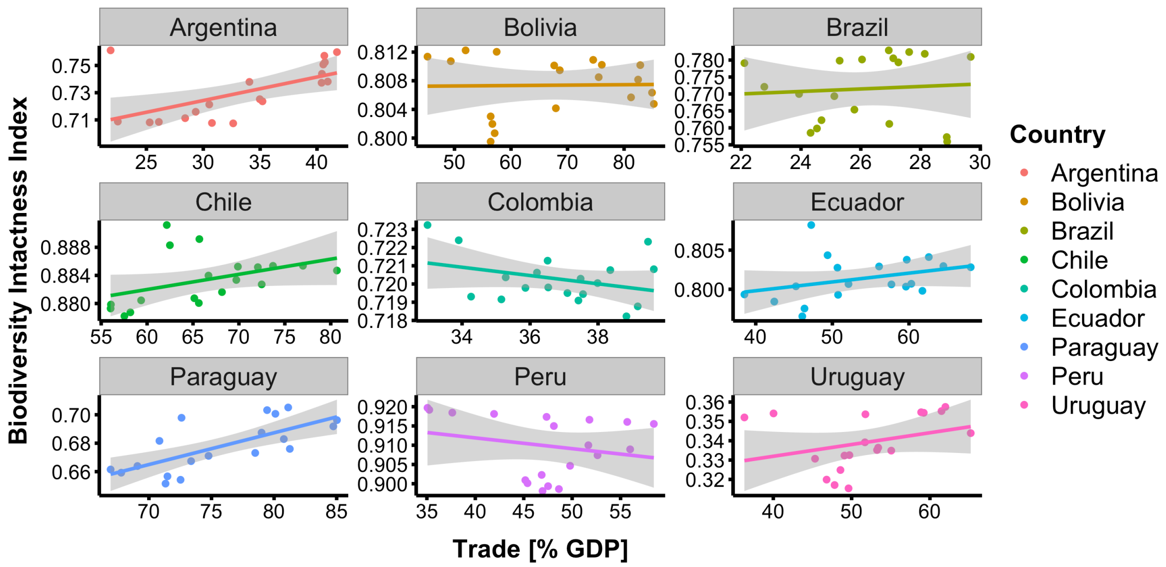


Figure 17

'Biodiversity Intactness Index' in Relation to 'Trade (% GDP)'



Note. Note the different scales on the y-axis for the different countries.

5 Discussion

The results and figures presented within the last chapter show different significant effects. Examining the figures that provide country level plots allows to somewhat affirm the initial conjecture that there are noteworthy country level effects. These effects may in some cases contradict trends that were asserted as a result of a continent-level regression analysis. While some of the presented significant effects seem intuitively logic and coherent with the desired outcomes that were previously elaborated, others call for additional explanation. Moreover, it is crucial to understand the limitations of the performed regression analysis. Regarding the presented results in context with previous elaborations on the underlying data and relevant literature is crucial to understand the reliability of the results and to draw further conclusions.

The statistical model for 'Forest area net change FRA' showed a significant effect of FDI and a slight influence of GDP per capita. This positive correlation of FDI indicates that with an increase of FDI net inflows measured as a percentage of GDP, forest area net change will increase. It is important to note, that forest area net change can be positive in case of a net increase of forest extent, negative in the case of net decrease of forest extent or zero if forest extent did not change. Of the examined South American countries, only Chile and Uruguay experienced a net increase of forest extent, resulting in positive values for forest area net change (Figure 8). All other countries experienced a net decrease in forest extent resulting in negative values for forest area net change (Figure 8). Overall, the positive correlation seems to be a desirable output in both cases. In countries with positive values, forest extent increases further with an increase of FDI net inflows (% GDP). At the same time, in countries with negative values, forest area net change decreases, meaning that less forest extent is lost from year to year. Differences in the overall scale might again play an important role. FDI net inflows seem to play a varyingly important role across different South American countries and over the observed time span. In Uruguay, Chile and Bolivia for example, FDI net inflows equal up to 10% and more in relation to the GDP for certain years (Figure 5). For Argentina, Brazil, Ecuador and Paraguay for example, FDI net inflows are less extensive and more stable when measured in relation to the GDP (Figure 5). Interesting to note is that the GDP per capita in Chile and Uruguay for example is higher in comparison to the other countries (Figure 6). When FDI net inflows are measured as a percentage of the GDP, the resulting relative values are directly influenced by changes in the GDP. Additionally, it is also likely that changes in FDI net inflows affect the GDP. Future models could be augmented by further adjusting the underlying data and considering additional variables. Nevertheless, the analysis of this simple linear model revealed a significant effect, which is compatible with previous findings and the anticipated outcome to a certain extent. Previous findings suggested that there is a relationship between FDI investments, economic growth, and environmental and forest cover change (Lokonon & Mounirou, 2019; Muhammad et al., 2021; Pradhan et al., 2022). Muhammad et al. (2021) described a significant relationship between FDI and environmental degradation which is dependent on the level of development of a country. According to the study, increased FDI decelerated environmental degradation in developed countries and accelerated it in developing and BRICS countries (Muhammad et al., 2021). When looking at Figure 9, it becomes apparent, that this statement might be true for some countries when using GDP per capita (Figure 6) as an indicator for the status of a country's economy. To precisely compare the results with the study by Muhammad et al. (2021) is however difficult as they included a different selection of countries and different calculations in their study. Further, a clear classification regarding the development status would be necessary.

The slight correlation of forest area net change and GDP per capita is, as it was the case for the Deforestation FRA model, negative. This implies that an increase in GDP per capita would lead to a decrease of forest area net change and vice versa. It is however important to note that the effect for this model is not of high statistical significance. Overall, the expectation that GDP per capita has a more or less significant effect in either direction was met across all four models. Nevertheless, it is again important to mention that GDP per capita is a very general measure. As mentioned earlier, it is highly probable that economic changes that impact the GDP have a different effect on the environment depending on many different factors such as the industry, location, etc.

For the two models with deforestation related dependent variables, the analysis revealed differences in the significant effects. This was to be expected due to earlier explained fundamental differences in the raw data. The model for analysing the FRA based dependent variable showed a negative significant effect of GDP per capita. Using the GFW based dependent variable in the corresponding model resulted in a significant effect of GDP per capita as well, but in this case, the correlation was positive. These results indicate that there are significant interlinkages between the GDP per capita and deforestation / tree cover loss in South American countries. Thus, this analysis is compatible with a variety of previous findings which were presented in the literature review of this thesis to some extent (Ewers, 2006; Tsurumi & Managi, 2014).

An FRA 2020 based dependent variable was used in the model ‘Deforestation FRA’. This model showed a highly significant negative effect of GDP per capita on deforestation. The negative correlation implies that an increase of GDP per capita would lead to a decrease of deforestation, meaning that less deforestation would occur and vice versa.

As previously elucidated, a second dependent variable and therefore a second model related to deforestation was featured to further assess the impact of the different drivers. The model for ‘Deforestation GFW’ indicates that there is significant positive correlation between GDP per capita and deforestation. This would mean that with an increase in GDP per capita an increase in tree cover loss would occur.

Although the chosen, rather simple models do not really allow for alignment with the Environmental Kuznets Curve theory, the effect observed for the ‘Deforestation GFW’ model would relate to the first phase of the curve. According to the EKC theory, in earlier development stages of a country’s economy, growing GDP per capita would lead to increased environmental deterioration. However, as there is no general consensus on the applicability and validity of the EKC theory, especially with regards to deforestation, this interpretation should be contemplated with caution (Ewers, 2006; Tsurumi & Managi, 2014). Generally speaking, this relationship would align to some extent with the findings of Ewers (2006), insofar as many South American countries have a comparably low GDP per capita and could therefore partially rely on deforestation to boost economic growth. Ewers (2006) further states that these countries lack financial and other resources to boost environmental protection. If one would try to align the observed opposite effect from the ‘Deforestation FRA’ model with the EKC theory, this would correspond to the part of the EKC past the ‘tipping point’, where an increase in GDP per capita would lead to a decrease in environmental deterioration. However, the regarded timespan is most likely too short to depict long-term economic development processes. In addition, the applicability of the EKC theory to deforestation is heavily disputed.

Furthermore, many South American countries share a strong economic focus on agricultural production and industry. Naturally, large scale agricultural production is rather land intensive and, in many cases, impacts the environment directly. Less stringent regulations and standards in some countries, especially regarding pollution are likely to worsen the negative impacts.

Although the significant effect of GDP per capita on ‘Deforestation FRA’ and on ‘Deforestation GFW’ differs in terms of the direction, there is an argument to be made for both cases. While both variables aim to capture deforestation / tree cover loss, the underlying data contains some substantial differences. These differences, which mainly arise from varying approaches in terms of data collection / measurement and differing scopes / intentions in reporting were elaborated in the previous chapters. While GFW data shows noticeable variation between yearly values, FRA values are much more stable and mostly change in the years where a new reporting period starts. The values within one FRA reporting period remain more or less stable, except for slight variations due to adjustments for losses in the previous year (see Figure 2). In some individual cases, substantial differences from one FRA reporting period to another likely lead to distortion of the trend, for example in Paraguay, Argentina, or Brazil (Figure 2). Further, a comparison of the mean values for the calculated FRA and GFW deforestation variables between 2001 and 2019 for each country reveals large differences in certain countries (see Table A6). Especially for Uruguay and Chile, the FRA values are drastically lower. For Ecuador, the FRA values are much higher, than the GFW values. These are two possible factors that might be responsible for the resulting opposite direction of the observed correlation.

Comparing the per country plots of both, FRA and GFW deforestation variables against GDP per capita provides further intel on country level differences (see Figure 11 and Figure 13). A direct comparison of the trends reveals that for Bolivia, Brazil, Paraguay, and Peru, the direction is similar. For the other countries, the direction is opposite when comparing the results from the FRA and GFW data-based models. Regarding the scale of both deforestation variables shows that overall, variation for both GFW and FRA based data is minor in some countries.

The different results show that it is difficult to find universally applicable theories for the effect of different drivers on deforestation / tree cover loss. However, it is interesting to see, that the analysis of both deforestation related models included in this thesis showed a significant effect of GDP per capita on the deforestation variables. As described in Chapter 3.4 it was expected that the analysis shows significant effects for GDP per capita. The results are in line with literature suggesting that the effect can indeed either go in a negative or positive direction.

Lastly, the model with the BII as the dependent variable showed the largest variety of significant effects. As previously explained, for biodiversity intactness, two models were examined. In 'Biodiversity model 2', the three forest related variables analysed in the previous models were included as independent variables in addition to the economic and financial drivers. Both deforestation related variables showed a significant effect on biodiversity intactness. The results of the analysis of the 'Biodiversity model 2' were not elaborated in detail in the results, however they can be found in Table A4. While the FRA based variable resulted in a positive correlation effect, the GFW based variable resulted in a negative correlation effect. The observed correlation for the FRA based variable indicates that an increase in deforestation would lead to an increase of the BII. This result is hard to justify from a theoretical standpoint as it implies a rather unintuitive mechanism. It is therefore rather likely that the observed correlation is caused by the applied definitions and aforementioned peculiarities of the FRA data. The observed positive correlation for the GFW based variable implies a more intuitive and realistic mechanism, where an increase of tree cover loss would lead to a decrease of biodiversity intactness and a decrease in tree cover loss would imply an increase of biodiversity intactness. While this might be applicable in certain cases, and increases in biodiversity intactness are possible, the upside potential is likely limited compared to the downside potential.

The inclusion of the forest related independent variables was dropped to achieve better comparability with the first three models and due to the inconclusive effects of the forest related variables explained above. Therefore, the results of the analysis of 'Biodiversity model 1' were elaborated in more detail in the results section and below. Both models resulted in the same significant effects for the economic and financial drivers which further supported the choice of 'Biodiversity model 1' as the main biodiversity model.

The analysis of the 'Biodiversity model 1' showed a highly significant negative correlation between the BII and GDP per capita. This effect indicates that an increase of GDP per capita leads to a decrease of biodiversity intactness and vice versa. Similar trends have been described previously in the literature (Asafu-Adjaye, 2003). Again, the case where decreasing GDP per capita would positively affect biodiversity intactness is, although theoretically possible, presumably limited to a certain threshold of biodiversity intactness (Dietz & Adger, 2003). There are several arguments to be made for and against the first case, in which increasing GDP per capita leads to decreasing biodiversity intactness. An increase in GDP per capita could imply a growing economy, more industry, intensified agricultural activity, etc., which could in return result in the destruction of biodiversity through the possible loss of valuable habitats or a surge in different kinds of pollution. However, as often implied, higher GDP per capita could generally imply higher development levels of a nation and more wealth, allowing for investments and initiatives to tackle environmental concerns and bolster efforts to recover biodiversity (van den Bergh, 2009). This could however lead to the displacement of environmental deterioration and pollution to poorer countries and therefore equal or higher overall levels of negative environmental impact.

Lastly, the model revealed a statistically significant positive correlation between 'Trade (% GDP)' and the 'BII'. This indicates that lower levels of trade as a percentage of GDP equal lower biodiversity intactness and higher percentages of trade in GDP result in higher biodiversity intactness. The exact mechanism behind this correlation is not clearly distinguishable as there likely are substantial differences depending on the composition of a nation's trade balance (in terms of industry, trade partners, etc.) for example. The opposite effect has been found in a study by Lenzen et al. (2012) where it was found that international trade caused 30% of global species threats. In general, there are several studies suggesting that international trade is a threat to biodiversity intactness (Green et al., 2019; Lenzen et al., 2012). Tsurumi and Managi (2014) however elucidate similar findings as in this thesis as part of what they call the composition effect within their analysis of the effects of trade openness on deforestation. The dataset for 'Trade (% GDP)' of the World Bank depicts trade as the sum of imports and exports of goods and services (World Bank, 2023c). A differentiation on the individual share of exports and imports in this sum is therefore not possible. Whether a country has an export- or import-oriented economy might have a substantial impact on the relationship between trade and biodiversity intactness that is not captured within this model. If a countries trade balance is mainly driven by agricultural exports for example, this likely has a different impact on biodiversity intactness compared to a country where a large part of the trade balance stems from the import of agricultural goods. There is some evidence to be found in literature that trade is a driver of deforestation-related emissions especially agricultural trade (Green et al., 2019; Pendrill et al., 2019). However, the effect is likely to be dependent on the development level of a country / economy (Tsurumi & Managi, 2014). It was previously found that while increased trade intensity abated deforestation in developed countries, the same was not the case for developing countries (Tsurumi & Managi, 2014). Due to the assumed linkage between deforestation and biodiversity intactness (which could partly be shown in this thesis), the same trend is expected for biodiversity intactness depending on the development level of a country.

5.1 Conclusion and Further Research

This thesis was written with the intention to assess the impact of different economic and financial drivers on forest cover change and biodiversity. Therefore, a general assessment of the impact of changes in GDP, FDI and trade on forests and biodiversity was made. The analysis of multiple models for different forest and biodiversity related variables has revealed several significant effects. The results indicate that there are observable relationships between some of the assessed economic and financial drivers and changes in forest cover and biodiversity intactness. Based on both a quantitative and qualitative analysis of the topic, it can be concluded that especially changes in GDP / GDP per capita affect how forest cover and biodiversity change.

The dataset used for the analysis was compiled to include the desired variables based on considerations that originated from the literature review. Based on existing literature it was to be expected that establishing universally applicable concepts for describing the role of different drivers may not be possible. Due to a variety of explained reasons, the empirical part of this thesis focused on South America. By focusing on this seemingly small selection of countries, it was possible to elaborate on some interesting peculiarities. While the focus on a specific continent and a selection of three relatively broad drivers limits the generalisability of the findings, the approach revealed some universally relevant constraints.

While it may be interesting to explore the impact of different drivers in a statistical manner, model calculations will likely never be universally applicable. Hence, it is crucial to understand the different, often indirect effects that impact forest cover change and biodiversity. By summarising previous findings, it became evident that a "magic" recipe to battle forest cover and biodiversity loss has yet to be found. Although there seems to be a widespread consensus that drastic measures need to be taken in order to battle forest cover loss and declining biodiversity, there are indications that the measures and policies in place are nowhere near sufficient to halt the trend on a global scale. An array of factors that determine the efficacy of conservation efforts, environmental initiatives and policies, etc. was presented. In conclusion, the urge to focus on stringent new regulations and conservation efforts has never been bigger. These measures have to be globally accepted and must be accompanied by considerations of a plethora of different challenges that arise. They call for adequate financing, monitoring, enforcement and reporting. An example would be the combination of forest and biodiversity protection efforts in developing countries with financial aid to offset economic disadvantages to limit local backlash. Special emphasis needs to be put on widespread acceptance. Otherwise, the displacement of environmental deterioration and pollution to countries with less stringent regulation would likely persist.

Working with forest and biodiversity related data revealed that data availability and quality is a major concern. Even though data accuracy seems to improve steadily, knowledge and data concerning both forest and biodiversity related topics is incomplete. New technologies may allow for more accurate, frequent and detailed measurement of different variables that could then be used in future studies. Nevertheless, differences in the definition of relevant variables remain an issue regarding the comparability and combability of different data sources. Reporting on forest and biodiversity related topics would desirably refer to universally applicable definitions and reporting standards in future research. This would not only improve the comprehensibility of available data but also allow for new and efficient frameworks to monitor the progress and the effectiveness of policies and initiatives. Improved data availability, accuracy and comparability would also enable researchers to construct more complex and realistic models to further examine the impact of different drivers on forest cover and biodiversity change.

References

Aitken, A. (2019). Measuring welfare beyond GDP. *National Institute Economic Review*, *249*(1), R3–R16. https://doi.org/10.1177/002795011924900110

Alroy, J. (2017). Effects of habitat disturbance on tropical forest biodiversity. *Proceedings of the National Academy of Sciences*, *114*(23), 6056–6061. https://doi.org/10.1073/pnas.1611855114

Arenas, D., Albareda, L., & Goodman, J. (2020). Contestation in multi-stakeholder initiatives: Enhancing the democratic quality of transnational governance. *Business Ethics Quarterly*, *30*(2), 169–199. https://doi.org/10.1017/beq.2019.29

Asafu-Adjaye, J. (2003). Biodiversity loss and economic growth: A cross-country analysis. *Contemporary Economic Policy*, *21*(2), 173–185. https://doi.org/10.1093/cep/byg003

Beer, C. M. (2023). Bankrolling biodiversity: The politics of philanthropic conservation finance in Chile. *Environment and Planning E: Nature and Space*, *6*(2), 1191–1213. https://doi.org/10.1177/25148486221108171

Bowler, K., Castka, P., & Balzarova, M. (2017). Understanding firms' approaches to voluntary certification: Evidence from multiple case studies in FSC certification. *Journal of Business Ethics*, *145*(2), 441–456. https://doi.org/10.1007/s10551-015-2880-1

Busch, J. (2015, September 21). Three reasons FAO's new forest numbers don't add up. *Center for Global Development* . https://www.cgdev.org/blog/three-reasons-fao%E2%80%99s-new-forest-numbers-don%E2%80%99t-add

Cain, Á. (2022, February 19). Ikea has come under fire over allegations it's eating up ancient forests in Romania. *INSIDER*. https://www.businessinsider.com/ikea-romania-forests-deforestation-allegations-environment-report-2022-2?r=US&IR=T

Croissant, Y., & Millo, G. (2008). Panel data econometrics in R: The plm package. *Journal of Statistical Software*, *27*(2). https://doi.org/10.18637/jss.v027.i02

Dietz, S., & Adger, W. N. (2003). Economic growth, biodiversity loss and conservation effort. *Journal of Environmental Management*, *68*(1), 23–35. https://doi.org/10.1016/S0301-4797(02)00231-1

Earthsight. (2020). *FLATPÅCKED FÖRESTS*. https://www.earthsight.org.uk/flatpackedforests-en

Earthsight. (2021). *Ikea's house of horrors*. https://www.earthsight.org.uk/news/investigations/ikea-house-of-horrors

Earthsight. (2023). *About Earthsight*. https://www.earthsight.org.uk/about

Ewers, R. M. (2006). Interaction effects between economic development and forest cover determine deforestation rates. *Global Environmental Change*, *16*(2), 161–169. https://doi.org/10.1016/j.gloenvcha.2005.12.001

FAO. (2020a). Global Forest Resources Assessment 2020 - Key findings. In *Global Forest Resources Assessment 2020*. FAO. https://doi.org/10.4060/ca8753en

FAO. (2020b). Global Forest Resources Assessment 2020 - Main report. In *Global Forest Resources Assessment 2020*. FAO. https://doi.org/10.4060/ca9825en

FAO. (2020c). *FRA 2020 terms and definitions*. FRA. https://fra-data.fao.org/definitions/fra/2020/en/tad#1

FAO. (2022). The state of the world's forests 2022. Forest pathways for green recovery and building inclusive, resilient and sustainable economies. In *The State of the World's Forests 2022*. FAO. https://doi.org/10.4060/cb9360en

FAO. (2023). *Global Forest Resources Assessment 2020*. https://fra-data.fao.org/assessments/fra/2020

Giam, X. (2017). Global biodiversity loss from tropical deforestation. *Proceedings of the National Academy of Sciences*, *114*(23), 5775–5777. https://doi.org/10.1073/pnas.1706264114

Global Forest Watch. (2023a). *Global Forest Watch dashboard - Global forest change*. https://www.globalforestwatch.org/dashboards/global/

Global Forest Watch. (2023b). *Grants & fellowships*. https://www.globalforestwatch.org/grants-and-fellowships/about/

Green, J. M. H., Croft, S. A., Durán, A. P., Balmford, A. P., Burgess, N. D., Fick, S., Gardner, T. A., Godar, J., Suavet, C., Virah-Sawmy, M., Young, L. E., & West, C. D. (2019). Linking global drivers of agricultural trade to on-the-ground impacts on biodiversity. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(46), 23202–23208. https://doi.org/10.1073/pnas.1905618116

Harris, N., Petersen, R., Davis, C., & Payne, O. (2016, August 1). *Global Forest Watch and the Forest Resources Assessment explained in 5 graphics*. Global Forest Watch Blog.

https://www.globalforestwatch.org/blog/data-and-research/global-forest-watch-and-the-forest-resources-assessment-explained-in-5-graphics-2/

Heilmayr, R., Echeverría, C., & Lambin, E. F. (2020). Impacts of Chilean forest subsidies on forest cover, carbon and biodiversity. *Nature Sustainability*, *3*(9), 701–709. https://doi.org/10.1038/s41893-020-0547-0

Holmgren, P. (2015a, September 7). The new global assessments and the forest. *FORESTS NEWS*. https://forestsnews.cifor.org/32995/the-new-global-assessments-and-the-forest#.VgEo37TbTaE

Holmgren, P. (2015b, October 5). Can we trust country-level data from global forest assessments? *FORESTS NEWS*. https://forestsnews.cifor.org/34669/can-we-trust-country-level-data-from-global-forest-assessments?fnl=en

ICIJ. (2023, March 1). *About the Deforestation Inc. investigation*. https://www.icij.org/investigations/deforestation-inc/about-deforestation-inc-investigation/

IKEA. (2023a). *Taking action to protect biodiversity*. https://about.ikea.com/en/sustainability/wood-forestry/is-wood-sustainable/biodiversity-through-forestry

IKEA. (2023b). *The IKEA forest positive agenda*. https://about.ikea.com/en/sustainability/wood-forestry/forestry-beyond-our-business/ikea-forest-positive-agenda

IKEA Foundation. (2023). *Themes and thematic areas*. https://ikeafoundation.org/themes/

Karger, D. N., Kessler, M., Lehnert, M., & Jetz, W. (2021). Limited protection and ongoing loss of tropical cloud forest biodiversity and ecosystems worldwide. *Nature Ecology & Evolution*, *5*(6), 854–862. https://doi.org/10.1038/s41559-021-01450-y

Kinda, H., & Thiombiano, N. (2021). The effects of extractive industries rent on deforestation in developing countries. *Resources Policy*, *73*. https://doi.org/10.1016/j.resourpol.2021.102203

Lenzen, M., Moran, D., Kanemoto, K., Foran, B., Lobefaro, L., & Geschke, A. (2012). International trade drives biodiversity threats in developing nations. *Nature*, *486*(7401), 109–112. https://doi.org/10.1038/nature11145

Lokonon, B. O. K., & Mounirou, I. (2019). Does foreign direct investment impede forest area in Sub-Saharan Africa? *Natural Resources Forum*, *43*, 230–240. https://doi.org/10.1111/1477-8947.12186

Miyamoto, M. (2020). Poverty reduction saves forests sustainably: Lessons for deforestation policies. *World Development*, *127*. https://doi.org/10.1016/j.worlddev.2019.104746

Moog, S., Spicer, A., & Böhm, S. (2015). The politics of multi-stakeholder initiatives: The crisis of the Forest Stewardship Council. *Journal of Business Ethics*, *128*(3), 469–493. https://doi.org/10.1007/s10551-013-2033-3

Muhammad, B., Khan, M. K., Khan, M. I., & Khan, S. (2021). Impact of foreign direct investment, natural resources, renewable energy consumption, and economic growth on environmental degradation: evidence from BRICS, developing, developed and global countries. *Environmental Science and Pollution Research*, *28*, 21789–21798. https://doi.org/10.1007/s11356-020-12084-1/Published

Natural History Museum. (2022). *Biodiversity indicators*. https://www.nhm.ac.uk/our-science/data/biodiversity-indicators.html

Natural History Museum. (2023a). *About the Biodiversity Intactness Index*. https://www.nhm.ac.uk/our-science/data/biodiversity-indicators/about-the-biodiversity-intactness-index.html

Natural History Museum. (2023b). *What is the Biodiversity Intactness Index?* https://www.nhm.ac.uk/our-science/data/biodiversity-indicators/what-is-the-biodiversity-intactness-index.html

NDR. (2023, March 2). *Illegaler Holzhandel: Norddeutsche Firmen unter Verdacht*. https://www.ndr.de/nachrichten/info/Illegaler-Holzhandel-Norddeutsche-Firmen-unter-Verdacht,tropenholz120.html

Nestlé. (2023). *Becoming Forest Positive*. https://www.nestle.com/sustainability/nature-environment/forest-positive

Newbold, T., Hudson, L. N., Arnell, A. P., Contu, S., De Palma, A., Ferrier, S., Hill, S. L. L., Hoskins, A. J., Lysenko, I., Phillips, H. R. P., Burton, V. J., Chng, C. W. T., Emerson, S., Gao, D., Pask-Hale, G., Hutton, J., Jung, M., Sanchez-Ortiz, K., Simmons, B. I., … Purvis, A. (2016). Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. *Science*, *353*(6296), 288–291. https://doi.org/10.1126/science.aaf2201

Okereke, C., & Stacewicz, I. (2018). Stakeholder perceptions of the environmental effectiveness of multi-stakeholder initiatives: Evidence from the palm oil, soy, cotton, and timber programs. *Society and Natural Resources*, *31*(11), 1302–1318. https://doi.org/10.1080/08941920.2018.1482037

Paiva, P. F. P. R., de Lourdes Pinheiro Ruivo, M., da Silva Júnior, O. M., de Nazaré Martins Maciel, M., Braga, T. G. M., de Andrade, M. M. N., dos Santos Junior, P. C., da Rocha, E. S., de Freitas, T. P. M., da Silva Leite, T. V., Gama, L. H. O. M., de Sousa Santos, L., da Silva, M. G., Silva, E. R. R., & Ferreira, B. M. (2020). Deforestation in protect areas in the Amazon: A threat to biodiversity. *Biodiversity and Conservation*, *29*(1), 19–38. https://doi.org/10.1007/s10531-019-01867-9

Pearce, F. (2018, October 9). Conflicting data: How fast is the world losing its forests? *Yale Environment 360*. https://e360.yale.edu/features/conflicting-data-how-fast-is-the-worlds-losing-its-forests

Pendrill, F., Persson, U. M., Godar, J., Kastner, T., Moran, D., Schmidt, S., & Wood, R. (2019). Agricultural and forestry trade drives large share of tropical deforestation emissions. *Global Environmental Change*, *56*, 1–10. https://doi.org/10.1016/j.gloenvcha.2019.03.002

Pradhan, A. K., Sachan, A., Sahu, U. K., & Mohindra, V. (2022). Do foreign direct investment inflows affect environmental degradation in BRICS nations? *Environmental Science and Pollution Research*, *29*, 690–701. https://doi.org/https://doi.org/10.1007/s11356-021-15678-5

R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.r-project.org/

Ritchie, H., & Roser, M. (2021). *Deforestation and forest loss*. Our World in Data. https://ourworldindata.org/deforestation

Rudel, T. K., Coomes, O. T., Moran, E., Achard, F., Angelsen, A., Xu, J., & Lambin, E. (2005). Forest transitions: Towards a global understanding of land use change. *Global Environmental Change*, *15*(1), 23–31. https://doi.org/10.1016/j.gloenvcha.2004.11.001

Seymour, F. (2023). *Why are tropical forests being lost, and how to protect them*. World Resources Institute . https://research.wri.org/gfr/tropical-forests-loss-deforestation-protection

Slough, T., Kopas, J., & Urpelainen, J. (2021). Satellite-based deforestation alerts with training and incentives for patrolling facilitate community monitoring in the Peruvian Amazon. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(29). https://doi.org/10.1073/PNAS.2015171118/-/DCSUPPLEMENTAL

Sustainable Forestry Initiative. (2023). *SFI conservation grant projects*. https://forests.org/conservationgrants/

Tsurumi, T., & Managi, S. (2014). The effect of trade openness on deforestation: empirical analysis for 142 countries. *Environmental Economics and Policy Studies*, *16*(4), 305–324. https://doi.org/10.1007/s10018-012-0051-5

van den Bergh, J. C. J. M. (2009). The GDP paradox. *Journal of Economic Psychology*, *30*(2), 117–135. https://doi.org/10.1016/j.joep.2008.12.001

Velux Foundation. (2023). *Climate change, biodiversity & forest products*. https://veluxstiftung.ch/funding-areas/forestry/

Vivid Economics, & Natural History Museum. (2020). *The urgency of biodiversity action*. https://www.vivideconomics.com/wp-content/uploads/2021/02/210211-The-Urgency-of-Biodiversity-Action.pdf

Watson, J. E. M., Evans, T., Venter, O., Williams, B., Tulloch, A., Stewart, C., Thompson, I., Ray, J. C., Murray, K., Salazar, A., McAlpine, C., Potapov, P., Walston, J., Robinson, J. G., Painter, M., Wilkie, D., Filardi, C., Laurance, W. F., Houghton, R. A., … Lindenmayer, D. (2018). The exceptional value of intact forest ecosystems. In *Nature Ecology and Evolution* (Vol. 2, Issue 4, pp. 599–610). Nature Publishing Group. https://doi.org/10.1038/s41559-018-0490-x

Weisse, M., & Goldman, L. (2022, April 28). *Forest loss remained stubbornly high in 2021*. Global Forest Watch Blog. https://www.globalforestwatch.org/blog/data-and-research/global-tree-cover-loss-data-2021/

Weisse, M., Potapov, P., Goldman, L., Carter, S., & Reytar, K. (2022, October 19). *Exploring new tree cover gain and net change on Global Forest Watch*. Global Forest Watch Blog. https://www.globalforestwatch.org/blog/data-and-research/new-gfw-tree-cover-gain-net-change-data/

Wickham, H. (2016). Package `ggplot2`: Elegant graphics for data analysis. *Springer-Verlag New York*.

World Bank. (2021). *The changing wealth of nations 2021: Managing assets for the future*. https://openknowledge.worldbank.org/handle/10986/36400

World Bank. (2023a). *Foreign direct investment, net inflows (% of GDP)*. World Development Indicators. https://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS?quantity=1

World Bank. (2023b). *GDP per capita (current US$)*. World Development Indicators. https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?quantity=1

World Bank. (2023c). *Trade (% of GDP)*. World Development Indicators. https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS?quantity=1

World Resources Institute. (2023). *Indicators of forest extent: Forest loss*. World Resources Institute - Global Forest Review. https://research.wri.org/gfr/forest-extent-indicators/forest-loss?utm_campaign=treecoverloss2021&utm_medium=bitly&utm_source=GFWBlog#how-much-tree-cover-is-lost-in-tropical-versus-temperate-and-boreal-forests

WWF. (2022). *Living Planet Report 2022 – Building a nature-positive society*. https://www.wwf.org.uk/our-reports/living-planet-report-2022

WWF. (2023). *Russell E. Train Education for Nature Program*. https://www.worldwildlife.org/initiatives/russell-e-train-education-for-nature

Appendix

Table A1

Results of the Random Effect Model for 'Forest Area Net Change FRA'

Coefficients	Estimate	Standard error	z-value	p-value
Intercept	-9.30e-4	3.18e-3	-0.292	0.770
FDI [% GDP]	2.37e-4	1.09e-4	2.181	**0.029**
GDP per capita [current US$]	-1.06e-7	6.22e-8	-1.712	0.087
Trade [% GDP]	-2.07e-5	2.74e-5	-0.754	0.451
Model parameters				
Total sum of squares	0.0010295			
Residual sum of squares	0.00098887			
R-Squared	0.039458			
Adj. R-Squared	0.022203			
Chi-squared	6.86024			
Degrees of freedom	3			
p-value	0.076488			

Note. Statistical significance is specified at $p < 0.05$. The p-values of statistically significant effects are printed bold.

Table A2

Results of the Random Effect Model for 'Deforestation FRA'

Coefficients	**Estimate**	**Standard error**	**z-value**	**p-value**
Intercept	5.8300e-03	1.4187e-03	4.1095	**< 0.001**
FDI [% GDP]	-1.4528e-05	4.4744e-05	-0.3247	0.745
GDP per capita [current US$]	-1.4030e-07	3.7116e-08	-3.7800	**< 0.001**
Trade [% GDP]	1.5407e-05	1.3390e-05	1.1506	0.250
Model parameters				
Total sum of squares	0.00047415			
Residual sum of squares	0.00043645			
R-Squared	0.079521			
Adj. R-Squared	0.062986			
Chi-squared	15.0744			
Degrees of freedom	3			
p-value	0.0017542			

Note. Statistical significance is specified at $p < 0.05$. The p-values of statistically significant effects are printed bold.

Table A3

Results of the Fixed Effect Model for 'Deforestation GFW'

Coefficients	Estimate	Standard error	z-value	p-value
FDI [% GDP]	1.7708e-04	2.0561e-04	0.8612	0.390
GDP per capita [current US$]	2.6573e-07	8.4568e-08	3.1422	**0.002**
Trade [% GDP]	4.1344e-05	3.4748e-05	1.1898	0.236
Model parameters				
Total sum of squares	0.0012217			
Residual sum of squares	0.0010796			
R-Squared	0.11632			
Adj. R-Squared	0.05519			
Chi-squared	5.16954			
Degrees of freedom	3 and 8			
p-value	0.028135			

Note. Statistical significance is specified at $p < 0.05$. The p-values of statistically significant effects are printed bold.

Table A4

Results of the Random Effect Model for 'Biodiversity Intactness Index'

Coefficients	Estimate	Standard error	z-value	p-value
Intercept	7.3828e-01	2.8234e-02	26.1483	**< 2.2e-16 *****
Deforestation FRA	1.6358	5.9561e-01	2.7464	**0.006024 ****
Forest area net change FRA	2.9202e-01	3.5752e-01	0.8168	0.414046
Deforestation GFW	-9.4961e-01	3.0216e-01	-3.1427	**0.001674**
FDI [% GDP]	3.2857e-04	2.9263e-04	1.1228	0.261516
GDP per capita [current US$]	-2.0442e-06	2.3847e-07	-8.5722	**< 2.2e-16**
Trade [% GDP]	1.9435e-04	6.7540e-05	2.8775	**0.004008**
Model parameters				
Total sum of squares	0.021503			
Residual sum of squares	0.0091156			
R-Squared	0.57608			
Adj. R-Squared	0.56058			
Chi-squared	180.187			
Degrees of freedom	6			
p-value	< 2.22e-16			

Note. Statistical significance is specified at $p < 0.05$. The p-values of statistically significant effects are printed bold.

Table A5

Results of the Random Effect Model for 'Biodiversity Intactness Index'

Coefficients	Estimate	Standard error	z-value	p-value
Intercept	7.4590e-01	5.7653e-02	12.9377	**< 0.001**
FDI [% GDP]	2.3330e-04	2.4668e-04	0.9458	0.344
GDP per capita [current US$]	-2.5503e-06	1.8229e-07	-13.9903	**< 0.001**
Trade [% GDP]	1.6905e-04	6.1757e-05	2.7373	**0.006**
Model parameters				
Total sum of squares	0.020197			
Residual sum of squares	0.0088399			
R-Squared	0.56231			
Adj. R-Squared	0.55445			
Chi-squared	199.907			
Degrees of freedom	3			
p-value	< 2.22e-16			

Note. Statistical significance is specified at p < 0.05. The p-values of statistically significant effects are printed bold.

Table A6

Comparison of the Mean Values of Deforestation FRA and Deforestation GFW for the Years 2001-2019

Country	Deforestation FRA	Deforestation GFW
Argentina	0.83%	0.86%
Bolivia	0.39%	0.49%
Brazil	0.64%	0.60%
Chile	0.07%	0.55%
Colombia	0.31%	0.29%
Ecuador	0.75%	0.23%
Paraguay	1.78%	1.51%
Peru	0.23%	0.21%
Uruguay	0.05%	0.99%

Note. Own representation of own calculations based on GFW and FRA data (FAO, 2023; Global Forest Watch, 2023a).