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Socioeconomic Modelling of Deforestation for the Assessment of National Development Plans in Ecuador

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Author’s declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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ABSTRACT OF THESIS submitted by:
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The present research seeks to evaluate how national development plans influence changes in forest cover by altering the underlying and immediate socioeconomic factors that may impact forest cover in Ecuador. This thesis explores the strength and direction of the relationships between socioeconomic factors and forest areas from 1990 to 2020. Additionally, it investigates causation between underlying and immediate factors of deforestation based on the Angelsen and Kaimowitz 1999 theoretical framework. Correlation, Multiple Linear regression, and Least Absolute Shrinkage and Selection Operator (LASSO) regression are used in this research to create a model that can predict deforestation as a function of socioeconomic factors. Techniques of machine learning are applied for the construction of the model. As the main results, the statistical analysis shows that socioeconomic factors related to the agriculture industry significantly influence deforestation. However, it is essential to acknowledge the limitations of this analysis due to data limitations, potential biases and assumptions made during the investigation. The goals of the National Development Plans (NDPs) heavily rely on the agriculture sector for increased economic growth, employment and development. However, the current approach to action does not incorporate effective environmental policies. As a result, if certain NDP's goals and demographic trends continue, the country will be lost around 1158.11 km^2.

Keywords: Deforestation, National Development Plans, LASSO regression, environment, policy, Socioeconomic Factors, Regression Analysis

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1. INTRODUCTION

Deforestation is considered one of the most critical problems in Ecuador. From 1990 to 2018, Ecuador lost approximately 2.1M hectares of forest (Mena et al., 2006). The loss of forests is especially concerning since Ecuador is one of the 17 megadiverse countries worldwide, with forest ecosystems making up more than half of its territory (Calderón, 2015). Forests provide ecosystem services, such as carbon sequestration, soil protection, climate regulation, hydrological services, sources of timber and non-timber products, and cultural and recreational services (Kleemann et al., 2022). However, expanding human activities in these ecosystems are resulting in declining forest areas.

Ecuador has been working to ensure fundamental human rights for all its people, and, at the same time, in its 2008 constitution the country guaranteed the rights of nature (Calderón, 2015). Harmonizing social and economic development policies along with the rights of nature is a challenge that Ecuador must address to achieve sustainability. This challenge occurs because development policies focus on extracting natural resources, such as oil, mining and exporting agricultural products as the engine for development - which have impacted the country's forests (Luna et al., 2020). Understanding the impact of national development plans on the drivers of deforestation is crucial for creating sustainable development strategies.

The fact that deforestation is a result of socioeconomic predictors is not new. Several studies have portrayed social and economic factors as drivers of deforestation (Busch and Ferretti-Gallon 2017; Luna et al. 2020; Geist and Lambin 2001). However, there is a lack of understanding of the processes that shapes socioeconomic predictors of deforestation, and thus are creating the context where stakeholders make decisions regarding deforestation (Bernhard, Zenobi, and Shapiro, 2021). National development plans (NDP) create policies that look to improve macroeconomic, social, and demographic factors; they build the road map of how development will be reached (Secretaria Nacional de Planificación, 2021). Under this logic, NDPs influence deforestation by swaying the socioeconomic predictors of deforestation. This thesis aims to examine to what extent NDP affect forest cover dynamics by configuring the underlying and immediate factors of deforestation in Ecuador thereby identifying the social and economic factors influencing deforestation in Ecuador. Through correlation and regression analysis and machine learning algorithms, it aims to establish a quantitative relationship between the objectives of the

NDP, deforestation predictors, and changes in land use, to provide a general idea of the environmental impact of national development policies.

This research seeks to contribute to environmental science and sustainability development by adapting a traditional framework of deforestation with machine learning and data mining techniques. Angelsen and Kaimowitz's 1999 conceptual framework is used as the theoretical framework for this research, which establishes macroeconomic factors, public policies, institutions, and markets to create a context where individuals decide to deforest. This research tries to further by incorporating the formative power of the national development plans into a model that can assess deforestation as a function of underlying and immediate factors of deforestation. Additionally, it tries to clarify how NDPs influence deforestation. This is especially important for policymakers and stakeholders who could re-evaluate the development approach to consider the environmental impacts it produces.

A quantifiable relationship between multilevel causes of deforestation is the basis for modelling these interactions and the outcomes of land change use. However, the multilevel aspects of economic, demographic, and social factors and their causal relationship with deforestation make it complicated to quantify them properly. This research uses machine learning algorithms to train and test the possible relationships between socioeconomic factors and forest areas. The result is an equation that describes the changes in forest area as a product of socio and economic factors that can be used to evaluate the impact of the NDPs. A model is the product of assumption and abstractions of reality; therefore, its interpretation must acknowledge the limitation of the model construction. Yet the predictions of a model are essential as it gives a starting point to discuss the possible impacts of development plans on forest areas even if it does not provide a defined answer to the deforestation dynamics in Ecuador.

1.1. Research question

To what extent do the goals of the National Development Plan impact forest dynamics by shaping the underlying and immediate cause of deforestation?

1.2. Objectives

1. Define the underlying and immediate factors of deforestation in Ecuador by performing an extensive literature review using previous studies and reports of the country.
2. Evaluate the correlation of deforestation's underlying and immediate factors with changes in forest area by analysing and exploring potential patterns, and the strength and direction of the trends between variables.
3. Analyse possible causation between the hypothesised deforestation factors and forest area changes by using a series of regression models.
4. Build a model to predict deforestation using regression models and machine learning algorithms to evaluate the influence of the national development plan on the underlying and immediate factors of deforestation.
5. Assess the course of social and economic development policies with respect to the environmental cost in terms of deforestation from 1990 to 2025.

2. LITERATURE REVIEW

This research investigates the intersection between economic, social, and political factors and their impact on land use and deforestation(Palo 1994; Santiago and Couto 2020a). From the ecological perspective, forests host valuable biodiversity and perform water regulation, soil protection, climate regulation, carbon sequestration, and other environmental functions that significantly impact the world balance (Eguiguren, Fischer, and Günter, 2019). Forest resources also hold economic, social, and cultural values. Forests have been shaped by historical economic chapters of Ecuador, like the rubber, cacao, coffee, and palm oil boom, that change the land cover of hundreds of thousands of hectares of forest (Castro et al. 2013). On a local scale, forests are the source of many Ecuadorians' food, combustibles, medicine, and ancestral knowledge (Delgado-Aguilar, Konold, and Schmitt, 2017). Forests are also very intertwined with social advances in the country, from the agrarian reform and the indigenous revindication to the exploitation of oil and the rights of nature. It is fair to say that forests are substantially valuable in the Ecuadorian legacy.

2.1. Ecological Functions of Forest in Ecuador

Ecosystems such as forests encompass many functions that feed into the global cycles of (Cramer et al. 2004). Forest resources are heavily involved in hydrological regulation and water security. Yet, forests near rivers are more susceptible to being transformed into agricultural land(Sierra, Campos, and Chamberlin 2002). The richness of the soils near rivers and the access to irrigation creates the perfect condition for agricultural production. The transformation of forests to agricultural land has an impact on water availability. Célleri and Feyen, 2009 They explain the changes in water yield in deforested areas; in the short-run there is an increase in water yield but less water regulation, as in the medium to long-run there is a diminishment in water yield due to soil erosion and a decrease in evapotranspiration.

Forests provide soil protection and heavily impact the nutrient cycle. Forest vegetation reduces water erosion by acting as a buffer by reducing the impact of rainfall on the soil. In a broad stroke, nutrients from vegetation and organic matter get recycled by microbial decomposition and later reabsorbed by vegetation. As vegetation gets removed, nutrients get loss from the ecosystems (Bormann et al. 1968). A routine practice of land change use in Ecuador is slash-and-burn agriculture, where forests are clear-cut and burned for establishing crops and pastures. These practices disrupt nutrient cycles by removing above biomass, exposing the soil to erosion and loss of nutrients by leaching, runoff, or gaseous emissions (Palm, Swift, and Woomer, 1996).

The road map of how to address issues water availability, soil protection, food production, and deforestation are heavily contentious topics in Ecuadorian society. According to the FAO, 2022, Ecuador is the second country in South America with the highest presence of malnutrition. Malnutrition is not a recent phenomenon in the country; in 2017, 11% of the population was malnourished (Salmoral et al. 2018), and by 2022 the prevalence of malnutrition reached 15% of the population (FAO et al. 2023). The Ecuadorian government has a series of agricultural reforms to encourage agricultural production and thus guarantee food security. Among the planned measures are transforming unproductive lands[1] into cultivated areas and introducing financing incentives into the agricultural sector (Sánchez, Moreno Izquierdo, and Espinosa 2022). Even though more than 90% of the deforested area was transformed into agricultural land, aquaculture, and forest plantations since 1990, the country has not achieved zero hunger (Sierra, Calva and Guevara, 2021). Forest resources are sources of food and income for rural families. Forest products and activities are estimated to represent 22% of the total income of a population near forests (Angelsen et al. 2014). Environmental income is significant for areas with high poverty and lacking employment.

Carbon sequestration is one of the most important forest ecosystem services (Beedlow et al. 2004). Vegetation takes carbon from the atmosphere, transforming it into biomass through photosystems (Lorenz and Lal 2009). As the life cycle of vegetation continues, the vegetation grows and later dies, emitting carbon back into the atmosphere by decomposition (Favero, Daigneault, and Sohngen 2020). Forests have an important role in climate change, as these ecosystems can be carbon sources through deforestation or sinks of carbon by increasing live biomass (Sedjo and Sohngen 2012). The IPCC reports that the concertation of GHG in 2019 is about 54% higher than in 1990. It is explained that the same CO_2 concentrations are the highest in 2 million years (IPCC 2022). This scenario urges the reduction of carbon emissions and the decrease of carbon concentrations in the atmosphere, a role that can be done by forests (Sedjo and Sohngen 2012). In 2016 around 30% of Ecuador's carbon emissions came from deforestation. There has been particular attention to protecting forests and reforestation plans to mitigate climate change(Ministerio del Ambiente del Ecuador 2016). Payment of ecosystem services schemes was implemented countrywide in 2008 to encourage stakeholders to protect forests and other vital ecosystems. It was reported that gross net emission from deforestation had been reduced from

[1] Unproductive lands are considered when they fail to fulfil their social function without being exploited or used for more than two consecutive years, when they do not fulfil the environmental function, when there is a large estate or property concentration(La Hora 2016).

52.784.480 tCO2eq/year-1 in 1990 to 38,586,447 (tCO2eq/year-1) in 2014 (Ministerio del Ambiente 2019).

2.2. Deforestation as a national problem

Deforestation is considered one of Ecuador's most severe environmental problems (El UNIVERSO 2020). Forests in Ecuador are a hotspot for biodiversity (Tapia-Armijos et al. 2015a; Brehm et al. 2008; Haro-Carrión and Southworth 2018; Mejia 2017). However, they have been under severe pressure due to the expansion of the agricultural frontier, colonization, urbanization, and overpopulation (J. Kleemann et al. 2022). The destruction and fragmentation of forests do not only endanger biodiversity but also ecosystem services(Eguiguren, Fischer, and Günter 2019), putting water security, soil fertility, and rural economies dependent on non-timber production at risk(Knoke et al. 2020). The deforestation in Ecuador during the twentieth century reached an average of 92,742 hectares per year (Mejia 2017). By 1990, the forest cover of Ecuador represented 68% of the national territory, and by 2018, there was a decrease of 16% of the natural forest cover from 1990 (Sierra, Calva, and Guevara 2021a). Measures were introduced to protect sensitive ecosystems and natural forests(Valdez Duffau and Cisneros Guachimboza 2020), the creation of protected areas (Janina Kleemann et al. 2022), environmental legislation and payment programs for ecosystem services such as the Socio Bosques (K. W. Jones et al. 2017)and REDD+ program.

The main pressure for deforestation in Ecuador is the expansion of the agriculture frontier (Wasserstrom and Southgate, 2013; Tapia-Armijos et al., 2015). The changes in agriculture and land use have two important antecedents: the agrarian reform in 1964 (Gondard et al. 2001)and the discovery of crude oil in the Amazon in 1967. What follow from these events significantly transformed the country's natural forest cover (Valdez Duffau and Cisneros Guachimboza 2020). Before the agrarian reform, Ecuadorian agricultural production maintained the model inherited from the colonial era, where large farms were under landowners' control (Gondard et al. 2001). Under this system, indigenous and peasant populations worked in semi-servitude models, where in exchange for labour, they received small parcels of land for survival agriculture(Wasserstrom and Southgate 2013). This system resulted in high population density in the Andean zone of the country, poverty, job insecurity (Zamosc 2022), overexploitation of fertile soils, and high deforestation in the Ecuadorian coast region (Jordán 2003). Gondard et al., 2001 and Jordán, 2003 explain that the objective of the agrarian reform was to build competitive agricultural production by dismantling the hacienda system and distributing vacant land to foster the economic development of the country.

The deforestation, especially in the Amazon, occurred thanks to the definition of forest as "*terrenos baldios*" land without property (Gondard et al. 2001). In 1875, the Ecuadorian government determined that the lands located in the Amazon region had no ownership and were underutilized, even when that territory was under the control of indigenous communities(Wasserstrom and Southgate 2013). Under this definition, the agrarian reform encouraged colonization and transformation of forested areas in Amazonian regions to agricultural land (Gondard et al. 2001). Yet, the colonization process was only possible when the oil companies began operations in the Amazon region. Oil activities required basic infrastructure and roads; as oil companies opened routes in the area, settlers arrived thanks at governmental incentives for agricultural production and the promise of property titles (Jordán 2003; Wasserstrom and Southgate 2013). The regions close to the highways were dedicated to agriculture since good connectivity allowed the trade of agricultural products. Territories far from the road network were used for raising cattle (Mena et al. 2017). The oil industry provided the physical mechanism for the colonization of natural forests in larger parts of the Amazon, and public policies gave the incentive to transform forests into agricultural systems(Barber et al. 2014). The agrarian reform is a clear example of national development plans to improve economic and social aspects with incredible environmental trade-offs (Valdez Duffau and Cisneros Guachimboza, 2020).

2.3. Understanding the socioeconomic factors of deforestation

There has been extensive research regarding the influence of socioeconomic drivers of deforestation on land change use, especially in deforestation (Ehrhardt-Martinez, 1998; Mena, Bilsborrow and McClain, 2006; Bernhard, Zenobi and Shapiro, 2021). Angelsen & Kaimowitz (1999) describe a framework to analyse the influence of socioeconomic variables by dividing them into tiers of influence, as shown in *Figure 1*. The first tier represents the underline factors of deforestation. These are the macroeconomic data and policies that indirectly affect land use. The second tier is the immediate causes of deforestation, which are external variables that directly influence the agents of deforestation. Finally, the sources of deforestation are the agents of deforestation and their personal choices of deforestation. This classification is a compartmentalization of the complex and interacting socioeconomic factors(Walsh et al. 2002). This is not a hierarchical classification, where the action flows come from the top down, but instead, there are interactions between levels. Deforestation drivers can influence immediate drivers of deforestation that change agricultural prices, or social unity movements can change state-level land use legislation (Angelsen and Kaimowitz, 1999; Mena, Bilsborrow and McClain, 2006a; Bernhard, Zenobi and Shapiro, 2021).

The main objective of this section was to select pertinent socioeconomic variables by understanding the complexity of the socioeconomic and socioecological systems in place that affect the dependent variable of deforestation. As pointed out by Bernhard et al., 2021, it is essential to ask which commodities, economic development policies, and social conditions have had the most impact on land change use dynamics, specifically regarding changes in forest areas and how they interact with each other to magnify deforestation. In Bernhard et al., 2021; Kleemann et al., 2022; Luna et al., 2020; Mena et al., 2006; Sierra et al., 2021, variables such as GDP per capita, rate of change in primary exports, income level, economic activity per household, as well as, poverty, level of scholarly, population growth and other factors are used for studying deforestation.

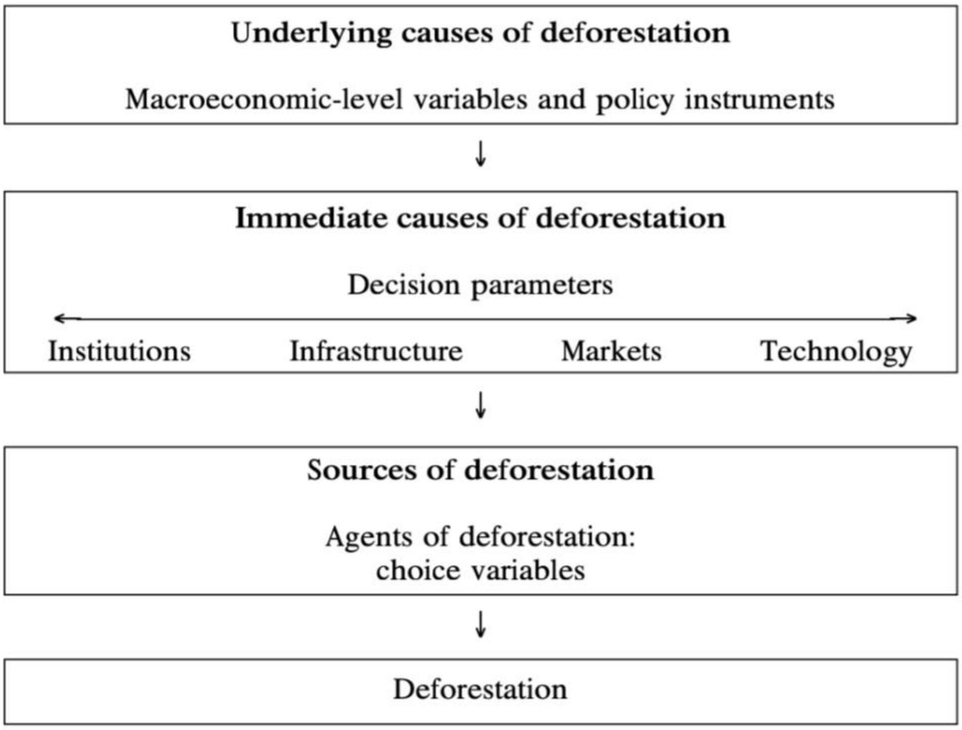

Figure 1 Variables Affecting Deforestation (Angelsen and Kaimowitz 1999)

2.3.1. *Underlying causes of deforestation*

2.3.1.1. Growth vs. development and deforestation.

Understanding economic growth as a synonym for development is widespread in the globalized and Westernized world (Jimenez et al. 2019), and even the term development has ambiguity (Khan et al. 2022). Tezanos Vázquez and Sumner, 2013 explain the multidimensional nature of development using four conceptual frames: structural transformation, human development, democratic participation, and improved governance and environmental sustainability. The most used framework is developed as a structural transformation (Herrendorf, Rogerson, and Valentinyi 2014). This conceptualization of development has been widespread since the 1950s (Tezanos Vázquez and Sumner 2013; Khan et al. 2022; Schlogl and Sumner 2020) and refers to the transformation from rural into urban and prioritizing industrialization and economic growth as the cornerstone of development (Tezanos Vázquez and Sumner 2013). Unsurprisingly, the initial association when talking about development in terms of economic growth has led to using economic growth indicators, such as GDP per capita, as an indicator of development (Haller 2012), disregarding the multidimensional nature of development. In the case of Ecuador, Fernández et al., 2006 explain that the conventional strategy of development (economic growth) based on financial technicalities has increased social inequality, political instability, and a disregard for the environment.

Even though that economic growth is not the same as development, the theoretical frameworks to analyse the intuitive link between economic development and the use of natural resources is still in terms of economic growth (Crespo Cuaresma et al. 2017) (Zilio 2012; Shahbaz, Haouas, and Hoang 2019; Alam and Paramati 2015; Fernández et al. 2006; Jimenez et al. 2019; Reyes et al. 2020; Stern 2018). The most used approach to describe this link is the Environmental Kuznets Curve (EKC)(Choumert, Combes Motel, and Dakpo 2013). EKC hypothesizes that the relationship between economic development and environmental degradation can be described as an inverse U-shape curve(Stern 2018). The first stages of economic growth led to environmental degradation. As economic development increases, it reaches a point where ecological degradation stops and decreases (Dasgupta et al., 2002; Bhattarai and Hammig, 2001). Based on this hypothesis, several studies have investigated the relationships between economic development and deforestation with mixed results (Kumar and Datta 2021; Choumert, Combes Motel, and Dakpo 2013; Crespo Cuaresma et al. 2017).

Crespo Cuaresma and Heger, 2019 found that countries with higher income per capita tend to have higher deforestation rates. However, this relationship is more evident in low-income and high-income countries. Following the research of Crespo Cuaresma et al., 2017, and Jimenez et al., 2019 establish a positive relationship between economic growth and environmental degradation in Ecuador. Reyes et al., 2020 found that economic growth in terms of GDP positively correlates with the expansion of the agricultural frontier. The Ministry of Environment, 2016 points out that changes in forest cover are mainly due to the development of the agricultural frontier. There could be an empirical relationship to be explored between the role of the agricultural sector and deforestation (Fischer et al. 2021), mainly when the agricultural industry contributes with contributes 7.81% of GDP in Ecuador (Banco Central del Ecuador, 2019 in Carrión Loaiza and Garzón Montealegre, 2020).

2.3.1.2. Poverty

Poverty in the republican age of Ecuador has as its main characteristic the replication of the productive extractive models inherited from the colonial era (Cuesta 2014). Acosta 2006 explained that the post-colonial economy of Ecuador was dominated by social stratification, where dominant groups controlled the economic and political power. They replicated the discrimination towards indigenous communities, afro-Ecuadorian, and peasants, leaving a legacy of generational poverty, especially in rural areas. Torres, Zumárraga and López 2019 argue that the paradox between an economy heavily dependent on natural resources, first with the agricultural booms (cacao and banana) and with the oil boom, has not been available to lift people out of poverty(Graziano Da Silva, Gómez, and CastañeDa 2010). Alvarado, Posso and Posso, 2019 explains that the proceeds from the sale of natural resources are destined for the payment of external debt, debt forgiveness, subsidies, tax reductions, payment to public employees, corruption, and other measures that do not contribute to the reduction of inequality and poverty.

Poverty in Ecuador is classified as the lack or deprivation of income that allows reaching a minimum standard of living (INEC 2021b). Minimum living standards refer to households that lack access to sanitation services, lack subsistence capacity, have one child not enrolled or attending school, and have three or more people sleeping in one room (Canelas 2019). Additionally, a person is considered poor by income if they receive a per capita family income of less than USD 84.7 per month and extremely poor if they receive less than USD 47.7 (Banco Central del Ecuador, 2021). According to the INEC, in December 2022, the national poverty level was 25.2 %, and extreme poverty was 8.2%. In the urban area, poverty reached 17.8%, and extreme poverty at 3.9%. Finally, poverty reached 41.0% in rural areas, and extreme poverty at 17.4% (INEC 2022). This definition and statistics are based on a reductionist definition of poverty that compresses economic well-being (Wagle 2002). Scheidel, 2013 explains that the complex phenomena of poverty can be present through understanding deprivation of needs, income, freedom, and other states of deprivation. There is the argument that depriving someone that does not engage in the predominate economic system of livelihood strategies can make a person poor(Rees 2002; Bennett 1944). Chambers, 1995 explains that hand-to-mouth rural livelihoods are based on long-term thinking and sustainable use of resources. Introducing short-term policies such as increasing agriculture yield can decrease soil fertility and endanger the long-term livelihood strategy (Scheidel 2013).

The tunnel vision that often afflicts development policies is to reduce income poverty as the main development objective. To avoid this biased vision of development policies, over the years a series of indicators have been created that seek a less reductionist vision of what poverty and development are. These indicators include the human development index. HDI is obtained by analyzing three axes: Health, Education and Standard of living. Although this index adds life expectancy and years of schooling(Sagar and Najam 1998), it still defines gross national income (GNI) as standard of living. This is the same reductionism that associates getting out of poverty with an increase in the income of a human being(Fosu 2007). Although it should be emphasized that the HDI is a widely cited statistic that is commonly used as a measure of well-being in different countries (Dasic et al. 2020).

The relationship between poverty, development and deforestation has been hypothesized as a trade-off, where the increase in rural income is correlated with land clearing. Peterson Zwane, 2002 raises a point regarding the perception that economic development is positively associated with deforestation. When soil productivity decreases due to intensive agriculture, low-income communities expand toward forest areas to acquire the lost income (Cristina Vallejo et al. 2020; de Koning et al. 2011). This relationship is under the assumption that low-income people cannot invest in soil quality (Peterson Zwane 2002). Luna et al., 2020 argue cash alleviation can influence land management decisions, meaning that the extra income can be used for investment in fertilizers or as complementary income, thus reducing the expansion of agriculture. However, Peterson Zwane, 2002 raises the point that in some cases, when the income of rural households increases, the stakeholders choose to expand the agricultural frontier as an investment to increase their income. In the case of Ecuador (Mena, Bilsborrow, and McClain 2006b) compared two areas in the Ecuadorian Amazon and found that the more affluent area had economic means to expand agriculture activities and ranching.

Additionally, Reyes et al. 2020; Luna et al. 2020; Canelas 2019; Kovacic and Viteri Salazar 2017 explain that the lack of formal employment and higher rates of poverty is a factor for people to seek income by expanding the use of forest resources through wood trade colonization of new territories for agricultural activities. Finally, according to Peterson 2002, there is a relationship between poverty, agricultural production, and investment decisions. Poverty can and does affect the agricultural production investment decisions of low-income rural households. To reinforce the first assumption Ehrhardt-Martinez 1998 theorized that low-income rural households are more likely to use colonization schemes for agricultural production, the increase in inequality and impoverishment will generate a higher dependency on forest resources and the expansion of the agriculture frontier.

2.3.1.3. Population density

There is the notion that higher population density creates an overuse of natural resources and adverse environmental effects (Ehrhardt-Martinez, 1998; Mena, Bilsborrow, and McClain, 2006a). Carr, Suter, and Barbieri, 2005 explain that population dynamics is a significant driver of deforestation. Population density is an underlying cause of deforestation (Geist and Lambin 2001). In the case of Ecuador, population density impacts land change use (Sierra, Calva, and Guevara 2021a); forests near areas with higher population density are more likely to transition into agricultural land (López 2022). A clear case of the effects of population dynamics on deforestation can be seen in the Amazon region of Ecuador. The Amazon was an inaccessible part of the country for a big part of the republican life of the country (Gondard et al. 2001). The Amazon colonization process began in the late sixties and seventies(Wasserstrom and Southgate 2013). The increase in population expanded the agriculture frontiers in remote areas, especially spaces not controlled by the black and indigenous people (Gondard et al. 2001; Jordán 2003). During the agrarian reform, colonists moved to territories owned by the indigenous population. Indigenous communities broke the community land scheme to protect their territories and started privatizing parts of the territory to gain titling and avoid settlers (Wasserstrom and Southgate 2013).

Carr, Suter and Barbieri, 2005 explain that population growth increases the need for land; as second and third-generation settlers look for subsistence, they migrate into the peripheries, expanding the agriculture frontier and the need for basic infrastructure. This phenomenon generates rural-to-urban transition (CEPAL 2002; Pichón 1997). The Ecuadorian population in 2010 was 14'483.499 people, and 62.7% lived in urban areas while 37.3 % in rural areas(SUBSECRETARÍA DE HÁBITAT Y ASENTAMIENTOS HUMANOS - SHAH 2015). By 2020 the population was 17´510.643, mostly in urban areas (64.0%), while there was a reduction of people in rural areas of 1.3% (Ministerio de Salud Pública 2021). In the last 25 to 30 years, the contraction of deforestation is explained by lower population density in rural areas, a transformation of the Ecuadorian economy towards an urban-commercial economy rather than a rural-agrarian economy(Mena, Bilsborrow, and McClain 2006b; Sierra, Calva, and Guevara 2021a). In addition, the stagnation in population density in these rural areas is explained by the closing of the colonization borders and the legalization of land ownership(López 2022; Castro et al. 2013).

2.3.1.4. Employment

One of the well-documented phenomena is the regional migration inside Ecuador (Espinoza and Achig 1981; Ordóñez-Cuenca 2016; Falconí Cobo 2010; Barbieri and Carr 2005; Pichón 1997). The internal movement of the population responds to economic factors, employment availability, and public policies of redistribution of land (Borrero 1995; Ordóñez-Cuenca 2016). There have been mixed results regarding the influence of employment on deforestation (Geist and Lambin, 2001; Sierra, 2013; Sierra, Calva, and Guevara, 2021a; Janina Kleemann et al., 2022). Angelsen and Kaimowitz, 1999 suggest that lack of employment puts pressure on forests and simulated deforestation, the understanding that off-farm employment opportunities make stakeholders less likely to engage in agriculture and forestry. Rural employment influences deforestation, and low urban employment can impact deforestation by driving rural wages down (Jones and O'Neill, 1994 in Angelsen and Kaimowitz, 1999). As described in Sierra, Calva, and Guevara, 2021 and Sanchez Calderón, 2015, an increase in formal employment generates the movement of the rural population to work in the cities. If jobs decrease in urban areas, people return to rural areas and start working in agriculture and substance farming. Therefore, lack of formal employment could have a positive effect on deforestation.

In the case of Ecuador, Pichón, 1997 describes that households with access to off-land employment have less pressure to transform the forest into agricultural land because off-farm activities give them less economic pressure to be deforested. However, in rural areas, employment is strongly linked to agrarian movements or is part of the agricultural production cycle, which limits off-farm employment (Martínez 1992). Most of the public policies to improve the living conditions of the rural sector have focused on increasing the agricultural sector (especially in the production and trade of products) to generate rural employment (Hollenstein and Carrión 2011). Employment in Ecuador (2017) shows that 26% of the employed persons work in the primary production sectors such as agriculture, forestry, livestock, and fishing (Olmedo 2018). The employment figures for March 2021 indicate that 79% of rural employment is unsuitable [2], likewise, 22% of rural employment is unpaid (Cobos 2021).

2.3.1.5. Education

There is no defined answer if education influences deforestation. Godoy, Groff, and O'Neill, 1998 describe the impact of education on the loss of forests as a non-linear relationship. Where less than two years of education forest clearing decrease, 2 to 4 years of education increase the odds of deforestation, and more than four years of scholarly curves logging. In Ecuador, some studies at the household level show that little or no education is linked with low deforestation (Luna et al. 2020). Similar results have been found in Mena, Bilsborrow, and McClain, 2006b, where more education increases deforestation rates. These first conclusions give the impression that the more education, the greater the desire to boost household consumption and production to improve the standard of living (Pichón 1997; Mena, Bilsborrow, and McClain 2006b; Luna et al. 2020; Pan and Bilsborrow 2005). People with relative education can access information to modernize and expand agricultural production(Luna et al. 2020). However, all these studies were conducted in rural communities with low levels of education(J. Kleemann et al. 2022). Pichón, 1997 explains that basic primary education does not curve deforestation. Still, technical and specialized education could reduce deforestation by increasing job opportunities outside the agricultural sector or accessing technologies for better agricultural production (Mena, Bilsborrow, and McClain, 2006).

Access to education in rural areas is more precarious (Morán 2019). According to the INEC, in 2021, schooling[3] in rural areas is only 7.7 years, while in urban areas, it is 11.5 years(Machado 2022). According to the 2010 national census, the indigenous population has the highest illiteracy rate at 22.6% (INEC 2010). The 2000 National Agricultural Census showed that 65% of agricultural producers only had basic primary education, and less than 4% had access to higher education (Contreras 2015). In 2017, 47% of the employed population only had basic primary education and mainly is employed in agricultural activities and construction (Olmedo 2018).

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[2] Employed people who, during the reference week, received income below the minimum wage and/or worked less than the legal working day and are willing and willing to work additional hours(INEC 2023).
[3] To obtain a high school's degree in Ecuador, a person must study for at least 12 years: six in school and six in college(Machado 2022).

2.3.1.6. Oil Extraction

There has been a lot of discussion regarding the role of the oil industry in deforestation (Mena et al. 2017; Barber et al. 2014; Fearnside 2015). Forest loss associated with establishing and operating the oil industry was marginal. However, deforestation caused by oil roads to open new areas for logging and colonization was significant (Wunder, 2003 in Wasserstrom and Southgate, 2013).Sierra, Calva and Guevara, 2021 describe that the oil economy of 1970 allowed agricultural expansion in inaccessible areas of the country since a road network was built to establish and maintain oil operations (Barber et al. 2014). The change in the country's economic model towards an economy based on oil export gave the government the power to directly plan territorial development and strategic plans to activate agriculture in the Amazon region(Burgos 1997; Baroja, Belmont Guerrón, and Peck 2017). The oil boom also attracted workers from all parts of the country to provide services and labour to multinational oil companies(Calderón and Reyes Pinengla 2015).

The new roadway allowed massive migration from different areas of the country to the Amazon(Castro et al. 2013; Wasserstrom and Southgate 2013). The development of road network increases the mobility of goods and decrease the price of transportation, making economically viable the transformation of remote regions (Wasserstrom and Southgate 2013). Barber et al., 2014 estimate that 95% of deforestation happens within 5.5 km of roads. The expansion of the agricultural frontier occurred from the north to the south; as new oil wells opened roads, activity increased, creating parallel roads and human settlements (Pan and Bilsborrow 2005).

2.3.2. Immediate factors of deforestation

2.3.2.1. Land under agricultural production

The agricultural frontier's expansion in Ecuador results from several socioeconomic factors, but it is mainly linked to the country's economic cycles and the demand for markets of agricultural products (Sierra, Calva, and Guevara, 2021). There has been an expansion of the allocation of land for agriculture. The territory under agricultural management in 1957 corresponded to 1.77 million hectares; by 2013, it increased to 2.47 million hectares, and in 2019 the land under agriculture management was more than doubled to 5.1 million hectares (Sánchez, Moreno Izquierdo, and Espinosa 2022).

The expansion of the agricultural frontier began in the 50s. The rural and peasant population of the Ecuadorian highlands experienced a demographic increase, which meant an increase in the demand for arable land. Until the 1950s, land tenure in Ecuador followed a farm and landlord model, where farmland was controlled by a few landowners(Gondard et al. 2001; Wasserstrom and Southgate 2013). The rural population was forced to colonize unproductive territories in the Andean region or to move to the coastal area and the Ecuadorian Amazon. This phenomenon was encouraged by public policies that guaranteed property titles if the colonized territories were under some productive system (Zamosc 2022; Sierra 2013). From 1950 to 1970, there was a contraction in the deforestation of the Ecuadorian highlands and an expansion in the deforestation of the coastal and Amazon forests. From the 1970s to the 1990s, the expansion of the agricultural frontier accelerated in the country, primarily due to population migration to recently deforested areas(Tapia-Armijos et al. 2015b). The banana boom encouraged deforestation of the Ecuadorian coast forests and began a phase of export agriculture in the country. From the 1990s to the present, there has been a slowdown in agricultural expansion in the country due to rural migration to the cities, modernized agrarian production systems, and the closure of colonization borders and legalization of land tenure(Sierra, Calva, and Guevara 2021a).

The expansion of the agricultural frontier responded to migratory processes, resulting in the diffusion of farming practices toward new territories. Pichón, 1997 explains that rural migrant populations from the Ecuadorian highlands brought inefficient cultivation practices to the soils and ecosystems of the coast and the Amazon region. This replication of agricultural production systems for rich volcanic soil was inefficient in areas with poor soils, such as the Amazon (Tapia-Armijos et al. 2015b; Fagua, Baggio, and Ramsey 2019). The low agricultural yield generated more deforestation in these areas (Walsh et al. 2002). Wasserstrom and Southgate, 2013 points out that the colonization of territories did not increase food production in Ecuador; wheat, potatoes, and corn production decreased by around 70% during the 1980s.

Another critical factor in the expansion of the agrarian frontier is the domestic cycle. Families migrating to new agricultural areas begin the settlement process by clearing native forests, significantly near roads or rivers, to grow annual subsistence crops (Thapa, Bilsborrow, and Murphy 1996). Mena, Bilsborrow, and McClain 2006b explain that when a family has settled for five years, there is a transition to short-term crops, pastures, and annual crops. As the children grow up and reach adolescence, raising cattle and short-lived crops intensifies, yearly crops are abandoned, and secondary succession begins. Finally, when the children reach adulthood, they leave the settlement (more than 15 years) in search of their plots of land. The initial farm returns to a period of subsistence cultivation where secondary forest growth predominates. The use of land for agricultural activities is strongly related to population growth.

2.3.2.2. Land management policies

Land use policies in Ecuador have been adjusted with the economic and productive visions of the state. In the mid-20th century, land colonization policies established that anyone actively using a territory could access property titles (Pichón 1997; Mesquita et al. 2015). This generated a migratory movement toward territories with native forests and, consequently, the massive clearing of forests(Gondard et al. 2001). This process of human mobility was rapid, disorganized, and anti-technical (Gómez de la Torre, Anda, and Bedoya Garland, 2017). For example, in 1987, the Ministry of Agriculture and Livestock established that of the 5.30 million hectares of the north-eastern region of Ecuador, only 17% (0.90 million hectares) were suitable for cultivation and recommended that the remaining 83% be conserved as forest. By then, 1.10 million hectares had already been colonized (Wasserstrom and Southgate 2013).

It was not until 1990 that the country introduced legislation for protecting nature with Basic Environmental Policies. In the 21st century, there is a restructuring of the role of the environment in the country's socioeconomic policies (Guardiola and García-Quero 2014). Through the constituent assembly of 2008, nature has been given rights under the paradigm of *Good Living* (*Buen Vivir*). The interaction of economic, social, and jurisdictional policies with nature goes from being extractivist to biocentric (Valdez Duffau and Cisneros Guachimboza 2020).To reduce deforestation, around 20% of Ecuador's continental territory was declared protected areas (Janina Kleemann et al., 2022; J. Kleemann et al., 2022). Payment programs for ecosystem services (Socio Bosque) have also been established to curb deforestation on the agricultural frontier. Sierra explains that voluntary conservation programs significantly slow deforestation in areas surrounding primary and secondary forests (K. W. Jones et al. 2017). These natural protection policies and the concepts of the right to nature conflicted with the economic policies of the last ten years. Kleemann et al., 2022 explain the Ecuadorian government has allowed the exploration of legal mining and the incursion of the oil industry in protected areas.

2.3.2.3. Demand for agricultural products

The change in land use from forest to agricultural land is related to the demand for agricultural products, both nationally and internationally (Sierra, Calva and Guevara, 2021). Historically, the country has experienced several productive booms in the agricultural sector

(Carrere, 1997). The cocoa boom in Ecuador began in 1890 and ended in 1920. Cocoa cultivation was one of the engines of the Ecuadorian economy at the beginning of the 20th century(Baquero and Mieles 2014). During this time, cocoa represented 70.3% of the country's exports(Abad, Acuña, and Naranjo 2020). Forests are transformed into cocoa monocultures, mainly in the coastal region and central highlands (Carrera, 2014). The expropriation of peasant territories and job insecurity are attributed to the cocoa boom (Abad et al., 2020). The high international demand for Ecuadorian cocoa resulted in the migration of peasants from the Andean region to the coast, initiating an expansion of the agricultural frontier on the Ecuadorian coast (Graziano Da Silva, Gómez, and CastañeDa, 2010; Baquero and Mieles, 2014).

The banana boom began in the '50s and ended in 1970 when oil production took over the country's economic reins (Baquero and Mieles, 2014; Abad, Acuña, and Naranjo, 2020). Banana production for export transformed the social structure of the country. Although the activity was agricultural, the urban population benefited the most from the income flow of the banana boom(Gonza1ez et al., 1991). The situation in rural areas was characterized by job insecurity and a sizeable migratory flow of the rural population from the Andean zone to the coast(Carrera 1997; Baquero and Mieles 2014). Both cocoa and banana productions were under multinational structures, with little state control. (Carrere, 1997) explains that during the banana boom era, 62 to 70% of the country's net deforestation was due to the expansion of banana plantations. In the last 20 years, the government has seen the growth of palm oil industry and shrimp industries grow (Ministerio del Comercio Exterior 2017; IPS 1999). The shrimp industry is credited with destroying 40% of the mangrove (Tanner and Ratzke 2022; IPS 1999). Oil palm monocultures extend into the country's Amazon; in 2016, there were around 280 thousand hectares under oil palm production(Tanner and Ratzke 2022; INEC 2021a). Sierra, Calva and Guevara, 2021 explain that palm oil plantations are lucrative enough to transform remote and rugged forests.

According to INEC, in 2021, 41.83% of permanent crops correspond to cacao, followed by palm oil (15.05%) and bananas (11.20%). Of the transitory crops, 37.12% is corn, followed by rice, with 34.08% (INEC, 2021). Cocoa, bananas, and palm oil are leading in current agricultural production systems (Sierra, Calva, and Guevara 2021a; Sierra 2013). On the other hand, family farming provides around 60% of the country's food production. They are mainly distributed in the Andean region of the country (Cobos 2021; International Land Coalition 2021; Martinez 2013). The agricultural systems are small parcels of land with little probability of expansion to new territories due to land rights (most of the productive land was distributed during the agrarian reform) and the protection of Andean forests (Pichón 1997; Martinez 2013). The new deforestation processes are not linked to agricultural production for domestic consumption. Instead, it is focused on the cost-opportunity of agricultural products for export (Sierra, Calva and Guevara, 2021).

3. METHODOLOGY

This research focus on understanding how policies and national development goals shape the context where changes in forest area happen. Deforestation is a complex process beyond cutting forests; it results from macro and micro socioeconomic decisions that influence the livelihoods of the deforestation actors (López-Carr 2021). Agricultural incentives, protected areas, land tenure, economic policies, and social and demographic factors are part of land change use decision-making processes (Geist and Lambin 2001). Therefore, it is crucial to define the underlying and immediate factors of deforestation in Ecuador and explore their impact on the loss of forest area. Following the theoretical framework of Angelsen and Kaimowitz 1999, this research explored the relationship between factors of deforestation and loss of forest area by studying trends and patterns of deforestation as the result of changes in economic growth, trade, education, poverty, agricultural activities, and other governmental policies. Finally, this work aims to find possible causation between the hypothesized deforestation factors to construct a model to evaluate the policies that structure economic and social development.

The chosen methods for analyzing deforestation due to social and economic factors were correlation analysis, regression analysis and Least Absolute Shrinkage and Selection Operator (LASSO) regression. A correlation analyst explored patterns between the socioeconomic factors and changes in the forest area. This analysis gave an overview of the strength and direction of the changes from 1990 to 2020 in economic growth, population, agricultural trade, exports, education and the decline of forests. Correlation does not imply causation(Sirén et al., 2022). The patterns identified from the correlation analysis could be the result of chance, so a regression analysis was developed to identify possible causal relationships between the independent variables (socioeconomic factors) and the dependent variable (changes in forest cover)(Millington, Perry, and Romero-Calcerrada 2007). A fundamental assumption when performing correlation and regression analysis is the absence of multicollinearity(Yong and Pearce, 2013). If multicollinearity between the independent variables is severe, a regularisation method defined as LASSO was used. This method uses an L1 penalty to reduce the independent variables to the most significant ones. The benefit of LASSO is that it uses machine learning methods, using data for training, and testing of the model(Holmes Finch Maria Hernandez Finch, Holmes, and Hernandez 2019). New data can be entered into the model to improve its performance. The expected result was a mathematical model that could explain the relationships between forest area and socioeconomic variables. This model was later used to evaluate the impact of national development goals on changes in forest areas.

3.1. Research Design

The analysis established for this study was quantitative and used secondary data obtained from various official sources of the Republic of Ecuador, such as the Ministry of the Environment, the National Institute of Statistics and Censuses, the Central Bank of Ecuador, and the database. World Bank and FAO data. The secondary analysis was chosen for the accessibility of historical macroeconomic data since this study seeks to analyse changes in the forest area due to economic, social and demographic factors at a national scale over 30 years. Wickham 2019 explains that secondary analyses can examine research questions in large data sets that may have been collected over time (longitudinal data). This study is considered retrospective since it seeks to historically analyse the factors of deforestation and land use change (Veiga et al. 2008) and understand the possible correlation and causality relationships between the dependent and independent variables.

3.1.1. Framework

The framework used for the current research was the Macroeconomic model described by Angelsen and Kaimowitz, 1999. This approach explores the relationships between the underlying and immediate socioeconomic factors with deforestation nationally. The underlying factors are the macroeconomic variables and policy instruments that may indirectly affect deforestation, and immediate factors are the decision parameters. Such parameters influence the agents of deforestation. Bernhard, Zenobi, and Shapiro, 2021 expand the framework of Angelsen and Kaimowitz, 1999 by establishing deforestation in time as a function of the underlying and immediate socioeconomic variables (Equation 1)

$$Deforestation_{it} = f(underlying_{it}, immediate_{it})$$

Equation 1 Deforestation as a function of underlying and immediate factors of deforestation
(Bernhard, Zenobi, and Shapiro 2021)

Angelsen and Kaimowitz, 1999 explain that the Macroeconomic Model leaves out the agents of deforestation. The model does not consider the stakeholders directly involved in the change in land use and their individual choices. By leaving out an essential dimension of deforestation, the model assumes that underlying factors influence the immediate parameters of deforestation (Bernhard, Zenobi, and Shapiro, 2021). Scrieciu, 2007 mentions that the macroeconomic approach to deforestation is under the impression that there is a potential causal relationship between macro-level economic variables and deforestation. The macroeconomics approach has been used in the current work. However, several studies have analysed the socioeconomic variable at household levels-agents of deforestation (Luna et al. 2020; Janina Kleemann et al. 2022; Tapia-Armijos et al. 2015b; Walsh et al. 2002).

According to Angelsen and Kaimowitz, 1999, the underlying factors are population pressures, income level, economic growth, external debt, trade, structural adjustment, and the indirect effects of technological change. On the other hand, the immediate variables are agricultural prices, agricultural inputs and credit, waged and off-farm employment, technological progress in agriculture, accessibility and roads, property regime and tenure security, and timber prices (Scrieciu, 2007; Bernhard, Zenobi, and Shapiro, 2021; Sierra, Calva and Guevara, 2021). No, all these variables were selected for the analysis. They were discriminated against based on an extensive literature review and previous studies on deforestation in Ecuador.

3.1.2. National development goals and Factors of Deforestation

It has been established this research focuses on evaluating national development plans and their effect on deforestation. However, it may not be as clear yet why the emphasis has been on establishing the relationships between social, economic, and demographic factors as predictors of deforestation. The rationale behind understanding deforestation's underlying and immediate factors is that policies are the ones shape factors of deforestation. Development plans and goals establish the context of deforestation (Torres et al., 2020). For example, policies for economic growth promoting agricultural exports may have a more significant impact on deforestation than economic policies that focus on exporting oil or minerals, thus the necessity to identify the predictors of deforestation for Ecuador.

The overall direction of the policies and goals for development is portrayed in the National Development Plans that each government has presented since 2007(CONSTITUCION 2008). The impact of NDP on forests can be assessed by analyzing the objectives and goals that directly influence any of the underlying or immediate factors of deforestation. The causal relationships between economic and social factors with deforestation can be used to build a mathematical expression to analyse the impact of the NDP objectives. Thus, if the plan establishes an increase in agricultural exports to 4.32% by 2025(CEPAL 2021), an effect could be predicted regarding the gain or loss of forest area.

3.1.3. Study Area and Scope

The study area is the continental territory of Ecuador. The country is located on the South American continent. Ecuador borders Colombia to the north, south, and east with Peru and west with the Pacific Ocean. Ecuador's capital is Quito, with a population of 17.23 million inhabitants (INEC 2021b) and an area of 256,370 km^2. Since 2000, the legal currency of Ecuador has been the United States dollar. The administrative division of Ecuador is in the form of 24 provinces and 221 cantons (Instituto Geografico Militar 2020; OFICINA DE INFORMACIÓN DIPLOMÁTICA 2021). The scope of the study only focuses on the socioeconomic factors that affect deforestation. Biophysical factors are not considered due to the nature of the study. Measuring elevation, slope, precipitation, and temperature will entitle location-based analysis. This study is based on national statistics rather than geographic-specific data.

3.2. Data Collection

The data collection focused on the period corresponding to 1990 to 2020. It is assumed that thirty years of data could establish relatively robust relationships between the independent and dependent variables. Another factor that influenced data collection is the continuity and availability of information. Socioeconomic data before 1990 are scarce. Deforestation factors were selected using the theoretical framework of Angelsen and Kaimowitz 1999 and extensive research from scientific sources from Ecuador and Latin America. The explanation of the selected variables is detailed in this section. Additionally, this section presents the expected effect of the socioeconomic variables on forest areas as described in Table 2. Appendix 1 and Appendix 2 show the complete data base used for this research and the source of the information and its definition.

3.2.1. Socioeconomic Data

The data collected for the current research was obtained from official national sources and international organizations. The entity that controls the statistical data in Ecuador is the National Institute of Statistics and Censuses (INEC). The organization contains a range of data, from sociodemographic to environmental data. However, more specialized data was taken from the National Central Bank of Ecuador, the Ministry of the Environment, Water and Ecological Transition, the Ministry of Agriculture and Livestock, and the Ministry of Energy and Non-Renewable Natural Resources. Additionally, data from the World Bank and FAOSTAD was used due to their historical recording and consistency in data. Ecuador had a restructuring of its methodological framework for collecting sample size, sample distribution, and presentation of socioeconomic data (INEC 2008; 2021c). This research used historical quantitative data from 1990 to 2020, depending on availability.

3.2.1.1. Underlying predictors for deforestation

Gross domestic product (GDP) per capita was selected as an indicator to study the relationship between economic growth and deforestation. This indicator was chosen assuming GDP per capita measures the national financial performance(Dobbs Richard et al. 2015). There has been a lot of criticism regarding the use of GDP to measure economic well-being and growth (Dynan et al. 2018; Chong and Calderón 2000; Bulin Daniel 2015), Pilling 2014 express that even though GDP can be anachronistic and fail to measure complex trades-offs of economic growth, it is a single concrete and continues indicator that can be used for analysis. The population density in people per sq. km of land area (PopD) was the indicator selected for analyzing the relationships between demographic pressure and changes in the forest area. Several studies used this indicator to track the effects of demographic factors on forests (Armenteras et al. 2006; Hauser and Norgrove 2013; Leblois 2018) primarily because it relates to the occupation of territory, in other words, counting the number of people per square km gives a vision of demographic expansion and land occupation. The increase in infrastructure is considered one of the factors for the change in land use(Angelsen and Kaimowitz 1999). The artificial surfaces (ArtifiSurfa) indicator analysed the relationships between deforestation and urban expansion and artificial structures such as roads, extraction sites and other industrial areas (FAOSTAT 2022).

Income level and poverty are also considered underlying predictors of deforestation. The indicator chosen to explore that relationship was the Humanitarian Development Index (HDI). This index quantifies the improvement of incomes, life expectancy and education resulting from economic growth (Jha and Bawa 2006). HDI is a measurement of well-being and is commonly used for macroeconomic policies and poverty reduction (Cashin, Mauro, and Sahay 2001). Exporting goods and services were used to explore the relationship between trade and deforestation. According to Banco Central del Ecuador 2022, Ecuador's main non-oil related export is raw agricultural and fishing products such as shrimp, bananas and plantains, cocoa and processed foods, tuna and fish, and coffee and processed foods. Angelsen and Kaimowitz 1999 explain that an increase in agricultural exports leads to an increase in higher prices received by farmers, thus increasing the expansion of the agriculture frontier. Finally, oil production was chosen to explore the relationship between the country's leading (oil and its derivatives) industry and its effect on forests.

3.2.1.2. Immediate predictors of deforestation

According to Angelsen and Kaimowitz 1999, selecting the immediate causes of deforestation is essential to define the primary sources of deforestation and asking the question: What factors make individuals decide to clear forests? In the case of Ecuador, 90% of the deforestation can be traced towards agricultural activities (Sierra 2018). Therefore, most of the factors are focused on agricultural activities. Agricultural land (AgriLand) was chosen as an indicator to assess the expansion of the agricultural frontier over time (Reyes et al. 2020). Rural population (RuPop) was used as a localized demographic pressure indicator to assess the changes in population in rural areas, and understating the expansion or contraction of the rural population can give an idea of infernal migratory trends, especially in the relationship of colonization of native forest near rural areas(Gondard et al. 2001; Wasserstrom and Southgate 2013). Angelsen and Kaimowitz 1999 and Bernhard, Zenobi, and Shapiro 2021 describe the importance of agricultural inputs and output as a decision factor in clearing forests. One of the most talked about agricultural inputs is fertilizer prices. However, due to the lack of national records of fertilizer prices in Ecuador, the consumption of fertilizers in tons of nitrogen (FerN) was chosen as a proxy for fertilizer prices. FerN still describe agricultural inputs in the system.

Also, as agricultural input, yield (Yield- Cereal yield) and livestock production (Livestock - Livestock production index) were chosen as an indicator of agricultural productivity. It has been hypothesized that higher productivity can reduce deforestation by making agricultural land profitable for extended periods(Luna et al. 2020). It also has been found that an increase in productivity can cause an increase in cost-opportunity scenarios, where additional income due to high productivity can cause farmers to expand their agricultural activities(Busch and Ferretti-Gallon 2017). The agricultural outputs were portrayed in this research by analyzing the export of banana (ExpBana), cacao (ExpCacao) and palm oil (ExpPalmOil). Bananas, cacao, and palm oil are the most representative agricultural product in Ecuador and have been a driver for deforestation(Graziano Da silva, Gómez, and CastañeDa 2010). Off-farm employment is viewed as a factor that can reduce deforestation. However, no information was available nationally over 30 years of employment by activity. The indicator of Employment in agriculture, forestry, and fishing (EmployR) was used to understand the effects of employment and deforestation. This indicator may have a negative impact on forest areas (Gómez de la Torre, Anda, and Bedoya Garland 2017b).

3.2.2. Land Use Data

Changes in forest area were tracked using World Bank data. According to the World Bank: Forest area is the land under natural or planted stands of trees of at least 5 meters in situ, whether productive or not, and excludes stands in agricultural production systems (for example, in fruit plantations and agricultural systems, agroforestry) and trees in urban parks and gardens (World Bank 2023). World Bank data was chosen instead of official data from Ecuador because forest cover data from 2001 to 2017 were presented as disaggregation of multiple forest ecosystems, not as total forest area. The data from 1990 to 2005 had a total number of forest areas; however, there was no clarity in the definition of forest in the database(SINAS 2023). Merging and creating a database using the available information could not guarantee that the methodologies used to measure forests were similar. Therefore, the World Bank database was selected since the indicator had temporal continuity and stable methods. This research aims to track macro trends; thus, obtaining land use data from geographic information systems was outside the scope of this analysis.

3.3. National Development goals

The current national development plan is "*Creando Oportunidades 2021-2025*" by President Guillermo LASSO. The plan has as its primary objective to create opportunities for all and to live in freedom (Secretaria Nacional de Planificación 2021). The plan has five axes, 16 objectives, 55 policies, and 130 goals. The five axes are the Economic and Employment Generation, Social, Comprehensive Security, Ecological Transition, and Institutional axis(CEPAL 2021). This research only used the axis and objectives aligned with the theoretical framework of Angelsen and Kaimowitz, 1999 and with the factors of deforestation described in the literature review. Therefore, to analyse the effect of national policies on deforestation, only the appropriate objectives within the economic, social, and environmental transition axis were used.

This selection of the axes of the national development plan was accompanied by a simplification of the objectives and goals of each of the indicators. The simplification or normalization of the goals refers to transforming the objectives in percentage terms. There is a disconnect between the indicators of the NDP and the socioeconomic variables used in this study. The disconnection is mainly since the national development plan created several indicators. These indicators do not have long-term historical data that can be used for a regression analysis. However, the objectives still refer to structural changes in the chosen socioeconomic variables. For example, one goal is to increase agricultural product exports from 13.35% to 17.67%(CEPAL 2021). This goal was transformed to increase agricultural exports by 4.32%. This percentage can be used for the Export of Bananas, Cocoa, and Palm Oil. The national development plan uses as base data the values for the year 2020 and the projections for the year 2025. It is then assumed that the plan seeks to increase exports from the base year 2020 by 4.32% by 2035. Table 1 shows the objectives and goals of the nation's development plan and the transformation of the goals in percentage terms.

Table 1 National Development Plan and its goals

	Objective	**Goal**
Economic axis	Objective 1.- Increase and promote, in an inclusive manner, employment opportunities and working conditions	1.1.1. Increase the suitable employment rate by 19.59%
	Objective 2.- Promote an economic system with clear rules that promotes foreign trade, tourism, investment attraction and modernization of the national financial system	2.1.2. Increase the share of non-traditional exports in total non-oil exports by 7.2%
	Objective 3.- Promote productivity and competitiveness in the agricultural, industrial, aquaculture, and fishing sectors under the circular economy approach.	3.1.2. Increase the yield of national agricultural productivity by 16,2%
		3.1.3. Increase agricultural and agro-industrial exports by 4,32%
	Objective 4.- Guarantee the management of public finances in a sustainable and transparent manner.	4.5.2. Achieve an annual growth of the Gross Domestic Product of 5% in 2025
Social Axis	Objective 5.- Protect families, guarantee their rights and services, eradicate poverty, and promote social inclusion	5.1.1. Reduce the extreme poverty rate by income from 15.44% to 10.76%.
	Objective 7.- Strengthen the capacities of citizens and promote innovative, inclusive, and quality education at all levels.	7.1.2. Increase the high school gross enrolment rate from 87.38% to 89.09%.
		7.1.3. Increase the gross enrolment rate of Basic General Education from 93.00% to 97.53%.
		7.4.2. Increase the gross enrolment rate in high school education from 37.34% to 50.27%.
	Objective 8.- Generate new opportunities and well-being for rural areas, emphasizing peoples and nationalities.	8.1.2. Reduce rural multidimensional poverty from 70% to 55%, emphasizing peoples, nationalities, and vulnerable populations.
		8.2.1. Increase the gross enrolment rate of Basic General Education in rural areas from 63.47% to 64.47%.
		8.2.2. Increase the gross enrolment rate for high schools in rural areas from 48.65% to 54.91%.
Ecologi cal Transiti on Axis	Objective 11.- Conserve, restore, protect, and use natural resources sustainably.	11.1.1. Maintain the proportion of national territory under conservation or environmental management at 16.45%.

3.4. Data Pre-processing

The data collected was pre-processed to be statistically analysed. Correlations, regression, and the LASSO regression have a series of assumptions regarding data composition. The data needs to be pre-processed to fulfil those requirements. If those assumptions are not met, the significance and results of the analysis could be misleading (Osborne and Waters 2019). The data was pre-processed using SPSS for the regression and correlations.

In SPSS, the data was pre-processed using the data preparation command: *Prepare data for modelling.* As part of the interactive pre-processing of SPSS, the data can be optimized to improve the speed of the analysis and its accuracy. In the case of this investigation, it was preferred to maximize the accuracy of the research. For this, the target variables of analysis (dependent) were specified, and the independent variables were labelled as input. This process resulted in a database whose quality has been improved, and the scale of fields or variables has been normalized. IBM SPSS n.d. explains that data transformation and normalization are done using the z-score[4] transformation. The data was not scaled or transformed pre-processes for the analysis in R studios. Even though there is a trade-off between some level of accuracy in the model, the back-transformation of the scores obtained using scaled and transformed data proves tricky on the LASSO regression. Additionally for the indicator FerN was supress for the analysis due to its similarity with Yield, to reduce overfitting the use of fertilizers was surprise as input in the LASSO regression.

3.5. Statistical Analysis

3.5.1. Correlation Analysis in SPSS

Correlation analysis was used to explore associations or relationships between quantitative variables, including the significance, strength, and direction of those associations (Gogtay and Thatte 2017). The output of a correlation analysis is a coefficient ranging from 0 to ± 1, where zero indicates that does not exist a relationship between the variables, and ±1 shows a perfect correlation(Senthilnathan 2019). If the coefficient is positive implies that an increase in variable one will correlate with the rise in variable 2. In contrast, a negative coefficient indicates an inverse relationship between variables, where variable one increase and variable two decreases(Taylor 1990).

[4] Z-score transformation. Using the observed mean and standard deviation as population parameter estimates, the fields are standardized and then the z scores are mapped to the corresponding values of a normal distribution with the specified Final mean and Final standard deviation. Specify a number for Final mean and a positive number for Final standard deviation. The defaults are 0 and 1, respectively, corresponding to standardized rescaling(IBM 2021).

Since the correlation coefficients portrayed the association between two variables, it was chosen as a good descriptor to explore the relationships between the underlying and immediate factors of deforestation described in the data collection section and Forest Area.

The correlation analysis has two types of coefficients: Pearson's Correlation Coefficient and Spearman's Rank Correlation Coefficient. The statistical test used was Pearson Correlation with a two-tailed p-value less than 0.05. Under Pearson's Correlation, the assumptions needed to be met were: (a) linear relationship between variables, (b) continuous random variables, (c) variables must be normally distributed, and (d) variables must be independent of each other ('Pearson's Correlation Coefficient 2008). The independent variables were the sixteen socioeconomic indicators, and the dependent variable was the forest area. The data was pre-processed to be normally distributed and reduce the presence of outliers. Since the assumption was met, the correlation analysis was performed.

3.5.2. Regression Analysis in SPSS

Multiple regression analyses the relationship between several predictor or independent variables and a single dependent variable. Each predictor value is weighed, the weights denoting their relative contribution to the overall prediction (Moore and Aryel 2006). Equation 2 describes the effect of several predictors with a dependent variable, where y is the dependent variable, x_1…. xp are the independent variables, βp are the regression coefficients or the average effect on Y if one unit of x_p increases. Finally, ε refers to the residuals or the error in the model (James et al. 2021).

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + \beta pXp + \varepsilon$$

Equation 2 Multiple Linear Regression (James et al. 2021)

A multiple regression analysis was performed by assuming that changes in forest area are the result of the interactions of the independent variables. The result is a generalized equation that describes changes in forest cover (3). This relationship was only accepted if the p-value was less than 0.05. The R^2 value was analysed to evaluate the model fit. If the value is close to 1 indicates that a large proportion of the variability in the response is explained by the regression (James et al. 2021).

The significance of the socioeconomic predictor in deforestation was evaluated by rejecting the null hypothesis with a *p-value* higher than 0.05(Grabowski 2016), meaning that we have a 95% confidence that the predictor holds a relationship with changes in forest cover (James et al., 2021). The statistical analysis was done using the SPSS package. The assumption under the MLR is that the relationships between socioeconomic factors and changes in forest areas have a linear nature (Santiago and Couto 2020. To perform an MLR, the following assumptions needed to be met: (1) linearity, (2) normality, (3) absence of multicollinearity, (4) homoscedasticity, and (5) independence of errors (CFA Institute 2023; Eberly 2007). The multicollinearity among the data was evaluated by performing a variance inflation factor (VIF). Miles 2014 explains that a rule of thumb is if the value of VIF is greater than 10, the data present multicollinearity. In case the data present collinearity, a regularisation method was used.

3.5.3. LASSO Regression in R

LASSO regression can be used to better parameters with high multicollinearity (Olive 2017). This technique improves a model's prediction by identifying variables and their corresponding regression coefficient, minimizing the predictor error (Ranstam and Cook 2018; Schreiber-Gregory 2018). LASSO regression used an L1 penalty with an alpha value of 1, the default value for the regularization in a LASSO regression (Bhattacharyya 2018). Ranstam and Cook 2018 explain that LASSO regression imposes a constraint on the model parameters; this constraint shrinks the regression coefficient toward zero by forcing the sum of the absolute value of the regression coefficients to be less than a fixed value (lamb λ). Figure 2 shows the regularization process of the coefficient becoming cero thanks to the penalization parameter. The program used for the LASSO Linear Regression was RStudio. The database was the same one used for MLR and the collinearity analysis. However, the data was not pre-processed. The code used in the analysis can be seen in Appendix 5.

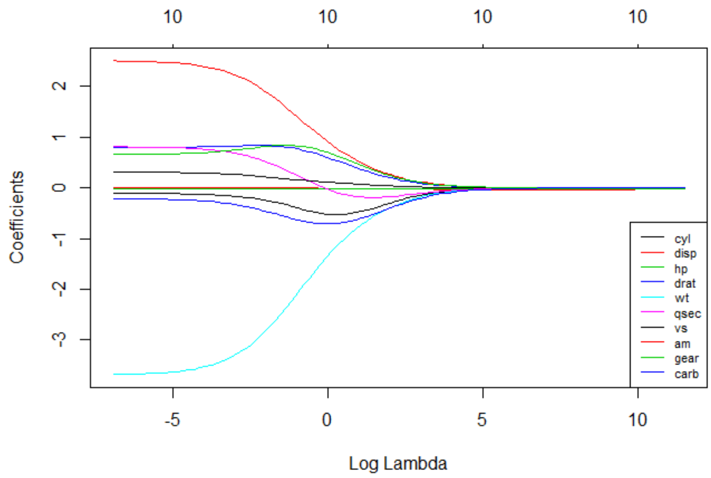

Figure 2 LASSO regression and L1 penalization from (datacamp 2019)

LASSO regression is a machine learning technique that uses 80% of the data to train the model and 20% left to test the model. This is known as the k-fold cross-validation approach, and this automatization gave the fixed values of λ (Ranstam and Cook 2018). Those values were obtained using k-fold cross-validations. The lambda values (λ) were later evaluated with a performance metric, in the case of this study, Root mean squared error (RMSE), Root squared (R-squared), and the mean absolute error (MAE). The optimal value of lambda was the one that minimizes the RMSE (Foley 2020). Once the best value of lambda was defined, the model gave the coefficient of the non-penalized variables. These coefficients are the regression coefficient of the model. Once the model was defined, its accuracy was evaluated using the test data. The model made predictions of forest area with the test data, and then the accuracy of the predictions was compared with the accuracy of the trained model by using RMSE and Root squared R-squared.

Finally, the equation for predicting deforestation was obtained using the coefficient of best lambda as seen in Equation 3

$$\text{ForestA} = \beta 0 + \beta 1 \text{ PopD} + \beta 2 \text{ Livestock} + \ldots + \beta n^{*} \text{ variable n}$$

Equation 3 Changes in forest area - LASSO regression

Where Forest Area is the dependent variable, β0 is the intercept term (where all the undelaying and immediate predictors of deforestation are cero) and β0…βn are the coefficients of the predictor obtained whit the LASSO regression that multiplies their corresponding variable.

3.6. Model and Predictions

Models are a representation of reality that highlight specific characteristics while abstracting others (De Micheli, Ernst, and Wolf 2002). Tee 2019 explains that a good model is a construct about reality, gives insights and possesses explanatory power about reality, but it is not reality. The model built in this research is a representation of reality that uses the abstractions of Angelsen and Kaimowitz's 1999 conceptual framework and seeks to predict deforestation quantitatively. Equation 3 describes changes in forest area as a function of underlying and immediate factors of deforestation. This equation was used to assess the impacts of national development plans on changes in forest areas. The data described *National Development Goals* was the input for predicting the changes in forest area by the year 2025 if all the objectives of NDP are fulfilled. Due to the nature of L1 penalization, only the coefficients that the model deemed necessary were used to construct the final model equation (shown in the result section).

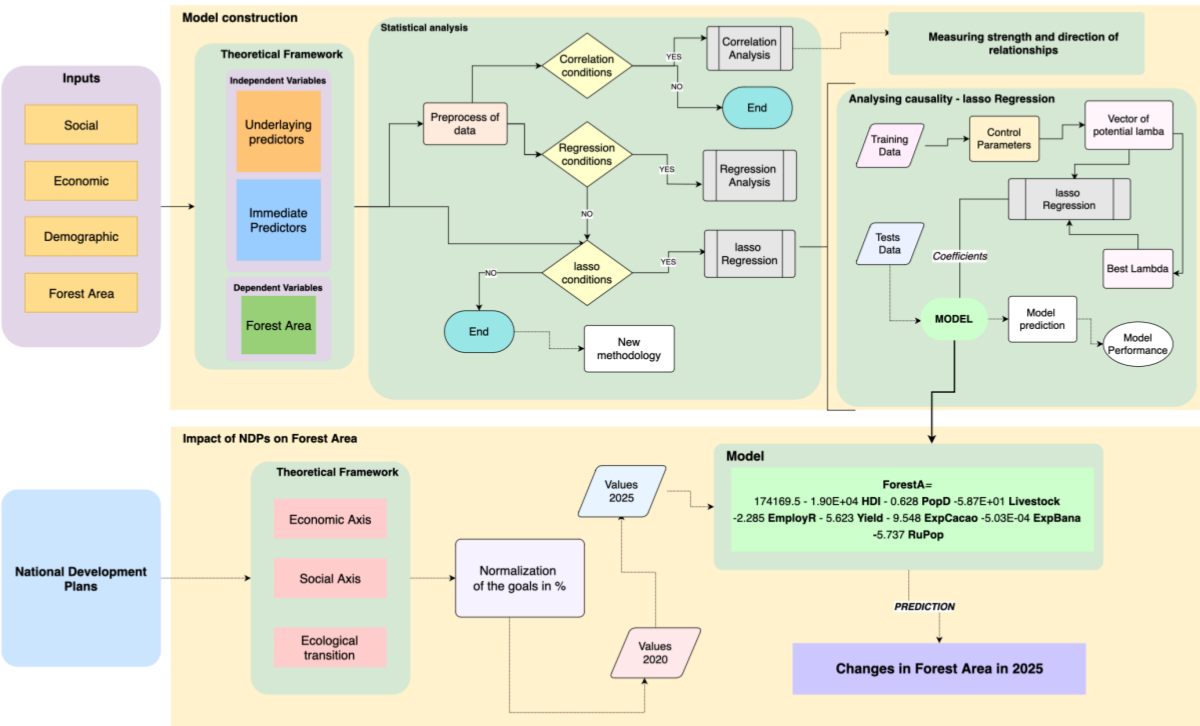

Figure 3 Flowchart of the model for predicting changes in forest area.

Figure 3 shows the construction of the model and the prediction of deforestation in 2025. The process started with the socio-economic data and the NDPs that are discriminated to obtain the relevant variables using Angelsen and Kaimowitz 1999 abstractions. In constructing the model, the data were evaluated to see if they met the necessary assumptions to perform the statistical analyses. LASSO regression was selected as the statistical analysis to study the possible causality relationships between the independent and dependent variables. LASSO regression is a penalty method that is used in machine learning algorithms. According to Sarker 2021, LASSO regression is a well-known and powerful technique typically used for building learning models in the presence of many features due to their capability to prevent over-fitting and reduce the complexity of the model. The result of the regression is a model that is later evaluated with the test database to verify its predictive power. The model is then fed with the goals for 2025. The values for 2025 are the projections in the percentage of the objectives of the national plan; the values for 2020 from the raw database were used as a baseline. The values of 2020 were increased by the percentage value of the objectives of the national development plan to obtain the inputs of 2025. The final output is a prediction of the forest area by 2025 if the goals of the NDP are achieved.

3.7. Limitations

This research worked based on serval assumptions and limitations. Regarding the methodological framework, this analysis did not study the agents of deforestation. It has been assumed that underlying and immediate factors of deforestation have a significant role in describing the national trends of changes in forest areas. Therefore, individual choices won't change the national deforestation context. However, it is essential to mention that the individual's agency can shape national policies. For example, the YASUNIDOS and indigenous communities promoted a referendum so that Ecuadorian society could decide (in 2023) at the polls to protect the Amazon forests of Yasuni against oil exploitation(Yasunidos 2021). The decision-making process of deforestation by individuals and an analysis of household factors of deforestation can be found in Luna et al. 2020 and Mena, Bilsborrow, and McClain 2006.

One of the most significant limitations of this study was data availability, mainly to track the development of protected areas and other related forest protection policies, such as payment of ecosystem services or reforestation programs. Data describing the land under forms of protection from the world bank ranged from 2016 to 2020(The World Bank 2023). The Ministry of Environment had data from 2008 onwards(SINAS 2023). Without this data, it is difficult to assess the counterbalance of the country's natural protection policies. The changes in indicators to track social, economic, and environmental development was a limitation in this study, especially from national sources such as the Ministry of Environment, INEC, and the Ecuadorian Central Bank.

Additionally, the data from this analysis represent only the visible or legal activities that the government manage, however, there is the influence of factors that are within the framework of illegality. Illicit economies affect the decision processes of deforestation actors, especially the immediate factors of deforestation. Among the main problems in Latin America are illegal logging, illegal mining and drug trafficking(Carrere 2022). Cozma et al. 2021 explains that illegal mining contributes to deforestation in the internal regions of the Amazon Forest and the remnants of evergreen forests on the Ecuadorian coast. Like the oil industry, illegal mining opens roads and creates illegal infrastructure for the processing and transporting mining material, which generates the illegal colonization of these lands(das Neves et al. 2021). Illegal mining in Ecuador is a severe problem not only because of the extensive environmental impact but also because of the economic and social impacts. Illegal mining and drug trafficking are strongly correlated in Latin America; Drug trafficking groups have used illicit mining activities to launder money from drug trafficking (Global Initiative against Transnational Organized Crime 2016). This creates an environment of risk and threats for the rural and indigenous communities of the surrounding areas. However, these factors are not considering when constructing the model due to the lack of data and understanding of how illegal economies influence the use of forest resources.

The assumption of linearity between the variables was a fundamental assumption made by this researcher. The correlation and linear regression were performed based on that assumption. Due to time limitations and the scope of this research, correlation and linear regression were chosen as the primary methods. Correlation analysis and linear regression are the most used methods for exploring relationships between variables because they have been considered solid and robust enough to predict an outcome(Palmer and O'Connell 2009; Uyanık and Güler 2013). The lack of multicollinearity is one of the assumptions for MLR. If this assumption was not met, the LASSO regression was performed. LASSO has its own assumptions, limitation, and biases. Freijeiro-González, Febrero-Bande, and González-Manteiga 2022 explain that the variable selection in a LASSO regression could be understood in two ways: the model tries to identify the set of accurate and relevant covariates, or the model perform a dimension reduction without guaranteeing the relevance of the variables.

Table 2 indicators and their expected effect on deforestation

	Variable	Indicators	**Expected effect on deforestation**
Underlying predictors	PopD	Population density (people per sq. km of land area)	The increase in population will decrease forest cover, as population increases more resources and space are needed.(Palo 1994; Jha and Bawa 2006)
	HDI	Human Development Index	Deforestation negatively correlates with HDI, areas with higher human development index experience lower rates of deforestation. (Jha and Bawa 2006)
	GDP	GDP per capita (constant 2015 US$)	Higher income per capita contributes to higher deforestation, following the EKC hypothesis, it is believed that developing countries are in the state of economic growth generates environmental damage(Crespo Cuaresma and Heger 2019; Choumert, Combes Motel, and Dakpo 2013).
	ExporGS	Exports of goods and services (constant 2015 US$)	Exporting raw products will increase deforestation as the agricultural frontier grows(Angelsen and Kaimowitz 1999).
	ArtifiSurfa	Artificial surfaces (including urban and associated areas) ha	Urbanization and the expansion of artificial surfaces opens paths towards colonization of territory and deforestation(Barber et al. 2014).
	MySchool	Mean years of schooling	Access to higher levels of education will curve deforestation, as skills for off-farm employment are acquired, however access to basic levels of education will increase deforestation as people will have the option to expand agriculture production via loans and early levels of technification.(Luna et al. 2020)
	ProducOil	Total production petroleum and other liquids (Mb/d)	Increased of oil production will positively correlates with deforestation due to the construction of auxiliar infrastructure for the oil industry(Wunder 2003; Mena et al. 2017).
Immediate predictors	RuPop	Rural population	The increase in rural population will generate a need for more resources and therefore there will be more deforestation.(D. W. Jones and O'Neill 1994; Angelsen et al. 2014)
	EmployR	Employment in agriculture, forestry, and fishing - ILO modelled estimates 1000 persons	Off-farm employment may reduce deforestation and employment in agriculture will increase land change use(Fagua, Baggio, and Ramsey 2019; Sierra, Calva, and Guevara 2021b).
	AgriLand	Agricultural land (sq. km)	the increase in agricultural land increases the probability of deforestation of nearby forests(Sierra, Calva, and Guevara 2021b; Thapa, Bilsborrow, and Murphy 1996).
	Livestock	Livestock production index (2014-2016 = 100)	Livestock production requires the clearing of forest for grasslands, therefore increasing deforestation(Sierra, Calva, and Guevara 2021a).
	FerN	Fertilizers tonnes Nutrient nitrogen N (total)	The used of fertilizer will increase productivity slowing down the expansion of the agricultural frontier(Luna et al. 2020).
	Yield	Cereal yield (kg per hectare)	Higher yield in crops generates a stable income therefore reduction the necessity to expand agricultural activities (Luna et al. 2020; Mena, Bilsborrow, and McClain 2006b)
	ExpBana	Export Banana tonnes	High demand of agriculture products generates a cost-opportunity effect, where framers go into difficult to reach forest areas to cultivate those high demand products (Graziano Da silva, Gómez, and CastañeDa 2010; Baquero and Mieles 2014)
	ExpCacao	Export Cacao Tonnes	
	ExpPalmOil	Export palm oil Tonnes	

4. RESULTS

This chapter presents the study's results that aimed to investigate the relationship between socioeconomic variables and deforestation in Ecuador. Using the conceptual framework of Angelsen and Kaimowitz 1999, where deforestation can be explained as the result of underlying and immediate predictors of deforestation, a total of sixteen independent variables were selected (seven variables for underlying factors and nine for immediate factors). Underlying factors of deforestation are those macroeconomic factors and policies that indirectly influence forest clearing. In contrast, the immediate predictors directly affect the decision parameter of the agents of deforestation. Data were obtained through a collection of state and international agency databases from 1990 to 2020. Socioeconomic factors were statistically analysed using the correlation and regression analysis described in Chapter 3.

The results focus on answering the research questions and hypotheses formulated previously. The results of this study give a perspective on the effect of economic and social factors on the change in land use, especially in the reduction of forest cover at the national level. The results emphasize the aspects that generate the most significant impact on deforestation in Ecuador. Additionally, it provides regression models that allow analyzing the socioeconomic policies of the national development plan on deforestation.

4.1. Measuring the strength and direction: Socioeconomic factors and deforestation

The conceptual framework Angelsen and Kaimowitz, 1999 theorized that certain socioeconomic factors have a relationship with deforestation. The objective of this section is to investigate whether socioeconomic factors are correlated with deforestation in Ecuador. It has been hypothesized that economic growth, trade, income, and demographic pressures (underlying predictors) influence the agents of deforestation by shaping the context of decisions regarding forest resource use. Under the same logic, the immediate factors of deforestation directly influence the agents of deforestation. These factors are outside the control of the agents of deforestation, but they heavily impact the decision-making process. Agricultural activities, off-farm employment, access to technology, and others create incentives for deforestation. Understanding the effect of socioeconomic factors on deforestation is especially important when considering that in 2018 the remaining native forest in Ecuador was 56%, suffering a reduction of 16% with respect to the native forest of 1990 (68%) (Sierra, Calva and Guevara, 2021). To test these hypotheses, a correlation analysis using SPSS was performed as describe in the methodology (see Appendix 4).

4.1.1. Underlying predictors of deforestation

Figure 4 visually represents the underlying deforestation and forest area predictors from 1990 to 2020. The dependent variable shows a linear behaviour with a steadily declining trend, meaning that Ecuador has lost forest area over time. The socioeconomic factors analysed as underlying predictors of deforestation were population density, HDI, GDP, Exports of goods and services, artificial surfaces, mean of schooling years, and oil production. All of them present an upward trend. The values of these underlying predictors have increased over time. Economic-related data (GDP, ExporGS, ProductOil) present spikes and drops of importance, but the tendency is linear over time; this also can be said of artificial surfaces. HDI, population density (PopD), and schooling years (MhSchool) present data with lower dispersion and a growing trend. This visual representation can be complemented with the results of the correlation analysis for a better interpretation of the relationship between underlying predictors of deforestation and loss of forest area.

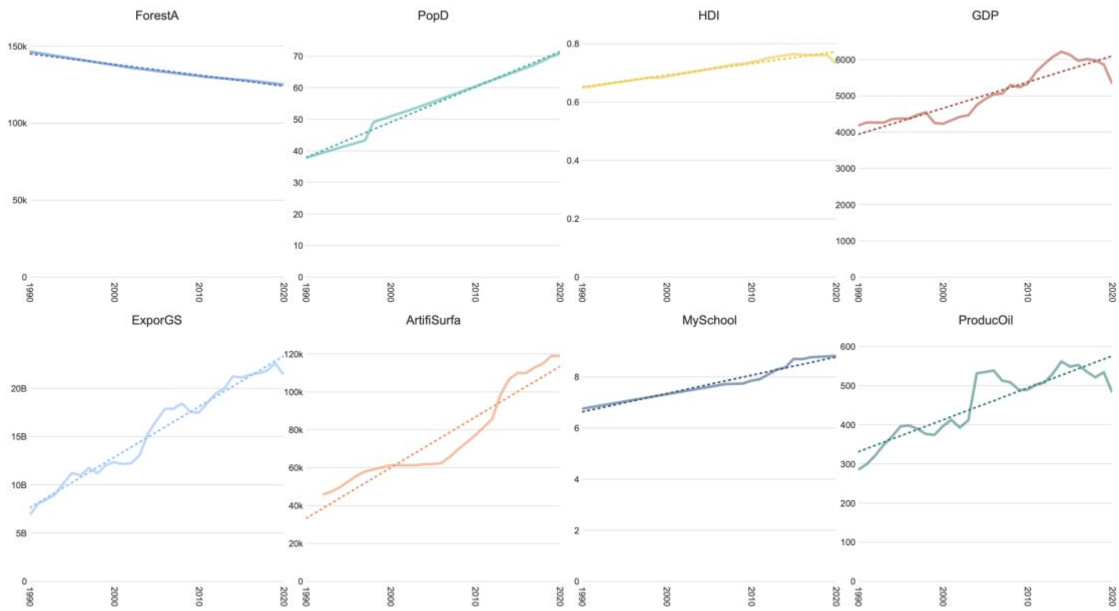

Figure 4 Underlying predictors of deforestation and forest area over time

Table 3 shoes the results obtain from the correlation analysis between the independent variables (underlying predictors of deforestation) and forest area (dependent variable). A strong negative correlation between population density and forest area is observe, meaning that as population density increases forest area decreases (r = -0.975, $p < 0.001$), confirming the hypothesis in Table 2 indicators and their expected effect on deforestation. The hypothesis presented in the method's chapter stated that areas with higher HDI experience less deforestation (HDI positive correlates with forest area). However, the analysis shows a strong negative correlation between the human development index and forest area (r = -0.915, $p < 0.001$). The expected positive correlation between HDI and forest area was under the impression that an increase in income (less poverty) and an increase in education will and life expectancy would curve deforestation (Jha and Bawa 2006). Nevertheless, the result contradicts that assumption. Furthermore, the mean of years of studying also negatively correlates with forest area (r = -0.974, $p < 0.001$), in line with results obtained in the HDI. The role of education in the loss of forest cover has had mixed results (Godoy, Groff and O'Neill, 1998). It was hypothesized that an increase in school years would positively correlate with forest area. The results rejected the initial assumptions.

Table 3 Correlation analysis of underlying predictors of deforestation

	Forest area (sq. km)				
	Pearson Correlation	Sig. (2-tailed)	N	Expected effect	Obtained effect
Population density (people per sq. km of land area)	-.975**	0.000	31	-	-
Human Development Index (HDI)	-.915**	0.000	31	+	-
GDP per capita (constant 2015 US$)	-.865**	0.000	31	-	-
Exports of goods and services (constant 2015 US$)	-.953**	0.000	31	-	-
Artificial surfaces (including urban and associated areas) ha	-.947**	0.000	29	-	-
Mean years of schooling	-.974**	0.000	31	+	-
Total production of petroleum and other liquids (Mb/d)	-.822**	0.000	31	-	-

Economic Growth (GDP) has had mixed results when analyzing its relationship with the loss of forest area (Robalino-López et al. 2014; Jimenez et al. 2019; Bernhard, Zenobi, and Shapiro 2021), following the EKC, it was hypothesized that early economic growth would have a negative impact on forest resources. This hypothesis was confirmed; economic growth and deforestation are strongly negatively correlated (r = -0.915, $p < 0.001$). Exports of goods and services show a robust negative correlation with forest area; this also can be said of the production of Petroleum with a correlation coefficient of -0.822. The assumption of the effect on trade and forest loss was a negative correlation, as explained in Angelsen and Kaimowitz's 1999 trade of raw agricultural products puts pressure on forest resources. With the results obtained, it can be assumed that much of the economic growth of Ecuador has a strong dependency on agricultural and raw materials. Finally, the independent variable Artificial Surfaces negatively correlates with forest area ($r = -0.947$, $p < 0.001$), accepting the hypothesis that an increase in artificial land results in a decrease in forest areas.

4.1.2. Immediate predictors of deforestation

The trends of the immediate factors of deforestation and the forest area are observed in Figure 5 and Figure 6. The dependent variable (forest area) presents a decreasing trend and a linear behaviour, which means that from 1990 to 2020, Ecuador has continuously lost forest area. As part of the independent variables, employment in agriculture has experienced a linear growth trend with a period of decrease from 2006 to 2014, followed by a recovery period until 2019. Agricultural Production indicators, such as using fertilizers, livestock production, and agricultural productivity, have a relatively linear growth trend. However, there are values out of trend (outliers). The presence of atypical values is significant in using fertilizers with a massive consumption (more than 200%) in 2001, followed by a recovery of the growing trend. For its part, there is a decrease in agricultural land with a prominent drop of 20,380 square kilometres in 2013, continuing a downward trend. The reduction of agricultural land and increased agricultural production (yield) suggests that using fertilizers has improved productivity and reduced the need to expand the agricultural frontier into forests.

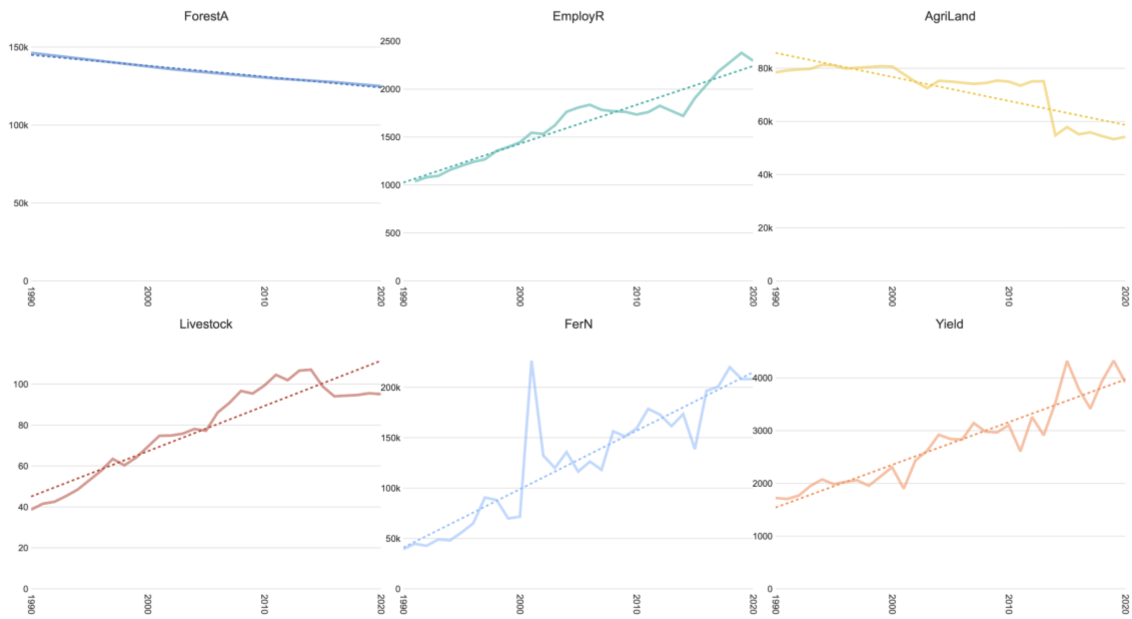

Figure 5 Immediate Factors of deforestation part 1

Figure 6 shows a linear growth of the rural population, with an increase of approximately 1,609,675 people in 30 years. A good indicator of the state of agriculture is the export of agricultural products such as bananas, cocoa, and oil palm. These three exports have a growing trend with oscillating values, mainly the export of oil palm. The increase in exports opens the way to internal markets for these products, generating an opportunity cost environment to transform forest areas into agricultural land(Sierra, Calva, and Guevara 2021a). A more robust analysis of the relationships between the immediate drivers of deforestation and changes in forest cover was obtained through a correlation analysis described in Table 4.

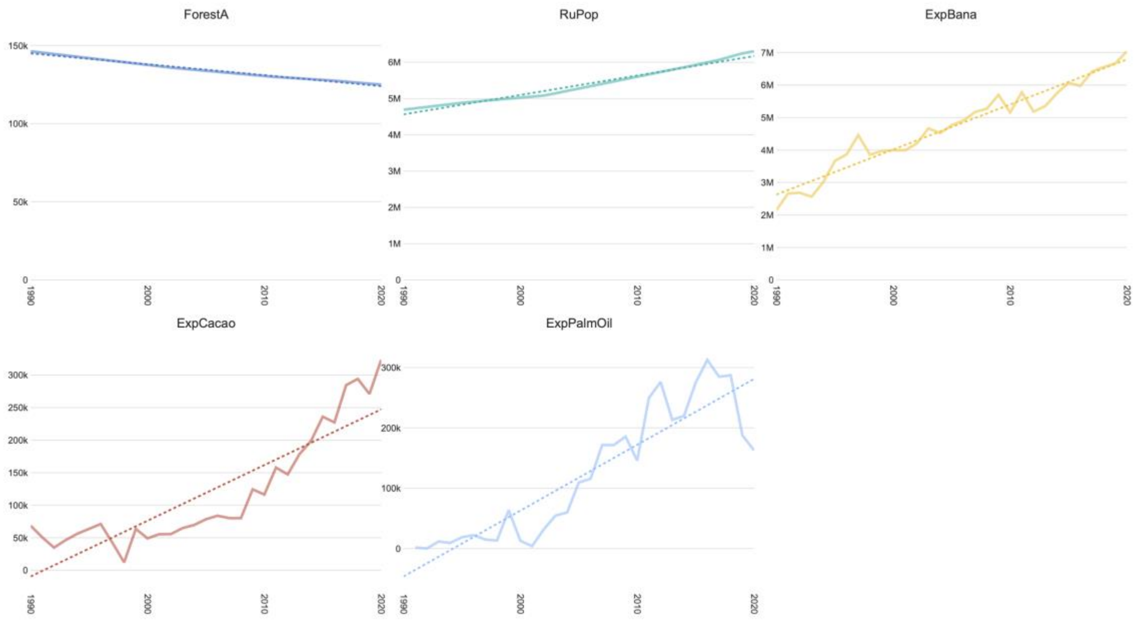

Figure 6 Immediate Factors of deforestation part 2

The correlation analysis results between immediate predictors of deforestation and forest area are shown in Table 4. The correlation analysis shows a strong significance with p-values less than 0.05. Among the result, the Rural population shows a strong negative correlation with forest area, meaning the expected negative effect was confirmed as of rural population increased and forest areas decreased. The results show a positive correlation between agricultural land and forest area, with a coefficient of 0.862. If the results are analysed out of context, it could be inferred that the increase in agricultural land generates an increase in forest cover. However, Figure 6 shows the downward trend of the agricultural area. The positive correlation occurs when the agricultural area decreases and the forest cover increases.

Table 4 Correlation analysis of immediate predictors of deforestation

	Forest area (sq. km)				
	Pearson Correlation	Sig. (2-tailed)	N	Expected effect	Obtained effect
Rural population	-.988**	0.000	31	-	-
Agricultural land (sq. km)	.862**	0.000	31	-	+
Livestock production index (2014-2016 = 100)	-.874**	0.000	31	-	-
Fertilizers tonnes Nutrient nitrogen N (total)	-.877**	0.000	31	+	-
Cereal yield (kg per hectare)	-.930**	0.000	31	+	-
Export Banana tonnes	-.964**	0.000	31	-	-
Export Cacao Tonnes	-.914**	0.000	31	-	-
Employment in agriculture, forestry, and fishing - ILO modelled estimates 1000 persons	-.957**	0.000	30	-	-
Export palm oil Tonnes	-.842**	0.000	30	-	-

The initial hypothesis on livestock production and forest area established that livestock production would generate a decrease in forest cover. This hypothesis was confirmed since there is a significant negative correlation -0.874 between livestock production and forest cover, the more livestock production, the less forest. The same negative correlation trend occurred in Fertilizers and cereal yield with a negative coefficient of $r = -0.877$ and $r = -0.930$, respectively. The hypothesis in Table 2 was that using a fertilizer would generate a higher crop yield and decrease deforestation (more forest area). However, the results contradict this hypothesis. The negative correlation implies that greater use of fertilizers generates a loss of forest cover. This interpretation could be biased. Suppose that the decreasing trend of the agricultural area is observed together with the help of fertilizers and agricultural productivity. In this case, it could be understood that using fertilizers reduces the loss of forest cover by increasing agricultural production per square kilometre, slowing down agricultural expansion. There is a strong negative correlation between exporting agricultural products such as bananas, cocoa, palm oil, and forest area. It was hypothesized that as the export of agricultural products increases, forests will decrease due to the expansion of the agricultural frontier; the results corroborate the hypothesis. Finally, a negative relationship was expected between agriculture and employment in the forestry area. The results support this assumption with a strong negative correlation ($r = -0.957$, $p < 0.001$) between employment in agriculture and forestry.

4.2. Relationships between socioeconomic factors and deforestation.

This section seeks to understand how social and economic factors change forest cover. The previous section analysed the relationships between deforestation factors and forest area. The correlation analyses were limited to understanding the degree of change and direction of one variable with respect to another variable. The correlation analysis does not imply causality between the two variables. The regression analyses in this section were carried out to establish possible causal relationships between socioeconomic factors and changes in the forested area of Ecuador. Using this method, it would be possible to answer the question: what is the impact of socioeconomic factors on forest cover? Causal relationships would allow some degree of prediction of the future effects of economic and social factors on forest cover. Understanding how economic, social and demographic factors influence the contraction or expansion of forest cover is essential to design public policies that ensure social and economic development while minimising environmental impact.

The data used for the regression analysis are the same as in the previous section. It consists of fifteen independent variables with data ranging from 1990 to 2020. This data has been transformed using the *Prepare Data for Modeling* command under the transform command. This command evaluates the data and addresses issues related to outliers, missing data, and normalised data using a z-score. The transformation of the research data was performed to increase the prediction accuracy of the ForestA variable (forest area). The fifteen independent variables and the dependent variable were transformed. The results can be found in Appendix 3. The output of the command was sixteen transformation variables; Figure 7 shows the rural population (RuPop) and Banana Exports (ExpBana) results. The transformation data offers a better normal distribution. They do not present missing values and have a high predictive power of 0.98 and 0.93, respectively.

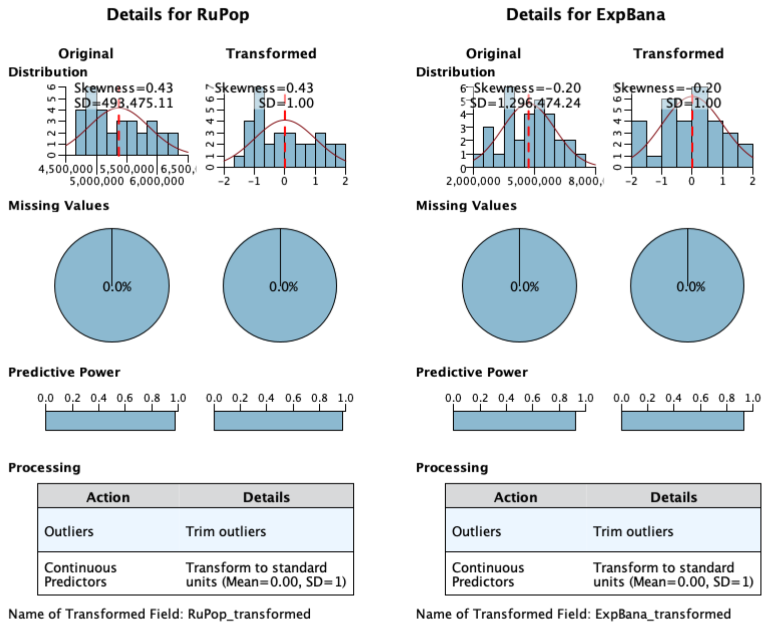

Figure 7 Data transformation with SPSS

4.2.1. Multiple linear regression

Multiple linear regression was the methodological approach proposed in the methods section to explore the interactions between the underlying and immediate factors of deforestation and forest area. The objective of multiple linear regression (MLR) is to obtain a statistical relationship between a single continuous output Y and the predictor's variables X_k ($k = 1, 2, . . ., p - 1$)(Eberly 2007). To perform an MLR, it is necessary to fulfil the following assumptions: linearity, data following a normal distribution, the independency between variables, and there is homoscedasticity (Eberly 2007; Krieger n.d.). The linear behaviour of the variables is shown through the linear correlation analyses of the previous section and the visualization of the data in Figure 5 and Figure 6. The variables fulfil the assumption of normality thanks to the pre-processing of the data. A collinearity diagnostic was run to determine if there was a correlation between predictors (Table 5). Collinearity was assessed using the variance inflation factor (VIF). If the VIF is greater than 10, there is a severe collinearity problem (Eberly 2007; Fahrmeir et al. 2013). The VIF values on Table 5 show a strong issue of collinearity. This implies that there is a correlation between explanatory variables. Siegel 2016 explains that the statistical consequences of strong collinearity are difficulties in testing individual regression coefficients due to inflated standard errors, which can result in a misinterpretation of the magnitude and direction of the predictors.

Table 5 Collinearity Diagnostics

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	0.012	0.018		0.676	0.512	-0.026	0.050		
	PopD_transformed	-0.367	0.098	-0.360	-3.753	0.003	-0.581	-0.154	0.004	233.001
	HDI_transformed	0.642	0.130	0.629	4.941	0.000	0.359	0.925	0.002	411.206
	GDP_transformed	-0.021	0.083	-0.022	-0.252	0.805	-0.201	0.160	0.005	186.583
	ExporGS_transformed	0.149	0.123	0.145	1.214	0.248	-0.118	0.416	0.003	360.076
	MySchool_transformed	-0.271	0.116	-0.273	-2.341	0.037	-0.523	-0.019	0.003	344.108
	ProducOil_transformed	-0.069	0.044	-0.064	-1.552	0.147	-0.165	0.028	0.023	42.971
	RuPop_transformed	-0.934	0.136	-0.946	-6.871	0.000	-1.230	-0.638	0.002	481.640
	AgriLand_transformed	-0.014	0.026	-0.015	-0.549	0.593	-0.071	0.043	0.051	19.766
	Livestock_transformed	-0.200	0.094	-0.191	-2.129	0.055	-0.405	0.005	0.005	205.184
	FerN_transformed	-0.018	0.026	-0.018	-0.703	0.496	-0.075	0.038	0.058	17.177
	Yield_transformed	-0.027	0.036	-0.027	-0.745	0.471	-0.104	0.051	0.030	33.158
	ExpBana_transformed	-0.080	0.042	-0.076	-1.892	0.083	-0.172	0.012	0.024	41.301
	ExpCacao_transformed	0.004	0.052	0.004	0.077	0.940	-0.109	0.117	0.013	77.878
	ArtifiSurfa_transformed	0.144	0.106	0.156	1.360	0.199	-0.087	0.375	0.003	334.116
	EmployR_transformed	-0.004	0.103	-0.004	-0.036	0.972	-0.228	0.221	0.004	285.397
	ExpPalmOil_transformed	0.033	0.040	0.035	0.818	0.429	-0.055	0.121	0.022	46.318

a. Dependent Variable: ForestA_transformed

The model can be misleading if despised the presence of multicollinear, and MLR analysis is used. Table 6 shows the model summary for MLR with forest area as the dependent variable and the 15 independent variables. The model appears to be significant with a p-value less than 0.05, and the R^2 of 1 implies that 100 of the variation of forest area can be explained by the model. However, the high value of R could indicate an overfitting of the model, worsening its prediction power (Fahrmeir et al., 2013).

Table 6 Model summary with overfitting values

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	1.000[a]	1.000	.999	.03172	1.000	1585.739	16	12	<.001

a. Predictors: (Constant), ExpPalmOil_transformed, FerN_transformed, AgriLand_transformed, ProducOil_transformed, ExpBana_transformed, ExpCacao_transformed, Yield_transformed, Livestock_transformed, EmployR_transformed, GDP_transformed, ArtifiSurfa_transformed, HDI_transformed, PopD_transformed, MySchool_transformed, ExporGS_transformed, RuPop_transformed

b. Dependent Variable: ForestA_transformed

4.2.2. Least Absolute Shrinkage and Selection Operator (LASSO) regression

A Least Absolute Shrinkage and Selection Operator (LASSO) regression was performed to solve issues with multicollinearity. The using k-fold cross-validation gave as a result a string of lambda values or penalization factors, each lambda create its own sub-model. Later one the performance of the sub-model is teste by Root mean squared error (RMSE), Root squared (R-squared) and the mean absolute error (MAE)(Ranstam and Cook 2018; Schreiber-Gregory 2018). The sub-model of the lambda value with the lowest RMSE was selected as the final model for the regression. Table 7 shows the results of the tuning parameters for a LASSO regression, where the best value of λ is 29.15, which has the lowest RMSE value and was used as the constraint of the model parameters for the regression.

Table 7 Tuning parameters using LASSO regression.

LAMBDA	RMSE	RSQUARED	MAE
1.149757E+01	255.3566	0.9987979	202.6522
1.450829E+01	255.3566	0.9987979	202.6522
1.830738E+01	255.3566	0.9987979	202.6522
2.310130E+01	255.3566	0.9987979	202.6522
2.915053E+01	255.0483	0.9987971	201.9239
3.678380E+01	255.2858	0.9987956	202.9468
4.641589E+01	257.1543	0.9988067	205.8811
5.857021E+01	261.6839	0.9988068	211.3697
7.390722E+01	267.0974	0.9988304	216.9866
1.149757E+01	255.3566	0.9987979	202.6522

Figure 8 is a visual representation of the tuning process; the lower RMSE value is the constrained condition RMSE<256, and only the lambda values around this condition are tested.

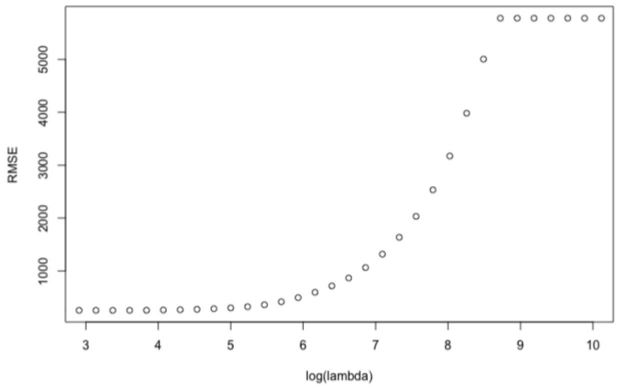

Figure 8 Log lambda vs RMSE

Once the best lambda value was obtained, the LASSO regression model obtained the coefficients for each independent variable that explain the changes in the dependent variable. As the principle of the LASSO model, the coefficient of certain variables was suppressed to maximize the accuracy of the linear model. Table 8 shows the coefficients of the linear regression. The model has hidden the values of AgriLand, ArtifiSurfa, ExporGS, ExpPalmOil, GDP, MySchool, and ProducOil. Additionally, the model quantifies the importance of each variable as a predictor of the dependent variables (Figure 9).

Table 8 Coefficient and Importance of Predictors

VARIABLES	COEFFICIENTS	IMPORTANCE
HDI	-1.895455E+04	100
POPD	-0.628117	1.39
LIVESTOCK	-5.870193E+01	0.31
EMPLOYR	-2.284873	0.01
YIELD	-5.62277	1.91E-04
EXPCACAO	-9.547818	2.93E-06
EXPBANA	-5.028251E-04	2.65E-06
RUPOP	-5.736944	9.16E-07
AGRILAND	-	0
ARTIFISURFA	-	0
EXPORGS	-	0
EXPPALMOIL	-	0
GDP	-	0
MYSCHOOL	-	0
PRODUCOIL	-	0
(INTERCEPT)	174169.5	

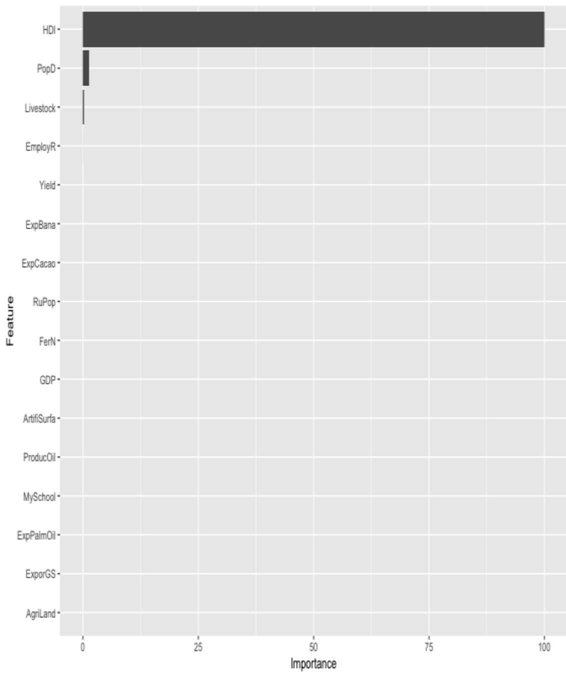

Figure 9 Importance of predictors

The coefficients can be used to construct the final expression for the LASSO regression in terms of a linear regression(Equation 4): y = b0 + b1x1 + b2x2 + ... + bn*xn, where y is the dependent variable, b0 is the intercept term (value of y when all the dependant variables are cero). The independent variables are x1, x2,…,xn, and b1, b2,…,bn correspond to the effect of the predictors on the dependent variable. The model equation corresponds to the following:

ForestA= 174169.5 - 1.90E+04 **HDI** - 0.628 **PopD** -5.87E+01 **Livestock** -2.285 **EmployR** - 5.623 **Yield** - 9.548 **ExpCacao** -5.03E-04 **ExpBana -**5.737 **RuPop**

Equation 4 Model: Forest Area as a Function of Underlying and immediate predictors of Deforestation

Model 1 was obtained using the training data (80% of the database). The remaining 20% of the data has been used to test the model's accuracy. Table 9 shows the metrics of the model with the test data vs. the model with the training data to test its accuracy.

Table 9 Test of Performance of the model

	Model	**Performance**
RMSE	255.0483	478.2911
Rsquared	0.9987971	0.9982559

The coefficient of determination R^2 (Rsquared) on the model and the performance indicate the proportion of the information in the data explained by the model(Kuhn and Johnson 2013). In this case, the model explains more than 99% of the changes in the forest. There is a difference of 0.1% in the accuracy of the model. The RMSE of the training data is lower than the RMSE of the test data. This could indicate overfitting or result from limiting data for testing (Dalpiaz 2020).

4.3. Forest Area as a Function of socioeconomic data

This section seeks to evaluate the changes in forest cover in response to public policies and the projections of the Ecuadorian state for 2025. The current national development plan *Creating Opportunities* has a series of public policies seeking to generate economic, social, and environmental development for Ecuador and is in force from 2020 to 2025. This plan uses as a starting point the values of the 2020 indicators and the improvement of the indicators for 2025 as an endpoint. Said improvement is measured in USD, ton/Hectare (t/Ha), and percentages. All the goals were transformed into percentage terms to evaluate these public policies.

Additionally, the base or initial data of 2020 of the different indicators was used, and the percentage value of the goals was added. These final data correspond to the values of the independent variables to be evaluated with Equation 4. Not only the corresponding data to the national development plan were used, but demographic projections and long-term state goals were also included in the analysis: population density for 2024, an annual increase of HDI of 0.57%. The inclusion of these variables is explained in the framework. Table 10 shows the values used to calculate changes in forest cover in Ecuador.

Table 10 National Development Plan and Governmental Predictions

	Goal	**Goal transform in %**	**Indicator**	**Value in 2020**	**Value in 2025**
NDP Goals	1.1.1. Increase the suitable employment rate from 30.41% to 50.00%.	1.1.1. Increase the suitable employment rate by 19.59%	EmployR	2296.19	2746.013621
	2.1.2. Increase the share of non-traditional exports in total non-oil exports from 41.16% to 48.36%.	2.1.2. Increase the share of non-traditional exports in total non-oil exports by 7.2%	ExporGS	21384640082	22924334168
	3.1.2. Increase the yield of national agricultural productivity from 117.78 to 136.85 ton/Hectare (t/Ha).	3.1.2. Increase the yield of national agricultural productivity by 16,2%	Yield	3914.7	4548.8814
	3.1.3. Increase agricultural and agro-industrial exports from 13.35% to 17.67%.	3.1.3. Increase agricultural and agro-industrial exports by 4,32%	Export Banana	7039838.64	7343959.669
			Export Cacao	323398.63	337369.4508
			Export palm oil	162655.11	169681.8108
	4.5.2. Achieve an annual growth of the Gross Domestic Product of 5% in 2025	4.5.2. Achieve an annual growth of the Gross Domestic Product of 5% in 2025	GDP	5331.976611	5598.575442
National	Increase the HDI by 2.12%, according to the (Gobierno del Ecuador 2020)		HDI	0.731	0.7518335
	Increase the population density in 2025(INEC n.d.)		PopD	70.8189523	72.41
	Increase in rural population in 2025(INEC n.d.)		RuPop	6302697	6728319.308

Table 11 shows the variables and coefficients resulting from the LASSO regression with the goal values 2025 of the NDP and National Projections. The variables that do not have a goal or projection for the year 2025 LIVESTOCK. For the projection of vegetation cover, it was assumed that the indicator did not suffer changes from 2020-2025. The prediction column is the result of multiplying the coefficients by the target value of the indicators in 2025. The changes in Ecuador's forest cover in 2025 is 123820.194 using Equation 4. This value is given under the assumption that the goals described in Table 8 have been met. The model predicted that from 2020 to 2025 the country will loss about 1158.106312 (sq. km), as the value in 2020 the forest area was 124978.3 km^2.

Table 11 Prediction 2025

VARIABLES	COEFFICIENTS	VALUE IN 2025	PREDICTION
POPD	-262.8117	72.41	-19030.195
HDI	-18954.55	0.7518335	-14250.666
EMPLOYR	-2.284873	2746.013621	-6274.2924
LIVESTOCK	-58.70193	95.07	-5580.7925
EXPBANA	-0.0005028	7343959.669	-3692.7273
RUPOP	-0.0001737	6728319.308	-1168.6714
EXPCACAO	-0.0005548	337369.4508	-187.16643
YIELD	-0.0362277	4548.8814	-164.79551
GDP	0	0	0
EXPORGS	0	0	0
ARTIFISURFA	0	0	0
MYSCHOOL	0	0	0
PRODUCOIL	0	0	0
AGRILAND	0	0	0
EXPPALMOIL	0	0	0
(INTERCEPT)	174169.5	174169.5	174169.5
FOREST AREA	-	-	123820.194

5. DISCUSSION AND INTERPRETATION OF FINDINGS

The results section shows various outcomes that can be used to explore the relationships between socioeconomic factors and deforestation. Furthermore, they can give a glimpse of how national development goals shape social and economic contexts and thus have an environmental impact on forest areas. The results must be interpreted cautiously since they do not represent Ecuador's social and economic complexity. They outcome from a representation based on assumptions and abstractions of said socioeconomic context. The results seek to explain in an oversimplified way the possible effects of forest cover of growth or contraction on the country's social, demographic, and economic development. The oversimplification does not mean that the result cannot illuminate the relationship between policies, development goals and deforestation. Still, instead, they can be guides or steppingstone in creating policies that can challenge current trends of forest loss.

The results showed the strength and direction of the correlations between the socioeconomic variables and changes in forests area. All the variables showed a strong negative correlation with forest area, except agricultural land, which had a positive correlation. The regression analysis was performed to understand if these variables are responsible for the dynamic in forest loss. However, due to high multicollinear, the MLR has been deemed an inappropriate method for statistical analysis of the data set. A LASSO regression was performed to solve the problem of multicollinear. The result was a model that describes deforestation because of exploring causality between underlying and immediate predictors of deforestation. Finally, this model was used to evaluate the impacts of national development policies towards deforestation factors, which in turn influence the loss or gain of forest cover. The outcomes' implications are discussed in this section.

5.1. The impact of National Development Plan on forest dynamics

This research sought to answer the question: *to what extent do the goals of the National Development Plan impact forest dynamics by shaping the underlying and immediate cause of deforestation?* It is fair to say that NDP goals affect deforestation by creating and shaping the context where agents of deforestation make decisions. The results describe a development model closely linked to the extraction of natural resources. If the objectives regarding social and economic development are fulfilled under the current economic trend, it will cost 1158.11 squared kilometres of the forest by 2025. The loss of 1% could have severe consequences in terms of loss of ecosystem services and emission of CO_2, contributing to global greenhouse emissions and jeopardizing the adaptability of rural populations.

One of the variables with the most significant weight in the model is the Human Development Index. This index comprises three factors: years of schooling, life expectancy, and income(HUMAN DEVELOPMENT REPORT n.d.). The country seeks to increase this index from 0.731 to 0.752 by 2025 by increasing the years of education, increasing life expectancy and economic income (GNI per capita). This index, however, does not show how this development is obtained. The HDI may result from an extractives economic policy, as seems to be the case in Ecuador. The increase in economic income appears to be related to higher deforestation rates in low-income countries (Crespo Cuaresma and Heger 2019). Interestingly, when discussing low-income countries and deforestation, there is an "understanding" that the less industrialised way of life is responsible for severe deforestation (Bhattarai and Hammig, n.d.), often associating deforestation with poverty or lack of development.

Even though HDI is not a measurement of poverty, it is closely related to the association of income as a measurement of well-being and development(Dasic et al., 2020). It has been found that poverty alleviation by increasing economic income does not mean reducing deforestation. Still, in Ecuador, the increase in rural income is a trade-off with forest area. The increase in years of schooling, life expectancy and income come at the expense of using natural resources, especially the use of forests. These trends align with the type of development the country is heading for, where poverty in rural areas is reduced with incentives for agricultural exploitation. The Ministry of Economic and Social Inclusion policies and the Ministry of Agriculture focus on reducing poverty by encouraging peasant families to use agricultural production to improve their quality of life(Ministerio de Agricultura y Ganadería 2019).

One of the goals of the national development plan is to increase adequate employment by 19.59%. In 2021, 32% of the economically active population was engaged in agricultural and mining activities. The government seeks to strengthen employment in the agricultural sector, especially in rural areas. The economic policies for creating employment focus on the agricultural industry since this represents 40% of non-oil exports. The government is betting on the country's economic development based on the trade of farming and fishing products(Presidencia de la República del Ecuador 2021). Some of the economic policies are based on the productive strengthening of peasant family agriculture, on promoting export opportunities, mainly linked to agriculture, and educational policies focused on the production and export of flowers, bananas, shrimp, and others (Ministerio de Gobierno 2022; Presidencia de la República del Ecuador 2021).

It should be noted that the plan contemplates an agroecological transition with training for the care and recovery of soils.

The Ecuadorian government seeks to strengthen the productive and industrial sectors. However, the focus continues to be the agricultural sector, as the former Minister of Agriculture, Tanlly Vera, mentioned: "It is urgent to increase Ecuador's agro-exportable offer. Through projects that we have taken care of strengthening, we are reaching young people and rural women. Family and peasant agriculture, that is where we are aiming" (Presidencia de la República del Ecuador 2021). According to Angelsen and Kaimowitz 1999; Luna et al. 2020; Hollenstein and Carrión 2011), farm employment and opportunities are essential to curb deforestation. While the country continues to bet on the agricultural sector as an engine of development, deforestation continues.

Unsurprisingly, banana and cacao exports are significant variables within the deforestation model. Historically, the agricultural and petroleum booms were the fundamental engines of the country's economic development. The exports of cocoa, banana and oil modified the economic context of the country, placing the agricultural sector as one of the largest non-oil economic sectors in the country(UNCTAD 2014). Ecuador has created a series of economic and monetary policies to encourage the production and export of agricultural products, such as the reduction and exoneration of the payment of income tax, credits for agricultural mechanisation, and exemptions from agricultural machinery tariffs (Salazar 2020). The country's agricultural export sustainability policies are based on markets, such as organic production certifications (CEPAL 2017). Two other indicators fall under the agriculture sector: yield and livestock production. It has been well established that the county has crafted a series of development policies to strengthen the agricultural sector. To improve agricultural and livestock productivity, the Ecuadorian government implements projects to promote products based on fundamental and applied research, access to technified plot irrigation systems, post-harvest and storage and logistics, and support infrastructure for agricultural production. In addition to access to financing and agricultural and livestock insurance (Ministerio de Agricultura y Ganadería 2020).

Variables related to agricultural production strongly influence the forest cover change model. This relationship is in line with Sierra, Calva, and Guevara 2021, which examined the driving factors and trends of deforestation in Ecuador from 1990 to 2018 and concluded that 99% of the deforested area was devoted to agricultural, aquaculture, and forest plantation land uses.

Seemingly, the national economic and social development agenda is firmly focused on agricultural development. This trend has been maintained since the agribusiness reform and is projected to continue until 2025. Ecuador continues to depend on primary natural resources for its development, although technification has been encouraged in the agricultural sector, it has not yet been successful. It must be remembered that this model does not represent the real impact of national development policies on deforestation. The lack of continuous data on environmental policies means that the model lacks counterweights in environmental and sustainability policies when predicting changes in forest cover. This limitation is evident in the lack of indicators of the ecological transition axis of the NDP. There are environmental policies in agriculture such as promoting environmental sustainability and adaptation to climate change, for which work is done on the protection of ecosystems, sustainable agriculture, and livestock; adaptation to climate change, bio-trade and urban agriculture(Ministerio de Agricultura y Ganadería 2020).

5.2. Correlations between the underlying and immediate factors of deforestation and changes in forest areas

The results show a strong correlation between deforestation factors and the loss of forest area. These correlations do not have to be interpreted as causal relationships. The regression model selects only eight variables as predictors of land use change; however, it is vital to analyse the results of the correlation analysis.

5.2.1. Understanding the underlying factors of deforestation

The correlation analysis accepted the hypotheses of most of the underlying predictors of deforestation except the humanitarian development index and the level of education (Table 12). It was hypothesised that the increase in these indicators (HDI and MySchool) would curve to deforestation. However, the results show the opposite effect. In the case of the human development index, Michinaka and Miyamoto 2013 and Jha and Bawa 2006 indicated that areas with a higher development index had less deforestation. The authors assume that development is equal to the industrialisation of the economy and urbanisation. At the same time, the perception of rurality is interwoven with poverty or underdevelopment. In the case of this research, the increase in the HDI index may indicate the country's extractivist economic model, which has encouraged the use of natural and forest resources for economic development(Presidencia de la República del Ecuador 2021). Indices that seek to assess the development and well-being of the population under an economic bias do not consider the other type of cosmologies, especially in rural sectors(Scheidel 2013; Wilson and Stammler 2016). Clear evidence of this is that during the agrarian reform of the 1960s, the Ecuadorian government sought to develop the country and reduce poverty using agriculture and the colonisation of territories. The indigenous communities were forced to assimilate the land tenure system to protect their territories, which led to the loss of large communal territories and the creation of single-family farms(Wasserstrom and Southgate 2013). This forced transition meant that many indigenous communities lost their way of life, falling into the sense of poverty that the government wanted to fight.

The increase in education was expected to reduce deforestation, under the slogan that the more education, the more job opportunities and economic income. The results show that the increase in schooling negatively affects the forest cover. Luna et al. 2020; Mena, Bilsborrow, and McClain 2006 explain that the relationship between education and deforestation occurs in the context of opportunities. Primary education is not enough to obtain economic income outside of agricultural activity, but it is enough to access information on modernisation and agricultural expansion. Godoy, Groff, and O'Neill 1998 suggest that to curb deforestation. Higher education is necessary for rural areas, which allows peasants to access technical agriculture and external markets that value agricultural products the most.

Table 12 Underlying effects of deforestation expected vs obtain effect on forest area.

Variable	**Indicators**	**Hypothesis**	**Expected effect**	**Obtained effect**
PopD	Population density (people per sq. km of land area)	The increase in population will decrease forest cover. As the population increases, more resources and space are needed.	-	-
HDI	Human Development Index	Deforestation negatively correlates with HDI, areas with higher human development index experience lower deforestation rates. (Jha and Bawa 2006)	+	-
GDP	GDP per capita (constant 2015 US$)	Higher-income per capita contributes to higher deforestation; following the EKC hypothesis, it is believed that developing countries are in a state of economic growth generate environmental damage (Crespo Cuaresma and Heger 2019; Choumert, Combes Motel, and Dakpo 2013).	-	-
ExporGS	Exports of goods and services (constant 2015 US$)	Exporting raw products will increase deforestation as the agricultural frontier grows(Angelsen and Kaimowitz 1999).	-	-
ArtifiSurfa	Artificial surfaces (including urban and associated areas) ha	Urbanisation and the expansion of artificial surfaces open paths towards the colonising territory and deforestation(Barber et al. 2014).	-	-
MySchool	Mean years of schooling	Access to higher levels of education will curve deforestation as skills for off-farm employment are acquired. However, access to basic levels of education will increase deforestation as people can expand agriculture production via loans and early classes of technification(Luna et al. 2020).	+	-
ProducOil	Total production of petroleum and other liquids (Mb/d)	Increased oil production will positively correlate with deforestation due to the construction of auxiliary infrastructure for the oil industry (Wunder 2003; Mena et al. 2017).	-	-

There is a strong negative correlation between population density and deforestation. Furthermore, this relationship was established with the LASSO regression as a predictor of deforestation (cause-effect relationship). The historical trend of population growth as a deforestation factor was evidenced in this research, not only from the perspective that a larger population requires a more significant number of resources but also from the public policies that shape the decision-making context. As described by Gómez de la Torre, Anda, and Bedoya Garland 2017b, deforestation trends in Ecuadorian territory also depend on family cycles. A family with young children has a dynamic of agricultural expansion generating deforestation, and as they grow up, the dynamic changes. There is a transition from labour-intensive agricultural production to less labour-intensive livestock production. When the family's children grow up, there is a process of secondary colonisation of territories close to the parents, or the children inherit the family territories. This process increases the population density of the agricultural frontier, creating risk scenarios for deforestation. Anda Basabe, Gómez de la Torre, and Bedoya Garland 2017 explain that deforestation processes in relation to population density depend on the type of public policies related to land tenure. During the agrarian reform, migration and demographic expansion towards primary forests were encouraged, which generated the destruction of primary forests and the expansion of the agricultural frontier. However, as indigenous lands, protected areas and protective forests were established, demographic expansion focused on clearing secondary forests within family farms and the illegal expansion of the agricultural frontier.

GDP, Exports of goods and services and Total petroleum production showed a strong negative correlation. According to the results of the LASSO regression, they were not selected as causes for deforestation. The country's economic growth does not seem to have a causal relationship with the deforestation process. However, it is essential to mention that the HDI indicator considers economic elements in its calculation, such as per capita income. It could be inferred that part of the economic growth is already represented in the HDI, and the GDP per-capital variable could be redundant for the model.

Additionally, the growth of the Ecuadorian economy is related to the oil industry and exports of agricultural and aquaculture products. CEPAL 2021 establishes that the agricultural and aquaculture sector has been an essential support for the Ecuadorian economy hit by volatile oil prices. The industries with the highest economic growth in Ecuador in 2021 were oil refining (23.9%), lodging and food services (17.4%), aquaculture and shrimp fishing (16.2%), and transportation (13.1%) (Central del Ecuador 2022). That is why the relationship between the economic growth of the country and deforestation is better represented with the indicators related to the export of Banana, Cocoa and Palm Oil.

Oil production and artificial area have strong negative correlations with forest areas. Nonetheless, there is no causal relationship, although it is believed that the oil industry in Ecuador is the cause of deforestation. Ferrante and Fearnside 2020, Barber et al. 2014 and Mena et al. 2017 explain that the support infrastructures (roads) generate deforestation. In other words, the initial phase of oil projects causes deforestation. The well's productive life (extraction of oil barrels) does not significantly affect deforestation. This does not mean the oil industry has no historical role in deforestation in Ecuador; oil production in the 1960s led to the construction of roads and infrastructure that facilitated deforestation in the Amazon region(Wasserstrom and Southgate 2013). From this perspective, the social actors in the country have dedicated themselves to stopping the spread of oil in the Amazon forests so that the expansion of the agricultural frontier and the colonisation of indigenous territories are not facilitated(Paz 2018). The oil barrels production indicator does not correctly reflect the impact of oil extraction on forests, and it would be better to trace roads and highways built by the oil industry. This information is very limited in the national context, but it has been analysed in a study on regional deforestation factors, as in the case of Thapa, Bilsborrow, and Murphy 1996; López 2022; Barber et al. 2014; Luna et al. 2020. In the same way, the artificial surface indicator tries to visualise urban structures and support infrastructures such as roads to study the effect of urbanisation and road connectivity in the country. Although it has a strong correlation with deforestation, it was not taken as a cause of change in vegetation cover in the model.

5.2.2. Understanding the immediate factors of deforestation

The immediate factors of deforestation represent the decision parameters that influence the agents of deforestation (Table 13). Employment in agriculture has a strong negative correlation with forest area and has been deemed a predictor of deforestation on the LASSO model. Opportunities outside of agriculture have been established to reduce deforestation, and the diversification of work in rural areas is essential to improve the quality of life of the rural population(Angelsen and Kaimowitz 1999). Agriculture is the sector that employs 71.9% of the rural population, followed by the service sector with 11.9%. In the country's rurality, there are no alternative sources of employment outside the agricultural sector (INEC 2023). Additionally, 84% of jobs in agriculture correspond to underemployment. According to the INEC, underemployment refers to employed persons who, during the reference week, received income below the minimum wage and/or worked less than the legal working day and are willing and willing to work additional hours. In the country, it is understood that underemployment is a form of job insecurity (INEC 2022). Luna et al. 2020; Peterson Zwane 2002 mention that the lack of sources of work encourages the rural population to supplement the lack and economic income by intensifying agriculture or migrating to the city.

The country's internal migratory processes have shaped the forest cover, so it is vital to establish rural population trends. The indicator rural population has a strong negative correlation with forest area. Sierra, Calva, and Guevara 2021explains that the expansion of the rural population at the beginning of the 1980s and 1990s because of agrarian colonisation policies influenced the deforestation of native forests in remote areas of the country. Additionally, fertility rates in rural areas are a crucial element in understanding the in-situ demographic pressures. In the same publication, Sierra comments that one of the restraints on the demand for new agricultural land was the precipitous drop in rural fertility rates, both in non-indigenous and indigenous populations. Anda Basabe, Gómez de la Torre, and Bedoya Garland, 2017 point out that part of the contraction of the rural population is due to the migration of young people to the urban areas of the country, where employment opportunities are better.

Table 13 Immediate effects of deforestation expected vs obtain effect on forest area.

Variable	**Indicators**	**Hypothesis**	**Expected effect**	**Obtained effect**
RuPop	Rural population	The increase in rural population will generate a need for more resources, so there will be more deforestation.	-	-
EmployR	Employment in agriculture, forestry and fishing - ILO modelled estimates 1000 persons	Off-farm employment may reduce deforestation, and employment in agriculture will increase land change use(Fagua, Baggio, and Ramsey 2019; Sierra, Calva, and Guevara 2021b).	-	-
AgriLand	Agricultural land (sq. km)	The increase in agricultural land increases the probability of deforestation of nearby forests(Sierra, Calva, and Guevara 2021b; Thapa, Bilsborrow, and Murphy 1996).	-	+
Livestock	Livestock production index (2014-2016 = 100)	Livestock production requires clearing forests for grasslands, increasing deforestation(Sierra, Calva, and Guevara 2021a).	-	-
FerN	Fertilisers tons Nutrient nitrogen N (total)	Using fertiliser will increase productivity, slowing down the expansion of the agricultural frontier(Luna et al. 2020).	+	-
Yield	Cereal yield (kg per hectare)	Higher yield in crops generates a stable income, therefore reducing the necessity to expand agricultural activities (Luna et al. 2020; Mena, Bilsborrow, and McClain 2006b)	+	-
ExpBana	Export Banana tonnes	High demand for agriculture products generates a cost-opportunity effect, where farmers go into difficulty in reaching forest areas to cultivate those high-demand products (Graziano Da Silva, Gómez, and CastañeDa 2010; Baquero and Mieles 2014)	-	-
ExpCacao	Export Cacao Tonnes			
ExpPalmOil	Export palm oil Tonnes			

The decreasing trend of agricultural land is due to reduced land access. The Ministry of the Environment explains that national colonisation policies encouraged the invasion of natural areas, and insecurity in land tenure promoted deforestation and weakened indigenous communal property regimes, which have traditionally promoted the conservation of natural forests(Ministerio del Ambiente 2013). Since 1999, the country has created a series of national policies for the sustainable forestry development of Ecuador. It was not until 2005 that the control and supervision of the Ecuadorian Forestry Sector were declared in a state of emergency. Among the policies for the protection of forests is limiting agricultural expansion by creating forest control units, forest audits, advisory systems for forest use and environmental protection schemes through payments for environmental services. Sierra, Calva, and Guevara 2021 mention that the decrease in agricultural expansion is due mainly to forest controls and forest protection policies.

It was hypothesised that the use of fertilisers and the increase in agricultural productivity would positively correlate with the forest area; however, the results show a negative correlation. The national government of Ecuador seeks to reduce deforestation by modernising agricultural production(Ministerio del Ambiente 2013). This goal aims to improve food sovereignty, improve the economy of farmers and prevent the expansion of the agricultural frontier by maximising productive land. For this, agricultural investment programs were installed, training for modernising crops for small and medium-sized producers, technical irrigation, and reducing tariffs for fertilisers and pesticides(Ministerio de Agricultura y Ganadería 2021). Fischer et al. 2021 and Luna et al. 2020 explain that in some instances, the support measures to improve agricultural production trigger deforestation. Because the extra income is reinvested in agricultural activity, this reinvestment often takes the form of expanding farm plots by cutting down adjacent forests.

Agricultural productivity and the use of fertilisers have grown during the last 30 years; there is a downward trend concerning agricultural land. It would be essential to analyse whether using fertilisers and modernising agriculture is responsible for this decrease or if it is a response to land tenure policies. Although productivity has grown, the country has malnutrition problems, and in 2022, 15% of the population was malnourished(FAO et al., 2023). It would be essential to investigate whether the increase in agricultural productivity occurs in large plantations of export products or family farms. Since it is family farming, it produces 60% of the food consumed in the country(Cobos 2021).

5.3. Models and Predictions: implications

The models seek to represent natural phenomena through simplified forms based on assumptions and abstraction. These models and predictions are not faithful representations of reality; however, they are tools that try to give an outline of clarity for studying a problem or topic(Murray 2007). The model of this research is far from predicting changes in forest cover in its entirety. Still, it provides a guide to the possible implications of the country's economic and social development and its impact on forests. The results of this model need to be analysed to understand the limitations of its construction. The data's temporality and quality and the statistical analyses' boundaries introduce uncertainty in the model.

One of the factors not analysed in this research but worth mentioning when analysing the data quality is the issue of representativeness. The data collected at the national level is based on what the state can see. Data related to activities within the framework of illegality are not studied. The issue of illegality in the loss of forests refers to deforestation processes as a product of clandestine economies(Amacher 2006). Organised crime and corruption affect the decision-making processes of deforestation agents. Cozma et al., 2021 explain that the indicators are not enough to justify the reality of deforestation in the country. To understand the effect that factors such as corruption, violence, and organised crime have on the performance of environmental policies, a conjunctural analysis focused on illicit economies is needed (Global Initiative against Transnational Organized Crime 2016). Future investigations would be pertinent to analyse the impact of clandestine economic companies and the role of organised crime in deforestation processes in Ecuador.

The interdependence between the independent variables is one of the assumptions that the MLR model and LASSO use to analyse data, which means that the model ignores the interrelationship between the socioeconomic variables. Scrieciu, 2007 explains that several studies that use regression as an analysis method present a high level of autocorrelation of the socioeconomic variables. This research also found this problem, so a LASSO regression was performed to reduce multicollinearity. The LASSO regression's performance testing (test and training data) still showed overfitting, which could create a model with low precision. Scrieciu, 2007 maintains that regression analyses are not the most reliable for conducting research on deforestation at the national level; however, they do not explore other alternatives to study the causality of socioeconomic relationships and deforestation. Future analyses should take advantage of the apparent relationships between the independent variables and integrate these relationships into deforestation models. Artificial intelligence, data mining, and machine learning could be tools that better capture the complexity of socioeconomic relationships with the environment. For now, this research focused on using regression (a known technique) to study changes in forest cover in relation to socioeconomic variables and the integration of some machine learning techniques.

6. CONCLUSION & RECOMMENDATIONS

This research found that National Development Plans affect forest cover by shaping the underlying and immediate factors of disforestation. According to the model's predictions, a loss of about 1158.11 km^2 of forest is expected by 2025 if the goals of NDP are fulfilled. The goals that significantly affect deforestation are related to the trend of agricultural production as an engine for development in Ecuador. This conclusion aligns with previous research on the social and economic factors of deforestation. It appears to be a consensus that agricultural factors, such as trade, financial incentives, land tenure policies and land productivity, influence the decision-making process of deforestation by the stakeholders. Not only do immediate factors of deforestation weigh in on the decision-making process, but macroeconomic factors, demographic pressures and institutions also influence the stakeholders.

This research aimed to define deforestation's underlying and immediate factors by performing an in-depth literature review. The results showed that economic growth, poverty, population density, employment, education, extraction of raw materials and the export of agricultural products have affected forest resources. However, the research also showed the constrictions and limitations of some of the perceptions of these factors and their role in the changes in forest dynamics. The homologation of economic growth and development proves short-sighted because it ignores the complexity of national development, and it frames in terms of economic performance as growth. Under the same perception, a concept like poverty is tackled in terms of financial income, ignoring the complexity of poverty as a state of deprivation. The fact that development and poverty are not well defined indicates the need for a national dialogue to determine what development is for Ecuadorian society. The current perception of development is still in terms of economic growth that heavily relies on extracting natural resources with some spectacles of sustainability adhering to it.

Defining what development is and how it's going to be achieved has a significant impact on the environment. As described in this research, in the 1960s, the government tried to improve the country's economic growth and reduce poverty by encouraging the migration and colonisation of native forests. This decision changed the country's forest cover and altered indigenous ways of life and agricultural practices. The country still heavily relies upon agriculture as a source of employment and economic development, failing to provide alternatives towards a development not as heavily dependent on natural resources.

Even though all the predictors of deforestation showed a strong correlation, not all showed causation. This research used MLR analysis to look for the relationship between the independent variables (socioeconomic predictors of deforestation) and the dependent variable (forest area); however, the high multicollinearity made it impossible to perform a linear regression. LASSO regression with machine learning algorithms was used to address the multicollinearity problem. The data was divided into train and test data to create a model that could explain the changes in forest areas. The advantage of machine learning algorithms and data training is that the model makes a series of loops that test all the performance of the variables as a predictor of deforestation, and only the ones with the best-predicted power are selected. Accomplishing the construction of a model that, to some extent, can predict deforestation.

The model selected PopD, HDI, EmployR, Livestock, ExpBana, RuPop, ExpCacao and Yield as probable causes of deforestation. The national development goals that seek to modify them by 2025 will affect forest areas. Thus, this model can evaluate the impact of NDP on forest dynamics. The current Plan of National Development seeks an increase of 4.3% in the export of agricultural products. It is adamant about creating suitable employment and wants to increase productivity by 16.2%. In conjecture with the projection of demographic pressure and an increase in the human development index, these goals create a scenario in which 1% of the forest area will be lost by 2025.

Deforestation is one of the most prominent environmental problems in Ecuador. The destruction of large amounts of forest area reduces ecosystem services, such as soil protection and regulation of water and mineral cycles, among others, which endangers agricultural activities. The loss of fertile soils and irrigation would affect the export of agricultural products such as bananas and cocoa, in addition to threatening the national and family economies in rural areas. Since the agricultural sector has been labelled as the economy's engine, it is necessary to safeguard the country's farming capacity. Sustainable development measures in the agricultural sector must be front and centre in national development plans.

Consistency is needed when establishing national development goals; aspects in the economic, social and ecological axes need to work for the same objective: guarantee the quality of life of Ecuadorians and simultaneously consider the rights of nature. The minimisation of contradictory goals and objectives is essential for the harmonisation between development and sustainability. The minimisation of conflicting goals and objectives is critical for the harmonisation between development and sustainability. This research tries to be a tool to understand the priorities of the Ecuadorian government and the cost of these in terms of forest cover. This research established that economic development is prioritised, with a strong dependence on natural resources. Still, fundamentally it fails to integrate sustainable development policies and provide alternative development sources. The model obtained from this research may be the first step to analysing the checks and balances that play a fundamental role in sustainable development.

Forest protection should not be limited to economic reasoning but should be expanded towards the intrinsic values of forests. The forests' recreational, cultural and ancestral values are not integrated into the national development plans. Environmental policies should be incorporated into development axes. The current plans separate economic, social, and environmental development objectives as isolated entities. Incorporating an ecological perspective in the axes of economic and social development would facilitate the integration of the rights of nature and the country's socioeconomic development.

The results of this model need to be analysed with the contextualisation of the model's limitations. A fundamental assumption in this model is that all socioeconomic factors influence deforestation but are independent. This simplification of reality generates a loss of connections and variations that the independent variables suffer as one or the other change; the high degree of collinearity could be a sign of the interrelationship of the independent variables. It is recommended to use another type of statistical analysis that considers the relationships between the independent and dependent variables and incorporates the interrelationships and the self-feeding of the independent variables. The lack of consistency in the national indicators was a significant limitation of the model, especially with the environmental indicators. The evaluation of national development plans is restrictive since the effect of the ecological axis is not considered. An analysis could be carried out in a shorter period to understand the impact of forest protection policies. Such an analysis could give a general view of deforestation trends. Finally, this model needs to be understood as a starting point for understanding the implications of national development on forest cover, not as a definitive answer.

Data and data processing are essential to analyse the cause-effect implication of economic and social policies on the environment. For environmental sciences and sustainability, it is necessary to have data that helps make decisions to ensure sustainable development and the long-term of communities, plans and regions. Standardising data collection and presentation is a first step for constructing tools that allow a deep analysis but, at the same time, direct analysis of the implications of public and monetary development policies in environmental terms. Machine learning and data mining would allow real-time analysis with better reasoning precision, as complex networks involving sustainable development could be programmed and fed with artificial intelligence and real-time data. Tools like machine learning and data mining could mean more complex analysis and straightforward answers. This would help decision-makers have a complete picture of the current situation, define where they want to go regarding social and economic development, and, above all, determine the best path to achieve it.

In conclusion, this research sheds light on the extent to which national development plans influence changes in forest areas by modifying the underlying and immediate factors of deforestation. NDPs are the route map that modifies the context where stakeholders take decisions regarding the use of forest areas. A route map that puts forward development based on agricultural expansion will have. As a result, more actors cut down forests. On the other hand, an approach that seeks to boost the agricultural sector with sustainable policies and maximising other economic sectors that are not dependent on natural resources will have another effect on the country's forest cover. In conclusion, sustainable development in Ecuador requires a shift in the paradigm of what is considered development and considers the intrinsic values of nature. Only then can the country harmonise the rights of people and nature.

7. APPENDIX

Appendix 1 Data base for the analysis

Year	ForestA	PopD	HDI	GDP	ExporGS	ArtifiSurfa	MySchool	ProducOil	RuPop	EmployR	AgriLand	Livestock	FerN	Yield	ExpBana	ExpCacao	ExpPalmOil	Exports Agricultural products
1990	146322.1	37.7468466	0.651	4180.33833	6888881967		6.752	285.041096	4693022		78460	38.67	39421.00	1723.6	2156617	68456		
1991	145420.39	38.6009211	0.652	4263.26862	8037601708		6.808	299.065753	4733060	1038.92	79140	41.56	44700.00	1704.2	2662750	50524	1650.00	2714924.00
1992	144518.68	39.4242956	0.658	4262.48666	8480977126	45799.2	6.865	320.999549	4777592	1081.04	79530	42.52	42700.00	1768.6	2682831	34787	100.00	2717718.00
1993	143616.97	40.2139467	0.662	4261.244	9007046677	47275.7	6.922	348.520548	4816062	1095.59	79750	45.33	49000.00	1951.6	2563223	46310	11626.00	2621159.00
1994	142715.26	40.9899292	0.667	4358.59349	10168206507	49600.8	6.979	369.920548	4850667	1157.60	81290	48.51	48000.00	2075	3007925	56184	9284.00	3073393.00
1995	141813.55	41.7630509	0.671	4374.26872	11221514165	52646.8	7.036	395.827397	4882961	1201.43	81080	53.17	56000.00	1984.3	3665182	63623	18768.00	3747573.00
1996	140911.84	42.5343917	0.674	4369.32102	10983327168	55791.5	7.093	397.878142	4912975	1241.28	79870	57.66	65000.00	2029.3	3866079	71100	22120.00	3959299.00
1997	140010.13	43.3024057	0.679	4477.57093	11750617134	57971.3	7.15	389.445205	4940787	1267.98	80120	63.47	90600.00	2058.7	4462099	42300	14906.00	4519305.00
1998	139108.42	49.1210058	0.684	4543.53648	11194035486	59035.1	7.206	376.29863	4966373	1356.63	80270	60.34	88100.00	1954.9	3855643	12135	13248.00	3881026.00
1999	138206.71	49.9760267	0.683	4254.15121	12048233641	60197.6	7.263	374.043836	4990139	1396.79	80750	64.07	69800.00	2123.1	3966126	63600	63581.00	4093307.00
2000	137305	50.8395354	0.687	4227.55252	12353797220	61273	7.32	396.31137	5012850	1446.07	80660	69.22	71600.00	2306	3993968	49046.55	12842.61	4055857.16
2001	136602.69	51.7213762	0.693	4322.34188	12157723330	61278.8	7.377	412.511308	5035573	1545.36	77850	74.75	226367.00	1899.4	3990427	55420	3929.00	4049776.00
2002	135900.38	52.6276735	0.698	4421.93442	12233560972	61278.8	7.434	392.718592	5082114	1532.14	74900	74.89	132311.00	2434.6	4199156	55598	31826.00	4286580.00
2003	135198.07	53.5560638	0.703	4463.59718	13115622201	61278.8	7.491	411.341769	5145430	1622.47	72500	75.8	119857.00	2617.3	4664814	64756	54435.00	4784005.00
2004	134495.76	54.4958649	0.71	4746.80717	15368672963	61825.2	7.548	531.005702	5208923	1763.67	75270	78.08	135632.00	2922.2	4521458	69626	59840.00	4650924.00
2005	133793.45	55.4437591	0.715	4912.52749	16695456088	61836.8	7.604	534.7554	5272400	1807.96	75000	77.2	116291.00	2841.6	4764193	78349	109537.00	4952079.00
2006	133091.14	56.4062691	0.72	5041.3338	17885174195	62458.8	7.661	538.388764	5336472	1836.96	74440	86.14	126268.00	2830	4908564	83820	115694.00	5108078.00
2007	132388.83	57.3837776	0.723	5063.98448	17888252642	65719.8	7.718	512.689986	5400875	1783.70	74120	90.8	118168.00	3144	5174565	80093	171638.00	5426296.00
2008	131686.52	58.3700958	0.729	5294.89931	18422028743	69690	7.726	507.757702	5465292	1769.96	74450	96.65	156382.00	2980.3	5270688	80143	171642.00	5522473.00
2009	130984.21	59.3604687	0.731	5236.05368	17539918092	73334.6	7.74	488.509197	5529274	1764.19	75344	95.39	151261.00	2965.5	5700696	124404	185536.00	6010636.00
2010	130281.9	60.354264	0.736	5331.38377	17498336545	77072.2	7.849	489.102877	5592614	1734.92	74977	99.3	159096.00	3106.2	5156477	116318	145781.00	5418576.00
2011	129863.88	61.3533902	0.743	5657.21302	18490100528	81304	7.907	502.134022	5660664	1760.00	73461	104.54	178586.00	2605.8	5778170	157782	249764.00	6185716.00
2012	129445.86	62.344512	0.751	5881.38117	19500876638	85686.9	8.097	507.643079	5730895	1825.90	75069	101.93	172934.27	3258.8	5183312	147329	276069.00	5606710.00
2013	129027.84	63.3072516	0.755	6078.43956	19999778318	98661.1	8.289	531.023408	5797852	1772.88	75130	106.6	161466.05	2911.5	5352000	178273	213290.00	5743563.00
2014	128609.82	64.2534788	0.76	6215.83809	21242750371	106711.8	8.361	561.542058	5862807	1720.25	54750	107.06	173443.72	3527.5	5746340.37	198889.53	219898.57	6165128.47
2015	128191.8	65.2113947	0.765	6130.58668	21107369000	109967	8.702	548.368841	5928024	1906.27	57890	98.88	138617.44	4322.9	6070351.89	236072.37	275119.50	6581543.76
2016	127549.1	66.1925632	0.762	5965.64327	21407321524	110013.5	8.693	552.40723	5994859	2044.89	55160	94.07	196435.87	3791.8	5974366.37	227213.68	312803.08	6514383.13
2017	126906.4	67.2287969	0.762	6012.80332	21560821032	112844.4	8.766	535.225288	6066000	2182.33	55900	94.22	200593.86	3416.1	6415232.42	284546.12	284804.38	6984582.92
2018	126263.7	68.5121276	0.762	5976.24535	21809646958	114966.1	8.783	521.081266	6156100	2279.19	54480	94.68	219923.07	3938.1	6553852.68	294062.84	287269.66	7135185.18
2019	125621	69.8330649	0.76	5863.91057	22604745084	118965.3	8.8	533.851689	6246175	2378.01	53300	95.54	208212.58	4326.1	6667584.13	270942.97	187494.02	7126021.12
2020	124978.3	70.8189523	0.731	5331.97661	21384640082	118901.3	8.817	482.338824	6302697	2296.19	54200	95.07	208212.58	3914.7	7039838.64	323398.63	162655.11	7525892.38

Appendix 2 Definitions of the indicators

Indicator	Source	Unit	Definition
ForestA	World Bank	Forest area (sq. km)	Forest area is land under natural or planted stands of trees of at least 5 meters in situ, whether productive or not, and excludes tree stands in agricultural production systems (for example, in fruit plantations and agroforestry systems) and trees in urban parks and gardens.
PopD	World Bank	Population density (people per sq. km of land area)	Population density is midyear population divided by land area in square kilometers. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship--except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. Land area is a country's total area, excluding area under inland water bodies, national claims to continental shelf, and exclusive economic zones. In most cases the definition of inland water bodies includes major rivers and lakes.
HDI	United Nations Development Programme	Human Development Index	A composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living. See Technical note 1 at http://hdr.undp.org/sites/default/files/hdr2022_technical_notes.pdf for details on how the HDI is calculated.
GDP	World Bank	GDP per capita (constant 2015 US$)	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for the depreciation of fabricated assets or for the depletion and degradation of natural resources. Data are in current U.S. dollars. (The World Bank 2023)
ExporGS	World Bank	Exports of goods and services (constant 2015 US$)	Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments. Data are in current U.S. dollars.
ArtifiSurfa	FAOSTAT	Artificial surfaces (including urban and associated areas)ha	Class 1 is composed of any type of areas with a predominant artificial surface. Any urban or related feature is included in this class, for example, urban parks (parks, parkland and laws). The class also includes industrial areas, and waste dump deposit and extraction sites.
MySchool	United Nations Development Programme	mean years of scholing	Average number of years of education received by people ages 25 and older, converted from education attainment levels using official durations of each level.
ProducOil	U.S. Energy Information Administration (EIA)	Total production petroleum and other	Petroleum supply includes the production of crude oil (including lease condensate), natural gas plant liquids, and other liquids, and it also includes refinery processing gain for volume (TBPD) only.(eia 2023)

		liquids (Mb/d)	
RuPop	World Bank	Rural population	Rural population refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population. Aggregation of urban and rural population may not add up to total population because of different country coverages.
EmployR	World Bank	Employment in agriculture, forestry and fishing - ILO modelled estimates 1000 persons	Employment is defined as persons of working age who were engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period or not at work due to temporary absence from a job, or to working-time arrangement. The agriculture sector consists of activities in agriculture, hunting, forestry and fishing, in accordance with division 1 (ISIC 2) or Categories A-B (ISIC 3) or Category A (ISIC 4). (The World Bank 2023)
AgriLand	World Bank	Agricultural land (sq. km)	Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures. Arable land includes land defined by the FAO as land under temporary crops (double-cropped areas are counted once), temporary meadows for mowing or for pasture, land under market or kitchen gardens, and land temporarily fallow. Land abandoned as a result of shifting cultivation is excluded. Land under permanent crops is land cultivated with crops that occupy the land for long periods and need not be replanted after each harvest, such as cocoa, coffee, and rubber. This category includes land under flowering shrubs, fruit trees, nut trees, and vines, but excludes land under trees grown for wood or timber. Permanent pasture is land used for five or more years for forage, including natural and cultivated crops.
Livestock	World Bank	Livestock production index (2014-2016 = 100)	Livestock production index includes meat and milk from all sources, dairy products such as cheese, and eggs, honey, raw silk, wool, and hides and skins.
FerN	FAOSTAT	Fertilizers tonns Nutrient nitrogen N (total)	The **FAOSTAT Fertilizers by Nutrient** domain contains information on *agricultural use, production,* and *trade* of chemical and mineral fertilizers, in tonnes of nutrient, for the three main plant nutrients: nitrogen (N), phosphorus (expressed as P2O5) and potassium (expressed as K2O)
Yield	World Bank	Cereal yield (kg per hectare)	Cereal yield, measured as kilograms per hectare of harvested land, includes wheat, rice, maize, barley, oats, rye, millet, sorghum, buckwheat, and mixed grains. Production data on cereals relate to crops harvested for dry grain only. Cereal crops harvested for hay or harvested green for food, feed, or silage and those used for grazing are excluded. The FAO allocates production data to the calendar year in which the bulk of the harvest took place. Most of a crop harvested near the end of a year will be used in the following year.
ExpBana	FAOSTAT	Export Banana tonns	Quantity of food and agricultural exports: Export quantity is defined by the IMTS as the physical quantity of domestic origin or manufactured products shipped out of the country. It includes re-exports. According to the FAO methodology, the quantity of food and agricultural exports included in the FAOSTAT database is expressed in terms of weight (tonnes) for all commodities except for live animals which are expressed in units (heads); poultry, rabbits, pigeons and other birds are expressed in thousand units. As a general rule, trade quantity refers to net weight, excluding any sort of container
ExpCacao	FAOSTAT	Export Cacao Tonns	
ExpPalm Oil	FAOSTAT	Export palm oil Tonns	

Appendix 3 Transform Data by SPSS

PopD_transformed	HDI_transformed	GDP_transformed	ExporGS_transformed	MySchool_transformed	ProducOil_transformed	RuPop_transformed	AgriLand_transformed	Livestock_transformed	FerN_transformed	Yield_transformed	ExpBana_transformed	ExpCacao_transformed	ArtifiSurfa_transformed	EmployR_transformed	ExpPalmOil_transformed	ExportsAgriculturalproducts_transformed	ForestA_transformed
-1.65	-1.62	-1.17	-1.77	-1.43	-2.01	-1.37	0.64	-1.83	-1.50	-1.32	-1.97	-0.57	0.00	0.00	0.00	0.00	1.48
-1.57	-1.59	-1.05	-1.54	-1.35	-1.84	-1.29	0.71	-1.70	-1.41	-1.34	-1.58	-0.77	0.00	-1.68	-1.15	-1.69	1.40
-1.49	-1.43	-1.05	-1.44	-1.26	-1.58	-1.20	0.75	-1.65	-1.44	-1.26	-1.56	-0.95	-1.29	-1.57	-1.17	-1.69	1.32
-1.41	-1.33	-1.05	-1.34	-1.17	-1.25	-1.12	0.77	-1.52	-1.33	-1.03	-1.66	-0.82	-1.23	-1.53	-1.06	-1.76	1.23
-1.33	-1.19	-0.92	-1.10	-1.09	-0.99	-1.05	0.93	-1.38	-1.35	-0.87	-1.31	-0.71	-1.13	-1.36	-1.08	-1.43	1.14
-1.26	-1.09	-0.90	-0.88	-1.00	-0.69	-0.98	0.91	-1.16	-1.22	-0.98	-0.81	-0.63	-1.00	-1.24	-0.99	-0.94	1.05
-1.18	-1.01	-0.90	-0.93	-0.92	-0.66	-0.92	0.78	-0.95	-1.06	-0.93	-0.65	-0.54	-0.87	-1.13	-0.96	-0.78	0.95
-1.11	-0.88	-0.75	-0.77	-0.83	-0.76	-0.86	0.81	-0.68	-0.63	-0.89	-0.19	-0.87	-0.77	-1.05	-1.03	-0.38	0.86
-0.54	-0.74	-0.66	-0.88	-0.75	-0.92	-0.81	0.82	-0.83	-0.67	-1.02	-0.66	-1.21	-0.73	-0.81	-1.04	-0.84	0.76
-0.45	-0.77	-1.06	-0.71	-0.66	-0.95	-0.76	0.87	-0.66	-0.98	-0.81	-0.57	-0.63	-0.68	-0.70	-0.56	-0.69	0.65
-0.37	-0.67	-1.10	-0.65	-0.58	-0.68	-0.72	0.86	-0.42	-0.95	-0.57	-0.55	-0.79	-0.63	-0.57	-1.05	-0.71	0.55
-0.28	-0.51	-0.97	-0.69	-0.49	-0.49	-0.67	0.58	-0.16	1.66	-1.09	-0.56	-0.72	-0.63	-0.30	-1.13	-0.72	0.46
-0.20	-0.37	-0.83	-0.67	-0.40	-0.72	-0.58	0.27	-0.16	0.07	-0.41	-0.39	-0.72	-0.63	-0.33	-0.87	-0.55	0.37
-0.10	-0.24	-0.77	-0.49	-0.32	-0.50	-0.45	0.03	-0.11	-0.14	-0.18	-0.03	-0.61	-0.63	-0.09	-0.65	-0.19	0.28
-0.01	-0.06	-0.38	-0.02	-0.23	0.93	-0.32	0.31	-0.01	0.13	0.21	-0.15	-0.56	-0.61	0.30	-0.60	-0.28	0.19
0.08	0.08	-0.15	0.25	-0.15	0.98	-0.19	0.28	-0.05	-0.20	0.11	0.04	-0.46	-0.61	0.42	-0.13	-0.06	0.09
0.17	0.21	0.03	0.49	-0.06	1.02	-0.06	0.23	0.36	-0.03	0.09	0.15	-0.40	-0.58	0.50	-0.07	0.05	-0.01
0.27	0.29	0.07	0.50	0.02	0.71	0.07	0.19	0.58	-0.16	0.49	0.36	-0.44	-0.44	0.36	0.46	0.28	-0.12
0.37	0.45	0.39	0.61	0.04	0.65	0.20	0.23	0.85	0.48	0.29	0.43	-0.44	-0.27	0.32	0.46	0.35	-0.23
0.46	0.50	0.31	0.42	0.06	0.42	0.33	0.32	0.79	0.39	0.27	0.76	0.06	-0.11	0.30	0.60	0.71	-0.35
0.56	0.63	0.44	0.41	0.22	0.43	0.46	0.28	0.97	0.53	0.45	0.34	-0.03	0.05	0.22	0.22	0.28	-0.48
0.66	0.82	0.89	0.62	0.31	0.59	0.59	0.13	1.22	0.86	-0.19	0.82	0.44	0.23	0.29	1.21	0.83	-0.55
0.76	1.03	1.21	0.83	0.60	0.65	0.74	0.29	1.09	0.76	0.64	0.36	0.32	0.42	0.47	1.46	0.41	-0.64
0.85	1.13	1.48	0.93	0.88	0.93	0.87	0.30	1.31	0.57	0.20	0.50	0.67	0.97	0.33	0.86	0.51	-0.72
0.94	1.27	1.67	1.19	0.99	1.30	1.00	-1.79	1.33	0.77	0.98	0.80	0.91	1.32	0.18	0.92	0.82	-0.81
1.04	1.40	1.55	1.16	1.51	1.14	1.14	-1.47	0.95	0.18	2.00	1.05	1.33	1.46	0.69	1.45	1.12	-0.91
1.13	1.32	1.32	1.22	1.49	1.19	1.27	-1.75	0.73	1.16	1.32	0.98	1.23	1.46	1.07	1.81	1.07	-1.07
1.23	1.32	1.39	1.25	1.60	0.98	1.42	-1.67	0.74	1.23	0.84	1.32	1.88	1.58	1.45	1.54	1.42	-1.25
1.36	1.32	1.34	1.30	1.63	0.81	1.60	-1.82	0.76	1.56	1.51	1.42	1.98	1.67	1.71	1.56	1.52	-1.47
1.49	1.27	1.18	1.47	1.65	0.96	1.78	-1.94	0.80	1.36	2.00	1.51	1.72	1.84	1.98	0.61	1.52	-1.75
1.59	0.50	0.44	1.22	1.68	0.35	1.90	-1.85	0.78	1.36	1.48	1.80	2.32	1.84	1.76	0.38	1.81	-2.40

Appendix 4 Correlation analysis

Correlations

		ForestA_transformed	PopD_transformed	HDI_transformed	GDP_transformed	ExporGS_transformed	MySchool_transformed	ProducOil_transformed	RuPop_transformed	AgriLand_transformed	Livestock_transformed	FerN_transformed	Yield_transformed	ExpBana_transformed	ExpCacao_transformed	ArtifiSurfa_transformed	EmployR_transformed	ExpPalmOil_transformed
ForestA_transformed	Pearson Correlation	1	-.975**	-.915**	-.865**	-.953**	-.974**	-.822**	-.988**	.862**	-.874**	-.877**	-.930**	-.964**	-.914**	-.947**	-.957**	-.842**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
PopD_transformed	Pearson Correlation	-.975**	1	.964**	.887**	.972**	.965**	.882**	.967**	-.815**	.936**	.898**	.923**	.962**	.843**	.916**	.962**	.877**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
HDI_transformed	Pearson Correlation	-.915**	.964**	1	.958**	.978**	.945**	.928**	.943**	-.781**	.956**	.857**	.911**	.929**	.807**	.891**	.897**	.943**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
GDP_transformed	Pearson Correlation	-.865**	.887**	.958**	1	.937**	.916**	.862**	.924**	-.789**	.881**	.766**	.872**	.855**	.838**	.893**	.799**	.955**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
ExporGS_transformed	Pearson Correlation	-.953**	.972**	.978**	.937**	1	.959**	.941**	.966**	-.808**	.938**	.848**	.938**	.961**	.842**	.908**	.938**	.923**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
MySchool_transformed	Pearson Correlation	-.974**	.965**	.945**	.916**	.959**	1	.839**	.989**	-.908**	.858**	.856**	.950**	.944**	.935**	.982**	.936**	.891**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
ProducOil_transformed	Pearson Correlation	-.822**	.882**	.928**	.862**	.941**	.839**	1	.836**	-.663**	.910**	.772**	.852**	.870**	.662**	.732**	.852**	.839**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
RuPop_transformed	Pearson Correlation	-.988**	.967**	.943**	.924**	.966**	.989**	.836**	1	-.886**	.874**	.859**	.944**	.952**	.939**	.971**	.937**	.898**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
AgriLand_transformed	Pearson Correlation	.862**	-.815**	-.781**	-.789**	-.808**	-.908**	-.663**	-.886**	1	-.636**	-.730**	-.884**	-.808**	-.925**	-.929**	-.826**	-.751**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
Livestock_transformed	Pearson Correlation	-.874**	.936**	.956**	.881**	.938**	.858**	.910**	.874**	-.636**	1	.854**	.822**	.908**	.684**	.776**	.841**	.864**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
FerN_transformed	Pearson Correlation	-.877**	.898**	.857**	.766**	.848**	.856**	.772**	.859**	-.730**	.854**	1	.759**	.863**	.747**	.794**	.875**	.738**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
Yield_transformed	Pearson Correlation	-.930**	.923**	.911**	.872**	.938**	.950**	.852**	.944**	-.884**	.822**	.759**	1	.908**	.868**	.903**	.915**	.847**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
ExpBana_transformed	Pearson Correlation	-.964**	.962**	.929**	.855**	.961**	.944**	.870**	.952**	-.808**	.908**	.863**	.908**	1	.844**	.906**	.948**	.853**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
ExpCacao_transformed	Pearson Correlation	-.914**	.843**	.807**	.838**	.842**	.935**	.662**	.939**	-.925**	.684**	.747**	.868**	.844**	1	.969**	.848**	.820**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	29	30	30
ArtifiSurfa_transformed	Pearson Correlation	-.947**	.916**	.891**	.893**	.908**	.982**	.732**	.971**	-.929**	.776**	.794**	.903**	.906**	.969**	1	.869**	.846**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000
	N	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29
EmployR_transformed	Pearson Correlation	-.957**	.962**	.897**	.799**	.938**	.936**	.852**	.937**	-.826**	.841**	.875**	.915**	.948**	.848**	.869**	1	.808**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000
	N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	29	30	30
ExpPalmOil_transformed	Pearson Correlation	-.842**	.877**	.943**	.955**	.923**	.891**	.839**	.898**	-.751**	.864**	.738**	.847**	.853**	.820**	.846**	.808**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	29	30	30

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 5 Model LASSO Regression in R

The code for the LASSO Regression was adapted from Laughlin 2020.

```
setwd("/Users/Diana/Documents/data r")
#install.packages("readr")
library(readr)
df <- read.csv("dataraw.csv")
str(df)
####partition
#install.packages("caret")
library(caret)
#set seed
set.seed(1995)
index <- createDataPartition(df$ForestA, p=.8, list=FALSE, times=1)
#create trainin and test
train_df <- df[index,]
test_df <- df[-index,]
#adrees error mesage, comverdf to object
####k-fold cross validation (1 fold cross validation)
ctrlspecs <- trainControl(method = "cv", number = 5,
                savePredictions="all")
##LASSO regresion
## create vector of potential lamba
lambda_vector <- 10^seq(5, -5, length=100) ###check this value 5,-2
#set a seed
set.seed(1995)
#scpecify LASS REGRESSIOn model to be stamate usiong training data ans 1 fold validation
model1 <- train(ForestA ~ PopD + HDI + GDP + ExporGS + ArtifiSurfa + MySchool + ProducOil + RuPop + EmployR + AgriLand + Livestock + Yield + ExpBana + ExpCacao + ExpPalmOil,
          data=train_df,
          method="glmnet",
          tuneGrid= expand.grid(alpha=1, lambda=lambda_vector),
          trControl=ctrlspecs,
          na.action=na.omit)
# PopD + HDI + GDP + ExporGS + ArtifiSurfa + MySchool + ProducOil + RuPop + EmployR + AgriLand + Livestock + Yield + ExpBana + ExpCacao + ExpPalmOil
sum(is.na(df))
boxplot(df)
model1$bestTune
model1$bestTune$lambda
#LASSO regression
coef(model1$finalModel, model1$bestTune$lambda)

#plo loglambda and rmse
plot(log(model1$results$lambda),
    model1$results$RMSE,
    xlab = "log(lambda)",
    ylab = "RMSE",
    xlim = c(3, 10))

varImp(model1)


#data visualulizaation
#install.packages("ggplot2")

library(ggplot2)
ggplot(varImp(model1))

####model prrediction

predictions1 <- predict(model1, newdata = test_df)

#model how wll the model prefor
mol1perf <- data.frame(RMSE=RMSE(predictions1, test_df$ForestA),
                Rsquared=R2(predictions1, test_df$ForestA),
                MAE=MAE(predictions1, test_df$ForestA))

# Print the model results
print(model1)

library(glmnet)

library(glmnet)

# Check for missing values
missing_rows <- which(!complete.cases(train_df))
train_df <- train_df[-missing_rows, ]  # Remove missing rows

# Verify column names and formula
formula <- as.formula("ForestA ~ PopD + HDI + GDP + ExporGS + ArtifiSurfa + MySchool + ProducOil + RuPop + EmployR + AgriLand + Livestock + Yield + ExpBana + ExpCacao + ExpPalmOil")
X <- model.matrix(formula, data = train_df)[,-1]
y <- train_df$ForestA

# Check the class of the response variable
if (!is.numeric(y))
  y <- as.numeric(y)

# Fit LASSO regression
fit_LASSO <- glmnet(X, y, alpha = 1)
plot(fit_LASSO, xvar = "lambda", label = TRUE)

plot(fit_LASSO)
# Assuming RMSE is stored in the variable 'RMSE'
RMSE <- as.numeric(255.0483)
# Define the desired confidence level
confidence_level <- 0.95
# Calculate the critical value based on the confidence level
critical_value <- qnorm(1 - (1 - confidence_level) / 2)

# Calculate the margin of error
margin_of_error <- critical_value * RMSE

# Assuming the predicted value is stored in the variable 'predicted_value'
predicted_value <- 2567

# Calculate the lower and upper bounds of the confidence interval
lower_bound <- 123820.1937 - margin_of_error
upper_bound <- 123820.1937 + margin_of_error

# Print the confidence interval
cat("Confidence Interval: [", lower_bound, ",", upper_boun
```

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