Identifying the determinants of deforestation and forest disturbances in tropical moist forests.

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Diplôme : Master en sciences économiques, orientation générale, à finalité spécialisée en economic, analysis and policy
Année académique : 2021-2022
URI/URL : http://hdl.handle.net/2268.2/15438

HEC LIÈGE
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Identifying the determinants of deforestation and forest disturbances in tropical moist forests.

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Master thesis by
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For a Master in Economic
Analysis and Policy
Academic year 2021/2022

Acknowledgements

First of all, it seems appropriate to start this master thesis report by thanking those who took their time to help me put this work in the right direction, and lead it to its term.

Foremost, I would like to express my sincere gratitude to my supervisor, Professor Artige, whose trust and support helped me in all the time of research and writing of this work. His enthusiasm, pieces of advice, and his availability made this research an enjoyable experience.

I also would like to address the warmest thanks to my committee members, Mr. Hébert and Professor Lejeune, for sharing with me their immeasurable expertise. Their perfectly nuanced, and judiciously chosen recommendations have allowed the general coherence of this thesis, as well as its relevance.

My gratitude also goes to Mrs. Ulm, for her expertise and kindness which helped me with the econometric part of this work.

This thesis allowed me to refine certain tracks and desires concerning my future professional project, and I thank all those who could, in one way or another, be part of it.

Of course, I do not forget all my relatives who accompanied and supported me at each step of the elaboration of this thesis. I thank in particular Anne Vanerum and Heather Hastie, for their numerous and diligent proofreadings, as well as Sandrine Kempeneers and Laurent Barvaux for their unwavering confidence.

For her enlightened advice and her daily moral support, I also address my warmest thank to Marie Dupuis, who really allowed me to go through these weeks of hard work more serenely.

This thesis is the culmination of my university studies, closing a period rich in meetings, learning, and experiences. Thank you all for your contribution.

Preface

This Master's thesis was written for the accomplishment of the Economic Analysis and Policy Master at HEC Liège, part of the University of Liège. It was supervised by Lionel Artige, professor at HEC Liège, as well as by Mister Hébert and Professor Lejeune, members of the reading committee.

Environmental issues have always been part of my interest. I consider no bigger challenge than the climatic and environmental one, and I am decided to make my contribution to the fight against climate change. Some lectures offered at H.E.C. such as *Economic growth and sustainable development* given by Professor Artige, or *Economie du développement* given by Professor Tharakan, strengthened my motivation to investigate such a topic.

Working on tropical moist forests made sense because of the importance of such forests at a worldwide level. However, the complexity of these environments, as well as their extent, did not ease the task. Thanks to M. Hébert, however, it has been possible to better understand the different issues at stake in such a subject and to study forest loss in the tropics in a consistent way.

As this thesis is supposed to end my Master's degree at HEC, and considering the importance of econometrics on my whole journey at the University, it seemed obvious to give empirical estimations a special place in this work. It is also a way to perform for the very first time an empirical study, from the beginning.

IV

Contents

List of abbreviations

ASM: Amazon Soy Moratorium

CO2: Carbon dioxide

CPI: Consumer Price Index

CRE: Correlated Random Effect

DRC: Democratic Republic of the Congo

EKC: Environmental Kuznets Curve

ENSO: El Niño – Southern Oscillation

EU: European Union (broad meaning)

EU27: European Union (Post-Brexit meaning)

FAO: Food and Agriculture Organization

FE: Fixed Effects Model

FLEGT: Forest Law Enforcement, Governance and Trade

FTM: Forest Transition Model

GDP: Gross Domestic Product

ha: Hectare

kg: Kilogram

LCU: Local Currency Unit

m^3: Cubic meter

mm: millimeter

MPI: Multidimensional Poverty Index

NASA: National Aeronautics and Space Administration

ODA: Official Development Aid

RE: Random Effects Model

REDD+: Reducing emissions from deforestation and forest degradation in developing countries

SFM: Sustainable Forest Management

TMFs: Tropical Moist Forests

UNFCCC: United Nations Framework Convention on Climate Change

Glossary

Autocorrelation (or Serial Correlation) : In a time series or panel data model, correlation between the errors in different time periods. (Wooldridge (2015)). 40

Correlated Random Effects : An approach to panel data analysis where the correlation between the unobserved effect and the explanatory variables is modeled, usually as a linear relationship. (Wooldridge (2015)). VII

Deforestation : The complete permanent removal of trees for the conversion of forest to another land use such as agriculture, mining, or towns and cities. (Ritchie and Roser (2021)). 11

Dutch disease : Phenomenon expressing how some countries may neglect some sectors of their economy because of important natural resources, such as fossil fuel for example. (Megevand and Mosnier (2013)). 13

El Niño − Southern Oscillation : A climatic phenomenon resulting in large positive anomalies in the surface temperature of the central and eastern Pacific Ocean. These anomalies occur on time scales ranging from biennial to decadal. (Vancutsem et al. (2021)). 16

Endogeneity : A term used to describe the presence of an endogenous explanatory variable. (Wooldridge (2015)). 19

Endogenous Explanatory Variable : An explanatory variable in a multiple regression model that is correlated with the error term, either because of an omitted variable, measurement error, or simultaneity. (Wooldridge (2015)). 50

Exogenous Explanatory Variable : An explanatory variable in a multiple regression model that is correlated with the error term, either because of an omitted variable, measurement error, or simultaneity. (Wooldridge (2015)). 21

Fixed Effects Model : An unobserved effects panel data model where the unobserved effects (fixed over time) are allowed to be arbitrarily correlated with the explanatory variables in each time period. (Wooldridge (2015)). VII

Forest degradation : A thinning of the canopy – a reduction in the density of trees in the area – but without a change in land use. The changes to the forest are often temporary and it is expected that they will regrow. (Ritchie and Roser (2021)). 15

Forest disturbances : Synonym of forest loss, used both to describe forest degradation or deforestation. 4

Heteroskedasticity : The variance of the error term, given the explanatory variables, is not constant. (Wooldridge (2015)). 40

Homoskedasticity : The errors in a regression model have constant variance conditional on the explanatory variables. (Wooldridge (2015)). 40

Idiosyncratic Error : In panel data models, the error that changes over time as well as across units (say, individuals, firms, or cities). (Wooldridge (2015)). 40

Neotropics : A zoogeographical or phytogeographical region comprising Central and South America, including the tropical southern part of Mexico and the Caribbean. (Oxford Language (2022). 6

Random Effects Model : The unobserved effects panel data model where the unobserved effect is assumed to be uncorrelated with the explanatory variables in each time period. (Wooldridge (2015)). VII

Tropical Moist Forests : Tropical Moist Forests (TMFs) contain two main forest types: the tropical rain forests and the tropical moist deciduous forests. The first type experiences constant humid climate with almost no variation in rainfall across the year, while the second one experiences a distinct dry season. Tropical moist deciduous forest is also sometimes called "monsoon forest". Whether one considers one or the other category, TMFs are especially developed on regions which experience humid climate (2000mm/year) with relatively constant temperatures. Gallery forests, created by the presence of a river in a drier region, may also be listed as tropical moist forests (Vancutsem et al. (2021)). 4

Introduction

The growing concern about climate change and global warming has been dragging the researchers' interest for years, and the number of studies working on such matters has been soaring since the 80's. Tropical moist forests have proved themselves primordial in the worldwide fight against climate change. Because of their incredible capacity to store and transform carbon, regulate temperature, and enable the proper functioning of the water cycle, tropical moist forests, and their management, have become a point of focus in this challenge the world has to take up. This thesis aims to make its contribution to the challenge by trying to identify and rank drivers and determinants of forest loss occurring in tropical moist forests.

Works on tropical forest loss have been lacking reliable data for years. The launching of the first version of Landsat in July 1972 surely initiated the building of a trustworthy database, but it took decades to analyse forest loss at an accurate enough level of precision. Previous studies took often the form of synthesis or meta-analysis, basing their conclusions on surveys or on a few "relevant" on-site observations. When empirical studies were carried out, they were often based on too small samples, studying a too short time period, or using incomplete or unreliable data. analysing drivers of forest disturbances at the national level was therefore not recommended, thus many studies have been conducting spatial econometric analyses, at the regional or sub-regional level. This thesis tends to enjoy the recent availability of reliable data about forest loss in tropical areas at the national level. The dataset made available by the European Commission, and constructed by Vancutsem et al. (2021), indeed provides reliable data about tropical moist forests, for the period between 1990 and 2020. Based on the 8th version of the Landsat project, this database provides information with an unprecedented level of precision, as the imagery allows to detect forest loss of 0.09 hectare. It also allows to distinguish between deforestation and forest degradation. This possibility of distinction between permanent and temporary loss constitutes a strong improvement allowing to palliate some recurrent limitations and drawbacks of previous studies.

The availability of reliable data at the national level has pushed this work to analyse forest loss by performing an econometric study at the macro level. If spatial econometrics have been fostered in previous studies, it could be due to the lack of information at the country or continental level. With this restriction lifted, nothing prevented this thesis to carry out analyses on a national scope. As the work of Vancutsem et al. (2021) presents a panel dataset of 34 countries on 30 years, fixed effects estimation should be considered. Such an estimations method could indeed allow to account for fixed features of countries, limiting therefore the risk of omitted variables bias.

This thesis tends to analyse tropical moist forest loss from the most comprehensive perspective possible, by trying to account for each particularity of the phenomenon. Nonetheless, the relevance of information presented in such a study should be the key to its results. Which is why the first part of this thesis consists of a literature review, which aims to be as exhaustive as possible. After a short review of methodologies used in previous studies, the one applied in this work will be detailed, such as the reasons explaining this choice. The third part will consist of the presentation of our database, with its advantages and particularities, before going into the part dedicated to the presentation and interpretations of the results. At the end of this thesis will be presented some conclusions about our

work.

This work aims to study the phenomenon of forest disturbances in tropical moist regions in a way that breaks up with overly complex analyses, dealing with a too narrow geographical scope, or presenting irrelevant or diverted conclusions. As everyone should bear a part of the climatic burden, information should be understandable by all. Even if this thesis is supposed to be readable by people without any particular knowledge or background, strong attention has been paid to the precision of the vocabulary. In this view, a glossary is presented at the beginning of this work. It contains definitions of technical terms related to the forest domain, to econometrics, and to economics. Conclusions are drawn and transposed carefully in order to answer the research question. However, it would be illusory to hope to have straightforward conclusions on such a complex matter as tropical moist forest loss. Conclusions have therefore been built in order to form the most homogeneous mix between clarity and nuances.

Readers should bear in mind that working on drivers of deforestation and forest disturbances should help policymakers to develop efficient ways to fight it. Even if local policies must be set up, such a worldwide matter requires interventions at a larger scale. If the global perspective does not seem to be appropriate, continental, or at least regional, aggregation should give decisions makers some models or patterns to work with, in order to design efficient policies. This point of view is shared by a few articles, reports, and books, which will constitute the general basement of this thesis, in terms of perspective followed. The works of Megevand and Mosnier (2013), Vancutsem et al. (2021), Busch and Ferretti-Gallon (2020), and Scrieciu (2007), all consider the phenomenon of forest deterioration from a relatively broad perspective. These authors all foster the main goal of analysing drivers of forest disturbances, which is to help policymakers design efficient policies to face the climatic challenge. By working on a continental basis, but allowing for national specificities, these authors emphasize the importance of facing such a challenge at a global or continental level. Besides their common geographical approaches, these works also aim to comprehensively study deforestation and forest degradation. Some papers in the literature clearly lack pieces of information, skipping some part of the problem, or ignoring some specificities. Even if these studies bring additional information to the understanding of the topic, they cannot be considered as being part of the core of this analysis. The four works chosen to form the basement of this thesis pursue an in-depth analysis of the causes of forest loss, whether it is by dressing a quasi-exhaustive meta-analysis of the topic, or by paying attention to every single detail in their econometric analyses. This thesis will try to follow the path these works have already taken, by first working on a continental basis, and secondly by analysing the phenomenon as comprehensively as possible.

Literature review

1.1 Forests overview

Forests are present all over the world, excluding the poles, and cover an area of 4.06 billion hectares. That is almost one third of the total land area of the Earth (FAO (2020)). This observation increases even up to 38% if we consider only habitable land areas (Ritchie and Roser (2021)). The country with the largest forest cover is Russia with approximately 815 million hectares of land occupied (Figure A.2). The second largest is Brazil with almost 500 million hectares. Together, these nations accounted for approximately 32% of the total area covered by forests in 2020 (FAO (2020)). Countries might also be compared in relative terms by looking at their shares of land covered by forests. Even if Brazil and Russia display ratios (59.4% and 49.8%) above the European Union[1] and the USA (39,8% and 33,9%), these figures are still far from those displayed by the countries with the highest shares of land covered by forests. With 97.4% of its territory being occupied by forests, Suriname was the most forested country in 2020. It is followed by the French Guyana and Guyana, while Gabon is in fifth place in this ranking and Papua New Guinea closes the top 10, only constituted by tropical and equatorial countries (Figure A.1).

However, different kinds of forest must be distinguished. According to FAO and UNEP (2020), there exists 60 082 tree species but the report of FAO (2020) regroups forest areas into four main subcategories, depending on climate conditions these regions are experiencing. The FAO considers 4 types of forests, depending on climatic domain: the boreal, temperate, subtropical and tropical forests. The tropical ones are prevalent with, according to FAO (2020), 1 834 136 thousands of hectares, followed in second position by boreal forests with 1 109 871 thousands of hectares. These ecosystems face completely distinct challenges and should therefore be treated separately. The FAO also makes the distinction between naturally regenerated forests and planted forests, which represents respectively 93% and 7% of global forests. Ritchie and Roser (2021) decompose these 93% between primary forests and regenerated ones, for respectively 61% and 32%. The FAO defines primary forests as "naturally regenerated forest of native species, where there are no clearly visible indications of human activities and the ecological processes are not significantly disturbed", while naturally regenerated ones are forests where there are clearly visible indications of human activities. It includes "selectively logged-over areas, areas regenerating following agricultural land use, areas recovering from human-induced fires, etc." (Ritchie and Roser (2021)).

The above paragraphs seem to suggest the immutability of the cited figures. However, the above statements must be understood as a current overview of the world's forests. The forest cover has indeed been subjected to mutation for thousands of years. Since its global recovery after the last ice age 10 000 years ago, the world has lost approximately one third of its forests. However, half of this loss would have occurred in the last century (Ritchie and Roser (2021)). Forest loss is actually a generic term for two different kinds of forest disturbances: deforestation and degradation. Deforestation is defined by Ritchie and Roser (2021) as "the complete removal of trees for the conversion of forest to

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[1]EU27

another land use such as agriculture, mining, or towns and cities". The idea is that the tree loss is permanent. The authors note that this permanent conversion can take two different forms: either the forest is transformed into another land uses for agriculture, mining or energy infrastructures , or into cities, towns, and roads. The first one is called "Commodity-driven deforestation" and the second one "urbanization". Degradation, on the opposite, suggest the temporary aspect of the forest loss. Trees are expected to regrow. Ritchie and Roser (2021) cite 3 types of degradation: shifting agriculture, forestry production and wildfires. The first concept is the temporary conversion of small area of forest for local subsistence agriculture. Forestry production implies the exploitation of planted forests, as a system to create value. Wildfires are episodic but can lead to serious damages as it has been experienced by some countries during some episodes of extreme drought. Figure 1.1 gives an example for each case of deforestation and forest degradation. Speaking for the Amazon region, Le Tourneau (2015) notes that Forest disturbances have always existed, but that the permanent aspect of forest loss is quite new. The permanence of the loss is really a central notion in the debate.
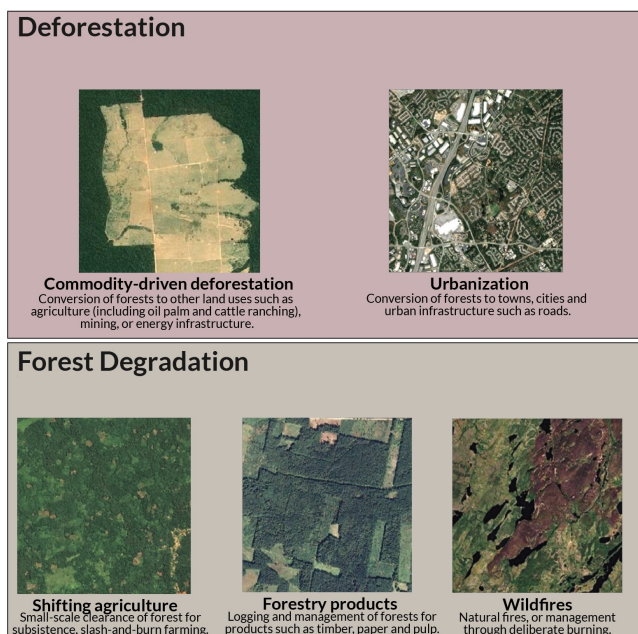
Forest losses do not bear the same consequences whether it occurs in primary forest or in planted forest, and it seems pretty straightforward to understand. By disturbing primary forest, the human activity impact irrevocably an ecosystem (Ritchie and Roser (2021)). According to FAO and UNEP (2020), almost half of the world's species live in tropical forests which makes each hectare of loss in tropical area more damaging for the global biodiversity than in any other forested area. It is even more true as many tropical species of animals and plants are endemic. In term of stock of C02, Karsenty (2021) asserts that approximately 55% of the global stock of carbon dioxide retained by trees is kept in tropical forests. By working as carbon sinks, forests bear even more responsibility in the fight against climate change. In light of this, the fact that the quasi totality of global annual deforestation occurs in the tropics, with 59% in Latin America and 28% in Southeast Asia, should be a concern (Ritchie and Roser (2021)). Even if the majority of forest degradation occurs in temperate forest according to Ritchie and Roser (2021), Vancutsem et al. (2021) assert that almost half cases of degradation is followed by deforestation. The role of degradation should not be underestimated. This idea is supported by Karsenty (2021) who notes that between 2010 and 2020, degradation of forested areas would have emitted three times more CO2 than deforestation, regarding the Brazilian Amazon.

Figure 1.1: Deforestation versus forest degradation: types and examples

Source: Our World In Data

This work, as the article of Vancutsem et al. (2021), focuses though on tropical moist forests (TMFs). Vancutsem et al. (2021) explain that TMFs contain two main forest types: the tropical rain forests and the tropical moist deciduous forests. The first type experiences constant humid climate with almost no variation in rainfall across the year, while the second one experiences a distinct dry season. The authors add that tropical moist deciduous forest is also sometimes called "monsoon forest". Whether one considers one or the other category, TMFs are especially developed on regions which experience humid climate (2000mm/year) with relatively constant temperatures. Gallery forests, created by the

presence of a river in a drier region, may also be listed as TMFs (Vancutsem et al. (2021)). Figure 1.2 gives an overview of the localisation of TMFs as they were in 1990.
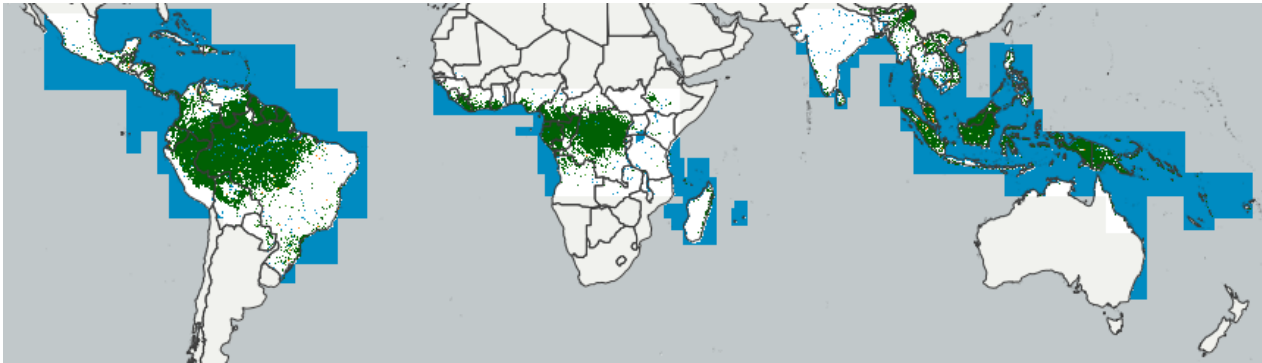

Figure 1.2: Tropical Moist Forests across the world in 1990

Source: EC JRC

This work will analyse drivers of forest disturbances between 1991 and 2020, on an annual basis. The studied time period, as well as the geographical area our work is working on, correspond to those chosen by Vancutsem et al. (2021). The geographical area obviously fits with the location of TMFs presented in figure 1.2, and regroups 33 tropical, sub-tropical and equatorial countries. These nations are depicted in figures A.1, A.2, and A.3 in the appendices. Table 3.3 also lists the studied countries by continent. The studied nations are located on the American continent, in Africa, and in Asia. The rest of our work will use the concept of "world" to refer to the whole set of countries included in our sample. It will be the same when using continental aggregates for example. Forest loss will obviously refer to tropical moist forest loss which would have occurred on our studied time span. The purpose of these shortcuts is to facilitate the reading of this work, by avoiding the heaviness that could be caused by the repetition of details that could just be implied.

1.2 Global versus local perspective

It is important to understand that the evaluation of resources as vast as forests is a constant work of estimation. Thanks to technology improvement, these estimations are getting everyday more solid and precise. The dataset made available by the European Commission and constructed by Vancutsem et al. (2021) is the result of years of improvement through Landsat development. Researchers have not always had such a precise dataset, which is why estimations, conclusions and theories, should be taken carefully. The launching of the first version of Landsat in July 1972 surely was the beginning of a new era of estimation, but it took decades to get a proper dataset policymakers could rely on. Through continuous succession of Landsat versions, NASA has been able to provide a continuous set of imagery for more than 30 years. The work of Vancutsem et al. (2021) relies on the 8th version of the Landsat technology, launched in February 2013. The 9th version has just been launched in 2021, continuously securing Earth imagery availability. Just in the same way we pay attention to who is the author of a paper, we should pay attention to when this paper has been written. Depending on data availability, precision and literature development, determinants this work tries to identify could be under or overestimated. Our work, based on the dataset of Vancutsem et al. (2021), will provide an empirical view of the situation, without having to question precision of data.

One also have to keep in mind that even if we try to regroup hundreds of millions of hectares under the same name, TMFs' challenges and stakes may greatly vary across the globe. Scrieciu (2007) argues

in his article that trying to identify economic causes of deforestation at a global level could be illusory. The paper shows that conclusions about worldwide determinants of deforestation lose significance beyond statistically acceptable levels when serial correlation is accounted for. The author criticizes some papers performing econometric analyses without correcting for serial correlation, but more than the econometric analyses, it is the idea of a unique model of deforestation which is challenged. A few years later, Armenteras et al. (2013) studied deforestation in Colombia using General Linear Models. The national perspective of this analysis was even detailed into some geo-ecological regions of Colombia. The concept and use of national borders when speaking about forest is questioned by the article. Armenteras et al. (2013) prefer the idea of geo-ecological or socioeconomic borders when dealing with deforestation. In the same vein, Twongyirwe et al. (2018) focus on western Uganda in their analysis. The methodology is strongly different as they conducted surveys of residents to capture the perception of the local population about deforestation. However, the idea is similar, as the authors criticize studies dealing with a too large territorial scope, which would then fail to capture local effects and particularities. To another extent, Margulis (2004) focuses on Brazilian Amazon for his analysis. The size of the studied area should not lead us to think that the point of view is different. The author chose to deal with a particular area because he is convinced that the drivers of deforestation he is analysing are particular to the region. Note that Margulis (2004) also questioned the relevance of national border in such a matter which is why he sometimes chose to use "economic borders" instead.

However, the risk with such a narrow perspective and level of detail is going too deep into microeconomics specifications and not being able to set up policies because no pattern would have been found. Jiagho and Banoho (2021) perform a quite comprehensive synthesis of drivers of deforestation and degradation of the woody cover in the national park of Waza in Cameroon. Even if the elements brought are interesting and allow in a certain way to understand factors leading to forests deterioration, they do not allow us to set up a model of analysis that could be transposed into some other African countries. Wassenaar et al. (2007) voluntarily break away from the narrow perspective discussed above in order to distance themselves from overly complex articles on regional determinants. By performing their projections on what they call "the Neotropics", they promote a continental point of view and are able to draw some patterns and projections for different countries and regions. More recently, the book written by Megevand and Mosnier (2013) and published by the World Bank focused on drivers of deforestation in the Congo Basin, regrouping 6 African countries. Karsenty (2021) also encourages a broader view of the problem as he looks at the geopolitics of tropical forests without making the distinction between regions the core of his article.

We should bear in mind that working on drivers of deforestation and forest disturbances should help policymakers to develop efficient ways to fight it. Even if local policies must be set up, such a worldwide matter requires interventions at a larger scale. If the global perspective does not seems to be appropriate, continental, or at least regional, aggregation should give decisions makers some models or patterns to work with, in order to design efficient policies.

1.2.1 Incentives and global consequences

As it has been shortly mentioned earlier in this work, some authors prefer using different kind of borders when speaking about phenomena such as deforestation. If the concept of nationality is discussed, it is partly because consequences of deforestation are not strictly restrained within the national area of a specific country. Taking the example of carbon sink, everybody may acknowledge that the service provided by forests is a worldwide concern. If the effect of carbon sinks is difficult to observe, some benefits from forested areas are far more easily apprehended. Karsenty (2021) speaks about "celestial rivers" created by the transpiration of TMFs which drain humidity through thousands of kilometers across countries. Megevand and Mosnier (2013) also mentioned the role of regulator of the hydrological cycle of the region, such as Walker (1993). The authors also explain that the evapotranspiration of

trees induces less variability in temperatures and climatic conditions. Margulis (2004) notes that the Amazon region counts for almost 20% of the world's freshwater resources. He also notices the equity that bring natural resources such as forests which are indeed assumed to bear a larger proportion of the assets of poor people than rich people. This notion of services provided by the environment is actually opposed to the notion of "resources" which is induced by the availability of natural elements. Karsenty (2021) notes that southern less developed countries generally focus on the "resources" pan, omitting to consider the whole potential of forest. This idea is actually also suggested by Mainardi (1998) and Margulis (2004) without being explicitly presented.

This obvious antagonism actually hides the concept of externality. If it is not explicitly mentioned in the literature, some articles clearly present some marks of this type of market failure. Mainardi (1998) for example speaks about incorrect pricing concerning commercial logging. He argues that the rent price for logging concessions does not take into account the price of reforestation as it should be if the area is deforested. The book from Megevand and Mosnier (2013) asserts that wood is considered as free in many cases. In both cases, incorrect pricing lead to over-exploitation of resources. Busch and Ferretti-Gallon (2020) also assert that economic agents tend to foster private consumption beyond what would be the social optimum if forests were seen from a public perspective. Even if prices were sustainably established, duration of exploitation mandates might also be misleading. Mainardi (1998) notes the difference between Ivory Coast and Gabon. While Gabon grants forest exploitation mandates for a period of 30 years, Ivory Coast grants these mandates for only 5 years. The author asserts that a short-term mandate cannot constitute an incentive to sustainable management of the concession. He supports this hypothesis by displaying deforestation rates for both countries, showing the unquestionable superiority of the Ivorian deforestation level.

If market failures are often an incentive problem, the externality attached to forest deterioration is even more difficult to correct as the undesired negative effect often has an international impact (Walker (1993)). As an illustration, global warming is a worldwide concern but tropical forest management falls under national or regional jurisdiction. Markets are also strongly interconnected and internationalized, which makes responsibilities less obviously determined. The article from Ritchie and Roser (2021) shows that tropical countries are generally losing forest area every year (Figure 1.3). However, it also explains that some part of this loss is due to trade, leading to the idea that countries could actually import and export deforestation through commercial activities. If some countries are currently experiencing positive net change in forest area, perhaps it is done at the expense of tropical forests. This idea is proposed by Ritchie and Roser (2021) but it is also immediately shaded in the same article. Indeed, when speaking about deforestation in its strict form, Ritchie and Roser (2021) assert that 71% of annual deforestation is induced by local demand, leaving 29% to trade. Four tenths of these 29% would effectively go to what the article called "rich countries". Under these circumstances rich countries would actually bear 12% of deforestation in the tropics. If this point of view might be arguable, the impact of international demand is in any case an element to be taken into account. We will by the way discuss it from another perspective later in this work.
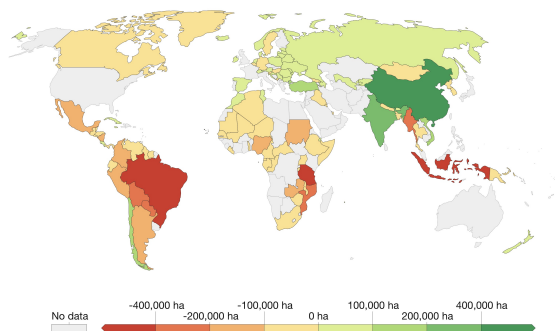
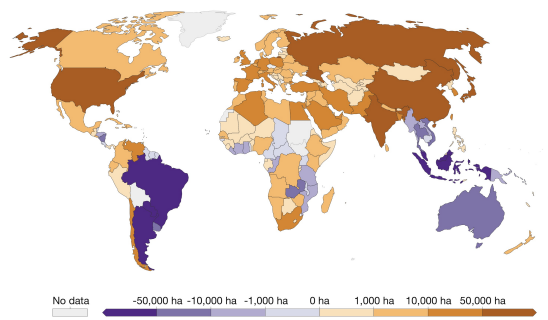Figure 1.3: Annual net forest change, 2015

Source: Our World In Data

Figure 1.4: Trade of deforestation, 2013

Source: Our World In Data

1.2.2 Policies

If consequences of forest loss are a worldwide concern, policies must be taken in accordance. The interactions between countries have pushed nations together in order to build some effective measures to fight forest disturbances. The Kyoto protocol in 1997 is considered as the first international agreement to fight climate change. This protocol recognizes the importance of forests and might be therefore considered as the basis of forests protection measures (Armenteras et al. (2017)). Launched and supported by the United Nations, the REDD+ program, introduced for the first time in 2007 at the UNFCCC Conference of Parties in Bali, aims to mitigate climate change at a global level. It focuses on Reducing Emissions from Deforestation and forest Degradation, and also try to foster the sustainable management of forests, and the conservation and enhancement of forest carbon stocks (Duchelle et al. (2018)). REDD+ is actually a framework aiming to correct incentives leading to deforestation. Countries, organizations and private "investors" can pay a country to not cut down its forests. It can be done through direct payments or through a "carbon credit" exchange system (Bertazzo (2019) and Angelsen (2014)). The report of Kissinger et al. (2012) is built in the framework of REDD+, aiming to identify drivers of forest disturbances in order to help policymakers to implement policies attached to REDD+ in a relevant and efficient way. Adopted in July 2006, the Brazil's Amazon Soy Moratorium (ASM) is also an example of international policy aiming to preserve forests. It is directly the international supply chain of soy which had been targeted as major soybean traders agreed not to buy soy that would have been grown on a land that was not deforested at the time of the signature of the moratorium (Gibbs et al. (2015)). In the same vein, the Forest Law Enforcement, Governance and Trade (FLEGT) initiated by the EU try to encourage sustainable and legal logging by forbidding trade of illegally logged wood in the EU (Megevand and Mosnier (2013)). Note that these mechanisms do not always work and that some criticize what they call a "fad". Rutt et al. (2018) express that kind of critics, explaining that FLEGT had not been really efficient by 2018 namely because of discrepancies between FLEGT goals and hopes, and on-the-ground realities. Nonetheless, some policies have proved themselves useful, in one way or another, and criticisms are just another proof that these measures have to be designed under an in-depth understanding of the context they are supposed to take place in.

1.3 Development and forest deterioration

If some policies aim to help developing countries to deal with deforestation by transferring financial resources from high income countries, it is because forest disturbances and other kinds of environmental degradation are assumed to be part of the natural path of economic development. A largely mentioned

theory in environmental economics is the Environmental Kuznets Curve (EKC). This theory supposed an inverted U-shaped curve between the level of some pollutants or degradation and the level of income per capita (figure 1.5). Environmental deterioration is supposed to increase with the wealth of a country up to a certain level where the additional unity of wealth is assumed to present negative marginal environmental degradation. As wealth is often taken as a proxy for development level, the EKC actually considers the relationship between development level and environmental deterioration (Dinda (2004)).
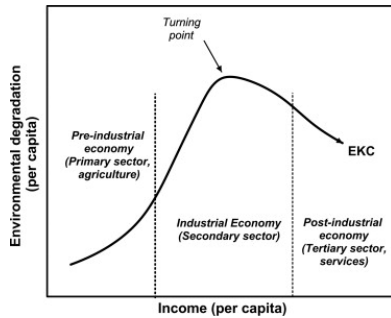

Figure 1.5: Environmental Kuznets Curve

Source: Science Direct

This theory actually supposes no environmental limit to growth as marginal deterioration is assumed to take negative values from a certain level of development. Scrieciu (2007) opposed some criticisms to this hypothesis. He first shades the direct relationship between wealth and environmental damages by explaining that it is not so much the wealth which is important but rather the evolution of the political and institutional system. The author then explains that if the EKC seems valid for general environmental damages, the relationship with the specific case of deterioration of forests gives less evidences. He also mentions that even if the theory seems to hold for continental regions, at the country level the inverted U-shaped relationship is less obviously obtained. When the theory is successfully tested and that the U-shaped curve is validated, the turning point is sometimes so high that this level is completely unrealistic. The EKC theory certainly contains some deficiencies but it also provides some interesting pieces of information (Kaika and Zervas (2013)).

The EKC may be compared to the Forest Transition Model (FTM) as they are sharing some features and hypotheses. This theory is namely mentioned by Ritchie and Roser (2021), Armenteras et al. (2013) and Megevand and Mosnier (2013). It distinguishes four stages of development which a country may go through: The pre-transition, the early transition, the late transition phase and the post-transition phase (Figure 1.2). During the first three phases, the country experiences negative annual change in forest while this rate becomes positive in the post-transition phase. As it can be seen in figure 1.6, the early transition phase and the late transition phase experience the highest levels of deforestation rate, even though this rate is increasing in the first one and decreasing in the latter. Note that phases can be skipped. Megevand and Mosnier (2013) explain that the REDD+ mechanism tries to help countries of the Congo Basin to avoid phase 2 and its negative consequences.

Figure 1.6: Forest transition model

Source: Our World In Data |

The figure 1.7 presents an overview of the world's situation in 2013. We can note that the majority of tropical countries were at that time still in the first two stages of the transition. Megevand and Mosnier (2013) explain that countries of the Congo Basin might have begun their second phase while these countries are supposed to be in pre-transition phase according to Ritchie and Roser (2021).

Armenteras et al. (2013) assert that Colombia is in the early transition phase but the authors explain that this statement does not hold for each region of Colombia. Once again it shows the authors' willingness to work on a more local level. The EKC theory and the Forest Transition Model ask to take account of the level of development of the area studied.
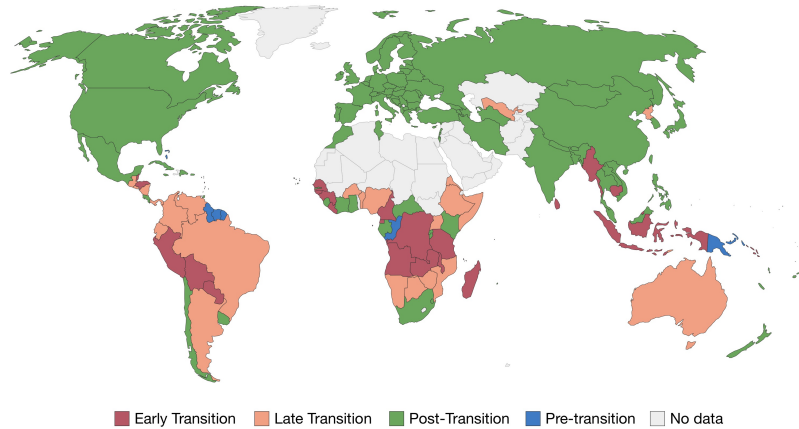
Figure 1.7: Forest transition phase by country, 2013

Source: Our World In Data

1.4 Drivers of forest disturbance

Speaking about transition and development is always kind of vague. The word "transition" induces the idea of change and this change is very unlikely to be exogenous. Going from one phase of the FTM to another should be induced by some variations in certain variables. Here we come to the drivers of deforestation and forest degradation. The question has been investigated but conclusions are quite hard to draw.

1.4.1 Population growth

Population growth has been largely depicted as a major factor of forest loss. In the article of Scrieciu (2007), variables on population are actually the only ones which remain significant when the model is corrected for serial correlation. Megevand and Mosnier (2013) mention the projection from the United Nations and assume that the expected population growth would have to be made, at least partially, at the expense of forests. Figure A.4 to A.12 in the appendices show some features about population dynamics in the area studied. In South-Eastern Asia and Latin America, projections describe a positive population growth for another 30 years. The turning point would come around 2050 where the population curve should begin to show a negative slope[2]. It seems that the population curve of these two regions has already passed the inflexion point, with a population growing at lower rate. This is not the case for Sub-Saharan countries. The population in this region is expected to double between 2020 and 2050, going from hardly 1 billion people to a bit more than 2 billions. The turning point expected around 2050 for the 2 other regions is not supposed to be reached before 2100 by Sub-Saharan countries, even with the lower variant projections.

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[2]medium variant projections

However, Megevand and Mosnier (2013) note that it is not the population growth *per se* that leads to deforestation, but the way the population consumes. The authors explain that demography is a threat to forests in the Congo Basin (and in Africa in general) but it is not necessarily the case for other tropical regions. The pressure put on forests in Africa is mainly caused by local subsistence agriculture while it is commercial agriculture and resources exploitation which are mainly cited for Latin America and South-Eastern Asia (Megevand and Mosnier (2013)). The age pyramids presented in the appendices may give us a clue to explain these differences. We can indeed see that Africa presents, for 1990 and 2020, a demographic structure which is typical of early stages of demographic transition, while the two other regions have age pyramids presenting signs of more advanced economies (Max Roser and Ortiz-Ospina (2013)).

Megevand and Mosnier (2013) and Karsenty (2021) mention the role of rural exodus, explaining that habits and way of consumption are radically different in cities. Wood takes too much place and is then replaced by charcoal, the demand for meat and grains is larger while roots and traditional food are left out, inducing more pressure on forested areas. Considering only deforestation, Megevand and Mosnier (2013) also assert that only peri-urban forested areas are threatened by population growth. In rural areas, degradation would occur at a smaller level than the level of forest natural regeneration. However, urbanization might have ambiguous consequences as a change in the way to consume generally increases the level of imports. If the resources are imported, the pressure on forests is displaced somewhere else (Megevand and Mosnier (2013)). The impact of population growth is however nuanced by some authors. Geist and Lambin (2002) assert that to much emphasis has been put on demographic transition, while some other direct and underlying factors might have a greater impact on forest loss. The authors' analyses show low significance levels for population growth, in contrast with the later analysis of Scrieciu (2007). Note that these analyses do not have the same form which makes direct comparison inadvisable.

1.4.2 Poverty and education

Population characteristics are also often mentioned as a driver of deforestation and forest degradation. Poverty has been largely investigated but its effect is quite controversial. The main idea is that poverty induces pressure on resources as people need natural resources to survive. As it has already been mentioned earlier, natural resources generally constitute a higher share of poor people's assets (Margulis (2004)). The "resource" dimension discussed earlier is therefore fostered in poor regions. The surveyed population by Twongyirwe et al. (2018) explains that dependence to forest is a consequence of poverty. The economic phenomenon called "Dutch Disease" seems to have fostered poverty in some tropical countries, namely in Africa. This phenomenon expresses how some countries, such as Angola and Gabon for example, may neglect their agriculture because of important resources in fossil fuel for example (Megevand and Mosnier (2013)). However we have to note that Gabon is largely spared by deforestation being the fifth country with the biggest share of land covered by forest (Ritchie and Roser (2021)). Megevand and Mosnier (2013) and Tchatchou et al. (2015) explain that energetic profiles of countries must be taken into account. Gabon have been subsidizing electricity consumption and gas network for years which is why its population is less dependent to forest resources. The role of poverty on pressure on forests seems to be largely accepted in the literature.

Karsenty (2021) develops the other side of the debate explaining that studies have shown that it is actually people who have accumulated some wealth that mainly drive deforestation. Geist and Lambin (2002) highlight the relationship between poverty-driven deforestation and capital-driven deforestation. They explain that poor people are more inclined to be deprived of their land which makes easier for investment funds to transform areas into large exploitation surfaces.
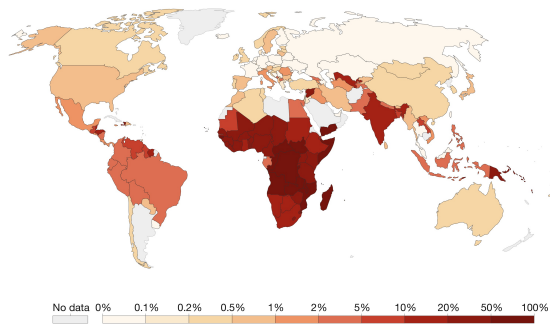
Figure 1.8: Share of people living under the International Poverty Line of 1.90 int.-$ per day, 2019
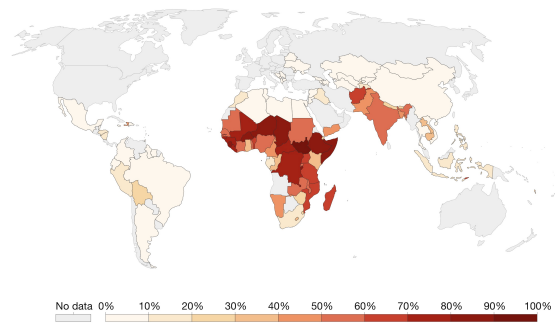
Source: Our World In Data

Figure 1.9: Share of people considered as poor according to the Multidimensional Poverty Index (MPI), 2015

Source: Our World In Data

Poverty is a broad concept, which might be interlinked with many other demographic variables. We could for example think of the level of education that Godoy et al. (1998) found out to be a factor influencing the probability of deforestation. Using different econometric models such as Tobit and Probit with survey responses, the authors found out that enhancing education in a region might substantially decrease the probability for old-grown forests to be deforested. It is more about finding the most pertinent demographic variable when speaking about forest loss than simply using data strictly related to poverty. Figures 1.8 and 1.9 provide an insight into the world's poverty level. On the left, figure 1.8 shows the share of people living in extreme poverty in each country. This concept of extreme poverty has been defined internationally as a stage of poverty where people have to live with less than 1.9$ per day. A quick look at the map shows that tropical regions this work studies are generally part of the world's poorest regions. This statement is even stronger for Africa in which the region studied in this work is largely displayed in dark red. However, poverty is not only about income, which is why figure 1.9 has been added. This map shows the share of people considered poor according to the Multidimensional Poverty Index[3] (MPI). The idea is similar to the one presented by Godoy et al. (1998), according to which poverty might take several forms. Excepted India, Asian sampled countries seem to be relatively spared by this type of poverty, such as American ones. However, this map highlights the inherent poverty attached to the African continent. Sub-Saharan countries indeed largely depict a strong level of multidimensional poverty. It seems therefore primordial to take into account this inherent poverty of the African continent.

1.4.3 International trade

Another discussed driver, which might be more subtle to understand, is the level of importation and exportation. Almost all the papers consulted have at least mentioned these economic variables. Margulis (2004) states that the increase in the level of exportation of meat from Brazil allowed the country to fight poverty, concluding that social gain comes from more exportation. For him, this boom in the exports has been allowed by the increase in the cattle herd, inducing a decrease in real term prices for meat which made the Brazilian meat more attractive on the international market. The author also notes the raise in rural income between 1970 and 1995 which would be linked to this increased competitiveness on global markets. If poverty increases the probability of deforestation, this could induces that exports should decrease forest losses.

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[3]a person is considered as "MPI poor" if she is deprived in a third or more of ten (weighted) indicators, accounting for health, education, and living standards

However, it is not so straightforward. We have already cited Ritchie and Roser (2021) explaining that some share of deforestation (12%) is driven by international demand. Geist and Lambin (2002) already hold this kind of speech when asserting that a boom on the international timber market increases pressure on tropical forests. Actually the main idea about foreign trade when dealing with forest disturbance is that a rise of the international demand makes the transformation of forest into exploitable areas more attractive. The opportunity cost of keeping a forest intact increases with the appreciation of term of trade. It is even more true in tropical areas where difficulties of access and exploitation generally discourage investment in those regions. However, if prices rise, some efforts might become profitable (Margulis (2004)). Megevand and Mosnier (2013) assume that deforestation could rise with the recent increase of the worldwide demand for minerals, one of the main resource of the Congo Basin. In this view, some can consider that the "Dutch disease" has actually helped forests so far, even if it is accused to have preserved the poverty level.

We see that direct interests of nations and the protection of forested areas might be in conflict as countries generally tend to foster exports. Scrieciu (2007) questions the devaluation of currencies as a piece of the deforestation's engine. A weaker currency would indeed boost exportation, increasing therefore the pressure on forests. Richards et al. (2012) give evidences of the role of exchange rate in South-American deforestation. The article explains that the strength of the American dollar compared to local currencies (sometimes voluntarily devalued) has favored the production of soybean in the 1990's. Exchange rate is therefore a major factor to deal with. It might be interesting to take account for the monetary status of nations studied, as flexibility of the exchange rate could matters. This impact of the exchange rate might also give some clue to understand the special case of Gabon. The extractive industry being quite strong, it induces a lot of exchange in national currency. This phenomenon is supposed to pull the exchange rate up making other industries or commercial activities less attractive for exportation (Megevand and Mosnier (2013)).

Gabon seems not to be the only country which is not heavily influenced by foreign trade in Africa. The whole tropical African region seems to be relatively isolated on the international market. Figure 1.4 highlights a different pattern in term of trade compared to other tropical regions. Almost every country of the region is net importer of deforestation while Latin American and Asian tropical countries are generally displayed in purple, indicating they are net exporters of deforestation. This actually means that African tropical nations contribute more to deforestation abroad than they do on their own territory. This could be due either to a strong level of trade between Africa and the rest of the world or to low level of deforestation in the region. FAO (2020) asserts that between 2010 and 2020, Africa had the largest annual rate of net forest loss, but the map is given for 2013. Megevand and Mosnier (2013) explain that the poor level of productivity that is attached to African countries, namely in the Congo Basin, requires the region to be very dependent of importation. Poor yields in tropical Africa have actually protected the region from forest deterioration. Megevand and Mosnier (2013) add that even if the region clearly have the potential to become one of the main actor in some sectors, the energy frontier is unlikely to be breached. With the rise of energy prices, yields and productivity have few chances to know a significant rise that would lead to a substantial decrease in domestic prices and therefore to a decrease in imports.

1.4.4   Political framework

Macroeconomics factors we have just discussed have been cited in the literature as bearing a certain influence on forest loss and disturbances. Besides these potential drivers, the institutional system and the political atmosphere have also been mentioned by authors dealing with deforestation and attached matters. Political instability seems to have an ambiguous effect. On one hand, it is assumed to have passively protected forests. Mainardi (1998) explains that political instability surely discourages foreign investment in the concerned region which is why they try to add the information in their

model by using several proxies for violence and political environment. Activities such as commercial logging, large cattle ranching and palm oil exploitation cannot be set up which therefore protects the forest cover. This point of view is also exposed in the book of Megevand and Mosnier (2013) where the authors cite the political instability as a major explaining factor for the relatively low deforestation rate of the Congo Basin. The authors note however that the relatively peaceful period African countries were experiencing in 2013 could allow the region to test its development potential. If instability is commonly perceived under the form of wars, geo-political troubles, terrorism or authoritarianism, Jiagho and Banoho (2021) add the power of traditional tribe authorities, so do Megevand and Mosnier (2013). This power seems to be more developed in Africa, where tribe chiefs still detained a significant amount of power. This overlay of power cannot be classified as "political instability" *per se* but it surely negatively impacts the business climate. On a larger scope it becomes difficult to take into account such regional characteristics of the institutional organisation.

On the other hand, the authors mentioned previously all agree on the fact that this instability makes it difficult to implement protection measures. Informal trade is difficult to limit and control, protected areas are barely watched, and aids are not transparently allocated for example. The lack of a stable political framework and superposition of power also decrease access to reliable data on forest cover (Mainardi (1998) and Megevand and Mosnier (2013)). Such an unstable environment may also launch some migration movements, for example from a country at war to its neighbor. The population surveyed by Twongyirwe et al. (2018) explains that migrants do not have the same cultural perception of forested areas and are therefore more inclined to deforest than local tribes for which logging is frowned upon. Migrations can be induced by war or terrorism such as presented by Jiagho and Banoho (2021), but it can also be the result of a better economic climate. Armenteras et al. (2017) explain that new opportunities have led population to migrate from one region to another, and that this phenomenon is particularly observed for low-income part of the population. Pioneer fronts are another form of migration, often cited in the literature as driving uncontrollable deforestation without the authorities' control (Margulis (2004)).

Besides political instability as a whole, researchers often mention ownership insecurity as possible driver of forest deterioration. Even if it could be seen as a consequence of the precedent discussed factor, it seems right to highlight the impact of legalization of property rights. Several papers have cited the potential influence untrustworthy property rights can bear on forest cover. This influence is not obvious though. Karsenty (2021), who asserts that property rights insecurity is more an Asian matter, begins with the most obvious idea: the investment is discouraged if ownership is not guaranteed. Its seems pretty clear, as investing time and money is not interesting if land titles are not safe. As it has already been mentioned, investment is supposed to lead to more deforestation, which is why an unstable ownership environment could passively protect forests. However, Karsenty (2021), such as Busch and Ferretti-Gallon (2020), also makes reference to a famous economic theory: the tragedy of the commons. The idea is that when scarce resources are displayed in free access, individuals tend to over-consume it beyond what would be socially optimal (Hardin (1968)). This dualistic position is shared by Geist and Lambin (2002) who assert that both stable and unstable property rights may induce forest disturbances. Megevand and Mosnier (2013), while analysing deforestation drivers in the Congo Basin, explain that ownership is actually shown by the exploitation of the area. Disturbing a forest is therefore the best way to prove the ownership. This undoubtedly leads to an increase in forest deterioration in areas where property rights are not well-defined.

1.4.5 Infrastructure

A less ambiguous driver is the level of infrastructure, namely transport infrastructure. Accessibility is an obvious obstacle to countries development and by consequences to forest clearance. Margulis (2004) speaks about "accessibility frontier" when referring to the accessible zone of the Brazilian Amazon.

Megevand and Mosnier (2013) highlight the international enclosure of some African countries because of the lack of infrastructure. It is even more true for Central African Republic which is landlocked without any access to the ocean. On the contrary, South-Eastern Asia is clearly more accessible. Archipelagos which constitute a large part of the region are easily reached by the ocean, which eases the exploitation of forests. Mainardi (1998) asserts that developed transport infrastructures is a major determinant of deforestation rate and Megevand and Mosnier (2013) cite the projections from the CongoBIOM model according to which improved transport infrastructure would be the most damaging change for the forests of the Congo Basin. The authors however explain that forest deterioration would not be a direct consequence of better infrastructure but would actually be induced indirectly by the improvement of connectivity. Busch and Ferretti-Gallon (2020) express it by citing the impact a better infrastructure can have by lowering transportation costs or by making migration easier for example. Note that Mainardi (1998) shortly admits that better infrastructures could also have a positive impact on forest cover as it could improve income and education for example. However, improved installations and commodities are generally seen as a threat to forested areas.

Countries are in general not able to fund such improvements. Megevand and Mosnier (2013) assert that mediocre infrastructure, together with political instability, are the main factors explaining why African tropical regions had not experienced large foreign investment in land by 2013. If government cannot afford to inject money in such installations, it is up to the private sector to undertake the investment. However, it demands quickly profitable projects, showing once again the influence prices, exchange rates, and international demand can bear on investments in tropical areas (Megevand and Mosnier (2013) and Margulis (2004)).

1.4.6 Land use conversion

Macroeconomics variables and political and institutional atmosphere are surely factors influencing forests deterioration. These underlying factors indirectly impact rates of forest deterioration. However, the most discussed domain of drivers of deforestation and forest degradation concerns the land use which forests are converted to, considered as proximate drivers. In this view, it is first important to distinguish 3 notions: adequacy, availability and accessibility. Adequacy concerns the types of land use depending on geo-ecological conditions. If TMFs are located in relatively wet areas, topography and soil composition for example may be appropriate to one or the other land use. Megevand and Mosnier (2013) assert for example that countries from the Congo Basin do not have any comparative advantage in cattle ranching, because climatic and biophysical conditions for that type of land use are not met, but that this region is particularly adapted to large culture such as soybean or palm oil. On the opposite, Margulis (2004) says that conditions in Brazilian Amazon are more favorable to cattle grazing than to agriculture. The second concept is availability. This condition is often respected as TMFs are rarely cultivated and generally display a very low level of population density. This condition actually mainly concerns the status of the forest, whether it constitutes a protected area or not. The single region of the Congo Basin was supposed to offer, in 2013, 12% of the world's available lands (Megevand and Mosnier (2013)). The third condition, as it has been mentioned several times, is the strongest obstacle to the development of tropical forests' full commercial potential, acting therefore as a protective factor (Megevand and Mosnier (2013)).

Ergo, geo-ecological conditions do play a major role in the attribution of land use and therefore in land conversion from forested areas to others type of cover. Beyond this land use consideration, it is also important to understand that even if TMFs are supposed to experience relatively few meteorological variation across the year (with constant humidity and temperatures), extreme climatic events may occur and have potential dramatic consequences on forests. Vancutsem et al. (2021) namely explain that deforestation seems to follow some patterns linked with policies or economic development and seems to be relatively independent from singular extreme climatic events. Forest degradation, however,

seems to react fiercely to extreme conditions. The authors take for example the El Niño – Southern oscillation (ENSO) which was responsible of large forest fires in 1998-1999 and 2015-2016.

Extractive industry

Resources from the extractive industry are one of the main business opportunities in tropical countries. Some nations such as Democratic Republic of Congo or Colombia are known for their mines of gold, silver, cobalt, or other minerals, some others for their large fuel fields such as Gabon or Venezuela. Figure A.13 in the appendices displays the oil rents in % of GDP for the top 4 tropical countries of our sample and compares it to the whole world average. Nonetheless, some countries have realized that the economic manna that their oil deposits brought them is not eternal which is why Megevand and Mosnier (2013) supposed that some nations such as Gabon could begin to develop others activities. Hannah Ritchie and Rosado (2020) indeed assert that the global resources of fossil oil should be sold out by 50 years, 110 years for coal[4]. We have already spoken about the impact such reserves in natural extractive resources may have on the exchange rate or on the development of other economic activities. However, extractive activities also have less subtle impact on forest deterioration rate. Mines for example demand a lot of logistics, infrastructures, and often induce economic migrations. The impact is indirect but still substantial and must be taken into account (Megevand and Mosnier (2013) and Jiagho and Banoho (2021). Mainardi (1998) however explains that his regressions suffer from bad proxies for mining. He indeed used the level of export of minerals as a proxy for the extractive production, but he argues that this approximation did not take into account the downstream contributions to domestic economy such as resources and infrastructure needed to transform minerals within the territory. It also omits the information about the location of the mine, whether it is an underground activity or an openpit mining, which should have an influence on the deforestation and degradation rate induced by the extractive activity. Note that other consulted papers have not found a better proxy yet.

Forestry

One of the most commonly assumed driver of forest loss is forestry. Ritchie and Roser (2021) assert that forestry is currently responsible for approximately 13% of global annual deforestation. We have to distinguish two kind of forestry: commercial logging and subsistence activities. If the logging and harvesting of wood is surely a driver of forest disturbances, the type of activity depends on the region analysed. Megevand and Mosnier (2013) and Ritchie and Roser (2021) explain that commercial forestry has been a larger driver of forest loss and deterioration in southeastern Asia, while domestic use of wood has more occurred in African countries. As it has already been discussed, subsistence logging does not seem to be a persistence problem for forest in rural area. However, Megevand and Mosnier (2013) show that this type of activity in urban area substantially reduces forests around the city or town. Dependence to wood as source of energy is the main issue of several African countries, which are unlikely to break the energy frontier in the coming years (see section 1.4.3).

Commercial forestry concerns more Asian tropical countries according to Geist and Lambin (2002), but it is still relevant for other tropical regions. Karsenty (2021) adds however that this driver is maybe not consistent anymore as it was a larger phenomenon in the 20th century. Even if Megevand and Mosnier (2013) assert that the Sustainable Forest Management (SFM) is increasing, with a particular rise in Africa, short-term concession mandates do not provide enough incentive to forest protections (see section 1.2.1) (Mainardi (1998)).

However the main idea to be gotten when speaking about commercial logging is the difference between exploiting a primary forest and harvesting planted trees on a commercial purpose. The

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[4]based on known reserves and annual production levels in 2015

problem would be the clearing of primary forests in order to plant trees, thus losing all the benefits that make primary forests a unique and rich environment. This is one of the reasons why Vancutsem et al. (2021) worked with the idea of undisturbed TMFs, in order to analyse the impact of losing primary forests. In this perspective, Karsenty (2021) criticizes the "Bonn Challenge" launched in 2011 which aims to restore 350 million hectares of forest by 2030. The author argues that such a challenge looses its interest because more than 80% of projects implemented concern the plantation of non-diversified woody species. Such plantation would stock less carbon and would be less conducive to the development of biodiversity. However, the paper written by Verdone and Seidl (2017) addresses counterarguments to such critics, by explaining that, depending on the discount factor that will be used, future gains from these plantations could actually exceed the initial costs of the challenge implementation. In any case, it is primordial to understand the differences between types of forest areas.

It is also important to take into account the permanence, or not, of forest clearing. Karsenty (2021) takes the example of Gabon which has experienced an increase in its naturally generated forest while being an important actor on the commercial logging market. Note that Gabon has restricted exports of round wood, which seems to limit the impact of logging in its territory. If it is true that logging generates a lot of degradation on the forest cover, natural regeneration may surely compensate it if the concession is operated in a sustainable way. Exploitation is therefore no synonym of deforestation, as it is commonly misunderstood.

Soybean and palm oil

We now come to the two major direct drivers of deforestation. If shifting agriculture generates degradation as Ritchie and Roser (2021) claim, then papers such as Geist and Lambin (2002) are right to affirm that shifting cultivation have been falsely accused to be a major driver of deforestation. In opposition, the land use conversion we will develop hereafter are clearly identified by the literature as drivers of deforestation, in its permanent perspective.
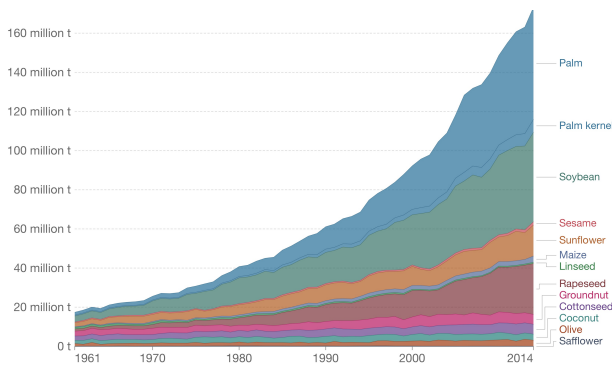
Figure 1.10: Vegetable oil production, World, 1961-2014

Source: Our World In Data
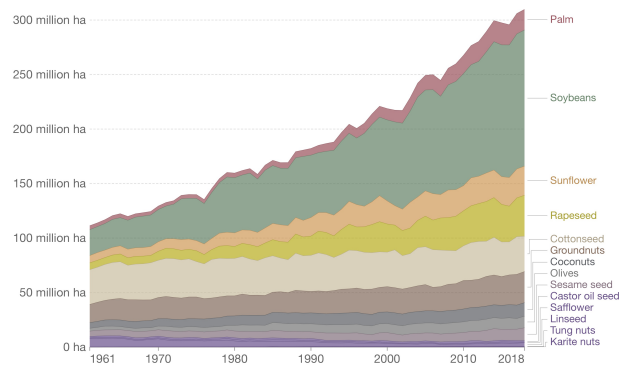
Figure 1.11: Land use for vegetable oil crops, World, 1961-2018

Source: Our World In Data

The first one regroups the plantation for soy and palm, even if they are not growing in the same part of the world. 69% of the global soy production is cultivated in Brazil and in the US. The interest for soy from Brazil is relatively new, as before 1990 the US alone produced more than 50% of the worldwide soy production, Brazil only 18%. Global soy production has increased a lot since 1970, going from a bit more than 40 million tons a year to almost 350 million tons a year in 2018. Yields have increased but not enough to follow the boom of production. Land use for soy had to be expended,

potentially on some forested areas. Palm oil production has also known a huge boom as it has been multiplied by 35 between 1970 and 2018. As for soybean production, two countries produce the large majority of global palm oil. Indonesia and Malaysia combined produce more than 80% of the global annual production of palm oil. Soybeans are use mainly (77%) to feed animal, essentially poultry. 19,2% goes to human which 13,2% in the form of oil. Palm oil is a versatile product. Even if it is mainly used in food preparation, it could also be used as fuel or for industrial purpose (Ritchie and Roser (2021)).

Figure 1.10, shows the strong increase in palm oil production between 1960 and 2014. Figure 1.11 shows that this strong increase in production has actually been made with a small proportion of forested land. This is partly due to the incredible yields which are inherent to palm production. Ritchie and Roser (2021) claim that the worldwide demand for vegetable oil has been fulfilled thanks to palm oil yields. Without this incredible source of vegetable oil, and because other oil sources display far lower yields, fulfilling the worldwide demand would have been clearly more demanding in term of surface. As it can be seen in figures 1.10 and 1.11, palm oil currently uses 6% of lands dedicated to vegetable oil production, but it provides 36% of the global production. Ritchie and Roser (2021) assert that if global demand was fulfilled only by soybean oil, we would need 486.76 million hectares of land of soy, while we would only need 76.97 million hectares with palm as the only source of vegetable oil. Yields for soybean production have also increased but not enough to follow the boom of production. Land use for soy had to be expended, potentially on some forested areas.
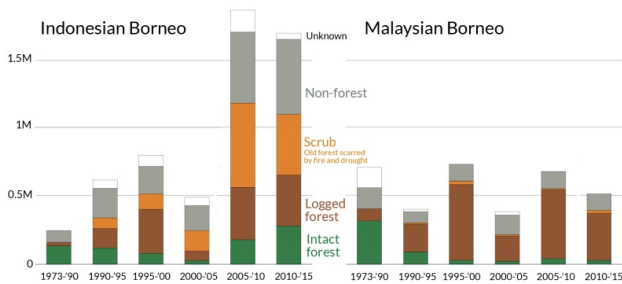
Figure 1.12: Type and magnitude of land conversion to palm oil plantation in hectares in Indonesian and Malaysian Borneo, 1973-2015

Source: Our World In Data
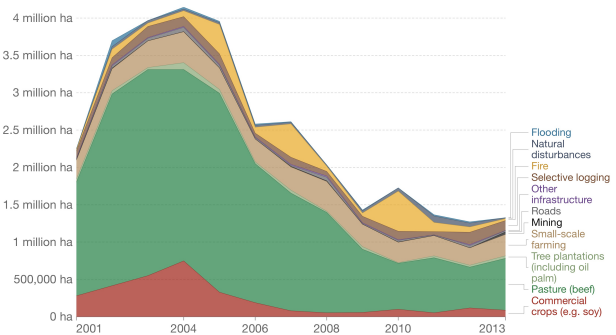
Figure 1.13: Annual forest loss in hectares by drivers in the Brazilian Amazon, 2001-2013

Source: Our World In Data

Here is actually the question we should focus on: Have soybean and palm oil increase in production been made at the expense of primary forests? The reason for regrouping palm oil production and soybean production comes from their indirect impact on deforestation. Gaveau et al. (2016) (as cited in Ritchie and Roser 2021) explain that the palm conversion in Borneo (shared between Indonesia and Malaysia) was made at the expense of planted forests, not primary forest (Figure 1.12). However, the authors claim that theses planted forests had been rapidly grown at the expense on primary forests which makes palm oil production indirectly responsible for deforestation. In the same vein, Barona et al. (2010), Ritchie and Roser (2021) and Mainardi (1998) all assert that if the expansion of soybean has not been made directly at the expense of forested areas, it has been made on previously deforested surface for cattle ranching or by fire for example. This should lead us to be well aware of the sequential timing of degradation and deforestation and to not underestimate the impact of soybean and palm oil production. Note that the growing surface of soybean can bee seen on figure 1.13 under the label commercial crops. We can spot the impact of the soy moratorium implemented in 2006, leading to a

decrease in annual forest loss induced by this driver.

Cattle ranching

Figure 1.13 gives us some clues to introduce our last driver of forest deterioration and deforestation. Margulis (2004) explains that during the 70's and 80's in Brazil, policies specifically aimed to foster transformation of forests into "productive areas". However, the author asserts that since the 90's and after the removal of these policies, large cattle ranching has been the main cause of deforestation. Because of its eco-geological conditions, Latin America is particularly adapted to this kind of activities, while Africa presents less dispositions for cattle ranching (Margulis (2004) and Megevand and Mosnier (2013)). Ritchie and Roser (2021) assert that 41% of tropical deforestation is driven by beef with more than 50% due to Brazilian cattle. The authors see in beef the most direct source of forest loss. Some could think that it is international demand in beef which drives deforestation in Brazil. Ritchie and Roser (2021) argue that it is actually Brazilian people's appetite for beef which induces such a production.

Wassenaar et al. (2007) put themselves in opposition with papers claiming that cattle ranching is an unprofitable activity since concessions subsidies were stopped. Their point of view is that market forces and failures make this activity viable, otherwise economic agents would have already left the market. Margulis (2004) describes the process that have fostered large cattle ranching implementation in the Brazilian Amazon: the increase in the cattle herd leads real term price of beef downwards which fosters exports. Note that the econometric analysis performed by Margulis (2004) shows that the impact of the increase of herd had decreased with time. With data from 1970 to 1985, an increase of one beast per hectare was supposed to lead to an increase of 1.26% in deforestation rate, while this value dropped to 0.53% with data from 1985 to 1995. This should be a sign of yields improvement, as ranching became more intensive.

Margulis (2004) also tried to understand micro-incentive leading economic agents to chose cattle grazing among other activities. He highlighted the role of risk. His analysis asserts that cattle ranching displays quite low level of risk in term of prices and market availability, compared to crops, in particular seasonal ones, which are supposed to lead to higher revenue but with a lower probability. With a risk free model, Margulis (2004) was able to apprehend the statement claiming that cattle ranching is no longer viable without subsidies. He indeed found that in such a model, only soybean would be planted and that the remaining area would be left to forests. However, when risk is taken into account, cattle ranching finds itself a place in land use. It even becomes the second widest land cover, just behind forested areas. This shows once again the importance of understanding factors and dynamics before getting into any analysis.

1.5   Sequential timing and feedback of forest loss

The factors and drivers we have just discussed must be understood in a dynamic perspective. The literature indeed generally agrees on the sequential timing of these drivers, and on the interactions between them. Geist and Lambin (2002) voluntarily make the distinction between proximate and underlying drivers of deforestation. The authors cite for example agriculture expansion and wood extraction as proximate (or direct) drivers of forest loss, while economic factors and institutional influences are assumed to bear a less direct impact. The idea is that some factors foster or inhibit the influence others might bear. These interactions should be taken into account, otherwise results could be misunderstood. These interlinkages might also be a source of endogeneity or multicollinearity problems in econometric studies. Armenteras et al. (2013), for example, had to acknowledge some limits to their analysis as they do not take into account interactions or sequential timing.

However, some authors explicitly emphasize the importance of consecutive factors. Ritchie and Roser (2021) explain that soybean production might be misleadingly assumed to have no influence on deforestation if no further investigation is made. Soybean fields are indeed planted on areas previously deforested for cattle ranching. In such a way, soybean cannot be seen as a relevant driver of deforestation. However, the authors explain that the growing demand for soy, and the soaring production it induces, actually requires cattle herds to be displaced, often into forested areas, driving therefore vicarious forest loss. The same phenomenon was observed in Asia, as it can be seen in figure 1.12. This figure shows that some but no all palm oil plantations have been made at the expense of intact forest. However, Ritchie and Roser (2021) explain that a large part of the intact forest had been cleared few years before palm plantations, giving to this graph a misleading insight. The same problem could occur in our analysis as our work only studies forest disturbances which occurred between 1991 and 2020. Previous case of forest deterioration are therefore not analysed.

Mainardi (1998) tries to pay more attention to sequential timing of some determinants and to some possible feedback effects in his analysis. Feedback effects are easily apprehended in a topic such as forest loss. We have previously spoken about services forests provide, such as hydrological regulation or temperature mitigation. Regions which have already been experiencing economic and social difficulties for years could be in even worse situations if the forest looses its role of regulator. Poverty could be worsened, extreme meteorological events could become more frequent, and agriculture could experience lower yields. As another feedback example, Busch and Ferretti-Gallon (2020) take the example of a growing population which is supposed to lead to more deforestation, but which can also be fostered by this increase in available lands. This is an example of negative feedback effect. However, positive ones could also be possible. If a higher level of infrastructure is supposed to be detrimental to forest cover, the better access this clearance would provide could actually lead to a higher level of education or to better incomes.

As it has been shown in this literature review, drivers of deforestation and forest disturbance are multiple, and work in several directions depending on the context they have been taken in or on factors they are interacting with. It would be illusory therefore to expect unambiguous, straightforward effects, which is why all precautions must be taken when interpreting results.

Hypotheses and methodology

2.1 Methodological patterns of previous studies

Studies and works on tropical moist forests disturbances have increased since the 90's because of the rising acknowledgment of the importance of such areas. They have been performed under different forms. Ritchie and Roser (2021) constructed an oriented synthesis of some key papers, adding a few descriptive statistical elements in order to underpin their work. Twongyirwe et al. (2018) conducted a survey among Ugandan population (263 households), as a way to focus on context specific drivers of deforestation. This method was also a way to bypass lack of data of the region. Karsenty (2021) built his article as a synthesis, trying to be relatively brief, while Megevand and Mosnier (2013) exhaustively compiled elements in a rapport aiming to cover every aspect of deforestation in the Congo Basin. As it has already been mentioned, scopes and perspectives of studies might be different, going from a global point of view to a region-specific scope. The articles from Jiagho and Banoho (2021) and Busch and Ferretti-Gallon (2020) have both been carried under the form of a meta-analysis, but the first one focused on a region of Cameroon while the latter speaks about deforestation in a broader perspective.

Besides these types of studies, many others have been carried out using econometrics. From Mainardi (1998) to Vancutsem et al. (2021), econometric studies have evolved through data improvement. The first one worked with a two-period panel dataset, on a 10 years time span, acknowledging substantial lack of data reliability. The latter worked with a recent panel dataset on 30 years and 34 countries, and bringing to the fore the precision this dataset can rely on. Margulis (2004) used a panel dataset of 26 years for 256 areas of the Brazilian Amazon to construct 3 models, static and dynamic. The author took into account both temporal and spatial interactions, on the contrary of Armenteras et al. (2013) who constructed a General Linear Model without accounting for sequential timing or interaction of any kind. Such an approach is likely to lead to failure of the strict exogeneity condition cited by Wooldridge (2015), as contemporaneous variables might be correlated with past factors bearing an influence on current forest deterioration. The recent meta-analysis from Busch and Ferretti-Gallon (2020) dwells at length on studies using spatial econometrics, more precisely explicit spatial econometrics. This kind of methodology allows researchers to account for spatial interlinkages, assuming that regions' actions are not independent from each other. Spatial econometrics is particularly adapted when working on a national analysis with sub-national entities, like Margulis (2004). At a macro level, spatial correlation is a thinner concern. Scrieciu (2007) focused on econometrics studies to see whether it is advisable to identify drivers of deforestation at a global level. Using a panel dataset of 50 tropical countries on 17 years (1980-1997), the author specified a fixed effects model in order to avoid as much as possible omitted variable bias. The main point of focus of this article is the emphasis put on the importance of taking serial correlation into account. Scrieciu (2007) indeed shows that significance is lowered beyond common acceptable levels when serial correlation has been accounted for.

Until recently, the literature had to acknowledge the lack of reliable data about deforestation. Megevand and Mosnier (2013) assert that reliability of data reported by authorities is a primary concern in the Congo Basin. Vancutsem et al. (2021) address the same concern as they assert that the availability of information is particularly problematic for tropical African countries until the early 90's.

Scrieciu (2007), Mainardi (1998), and Margulis (2004) also acknowledge weaknesses in their dataset, whether it is because of the precision of the satellite imagery or because of a too incomplete database. Busch and Ferretti-Gallon (2020) express it in their meta-analysis too. The authors explain that many studies have been based on a too narrow time span, generally expended on 5 to 10 years. They also highlight the fact that 6 countries [5] have been particularly studied and represent more than 50% of the papers incorporated in their synthesis. Note that none of these 6 nations lays on the African continent. Busch and Ferretti-Gallon (2020) also emphasize the lack of trustworthy information about degradation, leading to an apparent confusion between deforestation and forest degradation. The work of Vancutsem et al. (2021) seems to rely on a more comprehensive database, enjoying a panel dataset of 34 countries over 30 years, and an unprecedented precision of imagery allowing the differentiation between deforestation and degradation.

It is crucial to be aware of limits of studies we are basing our work on before drawing any conclusion. From the early 70's, the rising concern about forest preservation has surely allowed technology to be improved. Most studies have been lacking reliable data about forest disturbances so far. By focusing on a too narrow time span or on too few countries, by working with unsuitable proxies or by not being able to distinguish forest degradation from deforestation, previous works have surely missed some pieces of information.

2.2   Methodology

The TMFs_2020[6] dataset made available by the European Commission and constructed by Vancutsem et al. (2021) surely overcomes some problems previous dataset may have encountered. It gathered information about forest deterioration between 1991 and 2020 for 34 countries. This panel dataset, based on satellite imagery of an unprecedented precision[7], makes the distinction between degraded areas and deforested ones. It also displays information about undisturbed forested areas, defining them as forested areas where "no disturbance has been observed over the Landsat historical record over the period 1982-2021" (Vancutsem et al. (2021)).

This work aims to identify determinants of forest disturbances by performing an econometric analysis at the national level. If spatial econometrics, and more specifically explicit spatial econometrics, seems to have been the norm so far (Busch and Ferretti-Gallon (2020)), this could be mainly due to the poor quality of national level data undermining therefore results from econometric analyses at the national level. However, with a trustworthy database, there is no reason allowing us to think that such an analysis should be banned. On the contrary, such an improvement should be used to overcome limits previous studies might have encountered. A more reliable source of information should actually show whether limits have been overcome or if the national perspective is obviously inadequate. Moreover, in a topic such as forest loss, analyses should aim to provide keys for designing relevant and efficient policies. An econometric study on the national level might provide such elements, by allowing an in-depth understanding of countries' local characteristics.

The database this work is relying on has been built up from 3 main sources. Our dependent variables have been provided by the Tropical Moist Forests dataset of European Commission, constructed by the work of Vancutsem et al. (2021). This dataset provided us information about the area of forest undisturbed, degraded, deforested or being regrown for 34 tropical countries. Features are given in hectares. However, they have been transformed into relative terms by dividing them by the total surface of forested area of each country. This element has been given by the database of the FAO. By such a transformation, we have been able of accounting for the size of the forest we were analysing.

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[5]Mexico, Brazil, Costa Rica, China, Indonesia, and Thailand

[6]dataset updated during the writing of this work; see https://forobs.jrc.ec.europa.eu/TMF/data.php#update

[7]0.09 hectares (30mX30m)

Independent variables have been gathered from the databases from the World Bank[8], and the FAO. Climate variables such as average precipitations and temperatures have been downloaded on the Climate Change Knowledge Portal of the World Bank. As the World Bank does not display information for French Guyana, our work eventually relies on a panel dataset of 33 countries on 30 years.

The approach of this work is actually deductive. Patterns, hypotheses, and variables have been drawn up according to the literature review previously presented. This latter is assumed to be the basement of a theoretical model this work is going to test. It would have been quite utopian to hope to have one single theoretical model to test in such a complex matter. The literature is actually rather dispersed and models depend on the perspective chosen by the authors or the degree of precision used. However, after a quite exhaustive literature review, we tried to build up models by gathering similar information and points of view in the literature. This synthesis resulted in 2 models related to deforestation, and one for degradation. If pieces have been gathered from the whole literature, a few main article and studies have been the basement of these models.

There are different approaches in the literature concerning drivers of deforestation. A first pan seems to consider that the same drivers play a role in each continent, being however different in the way they are interacting and in their magnitude. Such a perspective is implicitly reported by Hosonuma et al. (2012) and Rudel et al. (2009). These article have regrouped drivers of deforestation in a worldwide perspective. Even if they cite and display differences and specific features, they have tried to built a homogeneous model of deforestation. As dealing with a worldwide concern and aiming to help drawing efficient policies, such an approach could be relevant. It is actually the nature of a model: simplifying a reality without dropping the essential features in order to have an easier, but still relevant, point of view. This point of view allows us to draw a global model besides continental ones. Models based on this approach are presented in Table 2.1.

Causes of deforestation are presented by continent, with an aggregate for the global perspective on the left. For each region, drivers are classified by their impact on deforestation rate (on the top the strongest one). Five determinants of deforestation are presented here: commercial agriculture, subsistence agriculture, infrastructure improvement, the development of the extractive industry, and the phenomenon of urbanization. The first thing to note is the global harmonization of these determinants. The power of the extractive industry and the growing urbanization always take the fourth and fifth position while factors related to agriculture sit on top of the list. This supremacy of agriculture has to be noted. In America, agricultural activities are actually supposed to cause approximately 90% of local deforestation (Hosonuma et al. (2012)). This predominance is the reason why other drivers are written in italic. According to this model, commercial agriculture is the predominant driver across the world and in each continent except in Africa where it is subsistence agriculture which leads deforestation. This shows once again the difference and delay in terms of economic development that the African continent have been experiencing. Infrastructure improvement, largely cited in the literature review, takes the third place in each region. However, signs might not be straightforward depending on what is called infrastructure. Transport infrastructure improvement should lead to an increase in deforestation. Extractive industry and urbanization are both supposed to lead to permanent forest loss. Asia seems to have more suffered from urbanization while other parts of the world have been more threatened by their mineral resources.

One might worry about the lack of precision this model might suffer from. Because regional features are barely taken into account, results are more likely to be misunderstood. However, this harmonized approach still displays some advantages. It first provides a worldwide canvas to apprehend deforestation, allowing direct comparison between regions and depicting a quite complex topic in its simplest version. Moreover, it requires few specific variables which clearly helped researchers carrying out the

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[8]World Development Indicators (WDI)

first studies on deforestation. Finally, such a global perspective fits the worldwide goal of setting efficient global policies against deforestation.

Table 2.1: Theoretical model of deforestation drivers, for the world and by continent, homogeneous approach

World	Africa	America	Asia
Commercial agriculture	Subsistence agriculture	Commercial agriculture	Commercial agriculture
Subsistence Agriculture	Commercial agriculture	Subsistence agriculture	Subsistence agriculture
Infrastructure improvement	Infrastructure improvement	*Infrastructure improvement*	Infrastructure improvement
Extractive industry	Extractive industry	*Extractive industry*	Urbanization
Urbanization	Urbanization	*Urbanization*	Extractive industry

Source: Hosonuma et al. (2012) and Rudel et al. (2009)

A second pan of the literature have been designing a more complex and region-adapted model of deforestation. Geist and Lambin (2001), Megevand and Mosnier (2013), and Rudel et al. (2009) are all working under this adaptive perspective. It consists in considering different drivers according to the studied region. Causes of permanent forest loss are therefore not systematically the same and their number might be different. Table 2.2 presents our synthesis of models drawn according to this adaptive perspective. The World column is left empty because this approach does not allow the aggregation as drivers are not the same across regions. This actually is the main drawback of such a perspective as conclusion might certainly be more precise at a regional level but cannot be drawn at a global one. Table 2.2 depicts once again the prominence of agriculture while speaking about deforestation as permanent cultivation is the first driver of permanent forest loss in each continent. The second and third place of cattle ranching in America and palm oil production in Asia even strengthen this predominance. Some drivers are common across continent such as infrastructure improvement for example, while some others are continent specific. As it has already been explained in the literature review, palm oil production is really an Asian matter, just as cattle ranching and soybean production are American ones. In Africa, population dynamics and the change of lifestyle it implies seem to be the main factors leading to permanent loss of forest cover, while it seems to be commercial activities which drives deforestation in Latin America and in South-East Asia. The impact of migrations is still investigated. Geist and Lambin (2001) do not report migration as being relevant in Africa, while Megevand and Mosnier (2013) do. The difference maybe comes from the definition of migration. Geist and Lambin (2001) focus more on colonial and economic migrations while Megevand and Mosnier (2013) approach migration more as a consequences of political instability and conflicts. In our synthesis we have decided not to integrate migration because economic migrations are actually already taken into account in the "population dynamics" title. The common point of each model is the underlying impact of economic development, driving all these factors up or down depending on circumstances. This underlying aspect is actually as strength of this second model as it allows impacts to differ across time and situations.

Even if table 2.1 and table 2.2 have been built in a very different perspective, broad lines of deforestation are maintained. The relative under-development of the African continent is indeed presented in each model, and the prominence of agriculture and the impact of infrastructure have also emerged from both models. The idea of our study is now to test whether or not a global model is suitable for deforestation and to analyse whether or not the ranking of these drivers can be verified.

The literature is far less developed about degradation drivers. Only recent studies have been able to distinguish permanent forest losses from temporary ones. The work of Vancutsem et al. (2021) allows us to dispose of a reliable dataset accounting for both types of forest disturbances. However,

Table 2.2: Theoretical model of deforestation drivers, for the world and by continent, adaptive approach

World	Africa	America	Asia
-	Permanent cultivation	Permanent cultivation	Permanent cultivation
-	Urbanization and population dynamics	Cattle ranching	Commercial wood extraction
-	Fuelwood extraction and charcoal production	Commercial wood extraction	Palm oil production
-	Infrastructure improvement	Infrastructure improvement	Infrastructure improvement
-	/	Migrations	Migration
-	ECONOMIC DEVELOPMENT	ECONOMIC DEVELOPMENT	ECONOMIC DEVELOPMENT

Source: Geist and Lambin (2001) and Megevand and Mosnier (2013) and Rudel et al. (2009)

most precedent studies did not have access to such information. In order to palliate this lack of information, researchers mainly worked with survey based studies or with on-site observations, basing their results on a few relevant observations and answers. Hosonuma et al. (2012) and Jayathilake et al. (2021) worked on degradation and came with some conclusions. Selective commercial logging, wood fuel extraction, and charcoal production were largely cited. Vancutsem et al. (2021) and Megevand and Mosnier (2013) also defend such opinion. To a smaller extent, livestock grazing and several specific agriculture methods such as anthropogenic fires were assumed to bear an impact on forest degradation. However, the literature is quite dispersed, most studies confound drivers of deforestation and degradation, and no clear model of degradation can therefore be distinguished. This work tries to come with a relevant model of degradation, building it in a worldwide perspective with continental specification in order to allow both for comparison and for relevance. Drivers have been chosen according to the literature review we have constructed and elements have been added only if their relevance was attested. Some descriptive statistics also provide some hints on the relevance of possible drivers (see section 3.2). Besides selective commercial logging, fuelwood extraction, and charcoal production, we added information about agriculture to see to what extent agricultural activities bear peripheral impacts. As infrastructure development is also assumed to have an impact on degradation rates, such as population dynamics, these information have also been added to our model. In a more specific perspective, information about soybean and palm oil production have been integrated in the model for the relevant continent. Economic control variables have also been added to follow the pattern of the specific model of deforestation.

In order to allow for comparison between degradation and deforestation drivers within a continent, we have worked as much as possible with the same variables across models. We expect some signs to differ depending on whether we are analysing deforestation or degradation.

Database and Descriptive statistics

In order to complete the literature review previously exposed, this section presents some descriptive statistics on both dependent and independent variables. These statistics aim to give a short but relevant insight on our database in order to ease the understanding of future results. This section need to be apprehended as being complementary to the literature review and it does not pretend to explain by itself a matter as complex as the decrease of the tropical forest cover. Figures used in this analysis are provided by the WorldBank, the FAO, and by the work of Vancutsem et al. (2021).

Our database is a panel dataset, regrouping information for 33 tropical, sub-tropical and equatorial countries, for the 30 years composing the time span between 1991 and 2020. The list of countries is decomposed by continent in table 3.3. Our sample contains 11 African countries, 12 American countries, and 10 Asian countries. This geographical choice has been made in accordance with the work of Vancutsem et al. (2021) and the dataset provided by the European Commission.

Table 3.3: List of countries by continent

Africa	America	Asia
Angola	Bolivia	Cambodia
Cameroon	Brazil	India
Central African Republic	Colombia	Indonesia
Congo. Dem. Rep.	Ecuador	Laos
Congo	Guatemala	Malaysia
Ivory Coast	Guyana	Myanmar
Gabon	Mexico	Papua New Guinea
Ghana	Nicaragua	Philippines
Liberia	Panama	Thailand
Madagascar	Peru	Viet Nam
Nigeria	Suriname	
	Venezuela	

Before entering the analysis, the variables used must be defined, as well as the code our work will use to mention them. Table 3.4 gives an exhaustive overview of variables displayed in this work. The left column gives the code used to denote each variable, and the right column presents the definition attached to each variable. Each variable is defined for a specific year t between 1991 and 2020 and for a specific country i, as the subscript it suggests in the presentation table. This allows our code to be consistent with our panel environment. Variables are presented in their original form in table 3.4. However, for the ease of comparison, our future econometric analyses will be performed with the standardized[9] version of these variables. The code for these standardized elements will be the code presented in table 3.4 to which the letter z will be added as a prefix. As an example, $percent\_degrad_{it}$ is the original version of the variable accounting for forest lost due to degradation in country i during year t, and $zpercent\_degrad_{it}$ is its standardized version.

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[9]mean=0 ; s.d=1

Table 3.4: List of variables used in the analyses

Variable code	Variable definition
$percent\_defor_{it}$[2;3]	: Forest loss due to direct deforestation in year t, in % of the total forested area in year t
$percent\_degrad_{it}$[2;3]	: Forest loss due to forest degradation in year t, in % of the total forested area in year t
$ag\_prd\_crop\_xd_{it}$[1]	: Crop production index (2014-2016 = 100)
$ag\_prd\_food\_xd_{it}$[1]	: Food production index (2014-2016 = 100)
$ag\_yld\_crel\_kg_{it}$[1]	: Cereal yield, measured as kilograms per hectare of harvested land
$is\_air\_good\_mt\_k1_{it}$[1]	: The volume of freight, express, and diplomatic bags carried on each flight stage, measured in metric tons times kilometers traveled.
$eg\_elc\_loss\_zs_{it}$[1]	: Electric power transmission and distribution losses (% of output)
$ny\_gdp\_petr\_rt\_zs_{it}$[1]	: Oil rents (% of GDP)
$ny\_gdp\_ngas\_rt\_zs_{it}$[1]	: Natural gas rents (% of GDP)
$ny\_gdp\_minr\_rt\_zs_{it}$[1]	: Mineral rents (% of GDP)
$sp\_pop\_grow_{it}$[1]	: Population growth (annual %)
$sp\_urb\_grow_{it}$[1]	: Urban population growth (annual %)
$sp\_dyn\_cdrt\_in_{it}$[1]	: Death rate, crude (per 1,000 people)
$woodcoalprod_{it}$[2]	: Wood charcoal production in tons
$woodfnoconifprod_{it}$[2]	: Non-coniferous wood fuel production, in cubic meter
$cattlehead_{it}$[2]	: Size of the cattle herd, as the number of heads
$soybeanprod_{it}$[2]	: Soybeans production in tons
$roundwoodproduction_{it}$[2]	: Round wood production, in cubic meter
$indroundwnoconiftrop\_xq_{it}$[2]	: Industrial round wood volume of exportation, in cubic meter
$palmoilprod_{it}$[2]	: Palm oil production, in tons
$soymorat2006_{it}$	: Binary variable that takes the value 1 if the observation date is between 2006 and 2020, 0 otherwise
$REDD$	: Binary variable that takes the value 1 if the observation date is between 2006 and 2020, 0 otherwise
$fp\_cpi\_totl\_zg_{it}$[1]	: Inflation, consumer prices (annual %)
$pa\_nus\_fcrf_{it}$[1]	: Official exchange rate (LCU per US$, period average)
$dt\_oda\_odat\_pc\_zs_{it}$[1]	: Net ODA received per capita (current US$)
$tempmoyenne_{it}$[1]	: Annual average temperature observed in the country, in Celsius degree
$precipit_{it}$[1]	: Annual average precipitation in the country, in mm
t_{it}	: Variable taking the value following the rule "year of observation" - 1990
tsq_{it}	: Variable taking the squared value of variable t
$percent\_degrad\_1_{it}$[2;3]	: Forest loss due to forest degradation in year t-1, in % of the total forested area in year t-1

Source: [1]WorldBank, [2]FAO, [3]Vancutsem et al. (2021)

The two first variables displayed in table 3.4 are those used as dependent variables. They respectively account for the annual forest loss due to direct deforestation and to degradation, in percentage of the contemporaneous forest area of the country. The annual loss in hectares was provided by the work of Vancutsem et al. (2021), and the forested surface in squared kilometers by the database of the FAO. The 28 variables that follow are explanatory variables. Their sources are given by the superscript at the end of their code. All variables have been chosen after the building and understanding of the literature review. They are all supposed to bring a particular information to our future models. Variables from $fp\_cpi\_totl\_zg_{it}$ to the bottom of table 3.4 are supposed to be control variables. They are not of primary interest but are placed in the regression in order to increase the ceteris paribus analysis of coefficient of interest. However, even if their coefficients are not the main interest of our work, they still bring some pieces of information to our results.

The first three control variables are purely economic factors. They aim to take into account the economic structure of the country. The general level of prices could play a role in forest loss dynamics. Prices underlay many market forces, which is why inflation has been chosen as a control variable in our models. Inflation, represented by the consumer price index, measures the annual percentage change for the average consumer to acquire a specified basket of goods. A positive change means an increase in price, while a negative change implies a smaller cost for the same basket of goods, compared to the previous year. An increase in the inflation rate could change forecasts of economic agents and could therefore change the pattern our model is supposed to take place in. Adding inflation as a control

variable allows to assume fixed anticipations from economic agents. The second economic control variable account for the official exchange rate. Accounting for the exchange rate allows to be sure that the rules under which international trade is developing do not change. The third one, which add the information about the net amount of official development aid (ODA) received per capita to our models, aims to provide the idea of relative poverty. A country with large net ODA per capita should be a less developed nation, comparatively with countries being less helped. Of course this is not a perfect information, as the rules of international diplomacy are complex and changing. However, we might consider that this variable should be more appropriate than GDP per capita for example, as it should be more directly related to general development and poverty.

Variables giving information about the average level of precipitation and the average temperatures aim to account for particular extreme climatic events, namely for the ENSO phenomenon which is supposed to have borne a substantial impact on forest (Vancutsem et al. (2021)). However, as ENSO might not be the only climatic event having influenced forest loss, purely climatic variables have been preferred to time dummy variables.

In order to avoid spurious regression, and because some variables such as food production index or agricultural yields are supposed to be upward trending, our models will contain time trends. The variables tsq_{it} aims to allow for non-linear trends. A third degree component could have been advised, as some future statistics will show. However, as our work consists in identifying drivers of forest deterioration and not in approximating a curve with polynomials, we have decided to not add this third degree trend component.

3.1   Dependent variables

As this work aims to identify drivers of forest loss, dependent variables obviously consist in data about the magnitude of these forest disturbances. It seems advisable to present an overview of forested areas and the loss they have experienced since 1991.

The world's most forested country included in our sample is unsurprisingly Brazil. With an average surface of forested land between 1991 and 2020 of 533.57 million of hectares, Brazil outperforms every other nation in our sample. On the African continent, the Democratic Republic of the Congo (DRC) is the most forested nation with an average of 139.41 million of hectares. Indonesia leads the ranking in Asia with a surface of forests averaged around 101.51 million of hectares. These values are of course strongly related to the size of the country they are referring to. Brazil, DRC, and Indonesia are all part of the largest countries in their respective continent. Which is why it should be more interesting to evaluate forested areas in relative term by accounting for the size of the country. In percentage of national land, on average on the studied time span, Brazilian forests account for 63.84% of the whole territory, Congolese (DRC) ones for 61.49%, and Indonesian ones for 55.70%. If these figures are still quite substantial, some other nations of our panel dataset display far higher percentages. On the worldwide and American side, Suriname was the leader with 97% of its land being covered by forests in 2020. Its neighbor, Guyana, was the second most forested country of our sample in 2020, in relative term, with a ratio of 94%. On the African continent, Gabon leads the ranking with a ratio of 91% in 2020. Papua New Guinea, with a share of 79% in 2020, is number one in Asia. (FAO (2020))

Between 1991 and 2020, TMFs have suffered from direct deforestation and degradation of the forest cover. The forest loss these disturbances induce did not have the same impact on each country or region. Table 3.5 presents the top five countries of our sample which have experienced the largest accumulated forest loss on the studied period. These results come from the addition of yearly forest loss from 1991 until 2020. Rankings are decomposed by type of forest loss (deforestation or degradation), and presented in absolute term (in millions of hectares accumulated through the period) and in relative term, by dividing the absolute cumulative forest loss by the size of the for-

est in 1991. Brazil, leads both rankings in absolute value due to the size of its forest. Indonesia follows with more than 25 millions of hectares lost from both kinds of disturbances since 1991.

Country	Period Average of forested area in millions of ha
Brazil	533.568835
Congo. Dem. Rep.	139.412144
Indonesia	101.507853333333
Peru	74.511133
Angola	74.0563066666667
India	68.5157
Mexico	67.742718
Colombia	61.7941361666667
Bolivia	54.0639198333333
Venezuela	48.4674066666667
Papua New Guinea	36.1869749
Myanmar	33.2188543333333
Nigeria	23.9948585
Gabon	23.6613221666667
Central African Republic	22.738
Ivory Coast	22.1281
Cameroon	21.270078
Thailand	19.5858666666667
Malaysia	19.5489115
Guyana	18.5267756666667
Lao People's Democratic Republic	17.174125
Suriname	15.3068068333333
Ecuador	13.4150253333333
Madagascar	12.8636985
Viet Nam	12.4893946666667
Cambodia	10.1729996666667
Ghana	8.53588583333333
Liberia	8.05621
Philippines	7.2010555
Nicaragua	4.79871683333333
Congo. Rep.	4.71770333333334
Panama	4.38702316666667
Guatemala	4.00131
Global mean	*48.1096923959595*

Figure 3.14: Ranking of averaged forested area over the period 1991 to 2020, by country, in millions of hectares

Source: FA0

Besides having one of the largest forests of our sample, Indonesia is also one of the countries which have know the more important cumulative forest loss in relative terms. The Asian country is indeed included in each ranking, taking the 4th and 5th place as the country having experienced the most important forest loss in percentage of original forested area since 1991, respectively due to deforestation and forest degradation. As it can be seen it figure 3.14, most of countries on top of absolute forest loss rankings are also leaders in terms of forested areas. Brazil, Indonesia, DRC, Malaysia and Colombia have average forested area above the world average for the studied period. Only Myanmar does not belong to the top 10 of most forested nation, being however not so far from the global average. On the other hand, as it was also relatively expected, most of the leading countries in relative loss rankings are actually relatively less forested countries. Philippines, Nicaragua, Congo, and Guatemala, are indeed part of the top 5 countries with the lowest forest cover (Figure 3.14). Cambodia, which is the 5th which have experienced the worst relative forest loss due to deforestation between 1991 and 2020, is also part of the top 10 countries with the smallest forest cover. Which is more surprising is the ranking of Indonesia and

Malaysia when analysing relative loss. Despite their large forested areas, these nations have experienced huge relative forest losses on the studied period. Indonesia have lost, both kinds of disturbances combined, more than 50% of its 1991 forest area. Malaysia, have lost almost 40% of its 1991 forest only looking at pure deforestation. While absolute columns of table 3.5 display information that was quite obvious, relative columns give an interesting insight on the strength of the loss of forest cover. This idea will be followed later, by using relative loss as dependent variable, instead of absolute degradation or deforestation.

Table 3.5: Top 5 countries with the largest cumulative forest loss between 1991 and 2020, in absolute and relative terms, by type of forest loss

Forest loss due to deforestation				Forest loss due to degradation			
In millions of hectares		In % of forested area in 1991		In millions of hectares		In % of forested area in 1991	
Brazil	52.12	Guatemala	40.72%	Brazil	29.02	Philippines	65.07%
Indonesia	25.11	Malaysia	39.28%	Indonesia	27.25	Nicaragua	57.38%
DRC	8.78	Nicaragua	27.65%	DRC	16.97	Congo Rep.	46.34%
Malaysia	7.52	Indonesia	27.25%	Colombia	7.08	Guatemala	36.27%
Myanmar	4.37	Cambodia	26.70%	Myanmar	5.83	Indonesia	29.58%

Source: WorldBank, FAO, and Vancutsem et al. (2021)

If the ranking of the biggest forest loss is quite different whether we consider one or the other type of forest disturbance, or whether or not we work in relative terms, it is not at all the case for the ranking of the smallest loss of tree cover. Three countries indeed form the top 3 of the smallest absolute and relative loss, both in term of forest degradation and in term of direct deforestation: Suriname, Gabon, and Guyana. These nations have indeed experienced a cumulative degradation around 2% of their 1991 forest area, and a cumulative deforestation around 1% (even 0.5% for Gabon). This corresponds to an absolute accumulated loss below one million hectares lost for each country since 1991. Gabon, Suriname, and Guyana are all three middle class countries on the ranking presented in figure 3.14. Note that these countries also compose the ranking displayed in figure A.1 in the appendices, relative to the most forested countries.

At the continental level, patterns also deserve to be analysed. Figure 3.15 presents the yearly deforestation in millions of hectares, by continent, between 1991 and 2020. Trends are also represented on the chart. They have been approximated by a 3rd degree polynomial. The chart highlights the dominance of American deforestation, pushed up by the case of Brazil. The same graph is presented in figure A.14 in the appendices. Note that, beside for the magnitude of the forest loss, conclusions are not different from those drawn when Brazil is included in the sample. Both America and Asia hit their peak of absolute deforestation in the late 90's, America in 1999 and Asia in 1998. Africa, as it was expected, presents a clear lower rate of deforestation on the studied time period. The continent hit its maximal level of deforestation in 2013. The years with the lowest level of forest loss due to deforestation are, respectively for Africa, America, and Asia, 1991, 2012 and 2017. Tendencies are also quite interesting. Both America and Asia seem to display a sinusoidal pattern, as deforestation peaked in the late 90's, observed a general decrease for 10 years, before showing some signs of a possible new rise. This sinusoidal pattern is clearer for America, as it can be seen on figure 3.15. For Africa, the 3rd degree polynomial approximation does not look quite different from what it would have been with a 2^{sd} or 1st degree approximation. The trend is upwards and looks relatively linear.

Figure 3.16 presents the evolution of the yearly deforestation in millions of hectares, by continent, between 1991 and 2020, by displaying charts of the dynamic mean (3 years) of yearly deforestation for each continent. The sinusoidal pattern is less obvious but the upward trend of the African deforestation and the peak years for Asia and America are clearly visible. American and Asian deforestation seem to present a more U-shaped pattern with a stagnation level, rather than a clear sinusoidal trend which would imply an upcoming raise. Figure A.14 in the appendices shows that the dominance of America when studying absolute deforestation plummets when Brazil is excluded from the analysis. Note that this would probably be the same with Asia if Malaysia and Indonesia were excluded. However, Brazil, Indonesia, and Malaysia are part of our sample and their impact should be taken into account. Figures in the appendices should be considered as a complementary piece of information, but figures 3.15 and 3.16 constitute the real topic of our analysis.

The same graphs, presented this time for forest degradation, are displayed in figures 3.17 and 3.18. In appendices can also be found the graph of yearly degradation by continent when Brazil is excluded (see Figure A.15). The American continent seems to be less dominant when studying degradation instead of deforestation. The highest level of yearly degradation is indeed given by Asia for the year 1998. Asian forest degradation seems to be generally dominant until 2010, after which the American tropical moist forests became the most degraded ones of our sample. Figure 3.15 seems to display two peaks between 1991 and 2020. The first one occurs in the late 90's or early 00's and the second one at the end of the second decade of the 21st century. These peaks are also shown in figure 3.18. This figure highlights the fact that the first peak seems actually to be lagged between continents. Asia indeed seems to have experienced its worst year in term of forest degradation in 1998, while American forest degradation peaked in 1999 and African ones in 2001. The ENSO phenomenon, cited by the literature as having worsen forest degradation, is supposed to have had an impact in 1998 (Vancutsem et al. (2021)). This could explain such a peak, if the ENSO effects may have lasted for 3 to 4 years.
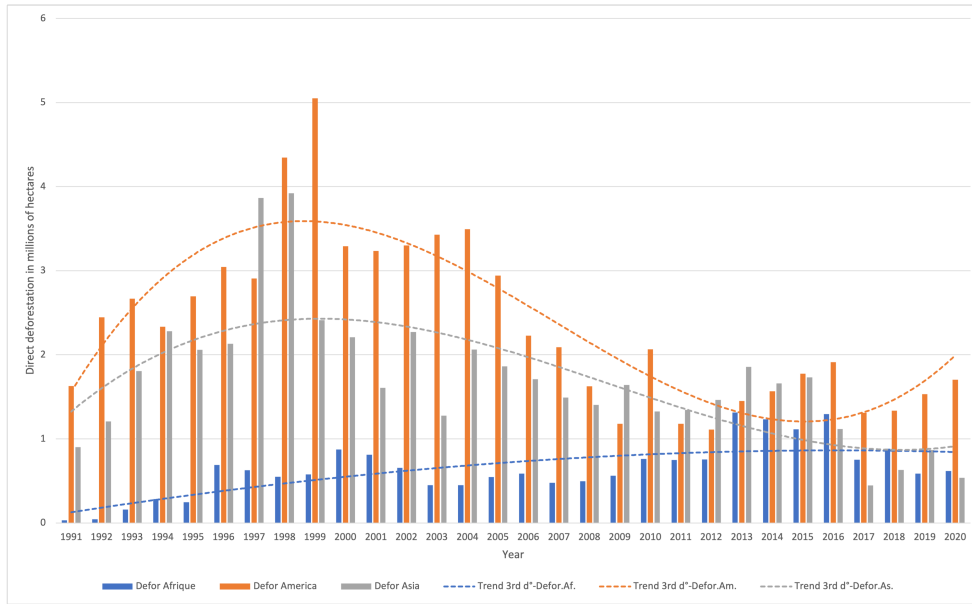
Figure 3.15: Yearly deforestation in millions of hectares, and trends, between 1991 and 2020, aggregated by continent
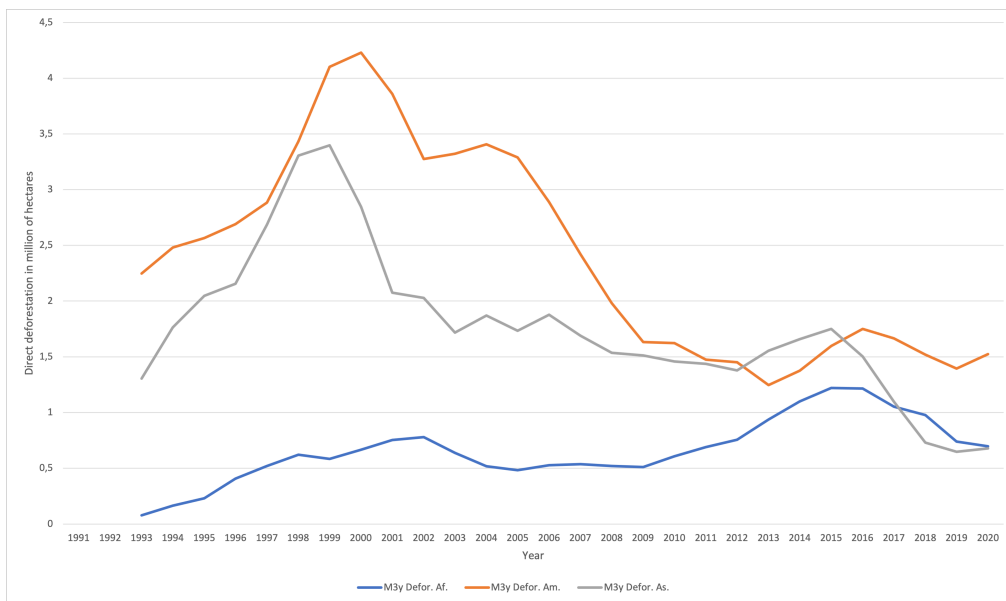
Source: FA0 and Vancutsem et al. (2021)

Figure 3.16: Evolution of the 3-year mean of annual deforestation in millions of hectares between 1991 and 2020, aggregated by continent

Source: FA0 and Vancutsem et al. (2021)

The second peak occurred around 2015 and could also be due the ENSO phenomenon. This second rush of degradation is however smallest in magnitude. Tendency curves displayed in figure 3.15 are quite similar to those presented in figure 3.15. The sinusoidal shape is however more smoothed, as the decrease experienced in the 00's is less pronounced. Note that Africa's trend looks more similar

to those for the other continents, losing therefore its upward linear aspect.

This rapid overview of forest loss trends aims to provide insight for a sound and consistent choice of control variables.
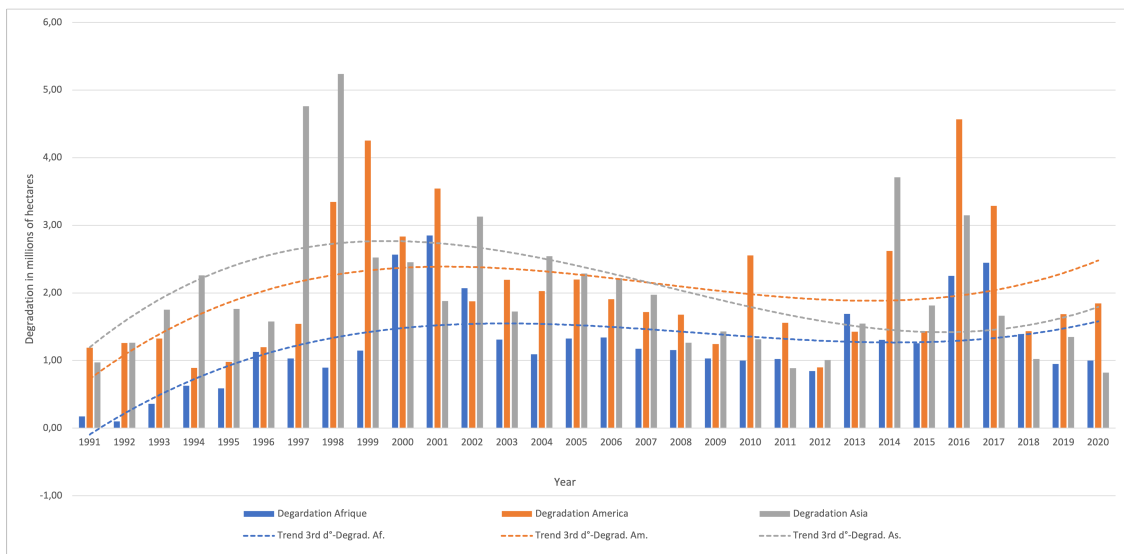

Figure 3.17: Yearly forest degradation in millions of hectares, and trends, between 1991 and 2020, aggregated by continent
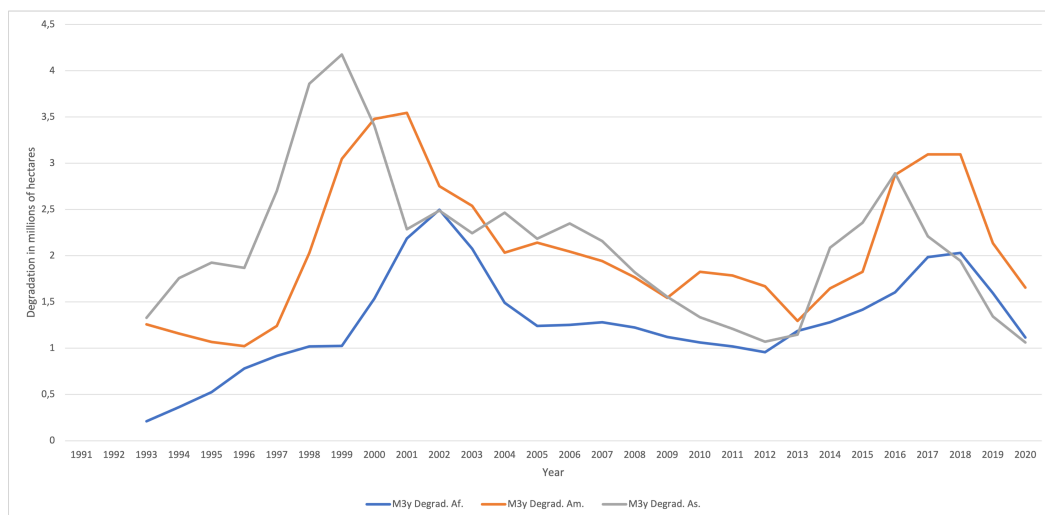
Source: FA0 and Vancutsem et al. (2021)

Figure 3.18: Evolution of the 3-year mean of annual deforestation in millions of hectares between 1991 and 2020, aggregated by continent

Source: FA0 and Vancutsem et al. (2021)

3.2 Independent variables

All independent variables won't be described in this section. Descriptive statistics aim to highlight some particular features our database may present, in order to meet our goals with well-adapted analyses. For the sake of clarity, and in order to avoid misunderstandings about the definition of the variables this section will analyse, variables will be mostly denoted by their code presented in table 3.4.
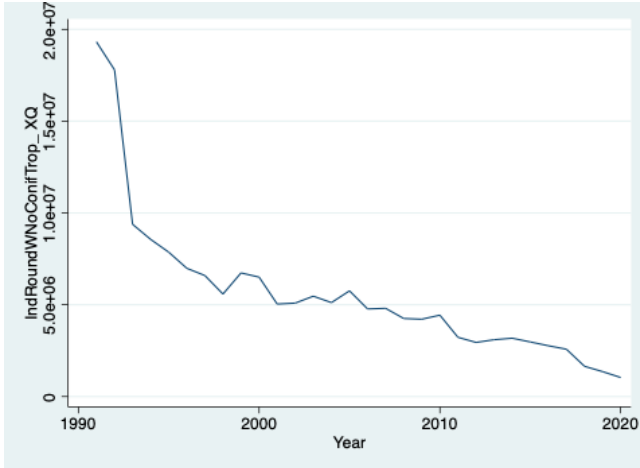

Figure 3.19: Evolution of yearly exports of industrial non-coniferous tropical round wood of Malaysia, in cubic meters

Source: FA0

A factor commonly assumed to drive forest loss is the round wood industry (see section 1.4.6). The variable $indroundwnoconiftrop\_xq_{it}$ accounts for the yearly volume of exportation of non-coniferous tropical round wood. According to the literature, Asian countries are leaders in this domain and most of the worldwide exports come from Asia . This is indeed verified in our database as the continental mean of $indroundwnoconiftrop\_xq_{it}$ over the studied period is substantially higher for Asia than for other part of the world (Geist and Lambin (2002)). With a mean of 1 008 717 cubic meters a year, Asia indeed largely overcomes Africa and America, whose means are respectively equal to 321 139.3 m^3 and 54 663.41 m^3 a year. However, the mean for Asia is not really representative because of the weight of the Malaysian exportation. Malaysia is indeed by far the largest exporter of industrial tropical round wood. As a proof, the continental averaged level of round wood exportation falls to 494 433.3 m^3 a year

when the Malaysian case is excluded. However, even with its biggest exporter being excluded, Asia still remains the world's leader in industrial round wood exportation. Note that Malaysian exports of industrial round wood have largely dropped since 1991 but remain substantial, as it can be seen in figure 3.19. This decrease is specific to Malaysia and is not systematically reported in other Asian countries.

Oil is supposed to bear an impact on forest loss, whether it is by passively protecting forest from agricultural development, or by allowing richer countries to invest in living accommodations such as gas or electricity supply (Megevand and Mosnier (2013) and Tchatchou et al. (2015)). The share of the GDP constituted by oil rents can provide information on the economic structure of a country. This information might however be difficult to interpret and such an exercise demands to be done with caution. A higher share in GDP might first suppose that the country is richer, and disposes of large oil resources. If it is the case, it could be a sign of better living standards, improved by better infrastructures and subsidised access to daily accommodations. On the other hand, a larger share of GDP coming from oil rents might suggest that the economy is poorly diversified. Cases may be combined, as a richer economy do not imply a broadly diversified market structure. However, we can assume that an economy which strongly relies on natural resources is a sign of a relatively low development level (Gylfason (2006)). The variable $ny\_gdp\_petr\_rt\_zs_{it}$ accounts for the share of GDP constituted by oil rents, in percentage. Over the studied period, African countries have on average a biggest proportion of their annual GDP being constituted by oil rents. The continental mean, between 1991 and 2020, is indeed equal to 10.78%, while it is of 3.69% for America and 2.20% for Asian countries. Once again, conclusion cannot be drawn directly from these results. Nonetheless, by

analysing the total natural resources dependence, we could have a more precise idea of the economic situation of our sample. The WorldBank provides a broad dataset about development indicators, including namely the total natural resources rents in share of GDP. Continental disparities are quite similar to those for oil rents, with African countries having on average, between 1991 and 2020, a GDP composed of 18.43% by natural resources rents, while this share is about 7% for both America and Asia. Combining both pieces of information, we may reasonably assume that Africa have faced a lower level of development, as its economic structure is supposedly less diversified. This is actually consistent with others economics clues which also assert that Africa is generally less advanced in its economic transition (see figure 1.7).

This idea is also corroborated by the continental analysis of the variable $ag\_yld\_crel\_kg_{it}$, accounting for the cereal yields, measured as kilograms per hectare of harvested land. Poor yields could be considered as a sign of under-development, because of lower access to agricultural technology for example. Once again, Africa is left behind with an average cereal yield between 1991 and 2020 of 1322.56 kilograms per hectare of harvested land. America follows with a mean of 2948.70 kg/ha, and Asia is once again at the top of the ranking with an average yield of 3375.29 kg/ha. One of course have to pay caution before concluding about the level of development of such regions, but these results are another hint allowing our conclusions and interpretations to become more precise and evidence-based. Besides this aspect of economic advancement, higher yields in agricultural production could also implies lower forest loss, as harvesting the same quantity could be made on a smaller area.

Some authors have cited charcoal production and consumption has being an important driver of forest loss. Megevand and Mosnier (2013) indeed assert that some richer countries of the Congo Basin have experienced lower rates of forest disturbances because they would be less dependent to charcoal as a source of energy. Kissinger et al. (2012) even assert that charcoal production is, with wood fuel extraction, the main driver of degradation in Africa. Charcoal is therefore a major factor to be analysed in this work, above all concerning the African continent. Actually, it is in its consumption perspective that charcoal will be analysed in our work. The addition of data about charcoal aims to add, by combining it with other related variables, the information about poverty in our models. The goal is to create some kind of "index" being able to take into account the idea of poverty, and charcoal consumption is one of the component of this "index". A nation which would be strongly dependent to charcoal as a source of primary and domestic energy might be considered as being in an earlier phase of development, at any case in the energy domain (Chidumayo and Gumbo (2013)). We could expect Africa to be more dependent of such an energy source, and Asia to rely more on more advanced energy sources such as oil, electricity of gas (Megevand and Mosnier (2013) and Bakehe (2022)). The averaged charcoal production per capita fits with these expectations, as African countries display on average for the period of analysis a charcoal production per capita ratio of 84.5 kg of charcoal per person per year, while the same ratio is 9.8 kg per capita for America, and 4.9 kg per capita for Asia. This higher reliance to charcoal, namely cited by Megevand and Mosnier (2013), could be interpreted as a sign of relative poverty.

Some type of agricultural products have been grown in some particular regions of our sample, and some of them are supposed to have borne an impact on forest loss on our analysed time span. It is the case for soybeans, which are grown mostly in Brazil, and for palm oil, which is mostly produced in Malaysia and Indonesia (Ritchie and Roser (2021)). Figure 3.20 shows the dominance of Brazil when speaking about soybean production. This dominant position is actually shared with the US, which are not part of our sample. Figure 3.21 shows the dominant position on the palm oil market of Indonesia and Malaysia. These nations were actually the only countries which produced more than 5 million tons of palm oil in 2018. These agricultural products should be considered as special features of continents they are grown in. However, in the case of soybeans, the dominant position of Brazil is so strong that soybeans production should almost be considered only at the Brazilian level, and not as an American characteristic. The continental mean on the studied period is indeed about 5.5 millions

of tons of soybeans produced per year, when Brazil is taken into account. With the exclusion of Brazil, this mean plummets to 216 301 tons. Brazil is therefore a real outlier in terms of soybeans production. The problem is that the Brazilian production is so important that excluding it means losing capacity of analysis. As soybean is assumed to be a major driver of forest loss, doing without the worldwide largest producer would not make much sense. The case is a bit different for palm oil. Indonesia and Malaysia are surely dominant on the market, but their monopoly is not as strong as the Brazilian one on soybeans. However, such a dominant position must be kept in mind when interpreting results.
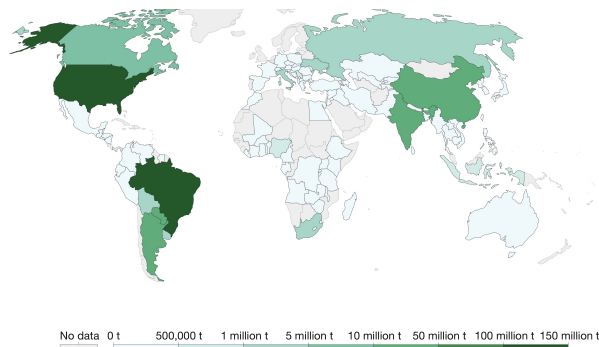

Figure 3.20: Soybeans production in 2018, measured in tons
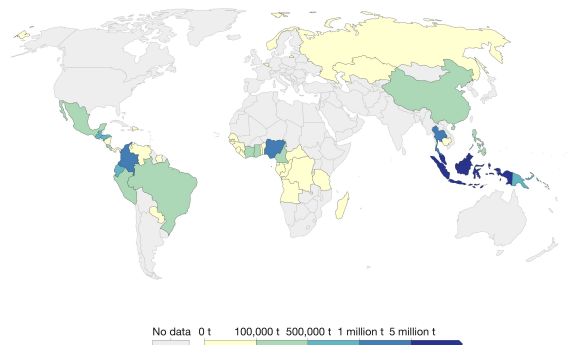
Source: Our World In Data

Figure 3.21: Palm oil production in 2018, measured in tons

Source: Our World In Data

A part of our methodology suggests to add purely economic variables as control variables. Among these variables there is namely the net official development aid (ODA) received by capita in current US\$, denoted by $dt\_oda\_odat\_pc\_zs_{it}$. Charts showing evolution of this variable are presented in the appendices (see Figure A.16, A.17, and A.18). The Asian mean on the studied period is more than two times smaller than those for America and Africa. Asia is indeed assumed to have received annually, on average between 1991 and 2020, 20.67 current US\$ per inhabitant, while Africa and America have received on average, respectively 47.54 current US\$ and current 42.07 US\$ per capita. Whether this difference is a mark of a more developed economy, being less in need for aid, or whether it is a sign of more complicated diplomatic relations between Asia and the rest of the World remains something to be determined.

As mentioned in the literature review, exchange rate might have an effect on forest disturbances through its influence on international trade (Richards et al. (2012)). A devalued currency is assumed to foster exports while a stronger currency increases importation capacity. The variable $pa\_nus\_fcrf_{it}$ gives the average annual amount of local currency units needed to make one US dollar. If the value of the variable increases, the local currency is devalued, as it requires more units to make one US\$. Devaluation is supposed to boost exports. Contrary, if $pa\_nus\_fcrf_{it}$ decreases, it means that the value of local currency compared to the US\$ increases. Such an appreciation should lead to a lower export level. Globally, local currencies of countries of our sample tend to have been devalued compared to the US\$ between 1991 and 2020. Figure 3.22 shows the Nigerian evolution of the official exchange rate represented by the variable $pa\_nus\_fcrf_{it}$. The upward trend displayed in this figure is also visible for almost every other country of the sample. The only countries which do not display such an upward tendency are those which have adopted the US\$ as national currency, or those which have linked their local currency to the US\$. Figure 3.23 shows the evolution of $pa\_nus\_fcrf_{it}$ for Panama. As Panama uses the US\$ as national currency, figure 3.23 of course displays a constant line equal to one. Note that Ecuador also uses the US dollar as national currency since 2000, after a huge

devaluation[10] of it previous national currency, the Sucre, in the late 90's. Even if $pa\_nus\_fcrf_{it}$ is added to our models as a control variable, as its value is supposed to foster or undermine exports, it could be interesting to analyse its coefficient to get an idea on how international trade can have an impact on forest loss.

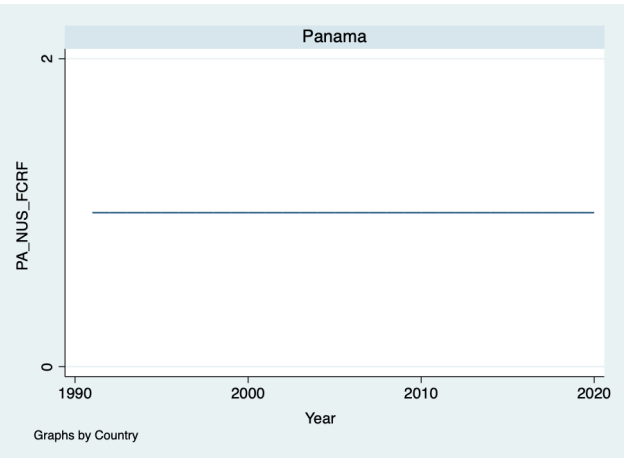| Figure 3.22: Evolution of the official exchange rate of Nigeria, LCU per US$, yearly average	Figure 3.23: Evolution of the official exchange rate of Panama, LCU per US$, yearly average
Source: WorldBank	Source: WorldBank

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[10]maximum: 11786.8 Sucre per US$

Results

All our models have been estimated using within-groups estimation methods, being fixed effects models. As this work tries to empirically assess the impact of drivers extracted from the literature, it is crucial to get the most unbiased coefficients possible. By working with fixed effects estimation methods (FE), we make sure to avoid omitted variable bias coming from fixed features of countries. However, the use of variables which are constant over time is impossible, and the variability of the dataset is lowered as a part of the information is taken out (Wooldridge (2015)). Before choosing to work with FE, alternatives had to be considered.

Random effect model (RE) was one of them. It would have allowed the use of time-constant variables, and variability would not have been reduced as this model does not imply to eliminate any part of the information. The question is whether or not the fixed part of the error in our model is correlated with the explanatory variables. The RE indeed assumes strict exogeneity of both part of the error term. Such a hypothesis is unlikely to hold in our case. The country specific location, which is by nature fixed over time, is surely correlated with one of our variable such as the average temperature for example. This leads to the breaking of the strict exogeneity assumption of RE. Nonetheless, Hausman tests have been performed in order to empirically test this assumption. Each Hausman test have rejected the null hypothesis of no systematic difference in coefficients obtained from FE and RE at a 10% significance level. Actually, only two tests have not rejected H0 at 1%: the test performed on the world degradation model has rejected the null hypothesis at 10% level and the test performed on the Asian degradation model has done the same at 5% level. These tests prove that Random Effect estimation method is not recommended, as strict exogeneity of both part of the error term cannot be ensured. Besides these Hausman tests, the Correlated Random Effect (CRE) approach also led us to think that FE should be preferred to RE. A t-test performed on CRE estimators obtained for the time averaged variables indeed shows that the null hypothesis, according to which these estimators would be equal to zero, could be rejected at a sufficiently small significant level. As assuming that these coefficients are equal to zero is an assumption attached to Random effect models, FE should be preferred. CRE analysis and Hausman tests therefore corroborate the idea according to which the fixed part of the error in our model is correlated with the explanatory variables, and that we should therefore work with fixed effects models and estimations methods (Wooldridge (2015)).

Fixed effects model will allow our models to get rid of the fixed, over time, component of the error term, eliminating therefore one cause of omitted variable bias. In the case of forest deterioration, these fixed features might be numerous and some straightforward examples can help to understand it. The accessibility of Asian archipelagos are clearly a fixed factor influencing the easiness of forest exploitation and therefore the rate of forest deterioration. On the contrary, the Central African Republic, which is landlocked, should be less easily exploited. As another example, the location of the country should be linked to the averaged temperature and precipitation, which are explanatory variables. Cultural characteristics could also be assumed to be fixed over time. A population whose culture would consider forest exploitation as being taboo for example (Twongyirwe et al. (2018)), should be less inclined to drive deforestation. Fixed effects estimation methods will therefore be a clear advantage in our analysis, by allowing to account for fixed over time unobserved factors.

It was also primordial to test whether or not our regressions could suffer from heteroskedasticity or from autocorrelation. Tests have therefore been performed in order to investigate these possibilities. To investigate heteroskedasticity, a modified Wald statistic for groupwise heteroskedasticity in fixed effect model[11] have been computed for each model. The null hypothesis of homoskedasticity have been rejected each time at a 1% level. This means that the hypothesis of equal variances across cross-sectional units is very unlikely to hold, and that should be taken in account.

The second threat to our analysis is autocorrelation (Wooldridge (2015) and Scrieciu (2007)). The question is actually whether or not the idiosyncratic errors of our linear panel-data models are serially correlated. The command *xtserial* on Stata17 tests the assumption of no first-order autocorrelation. A p-value approaching zero would therefore mean that the error terms are likely to be correlated from one time period to another. This test have been performed for each model. On 11 tests performed, three have rejected the null hypothesis of no first-order autocorrelation at 10% level. The model about African degradation has rejected the null hypothesis at 1% level, while tests on deforestation models in their specific perspective for America and Asia presented p-value around 8%. Note that the test on homogeneous model of deforestation for America displayed a p-value equal to 0.1283. In order to take into account the recommendations of Scrieciu (2007) about the importance of correcting for serial correlation, and because of these three (four) models being at stake of autocorrelation, we have decided to make standard errors robust to both serial correlation and heteroskedasticity for each model.

For an easier interpretation, variables have been standardized[12], as Mrs. Ulm advised during a private interview the 22$^{\text{sd}}$ of June 2022. This work indeed aims to identify and rank drivers of forest disturbances, if it is possible. Thanks to standardization, coefficients are made comparable, even if their interpretation is quite tricky. Signs are still valid, and theoretical models can therefore be tested. Note that when interpreting the results, the use of "positive impact/effect" or "negative impact/effect" has no subjective meaning. The idea behind these expressions is strictly related to the direction of the analysed relationship, and has nothing to do with any ethical considerations about forest loss.

4.1 Models of deforestation

We first worked on the phenomenon of deforestation in its strict meaning, considering only permanent forest loss. The dependent variable is the annual percentage loss of forested area due to direct deforestation.

4.1.1 Homogeneous perspective

$$zpercent\_defor_{it} = \gamma_0 + \sum_{j=1}^{k} \beta_j x_{itj} + \sum_{l=1}^{m} \delta_l c_{itl} + a_i + u_{it} \tag{4.1}$$

Homogeneous models to be estimated take the form of the equation 4.1 for each aggregate. They are unobserved effects models depicting the fixed part of the error term, denoted a_i. The term u_{it} denotes the idiosyncratic part of the error term. The letter i accounts for the country, t for the year of observation. Variables of interest which are common across continents have been denoted by a x, while control variables have been denoted by a c. Estimation should therefore focus on getting on biased estimates of the β coefficients. As equation 4.1 describes the homogeneous perspective of our analysis, variables of interest are all common across regions, and all variables are therefore presented for each model. γ_0 is the intercept of our regression, and present few interest.

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[11]xttest3 command in Stata17, which is workable when the assumption of normality is violated

[12]mean=0 and standard error=1

Table 4.6: Deforestation model, Homogeneous perspective, Fixed Effect model with standard errors robust to heteroskedasticity and autocorrelation

Source: FAO, WorldBank, and Vancutsem et al. (2021)

	World $zpercent\_defor_{it}$	Africa $zpercent\_defor_{it}$	America $zpercent\_defor_{it}$	Asia $zpercent\_defor_{it}$
$zag\_prd\_crop\_xd_{it}$	-0.122	-1.628*	-0.229	0.0731
	(0.206)	(0.744)	(0.176)	(0.268)
$zag\_prd\_food\_xd_{it}$	0.0312	1.682*	-0.0363	0.255
	(0.367)	(0.865)	(0.220)	(0.393)
$zag\_yld\_crel\_kg_{it}$	-0.520	-1.632*	0.325	-0.830*
	(0.453)	(0.837)	(0.295)	(0.387)
$zis\_air\_good\_mt\_k1_{it}$	-0.0864	-2.654	0.148	0.203
	(0.101)	(2.504)	(0.127)	(0.138)
$zeg\_elc\_loss\_zs_{it}$	-0.0882	-0.0246	-0.0220	0.431*
	(0.0950)	(0.0858)	(0.117)	(0.209)
$zny\_gdp\_petr\_rt\_zs_{it}$	-0.0668	0.0402	-0.0174	-1.150***
	(0.0478)	(0.0568)	(0.0781)	(0.179)
$zny\_gdp\_ngas\_rt\_zs_{it}$	-0.00967	-0.114	0.0385	-0.0298
	(0.0871)	(0.365)	(0.0475)	(0.0813)
$zny\_gdp\_minr\_rt\_zs_{it}$	0.110	0.421*	0.0517	0.103
	(0.0874)	(0.192)	(0.0289)	(0.141)
$zsp\_pop\_grow_{it}$	0.0610	-0.753	0.256	0.414
	(0.297)	(0.479)	(0.294)	(0.532)
$zsp\_urb\_grow_{it}$	0.0733	0.0615	-0.343	-0.0160
	(0.133)	(0.228)	(0.264)	(0.0701)
t_{it}	0.0204	0.0105	-0.0288	-0.00664
	(0.0304)	(0.0245)	(0.0348)	(0.0348)
tsq_{it}	0.000326	0.00176	0.000336	0.000514
	(0.000763)	(0.00183)	(0.000702)	(0.00133)
$REDD_{it}$	-0.101*	-0.163	-0.0414	-0.182
	(0.0540)	(0.195)	(0.0678)	(0.173)
$ztempmoyenne_{it}$	0.423*	0.161	0.328	0.156
	(0.212)	(0.256)	(0.310)	(0.144)
$zprecipit_{it}$	-0.113	-0.488	0.0549	0.238
	(0.142)	(0.332)	(0.104)	(0.160)
$zpercent\_degrad_{it}$	0.446**	0.0638	0.974**	0.600***
	(0.164)	(0.0453)	(0.375)	(0.151)
$zpercent\_degrad\_1_{it}$	-0.0401*	-0.0219	-0.0990	-0.0264
	(0.0223)	(0.0690)	(0.0821)	(0.0416)
_cons	-0.212	-3.827	0.365	0.821*
	(0.426)	(2.136)	(0.460)	(0.408)
N	530	147	221	162
R^2 within	0.339	0.656	0.610	0.683

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table 4.6 presents the results obtained with a fixed effects model, when pattern of deforestation is considered in a homogeneous perspective. Variables have been classified in order to fit with the ranking displayed in table 2.1. The first column is the aggregate for the world, the following ones present the results by continent. Table 4.6 seems to not display a general pattern. Few coefficients are significant at a reasonable level, and comparison is actually quite difficult because coefficients are rarely significant on several continents at a time. The impact of degradation is however worth noticing as its coefficient is significant at the world level and on the American and Asian aggregate. Its sign is positive as the literature has expected (Vancutsem et al. (2021)). According to our results, an increase in the forest loss due to degradation is supposed to increase on average the percentage of loss due to direct deforestation. One can also note the negative coefficient attached to the dummy variable *REDD*. The REDD+ policy seems to have had an impact on deforestation, at least at a global level. We can also note the coefficient on the share of GDP generated by oil rents for the Asian continent as it is both significant at 1% level and economically substantial, being the only coefficient for Asia larger than 1 in absolute value. Its negative sign supposes a decreasing relationship between the share

of oil rents in GDP and the rate of deforestation in Asia.

For Africa, coefficients attached to agriculture are significant at 10% level, and their sign deserve to be analysed. As expected, an increase in yields, ceteris paribus, is supposed to decrease deforestation. More can be produced on the same area and there are therefore less reasons to cut down trees to free up more space. The sign on the crop production index variable is less obviously expected, even if it remains relevant. As the food production index is also taken into account, the crop production index variable actually accounts only for variations in agricultural products which are not food. This is actually the reason why these variables have been put together in the model, in order to integrate the idea of commercial and subsistence agriculture. Many previous studies have mentioned the difficulty to make the difference between those two types of agriculture, namely Margulis (2004) and Geist and Lambin (2001)). Our study is no exception but it remains interesting to mark, by one way or the other, the difference between subsistence and commercial agriculture. Even if we can assume that all food production is not intended to feed only local population, the food production index can give an insight on how feeding people drives deforestation. As expected, the related coefficient is positive and quite substantial. Even if its significance level is not particularly strong, we can be reasonably confident about the direction of the relationship between the production of food and the rate of deforestation. The negative sign of the coefficient on the crop production index variable actually asserts that an increase in crop production which would not occur in the feeding pan of agriculture, would decrease deforestation rate.

It seems pretty clear that the homogeneous perspective does not provide an adapted framework to analyse deforestation. Comparison is barely feasible and ranking coefficient does not make any sense. However, these results actually verify the assumption we had made in the beginning of this work, assuming that the worldwide analysis of deforestation should not be advised (Scrieciu (2007)).

4.1.2 Adaptive perspective

$$zpercent\_defor_{it} = \gamma_0 + \sum_{j=1}^{k} \beta_j x_{itj} + \sum_{n=1}^{o} \alpha_n s_{itn} + \sum_{l=1}^{m} \delta_l c_{itl} + a_i + u_{it} \qquad (4.2)$$

Equation 4.2 presents the general form of the adaptive models of deforestation to be estimated. Besides the error term, which still presents a fixed part a_i and a time-varying part u_{it}, equation 4.2 depicts 3 kinds of variables: the variables which are common across aggregates, denoted by x_{itj}, the variables which are specific to the continental aggregate, denoted by s_{itn}, and the control variables which are common across regional aggregates, denoted by c_{itl}. Other notations should be understood as in equation 4.1.

Table 4.7 presents the results for models in their adaptive version. The aggregate for the world made no sense, and has therefore not been estimated. Blanks in the table show that variables have not been added for each model, as some of them should be considered as special features of a region. Variables about population dynamics, fuelwood extraction and charcoal production are assumed to bear a specific impact in Africa, so do cattle ranching and soybean production in America, or palm oil production in Asia. Information about commercial wood extraction has been integrated in the model for both America and Asia, as it was advised by table 2.2. Economic control variables have also been added. They account for inflation[13], official exchange rate[14], and net ODA received per capita[15].

Before getting into continental analysis, similarities and general patterns of this model must be investigated. REDD mechanism does not seem to bear any continental impact, while contemporaneous

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[13]Consumer Price Index (annual %)
[14]LCU per US\$, period average
[15]Current US\$

Table 4.7: Deforestation model, Specific perspective, Fixed Effect model with standard errors robust to heteroskedasticity and autocorrelation

Source: FAO, WorldBank, and Vancutsem et al. (2021)

	Africa	America	Asia
	$zpercent\_defor_{it}$	$zpercent\_defor_{it}$	$zpercent\_defor_{it}$
$zag\_prd\_crop\_xd_{it}$	-2.229**	-0.185*	0.409***
	(0.841)	(0.0983)	(0.0181)
$zag\_prd\_food\_xd_{it}$	2.294**	0.136	-0.603
	(0.904)	(0.128)	(0.395)
$zag\_yld\_crel\_kg_{it}$	-1.072**	0.208	-0.135
	(0.398)	(0.155)	(0.357)
$zis\_air\_good\_mt\_k1_{it}$	-0.896	0.0113	0.166
	(0.742)	(0.0321)	(0.111)
$zeg\_elc\_loss\_zs_{it}$	-0.0936	-0.140*	-0.171
	(0.0498)	(0.0689)	(0.517)
$zsp\_pop\_grow_{it}$	-0.541*		
	(0.249)		
$zsp\_dyn\_cdrt\_in_{it}$	-0.294		
	(0.170)		
$zsp\_urb\_grow_{it}$	0.466*		
	(0.244)		
$zwoodcoalprod_{it}$	-1.500***		
	(0.321)		
$zwoodfnoconifprod_{it}$	5.326***		
	(1.029)		
$zcattlehead_{it}$		0.335**	
		(0.124)	
$zsoybeanprod_{it}$		-0.272***	
		(0.0482)	
$soymorat2006_{it}$		-0.0480	
		(0.0565)	
$zroundwoodproduction_{it}$		0.378*	-2.509**
		(0.186)	(0.696)
$zindroundwnoconiftrop\_xq_{it}$		0.884	-0.0781***
		(0.603)	(0.0155)
$zpalmoilprod_{it}$			-0.183
			(0.102)
$zfp\_cpi\_totl\_zg_{it}$	-0.0120*	-0.0882***	19.97**
	(0.00539)	(0.0218)	(5.592)
$zpa\_nus\_fcrf_{it}$	2.913	-0.00507	0.0560
	(1.563)	(0.0325)	(0.165)
$zdt\_oda\_odat\_pc\_zs_{it}$	-0.0429	0.00267	-1.429**
	(0.0331)	(0.0116)	(0.506)
t_{it}	-0.0143	-0.0219	-0.115*
	(0.0357)	(0.0139)	(0.0445)
tsq_{it}	0.00157	0.000243	0.00403**
	(0.00145)	(0.000342)	(0.00103)
$REDD_{it}$	-0.176	-0.0294	-0.153
	(0.168)	(0.0265)	(0.201)
$ztempmoyenne_{it}$	0.281	0.106	-0.252
	(0.167)	(0.109)	(0.391)
$zprecipit_{it}$	-0.317	-0.0161	0.0348
	(0.247)	(0.0379)	(0.157)
$zpercent\_degrad_{it}$	0.121**	0.639***	0.544**
	(0.0420)	(0.104)	(0.122)
$zpercent\_degrad\_1_{it}$	-0.0662	-0.126	-0.0364
	(0.0477)	(0.0869)	(0.0237)
_cons	-0.540	0.366	2.437**
	(0.963)	(0.245)	(0.833)
N	145	190	97
R^2 within	0.759	0.715	0.712

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

degradation does. This corroborates conclusions taken out of the homogeneous approach. Inflation seems to bear an impact on each continent as the three coefficients are significant at 10% minimum. However, the sign and magnitude of the Asian coefficient is strikingly different from the others. Inflation is typically a tricky phenomenon to analyse which is why interpretation should be taken even more carefully.

The first piece of explanation concerning the coefficient of inflation in Asia comes from descriptive statistics provided in table 4.8. Note that values in this table correspond to inflation rates and should therefore been understood as percentages. Asia has experienced the lowest average level of inflation between 1991 and 2020, compared to Africa and America. The standard deviation of the variable is also the lowest for Asian countries, so is the coefficient of variation. Africa, on the other hand, presents the strongest level for each statistic, with a mean almost 20 times greater than the one displayed for Asian countries. The global mean of the inflation variable is equal to 65.1487%, with a standard deviation of 823.8998%, which is even higher than the maximum value observed in the sample for Asian countries. A standardized coefficient called for the example $\hat{\beta}_1$ must be interpreted as follows: a change of one standard deviation in the independent variable should on average induce a change of $\hat{\beta}_1$ standard deviation in the dependent variable. As the global standard deviation for inflation is extremely high compared to the Asian pattern, such an extreme magnitude of coefficient could have been expected, as the worldwide standard deviation could be considered as an unexpected variation for the Asian continent.

This statistical part of the explanation could lead to an economic interpretation, with caution. If high inflation, and more specifically high inflation volatility, can be seen as an indication of development, this would mark once again the relative development delay of Africa, contrasting with the relatively high level of development displayed by Asian countries. Bowdler and Malik (2017) assert, through a panel data analysis, that openness to trade should reduce inflation volatility, above all in developing and emerging countries. The study of Banerjee (2017) also shows the relative instability of inflation rate in less developed parts of the world. As commercial activity is supposed to be more developed in the Asian continent, the stronger stability of inflation levels seems consistent. The strikingly high magnitude of the coefficient on inflation for Asia could actually reflect this lower probability of such a sudden and substantial inflation rate variation. The inflation variable was not *per se* a variable of interest but its coefficient deserved a word of explanation.

Table 4.8: Continental descriptive statistics for the variable about inflation, code: $fp\_cpi\_totl\_zg\_it$

Source: WorldBank

Statistics	**World**	**Africa**	**America**	**Asia**
Mean	65.14865	154.8177	30.85603	7.799658
Standard deviation	823.8998	1409.579	170.4767	11.68113
Coefficient of variation	12.64646	9.104768	5.524907	1.497646
Maximum	23773.13	23773.13	2075.888	125.2721
Minimum	-11.68611	-11.68611	-1.550275	-1.710337

Coefficients related to permanent cultivation present the same characteristics as in table 4.6 for Africa. The production of edible agricultural products is assumed to increase deforestation while production of inedible products does the inverse. Significance levels are higher which gives more credits to the results. At a smaller extent, conclusions are the same for America. However, the coefficient on the crop production index variable is positive and significant at 1% level in Asia. This striking difference might be due to a totally different type of production in Asia. A more opened

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or a more developed economy could push a nation away from food production as this nation breaks up with the subsistence point. This difference in development can be observed by looking at the difference in cereal yields (kg per hectare) for the two continents. With a mean of 1332.556 kg per hectare, against 3375.293 kg per hectare for Asia, African countries seem to be less inclined to produce other agricultural products than edible ones. In this perspective, one might suppose that the positive coefficient on crop production for Asia actually shows the impact of commercial agriculture on deforestation. This would fit the literature's point of view, but we have to keep in mind that our variables do not perfectly make the distinction between subsistence and commercial agriculture, and that interpretations must be drawn carefully.

Variables related to population dynamics and urbanization, which are specific to the African model, also deserve of word of analysis. If the sign of the coefficient on the total population growth might seem contradictory, it is because it must be understood in its ceteris paribus approach. By controlling for urban growth in line 6, the model actually analyses the effect of rural growth while estimating the coefficient on total population growth. The idea is that if the population increases without growing in urban areas, it must occur in rural ones. The negative coefficient on $zsp\_pop\_grow_{it}$ actually asserts that an increase in rural population would not be a driver of deforestation. The coefficient on urban population growth says that urbanization does drive deforestation. This fits with the literature which asserts that changes that follow rural exodus lead to more deforestation (Megevand and Mosnier (2013) and Karsenty (2021)).

Variables related to woody energy in Africa are both significant at 1% level, and the sign and magnitude of their coefficient deserve to be investigated. The negative impact of charcoal production seems to be contradictory with the positive sign of the coefficient on wood fuel extraction. However, these impacts must be interpreted in their ceteris paribus perspectives. Charcoal is a source of energy mainly used in urban areas, while rural populations do not especially transform wood before using it (Megevand and Mosnier (2013)). A kilogram of charcoal displays higher yields than wood as an energy source (Chidumayo and Gumbo (2013)). If no increase in population occurs, but that use of charcoal instead of wood grows, pressure on forest cover should be decreased. The coefficient on $zwoodcoalprod_{it}$ actually shows this difference in yields. The inverse is true while analysing the coefficient on fuelwood production. Note the magnitude of this last coefficient which is the highest for the African model, as Kissinger et al. (2012) had suggested.

These variables are quite significant but it is also important to notice that it is not especially the case for other variables. This could be seen as a proof of the relevance of population dynamics and energy use when speaking about deforestation in Africa.

Concerning America, specific variables for cattle ranching and soybean production have been added to the model. Their coefficients' signs are such as the literature had assumed. Cattle ranching is supposed to increase deforestation rate while soybean production seems to decrease it (Ritchie and Roser (2021)). Large cattle ranching seems to bear the largest impact on deforestation among interest variables, which is consistent with the theory (Kissinger et al. (2012) and Margulis (2004)). It is important to keep in mind the caution the literature had addressed while interpreting soybean impact. If soybean seems not be a driver of deforestation, it might be due to sequential timing. Large soy plantations indeed lay on previously deforested areas. As our model focuses on direct deforestation, impact of soybean production could be underestimated. We should expect inverse signs while analysing degradation. Note the insignificance of the dummy variable accounting for the launching of the moratorium on soybean production.

The American model is the only one depicting a relevant impact for the level of infrastructure. The coefficient on electric loss is indeed significant at 10% level. Its negative sign should lead us to think that infrastructure is quite developed in Latin America and that a less efficient electricity network should lead to a decrease of deforestation. The variable used as a proxy for the level of infrastructure is surely not perfect but it provides some pieces of information. By using the percentage of electricity

loss, our variable gives information about the level of efficiency of the electric network, which can be derived to have an idea of the global infrastructure level. However, it was transport infrastructure which was supposed to bear the biggest impact on forest loss, and it would have been better to integrate variable(s) giving information about this specific type of development. The proxy used in this model fails to capture the idea of transportation and this could actually partially explain the insignificance observed for other part of the world.

The impact of contemporaneous degradation is the strongest for America, and is actually the most powerful driver of deforestation for the continent. This is another mark of the importance to take degradation into account when working on forest loss. Being able to understand how degradation is driven could also help reducing deforestation, and being therefore dually efficient.

Patterns for Asia, as it has already been mentioned, are quite specific, and results distinguish themselves from coefficients for other parts of the World. Being more developed, industrialized, easier of access, and fostering international trade, Asian countries display unsurprisingly very different coefficients than the other continents. The positive coefficient on crop production, contrasting with the strong negative impact observed for Africa, could be a mark of an agriculture more turned towards trade, as Asia breaks up with the subsistence point. Keeping in mind that the variables used are not perfectly showing the difference between local consumption and agricultural trade, this interpretation still seems relevant. Industrial logging was expected to have a substantial impact on deforestation (Geist and Lambin (2001)), but signs are quite unexpected. It seems pretty contradictory for the variable about round wood production to have a negative impact on deforestation rates. However, as the model analyses direct deforestation, the negative sign actually makes sense. It is indeed pretty rare to cut down all trees on a parcel in tropical moist forest. Species are mixed, stands are composed of trees of different ages, and logging is therefore performed in a more or less selective way. Industrial logging and forest exploitation should then cause more degradation than they imply deforestation. Such an assumption should be verified in the degradation model. Note that the coefficient on palm oil is not significant and cannot be interpreted, but it remains interesting to account for palm oil production in order to analyse the impact of round wood exploitation in its ceteris paribus perspective.

The model for Asia is also the only one displaying a significant coefficient for the control variable about Official Development Aid (ODA). With a negative sign, ODA are supposed to substantially decrease deforestation rate in Asia. Note that the dummy variable for the launching of the REDD+ program does not present any coefficient with an acceptable significance level. This was already the case in the homogeneous model presented in table 4.6, except for the world aggregate.

The specific perspective used to construct this model gives more results than its homogeneous partner. A more adaptive point of view allows to account for more specificities and regional features, without being blocked by a too narrow set of characteristics. As only theoretically relevant variables have been added to regional models, multicollinearity issues have been minimized and coefficient are therefore more precise. However, it makes comparison between variables of interest more difficult as interactions are changed.

4.2   Degradation

$$zpercent\_degrad_{it} = \gamma_0 + \sum_{j=1}^{k} \beta_j x_{itj} + \sum_{n=1}^{o} \alpha_n s_{itn} + \sum_{l=1}^{m} \delta_l c_{itl} + a_i + u_{it} \qquad (4.3)$$

Equation 4.3 presents the general form of models for the forest degradation phenomenon. It is actually quite similar to the one presented for the adaptive perspective of deforestation. Only the dependent variable has changed from equation 4.2. Nonetheless, we should bear in mind that equation

4.3 will be used for four models when analysing degradation, as a worldwide aggregate will also be estimated. Notations are similar to those used in previous equations.

As the literature is far less developed about degradation than deforestation, the model we have built has a weaker basement on the literature. Results are expected to be less obvious and models should be more poorly specified. This can be seen by looking at the R^2 presented at the bottom of table 4.9. Fixed effect estimation method is supposed to overestimate the goodness of fit of regressions Wooldridge (2015). However, R^2 are lower for the degradation model than for both deforestation models, even with this overestimation.

Nonetheless, models have been specified in order to avoid bias as much as possible, and to get precise estimators. As no pattern had been previously drawn in the literature, our model is a mix between homogeneous and adaptive perspectives. This mix aims to allow for both comparison and regional specificities. The number of variables added has been restricted in order to limit multicollinearity problems, as each variable is almost presented for each continental model. The left column of table 4.9 is a worldwide aggregate, composed with variables presented in every continental pattern. The binary variable for the ASM and the variable about soybean production are specific to the American model, variables about woody energy are presented only for Africa, and the variable about palm oil production only for Asia. The variable $zcattlehead_{it}$, accounting for cattle ranching, is no more a special feature of the American continent. The literature indeed speaks about small herds grazing in forest as being a source of forest degradation (Hosonuma et al. (2012)). As large cattle ranching is not common beyond American borders, adding information about the size of the cattle herd in Africa and Asia allows our models to take into account the impact of these small herds.

The first thing to notice might be the impact of agriculture being similar to the one observed for deforestation. Food production is assumed to increase degradation at the world level and in America, while non-edible agricultural production does the inverse. Note that no conclusion can be drawn on the Asian case anymore, as coefficients on agricultural production are not significant at 10% level. It is a bit tricky to speak about agriculture as being a factor of degradation, as agriculture often supposes total conversion of forested areas. In this case, adding variables about agriculture aims to account for the shifting cultivation phenomenon. Forested areas are transformed into cultivated areas for some seasons before being abandoned. The permanent perspective of the conversion is therefore not fulfilled, and forest loss is about degradation and not deforestation. Degradation may also occur in peripheral areas around a permanently converted land. The precision of the dataset allows for such interpretation. For the world aggregate, for which both crop production and food production variables are significant at 1% level, a general raise in agricultural production should lead to an increase in degradation rate. This increase should however be quite mitigated by the opposite signs of estimators. Coefficients are indeed of similar magnitude but display opposed effects. A similar raise in both edible and non-edible agricultural production should therefore have on average a relatively small impact on degradation rates.

The impact of infrastructure is also generally significant. Only Asia does not present a coefficient with a statistically acceptable significance level on the electricity loss variable. The aggregate for the world, and both the model for African and American countries, display coefficients significant at at least 5%. These coefficients are quite substantial, but their positive signs contrast with the interpretation made on deforestation models. In table 4.9, a better infrastructure, proxied by less electric losses, is supposed to decrease degradation, while the same improvement was supposed to increase deforestation. This shows once again the ambiguous effect of an improved infrastructure. Our work seems to suggest that improving the level of commodities should increase forest loss in its permanent perspective, and reduce it in its temporary aspect. Note that only one coefficient was significant for deforestation which could make conclusions more doubtful. Even if the variable on electricity is only used as a proxy for the level of infrastructure, its use can bring some useful information to our results. Bakehe (2022) indeed found out that a better access to electricity should

Table 4.9: Degradation model, Fixed Effect model with standard errors robust to heteroskedasticity and autocorrelation

Source: FAO, WorldBank, and Vancutsem et al. (2021)

	World $zpercent\_degrad_{it}$	Africa $zpercent\_degrad_{it}$	America $zpercent\_degrad_{it}$	Asia $zpercent\_degrad_{it}$
$zag\_prd\_crop\_xd_{it}$	-0.540***	-0.819	-0.485**	-1.381
	(0.149)	(1.002)	(0.191)	(0.764)
$zag\_prd\_food\_xd_{it}$	0.597***	1.128	0.679*	0.305
	(0.196)	(1.036)	(0.321)	(0.682)
$zag\_yld\_crel\_kg_{it}$	-0.6306	-0.0452	0.2001	-0.1102
	(0.422)	(0.379)	(0.369)	(0.0881)
$zeg\_elc\_loss\_zs_{it}$	0.449**	0.622***	0.277**	0.598
	(0.172)	(0.173)	(0.108)	(0.801)
$zsp\_pop\_grow_{it}$	0.199	-0.420	-0.294	1.646
	(0.124)	(0.395)	(0.276)	(1.105)
$zsp\_urb\_grow_{it}$	0.0906	-0.0452	0.186	-0.0902
	(0.142)	(0.397)	(0.369)	(0.0679)
$zwoodcoalprod_{it}$		1.472*		
		(0.641)		
$zwoodfnoconifprod_{it}$		-16.99		
		(11.24)		
$zcattlehead_{it}$	0.112	6.761	-0.194*	12.44
	(0.173)	(3.690)	(0.105)	(7.821)
$zsoybeanprod_{it}$			0.152	
			(0.0856)	
$soymorat2006_{it}$			-0.286	
			(0.169)	
$zroundwoodproduction_{it}$	-0.306	16.60	-0.626	1.121
	(0.275)	(12.04)	(0.542)	(1.812)
$zindroundwnoconiftrop\_xq_{it}$	0.0406*	-0.683*	2.761	0.132
	(0.0202)	(0.309)	(1.551)	(0.112)
$zpalmoilprod_{it}$				-0.282
				(0.188)
$zfp\_cpi\_totl\_zg_{it}$	0.00101	0.00693	0.0464	18.46
	(0.00703)	(0.0163)	(0.0428)	(23.98)
$zpa\_nus\_fcrf_{it}$	-0.00964	2.635	-0.00501	-0.0798
	(0.131)	(2.081)	(0.0759)	(0.309)
$zdt\_oda\_odat\_pc\_zs_{it}$	-0.147*	-0.186**	-0.0553	-0.0343
	(0.0843)	(0.0647)	(0.0685)	(0.549)
t_{it}	0.0918***	0.0452	0.0295	0.316
	(0.0240)	(0.0454)	(0.0324)	(0.162)
tsq_{it}	-0.00343***	-0.00411**	-0.00203*	-0.00557**
	(0.000708)	(0.00142)	(0.00108)	(0.00145)
$REDD_{it}$	0.0317	0.593	0.121	-0.240
	(0.0917)	(0.415)	(0.152)	(0.200)
$ztempmoyenne_{it}$	0.175	-1.238**	0.0581	1.797
	(0.295)	(0.368)	(0.317)	(1.789)
$zprecipit_{it}$	-0.482**	-1.893	-0.00600	-0.761*
	(0.191)	(1.089)	(0.103)	(0.314)
_cons	-0.487*	2.999	0.875**	3.182
	(0.251)	(2.361)	(0.341)	(1.945)
N	586	184	219	101
R^2 within	0.270	0.552	0.140	0.386

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

decrease forest loss, which gives credit to our findings about the relationship between electricity loss and degradation.

Note that variables on population dynamics, namely population growth, are not significant at 10% level in any model. The binary variable $REDD_{it}$ shows no significance either, questioning therefore the efficiency of such a policy. REDD+ had indeed not shown particular significance in deforestation model presented in table 4.7 either. Only the world aggregate in table 4.6 seemed to show the impact

of this worldwide policy at 10% level.

However, official development aids (ODA) seem to have born an impact on degradation rates as coefficients on the variable $zdt\_oda\_odat\_pc\_zs_{it}$ for the World and for Africa are significant at 10% level. With a negative impact on forest loss, ODA are supposed to present a decreasing relationship with degradation rate. Before being tested, this relationship was quite ambiguous. In one way, aids could help a country for the implementation of protection policies, towards a more transparent economy, or with dealing with illegal resources extraction (Karsenty (2021) and Busch and Ferretti-Gallon (2020)). On the other hand, ODA are supposed to increase trade, consumption, and living standards, which is likely to lead to more forest loss (Mainardi (1998) and Megevand and Mosnier (2013)). Our model seems to suggest that the first pan of consequences overtakes the second one, at least at the degradation level. Conclusion were less clear for the deforestation model as coefficients were not significant at general acceptable level, except for Africa.

For Africa, charcoal production presents this time a positive coefficient, significant at 10% level. If charcoal, because of its higher energy yield, was supposed to decrease deforestation, it was strongly unlikely that its production had no impact on the forest cover. Among significant coefficients, charcoal production displays the highest magnitude in the African model (Kissinger et al. (2012), Megevand and Mosnier (2013), and Chidumayo and Gumbo (2013)). This result could imply that an increase in the use of charcoal, for example induced by a change in consumption behavior, could lead to an increase in degradation rate in Africa.

Table 4.9 presents an unexpected result. For African countries, a raise in the export of industrial round wood is supposed to decrease degradation rate, and this seems counterintuitive. This result might come from a specific feature attached to the history of African wood trade. During a personal phone call the 14th of July 2022, Mr. Hébert Jacques explained that wood species in Africa are classified in a very precise and detailed way. This is a legacy of the region's colonial past. Exports are therefore strictly referenced and this contributes to the control of international trade of tropical round wood in Africa. The referencing is much less precise in Asia for example, where many subspecies of trees are grouped under the same name, and sold indifferently. The precision of the referencing in Africa contrasts with the global dominance of informal activity on the local economy. By forecasting an increase in the round wood exportation level, without expecting an increased production, our model actually assumes a more controlled trading system of tropical round wood, and this could be positive to the forest cover. This paragraph reminds us to pay caution when analysing results in such a complex matter, on a worldwide scope. Beside the coefficient for Africa, result for the World seems pretty expected. Note however that its magnitude is relatively low compared to other potential drivers. Selective logging does therefore seems to increase degradation on a worldwide level but its impact could be lower than it could be commonly assumed.

Soybean production, specific to the American model is only marginally significant at 10% level (10.6%). Its positive sign corroborates the idea that soy production in Latin America drives forest loss, in its temporary version. The impact of soybean plantations might occurs in peripheral areas around previously deforested lands, for example for cattle ranching. However, such an idea is impossible to test with the methodology applied in this work as proximity of areas have not been accounted for. Note that the binary variable for the soy moratorium is also marginally significant at a 10% (12.1%), giving credit to the idea that soy has its part of responsibility in tropical forest loss in Latin America. We should however account for the fact that Brazil holds a strong monopoly on soy production (see section 1.4.6). A study on the specific case of Brazil could give stronger evidence on the impact of soybean production. In such a case, spatial econometrics could help to get the idea of contiguity of forested areas and the role of sequential timing.

Table 4.9 displays some interesting results, in a worldwide perspective and at the continental level for Africa and America. However, it must be said that the Asian model suffers from mispecifications. No clear driver has been identified, making our work unable to draw any conclusion about degradation

of the forest cover in Asia. The gap in the literature about degradation of tropical forests is a problem for model specification, and maybe our research lacked information about the Asian continent and its special features. Perhaps the Asian case should have been more specifically studied in order to get some significant results. This failure of bringing to the fore some Asian drivers of forest loss is another proof of the importance of an in-depth understanding of cultural, economic, and social characteristics of a region. The only conclusion our model allows us to make consists in admitting that maybe our approach does not fit the Asian reality, and that other drivers or an another method should be considered.

4.3   Limits and opportunities for improvement

This section will present some limitations this thesis should acknowledge. As far as it is possible, improvement clues have been suggested in order to correct those limits. Some limits concern the econometric part of this study or the chosen methodology, while some others are related to the core of the tropical moist forest analysis.

4.3.1   Failure of the exogeneity assumption

The first limit this work should acknowledge is inherent to econometric analysis and concerns the hypothesis of exogeneity of explanatory variables. Everything has been set up in order to avoid as much as possible omitted variables bias. FE allows to account for unobserved fixed features of cross-sectional units which could have been correlated to some explanatory variables, as it has already been mentioned. In addition, other precautions have also been taken. The variables about charcoal and wood fuel, namely, were clearly at stake of suffering from endogeneity. Megevand and Mosnier (2013), as some other authors, explain that the use of charcoal should be linked to access to other energy sources, namely electricity, as the example of Gabon could suggest. The addition, in the models, of the variable accounting for the electricity loss allowed to integrate a part of the information about this accessibility of other energy sources. Therefore, besides its role as a proxy for the level of infrastructure, the variable $eg\_elc\_loss\_zs_{it}$ also allowed to reduce endogeneity of the variables about charcoal production and wood fuel extraction. Variables about poverty, such as the level of official development aids received per capita, the death rate, or the yields of agriculture production have helped correct for endogeneity of variables that could be correlated with the level of poverty. As another example, adding yields of agriculture in the regressions has allowed to analyse the change in agricultural production in its ceteris paribus aspect. As agricultural yields surely influence the level of forest loss, and are surely correlated with the level of the production of agricultural products, keeping them in the error term would have led to a clear failure of the exogeneity assumption.

However, exogeneity is *per se* a extremely difficult assumption to perfectly verify, and it is even more true in such a complex matter. One could imagine for example that forest loss could be influenced by fashion or architectural trends in western countries. As such information is barely possible to account for, this part of the information would be kept in the error term. However, international demand is assumed to bear an influence on the level of round wood exportation, leading therefore to the failure of the exogeneity assumption. Such examples are even more probable if we consider exogeneity in its strict version. Although such a limitation must be acknowledge, it is however important to be aware that endogeneity will always be part of econometrics, and that the most important part consists in trying to minimize it.

4.3.2 National specificities

The methodology followed in this thesis has been mostly suggested by the literature, and results generally confirm its choice. However, the failure of the Asian forest degradation analysis should lead us to consider another approach. As it has already been mentioned, maybe some specificities of the Asian continent had not been taken into account, leading our model to be inconsistent with the Asian reality. Perhaps information about trade should have been widely integrated as Asia is supposed to be a major actor in international trade.

This failure could address a broader remark to this work: the continental perspective could skip some important national or regional specificities. Even if it has not caused any other major relevant problem, the continental perspective could have led to a general failure of this thesis. This once again highlights the importance of an in-depth study of the topic before considering the econometric analysis of such a complex matter. The literature review presented at the beginning of this thesis largely covers African and American characteristics, allowing our models to show some consistency. Information about Asia was maybe a bit incomplete, above all concerning forest degradation. While African and American countries were mentioned together in the literature, forming a consistent pack of similar countries, it was not especially the case for Asia. Indonesia and Malaysia clearly dominated the debate, and maybe we were wrong considering other Asian nations as following the same pattern as the archipelagos. Fortunately, our literature review has been constructed in a strong enough way to allow for the relevancy of 10 on 11 models, but this limit had to be acknowledged.

4.3.3 Cross-sectional independence in panel data models

Table 4.10: For each model, Peseran test for cross-sectional independence

Source: FAO, WorldBank, and Vancutsem et al. (2021)

Model	P-value
Homogeneous approach, Deforestation, World	/
Homogeneous approach, Deforestation, Africa	0.1261
Homogeneous approach, Deforestation, America	/
Homogeneous approach, Deforestation, Asia	0.1280
Adaptive approach, Deforestation, Africa	0.2543
Adaptive approach, Deforestation, America	/
Adaptive approach, Deforestation, Asia	0.0001
Degradation, World	0.0000
Degradation, Africa	0.9856
Degradation, America	0.0000
Degradation, Asia	0.8297

HO: independence of cross-sectional units

Our models have been estimated using FE, assuming therefore independence across cross-sectional units. This assumption actually states that in the panel data models, what happens in a country does not influence what happens in an other country of the dataset. A failure in this assumption would

actually lead at best to inefficient estimators and invalid test statistics, at worst to biased estimators due to contemporaneous endogeneity.

Table 4.10 shows the results of pesaran test[16] for cross-sectional independence. Some results could not be computed because of a too unbalanced dataset, as the slash bar shows. On 8 tests successfully performed, 5 show no evidence of rejection of the independence assumption. However, 3 others seem to suggest that cross-sectional units are not independent. This actually lower the strength of our analysis, as FE should not be performed if the assumption of cross-sectional independence does not hold. As this failure occurs on 3 on 8 cases, FE has been used anyway. However, it was primordial to acknowledge such a limits, in order to allow further studies to account for such dependence. (Tugcu (2018) and Wooldridge (2015))

4.3.4   Informal sector and changing world

It is first important to understand that the variables used in this work may not constitute a comprehensive overview of the sector they are related to. Informal activities weigh heavily on the economies of developing countries. However, these activities are by nature absent from official statistics. This work therefore analyses the effect of observable factors related to tropical forest loss, but must admit to omitting some information due to informal activities. Unfortunately, this omission could strengthen endogeneity of explanatory variables in our models, leading to biased coefficients. However, even if their weight is heavier for emerging and developing countries, informal trade and economic activities are present all over the world, and few things can be done to correct this.

The last limitation this section wants to address is a bit less technical, but has its importance. The results we have obtained in this work make statements about current and past drivers of deforestation and forest disturbances. The reality we have tried to study is likely to change in the coming years, leading our conclusions to become weaker if not obsolete. Future studies should be aware that statements concerning a fairly complex matter such as tropical forest loss, in a changing world, should be understood as a current overview of the situation. As it has already been mentioned, Africa is likely to know strong demographic, technological, and ideological changes in the coming decades. This thesis has presented poverty as being a major factor influencing forest loss in Africa, while trade has been highlighted for Asia. Such a perspective could not hold in the medium term, and analysis should be performed in accordance.

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[16]command xtcsd, pesaran on Stata17. xtcsd test the hypothesis of cross-sectional independence in panel data models

Conclusions

Although some limits had to be admitted, this thesis, and the results it contains, can draw some conclusions about tropical moist forest loss drivers. As it has been the case in each part of this work, caution, nuances, and critical thinking must be inherent to this concluding part. It is indeed the nature of the researcher to pepper his own words, and to be aware of the limits and possible improvements that his work might entail. At the beginning of this thesis, the goal consisted of ranking drivers of forest loss by magnitude. However, only a few drivers were statistically significant at the same time, which made such a ranking difficult, if not impossible. Nonetheless, thanks to its empirical approach, this study has tried to assess some statements in the literature, and conclusions should be drawn when it is possible.

Some statements and common ideas about tropical forest loss have been corroborated by this study. The most obvious case concerns the impact of agricultural production. Each part of the literature indeed cited agricultural activities as being one of the main drivers of TMFs deterioration. Our results assess this impact with strength, as agricultural variables seem more or less significant in each model. It is the production of food that dominates the debate, displaying relatively strong positive coefficients for several models. Production of non-edible agricultural products is supposed to decrease forest loss when the production of food is accounted for. This distinction between edible and non-edible products aimed first to distinguish subsistence agriculture from commercial agriculture. Readers have to be aware of the imperfection of proxies used, however, coefficients obtained on each type of agricultural production seem to show the prevalence of the impact of subsistence agriculture in Africa, and to a lower extent in America, while commercial agriculture could be supposed to bear a larger influence on deforestation in Asia. Our analysis, however, shades the general impact of a rise in agricultural production. The same raise occurring both on the edible and on the non-edible part of the production should indeed increase forest loss in tropical regions, but this increase should be relatively weak as effects could partially neutralize each other. These results, therefore, weaken the statement asserting that agriculture is the biggest threat to TMFs. It should be noted that the literature did not have a clear view of the effect of improved agricultural yields. Higher yields obviously meant more production from the same area, but it could also push up production and encourage investment in agriculture (Megevand and Mosnier (2013)). Our study does not remove this doubt, since the coefficient for yields, although negative, is given by fixing the level of agricultural production. Therefore, our analysis did not allow us to settle the question of improving agricultural yields.

From a broader perspective, continental sets of drivers of tropical forest loss have been confirmed. Poverty-related and demographic variables seem to bear the largest influence in Africa where the urbanization phenomenon, and charcoal production, which are clearly correlated, are on top of the ranking of influencing factors. Note that the impact of rural exodus could be slightly compensated, regarding deforestation rates, by wider use of charcoal which experiences higher yields than wood fuel as an energy source. On the American continent, the dominant position of cattle ranching seems also to be confirmed empirically (Ritchie and Roser (2021)). The coefficient attached to cattle exploitation is indeed the second largest when analysing American deforestation rates, just behind contemporaneous forest degradation. In Asia, the prominence of trade seems confirmed. Marks of a more open economy

are clear, and even if models for Asia maybe do not have the level of specification we could have hoped for, the positive coefficient on the crop production variable could be considered as a proof of the impact of trade on the Asian continent. At a global level, the positive relationship between degradation rates and deforestation rates has also been highlighted. A results which is not striking but deserves to be mentioned is the relatively weak relevance of a worldwide aggregate. Worldwide models have indeed displayed low relevance, as it should have been expected regarding the literature (Scrieciu (2007)).

If some drivers have been confirmed, some others have been denied. The round wood market, inducing logging, which is commonly assumed to be a driver of deforestation, has displayed negative coefficients on the Asian deforestation model. If this can be relatively easily explained, as selective logging induces degradation and not deforestation, this in any case breaks with the idea that one might have had of forestry. More surprisingly, even degradation could be reduced with forestry, as proven by the coefficient attached to round wood exports on the African degradation model. As another example, development was supposed to induce more forest loss, following the EKC (Dinda (2004) and (Ritchie and Roser (2021))). However, the coefficients related to official development aids received per capita displayed negative signs. As ODA should boost consumption and living standards, in theory, one could see in these negative signs proof that development is not systematically detrimental to forest cover.

The ambiguous effect of certain factors has not always been clear-cut, and some impacts remain controversial. This is the case for the impact of infrastructure improvements, which according to our analysis could reduce temporary forest losses but would, to some extent, promote the permanent conversion of forest areas. It should be noted, however, that this impact on deforestation is less reliable. In America, there are doubts about the effect of soybean production on forest cover. This work shows that soybean production seems to have a negative impact on the rate of deforestation but may increase the signs of forest degradation. The somewhat dubious significance of this last coefficient, added to the fact that the effect of soy has been analysed over the whole of the American continent, whereas the vast majority of its production takes place in Brazil, leads us to consider these results with extreme caution.

Finally, the impact of some factors could not be assessed, so no conclusions can be drawn with certainty. This is the case for palm oil and the exchange rate, both of which are widely cited in the literature (Hosonuma et al. (2012) and Richards et al. (2012). The REDD mechanism and the soy moratorium have also not shown conclusive evidence of effectiveness.

At the beginning of this work, there was no indication that the identification and classification of forest damage factors were easy. However, this thesis has come to some conclusions that seem to be consistent and supported by reliable analytical evidence. As it has been said earlier in this work, it would have been illusory to hope to come with straightforwards conclusions on such a complex matter. Tropical moist forests cover a vast territory, experiencing multiple changes, interactions, and population dynamics. The diversity of the regions covered and analysed could not lead this thesis to unequivocal results and interpretations. Such a situation would actually have been more doubtful and would have questioned the validity of this work. Through its analyses, this thesis presents some relevant conclusions about tropical forest loss, which should be accounted for when setting up policies. The main goal of this work was indeed to provide reliable information to decisions makers in order to contribute to the fight against climate change. Because it has been done conscientiously, because the data used are reliable, and because it presents nuanced and justified conclusions, we believe that this thesis can bring some additional information to policymakers who would desire to limit environmental damages.

Appendix A

Appendices

A.1 Tables

Table A.1: World top 10 countries and territories with the highest share of forested area, percentage of total land area, 2020

Source: FA0 | Global Forest Resources Assessment 2020

Ranking	Country	Forest area	
		1000 ha	*% of total land area*
1	Suriname	15 196	97
2	French Guyana	8003	97
3	Guyana	18 415	94
4	Micronesia	64	92
5	Gabon	23 531	91
6	Solomon Islands	2523	90
7	Palau	41	90
8	Equatorial Guinea	2448	87
9	America Samoa	17	86
10	Papua New Guinea	35 856	79

Table A.2: World top 10 of countries with the largest forest area, thousands of hectares, 2020

Source: FA0 | Global Forest Resources Assessment 2020

Ranking	Country	Forest area	
		1000 ha	*% of world forest area*
1	Russian Federation	815 312	20
2	Brazil	496 620	12
3	Canada	346 928	9
4	United States of America	309 795	8
5	China	219 918	5
6	Australia	134 005	3
7	Democratic Republic of the Congo	126 155	3
8	Indonesia	92 133	2
9	Peru	72 330	2
10	India	72 160	2

A.2 Figures

Figure A.1: Map of sampled American countries

Source: Mapcreator.io

Figure A.2: Map of sampled African countries

Source: Mapcreator.io

Figure A.3: Map of sampled Asian countries

Source: Mapcreator.io
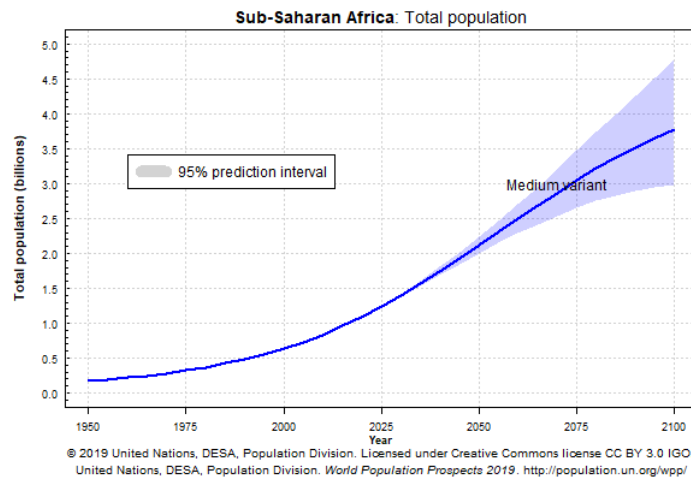
Figure A.4: Evolution and projections of total population in billions of individuals, Sub-Saharan Africa, 1950-2100
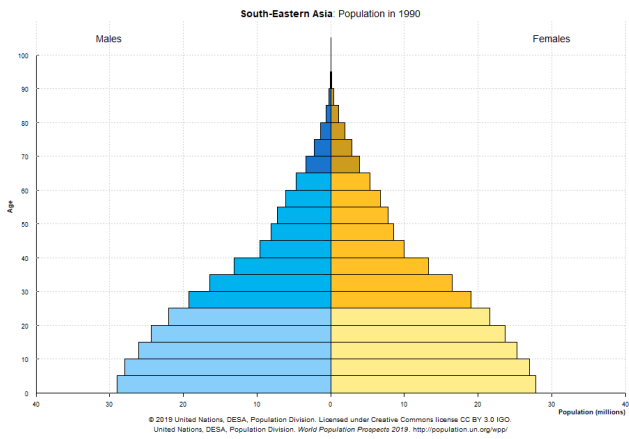
Source: United Nations | Population Division
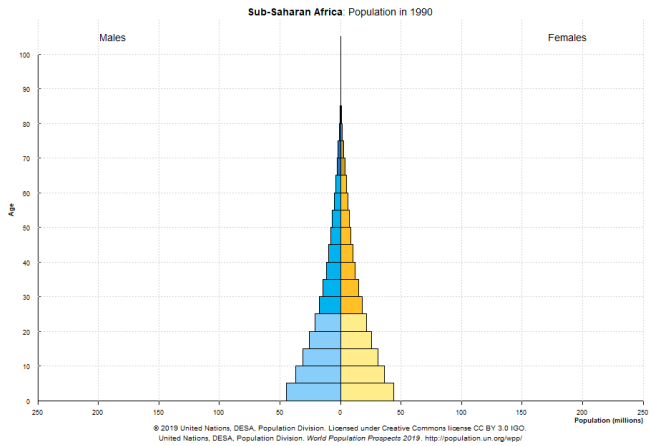
Figure A.5: Age pyramid in 1990, Sub-Saharan Africa
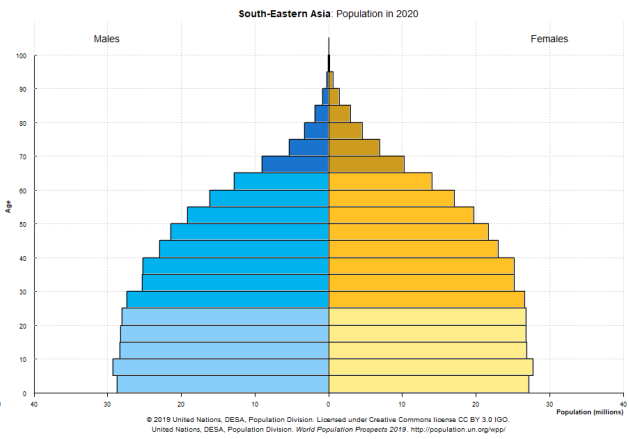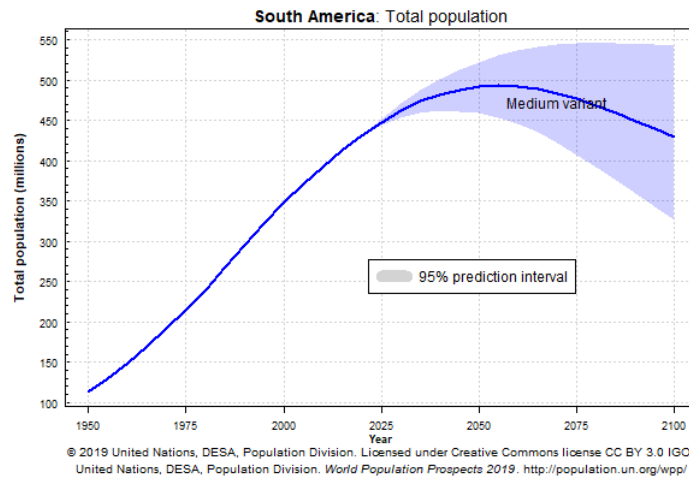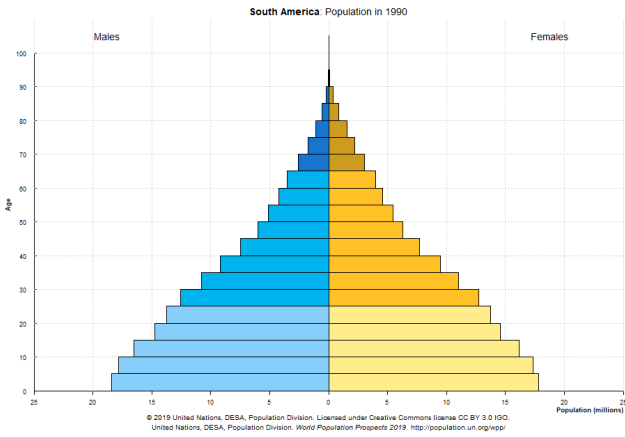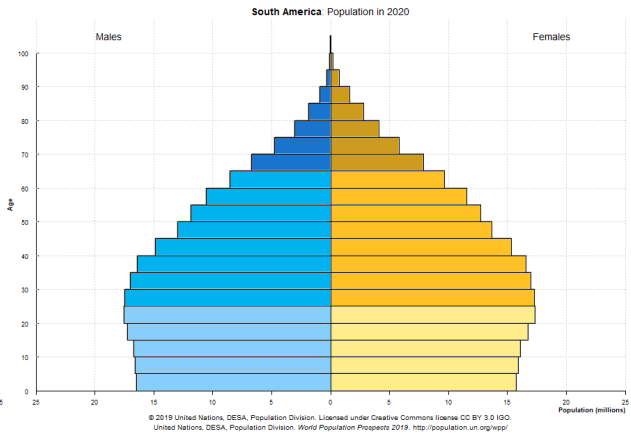
Source: United Nations | Population Division
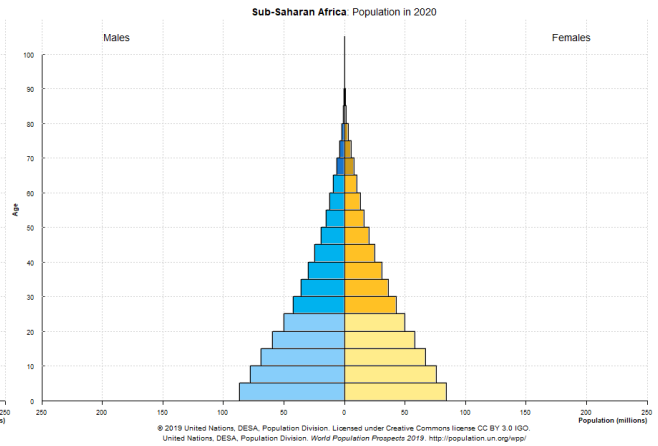
Figure A.6: Age pyramid in 2020, Sub-Saharan Africa

Source: United Nations | Population Division
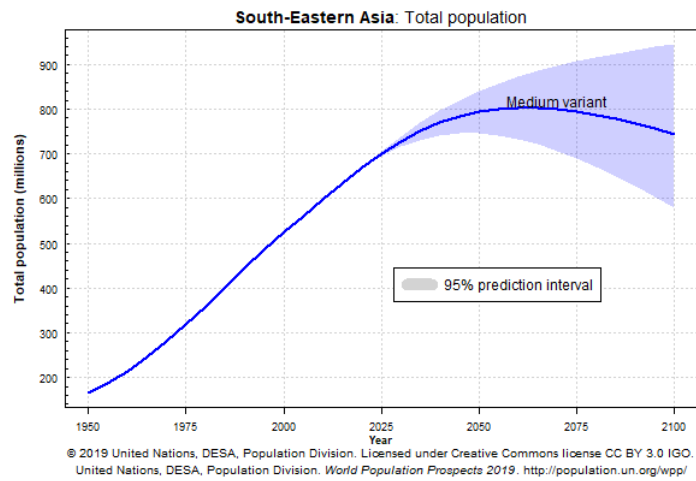
Figure A.7: Evolution and projections of total population in billions of individuals, South-Eastern Asia, 1950-2100

Source: United Nations | Population Division

Figure A.8: Age pyramid in 1990,
South-Eastern Asia

Source: United Nations | Population Division

Figure A.9: Age pyramid in 2020,
South-Eastern Asia

Source: United Nations | Population Division

Figure A.10: Evolution and projections of total population in billions of individuals, South America,
1950-2100

Source: United Nations | Population Division

Figure A.11: Age pyramid in 1990, South America

Source: United Nations | Population Division

Figure A.12: Age pyramid in 2020, South America

Source: United Nations | Population Division
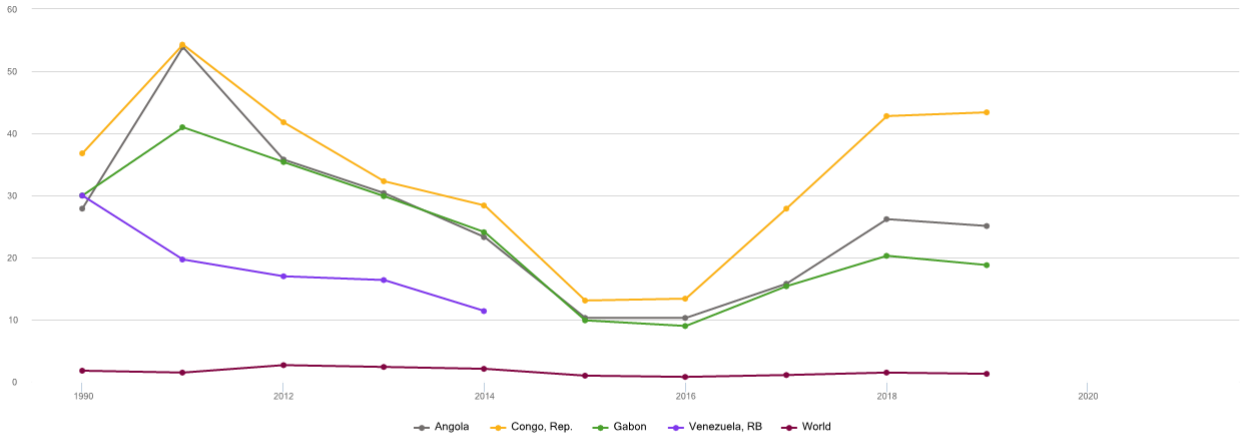
Figure A.13: Oil rents in % of GDP, Angola, Congo, Gabon and Venezuela vs World (strict meaning)
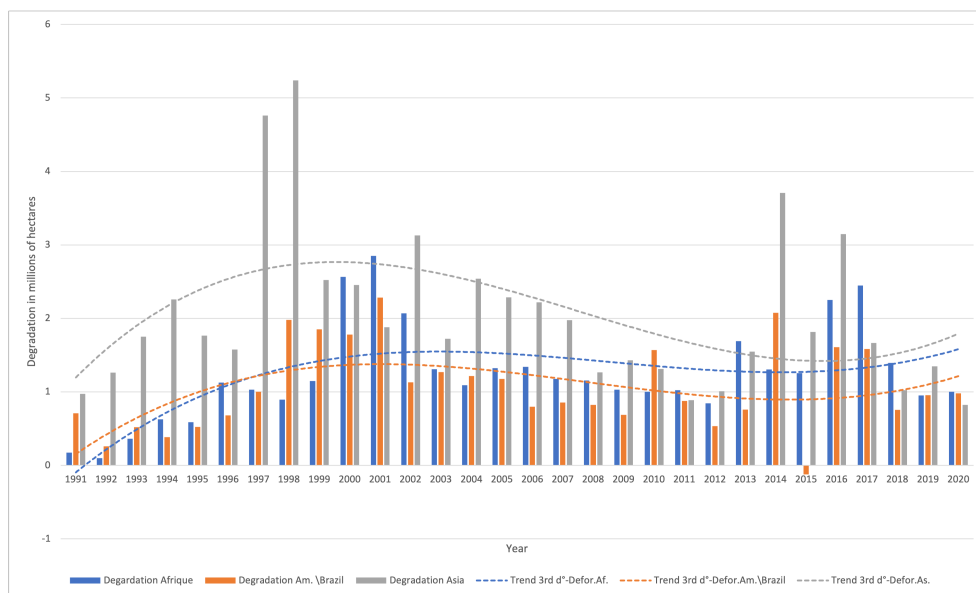
Source: World Bank | World Development Indicators
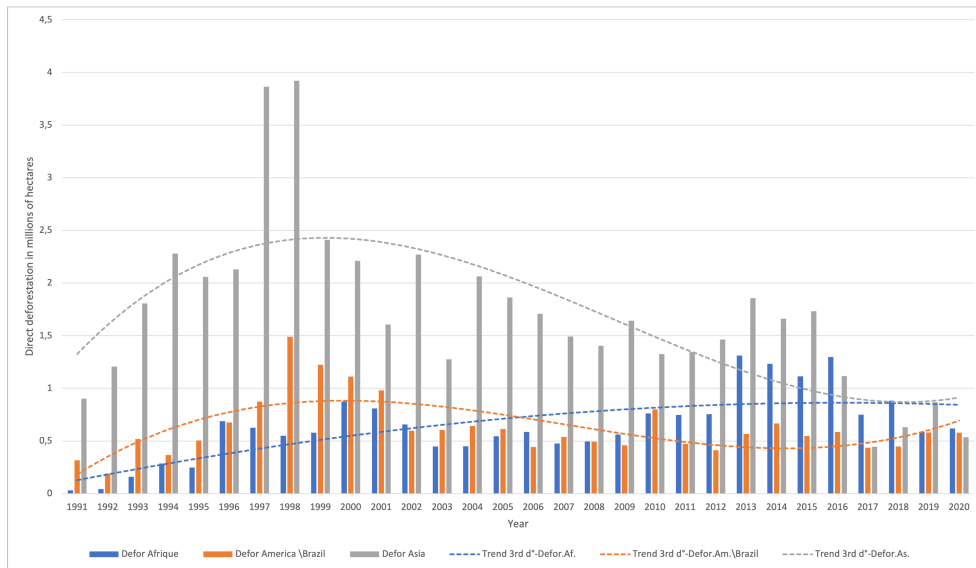
Figure A.14: Yearly deforestation in millions of hectares and trends between 1991 and 2020, aggregated by continent Brazil excluded

Source: FA0 and Vancutsem et al. (2021)

Figure A.15: Yearly forest degradation in millions of hectares and trends between 1991 and 2020, aggregated by continent, Brazil excluded
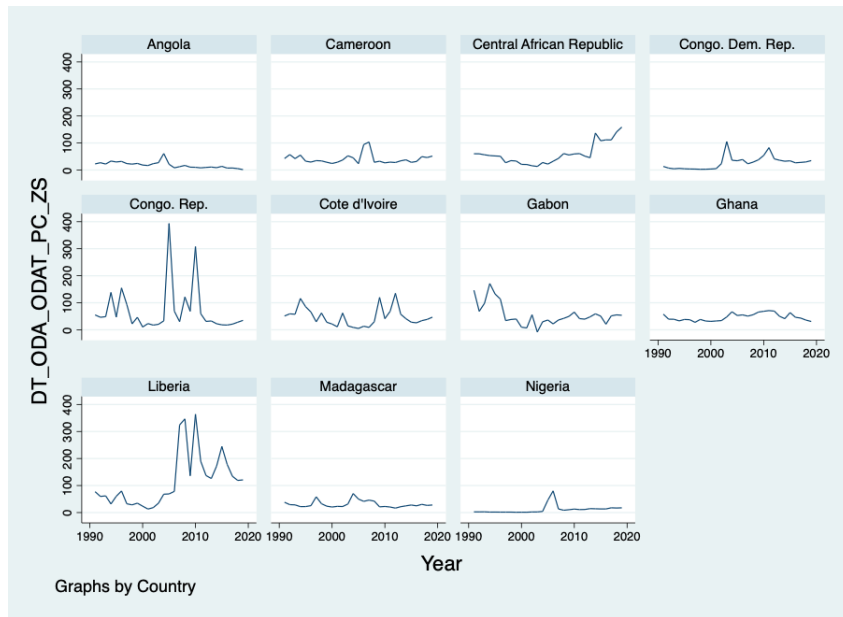
Source: FA0 and Vancutsem et al. (2021)

Figure A.16: Evolution of the net official development aid received per capita, between 1991 and 2020, for the African sampled countries
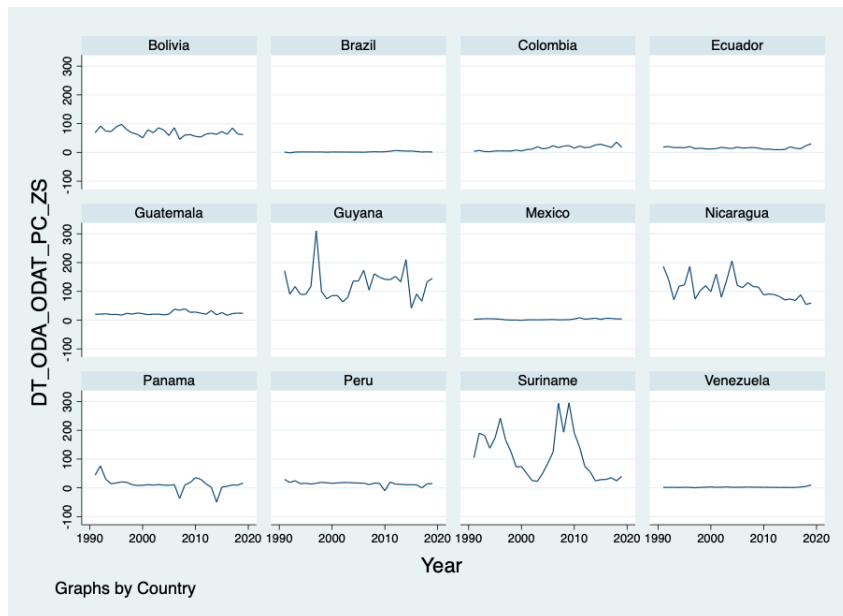
Source: WorldBank

Figure A.17: Evolution of the net official development aid received per capita, between 1991 and 2020, for the American sampled countries
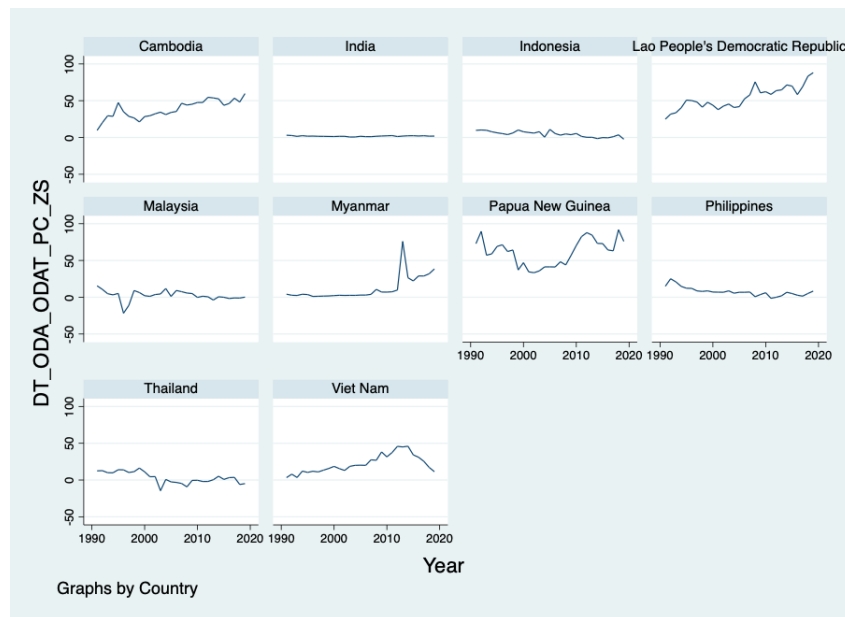
Source: WorldBank

Figure A.18: Evolution of the net official development aid received per capita, between 1991 and 2020, for the Asian sampled countries

Source: WorldBank

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Executive summary

The climatic concern rises every day, and has become one of the most important issues humanity has to deal with. Because of their incredible capacity to store and transform carbon, regulate temperature, and enable the proper functioning of the water cycle, tropical moist forests, and their management, have become a point of focus in this challenge the world has to take up. In this perspective, being able to apprehend factors which drive forest deterioration in tropical regions seems primordial.

Works on tropical forest loss have been lacking reliable data for years, weakening results and drawing misleading conclusions. Recently, the dataset made available by the European Commission, and constructed by Vancutsem et al. (2021), has provided a way to overcome this problem, by making available reliable data about tropical moist forests, for the period between 1990 and 2020. The provided dataset, thanks to its unprecedented precision of imagery, allows to distinguish permanent and temporary forest losses, respectively called "deforestation" and "forest degradation" in this work.

This thesis[1] conducts an econometric analysis at the continental level using the dataset of Vancutsem et al. (2021). Using fixed effects models, this work tries to empirically assess statements and assertions made in the literature concerning drivers of forest disturbances. It makes the distinction between permanent and temporary forest loss, which constitutes an improvement compared to previous studies on the topic.

Among conclusions which have been drawn, the prominence of agriculture has been assessed on each continent. This thesis also highlights the different continental general patterns which drive forest loss. Poverty-related factors seem to bear a major influence on forest deterioration in Africa, while large cattle ranching dominates in America. International trade would be the key factor in Asia. This paper does not intend to provide policy recommendations but aims to help policymakers to focus on evidence-based drivers of tropical moist forest loss.

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[1]which contains 26 097 words