Cutting down trees does not build prosperity: On the continued decoupling of Amazon deforestation and economic development in 21st century Brazil

Darren Norris[1,2,3*], Terciane Sabadini Carvalho[4], Angela M. Guerrero [5], Maria Isabel Sobral Escada[6], Ane Alencar[7] , Liz Kimbrough[8], Rhett A. Butler[8]

[1] Coordenação de Ciências Ambientais, Federal University of Amapá, Macapá, Amapá, Brazil.

[2] Postgraduate Programme in Tropical Biodiversity, Federal University of Amapá, Macapá, Amapá, Brazil

[3] Ecology and Conservation of Amazonian Vertebrates Research Group, Federal University of Amapá, Macapá, Amapá, Brazil.

[4] Federal University of Paraná

[5] Queensland University of Technology, Brisbane, QLD, 4000, Australia

[6] Instituto Nacional de Pesquisas Espaciais (INPE)

[7] Instituto de Pesquisa Ambiental da Amazônia (IPAM)

[8] Mongabay

Corresponding author Email:

*DN: dnorris75@gmail.com

Abstract

Background and aims:

We present evidence examining spatial and temporal patterns in forest cover changes and economic indicators in Brazilian Amazonia. Specifically, we tested two predictions embedded in arguments used by influential interest groups: i) where there is less forest indicators of economic progress should increase and ii) areas with most recent deforestation should have increased economic indicators.

Methods:

Complementary methods assessed variation in economic indicators across 794 administrative districts (municipalities) covering 4.9 Mkm^2 of the Brazilian Amazon from 2002 to 2019. A representative subset of municipalities was used to compare economic and socioeconomic indicators across municipalities with contrasting forest cover.

Results:

Contrasting results between the full and a representative subset of municipalities suggests that municipality-level economic indicators cannot be directly attributed to loss of natural forests. There was no association between forest loss and economic (average salary) or socioeconomic indicators (existence of sanitation plans and internet connectivity). The economic indicators of municipalities with less than 40% forest cover in 1986 were no different to that of similar municipalities with more than 60% forest cover from 1986 to 2019.

Conclusion:

The evidence contradicted both of the predictions tested. Reducing forest cover does not appear to directly promote socioeconomic progress. Any localized associations between forest cover and poverty most likely result from other more plausible alternatives including lack of opportunity and a widespread failure to effectively implement and enforce existing policies within the local socioeconomic context.

Implications for Conservation:

Our findings support evidence from across the tropics that show deforestation does not necessarily generate transformative and equitable food production systems or lead to poverty alleviation.

Keywords: Amazon, agriculture, deforestation, economics, forest loss, Gross Domestic Product, Gross Value Added, income, MapBiomas, land cover, poverty, prosperity, socioeconomics, sustainable development

Highlights

- No evidence of direct associations between forest loss and socioeconomic progress indicators.
- Approximately 292,000 km^2 of natural forest cover was lost between 2002 and 2019.
- By 2019 only 9% of municipalities had both approved sanitation plans and full internet connectivity.

Background: Forest loss, agriculture and poverty in Brazilian Amazonia

In 2021, deforestation in the Brazilian Amazon increased to the highest level since 2006 (Butler, 2021), while the contribution of agribusiness to the Brazilian Gross Domestic Product (GDP) declined to its lowest level since 2012 (Amorim et al., 2021; Crelier, 2021). Yet at the same time, the Brazilian national statement to the 2021 United Nations Climate Change Conference asserted that “where there is a lot of forest there is also a lot of poverty”(Brazil, 2021)– implying a direct cause-effect relationship between forest cover and poverty in 21st century Brazil. While such statements follow a mainstream narrative of environmental destruction as a "necessary cost" of development, they do not align with a growing evidence base demonstrating relationships between 21st century deforestation and human development are complex and dynamic (Borda-Niño et al., 2020; Busch & Ferretti-Gallon, 2017; Fischer et al., 2020; Lambin et al., 2018; Meyfroidt et al., 2022). These complex dynamics have been demonstrated at regional (Caviglia-Harris et al., 2016; Kauano et al., 2020; Silva et al., 2017) and local scales (Mullan et al., 2018). However, pathways to increase prosperity and reduce poverty remain uncertain across Brazilian Amazonia (Alves-Pinto et al., 2015; Garrett et al., 2021; Silva et al., 2017).

Poverty, as defined by the United Nations is a denial of choices and opportunities resulting in a lack of basic capacity to participate effectively in society. Poverty in capitalist societies is often linked with economic “capacity” through measures such as GDP and income (World Bank, 2022). Yet, economic capacity may not guarantee poverty alleviation. This has been argued in the case of expansion of the agricultural frontier in regions of Brazil where the use of monocultures, mechanization, and land concentration, has resulted in displacement and exclusion of local populations, social conflicts, and the loss of subsistence and access to resources that used to belong to the traditional local populations (Sauer, 2018). And so, as evidenced by Russo Lopes et al. (2021) the improvement of economic indicators can reveal maldevelopment, which implies unequal and exclusive change processes that deprive most local actors, particularly the most vulnerable, of their social and material capacities. Nonetheless, economic mechanisms to reduce poverty represent key aspects of Brazilian post-colonial society (Naritomi et al., 2012), both historically (a national minimum salary was implemented in 1938 by president Getúlio Vargas) and more recently via cash transfer programs established after the 1988 Constitution. These cash transfer programs include “Bolsa Escola”, which was implemented in 2001 by the government under Fernando Henrique Cardoso, and then expanded by president Luís Ignacio da Silva as “Bolsa Família” and most recently “Auxílio Brasil” under the current president Jair Bolsonaro (Ministério da Cidadania, 2022). Despite these actions, it is estimated that in 2018 approximately 23 million people lived below the poverty threshold in Brazil (FGV social, available at https://cps.fgv.br/Pobreza-Desigualdade, accessed 11 May 2022).

People experiencing poverty may go without basic necessities such as proper housing, clean water, medical attention– and access to healthy food. Meeting present and future needs to simultaneously increase food access and reduce biodiversity loss is a critical component of Sustainable Development Goals and the Post 2020 Global Biodiversity Framework (CBD, 2021) to which Brazil is party. Indeed, loss of rainfall and climate changes associated with continued Amazon deforestation (Lovejoy & Nobre, 2018) are likely to generate not only reduced revenue but also irreversible losses on agricultural capacity to meet the needs of future generations (Leite-Filho et al., 2021; Tanure et al., 2020). At the same time, the continued concentration of relatively poor rural populations on degraded and poorly productive agricultural land has implications not only for the living standards of millions of rural households but also for poverty alleviation (Barbier & Di Falco, 2021).

Although an economic focus for examining poverty alleviation remains debatable, the timing of such a focus is relevant, considering the upcoming presidential election in Brazil, which is one of the world’s largest democracies and economic powers (EIU, 2021). Despite decades of studies, it remains intensely debated whether the erosion of environmental protection as measured via forest loss (the most obvious measure of protection) is economically and socially justifiable (Abessa et al., 2019; Bastos Lima et al., 2021; Silva Junior et al., 2020). Here we compile evidence to test two predictions that follow from the Brazilian national statement, which implied a direct cause-effect relationship between forest cover and poverty. First, economic indicators should be greater where there is less forest cover relative to areas with more forest cover. Secondly, the population within areas with the most recent deforestation should have higher average salaries and improved socioeconomic indicators compared to places with less recent deforestation.

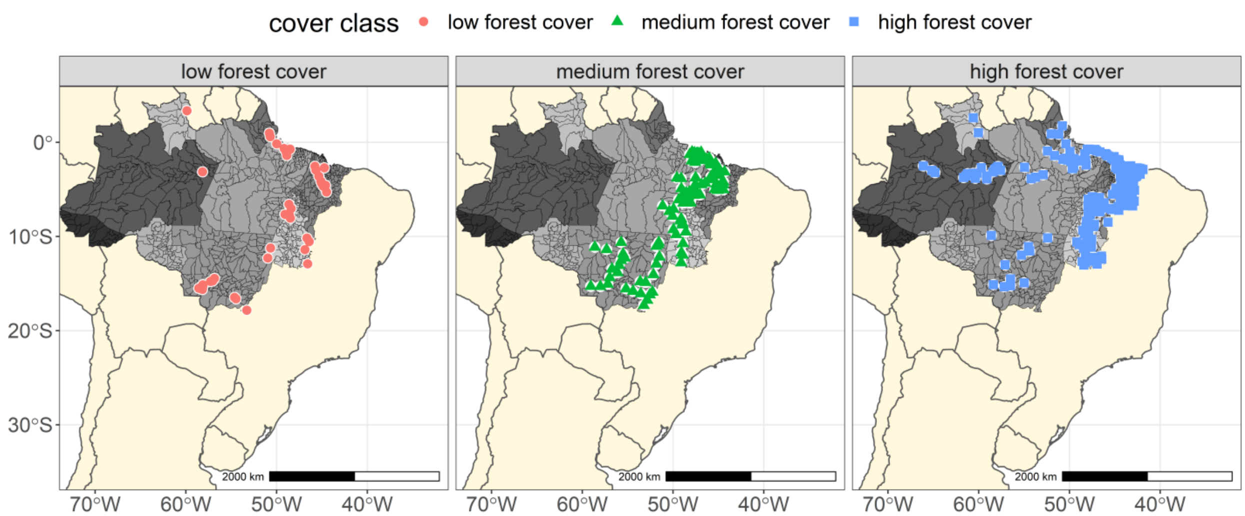


Figure 1: Study area. Brazilian Amazonia in South America. Showing nine Brazilian states in grey shading with grey lines showing municipality borders. Colored symbols show locations of the subset of 357 municipalities used to isolate effects of forest cover change on socioeconomic indicators. This cover subset was grouped into three forest cover classes using percent of natural forest cover in 1986 as a reference level ("low": less than 40%, "medium": more than 60% in 1986 but less than 50% in 2019 and "high" more than 60% in 1986 and 2019 [full subset details in Methods]). Symbol sizes have been enlarged to aid visualization and locations can overlap.

We evaluated annual changes in forest cover together with economic and socioeconomic indicators to test the two predictions across administrative districts (municipalities). The analysis included municipalities from nine states to reflect the Brazilian political and administrative hierarchy (Figure 1). Hereafter the region covered by the nine states is referred to as Brazilian Amazonia. Diverse forest types are found within and among the municipalities, including those from Amazon and Cerrado (savanna) biomes. For this analysis, we included both natural forest and savanna vegetation types as forest cover (MapBiomas 2021). The most up to date forest cover and economic data from 2002 to 2019 (IBGE, 2021; MapBiomas 2021) was used to test predictions both across 794 municipalities covering 4.9 M km^2 and a subset of 357 municipalities (877 K km^2). This subset was identified to isolate the effects of forest cover and loss since 1985 (see Methods for subset selection details). The 357 municipality cover class subset included a resident population of 7,988,731 in 2019 (37.8% of the overall resident population across 794 municipalities in 2019). Only 6 of the 357 municipalities included an urban concentration (see Methods for full details of municipality characteristics). The data and code used to produce the analysis and figures are available from Norris (2022).

Forest loss is not associated with economic indicators

Continued deforestation in Brazilian Amazonia is largely driven by economic and political interests (Garrett et al., 2021; Schneider et al., 2021). The pace and scale of forest loss across Brazilian Amazonia is not constant due in large part to the high cultural, social and environmental heterogeneity. Between 2002 and 2019 median Gross Domestic Product (GDP) per capita increased more than fivefold (from 679 to 3401 US$) and agriculture Gross Value Added (GVA) per capita increased nearly fourfold over the same period (from 149 to 536 US$). In contrast, the median salary remained relatively stagnant, increasing from 1.7 to 1.9 times the national minimum salary value from 2006 to 2019 (1.9 corresponded to an average salary of R$ 1862 or US$ 472 per month in 2019). This stark contrast among rates of increase is a clear indication of the profound inequalities that continue to surround economic maldevelopment across Brazilian Amazonia (Garrett et al., 2021; Russo Lopes et al., 2021).

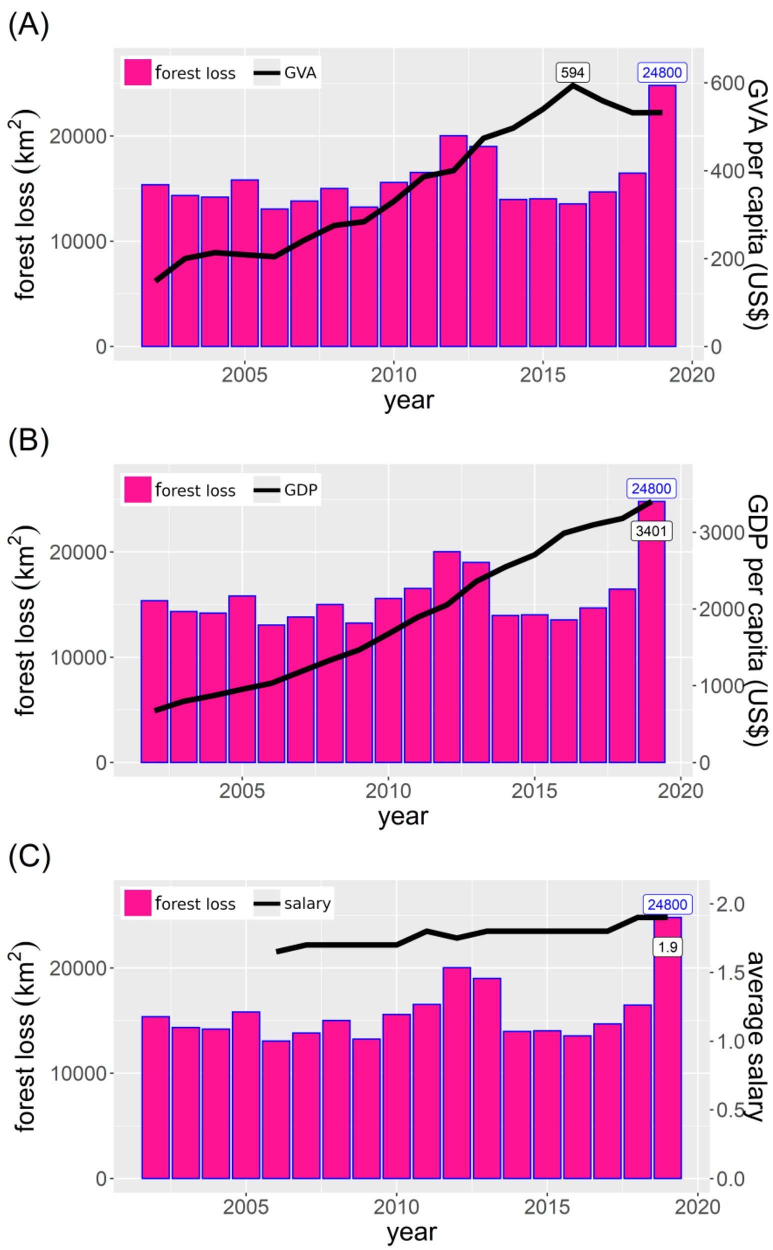


Figure 2. Economic indicators and forest loss in Brazilian Amazonia. Annual values of forest loss and (A) agriculture Gross Value Added per capita, (B) Gross Domestic Product per capita and (C) salaries from 2002 – 2019 across the Brazilian Amazon. The pink bars represent annual values of forest loss showing totals of transition from natural forest (including savanna and forest formations) to anthropogenic land uses (MapBiomas 2021). Salaries expressed as a proportion of the annual minimum salary value (full details of economic indicators in Methods). Solid black lines are the median values from 794 municipalities. Text labels show maximum values for each series (blue for forest cover and black for economic indicators).

Deforestation has been accompanied by an economic recession in Brasil, which according to Nobre and Nobre (2018) shows the decoupling of deforestation with economic growth. A total of approximately 292,194 km^2 of natural forest cover was converted to human land use from 2002 to 2019 (Figure 2). Correlations among summarized annual economic indicators and forest loss values were weak and not significant (Spearman rho = 0.26, 0.15, 0.52 for GDP per capita, agriculture GVA per capita, and average salary respectively, $P > 0.05$). Economic indicators at the level of municipalities were also very weakly correlated with forest loss over the same period (Supplemental Material S1). Analysis controlling for spatial and temporal autocorrelations showed weak and insignificant associations of forest loss expressed as both km^2 and proportion of forest cover in 1986 and economic indicators (Supplemental Material S2 for full model results). Further studies are required to examine these patterns in more depth to understand the contribution of other factors including industrial activities (e.g. construction, hydropower dams, and mining) that are likely to contribute to the variation in socioeconomic indicators across the 794 municipalities (Abessa et al., 2019; Busch & Ferretti-Gallon, 2017; Caviglia-Harris et al., 2016; Garrett et al., 2021; Stabile et al., 2020).

Analysis across the representative subset of 357 municipalities indicated no significant difference in economic indicators from 2006 to 2019 among forest cover classes (Figure 3). This analysis is the first we are aware of that provides empirical evidence for the continued decoupling of economic indicators and forest loss across Brazilian Amazonia controlling for both temporal and spatial autocorrelation. Controlling for spatial and temporal autocorrelations confirmed that there were no statistical differences in agriculture GVA per capita, GDP per capita, or salary among the three cover classes (Generalized Additive Models [GAMs], $P > 0.12$ for cover classes explaining agriculture GVA per capita, GDP per capita and salary, Supplemental Material S3 for model results). The same comparison made using the longer time series (2002 – 2019) for GDP and agricultural GVA per capita also showed no statistical difference in economic indicators among the three cover classes. There was no evidence of differences in sample sizes or unobserved omitted selection variables generating any systematic bias (Supplemental Material S5).

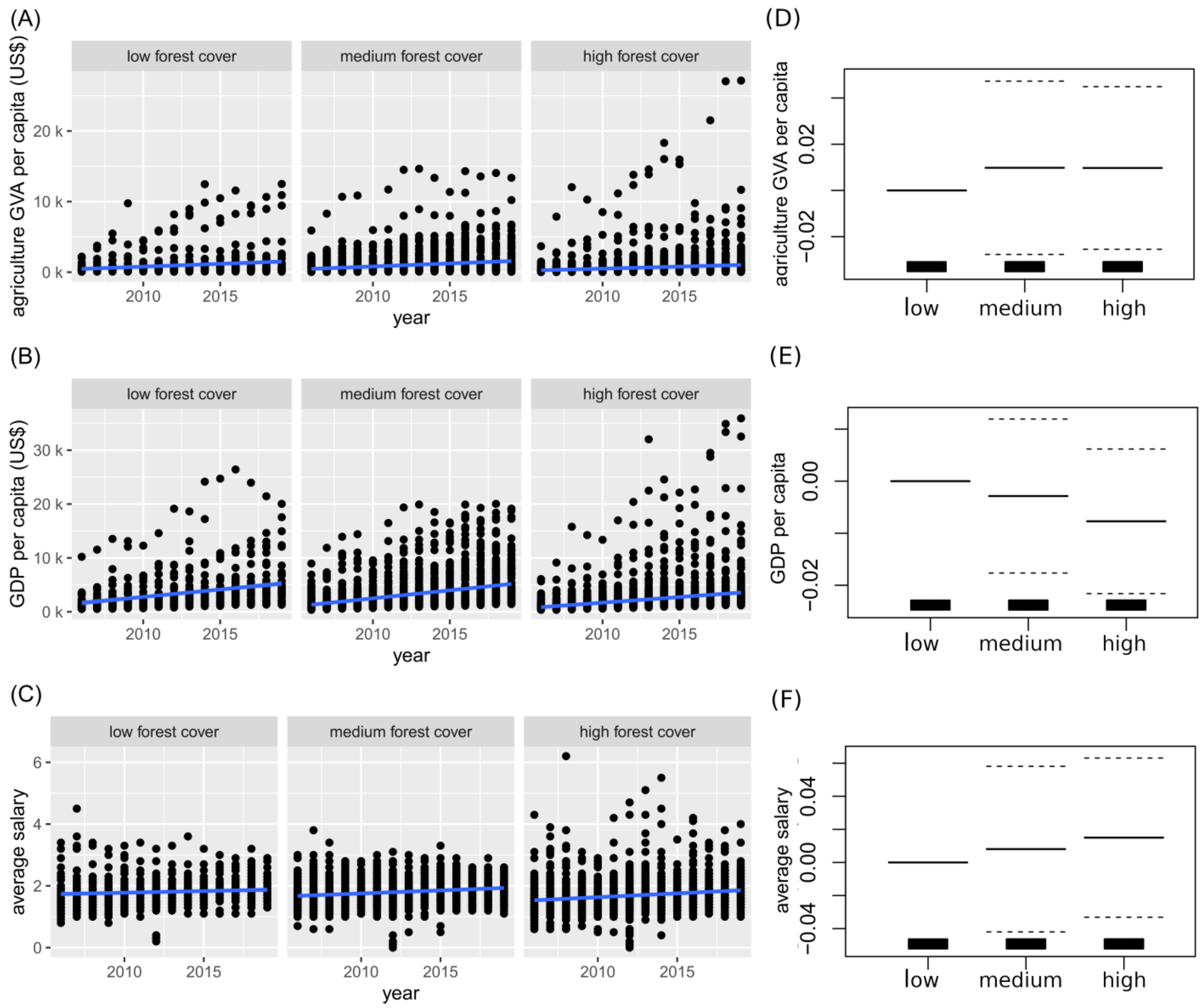


Figure 3. Economic indicators and forest cover change. Comparison of three economic indicators among forest cover classes. Annual trends from 2006 to 2019 (A to C) and GAM partial plots (D to F) of three economic indicators, row wise top to bottom: agriculture Gross Value Added per capita, Gross Domestic Product per capita and salaries (expressed as a proportion of the annual minimum salary value). These indicators are compared among a subset of 357 municipalities with contrasting proportions of natural forest cover. (A to C) Solid blue line is linear trend over time added to aid visual interpretation. (D to F) Partial plots show marginal effects of cover classes on the economic indicators. Marginal effects presented on the link scale, and centered about the model constant term (solid horizontal lines are mean values, dashed horizontal lines are 2X Standard Error of the mean). The subset was selected to isolate effects of forest cover change on economic indicators; with municipalities grouped into three forest cover classes using percent of natural forest cover in 1986 as a reference level (“low”: less than 40%, “medium”: more than 60% in 1986 but less than 50% in 2019 and “high” more than 60% in 1986 and 2019 [full subset details in Methods]).

Forest loss is not associated with socioeconomic indicators

Current economic development paths are leading not only to forest loss but may also lead to poverty and increased conflicts across Brazilian Amazonia (Bastos Lima et al., 2021; Rodrigues et al., 2009; Silva Junior et al., 2020). Continued agribusiness development arises (at least in part) from decades without viable economic alternatives across Brazilian Amazonia (Garrett et al., 2021; Schneider et al., 2021). Agribusiness development is widespread, with regions experiencing agribusiness development including states not only with rapidly expanding deforestation such as Tocantins, but also the most protected Brazilian state Amapá (Schneider et al., 2021). In addition to environmental degradation, current agribusiness production chains have limited inclusiveness for the rural poor (Ferrante & Fearnside, 2019; Garrett et al., 2021; Russo Lopes et al., 2021). It is therefore unsurprising that only 8.7% of 794 municipalities (with a median fivefold increase in GDP over 18 years) had both an approved sanitation plan and complete internet connectivity among administrative centers by 2019 (see Methods for definitions of sanitation plan and complete internet connectivity).

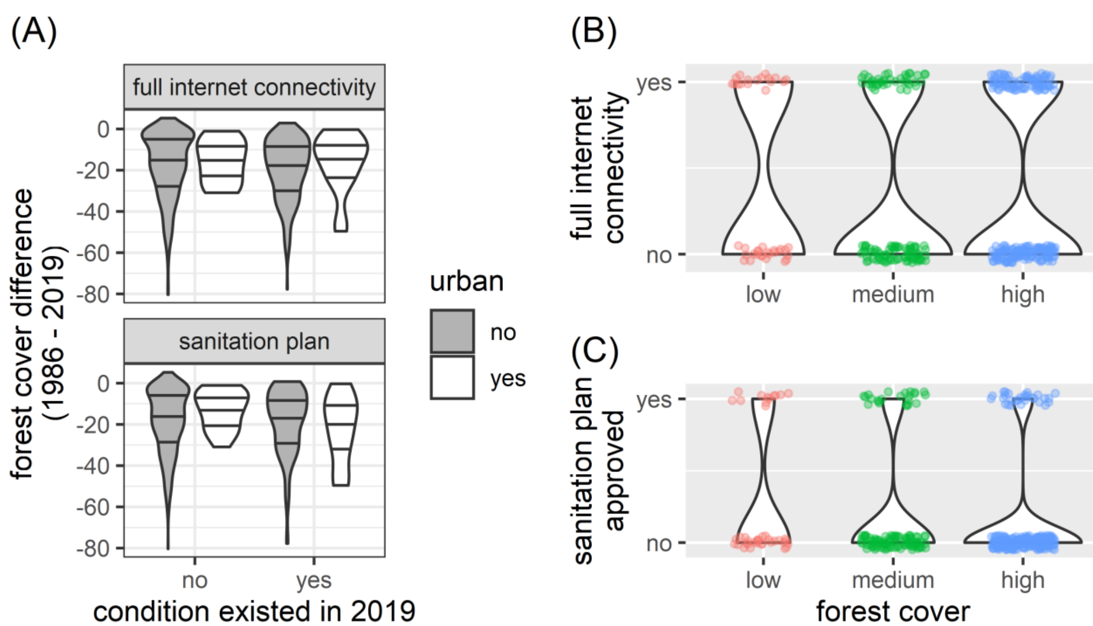


Figure 4. Forest loss and socioeconomic indicators. Comparison of the existence of two socioeconomic conditions and forest cover change among (A) all 794 municipalities and (B, C) representative subset of 357 municipalities. The subset was selected to isolate effects of forest cover change on socioeconomic indicators. This cover subset was grouped into three forest cover classes using percent of natural forest cover in 1986 as a reference level ("low": less than 40%, "medium": more than 60% in 1986 but less than 50% in 2019 and "high" more than 60% in 1986 and 2019 [full subset details in Methods]).

There was complete internet connectivity among the administrative centers in less than half (40.9%) of municipalities and less than one in five municipalities (19.9%) had a sanitation plan approved by 2019 (Figure 4). Forest loss (% of 1986 area) between 1986 and 2019 was the same among municipalities with or without these indicators, with similar central tendency and distribution of forest cover change among municipalities with or without the condition (Figure 4, A). There was also no significant difference in the proportion of municipalities with both a sanitation plan and complete internet connectivity among the three different forest cover classes (χ^2 1.44, df = 2 P = 0.4876, Figure 4 C, D).

Changes in land use for food production can in some cases improve living conditions, however extensive change in forest cover does not seem to have a similar effect in the Brazilian Amazon. A widespread lack of basic conditions across Brazilian Amazonia is well documented. For example, a recent government report showed that only 58.9% of the population in the North region (comprising Acre, Amapá, Amazonas, Pará, Roraima, Rondônia, and Tocantins) had access to clean water by 2020 (MDR, 2021). Such failures were also reflected in a recent analysis that showed Brazil — a member of the G20 and the sixth most populous nation— ranked only 71 in an assessment of human capital that takes into consideration mortality and education (Lim et al., 2018). As there are clear systematic weaknesses in the current development trajectory it is important to reinforce alternative sustainable development pathways that can accelerate poverty alleviation without deforestation (Carvalho et al., 2022; Garrett et al., 2021; Moutinho et al., 2016; Stark et al., 2022). Additionally, as forest loss does not appear to benefit the municipalities where deforestation is happening our analysis provides empirical evidence not only of continued decoupling but also of marked inequalities and maldevelopment across Brazilian Amazonia (Russo Lopes et al., 2021).

Although there is a solid theoretical background for the development of sustainable futures (Daw et al., 2011; Shyamsundar et al., 2020; Stark et al., 2022), examples of zero deforestation alternatives that meet present and future needs remain rare in tropical regions (Pinho et al., 2014). The Brazilian government has committed to zero illegal deforestation, however, considering the recent weakness in enforcing environmental legislation (Carvalho et al., 2022) such compromises may fall far short of ensuring conservation of the vast natural capital for future generations together with commensurate improvements in local wellbeing before critical tipping points are reached (Bastos Lima et al., 2021; Boucher & Chi, 2018; Boulton et al., 2022; Carvalho et al., 2022; Ferrante & Fearnside, 2019; Lovejoy & Nobre, 2018; Moutinho et al., 2016; Pereira et al., 2020; Silva Junior et al., 2020). Additionally, legal deforestation associated with agribusiness development can create inequalities; with zero illegal deforestation currently relying on market-based solutions. Research suggests however that market initiatives on their own, without additional measures including effectively enforced regulatory policies, will not achieve the environmental or social outcomes needed (Boulton et al., 2022; Moutinho et al., 2016; Pereira et al., 2020; Russo Lopes et al., 2021; Silva Junior et al., 2020).

Due to the heterogeneity and inequality that persists in the Brazilian Amazonia, government policies should facilitate the creation of diverse alternatives for sustainable development, exploring the underutilized potential of existing natural resources including biodiversity. This could include sustainably exploiting the potential of biodiversity to maintain standing forests while being socially inclusive (Nobre & Nobre, 2018). One such avenue is through a “bioeconomy”, in which natural resources are appropriated in such a way that maintains the integrity and autonomy of the resources, without following large-scale industrial systems in which the exploitation of natural resources is supported by the control of production (Abramovay et al., 2021; Costa et al., 2021). In this case, strategies that reduce poverty could even represent an effective method for reducing deforestation, combining forest conservation with social well-being (da Silva Medina et al., 2022; Miyamoto, 2020).

The recent outbreak of war in Ukraine highlights the impacts of relying on globalized-agricultural markets and reinforces the need for alternative development pathways. Despite clearing forest areas larger than many of the world’s nations, a dependence on global agricultural supply chains can pose a risk to food security in Brazil. For example, President Jair Bolsonaro emphasized issues surrounding food security and was quoted in March 2022 as saying that if the war in Ukraine continues drastic measures could be required to address basic nutritional needs (Paraguassu, 2022). This preoccupation comes from intensive fertilizer inputs required by major crops such as soy that depend on imported potassium from Russia. Such preoccupations further reinforce the need for sustainable pathways to an Amazonian bioeconomy (Abramovay et al., 2021; Costa et al., 2021). For this to happen, Abramovay et al. (2021) highlighted four fundamental elements: “a) Recognition that, by ethical principles, strengthening the forest economy should support the improvement of local livelihoods; b) Institutional signaling against illegality and deforestation; c) Improvement in the quality of information about different products and their value chains; and d) Provoking the emergence of dynamic markets as alternatives to the incomplete, socially unfair, and imperfect markets that dominate the forest economy today”.

Adopting practices that avoid both deforestation and degradation could go hand-in-hand with strategies for poverty alleviation (Di Sacco et al., 2021). Forest loss in Amazonian agricultural frontiers continues to be subsidized by (1) land tenure regularization that incentivizes land-grabbing, (2) land reform programs,

(3) rural credit that is decoupled from formal land ownership, (4) downgrading of environmental legislation and its effectiveness and (5) amnesty for violations of illegal deforestation and incitements for noncompliance and the substitution between markets and actors which diminishes the effectiveness of regulations. (Azevedo-Ramos & Moutinho, 2018; Boucher & Chi, 2018; Ferrante & Fearnside, 2019; Garrett et al., 2021; Guimarães de Araújo, 2020; le Polain de Waroux et al., 2019; Pereira et al., 2020; Rajão et al., 2020). In addition to forest loss, forest degradation is an increasing challenge (Bullock et al., 2020). Regeneration and restoration can simultaneously counteract degradation, reduce greenhouse gas emissions and improve local climates and ecosystem resilience (Rajão et al., 2020). Yet, such active management adds additional time and costs, which can be disproportionally prohibitive for small scale farmers who may become even more indebted without appropriate investments such as interest free loans and capacity building (Gil et al., 2016).

A potential caveat to our findings is that our analysis specifically focuses on the direct associations between forest loss and socioeconomic indicators. We did not assess effects through and/or across production chains that can, directly and indirectly, contribute to the variation in economic indicators (e.g. GDP) across the municipalities. Such effects are however likely to be secondary/marginal considering the temporal and spatial scale of our analysis. The broad agreement between our findings and previous studies also suggests that the patterns are a fair and unbiased reflection of forest cover changes and their associations across 5 Mkm^2. Additionally, the division of cover classes and subset identification was driven largely by the sample size of municipalities with different proportions of natural forest cover. Based on the temporal and spatial scale of our analysis we assume the trends found will be robust to potential uncertainty associated with the criteria used to select a representative subset of municipalities. There is potential for future studies to adopt techniques such as statistical matching and panel regressions (Schleicher et al., 2020) that may provide additional insight for comparisons among municipalities. Such studies could also include a broader range of socioeconomic variables that can help to provide a more detailed assessment of local scale patterns to identify what is driving socioeconomic development and maldevelopment across Brazilian Amazonia.

Implications for conservation

Our findings support evidence from across the tropics that show deforestation may be a short-term boon for agricultural economies, but does not necessarily generate transformative and equitable production systems or poverty alleviation. Poverty alleviation could be achieved across Brazilian

Amazonia without forest loss through measures that directly improve sanitation and education, facilitate greater access to resources, and create opportunities to take advantage of available technologies and policies.

Methods

Data sources

We compiled the most up to date data from publicly available sources (Table 1) to test two predictions embedded in an implied direct cause-effect relationship between forest cover and poverty among municipalities from nine Brazilian states (Amapá, Amazonas, Acre, Maranhão, Mato Grosso, Para, Tocantins, Rondônia, Roraima). The results presented come from 794 of the 808 municipalities with economic data available in 2019 (IBGE, 2021). State capital municipalities were not included in any of the analyses as these represent distinct socioeconomic development trajectories within and between States and are unlikely to be representative of changes due to forest loss. Although the capital municipalities include a major proportion of the state population (IBGE, 2021), they were not included as we were interested in the direct relationships between forest cover and economic indicators not a quantification of consumption chain pathways. Municipalities whose geographic borders changed from 2002 to 2019 were also excluded.

Table 1. Annual data for municipalities across the Brazilian Amazonia.

Variable	Source	Years	Expected relationship if predictions are true
Forest loss			
Forest cover and loss	(MapBiomas 2021)	1985 - 2019	
Economic indicators			
GDP and GVA for municipalities (standardized currency values)	(IBGE, 2021)	2002 - 2019	Positive association with increasing forest loss.
Average salary	(IBGE, 2019a)	2006 - 2019	Positive association with increasing forest loss.
Socioeconomic indicator			
Sanitation plan	(IBGE, 2019b)	2019	Positive association with increasing forest loss.
Internet connectivity	(IBGE, 2019b)	2019	Positive association with increasing forest loss.

Spatial data including municipality location and size were obtained from the Brazilian Institute of Geography and Statistics (IBGE) available at https://www.ibge.gov.br/geociencias/downloads-geociencias.html.

Forest loss

We used recent forest loss (cumulative sum of loss from the previous five years) to compare changes among municipalities. This five-year timespan was chosen based on strong correlations that prevented the inclusion of different forest loss timespans in the same model (Pearson correlations >0.87 among two to five-year timespans, Supplemental Material S1) and cross-correlation analysis of the temporal association between economic measures and forest loss (Supplemental Material S4). As the pairwise correlations were so strong (Supplemental Material S1) here we assume that results at the scale of our analysis will be consistent across the range of lag values. The five-year period used in our study follows the timescale adopted by a previous study linking deforestation and cattle pasture expansion (zu Ermgassen et al., 2020). Forest loss was quantified using data derived from freely available annual land use and land cover data from 1985 to 2020 (MapBiomas 2021). The Brazilian Annual Land Use and Land Cover Mapping Project (MapBiomas) is a collaboration between scientists that started in 2015. Remote sensing techniques are used to calculate a variety of land cover and land use data obtained from Landsat images (30 x 30 m resolution); with the raster data processed into different products that are freely available (Souza et al., 2020). Annual values of forest loss per municipality were obtained from pre-calculated summaries of the areas where a transition occurred from natural forest (including savanna and forest formations) to anthropic cover (MapBiomas Collection 6, available from https://mapbiomas.org/en/statistics, (MapBiomas 2021)). As the focus was on broad scale changes among municipalities, forest loss was expressed as the total summed forest area per municipality (including natural savanna and forest formations) that was converted to human land use each year.

Economic indicators

To compare economic indicators we used annual municipality level data compiled and maintained by the IBGE (IBGE, 2021). There is a two-year delay between collection and publication of the official Brazilian national accounts and the most recent municipality level economic data available was from 2019 (released 17 December 2021) and does not, therefore, include any changes due to the Covid-19 pandemic. Three economic response variables were Gross Domestic Product (GDP) per capita, agriculture Gross Value Added (GVA) per capita, and average salary per municipality. These three indicators were chosen to represent distinct components of economic growth across the study area. GDP is the sum of all goods and services, and agriculture GVA is the contribution of the agricultural sector to GDP (Kauano et al., 2020; Lipscomb & Prabakaran, 2020; Nobre et al., 2016). As agriculture is the main driver of forest loss across Brazilian Amazonia (Faria & Almeida, 2016; Garrett et al., 2021), we also included agriculture GVA per capita as the economic returns from forest loss would be expected to be stronger and sooner reflected in agriculture GVA than in GDP. Resident population, agriculture GVA, and GDP from 2002 to 2019 were used to calculate agriculture GVA per capita and GDP per capita. All final currency values were standardized (e.g. corrected for inflation) as part of the IBGE data compilation process and are directly comparable among years from 2002 to 2019. The average salary per municipality was used to more closely represent the economic situation of the population from 2006 to 2019. The average salary was expressed as a proportion of the national minimum salary, thereby representing the purchasing power of workers within each municipality. The national minimum salary is updated annually by the Brazilian Federal Government using a calculation including the previous year's inflation and GDP. Although this national minimum salary does not directly represent the population living subsistence livelihoods and/or with informal employment we include it as it is likely to represent a best-case indicator of income among municipality populations.

Socioeconomic indicators

In addition to economic indicators, we also compared forest cover/loss with two socioeconomic indicators: the existence of a sanitation plan and internet connectivity. Care must be taken to represent poverty and the context of the use of this word. Poverty has complex definitions and forms of measurement that differ with context and usage. Here we consider poverty to be a state or condition in which a person or community lacks the resources and essentials for a minimum standard of living (well-being). The choice of two socioeconomic indicators followed principles laid out by frameworks such as the Sustainable Livelihood Approach (Scoones, 1998) and was based on available annual data and the scale and context of the study objectives. These two indicators were selected as they are proxies for a broad range of basic indicators, are necessary to enable future socioeconomic development, and were also likely to change over the 18-year study period (2002 to 2019). The existence of a municipality sanitation plan was used to broadly represent sanitation and health conditions. Internet connectivity was included as a proxy for infrastructure, access, and opportunity. An approved sanitation plan is a fundamental step necessary for investment and improvements in sanitation and health care within municipalities. Internet is widely used across Brazil and many of the national level administration systems (e.g. taxes, loans, benefits, entrance to public universities and banks) are accessed solely or predominantly via online systems. Internet access was represented by the connectivity in 2019 among the government administrative offices/centers in each municipality. This was included as complete connectivity between administrative centers was likely to represent a best-case scenario for internet availability and coverage for the local populations in each municipality.

Subset identification and selection of comparable municipalities.

A subset from the 794 municipalities was selected to help isolate the effects of forest cover change and control variation caused by characteristics that could confoundingly influence the economic indicators. We did not follow the binning previously adopted by Rodrigues et al. (2009), rather we established clearly separate cover class groups. Municipalities were first grouped based on the proportion of natural forest cover in 1986. As there could be annual variation in satellite image quality a median of natural forest cover from 1985, 1986, and 1987 was used (forest cover 1986 hereafter). A threshold of less than 40% for a “low” forest cover class was chosen as there were very few municipalities with both less than 30% forest cover and less than 50% indigenous area in 1986 (n=16). Municipalities with high (at least 50%) indigenous area cover were not included, as due to profound cultural, social, administrative and legal differences these areas are likely to experience distinct development trajectories in comparison to those with no or little indigenous area cover.

To include the same gradient range (0 to 40%), a forest cover range of 60 – 100% was chosen to represent municipalities with more forest, thereby excluding intermediate cover values and generating clearly distinguishable “less” and “more” cover class groups. The more forest group (municipalities with more than 60% natural forest cover and less than 50% indigenous area) was further separated into municipalities that still retained at least 60% natural forest cover in 2019 (“high cover”) and those with less than 50% natural forest cover in 2019 (“medium cover”). This 50 % value is. below both the “half-world” threshold necessary for biodiversity conservation (Dinerstein et al., 2017; Leite-Filho et al., 2021) and the 60 % value estimated with the planetary boundaries framework as the minimum natural tropical forest cover necessary to stay within Earth`s "safe operating space" (Steffen et al., 2015). Forest cover in 2019 was obtained from the median of values from 2018, 2019, and 2020 (2019 hereafter).

To provide a valid comparison of differences due to forest cover change the distribution of values for key socioeconomic proxy variables from the low forest class was used to select the subset of the other two classes. The low forest cover class was used as a reference class, with the variable values of this reference class used to select municipalities with medium and high forest cover that were otherwise broadly comparable in terms of socioeconomic characteristics from 2002 to 2019. The low forest cover class included municipalities from 7 states (Amapá, Amazonas, Maranhão, Mato Grosso, Pará, Roraima and Tocantins). Municipalities were therefore only included from these seven states as different states have contrasting historic and present day development and administration patterns.

Table 2. Socioeconomic characteristics from the selected subset of municipalities. This cover subset was grouped into three forest cover classes using percent of natural forest cover in 1986 as a reference level ("low": less than 40%, "medium": more than 60% in 1986 but less than 50% in 2019 and "high" more than 60% in 1986 and 2019).

	Low		Medium		High	
Subset description						
Number of municipalities	41		111		205	
Number of states	7		4		7	
Total municipality area (km^2)	89 K		243 K		557 K	
Urban concentration (total yes:no)	1:40		2:109		3:202	
Gold mining processes	0		0		0	
Characteristics	median	range	median	range	median	range
Forest cover 1986	32.9	(4.8 – 39.6)	70.5	(60.2 – 92.7)	85.8	(60.6 – 99.5)
Forest cover 2019	21.7	(4.7 – 39.1)	38.9	(8.9 – 49.9)	74.7	(60.2 – 99.4)
Municipality size (km^2)	1288	(200 – 12535)	1392	(150 –11355)	1632	(159 –12274)
Distance to state capital (km)	211	(44.1 – 753)	269	(40.9–735)	215	(19.4–741)
Population density	7.7	(0.2 – 150)	13.2	(0.8– 103)	9.1	(0.4 – 88.7)
Industry Gross Added Value	5.0	(1.6– 41.5)	4.9	(2.0 – 36.0)	4.7	(1.3– 41.5)
Indigenous lands	0	(0– 21.1)	0	(0– 17.0)	0	(0– 17.8)

The key socioeconomic proxy variables were used to select a representative sample of municipalities with a similar central tendency (median) and range of values (Table 2).

- Municipality size: Size can, directly and indirectly, affect development through issues such as logistics, diversity of habitats, and natural resources.
- Distance to the state capital: Municipalities closer to state capitals are likely to have improved infrastructure, logistics, and market access.
- Industrial activities contribute strongly to economic development across Brazilian Amazonia. This sector includes mining, electricity generation (e.g. hydropower), and construction. The

contribution of the industrial sector was expressed as the % of the total Gross Value Added per year per municipality.

- Population density is a proxy for the needs and consumption of the population.

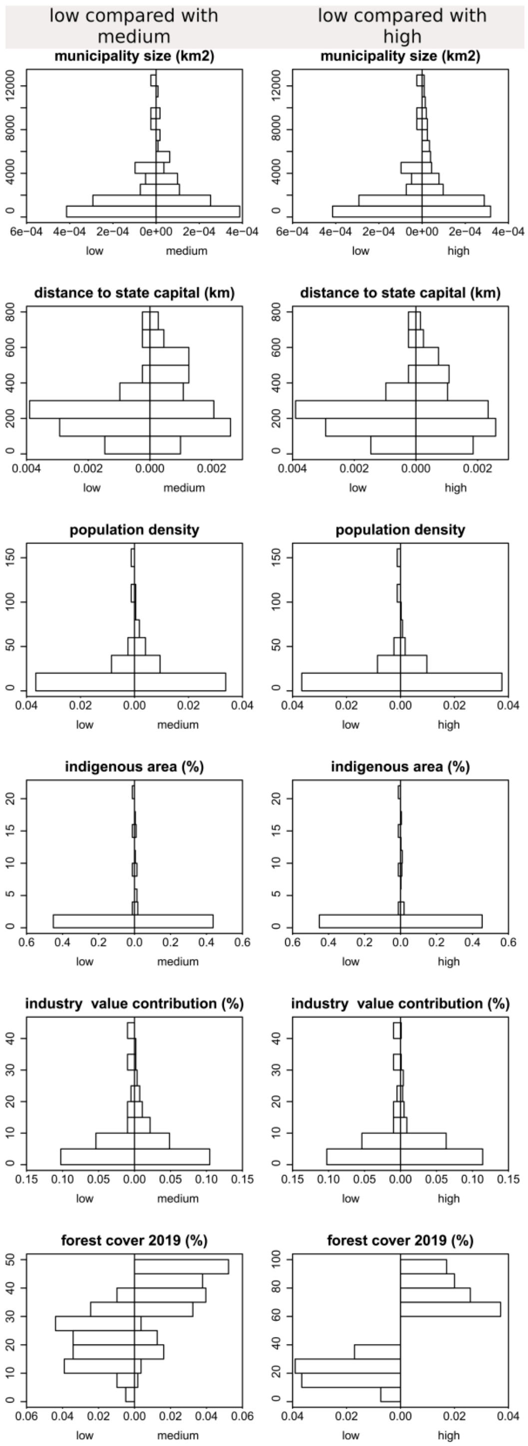


Figure 5. Distribution of socioeconomic proxy variable values across municipalities grouped into three forest cover classes. Subset grouped into three forest cover classes using percent of natural forest cover in 1986 as a reference level (“low”: less than 40%, “medium”: more than 60% in 1986 but less than 50% in 2019 and “high” more than 60% in 1986 and 2019.

Pair-wise comparisons also showed that the distribution of socioeconomic variable values was similar among forest cover classes (Kolmogorov-Smirnov $P > 0.05$ for all pair-wise comparisons with the exception of forest cover percentages, Figure 5).

Analysis

All analysis was run with original Brazilian currency values. Currency values were converted to US$ in text, figures, and tables to facilitate comparison with previous studies (2019 rate of US$1 to R$3.946).

Generalized Additive Models (GAMs) were used to establish evidence of associations between forest loss and economic indicators. GAMs are a powerful and flexible modeling technique (Pedersen et al., 2019; van Rij et al., 2019) that were chosen to develop models for testing the two predictions with the available data, as the responses representing economic indicators could be explained using generalized additive mixed effect models with a combination of parametric, non-parametric (smoothed non-linear) and random terms (Pedersen et al., 2019; van Rij et al., 2019; Wood, 2006; Wood, 2020). This approach provides a systematic description of the patterns in the data rather than focusing solely on the statistical significance of the differences between the response and explanatory variables (Pedersen et al., 2019; van Rij et al., 2019). An iterative model checking process was adopted to ensure that numerically stable model fits and robust inference were possible (Wood, 2006; Zuur et al., 2010), copies of the data and code used are available from https://doi.org/10.5281/zenodo.6536826.

All models were run with the Tweedie error family (Dunn, 2017; Tweedie, 1984) and estimated using restricted maximum likelihood (REML, (Pedersen et al., 2019; Wood, 2006)). The three economic indicator responses were modeled with annual forest loss (the cumulative sum of loss from previous five years) expressed in km^2 and as % of the 1986 forest cover in each municipality (Supplemental Material S2 for model specifications and results). Spatial relationships were included using geographic coordinates of the Mayors' office (administrative center) of each municipality. The Euclidian distance (km) from each municipality to the state capital was calculated between the coordinates of the respective Mayors' offices. Temporal relationships were modeled by including year as a smoothed explanatory variable and an AR1 process for residual correlation matrix (autoregressive correlation structure). To test if the different cover classes in the selected subset of municipalities explained variation in the three economic indicators cover class was included as a categorical factor in the GAMs instead of annual forest loss (Supplemental Material S3 for model specifications and results). All models were checked for spatial autocorrelation via semivariograms of model residuals and for temporal autocorrelation via autocorrelation plots of model residuals (Wood, 2006; Zuur et al., 2010).

Acknowledgements

We would like to thank Willie Shubert for useful discussions that helped to develop the text and the anonymous reviewers and the Associate Editor for their constructive comments.

Data availability

The data that supports the findings of this study are available in the supplementary information of this article. A copy of the data and code is also available at https://doi.org/10.5281/zenodo.6536826.

Declaration of competing interest

The Authors declare that there is no conflict of interest..

References

Abessa, D., Famá, A., & Buruaem, L. (2019). The systematic dismantling of Brazilian environmental laws risks losses on all fronts. Nature Ecology & Evolution, 3(4), 510-511. doi:https://doi.org/10.1038/s41559-019-0855-9

Abramovay, R., Ferreira, J., Costa, F. d. A., Ehrlich, M., Castro Euler, A. M., Young, C. E. F., . . . Villanova, L. (2021). The New Bioeconomy in the Amazon: Opportunities and Challenges for Healthy, Standing Forests and Flowing Rivers. In C. Nobre, A. A. Encalada, E, F. B. Roca Alcazar, M Mena, C, M. Peña-Claros, G. Poveda, Rodriguez, JP Saleska, S Trumbore, S, Val AL, L. Villa Nova, R. Abramovay, A. R. A. Alencar, C , D. Armenteras, P. Artaxo, S. Athayde, H. B. Barretto Filho, J Berenguer, E Bortolotto, F , F. Costa, M. Costa, N. Cuvi, P. F. Fearnside, J, B. Flores, S. Frieri, L. Gatti, J. Guayasamin, S. Hecht, M. Hirota, C. Hoorn, C. Josse, D. Lapola, C. Larrea, D. Larrea-Alcazar, Z. M. Lehm Ardaya, Y, J. M. Marengo, J, R. M. M. Moraes, P Murmis, MR, E. Neves, B. Paez, L. Painter, A. Ramos, M. Rosero-Peña, M. Schmink, P. Sist, H. ter Steege, P. Val, H. van der Voort, M. Varese, & G. Zapata-Ríos (Eds.), *Amazon Assessment Report 2021*. New York, USA: United Nations Sustainable Development Solutions Network.

Alves-Pinto, H. N., Newton, P., & Pinto, L. F. G. (2015). Reducing Deforestation and Enhancing Sustainability in Commodity Supply Chains: Interactions between Governance Interventions and Cattle Certification in Brazil. Tropical Conservation Science, 8(4), 1053-1079. doi:https://doi.org/10.1177/194008291500800414

Amorim, D., Neder, V., & Duarte, I. (2021, 02/12/2021). Queda de 8% no PIB da agropecuária no 3º trimestre é a maior desde 2012. Estadão. Retrieved from https://www.msn.com/pt-br/dinheiro/economia-e-negocios/queda-de-8percent-no-pib-da-agropecu%c3%a1ria-no-3%c2%ba-trimestre-%c3%a9-a-maior-desde-2012/ar-AARohPT?li=AAggXC1.

Azevedo-Ramos, C., & Moutinho, P. (2018). No man's land in the Brazilian Amazon: Could undesignated public forests slow Amazon deforestation? Land Use Policy, 73, 125-127. doi:https://doi.org/10.1016/j.landusepol.2018.01.005

Barbier, E. B., & Di Falco, S. (2021). Rural Populations, Land Degradation, and Living Standards in Developing Countries. Review of Environmental Economics and Policy, 15(1), 115-133. doi:https://doi.org/10.1086/713152

Bastos Lima, M. G., Harring, N., Jagers, S. C., Löfgren, Å., Persson, U. M., Sjöstedt, M., . . . Alpízar, F. (2021). Large-scale collective action to avoid an Amazon tipping point - key actors and interventions. Current Research in Environmental Sustainability, 3, 100048. doi:https://doi.org/10.1016/j.crsust.2021.100048

Borda-Niño, M., Meli, P., & Brancalion, P. H. S. (2020). Drivers of tropical forest cover increase: A systematic review. Land Degradation & Development, 31(11), 1366-1379. doi:https://doi.org/10.1002/ldr.3534

Boucher, D., & Chi, D. (2018). Amazon Deforestation in Brazil: What Has Not Happened and How the Global Media Covered It. Tropical Conservation Science, 11, 1940082918794325. doi:https://doi.org/10.1177/1940082918794325

Boulton, C. A., Lenton, T. M., & Boers, N. (2022). Pronounced loss of Amazon rainforest resilience since the early 2000s. Nature Climate Change, 12(3), 271-278. doi:https://doi.org/10.1038/s41558-022-01287-8

Brazil. (2021). *Brazil - High-level Segment Statement COP 26*. Glasgow Climate Change Conference - October/November 2021 Retrieved from https://unfccc.int/documents/310808.

Bullock, E. L., Woodcock, C. E., Souza Jr, C., & Olofsson, P. (2020). Satellite-based estimates reveal widespread forest degradation in the Amazon. Global Change Biology, 26(5), 2956-2969. doi:https://doi.org/10.1111/gcb.15029

Busch, J., & Ferretti-Gallon, K. (2017). What Drives Deforestation and What Stops It? A Meta-Analysis. Review of Environmental Economics and Policy, 11(1), 3-23. doi:https://doi.org/10.1093/reep/rew013

Butler, R. A. (2021). Amazon deforestation unexpectedly surges 22% to highest level since 2006. Mongabay News. Retrieved from https://news.mongabay.com/2021/11/amazon-deforestation-unexpectedly-surges-22-to-highest-level-since-2006/

Carvalho, R., Coelho-Junior, M. G., Valdiones, A. P., Silgueiro, V., & Thuault, A. (2022). Lack of transparency and social participation undermine the fight against deforestation in Brazil. DIE ERDE – Journal of the Geographical Society of Berlin, 153(1). doi:https://doi.org/10.12854/erde-2021-605

Caviglia-Harris, J., Sills, E., Bell, A., Harris, D., Mullan, K., & Roberts, D. (2016). Busting the Boom–Bust Pattern of Development in the Brazilian Amazon. World Development, 79, 82-96. doi:https://doi.org/10.1016/j.worlddev.2015.10.040

CBD. (2021). The Convention on Biological Diversity: Post 2020. Retrieved from https://www.cbd.int/conferences/post2020

Costa, F. A., Schmink, M., Hecht, S., Assad, E. D., Bebbington, D. H., Brondizio, E. S., . . . Pinedo-Vazquez, M. (2021). Complex, Diverse and Changing Agribusiness and Livelihood Systems in the Amazon. In C. Nobre, A. A. Encalada, E, F. B. Roca Alcazar, M Mena, C, M. Peña-Claros, G. Poveda, Rodriguez, JP Saleska, S Trumbore, S, Val AL, L. Villa Nova, R. Abramovay, A. R. A. Alencar, C , D. Armenteras, P. Artaxo, S. Athayde, H. B. Barretto Filho, J Berenguer, E Bortolotto, F , F. Costa, M. Costa, N. Cuvi, P. F. Fearnside, J, B. Flores, S. Frieri, L. Gatti, J. Guayasamin, S. Hecht, M. Hirota, C. Hoorn, C. Josse, D. Lapola, C. Larrea, D. Larrea-Alcazar, Z. M. Lehm Ardaya, Y, J. M. Marengo, J, R. M. M. Moraes, P Murmis, MR, E. Neves, B. Paez, L. Painter, A. Ramos, M. Rosero-Peña, M. Schmink, P. Sist, H. ter Steege, P. Val, H. van der Voort, M. Varese, & G. Zapata-Ríos (Eds.), *Amazon Assessment Report 2021*. New York, USA: United Nations Sustainable Development Solutions Network.

Crelier, C. (2021, 29 December 2021). PIB fica em -0,1% no terceiro trimestre influenciado por queda na agropecuária. Retrieved from https://agenciadenoticias.ibge.gov.br/agencia-noticias/2012-agencia-de-noticias/noticias/32387-pib-fica-em-0-1-no-terceiro-trimestre-influenciado-por-queda-na-agropecuaria

da Silva Medina, G., Pokorny, B., & Campbell, B. (2022). Forest governance in the Amazon: Favoring the emergence of local management systems. World Development, 149, 105696. doi:https://doi.org/10.1016/j.worlddev.2021.105696

Daw, T. I. M., Brown, K., Rosendo, S., & Pomeroy, R. (2011). Applying the ecosystem services concept to poverty alleviation: the need to disaggregate human well-being. Environmental Conservation, 38(4), 370-379. doi:https://doi.org/10.1017/S0376892911000506

Di Sacco, A., Hardwick, K. A., Blakesley, D., Brancalion, P. H. S., Breman, E., Cecilio Rebola, L., . . . Antonelli, A. (2021). Ten golden rules for reforestation to optimize carbon sequestration, biodiversity recovery and livelihood benefits. Global Change Biology, 27(7), 1328-1348. doi:https://doi.org/10.1111/gcb.15498

Dinerstein, E., Olson, D., Joshi, A., Vynne, C., Burgess, N. D., Wikramanayake, E., . . . Saleem, M. (2017). An Ecoregion-Based Approach to Protecting Half the Terrestrial Realm. BioScience, 67(6), 534-545. doi:https://doi.org/10.1093/biosci/bix014

Dunn, P. K. (2017). Tweedie: Evaluation of Tweedie exponential family models (Version R package version 2.3). Retrieved from https://cran.r-project.org/web/packages/tweedie

EIU. (2021). *Democracy Index 2021*. Retrieved from https://www.eiu.com/n/campaigns/democracy-index-2021/

Faria, W. R., & Almeida, A. N. (2016). Relationship between openness to trade and deforestation: Empirical evidence from the Brazilian Amazon. Ecological Economics, 121, 85-97. doi:https://doi.org/10.1016/j.ecolecon.2015.11.014

Ferrante, L., & Fearnside, P. M. (2019). Brazil's new president and 'ruralists' threaten Amazonia's environment, traditional peoples and the global climate. Environmental Conservation, 46(4), 261-263. doi:https://doi.org/10.1017/S0376892919000213

Fischer, R., Giessen, L., & Günter, S. (2020). Governance effects on deforestation in the tropics: A review of the evidence. Environmental Science & Policy, 105, 84-101. doi:https://doi.org/10.1016/j.envsci.2019.12.007

Garrett, R. D., Cammelli, F., Ferreira, J., Levy, S. A., Valentim, J., & Vieira, I. (2021). Forests and Sustainable Development in the Brazilian Amazon: History, Trends, and Future Prospects. Annual Review of Environment and Resources, 46(1), 625-652. doi:https://doi.org/10.1146/annurev-environ-012220-010228

Gil, J. D. B., Garrett, R., & Berger, T. (2016). Determinants of crop-livestock integration in Brazil: Evidence from the household and regional levels. Land Use Policy, 59, 557-568. doi:https://doi.org/10.1016/j.landusepol.2016.09.022

Guimarães de Araújo, S. M. V. (2020). Environmental Policy in the Bolsonaro Government: The Response of Environmentalists in the Legislative Arena. Brazilian Political Science Review, 14(2). doi:https://doi.org/10.1590/1981-3821202000020005

IBGE. (2019a). Estatísticas do Cadastro Central de Empresas. Retrieved from https://www.ibge.gov.br/estatisticas/economicas/comercio/2000-estatisticas-do-cadastro-central-de-empresas/9016-estatisticas-do-cadastro-central-de-empresas.html?=&t=downloads

IBGE. (2019b). MUNIC - Pesquisa de Informações Básicas Municipais. Retrieved from https://www.ibge.gov.br/estatisticas/sociais/educacao/10586-pesquisa-de-informacoes-basicas-municipais.html?=&t=downloads

IBGE. (2021). Produto Interno Bruto dos Municípios 2019. Retrieved 6 January 2021 https://www.ibge.gov.br/estatisticas/economicas/contas-nacionais/9088-produto-interno-bruto-dos-municipios.html?=&t=sobre

Kauano, É. E., Silva, J. M. C., Diniz Filho, J. A. F., & Michalski, F. (2020). Do protected areas hamper economic development of the Amazon region? An analysis of the relationship between protected areas and the economic growth of Brazilian Amazon municipalities. Land Use Policy, 92, 104473. doi:https://doi.org/10.1016/j.landusepol.2020.104473

Lambin, E. F., Gibbs, H. K., Heilmayr, R., Carlson, K. M., Fleck, L. C., Garrett, R. D., . . . Walker, N. F. (2018). The role of supply-chain initiatives in reducing deforestation. Nature Climate Change, 8(2), 109-116. doi:https://doi.org/10.1038/s41558-017-0061-1

le Polain de Waroux, Y., Garrett, R. D., Graesser, J., Nolte, C., White, C., & Lambin, E. F. (2019). The Restructuring of South American Soy and Beef Production and Trade Under Changing Environmental Regulations. World Development, 121, 188-202. doi:https://doi.org/10.1016/j.worlddev.2017.05.034

Leite-Filho, A. T., Soares-Filho, B. S., Davis, J. L., Abrahão, G. M., & Börner, J. (2021). Deforestation reduces rainfall and agricultural revenues in the Brazilian Amazon. Nature Communications, 12(1), 2591. doi:https://doi.org/10.1038/s41467-021-22840-7

Lim, S. S., Updike, R. L., Kaldjian, A. S., Barber, R. M., Cowling, K., York, H., . . . Murray, C. J. L. (2018). Measuring human capital: a systematic analysis of 195 countries and territories, 1990–2016. The Lancet, 392(10154), 1217-1234. doi:https://doi.org/10.1016/S0140-6736(18)31941-X

Lipscomb, M., & Prabakaran, N. (2020). Property rights and deforestation: Evidence from the Terra Legal land reform in the Brazilian Amazon. World Development, 129, 104854. doi:https://doi.org/10.1016/j.worlddev.2019.104854

Lovejoy, T. E., & Nobre, C. (2018). Amazon Tipping Point. Science Advances, 4(2), eaat2340. doi:https://doi.org/10.1126/sciadv.aat2340

MapBiomas (2021). Projeto MapBiomas – Coleção 6 da Série Anual de Mapas de Cobertura e Uso de Solo do Brasil. Retrieved 15 December 2021 https://plataforma.brasil.mapbiomas.org

MDR. (2021). Ministério do Desenvolvimento Regional: Sistema Nacional de Informações sobre Saneamento 2020: Região Norte. Retrieved from http://snis.gov.br/painel-informacoessaneamento-brasil/web/

Meyfroidt, P., de Bremond, A., Ryan Casey, M., Archer, E., Aspinall, R., Chhabra, A., . . . zu Ermgassen Erasmus, K. H. J. (2022). Ten facts about land systems for sustainability. Proceedings of the National Academy of Sciences, 119(7), e2109217118. doi:https://doi.org/10.1073/pnas.2109217118

Ministério da Cidadania. (2022). Auxílio Brasil. Retrieved from https://www.gov.br/cidadania/pt-br/auxilio-brasil

Miyamoto, M. (2020). Poverty reduction saves forests sustainably: Lessons for deforestation policies. World Development, 127, 104746. doi:https://doi.org/10.1016/j.worlddev.2019.104746

Moutinho, P., Guerra, R., & Azevedo-Ramos, C. (2016). Achieving zero deforestation in the Brazilian Amazon: What is missing? Elementa: Science of the Anthropocene, 4, 000125. doi:https://doi.org/10.12952/journal.elementa.000125

Mullan, K., Sills, E., Pattanayak, S. K., & Caviglia-Harris, J. (2018). Converting Forests to Farms: The Economic Benefits of Clearing Forests in Agricultural Settlements in the Amazon. Environmental and Resource Economics, 71(2), 427-455. doi:https://doi.org/10.1007/s10640-017-0164-1

Naritomi, J., Soares, R. R., & Assunçâo, J. J. (2012). Institutional Development and Colonial Heritage within Brazil. The Journal of Economic History, 72(2), 393-422. doi:https://doi.org/10.1017/S0022050712000071

Nobre, C. A., Sampaio, G., Borma, L. S., Castilla-Rubio, J. C., Silva, J. S., & Cardoso, M. (2016). Land-use and climate change risks in the Amazon and the need of a novel sustainable development paradigm. Proceedings of the National Academy of Sciences, 113(39), 10759-10768. doi:https://doi.org/10.1073/pnas.1605516113

Nobre, I., & Nobre, C. A. (2018). The Amazonia Third Way Initiative: The Role of Technology to Unveil the Potential of a Novel Tropical Biodiversity-Based Economy. In L. C. Loures (Ed.), *Land Use - Assessing the Past, Envisioning the Future*: IntechOpen.

Norris, D. (2022). *CuttingDownTrees: data and R code*. Retrieved from: https://doi.org/10.5281/zenodo.6536826

Paraguassu, L. (2022). Se guerra aumentar prejudicará produção de alimentos, diz Bolsonaro [Press release]. Retrieved from https://www.msn.com/pt-br/noticias/brasil/se-guerra-aumentar-prejudicar%c3%a1-produ%c3%a7%c3%a3o-de-alimentos-diz-bolsonaro/ar-AAVddgZ?li=AAggXC1

Pedersen, E. J., Miller, D. L., Simpson, G. L., & Ross, N. (2019). Hierarchical generalized additive models in ecology: an introduction with mgcv. PeerJ, 7, e6876. doi:https://doi.org/10.7717/peerj.6876
Pereira, R., Rausch, L. L., Carrara, A., & Gibbs, H. K. (2020). Extensive Production Practices and Incomplete Implementation Hinder Brazil's Zero-Deforestation Cattle Agreements in Pará. Tropical Conservation Science, 13, 1940082920942014. doi:https://doi.org/10.1177/1940082920942014
Pinho, P. F., Patenaude, G., Ometto, J. P., Meir, P., Toledo, P. M., Coelho, A., & Young, C. E. F. (2014). Ecosystem protection and poverty alleviation in the tropics: Perspective from a historical evolution of policy-making in the Brazilian Amazon. Ecosystem Services, 8, 97-109. doi:https://doi.org/10.1016/j.ecoser.2014.03.002
Rajão, R., Soares-Filho, B., Nunes, F., Börner, J., Machado, L., Assis, D., . . . Figueira, D. (2020). The rotten apples of Brazil's agribusiness. Science, 369(6501), 246-248. doi:https://doi.org/10.1126/science.aba6646
Rodrigues, A. S. L., Ewers Robert, M., Parry, L., Souza, C., Veríssimo, A., & Balmford, A. (2009). Boom-and-Bust Development Patterns Across the Amazon Deforestation Frontier. Science, 324(5933), 1435-1437. doi:https://doi.org/10.1126/science.1174002
Russo Lopes, G., Bastos Lima, M. G., & Reis, T. N. P. d. (2021). Maldevelopment revisited: Inclusiveness and social impacts of soy expansion over Brazil's Cerrado in Matopiba. World Development, 139, 105316. doi:https://doi.org/10.1016/j.worlddev.2020.105316
Sauer, S. (2018). Soy expansion into the agricultural frontiers of the Brazilian Amazon: The agribusiness economy and its social and environmental conflicts. Land Use Policy, 79, 326-338. doi:https://doi.org/10.1016/j.landusepol.2018.08.030
Schleicher, J., Eklund, J., D. Barnes, M., Geldmann, J., Oldekop, J. A., & Jones, J. P. G. (2020). Statistical matching for conservation science. Conservation Biology, 34(3), 538-549. doi:https://doi.org/10.1111/cobi.13448
Schneider, M., Biedzicki de Marques, A. A., & Peres, C. A. (2021). Brazil's Next Deforestation Frontiers. Tropical Conservation Science, 14, 19400829211020472. doi:https://doi.org/10.1177/19400829211020472
Scoones, I. (1998). *Sustainable Rural Livelihoods: A Framework for Analysis. IDS Working Paper 72*. Retrieved from Sussex:
Shyamsundar, P., Ahlroth, S., Kristjanson, P., & Onder, S. (2020). Supporting pathways to prosperity in forest landscapes – A PRIME framework. World Development, 125, 104622. doi:https://doi.org/10.1016/j.worlddev.2019.104622
Silva, J. M. C. d., Prasad, S., & Diniz-Filho, J. A. F. (2017). The impact of deforestation, urbanization, public investments, and agriculture on human welfare in the Brazilian Amazonia. Land Use Policy, 65, 135-142. doi:https://doi.org/10.1016/j.landusepol.2017.04.003
Silva Junior, C. H. L., Celentano, D., Rousseau, G. X., de Moura, E. G., Varga, I. v. D., Martinez, C., & Martins, M. B. (2020). Amazon forest on the edge of collapse in the Maranhão State, Brazil. Land Use Policy, 97, 104806. doi:https://doi.org/10.1016/j.landusepol.2020.104806
Souza, C. M., Z. Shimbo, J., Rosa, M. R., Parente, L. L., A. Alencar, A., Rudorff, B. F. T., . . . Azevedo, T. (2020). Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. Remote Sensing, 12(17). doi:https://doi.org/10.3390/rs12172735
Stabile, M. C. C., Guimarães, A. L., Silva, D. S., Ribeiro, V., Macedo, M. N., Coe, M. T., . . . Alencar, A. (2020). Solving Brazil's land use puzzle: Increasing production and slowing Amazon deforestation. Land Use Policy, 91, 104362. doi:https://doi.org/10.1016/j.landusepol.2019.104362
Stark, S., Biber-Freudenberger, L., Dietz, T., Escobar, N., Förster, J. J., Henderson, J., . . . Börner, J. (2022). Sustainability implications of transformation pathways for the bioeconomy. Sustainable Production and Consumption, 29, 215-227. doi:https://doi.org/10.1016/j.spc.2021.10.011
Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., . . . Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. Science, 347(6223), 1259855. doi:10.1126/science.1259855
Tanure, T. M. d. P., Miyajima, D. N., Magalhães, A. S., Domingues, E. P., & Carvalho, T. S. (2020). The Impacts of Climate Change on Agricultural Production, Land Use and Economy of the Legal Amazon Region Between 2030 and 2049. EconomiA, 21(1), 73-90. doi:https://doi.org/10.1016/j.econ.2020.04.001
Tweedie, M. (1984). *An index which distinguishes between some important exponential families.* Paper presented at the Statistics: Applications and new directions: Proc. Indian Statistical Institute Golden Jubilee International Conference.

van Rij, J., Hendriks, P., van Rijn, H., Baayen, R. H., & Wood, S. N. (2019). Analyzing the Time Course of Pupillometric Data. Trends in Hearing, 23, 2331216519832483. doi:https://doi.org/10.1177/2331216519832483

Weinhold, D., Reis, E. J., & Vale, P. M. (2015). Boom-bust patterns in the Brazilian Amazon. Global Environmental Change, 35, 391-399. doi:https://doi.org/10.1016/j.gloenvcha.2015.09.013

Wood, S. (2006). Generalized additive models: an introduction with R: CRC press.

Wood, S. N. (2020). mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness Estimation (Version 1.8-34). Retrieved from https://CRAN.R-project.org/package=mgcv

World Bank. (2022). Understanding poverty. Retrieved from https://www.worldbank.org/en/understanding-poverty

zu Ermgassen, E. K. H. J., Godar, J., Lathuillière Michael, J., Löfgren, P., Gardner, T., Vasconcelos, A., & Meyfroidt, P. (2020). The origin, supply chain, and deforestation risk of Brazil's beef exports. Proceedings of the National Academy of Sciences, 117(50), 31770-31779. doi:https://doi.org/10.1073/pnas.2003270117

Zuur, A. F., Ieno, E. N., & Elphick, C. S. (2010). A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution, 1(1), 3-14. doi:https://doi.org/10.1111/j.2041-210X.2009.00001.x

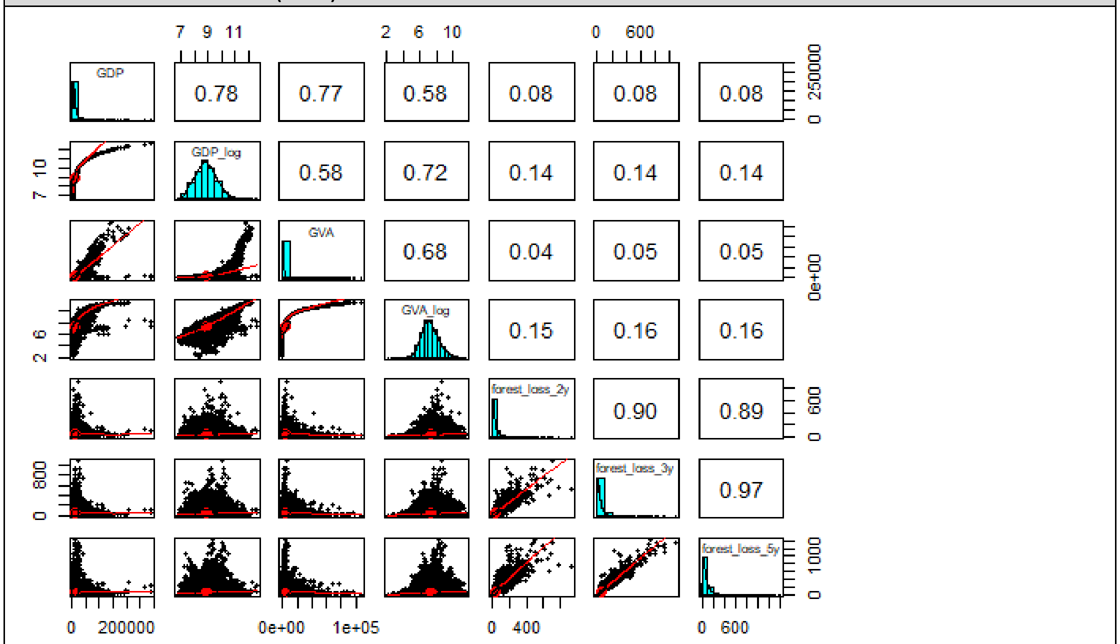
This is a non-peer reviewed preprint submitted to EarthArXiv

Supplemental Material

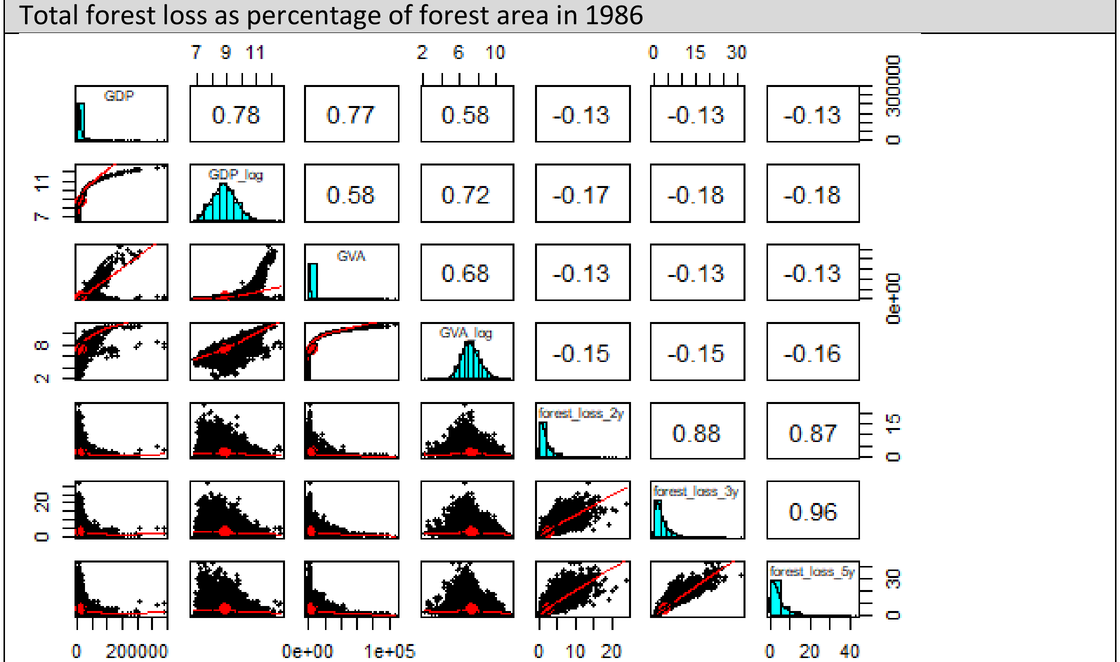
S1 Correlations

Correlations used to decide which years of forest loss to use. Loss are summed annual values (i.e. cumulative totals) during the time frame: “loss 2y” is summed total of losses from current and previous year, “loss 3y” and “loss 5y” are summed total of losses from the previous 3 and 5 years respectively, not including the current years data.

Total forest loss area (km^2)



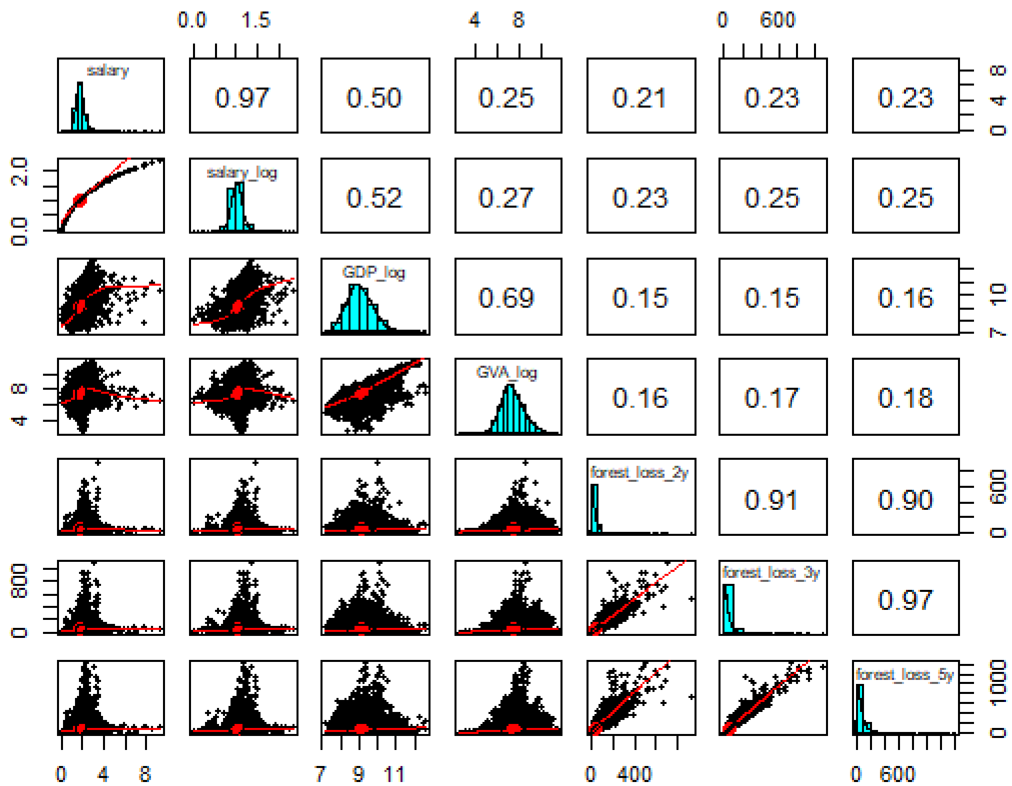
Total forest loss as percentage of forest area in 1986



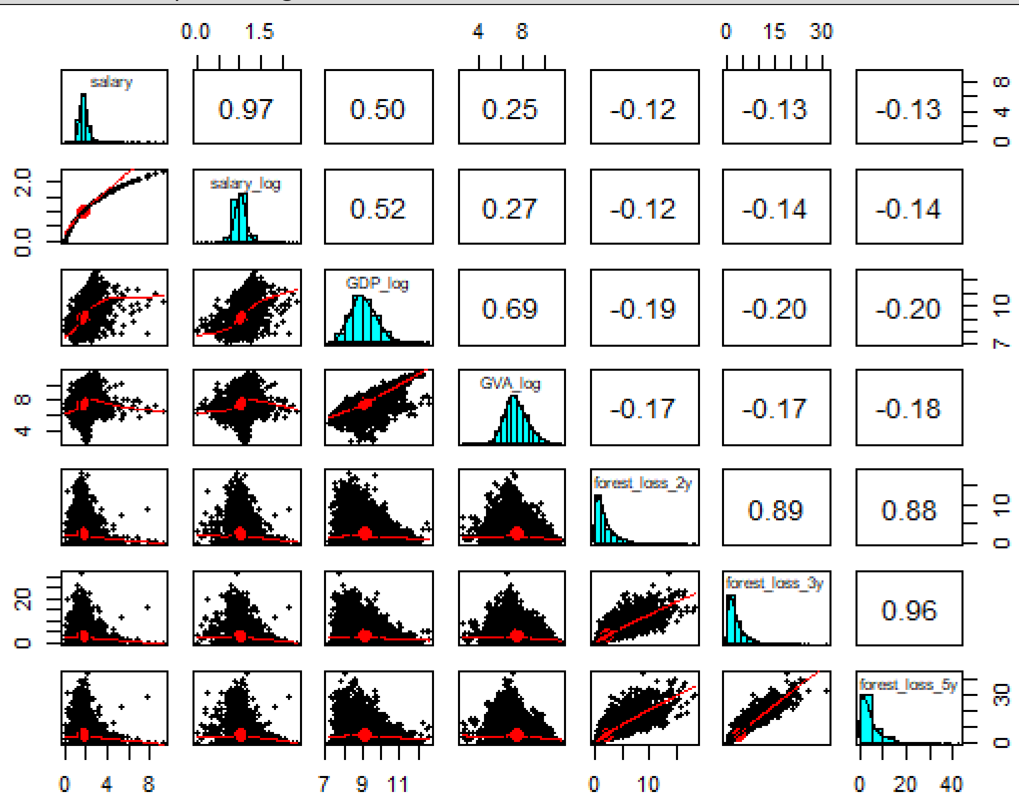
This is a non-peer reviewed preprint submitted to EarthArXiv

Salary correlations 2006 - 2019

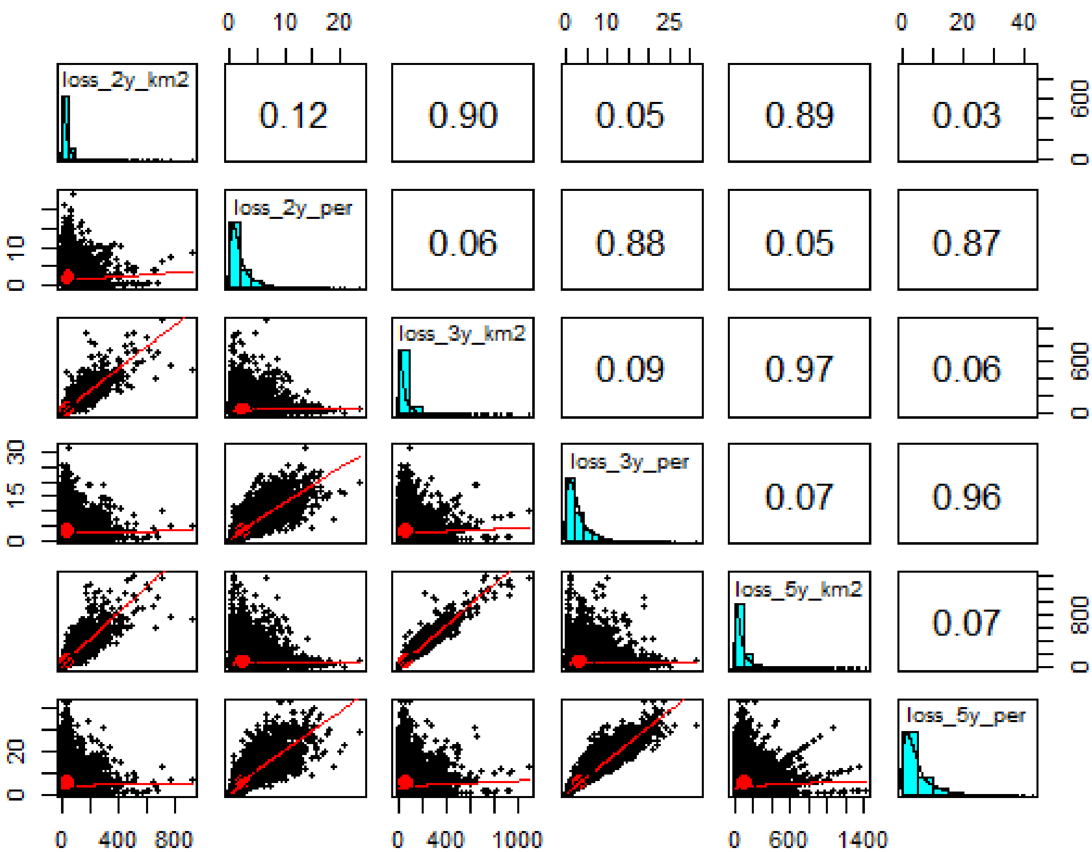
Total forest loss area (km^2)



Total forest loss as percentage of forest area in 1986



Correlations between annual forest loss from 2002 to 2019 expressed as km^2 (“km2”) and as percentage (“per”) of forest cover in 1986. Loss values are summed over different timeframes: “loss 2y” is summed total of losses from current and previous year, “loss 3y” and “loss 5y” are summed total of losses from the previous 3 and 5 years respectively, not including the current years data.



S2 GAMs

Generalized Additive Models (GAMs) were used to establish evidence of associations between forest loss and economic progress indicators. GAMs are an extension of Generalized Linear Models, but have important and fundamental differences in their estimation as they relax parametric assumptions (Wood, 2006). GAMs were chosen to develop models for testing predictions with the available data as the responses representing economic indicators could be modelled against covariates using a combination of parametric, non-parametric (smoothed non-linear) and random terms (Pedersen et al., 2019; Wood, 2006; Wood, 2020). This approach enabled us to control spatial and temporal autocorrelation and provided a more robust and comprehensive evaluation of spatial and temporal patterns than previous studies. For example, Caviglia-Harris et al. (2016) used panel data to examine associations in Human Development Index and deforestation using three time points from the consolidated decadal IBGE census data (1991, 2000 and 2010), but did not consider spatial autocorrelation. Spatial correlation has been shown to generate strong biases in estimates of direction and strength of cross-sectional associations, e.g. (Weinhold et al., 2015) established that "Previous cross-sectional findings of 'boom-bust' are a spurious artifact of spatial correlation." . GAMs are flexible and enabled us to explicitly model temporal and spatial autocorrelation and take advantage of annual data across 794 local government administrative units (municipalities).

The availability of comprehensive annual land cover data (MapBiomas 2021) also enabled us to include spatial scales that were not previously possible. Previously it was necessary to exclude municipalities due to issues such as cloud cover affecting the quality satellite images (Caviglia-Harris et al., 2016; Rodrigues et al., 2009; Weinhold et al., 2015). Across Brazilian Amazonia cloud cover is regional, e.g. the majority of municipalities from the state of Amapá are typically omitted due to cloud cover issues (this can be seen via the associated quality control data provided by the Brazilian Space Agency INPE). In our case, image processing has advanced and the methods we adopted with the annual MapBiomas data also helped to avoid these issues.

The approach taken follows guidance and recommendations presented by Pedersen et al. (2019), van Rij et al. (2019) and Wood (2006); adopting methods described in the following online tutorials:

https://jacolienvanrij.com/Tutorials/GAMM.html#model-terms-partial-effects

http://jacolienvanrij.com/PupilAnalysis/SupplementaryMaterials-2.html

https://petolau.github.io/Analyzing-double-seasonal-time-series-with-GAM-in-R/

https://fromthebottomoftheheap.net/2014/05/09/modelling-seasonal-data-with-gam/

https://fromthebottomoftheheap.net/2021/02/02/random-effects-in-gams/

All models were run with the Tweedie error family (Dunn, 2017; Tweedie, 1984) and estimated using restricted maximum likelihood (REML, (Pedersen et al., 2019; Wood, 2006)). A total of six variables were included to model spatial and temporal associations that were otherwise not explained by patterns in forest loss (Table S2). A combination of non-parametric smooths, random effects and residual correlation structures were employed to model the data and account for spatial and temporal autocorrelation. Temporal autocorrelation was modelled by including an AR1 process for the residual correlation matrix (autoregressive correlation structure).

Table S2. Variables included to model temporal and spatial patterns.

	Variable	Term type	Term specification
Spatial			
	Geographic location (coordinates of Mayors office).	Non-parametric smooth term	s(long, lat)
	Distance to state capital (km)	Interaction	s(dist_statecapital_km, state_namef, bs='fs', m=1)
Temporal			
	Annual smooth differs by state.	Interaction	s(year, state_namef, bs='fs', m=1)
	Intercept differs among years.	Random effect	s(yearf, bs = "re") +
Unmeasured random variation			
	Intercept differs by State.	Random effect	s(state_namef, bs="re")
	Intercept differs by municipality.	Random effect	s(muni_factor, bs="re")

This is a non-peer reviewed preprint submitted to EarthArXiv

In addition to the six variables forest loss (cumulative sum of loss from previous five years) expressed in km^2 and as % of the 1986 forest cover in each municipality was included as a non-parametric smooth term to explain patterns in log transformed responses of economic progress.

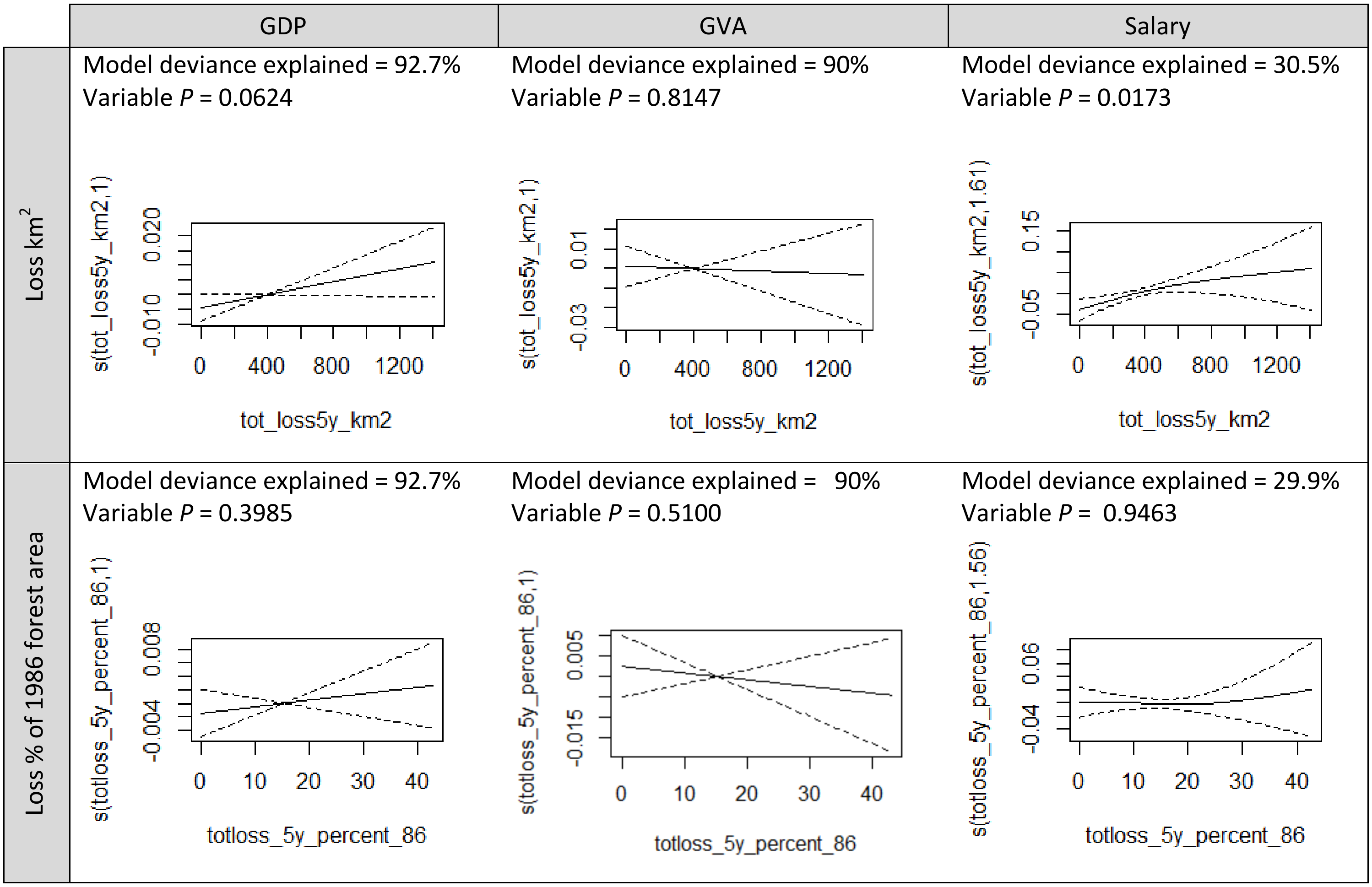


Figure S2. Partial effects of forest loss. Showing results for three economic responses (column wise) as explained by forest loss expressed in km^2 and as percentage of natural forest cover in 1986 (row wise).Graphs show the regression lines for each of the six GAM s with pointwise 95% confidence intervals.

S3 GAMs cover class

As the prime interest was in inference about the terms in the fixed parametric effects (cover class), model formula including non-parametric smooths, random effects and correlation structures were employed primarily to model residual correlation in the data and account for spatial and temporal autocorrelation.

Table S3. Results from GAMs comparing economic indicators among representative subset of municipalities with contrasting forest cover. The three economic response variables were GDP per capita("GDP"), agriculture GVA per capita ("GVA") and average salary ("salary") per municipality.

	GDP			GVA			Salary		
Parametric	Est	T	P	Est	T	P	Est	T	P
intercept	2.19	132.3	<0.001	1.96	80.0	<0.001	-0.01	-0.4	0.694
cover class									
more vs less	-0.01	-1.1	0.267	0.01	0.6	0.581	0.01	0.6	0.533
more loss vs less	-0.00	-0.4	0.699	0.01	0.5	0.601	0.01	0.3	0.747
Non-parametric	EDF	F	P	EDF	F	P	EDF	F	P
s(long,lat)	11.8	3.7	<0.001	13.7	3.1	<0.001	4.4	2.5	0.020
s(dist_statecapital_km,state_namef)	17.3	0.7	0.021	9.9	0.9	0.019	1.1	0.0	0.055
s(year,state_namef)	52.3	144.9	<0.001	49.1	109.0	<0.001	25.2	2.9	<0.001
† (yearf)	5.5	5.6	<0.001	6.5	9.9	<0.001	9.6	9.1	<0.001
† (state_namef)	1.3	0.0	0.999	0.7	0.1	0.016	1.1	0.2	0.002
† (muni_factor)	150.0	0.9	<0.001	236.5	2.4	<0.001	0.0	0.0	1.000
Model deviance explained	90.8%			90.3%			29.1%		
R^2 adj	89.7%			89.9%			31.0%		
Obs	4998			4998			4998		

EDF: Estimated degrees of freedom for the model terms. Values close to zero indicate no relationship with the response, close to 1 may suggest a linear relationship and values greater than 1 suggest a non-linear relationship.
s: Non-parametric smooth terms
† Random effects
R^2_{adj}: Adjusted R squared for the model
Model deviance explained. (%): Percent of total deviance explained

S4 Cross correlations

Temporal correlations between variables compared using cross correlation (CCF). CCF values calculated for each municipality. Figures show values grouped by State to aid visual interpretation. Dashed horizontal line at 0.7 included as a visual reference indicating strong correlation values. Forest loss values (km2) were summed over different timeframes: “loss 2y” is summed total of losses from current and previous year and “loss 5y” are summed total of losses from the previous 5 years, not including the current years data.

This is a non-peer reviewed preprint submitted to EarthArXiv

S5 Sample size

Jacknife randomization was used to establish if differences in sample sizes generated any systematic bias in the comparison between cover classes. As there were 41 municipalities in the less cover reference class, a random selection of 41 municipalities was obtained from each of the more cover classes and GAMs run with the randomized selection with equal sample sizes through 999 iterations.

A significant ($P < 0.05$) difference between cover classes was found in less than 10% of randomized iterations (Figure S5). As such there was no support for sample sizes generating systematic bias, rather these results provide evidence that localized patterns may differ from the general trends.

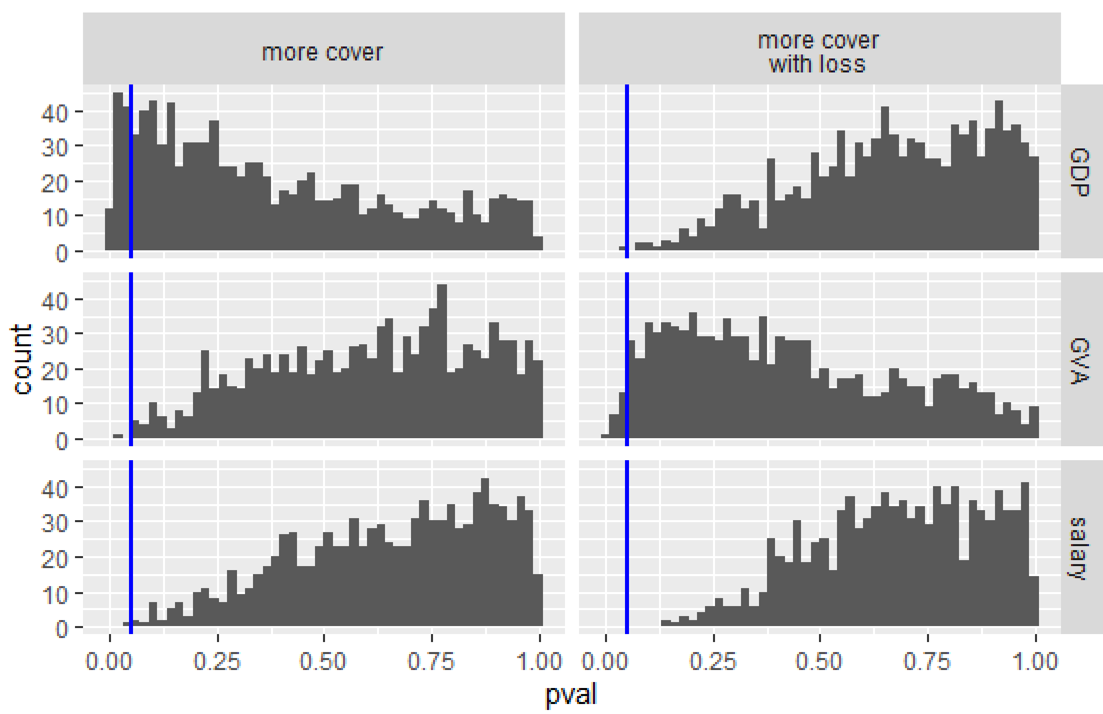


Figure S5. Results show P values ("pval") from GAMs with equal sample sizes of municipalities grouped into cover classes. The three economic response variables were GDP per capita("GDP"), agriculture GVA per capita ("GVA"), and average salary ("salary") per municipality.

References

Pedersen, E. J., Miller, D. L., Simpson, G. L., & Ross, N. (2019). Hierarchical generalized additive models in ecology: an introduction with mgcv. PeerJ, 7, e6876. doi:https://doi.org/10.7717/peerj.6876

van Rij, J., Hendriks, P., van Rijn, H., Baayen, R. H., & Wood, S. N. (2019). Analyzing the Time Course of Pupillometric Data. Trends in Hearing, 23, 2331216519832483. doi:10.1177/2331216519832483

Wood, S. (2006). Generalized additive models: an introduction with R: CRC press.

Wood, S. N. (2020). mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness Estimation (Version 1.8-34). Retrieved from https://CRAN.R-project.org/package=mgcv