EL COLEGIO DE MÉXICO
CENTRO DE ESTUDIOS ECONÓMICOS

MAESTRÍA EN ECONOMÍA

TRABAJO DE INVESTIGACIÓN PARA OBTENER EL GRADO DE MAESTRO EN ECONOMÍA

DOES DEFORESTATION AFFECT THE HEALTH OF THE NEWBORNS IN MEXICO? EVIDENCE FROM SATELLITE DATA

JOB BENJAMÍN ELIHU GARCÍA VARA

PROMOCIÓN 2021-2023

ASESORA:

DRA. FERNANDA MÁRQUEZ PADILLA CASAR

AGOSTO 2023

To my family, who made this work and
all my achievements possible.

Acknowledgements

I want to dedicate this thesis to my parents and my brother. All this would not be possible without their help and effort. Thank you for all your support and unconditional love.

Thanks to Dr. Fernanda Márquez-Padilla for her constant guidance during this work and for her support as my thesis advisor. I also thank Dr. Alejandro López-Feldman for his contribution to the development of this research.

To my friends: Daniel, Paco, and Eloísa, who have always been there for me. I would like to thank my friends from the master's program, Gabriel and Arlene, for all the fun times and hours of study we had together.

To Marco for his invaluable help and guidance.

Abstract

The purpose of this investigation is to assess the impact of deforestation on the health of Mexican newborns. High-definition satellite images are used to detect deforestation in Mexican territory. I exploit geographic and time variation in deforestation at the municipal level to identify causal effect. The main results suggest that deforestation reduces the weight of newborns in Mexico, while increasing the probability of low birth weight and low Apgar scores. However, the results indicate that deforestation is not associated with maternal survival at birth and it decreases the chance of being premature. The research aims to use unprecedented satellite imagery to develop effective policies and interventions to safeguard the health of mothers and newborns.

Contents

1 Introduction **1**

2 Data **4**

2.1 Mexican birth certificate data 5

2.2 Tree canopy cover and deforestation 8

3 Empirical strategy **13**

4 Results **15**

5 Mechanisms **18**

6 Robustness **20**

6.1 Alternative definition of deforestation 20

6.2 Pre-pandemic period 21

6.3 Outlier exclusion 23

7 Discussion and Conclusion **24**

8 Appendix **26**

A References **44**

1 Introduction

The impact of climate change on the global environment has become increasingly relevant due to its broad range of effects, going from the loss of biodiversity to the alteration of sociodemographic characteristics of entire populations. In this sense, the study of the effects of deforestation on human health is essential for the development of future societies.

The World Health Organization estimates that environmental risk factors, such as air pollution, poor water quality, and soil degradation, contribute to nearly 25% of the global burden of disease and are major factors to increase neonatal and infant mortality (Prüss-Üstün et al. 2016). Deforestation can have a significant impact on the health of newborn infants, as it reduces the availability of trees and vegetation, which can alter the proper functioning of the ecosystem.

For example, the destruction of forests can cause soil erosion, decreased water quality, and high air pollution, all of which are directly related to the health of pregnant women and their infants. Deforestation can also be related to changes in local weather patterns, including increased temperatures and low rainfall, which can also have negative effects on newborn health (Myers and Patz 2009).

Furthermore, the loss of trees and vegetation may rise exposure to harmful chemicals and toxins, like pesticides, which can adversely affect fetal development and cause a variety of health issues in babies. In terms of wildlife, the destruction of forests can harm animal populations, which can increase the risk of diseases being passed from animals to humans (McMichael and Lindgren 2011).

Deforestation has been a major issue in Mexico in recent years. Between 2001 and 2017, the country experienced a forest loss of approximately 2.7 million hectares, representing a loss of about 1.3% of its total forest area (United Nations Environment Programme and United Nations 2020). This deforestation has been driven by a variety of factors, including agricultural expansion, illegal logging, and urbanization.

The impact of deforestation on the health of newborn babies in Mexico is an important area of study, since the country has one of the highest rates of neonatal mortality in Latin America (UNICEF 2023). However, reliable data on the health effects of deforestation in Mexico are limited, making it difficult to fully understand the extent of the problem and develop effective solutions.

The health effect of deforestation on newborn babies in Mexico can have far-reaching consequences beyond individual health outcomes. There is growing evidence that poor health among the population, especially among neonates, can have significant economic consequences for a country. Economic growth can be hindered by reduced productivity and increased healthcare costs when a significant part of the population is unhealthy (Bloom et al. 2013). There is increasing evidence of the long-term effects of poor health at birth on future outcomes. For example, low birth weight has been linked to future health problems and lower educational attainment (Currie 2009). Better health in childhood is related to higher incomes, higher wealth, more weeks worked, and a higher growth rate in income (Smith 2007).

Consequences of poor health outcomes on Mexico have been estimated to be billions of dollars in lost productivity and increased healthcare expenditure each year (WorldBank 2023). Additionally, the economic impact of poor health is often felt most acutely by vulnerable populations, including women and children. These populations may be especially affected by the health effects of deforestation.

It is therefore essential to study the impact of deforestation on the health of newborn babies in Mexico and the factors that contribute to it. The process will provide a deeper understanding of the specific challenges facing Mexico and enable the development of effective policies and interventions to safeguard the health of mothers and newborns. Furthermore, this research could contribute to a better understanding of the global impact of deforestation on human health.

The research methodology employed involves the collection and processing of high-definition satellite images in order to identify deforestation in Mexican territory. Thus, the relationship between this phenomenon and the health of newborns in the country was the nuclear concern. We postulate the following research question: Does deforestation affect the health of newborns in Mexico?

The processing of high-definition satellite images represents a contribution to the literature by itself. The creation of a database at the municipal level on annual deforestation in Mexico allows us to quantify the impact of deforestation on various socioeconomic dimensions and contributes to the literature for decision-making in the national context.

The main results suggest that deforestation decreases the weight of newborns in Mexico, while increasing the probability of low birth weight (LBW) and an Apgar score smaller than 9. These outcomes, particularly LBW, have been found to be strong predictors of future health. Despite the absence of a significant association between deforestation and maternal survival, a decrease in the probability of premature birth was observed, in contrast to the consensus in the literature on this subject. This is discussed in Section 4.

These results significantly contribute to the literature by pioneering the exploration of the direct connection between deforestation and newborn health in Mexico. This study reveals novel implications of environmental degradation, revealing that deforestation decreases newborn weight and increases the likelihood of LBW and lower Apgar scores. These findings not only deepen academic understanding, but also hold crucial implications for public health policy and environmental conservation, particularly in deforestation-prone regions like Mexico. Moreover, this thesis contributes significantly to the existing body of literature that studies the mechanisms affecting the health of newborns, as well as to the literature related to the implications of environmental damage on population health.

The present research is divided as follows: Section 2 discusses the sources of information used, their temporality, characteristics, as well as their novelty. The section also introduces an exploratory analysis of the most relevant health and deforestation data, which provides a preliminary understanding of their interrelationship.

In Section 3, we summarize the empirical strategy used to answer the research question, including the formal postulation of the model to be estimated, its assumptions, and the description of the dependent and independent variables.

Section 4 provides a summary of the major findings regarding the detrimental effects of deforestation on the health of newborn infants. Section 5 incorporates an in-depth analysis of the mechanisms underlying this effect. The three robustness tests applied to the research findings are presented in Section 6. Changes were made to the definition of deforestation, the analysis period, and the sample of geographical units observed.

Finally, Section 7 provides a synthesis of the research results and their relevance to the broader field of study. It discusses the limitations of the document and suggests avenues for further research. The section concludes by highlighting the significance of the research and its potential contributions to policy and practice.

2 Data

We emphasize satellite data because their processing represents a contribution to the literature by itself. The creation of a database at the municipal level on annual deforestation in Mexico allows us to quantify the impact of deforestation on various socioeconomic dimensions and contributes to the literature for decision-making in the national context.

This database is unprecedented since its processing takes into account the administrative boundaries of INEGI's Geostatistical Framework. The calculations of deforested and forested areas follow the geographic coordinate system, as well as the projection method used by INEGI. This guarantees the compatibility of the deforestation measure with other available geostatistical indicators. Another particularity is the periodicity, since the information on deforestation is annual. Finally, since it is a set of global satellite images, deforestation can be calculated at a very atomized level, for example, among neighborhoods or localities.

For the two sources of information explained below, the time window ranges from 2011 to 2021. Due to the updating of deforestation data, 2011 was chosen as the first year of study. From this year onwards, the measurement of forest loss was reprocessed. These changes led to a different and improved detection of overall forest loss. The last year of study, 2021, is the last period in which satellite information on deforestation is currently available.

2.1 Mexican birth certificate data

The data on the health of newborns was obtained from the Ministry of Health of the Federal Government through the Birth Information Subsystem (SINAC). The information contained in this dataset relates to live births in the country and the conditions under which they were born. It is used to plan, allocate resources and evaluate programs that help the maternal and child populations.

The variables of interest are: weight, height and gender of the newborn; age, schooling, number of pregnancies of the mother, total prenatal visits, place of birth of the newborn and place of residence of the mother (INEGI geostatistical code), Apgar score, gestation weeks, mother survival at delivery, pregnancy product (single, twin or more), among others.

In order to assess newborn health, four variables were used: weight, LBW, Apgar<9 and premature. Also, we take mother survival at delivery as dependent variable.[1]

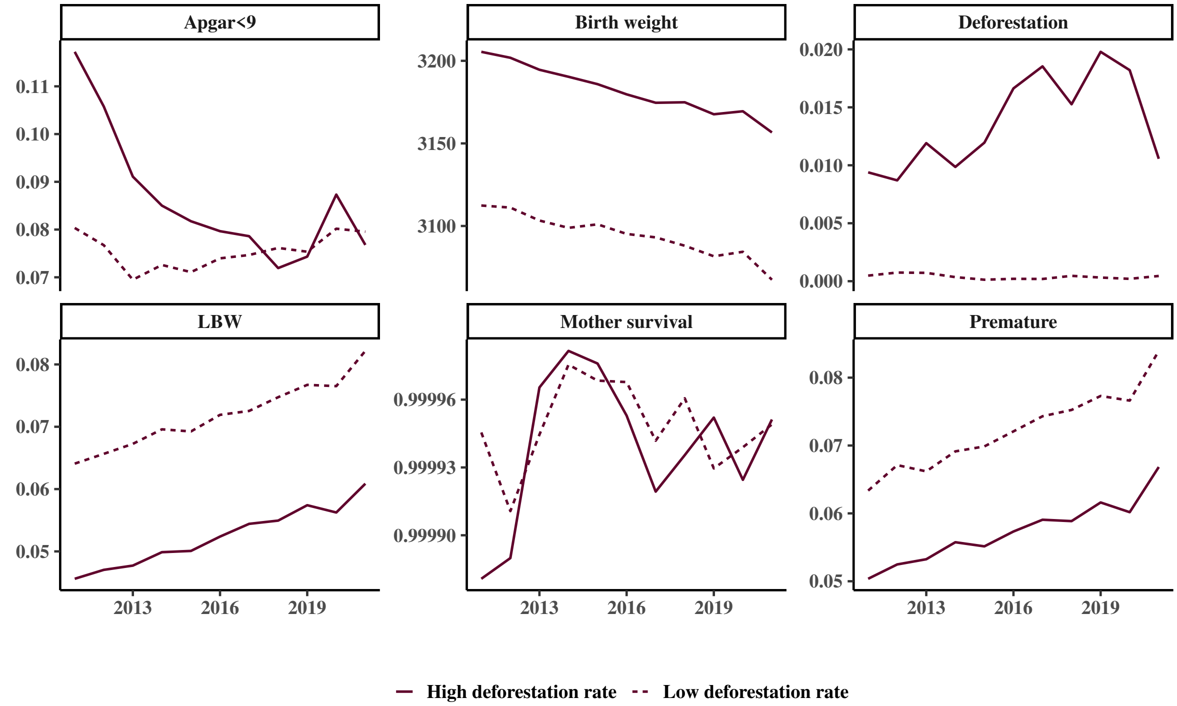
The variable LBW is a dummy variable for having weight lower than 2,500 gr. Mother survival is a dummy for maternal survival at delivery. Premature is a dummy variable for whether mothers have 37 or less gestation weeks at delivery. Schooling is a dummy variable for whether the mother finished high school. Finally, the Apgar test is used to evaluate the newborns respiratory effort, heart rate, muscle tone, reflexes, and skin color. The test takes values from zero to ten, where the highest score is associated with a good state of health. The Apgar<9 variable is a dummy variable for whether the Apgar is less than 9.

Figure 1 shows the trends of our variables of interest. We can see that the average weight of newborns has been getting smaller over time, and the number of low birth weight newborns has been growing. Furthermore, the number of babies with an Apgar below nine has been decreasing, but there has been an upturn recently. On the other hand, the rate of premature births has been increasing over the

1. It is important to note that the weight of infants are limited by gestational age. These ranges were considered when the empirical strategy was adjusted.

years. Finally, the survival rate of mothers to delivery has not shown a clear trend over time. These trends are probably due to multiple factors. The objective of this research is to evaluate the impact of deforestation on this cause.

Figure 1: **Trends of the main variables by deforestation rate**



Notes: Birth weight is the weight of the newborn in grams (gr). LBW is a dummy variable of low birth weight (lower than 2,500 gr). Apgar< 9 is a dummy variable for whether the Apgar is less than 9. Mother survival is a dummy for mother survival at delivery. Premature is a dummy variable for whether mothers have 37 or less gestation weeks at delivery. The series correspond to the municipal average per year. Deforestation corresponds to the annual municipal tree loss divided by municipal tree cover in 2000. Municipalities with a high rate of deforestation are those that lost more than 7% of the tree cover in 2000 in the period 2011-2021, while municipalities with a low rate of deforestation are those that lost less than 2%. These values represent the first and third quartiles.

Table 1 shows descriptive statistics of the main variables in two periods, 2011 and 2021. Regarding mothers' characteristics, there are statistically significant differences between 2011 and 2021 in women's age, schooling and marital status. In 2021, mothers are slightly older and more educated, and the percentage of mothers who are married is lower. Several papers have shown that these

Table 1: **Summary statistics**

	2011		2021			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff	t-test
Panel A: Mother characteristics						
Age	25.26	6.34	26.07	6.30	0.82***	(-107.2)
Schooling	0.70	0.38	0.83	0.46	0.13***	(-247.5)
Married	0.46	0.46	0.32	0.50	-0.14***	(244.85)
Panel B: Birth outcomes						
Mother Survival	999.92	8.66	999.95	6.70	0.03***	(-3.2)
Apgar 9	0.10	0.26	0.07	0.30	-0.03***	(73.05)
No. prenatal visits	7.24	3.27	7.33	3.22	0.09***	(-22.1)
Gestational weeks	38.81	1.59	38.57	1.67	-0.23***	(-119.55)
Single birth	0.99	0.12	0.99	0.12	0.00***	(3)
First-time mother	0.37	0.47	0.34	0.48	-0.03***	(56.3)
Male	0.51	0.50	0.52	0.50	0.01**	(-2.3)
Weight	3156.24	463.79	3116.41	456.44	-39.82***	(71.8)
LBW	0.06	0.25	0.07	0.23	0.01***	(-48.55)
Premature	0.06	0.26	0.07	0.23	0.02***	(-51.05)
Panel C: Deforestation						
Deforestation	0.01	0.09	0.02	0.01	0.01***	(-155.85)

Notes:* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Birth weight is the weight of the newborn in grams (gr). LBW is a dummy variable of low birth weight (weight lower than 2,500 gr). Apgar< 9 is a dummy variable for whether the Apgar is less than 9. Mother survival is a dummy for mother survival multiplied by 1000. Premature is a dummy variable for whether mothers have 37 or less gestation weeks. Schooling is a dummy variable for whether the mother finished high school. Deforestation standardized annually.

variables are strongly related to newborn health, so all of our models control for these mother characteristics. Some authors who wrote on this subject are Kabir et al. (2017): they found that maternal factors such as age, schooling, prenatal visits, gestation weeks and number of deliveries affect newborn size. Premature delivery had the greatest negative influence on newborn size. Shah, Zao, and Ali (2011) conclude that maternal singleness is associated with an increased risk of premature delivery and an increased likelihood of low birth weight and small size in the newborn.

Regarding birth outcomes, we find statistically significant differences between 2011 and 2021 in number of prenatal visits, gestational weeks, weight of newborn, frequencies of mother survival, Apgar<9, single birth, first-time mother, low birth weight and premature.

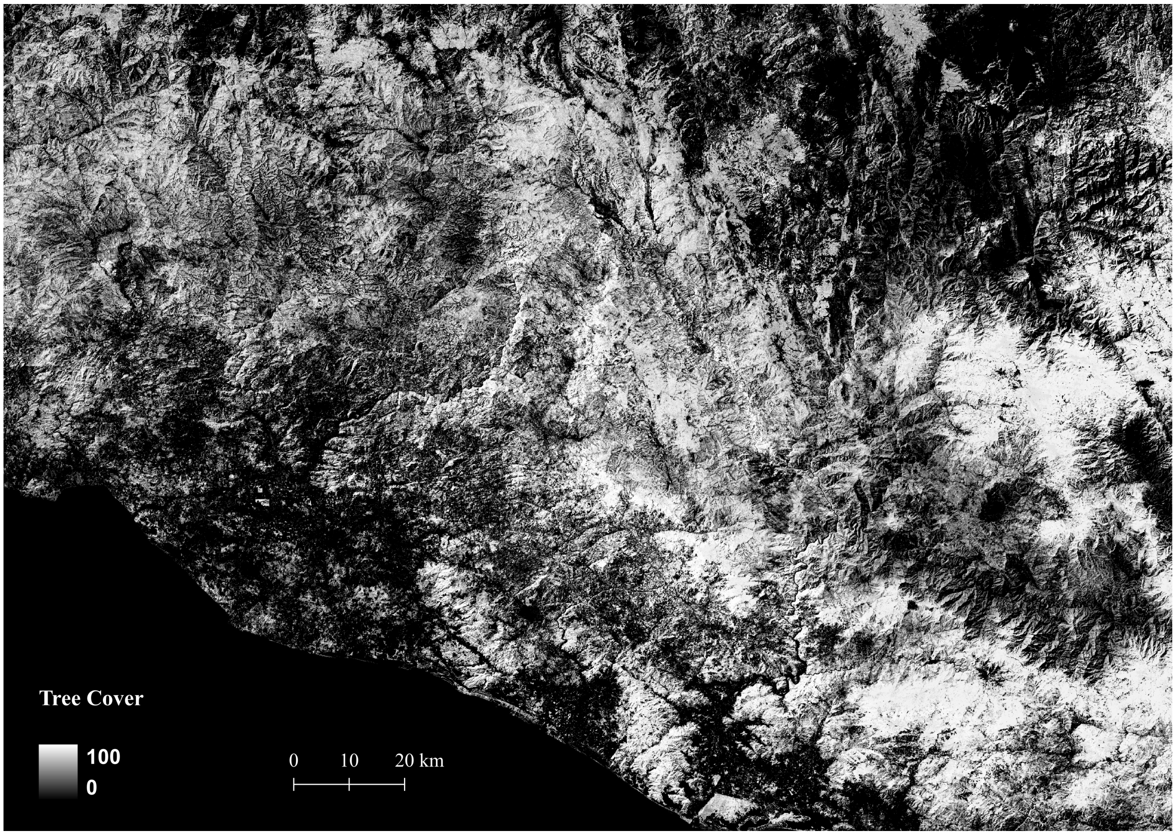
2.2 Tree canopy cover and deforestation

The data on tree cover and deforestation were obtained from the set of high-resolution satellite images published by Hansen et al. (2013). This dataset consists of six layers: tree canopy cover for the year 2000, year of gross forest cover loss event, forest cover gain in the period 2000-2012, a soil type layer (permanent water body or land surface), and two reference multispectral images for the first and last year of available information. For this work, we focus on the first two layers. Both images have a resolution of 30 meters $\times$ 30 meters per pixel. To exemplify how big this information is, over two billion pixels are needed to show the whole surface of Mexico.

The satellite images are public and can be downloaded in individual 10 $\times$ 10 degree granules (see Figure A.2). For Mexico, nine granules are needed: 20N-90W, 20N-100W, 20N-110W, 30N-90W, 30N-100W, 30N-110W, 30N-120W, 40N-110W and 40N-120W; these images together constitute the picture of the whole country.

Figure 2 illustrates a fragment of the satellite information published by Hansen et al. (2013). It shows a piece of a satellite image of the tree cover, where pixels in white represent areas with 100% tree canopy cover and the pixels in black represent no trees at all. As showed, the resolution of the image is high, which results in detailed information. Zooming in on the previous image, we can see what is represented in Figure A.3. Our objective is to extract the information from each pixel, calculate its area and locate it in the corresponding municipality. This procedure must be performed for two layers: tree cover in the year 2000 and gross loss of forest cover.

Figure 2: **A fragment of a satellite image of the tree cover**

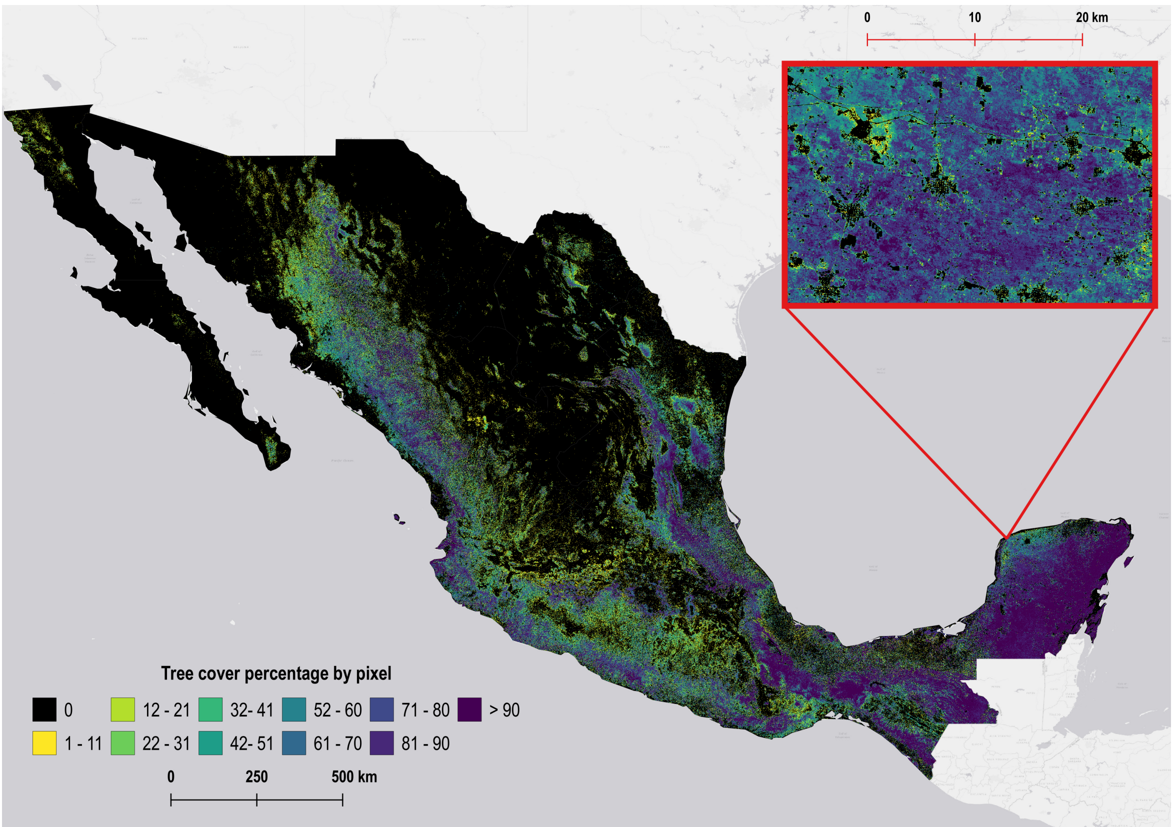


Notes: In black, the pixels with a tree cover equal to zero, and in white, the pixels with a tree cover of 100%. Each pixel represents an area of 30 meters × 30 meters.

The use of this dataset presents several advantages: 1) High resolution: The data have a resolution of 30 meters by 30 meters, allowing the detection of small-scale changes in forest cover. 2) Global coverage: The data cover the entire planet, providing a complete picture of deforestation on a global scale. 3) Long-term monitoring: The data cover a period of more than two decades (2000-2021), making it easy to identify trends and patterns of deforestation. 4) Accessibility: Data is freely available. 5) Consistency: Data were generated using a consistent methodology, allowing for reliable comparisons over time and space. (Hansen et al. 2013).

Tree cover in the year 2000 is defined as canopy closure for all vegetation taller than 5 meters in height. Each output grid cell is encoded as a percentage of the cell, which corresponds to tree cover, and takes integer values between zero and one hundred. (See Figure 3)

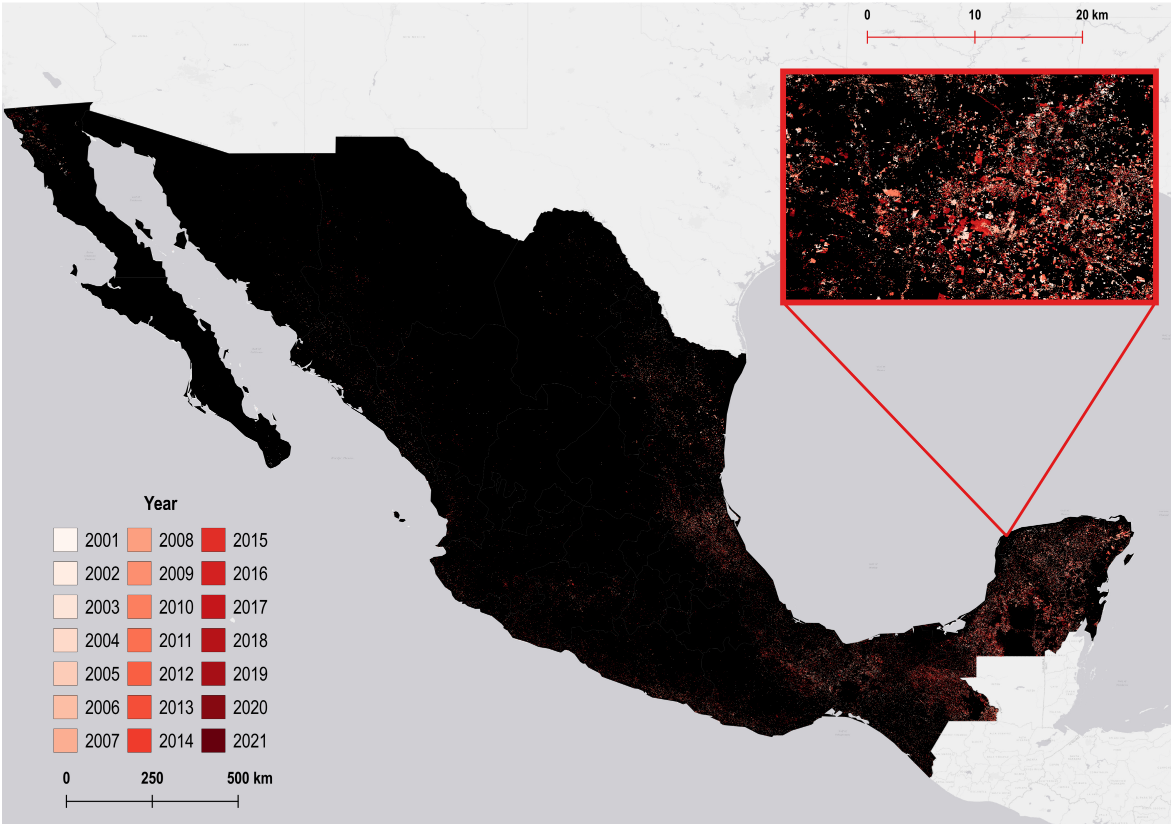
Figure 3: **Tree canopy cover for year 2000 in Mexico**



Notes: In light colors, pixels with low tree cover are shown, while in dark colors, pixels with higher tree cover are shown. The black pixels indicate that there are no trees greater than 5 meters high. Each pixel represents an area of 30 meters × 30 meters.

Forest loss is defined as a stand-replacement disturbance, or a change from a forest to non-forest state. This layer is coded with zero in the case of no tree loss or an integer between 1-21, representing the year in which the tree loss occurred, see Figure 4. Deforestation occurs when the area of trees covering a pixel disappears; the value coded in the layer indicates the year in which the area of trees greater than five meters was completely lost.

Figure 4: **Forest loss in Mexico**



Notes: Forest loss during the period 2000–2021, defined as a stand-replacement disturbance, or a change from a forest to non-forest state. Coded as the year in which the loss was detected. In black, pixels with no tree loss. Each pixel represents an area of 30 meters × 30 meters.

It is important to note that the definition of forests proposed by Hansen et al. (2013) is based on the definition of the Food and Agriculture Organization of the United Nations (FAO), which is widely and internationally used and accepted. FAO defines a forest as an area of at least 0.5 hectares, with a minimum canopy cover of 10 percent and trees capable of reaching a height of at least 5 meters at maturity. The definition also includes land that is temporarily depopulated due to human intervention or natural causes, but is expected to return to forest cover. Land that is predominantly in agricultural or urban use is not included (Food and United Nations (FAO) 2020). This definition is not universal and that other criteria, such as canopy and density cover, may also be used to define forests depending on the context and purpose of the study.

With this definition, Hansen et al. (2013) was able to identify and map changes in global forest cover over time. This definition also provided a standardized way to monitor and assess forest cover and deforestation on a global scale.

In order to obtain information from each satellite image and map it geographically, the pixels were transformed into polygons. Annual tree loss was obtained by aggregating information at the municipal level and adding the area corresponding to all pixels within the geographic delimitation of each municipality according to the Geostatistical Framework of INEGI, 2020. The area of a cell within municipal boundaries is allocated proportionally according to the area of the pixel within each municipality. The processing of tree cover for the year 2000 is similar, except this time, the sum corresponds to the proportion of tree cover of each cell. Mathematically:

$$Tree\ Loss\,_m^t = \sum_n^N Area(pixel\,_{mn}^t) \tag{1}$$

The variable $Tree\ Loss\,_m^t$ represents the loss of forest cover in municipality m in year t. The above is obtained by adding the areas of the N cells with information about the year t within the municipality m. The data to generate this variable are obtained from the *Year of gross forest cover loss event layer* of the Hansen et al. (2013) dataset.

$$Tree\ Cover\,_m^{2000} = \sum_n^N Area(Pixel\,_{mn}^{2000}) \cdot Coverage(Pixel\,_{mn}^{2000}) \tag{2}$$

The variable $Tree\ Cover\,_m^{2000}$ refers to the tree cover in the year 2000 in the municipality m and is obtained by multiplying the pixel area by the percentage of tree cover of the cell. In equation 2, function $Coverage(\cdot)$ refers to the percentage of the cell that is covered by trees.The data for generating this variable are obtained from the *Tree canopy cover for year 2000 layer* of the Hansen et al. (2013) dataset.

Thus, our standardized measure of deforestation is defined as follows:

$$Deforestation_{tm} = \frac{Tree\ Loss_{m}^{t}}{Tree\ Cover_{m}^{2000}} \tag{3}$$

In equation 3, we represent deforestation in year t in the municipality m relative to the forest area of that municipality in 2000, the first period for which Hansen et al. (2013) provides data. Tree gain is not considered part of the denominator, so it is important to highlight that the ratio can be greater than one. To clarify doubts about our measure of deforestation, a robustness test was performed by varying the proposed definition. The results are detailed later in the document.

Figure A.8 shows the proportion of tree cover in 2000 by state; this ratio is obtained by dividing the sum of state tree cover (see Figure A.7) by the total area of the state. It is important to note that the definition of tree cover, described in Equation 2 and represented in figures A.7 and A.4, considers only trees over 5 meters high, so a low tree cover rate does not indicate the absence of natural areas. For example, the main ecosystem in Baja California is the xerophytic scrub, which makes up 92% of the surface and has a height of 15 centimeters to 4 meters (Sanidad Forestal 2022).

The relationship between the logarithm of the cumulative deforestation rate and the proportion of tree cover by state is shown in Figure A.9. This graph suggests that high rates of forest loss do not necessarily occur in states with a high presence of forests, such as Baja California, Nuevo León, and San Luis Potosí (see Table A.1).

3 Empirical strategy

The empirical strategy used to answer the research question is a fixed effects model. According to Kempf-Leonard (2004), a fixed effects model estimates the effects of variables that change over time. It further assumes that the effects of unmeasured variables that do not change can be captured by municipality-specific dummy variables. We estimate the following model:

$$Y_{itm} = \alpha + \beta \cdot Deforestation_{tm} + \gamma \cdot X_{itm} + \theta_m + \lambda_t + \varepsilon_{imt} \tag{4}$$

where Y_{itm} represents the health variable of the newborn i in year t in municipality m. $Deforestation_{tm}$ is the measure described in equation 3. X_{itm} is a set of control variables associated with birth i in year t in municipality m. Such as age, schooling, marital status of the mother, number of pregnancies, total prenatal visits, place of birth of the newborn and place of residence of the mother, gestation weeks, pregnancy product (single, twin or more) and gender of the newborn. θ_m are municipal fixed effects. λ_t are year fixed effects. ε_{imt} is the error term. We cluster the standard errors at the municipal level. The coefficient of interest is β, the effect of deforestation on the health of newborns. This coefficient is obtained by OLS.

The key assumptions of our fixed effects model are no correlation between the municipal specific effects and the explanatory variables, no other municipal level variables correlated with both deforestation and health outcomes, it is also assumed that the error term is homocedastic, not serially correlated and that there is no multicollinearity in the independent variables.

In addition, to fit the model, the following considerations were considered: 1) The time window is from 2011 to 2021, 2) only the complete records of newborns were used, 3) only records of newborns who were born in municipalities where deforestation was present for at least one year of the research period were used.

As a robustness test, we explore whether changes in the forest definition, the time window and the sample of municipalities affect our results. We present our results in Section 4. We use an alternative measure of deforestation to estimate our models. We also estimate the effects of deforestation in two different samples, one with a shorter time window discarding the years of the coronavirus pandemic, and another sample with municipalities with deforestation rates less than one, excluding possible outliers.

4 Results

Table 2 Panel A presents the coefficients associated with the baseline models for the five variables of interest: birth weight, LBW, Apgar<9, mother survival and premature birth. The base models include fixed effects by year and municipality, and for the models relating to weight, we add fixed effects for week of gestation. The coefficient of interest is the one associated with the deforestation variable, which appears in the first row of the table. For the values of each coefficient and their standard error for all the variables in the model, see the Table A.2.

The first column of Table 2 Panel A represents the model associated with newborn weight. The coefficient for deforestation indicates that an increase in one unit of deforestation decreases newborn weight by 18.43 grams. Column two represents the model linked to the low birth weight condition. An increase of one standard deviation in deforestation increases the chance of having a low birth weight by 0.439%. Column three shows that an increase in deforestation of one standard deviation is associated with an increase in the probability of having an Apgar score below nine of 0.438 percentage points. The model associated with maternal survival is represented in column four, the coefficient associated with deforestation is not statistically significant. Finally, the model associated with premature infants is presented in column 5. The coefficient of deforestation shows that an increase of one standard deviation in deforestation reduces the probability of being premature by 1.73%.

The baseline models were adjusted to include additional covariates, which represent sociodemographic characteristics of the mother and are strongly associated with the health of the newborn. Table 2 Panel B represents the fit of these models. The coefficient of interest is the one that is related to the deforestation variable. To see the value of each coefficient and its standard error for all the variables in the model, see Table A.3.

As shown in Table 2 Panel B, the coefficients associated with deforestation are similar to the coefficients presented in Table 2 Panel A, which adds confidence to the interpretation of our results as causal. Adding controls to the baseline models, we find that an increase of one unit of deforestation

Table 2: **Results**

	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature
Panel A: Baseline models					
Deforestation	-18.434***	0.004***	0.044***	0.062	-0.017***
	(2.969)	(0.001)	(0.007)	(0.040)	(0.001)
Adjusted R^2	0.398	0.471	0.036	0.000	0.011
Panel B: Models with controls					
Deforestation	-19.347***	0.004***	0.047***	0.057	-0.015***
	(2.867)	(0.001)	(0.007)	(0.040)	(0.001)
2011 dep. var. mean	3,156.238	0.055	.099	999.924	0.058
Observations	16,176,566	16,176,566	16,176,566	16,176,566	16,359,152
Adjusted R^2	0.415	0.481	0.077	0.000	0.072
Clusters	2,062	2,062	2,062	2,062	2,062

Notes: Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard error clustered at the municipality level. Birth weight is the weight of the newborn in grams (gr). LBW is a dummy variable of low birth weight (lower than 2,500 gr). Apgar< 9 is a dummy variable for whether the Apgar is less than 9. Mother survival is a dummy for mother survival at delivery multiplied by 1000. Premature is a dummy variable for whether mothers have 37 or less gestation weeks at delivery. Deforestation standardized annually. Panel A: All models control for year and municipality fixed effects. Models (1)-(2) also control for gestational weeks fixed effects. Panel B: All models control for a mother's age, schooling, marital status, newborn's sex, number of births, first time mother, month, year and municipality fixed effects, all models control for the number of prenatal visits. Models (1)-(4) also control for gestational weeks fixed effects.

decreases the weight of the newborn by 19.35 grams. Additionally, an increase of one standard deviation in deforestation increases the probability of the newborn having a low birth weight and an Apgar score of less than nine by 0.39% and 4.69%, respectively. In terms of the 2011 rates, this corresponds to an increase in LBW of approximately 7% and an increase in Apgar below nine of 47.1%. Finally, a one standard deviation increase in deforestation is associated with a reduction in the probability of being premature by 1.54 percentage points, or -26.5% with respect to the outcome mean in 2011.

A decrease in the probability of premature birth was observed, contrary to the consensus in the literature on this subject. It is speculated that at least some of the difference in findings across studies relates to differences in the phenomenon of deforestation between Mexico and other regions, and thus the channels through which deforestation leads to changes in the health of the newborns. The variance in the findings compared to the existing literature, which primarily focuses on regions like Brazil and Indonesia, could be attributed to differences in regional environmental and social contexts. According to Carrillo et al. (2018), deforestation increases the probability of premature birth in Brazil. The channel they propose is through malaria. Several articles, such as Berazneva and Byker (2017) and Garg (2019), have shown that deforestation contributes to the increase in cases of malaria. This study proposes that the mechanism is different from malaria because in Mexico there were only 242 cases in 2021 (SSA 2022) compared to 132,971 in Brazil (SVS 2022). This result strongly suggests that the connection between deforestation and premature birth is complex and specific to each region. In other words, the observed difference is thought to be a result of the underlying mechanism.

Table A.3 shows that the number of prenatal visits has a positive effect on four dependent variables of interest: birth weight, low birth weight, Apgar<9 and premature. An increase in the number of visits increases birth weight and reduces the chance of having a low birth weight, an Apgar score below nine, or being born prematurely. Similarly, if the mother completed high school, positive effects on weight, LBW, and Apgar<9 are obtained compared to those who did not.

If the pregnancy product is unique, there is a positive effect on newborn weight and maternal survival, as well as a decrease in the probability of LBW and premature birth in relation to deliveries with more than one product. If the newborn is male, the weight increases regarding being female; increased expectations of showing an Apgar less than nine and being premature increases. If the mother is married, the weight of the newborn increases in comparison with the children of single mothers; the probability of being premature increase. Lastly, if the mother is a first-time mother, the weight of the newborn is lower compared to infants born to women who have already had a child. Similarly, the probability of having a low birth weight and an Apgar score below nine is higher.

In conclusion, deforestation has a negative effect on the weight of newborns; the greater the loss of trees, the lower the birth weight. Similarly, forest loss increases the probability that the newborn will have a low birth weight and an Apgar score of less than nine. Deforestation decreases the probability that the newborn will be premature. We found that deforestation is not statistically significant in describing maternal survival.

5 Mechanisms

Different authors have demonstrated the effects of deforestation on human health, which are propagated through different mechanisms. These include increased risk of vector-borne diseases, increased exposure to air pollution, increased risk of respiratory and water-related diseases and weather effects.

Concerning the increased risk of vector-borne diseases, Santos and Almeida (2018) find that deforestation has direct and spillovers effects on malaria cases; they find a quadratic relationship between deforestation and malaria, where deforestation areas increase the cases of such disease.

On the other hand, air pollution can have a wide range of health effects, depending on the type of pollutant. Some health impacts include infant mortality and low birth weight (Emden and Murphy 2018). The impact of deforestation on access to clean drinking water has health consequences. Naito and Mapulanga (2019) find that deforestation has a negative impact on access to drinking water, while Pruss-Ustun, WHO, et al. (2008) mention that almost one tenth of the global disease burden could be prevented by improving water supply, sanitation, hygiene and management of water resources. Finally, McElroy et al. (2022) found that experiencing higher maximum temperatures and smaller diurnal temperature range during the last week before birth increased the risk of preterm birth and stillbirth.

In the context of this research, we examine two mechanisms, air pollution and weather. Currie and Walker (2011) conducted empirical work on the relationship between air pollution and infant health. They found that a decrease in automobile congestion, the major source of air pollution, reduces the likelihood of low birth weight in newborns. To establish a relationship between deforestation and air

Table 3: **Mechanisms**

	(1)	(2)
	Good Air Days per Year	Average Annual Temperature
Deforestation	-220.980 *	5.880**
	(108.598)	(1.904)
2011 dep. var. mean	100	21.519
Observations	160	352
Adjusted R^2	0.653	0.988
Clusters	50	32

Notes: Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. **Column 1:** The model controls for year and municipality fixed effects. Years range from 2011 to 2016. We took only the municipalities with air quality monitoring stations. Standard errors clustered at the municipality level. Good Air Days is the number of days with good air quality per year, pollutant PM_{10}. Deforestation standardized annually. **Column 2:** The model controls for year and state fixed effects. Years range from 2011 to 2021. Standard errors clustered at the state level. Average Annual Temperature is the average monthly temperatures by state. Deforestation standardized annually.

quality in Mexico, we analyzed data from SEMARNAT.

From 2011 to 2016, available data represent the number of days with good air quality per year, and by pollutant type; we considered data for Particulate Matter (PM_{10}). Emden and Murphy (2018) found that this type of pollutant affects the health of newborns. Table 3 column 1 shows that there is a negative relationship between deforestation and good air days.

Regarding weather, Keivab and Cozzani (2022) results suggest that the incidence of negative birth outcomes increased for children exposed to extreme heat in early gestation. The particular outcomes are preterm birth, low birth weight, and very low birth weight. In order to investigate the relationship between deforestation and temperature in Mexico, we inspected the behavior of such variables at a state level: the available data consists of the monthly average temperature by state. Table 3 column 2 exhibits a positive relationship between deforestation and the average temperature, which strengthen the hypothesis that deforestation increases temperature.

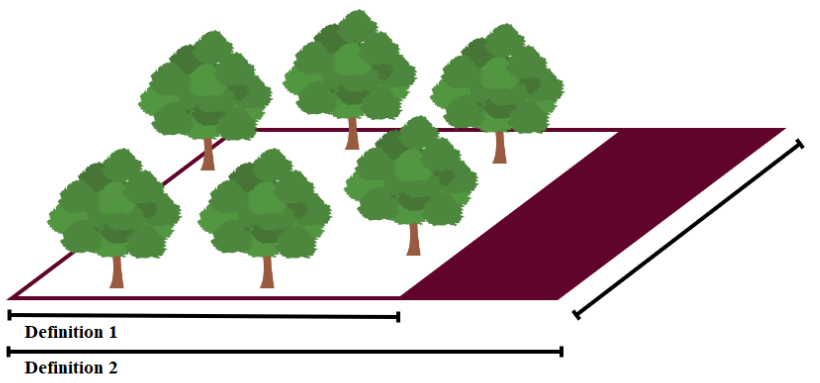
6 Robustness

6.1 Alternative definition of deforestation

To further reinforce the validity of the results and dispel doubts about the measurement of deforestation, we conducted a conceptual transformation to observe whether the effects found persist even with a change in the way of measurement. The change is analogous to varying the denominator in Equation 3.

Figure 5: **Change in the definition of deforestation**

Pixel representation



Notes: In white, the area of the pixel that corresponds to the percentage of tree cover. In cherry, the part of the pixel that does not have any trees. The updated definition focuses on the pixel's entire surface area.

The new definition of tree cover considers the total area of the pixel where there are trees of at least 5 meters in height and, together with the surrounding pixels, the total area exceeds 0.5 hectares. The new definition is consistent with the definition proposed by the FAO. Figure A.10 of the Appendix illustrates the motivation for the change in the definition of tree cover for the year 2000.

Figure 5 illustrates the change in definition. In the image, Equation 2 refers to the white area, while the new definition considers the whole area of the pixel, i.e. the sum of the white and cherry area. Figure 5 is illustrative, and the motivation for this new definition is to consider the total area of the forest, since the canopy can have holes in between, and still be the same ecosystem.

Thus, the new tree cover measure for the year 2000 is defined as:

$$\widetilde{Tree\ Cover}_{m}^{2000} = \sum_{n}^{N} Area(Pixel_{mn}^{2000}) \tag{5}$$

Then, the measure of deforestation is given by the following expression:

$$\widetilde{Deforestation}_{tm} = \frac{Tree\ Loss_{m}^{t}}{\widetilde{Tree\ Cover}_{m}^{2000}} \tag{6}$$

Table 4 Panel A shows the results of calibrating the models with the new definition of deforestation described in equation 6. In the table, the coefficients associated with deforestation maintain the same sign as those of the models adjusted in Section 4. The changes in the magnitude of the coefficients are due to changes in the measure of tree cover and therefore in the standardized measure of deforestation, the measure of deforestation becomes smaller. Consistent with our results, we find that deforestation increase the likelihood of being LBW and having an Apgar score below nine. Furthermore, Table 4 Panel A also shows that deforestation decreases the birth weight and decreases the probability of being premature. We also validate that the deforestation does not affect the probability of mother survival. These results show that our results are also robust to this alternative specification of deforestation.

6.2 Pre-pandemic period

The World Health Organization declared the COVID-19 pandemic a public health emergency of international concern on January 30, 2020. The first case in Mexico was registered on February 28, 2020. This pandemic has had various effects on different dimensions, most of them unknown at the

Table 4: **Robustness tests**

	(1)	(2)	(3)	(4)	(5)
	Birth weight	LBW	Apgar< 9	Mother survival	Premature
Panel A: Alternative definition of deforestation					
Deforestation	-74.831***	0.015***	0.153**	0.325	-0.061***
	(15.412)	(0.004)	(0.054)	(0.225)	(0.007)
2011 dep. var. mean	3,156.238	0.055	0.099	999.924	0.058
Observations	16,176,566	16,176,566	16,176,566	16,176,566	16,359,152
Panel B: Pre-pandemic period					
Deforestation	-20.468***	0.003**	0.074***	0.078	-0.015***
	(4.881)	(0.001)	(0.019)	(0.065)	(0.003)
2011 dep. var. mean	3,156.238	0.055	0.099	999.924	0.058
Observations	12,229,654	12,229,654	12,229,654	12,229,654	12,381,801
Panel C: Municipalities with deforestation less than 1					
Deforestation	-72.921***	0.015***	0.135*	0.293	-0.062***
	(15.257)	(0.004)	(0.065)	(0.213)	(0.008)
2011 dep. var. mean	3,154.491	0.055	0.100	999.924	0.058
Observations	14,486,305	14,486,305	14,486,305	14,486,305	14,650,866

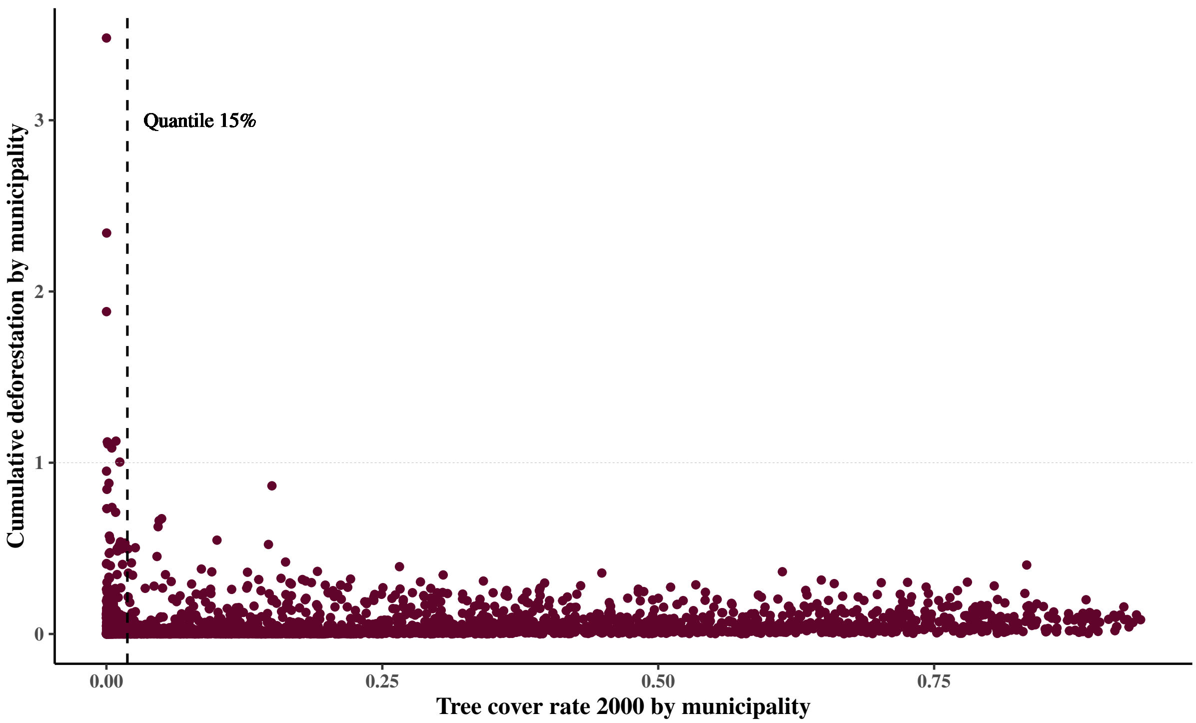
Notes: Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models control for a mother's age, schooling, marital status, number of prenatal visits, newborn's sex, number of births, first time mother and month, year and municipality fixed effects. Models (1)-(4) also control for gestational weeks. Standard error clustered at the municipality level. Birth weight is the weight of the newborn in grams (gr). LBW is a dummy variable for having low birth weight (lower than 2,500 gr). Apgar< 9 is a dummy variable for whether the Apgar is less than 9. Mother survival is a dummy for mother survival at delivery multiplied by 1000. Premature is a dummy variable for whether mothers have 37 or less gestation weeks at delivery. Deforestation standardized annually.

time of writing this research. For that reason, models were fitted for a shorter time window, from 2011-2018. This does not consider the period in which the pandemic occurred.

Panel B of Table 4 shows that deforestation has a negative relationship with newborn weight. It also increases the likelihood of having a low birth weight and an Apgar less than nine. On the other hand, it decreases the chance of being premature. We also validate that the deforestation does not affect the probability of mother survival. These results are in line with those presented in Section 4 and show that our main results are robust in pre-pandemic periods.

6.3 Outlier exclusion

Figure 6: **Cumulative deforestation rate v.s. Tree cover rate by municipality**



Notes: The X-axis represents the proportion of forest in relation to the total area of the municipality. The Y-axis represents the cumulative deforestation rate for the municipality for the period 2011-2021 relative to the forest in 2000.

A final validation test is to consider only municipalities with a given percentage of forest, to avoid deforestation outliers. As shown in Figure 6, municipalities with a higher rate of deforestation are those with a reduced proportion of forest. To clarify doubts about whether deforestation rates are biased by the tree cover ratio, we use a sample of municipalities in which forest represents approximately more than 2% of their area, this is the quantile 15 represented in Figure 6. It is evident from the figure that municipalities with a cumulative deforestation rate higher than 1 are excluded.

We show in Table 4 Panel C that the results of our analyses of deforestation on health variables are consistent in a group of municipalities with a deforestation rate below one. Therefore, high rates of deforestation due to low tree cover in 2000 are not a concern. This shows that our results remain robust to a sample of municipalities.

7 Discussion and Conclusion

The present thesis examines the impact of deforestation on birth outcomes, with a particular focus on birth weight, the Apgar score, maternal survival at delivery, and preterm birth. Environmental issues, such as deforestation, have a significant impact on people's well-being in Mexico. The degradation of natural habitats, the loss of biodiversity, and the increase in exposure to air pollution can have adverse health consequences and exacerbate existing health disparities.

To better understand the impact of deforestation on human health in Mexico, high-quality satellite images and data are essential. The synthesis of these data sources provides a unique perspective on the scale and location of deforestation, which is often difficult to quantify. Furthermore, satellite data can provide valuable insights into areas where deforestation is most prevalent, allowing for targeted interventions to improve environmental and health outcomes.

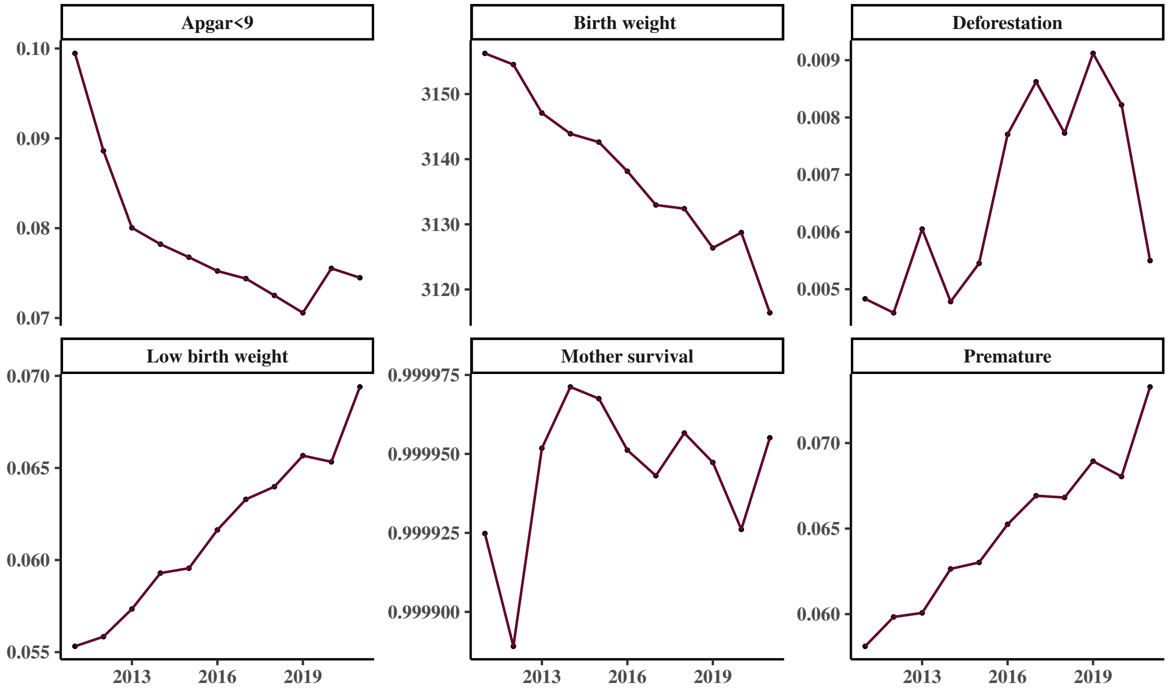
The analysis and processing of satellite data to identify patterns of deforestation may pose significant challenges. Nevertheless, the insights gained from such data can help policymakers and healthcare professionals to make informed decisions about improving the health and well-being of the population and protecting Mexico's natural resources for future generations.

The findings of this research suggest that deforestation reduces the weight of newborns in Mexico, while increasing the probability of LBW and an Apgar score smaller than 9. However, the results indicate that deforestation is not associated with maternal survival at birth and indicate that deforestation decreases the chance of being premature. Moreover, it was found that the channels through which this effect takes place are associated with environmental temperature and air pollution.

This research work not only identified the effects of deforestation on newborn health in Mexico, but also constructed a unique set of data to achieve this purpose. The data set utilized in this study provides a comprehensive assessment of the detrimental effects of deforestation on Mexican birth outcomes. Combining this information with traditional health data can help researchers and policy-makers figure out how deforestation and birth outcomes are connected. The findings of this study underscore the importance of using innovative methods and data sources to gain a more profound understanding of environmental health issues to improve population health outcomes.

8 Appendix

Figure A.1: **National trends of the main variables**



Notes: Birth weight is the weight of the newborn in grams (gr). LBW is a dummy variable of low birth weight (lower than 2,500 gr). Apgar< 9 is a dummy variable for whether the Apgar is less than 9. Mother survival is a dummy for mother survival at delivery. Premature is a dummy variable for whether mothers have 37 or less gestation weeks at delivery. The series correspond to the national average per year. Annual deforestation corresponds to national tree loss divided by national tree cover in 2000.

Table A.2: **Baseline models**

	(1) Birth weight	(2) LBW	(3) Apgar<9	(4) Mother survival	(5) Premature
Deforestation	-18.434***	0.004***	0.044***	0.062	-0.017***
	(2.969)	(0.001)	(0.007)	(0.040)	(0.001)
Year = 2011	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Year = 2012	2.894***	-0.001*	-0.011*	-0.035*	0.002***
	(0.737)	(0.000)	(0.004)	(0.015)	(0.001)
Year = 2013	-4.310***	0.001	-0.020***	0.029*	0.003***

	(0.948)	(0.000)	(0.005)	(0.013)	(0.001)
Year = 2014	-2.591*	0.000	-0.021***	0.048***	0.005***
	(1.076)	(0.000)	(0.005)	(0.012)	(0.001)
Year = 2015	-1.741	-0.000	-0.023***	0.044***	0.006***
	(1.161)	(0.000)	(0.005)	(0.012)	(0.001)
Year = 2016	-1.901	0.000	-0.025***	0.028*	0.008***
	(1.337)	(0.000)	(0.005)	(0.013)	(0.001)
Year = 2017	-5.141***	0.001	-0.026***	0.020	0.009***
	(1.366)	(0.000)	(0.006)	(0.013)	(0.001)
Year = 2018	-3.192*	0.001*	-0.028***	0.033**	0.010***
	(1.329)	(0.000)	(0.006)	(0.012)	(0.001)
Year = 2019	-4.647**	0.001	-0.029***	0.025*	0.012***
	(1.470)	(0.000)	(0.005)	(0.012)	(0.001)
Year = 2020	-2.510	0.001*	-0.025***	0.004	0.012***
	(1.549)	(0.000)	(0.005)	(0.013)	(0.001)
Year = 2021	-6.199***	0.001	-0.028***	0.034*	0.017***
	(1.553)	(0.000)	(0.006)	(0.013)	(0.001)
Gestational weeks = 18	0.000	0.000			
	(.)	(.)			
Gestational weeks = 19	41.390*	0.012**			
	(16.235)	(0.004)			
Gestational weeks = 20	101.640***	0.016***			
	(12.037)	(0.002)			
Gestational weeks = 21	180.000***	0.015***			
	(9.584)	(0.002)			
Gestational weeks = 22	244.789***	0.015***			
	(7.143)	(0.001)			
Gestational weeks = 23	332.549***	0.014***			
	(8.163)	(0.001)			
Gestational weeks = 24	406.300***	0.014***			
	(7.396)	(0.001)			
Gestational weeks = 25	486.018***	0.014***			
	(8.006)	(0.001)			
Gestational weeks = 26	579.914***	0.013***			
	(7.702)	(0.001)			
Gestational weeks = 27	691.493***	0.013***			
	(6.980)	(0.001)			
Gestational weeks = 28	806.696***	0.012***			
	(6.996)	(0.002)			
Gestational weeks = 29	927.045***	0.012***			
	(6.421)	(0.002)			
Gestational weeks = 30	1097.044***	0.012***			
	(6.267)	(0.001)			
Gestational weeks = 31	1251.785***	0.013***			
	(6.090)	(0.002)			
Gestational weeks = 32	1433.990***	0.012***			
	(5.813)	(0.001)			
Gestational weeks = 33	1642.973***	-0.013***			

	(1)	(2)	(3)	(4)	(5)
	(5.456)	(0.001)			
Gestational weeks = 34	1878.495***	-0.129***			
	(5.033)	(0.003)			
Gestational weeks = 35	2104.546***	-0.316***			
	(3.840)	(0.006)			
Gestational weeks = 36	2373.746***	-0.597***			
	(2.862)	(0.006)			
Gestational weeks = 37	2646.060***	-0.840***			
	(1.826)	(0.002)			
Gestational weeks = 38	2850.614***	-0.951***			
	(1.239)	(0.000)			
Gestational weeks = 39	2966.528***	-0.984***			
	(1.099)	(0.001)			
Gestational weeks = 40	3063.693***	-0.988***			
	(1.232)	(0.001)			
Gestational weeks = 41	3134.117***	-0.988***			
	(1.662)	(0.001)			
Constant	249.662***	0.987***	0.100***	999.923***	0.057***
	(0.190)	(0.000)	(0.005)	(0.010)	(0.001)
Observations	16,176,566	16,176,566	16,359,152	16,359,152	16,359,152
Adjusted R^2	0.398	0.471	0.036	0.000	0.011
Clusters	2,062	2,062	2,062	2,062	2,062

Notes: Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models control for year and municipality fixed effects. Models (1)-(2) also control for gestational weeks. Standard error clustered at the municipality level. Birth weight is the weight of the newborn in grams (gr). LBW is a dummy variable for having low birth weight (lower than 2,500 gr). Apgar< 9 is a dummy variable for whether the Apgar is less than 9. Mother survival is a dummy for mother survival at delivery multiplied by 1000. Premature is a dummy variable for whether mothers have 37 or less gestation weeks at delivery. Deforestation standardized annually.

Table A.3: **Models with controls**

	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature
Deforestation	-19.347***	0.004***	0.047***	0.057	-0.015***
	(2.867)	(0.001)	(0.007)	(0.040)	(0.001)
Year = 2011	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Year = 2012	2.617***	-0.000	-0.011*	-0.033*	0.003***
	(0.754)	(0.000)	(0.004)	(0.015)	(0.001)
Year = 2013	-4.785***	0.001**	-0.020***	0.028*	0.003***
	(0.920)	(0.000)	(0.005)	(0.013)	(0.001)
Year = 2014	-3.879***	0.001*	-0.022***	0.047***	0.006***
	(1.050)	(0.000)	(0.005)	(0.012)	(0.001)
Year = 2015	-3.935***	0.000	-0.023***	0.042***	0.006***

Table A.3: **Models with controls**

	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature
	(1.182)	(0.000)	(0.005)	(0.012)	(0.001)
Year = 2016	-5.107***	0.001*	-0.025***	0.026	0.008***
	(1.362)	(0.000)	(0.005)	(0.014)	(0.001)
Year = 2017	-8.848***	0.001***	-0.026***	0.017	0.010***
	(1.401)	(0.000)	(0.006)	(0.013)	(0.001)
Year = 2018	-8.030***	0.002***	-0.028***	0.030*	0.010***
	(1.369)	(0.000)	(0.006)	(0.012)	(0.001)
Year = 2019	-10.474***	0.002***	-0.030***	0.024	0.012***
	(1.510)	(0.000)	(0.005)	(0.013)	(0.001)
Year = 2020	-7.653***	0.002***	-0.027***	0.005	0.011***
	(1.555)	(0.000)	(0.005)	(0.014)	(0.001)
Year = 2021	-12.149***	0.002***	-0.029***	0.035*	0.017***
	(1.580)	(0.000)	(0.006)	(0.014)	(0.001)
Month = 1	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Month = 2	-0.156	0.000	-0.003***	-0.004	0.001
	(0.556)	(0.000)	(0.001)	(0.009)	(0.000)
Month = 3	-2.250***	0.000	-0.000	-0.006	0.002***
	(0.679)	(0.000)	(0.001)	(0.009)	(0.000)
Month = 4	-2.593***	0.000	-0.002**	0.004	0.002***
	(0.641)	(0.000)	(0.001)	(0.009)	(0.000)
Month = 5	-5.371***	0.001*	-0.001	-0.005	0.004***
	(0.695)	(0.000)	(0.001)	(0.010)	(0.000)
Month = 6	-11.299***	0.002***	-0.004***	0.006	0.005***
	(0.721)	(0.000)	(0.001)	(0.009)	(0.000)
Month = 7	-13.309***	0.001***	0.000	0.003	0.007***
	(0.761)	(0.000)	(0.001)	(0.009)	(0.001)
Month = 8	-14.257***	0.001***	-0.003*	-0.001	0.006***
	(0.787)	(0.000)	(0.001)	(0.009)	(0.000)
Month = 9	-13.021***	0.001***	-0.003**	-0.012	-0.001
	(0.762)	(0.000)	(0.001)	(0.010)	(0.000)
Month = 10	-16.198***	0.002***	-0.005***	0.006	0.001**
	(0.806)	(0.000)	(0.001)	(0.009)	(0.000)
Month = 11	-9.800***	0.001***	-0.005***	-0.003	0.001
	(0.680)	(0.000)	(0.001)	(0.010)	(0.000)
Month = 12	-8.325***	0.001**	-0.008***	-0.020*	0.001
	(0.633)	(0.000)	(0.001)	(0.010)	(0.000)
Mother's age = 12	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Mother's age = 13	-8.126	-0.006	-0.000	0.169	0.014***
	(6.093)	(0.003)	(0.005)	(0.232)	(0.004)
Mother's age = 14	1.881	-0.007*	-0.001	0.188	0.003
	(5.394)	(0.003)	(0.005)	(0.227)	(0.004)
Mother's age = 15	5.756	-0.008*	-0.001	0.168	-0.005

Table A.3: **Models with controls**

	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature
	(5.602)	(0.003)	(0.004)	(0.226)	(0.004)
Mother's age = 16	6.820	-0.007*	-0.001	0.158	-0.012**
	(5.480)	(0.003)	(0.004)	(0.226)	(0.004)
Mother's age = 17	7.991	-0.007*	-0.001	0.168	-0.015***
	(5.548)	(0.003)	(0.004)	(0.226)	(0.004)
Mother's age = 18	10.742*	-0.007*	-0.001	0.158	-0.017***
	(5.477)	(0.003)	(0.004)	(0.225)	(0.004)
Mother's age = 19	14.533**	-0.007*	0.000	0.152	-0.018***
	(5.490)	(0.003)	(0.004)	(0.226)	(0.004)
Mother's age = 20	19.208***	-0.007*	0.000	0.137	-0.020***
	(5.449)	(0.003)	(0.004)	(0.226)	(0.004)
Mother's age = 21	25.355***	-0.008*	0.001	0.137	-0.021***
	(5.458)	(0.003)	(0.004)	(0.225)	(0.004)
Mother's age = 22	30.339***	-0.008**	0.001	0.142	-0.020***
	(5.523)	(0.003)	(0.004)	(0.226)	(0.004)
Mother's age = 23	36.125***	-0.009**	0.002	0.144	-0.021***
	(5.510)	(0.003)	(0.004)	(0.225)	(0.004)
Mother's age = 24	41.841***	-0.009**	0.002	0.145	-0.020***
	(5.485)	(0.003)	(0.004)	(0.224)	(0.004)
Mother's age = 25	46.750***	-0.009**	0.003	0.137	-0.020***
	(5.484)	(0.003)	(0.004)	(0.227)	(0.004)
Mother's age = 26	51.854***	-0.009**	0.002	0.136	-0.018***
	(5.471)	(0.003)	(0.004)	(0.227)	(0.004)
Mother's age = 27	56.946***	-0.009**	0.003	0.121	-0.018***
	(5.493)	(0.003)	(0.005)	(0.226)	(0.004)
Mother's age = 28	60.300***	-0.010**	0.003	0.126	-0.017***
	(5.572)	(0.003)	(0.005)	(0.226)	(0.004)
Mother's age = 29	63.634***	-0.010***	0.003	0.129	-0.016***
	(5.503)	(0.003)	(0.005)	(0.224)	(0.004)
Mother's age = 30	67.615***	-0.010***	0.003	0.123	-0.013***
	(5.607)	(0.003)	(0.005)	(0.225)	(0.004)
Mother's age = 31	69.881***	-0.011***	0.003	0.126	-0.012**
	(5.611)	(0.003)	(0.005)	(0.225)	(0.004)
Mother's age = 32	71.541***	-0.010***	0.003	0.101	-0.008*
	(5.732)	(0.003)	(0.005)	(0.226)	(0.004)
Mother's age = 33	73.882***	-0.011***	0.004	0.105	-0.007
	(5.668)	(0.003)	(0.005)	(0.225)	(0.004)
Mother's age = 34	75.697***	-0.011***	0.004	0.131	-0.004
	(5.653)	(0.003)	(0.005)	(0.227)	(0.004)
Mother's age = 35	77.690***	-0.011***	0.004	0.106	-0.000
	(5.634)	(0.003)	(0.005)	(0.225)	(0.004)
Mother's age = 36	78.090***	-0.011***	0.005	0.089	0.003
	(5.592)	(0.003)	(0.005)	(0.228)	(0.004)
Mother's age = 37	77.899***	-0.010***	0.006	0.080	0.005

Table A.3: **Models with controls**

	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature
	(5.640)	(0.003)	(0.005)	(0.225)	(0.004)
Mother's age = 38	76.343***	-0.009**	0.007	0.071	0.009*
	(5.878)	(0.003)	(0.005)	(0.229)	(0.004)
Mother's age = 39	75.560***	-0.010**	0.008	0.057	0.012**
	(5.951)	(0.003)	(0.005)	(0.223)	(0.004)
Mother's age = 40	70.992***	-0.009**	0.008	0.117	0.015***
	(5.732)	(0.003)	(0.005)	(0.228)	(0.004)
Mother's age = 41	68.690***	-0.008*	0.009	0.075	0.019***
	(5.784)	(0.003)	(0.005)	(0.219)	(0.004)
Mother's age = 42	61.949***	-0.008*	0.013*	0.014	0.025***
	(5.949)	(0.003)	(0.005)	(0.236)	(0.005)
Mother's age = 43	54.035***	-0.004	0.013*	-0.037	0.030***
	(5.945)	(0.003)	(0.005)	(0.245)	(0.005)
Mother's age = 44	51.089***	-0.004	0.017**	0.020	0.038***
	(6.485)	(0.004)	(0.006)	(0.249)	(0.005)
Mother's age = 45	37.525***	0.000	0.018**	-0.033	0.047***
	(6.697)	(0.004)	(0.007)	(0.278)	(0.007)
Mother's age = 46	36.797***	0.004	0.014*	0.205	0.041***
	(8.346)	(0.005)	(0.007)	(0.227)	(0.007)
Mother's age = 47	27.657**	0.014*	0.010	0.198	0.062***
	(9.258)	(0.006)	(0.008)	(0.227)	(0.010)
Mother's age = 48	15.054	0.016	0.039***	0.191	0.065***
	(12.287)	(0.009)	(0.011)	(0.227)	(0.012)
Mother's age = 49	35.983**	-0.007	0.021	0.242	0.039**
	(13.283)	(0.008)	(0.013)	(0.229)	(0.014)
Mother's age = 50	35.461*	0.007	0.012	0.223	0.067***
	(15.315)	(0.010)	(0.013)	(0.227)	(0.014)
Mother's age = 51	43.040*	-0.005	0.059***	0.230	0.058**
	(16.962)	(0.012)	(0.017)	(0.227)	(0.020)
Mother's age = 52	24.677	0.006	0.025	-2.057	-0.004
	(18.147)	(0.010)	(0.016)	(2.278)	(0.015)
Mother's age = 53	23.378	0.005	0.014	0.207	0.026
	(18.225)	(0.013)	(0.017)	(0.226)	(0.019)
Mother's age = 54	19.138	0.015	-0.009	0.186	0.027
	(29.582)	(0.019)	(0.024)	(0.225)	(0.027)
Mother's age = 55	14.086	0.027	0.000	0.197	0.034
	(30.265)	(0.018)	(0.027)	(0.226)	(0.030)
Mother's age = 56	70.628	-0.014	0.024	0.206	0.048
	(42.437)	(0.019)	(0.027)	(0.228)	(0.033)
Mother's age = 57	42.385	0.020	-0.003	0.216	-0.003
	(36.918)	(0.021)	(0.030)	(0.225)	(0.024)
Mother's age = 58	71.052	-0.035***	-0.027	0.191	-0.016
	(37.604)	(0.011)	(0.026)	(0.225)	(0.024)
Mother's age = 59	18.867	-0.001	0.079	0.181	-0.086***

Table A.3: **Models with controls**

	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature
	(65.812)	(0.024)	(0.073)	(0.228)	(0.021)
Mother's age = 60	-30.020***	-0.138***	-0.033***	0.103	-0.042***
	(5.991)	(0.004)	(0.005)	(0.225)	(0.004)
Gestational weeks = 18	0.000	0.000	0.000	0.000	
	(.)	(.)	(.)	(.)	
Gestational weeks = 19	217.105**	-0.065	0.043***	-0.164***	
	(73.279)	(0.052)	(0.010)	(0.031)	
Gestational weeks = 20	187.532***	-0.024	-0.109*	-0.125***	
	(26.247)	(0.013)	(0.048)	(0.031)	
Gestational weeks = 21	243.853***	-0.015*	-0.083***	-0.137***	
	(13.338)	(0.007)	(0.022)	(0.028)	
Gestational weeks = 22	304.735***	-0.009*	-0.080***	-0.135***	
	(7.342)	(0.003)	(0.015)	(0.027)	
Gestational weeks = 23	394.264***	-0.010***	-0.070***	-0.136***	
	(8.649)	(0.002)	(0.009)	(0.027)	
Gestational weeks = 24	465.424***	-0.008***	-0.101***	-0.418	
	(7.333)	(0.002)	(0.008)	(0.289)	
Gestational weeks = 25	545.864***	-0.010***	-0.132***	-0.776*	
	(8.316)	(0.002)	(0.009)	(0.373)	
Gestational weeks = 26	638.388***	-0.010***	-0.178***	-0.519*	
	(7.391)	(0.002)	(0.009)	(0.231)	
Gestational weeks = 27	746.277***	-0.009***	-0.247***	-0.747**	
	(6.991)	(0.002)	(0.010)	(0.242)	
Gestational weeks = 28	862.895***	-0.010***	-0.318***	-0.418**	
	(7.171)	(0.002)	(0.009)	(0.130)	
Gestational weeks = 29	979.567***	-0.009***	-0.386***	-0.435**	
	(6.610)	(0.002)	(0.011)	(0.152)	
Gestational weeks = 30	1151.917***	-0.011***	-0.453***	-0.448***	
	(6.466)	(0.002)	(0.010)	(0.115)	
Gestational weeks = 31	1304.182***	-0.012***	-0.511***	-0.290**	
	(6.816)	(0.003)	(0.012)	(0.092)	
Gestational weeks = 32	1489.720***	-0.013***	-0.587***	-0.517***	
	(5.941)	(0.002)	(0.010)	(0.104)	
Gestational weeks = 33	1698.425***	-0.039***	-0.658***	-0.365***	
	(5.829)	(0.002)	(0.009)	(0.063)	
Gestational weeks = 34	1929.724***	-0.152***	-0.728***	-0.318***	
	(5.013)	(0.003)	(0.007)	(0.051)	
Gestational weeks = 35	2149.823***	-0.334***	-0.785***	-0.248***	
	(3.956)	(0.006)	(0.006)	(0.035)	
Gestational weeks = 36	2406.915***	-0.607***	-0.839***	-0.235***	
	(2.997)	(0.006)	(0.005)	(0.031)	
Gestational weeks = 37	2664.538***	-0.838***	-0.884***	-0.200***	
	(2.449)	(0.002)	(0.005)	(0.028)	
Gestational weeks = 38	2861.351***	-0.943***	-0.901***	-0.200***	

Table A.3: **Models with controls**

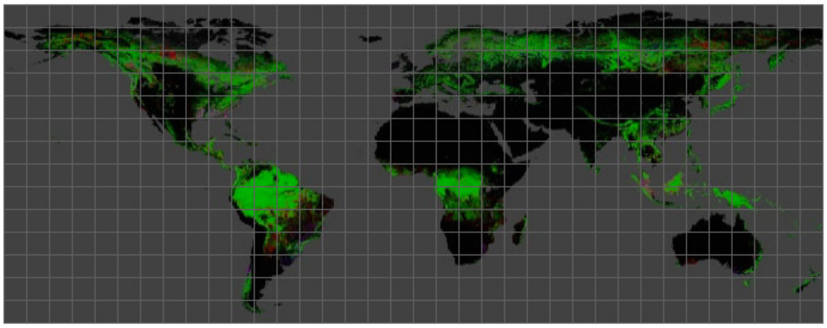
	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature
	(2.128)	(0.001)	(0.005)	(0.028)	
Gestational weeks = 39	2979.139***	-0.975***	-0.910***	-0.193***	
	(2.014)	(0.001)	(0.006)	(0.028)	
Gestational weeks = 40	3077.825***	-0.979***	-0.907***	-0.190***	
	(1.945)	(0.001)	(0.006)	(0.027)	
Gestational weeks = 41	3148.435***	-0.979***	-0.899***	-0.185***	
	(2.167)	(0.001)	(0.006)	(0.027)	
Number of prenatal visits	4.186***	-0.001***	-0.001**	0.006***	-0.004***
	(0.216)	(0.000)	(0.000)	(0.001)	(0.000)
Mother finished high school? = No	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Mother finished high school? = Yes	14.180***	-0.003***	-0.006***	0.013*	0.003***
	(1.005)	(0.000)	(0.001)	(0.006)	(0.000)
The birth was unique? = No	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
The birth was unique? = Yes	264.202***	-0.198***	0.016***	-0.019	-0.489***
	(3.447)	(0.002)	(0.002)	(0.025)	(0.010)
Gender = Female	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Gender = Male	58.125***	-0.001**	0.003***	0.007*	0.006***
	(0.684)	(0.000)	(0.000)	(0.004)	(0.000)
Mother is married ? = No	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Mother is married ? = Yes	9.339***	-0.002***	0.002	-0.007	0.003***
	(0.644)	(0.000)	(0.001)	(0.004)	(0.000)
First-time mother? = No	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
First-time mother? = Yes	-41.963***	0.008***	0.008***	-0.007	-0.001
	(1.080)	(0.000)	(0.001)	(0.005)	(0.000)
Mother's age = 62					-0.063***
					(0.004)
Constant	-118.978***	1.192***	0.982***	999.958***	0.575***
	(7.139)	(0.003)	(0.005)	(0.238)	(0.010)
Observations	16,176,566	1,6176,566	16,176,566	16,176,566	16,359,152
Adjusted R^2	0.415	0.481	0.077	0.000	0.072
Clusters	2,062	2,062	2,062	2,062	2,062

Table A.3: **Models with controls**

	(1) Birth weight	(2) LBW	(3) Apgar< 9	(4) Mother survival	(5) Premature

Notes: Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models control for a mother's age, schooling, marital status, number of prenatal visits, newborn's sex, number of births, first time mother and month, year and municipality fixed effects. Models (1)-(4) also control for gestational weeks. Standard error clustered at the municipality level. Birth weight is the weight of the newborn in grams (gr). LBW is a dummy variable for having low birth weight (lower than 2,500 gr). Apgar< 9 is a dummy variable for whether the Apgar is less than 9. Mother survival is a dummy for mother survival at delivery multiplied by 1000. Premature is a dummy variable for whether mothers have 37 or less gestation weeks at delivery. Deforestation standardized annually.

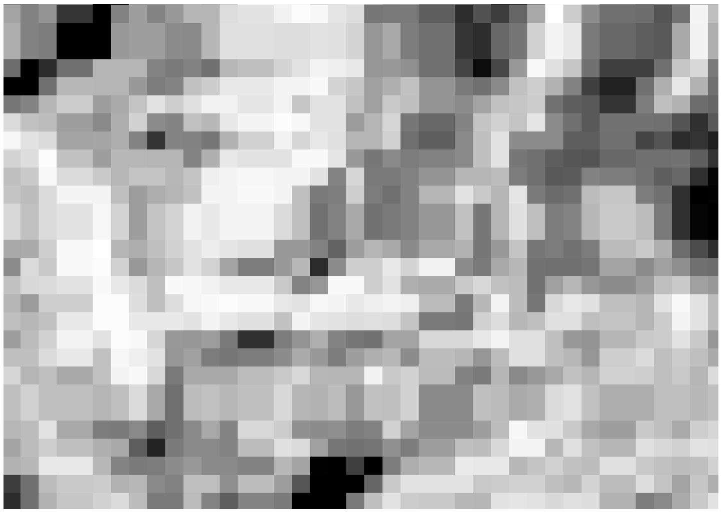
Figure A.2: **Satellite images download**



Source: Image taken from Global Forest Change 2000–2021

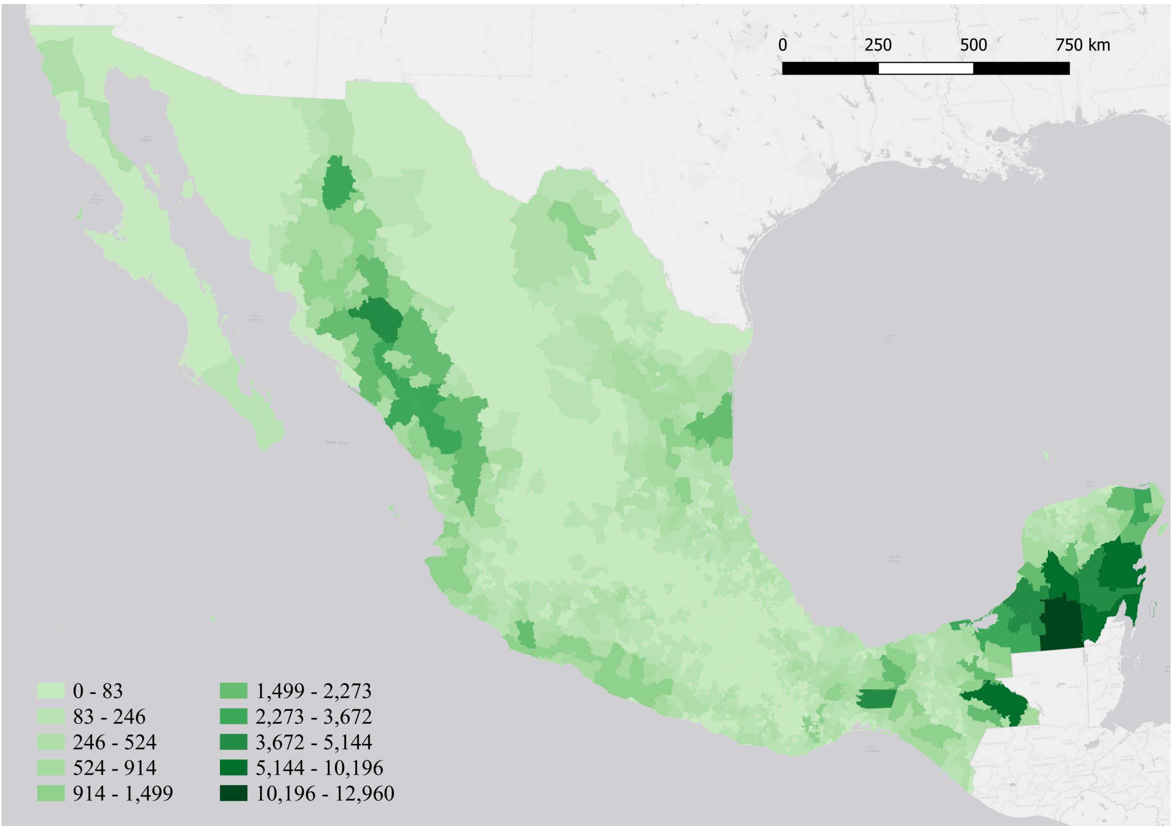
Notes: Each square of the grid represents a granule.

Figure A.3: **Close-up of a satellite image of tree cover**



Notes: In white, the pixels are completely covered by trees, and in black, they don't have any trees. Each pixel represents an area of 30 meters $\times$ 30 meters.

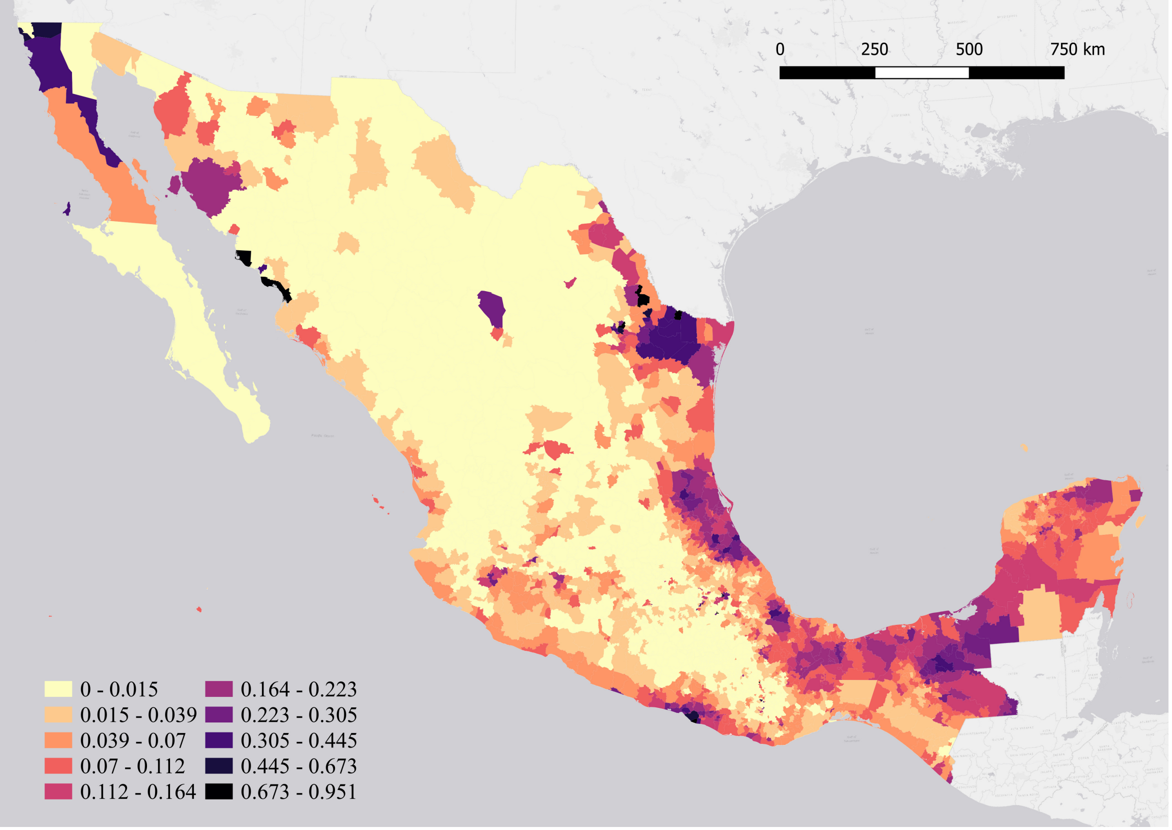
Figure A.4: **Tree cover in the year 2000 by municipality** (km^2)



Notes: Tree cover in 2000 by municipality is shown on the map. The municipalities with the highest amount of tree cover are dark green. Equation 2 was used to calculate this area.

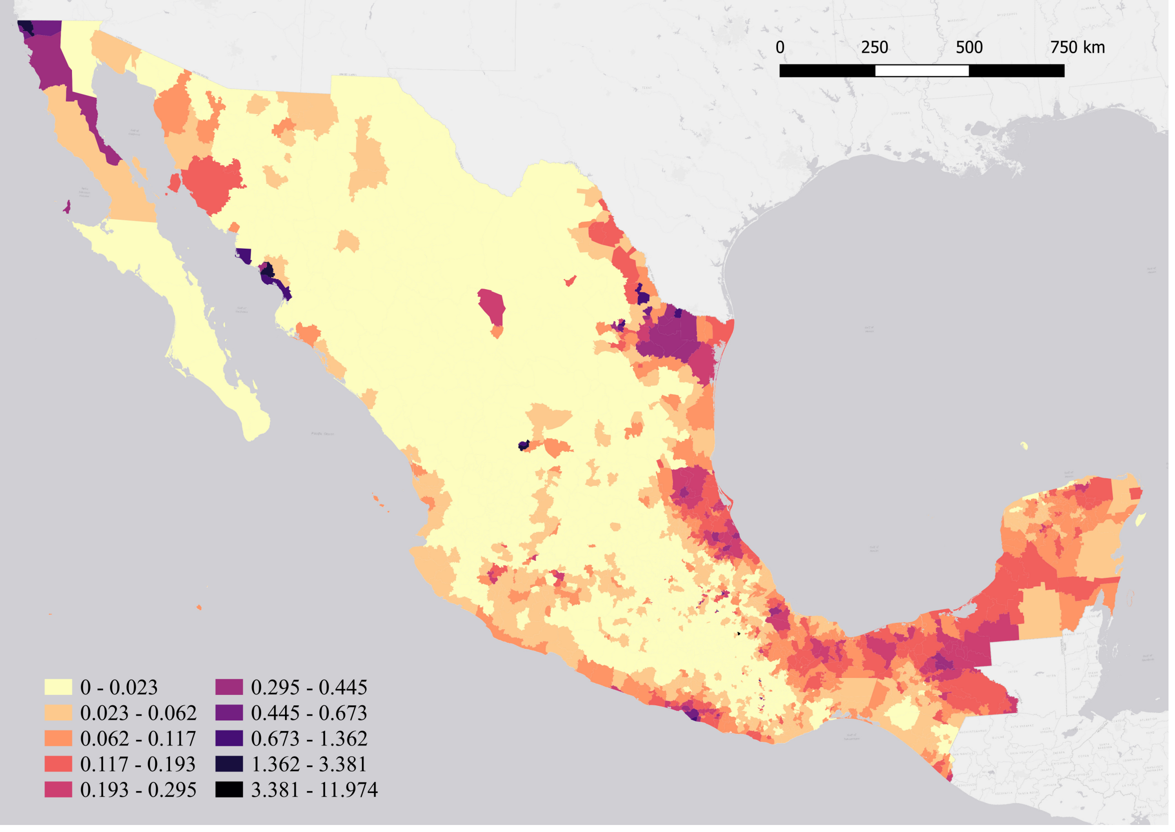
Figure A.5: **Cumulative tree loss (2011-2021) / Tree cover (2000)**

Municipalities with a ratio below one



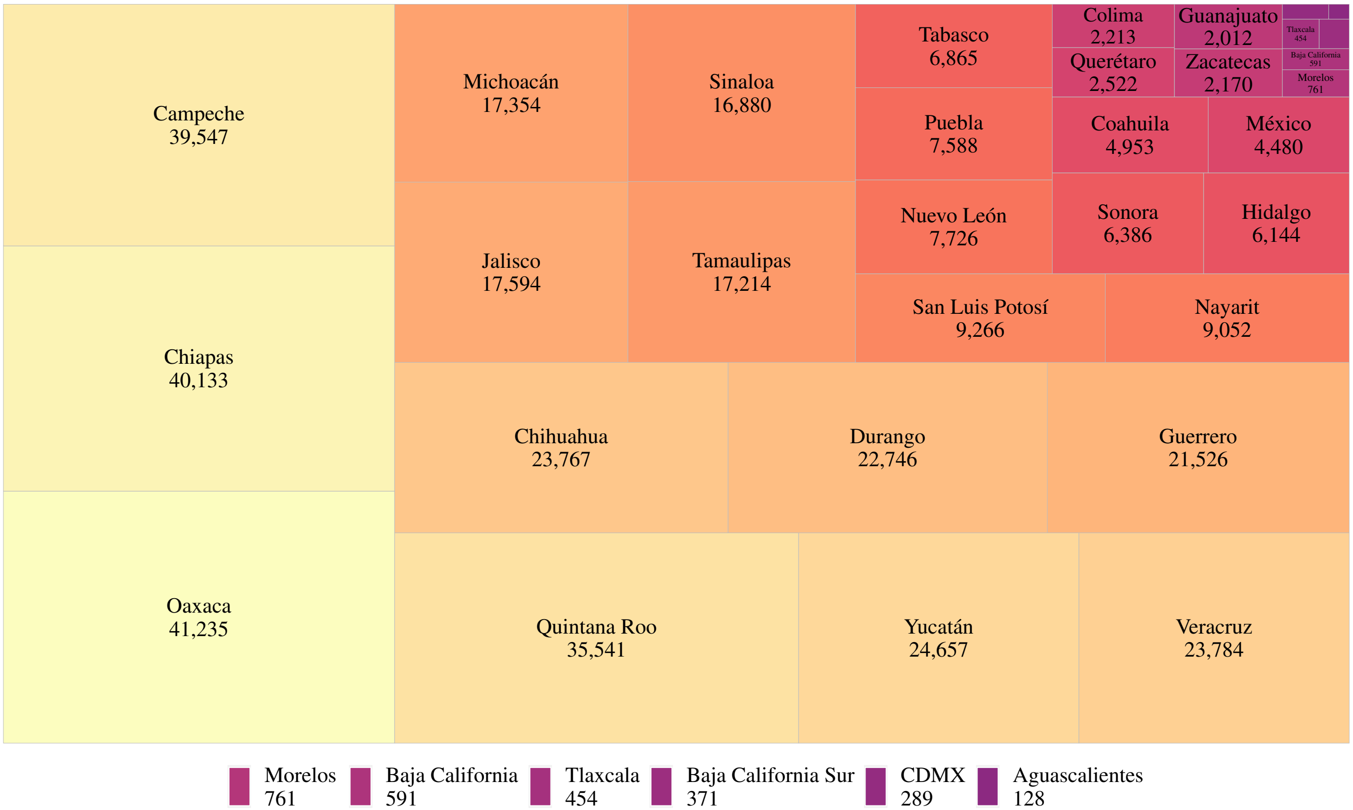
Notes: The map represents the cumulative tree loss from 2011 to 2021, divided by the tree cover in 2000. Since we do not consider the gain of new forest or the recovery of lost forest, this ratio might be higher than one. In this graph, we only show the municipalities with coefficients less than one.

Figure A.6: **Cumulative tree loss (2011-2021) / Tree cover (2000)**



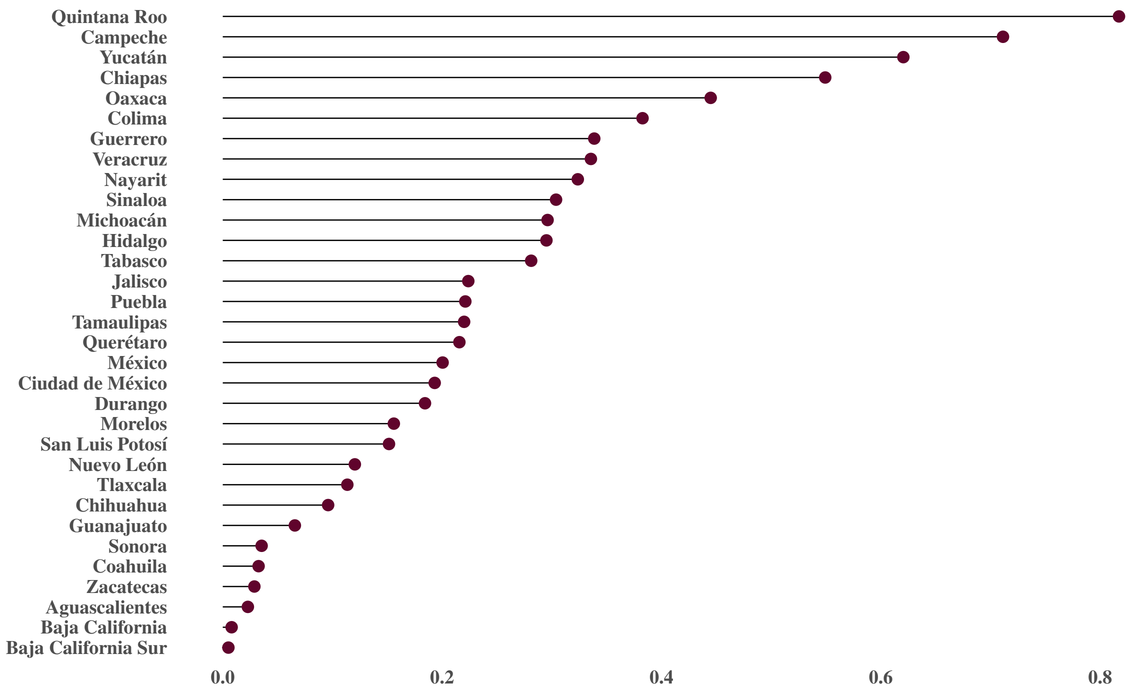
Notes: The map represents the cumulative tree loss from 2011 to 2021, divided by the tree cover in 2000. Since we do not consider the gain of new forest or the recovery of lost forest, this ratio might be higher than one.

Figure A.7: **Tree cover in the year 2000 (km^2)**



Notes: The tree cover at the state level in 2000 is shown in the graph. The state tree cover was obtained by adding the tree cover of the municipalities that constitute the state.

Figure A.8: **Proportion of tree cover in 2000**



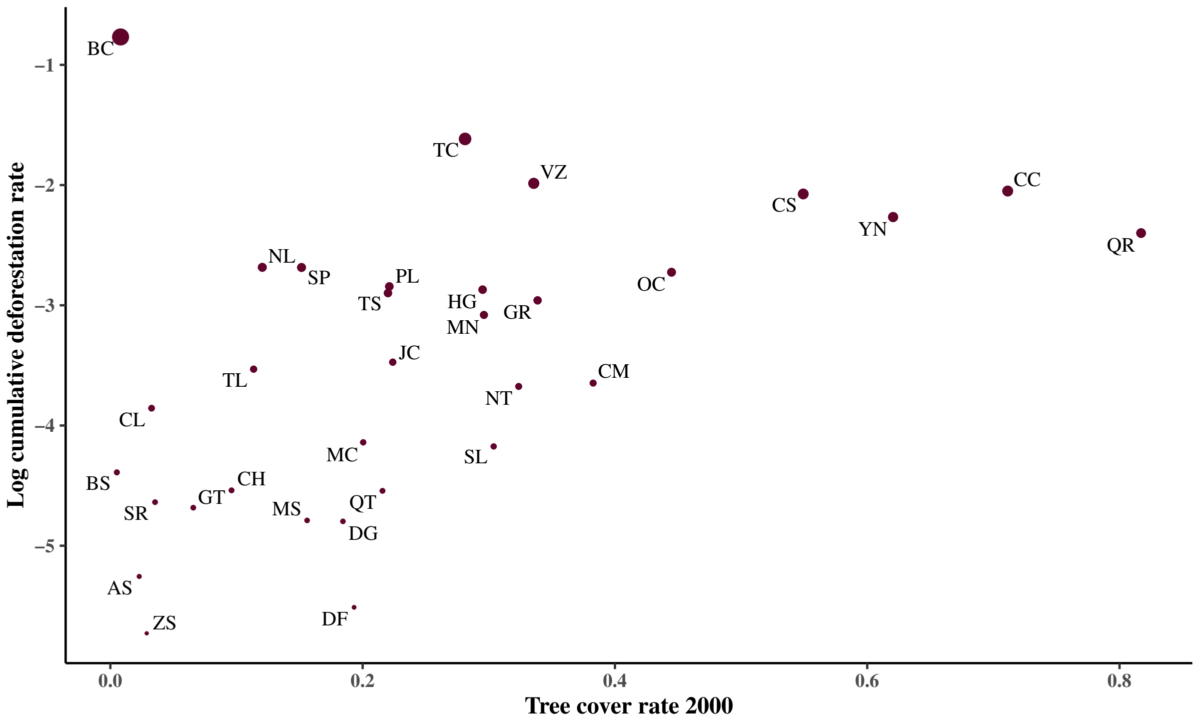
Notes: The figure shows the ratio between the states' tree cover and its area. This measure refers to tree cover rate.

Table A.1: **Average deforestation by state**

State	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
AS	0.14%	0.04%	0.05%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	0.01%	0.00%
BC	0.37%	0.52%	0.70%	8.23%	2.19%	0.59%	6.09%	26.17%	1.58%	18.21%	24.59%
BS	0.55%	0.47%	0.19%	0.13%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.00%
CC	0.37%	0.90%	1.26%	0.82%	0.98%	1.77%	1.95%	1.22%	1.53%	2.37%	0.98%
CS	0.73%	0.56%	0.74%	0.75%	0.64%	1.56%	1.08%	1.25%	1.38%	1.00%	0.60%
CH	0.06%	0.24%	0.11%	0.04%	0.01%	0.04%	0.08%	0.24%	0.02%	0.02%	0.17%
DF	0.04%	0.03%	0.05%	0.03%	0.01%	0.05%	0.03%	0.07%	0.02%	0.01%	0.01%
CL	1.55%	0.91%	0.15%	0.24%	0.33%	0.44%	0.32%	0.40%	0.12%	0.34%	0.16%
CM	0.10%	0.20%	0.27%	0.14%	0.28%	0.37%	0.34%	0.35%	0.40%	0.37%	0.37%
DG	0.04%	0.14%	0.11%	0.03%	0.02%	0.03%	0.03%	0.07%	0.03%	0.02%	0.05%
GT	0.11%	0.14%	0.21%	0.09%	0.02%	0.01%	0.02%	0.05%	0.04%	0.07%	0.38%
GR	0.24%	0.61%	0.78%	0.60%	0.54%	0.67%	0.48%	0.83%	0.54%	0.55%	0.46%
HG	0.23%	0.42%	0.40%	0.20%	0.14%	0.23%	0.28%	0.31%	0.37%	0.51%	0.34%
JC	0.11%	0.22%	0.46%	0.22%	0.08%	0.20%	0.16%	0.58%	0.54%	0.24%	0.31%
MC	0.21%	0.14%	0.22%	0.15%	0.03%	0.15%	0.10%	0.28%	0.08%	0.08%	0.37%
MN	0.23%	0.27%	0.56%	0.37%	0.29%	0.46%	0.34%	0.57%	0.32%	0.28%	0.47%
MS	0.21%	0.25%	0.25%	0.17%	0.04%	0.08%	0.08%	0.18%	0.02%	0.02%	0.03%
NT	0.06%	0.21%	0.42%	0.30%	0.29%	0.26%	0.31%	0.46%	0.32%	0.29%	0.36%
NL	1.81%	1.36%	1.81%	1.90%	0.85%	2.04%	1.44%	1.37%	0.90%	0.73%	2.72%
OC	0.27%	0.27%	0.31%	0.36%	0.31%	0.55%	0.59%	0.72%	0.64%	0.53%	0.46%
PL	0.14%	0.14%	0.26%	0.23%	0.17%	0.30%	0.30%	0.39%	0.41%	0.52%	0.51%
QT	0.09%	0.12%	0.08%	0.03%	0.01%	0.03%	0.06%	0.06%	0.03%	0.02%	0.06%
QR	1.20%	0.34%	0.62%	0.42%	1.65%	0.40%	0.92%	0.40%	0.84%	1.53%	0.46%
SP	1.40%	0.55%	0.73%	0.48%	0.45%	0.55%	1.01%	0.94%	1.04%	0.71%	0.52%
SL	0.26%	0.30%	0.39%	0.18%	0.11%	0.37%	0.16%	0.24%	0.15%	0.14%	0.15%
SR	0.05%	0.18%	0.32%	0.10%	0.02%	0.07%	0.49%	0.53%	0.11%	0.15%	0.04%
TC	0.43%	0.51%	0.90%	0.94%	0.99%	1.69%	2.36%	2.07%	4.90%	1.91%	1.16%
TS	1.16%	2.28%	1.05%	1.10%	0.33%	1.36%	1.06%	1.07%	0.68%	0.59%	0.85%
TL	0.11%	0.08%	0.10%	0.03%	0.01%	0.01%	0.14%	0.14%	0.35%	1.46%	5.66%
VZ	0.87%	0.60%	0.82%	0.78%	0.76%	1.20%	1.25%	1.42%	1.83%	1.22%	1.04%
YN	0.64%	0.74%	0.86%	0.87%	0.86%	1.06%	1.24%	0.87%	1.02%	1.07%	0.83%
ZS	0.04%	0.19%	0.13%	0.06%	0.00%	0.00%	0.02%	0.01%	0.00%	0.00%	0.02%

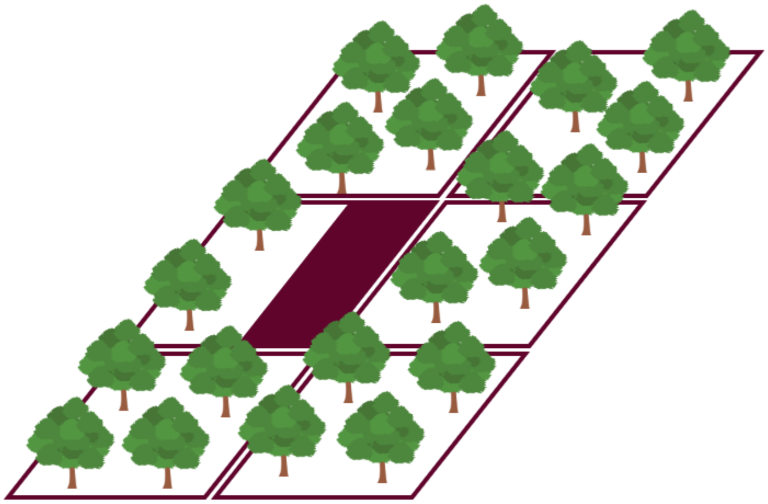
Notes: Percentage with respect to tree cover in 2000.

Figure A.9: **Cumulative deforestation rate v.s. tree cover rate by state**



Notes: The graph illustrates the relationship between the logarithm of cumulative deforestation from 2011 to 2021 and the tree cover rate in 2000 by state.

Figure A.10: **Motivation of the new tree cover definition**



Description: The graph represents a forest. Despite the low percentage of trees in one pixel, they still form a forest. Therefore, the new definition considers the total area of the pixels instead of only taking the percentage of the area with trees. The cluster of pixels must measure more than 0.5 hectares to exclude outliers.

A References

Berazneva, J., and T. S. Byker. 2017. Does Forest Loss Increase Human Disease? Evidence from Nigeria. *The American Economic Review* 107 (5): 516–521. ISSN: 00028282, accessed January 20, 2023. http://www.jstor.org/stable/44250452.

Bloom, D., E. T. Cafiero, M. McGovern, K. Prettner, A. Stanciole, J. Weiss, S. Bakkila, and L. Rosenberg. 2013. *The Economic Impact of Non-Communicable Disease in China and India: Estimates, Projections, and Comparisons.* NBER Working Papers 19335. National Bureau of Economic Research, Inc. https://EconPapers.repec.org/RePEc:nbr:nberwo:19335.

Bonan, G. B. 2008. Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests. *Science* 320 (5882): 1444–1449. https://doi.org/10.1126/science.1155121. eprint: https://www.science.org/doi/pdf/10.1126/science.1155121. https://www.science.org/doi/abs/10.1126/science.1155121.

Carolan, M., and D. Frankowska. 2011. Advanced Maternal Age and Adverse Perinatal Outcome: A Review of the Evidence. *Midwifery* 27 (6): 793–801. ISSN: 0266-6138. https://doi.org/https://doi.org/10.1016/j.midw.2010.07.006. https://www.sciencedirect.com/science/article/pii/S0266613810001208.

Carrillo, B., D. K. Branco, J. C. Trujillo, and J. E. Lima. 2018. The Externalities of a Deforestation Control Policy in Infant Health: Evidence from Brazil. *Economic Development and Cultural Change, The University of Chicago.*

Currie, J. 2009. Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. *Journal of Economic Literature* 47, no. 1 (March): 87–122. https://doi.org/10.1257/jel.47.1.87. https://www.aeaweb.org/articles?id=10.1257/jel.47.1.87.

Currie, J., and R. Walker. 2011. Traffic Congestion and Infant Health: Evidence from E-ZPass. *American Economic Journal: Applied Economics* 3 (1): 65–90. ISSN: 19457782, 19457790, accessed May 2, 2023. http://www.jstor.org/stable/25760246.

Emden, J., and L. Murphy. 2018. *Lethal but Legal: Air Pollution From Domestic Burning.* Technical report. Institute for Public Policy Research (IPPR). Accessed May 2, 2023. http://www.jstor.org/stable/resrep21884.5.

Food and A. O. of the United Nations (FAO). 2020. *Terms and Definitions.* Food / Agriculture Organization of the United Nations (FAO). https://www.fao.org/3/I8661EN/i8661en.pdf.

Garg, T. 2014. Public Health Effects of Natural Resource Degradation: Evidence from Deforestation in Indonesia. *Job Market Paper, Cornell University, Ithaca.*

———. 2019. Ecosystems and Human Health: The Local Benefits of Forest Cover in Indonesia. *Journal of Environmental Economics and Management* 98:102271. ISSN: 0095-0696. https://doi.org/https://doi.org/10.1016/j.jeem.2019.102271. https://www.sciencedirect.com/science/article/pii/S0095069619304760.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, et al. 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* 342 (6160): 850–853. https://doi.org/10.1126/science.1244693. eprint: https://www.science.org/doi/pdf/10.1126/science.1244693. https://www.science.org/doi/abs/10.1126/science.1244693.

Kabir, A., M. Rahman, A. Shamim, R. Klemm, A. Labrique, M. Rashid, P. Christian, and K. West Jr. 2017. Identifying Maternal and Infant Factors Associated with Newborn Size in Rural Bangladesh by Partial Least Squares (PLS) regression analysis. *PLOS ONE* 12 (December): e0189677. https://doi.org/10.1371/journal.pone.0189677.

Keivab, R. C., and M. Cozzani. 2022. Extreme Heat, Birth Outcomes, and Socioeconomic Heterogeneity. *Demography* 59 (5): pp. 1631–1654. ISSN: 00703370, 15337790, accessed May 6, 2023. https://www.jstor.org/stable/48687810.

Kempf-Leonard, K. 2004. *Encyclopedia of Social Measurement.* Elsevier.

Kumar, M. D., and C. Tortajada. 2020. Health Impacts of Water Pollution and Contamination. In *Assessing Wastewater Management in India,* 23–30. Singapore: Springer Singapore. ISBN: 978-981-15-2396-0. https://doi.org/10.1007/978-981-15-2396-0_5. https://doi.org/10.1007/978-981-15-2396-0_5.

McElroy, S., S. Ilango, A. Dimitrova, A. Gershunov, and T. Benmarhnia. 2022. Extreme Heat, Preterm Birth, and Stillbirth: A Global Analysis Across 14 Lower-Middle Income Countries. *Environment International* 158:106902. ISSN: 0160-4120. https://doi.org/https://doi.org/10.1016/j.envint.2021.106902. https://www.sciencedirect.com/science/article/pii/S0160412021005274.

McMichael, A. J., and E. Lindgren. 2011. Climate Change: Present and Future Risks to Health, and Necessary Responses. *Journal of Internal Medicine* 270 (5): 401–413. https://doi.org/https://doi.org/10.1111/j.1365-2796.2011.02415.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2796.2011.02415.x. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2796.2011.02415.x.

Myers, S. S., and J. A. Patz. 2009. Emerging Threats to Human Health from Global Environmental Change. *Annual Review of Environment and Resources* 34 (1): 223–252. https://doi.org/10.1146/annurev.environ.033108.102650. eprint: https://doi.org/10.1146/annurev.environ.033108.102650. https://doi.org/10.1146/annurev.environ.033108.102650.

Naito, H., and A. Mapulanga. 2019. Effect of Deforestation on Access to Clean Drinking Water. *Proceedings of the National Academy of Sciences* (March). https://doi.org/10.1073/pnas.1814970116.

Pruss-Ustun, A., W. H. O. WHO, et al. 2008. *Safer Water, Better Health: Costs, Benefits and Sustainability of Interventions to Protect and Promote Health.* World Health Organization.

Prüss-Üstün, A., J. Wolf, C. F. Corvalán, R. Bos, and M. P. Neira. 2016. *Preventing Disease Through Healthy Environments: A Global Assessment of the Burden of Disease from Environmental Risks.* 147 p. World Health Organization. Publications.

Salud, S. de. 2013. *Cesárea Segura. Lineamiento Técnico.* https://www.gob.mx/cms/uploads/attachment/file/11089/Cesarea_Segura_2014.pdf. (Accessed on 04/04/2023).

Sanidad Forestal, C. T. E. de. 2022. *Programa Operativo de Sanidad Forestal 2022 del Estado de Baja California.* CONAFOR.

Santos, A. S., and A. N. Almeida. 2018. The Impact of Deforestation on Malaria Infections in the Brazilian Amazon. *Ecological Economics* 154:247–256. ISSN: 0921-8009. https://doi.org/https://doi.org/10.1016/j.ecolecon.2018.08.005. https://www.sciencedirect.com/science/article/pii/S092180091730770X.

Shah, P. S., J. Zao, and S. Ali. 2011. Maternal Marital Status and Birth Outcomes: A Systematic Review and Meta-Analyses. *Maternal and Child Health Journal* 15:1097–1109.

Smith, J. P. 2007. The Impact of Socioeconomic Status on Health over the Life-Course. *The Journal of Human Resources* 42 (4): 739–764. ISSN: 0022166X, accessed May 21, 2023. http://www.jstor.org/stable/40057328.

SSA. 2022. 539. En Cuatro Años Disminuyeron 69.8% Los Casos de Paludismo en México, https://www.gob.mx/salud/prensa/539-en-cuatro-anos-disminuyeron-69-8-los-casos-de-paludismo-en-mexico#:~:text=En%5C%20los%5C%20%5C%C3%5C%BAltimos%5C%20cuatro%5C%20a%5C%C3%5C%B1os,de%5C%20la%5C%20Secretar%5C%C3%5C%ADa%5C%20de%5C%20Salud..

SVS. 2022. Panorama Epidemiológico da Malária em 2021: Buscando o Caminho Para a Eliminação da Malária no Brasil, https://www.gov.br/saude/pt-br/assuntos/saude-de-a-a-z/m/malaria/situacao-epidemiologica-da-malaria-1/boletins-epidemiologicos-de-malaria/boletim-epidemiologico-vol-53-no17-2022-panorama-epidemiologico-da-malaria-em-2021-buscando-o-caminho-para-a-eliminacao-da-malaria-no-brasil.

Understanding the Roles of Forests and Tree-based Systems in Food Provision. 2015. In *Forests and Food: Addressing Hunger and Nutrition Across Sustainable Landscapes,* 1st ed., 29–72. Open Book Publishers. ISBN: 9781783741939, accessed May 2, 2023. http://www.jstor.org/stable/j.ctt19b9jsg.7.

UNICEF. 2023. *Neonatal mortality.* https://data.unicef.org/topic/child-survival/neonatal-mortality/. (Accessed on 05/03/2023).

United Nations Environment Programme, F., and A. O. of the United Nations. 2020. *The State of the World's Forests 2020: Forests, Biodiversity and People.* https://wedocs.unep.org/20.500.11822/32472.

WorldBank. 2023. *World Development Indicators: DataBank.* https://databank.worldbank.org/source/world-development-indicators#health. (Accessed on 05/03/2023).

List of Figures

1 **Trends of the main variables by deforestation rate** 6

2 **A fragment of a satellite image of the tree cover** 9

3 **Tree canopy cover for year 2000 in Mexico** 10

4 **Forest loss in Mexico** 11

5 **Change in the definition of deforestation** Pixel representation 20

6 **Cumulative deforestation rate v.s. Tree cover rate by municipality** . 23

A.1 **National trends of the main variables** 26

A.2 **Satellite images download** 35

A.3 **Close-up of a satellite image of tree cover** 35

A.4 **Tree cover in the year 2000 by municipality** (km^2) 36

A.5 **Cumulative tree loss (2011-2021) / Tree cover (2000)** Municipalities with a ratio below one 37

A.6 **Cumulative tree loss (2011-2021) / Tree cover (2000)** 38

A.7 **Tree cover in the year 2000** (km^2) 39

A.8 **Proportion of tree cover in 2000** 40

A.9 **Cumulative deforestation rate v.s. tree cover rate by state** 42

A.10 **Motivation of the new tree cover definition** 43