POLICY BRIEF

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SPATIOTEMPORAL SCENARIOS FOR DEFORESTATION IN BRAZIL'S LEGAL AMAZON

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Abstract

In light of the consequences of deforestation in the Brazilian Amazon for climate change and biodiversity erosion at global and regional scales, this study explores future deforestation scenarios, their application in a publicly available online dashboard [https://forestatrisk.ipam.org.br], and relationships with public policies. We move beyond deforestation projections, which use a constant rate or moving average assumptions to describe the historical reference level (HRL). Instead, we project deforestation using a novel business-as-usual (BAU) baseline, which predicts the amount of forest loss due to macroeconomic factors alone. We then develop a policy scenario with stronger conservation effort, where non-designated public forests are designated as protected areas (GOV). We estimate our model using data from 1999 to 2021, validate using data from 2022 and forecast deforestation and its spatial allocation from 2023 to 2025. Total observed deforestation area is 32% larger in 2022 compared to the BAU baseline, likely indicating weakened forest governance in 2018-2022. Still, we find a good spatial allocation match between modelled BAU deforestation areas and observed deforestation areas, with an overall mean spatial accuracy corresponding to 80% with a 12 x 12 km window size, and 90% with a 20x20 km. If deforestation would continue at the HRL rate, we would accumulate 35% more deforestation until 2025 than what we estimate for our preferred BAU baseline, indicating that macroeconomic conditions are projected to be conducive for reduced deforestation. All models show large areas of expected deforestation concentrated in central Pará (PA) and in southern Amazonas (AM), especially along the main roads. Another smaller deforestation patch is observed along the border between the Brazilian Amazon and the Cerrado Biome, an older deforestation frontier. In the GOV scenario we simulate that leakage to other areas mainly occurs in rural settlements and rural properties. The study contributes to a better understanding of the factors influencing the amount of deforestation and its distribution in time and space. The spatially explicit model can help identify risk areas for targeted policy responses as well as shed light on where leakage can be expected when local protection mechanisms are enforced.

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1. Introduction

Native vegetation clearing has emerged as one of the most significant environmental challenges of our time. The consequences are disruptive in a coupled human–environment system, affecting a range of ecosystem services, including lacking support to biodiversity and climate regulation (MEA, 2005; Shukla et al. 1990). Agriculture, Forestry and Other Land Use are responsible for 23% of greenhouse gas emissions (GHG) in the world every year and 49% of this GHG is emitted yearly in Brazil (SEEG, 2023). Still, clearings are part of human actions promoting local economic activities related to natural resource extraction, agriculture expansion and land speculation, among others. With the discussion about different mechanisms to reduce deforestation, we show how macroeconomic cycles can drive deforestation dynamics and how interventions towards conservation can affect these dynamics.

Economic conditions impact deforestation by changing the relative prices of products and production factors (labor, capital, and land). Macroeconomic factors include commodity prices and exchange rates: higher commodity prices fuel demand for agricultural land at the expense of natural forests (Assunção et al. 2015, Curtis et al. 2018, Ferreiro Filho & Hanusch, 2022); a depreciating real exchange rate raises the external competitiveness of Brazilian agriculture and also raises the demand for agricultural land (Arcand et al. 2008, Richards et al. 2012, Garcia et al. 2019, Hanusch 2023). With respect to the spatial allocation of deforestation, microeconomic factors of local conditions are important, as reviewed in a recent meta-analysis covering 320 spatially explicit studies from 1996 to 2019 (Busch and Ferretti-Gallon 2023). In the context of the Legal Amazon, important factors include biophysical conditions or measures that, for example, improve market access to Amazon farmers (such as rural roads), reduce the cost of production (such as subsidies), or impact land tenure (Cattaneo 2001, Roebeling & Hendrix 2010, Vilela et al. 2020, World Bank 2021, Porcher and Hanusch 2022, Hanusch 2023, Assunção et al. 2023). While macroeconomic factors tend to impact deforestation in the aggregate, microeconomic factors often have a strong spatial dimension (e.g., the varying quality of agricultural lands across the Amazon or the location of roads). This is not to say that policy choices do not matter, but simply to acknowledge the fact that deforestation is a choice based on economic trade-offs.

Our study contributes to this literature by combining a spatially explicit model of deforestation with a macroeconomic time-series model suitable to estimate counterfactual deforestation net of policy efforts. This allows us to create a spatially explicit baseline forecast for deforestation, generate insights into how much deforestation can be expected in a near future and where it is likely to occur and use this as a basis for scenario analyses to see how policy measures could affect deforestation dynamics. We estimate our model for the nine Brazilian states comprising the Legal Amazon, including Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, Tocantins, and (parts of) Maranhão. Our results are accessible through an innovative, interactive online dashboard [https://forestatrisk.ipam.org.br].

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Mechanisms to reduce deforestation have been implemented in the Amazon with different levels of success. Public policies are certainly responsible for significant past reductions in deforestation – the Plan for Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) is an exemplary case of success involving a multisectoral execution plan. It involved actions such as enforcement of command and control, delimitation of protected areas and programs aimed at families in extreme poverty (Mello & Artaxo 2017, Assunção et al. 2015, Assunção et al. 2023). Private policies such as the soybean moratorium also contributed to decreasing deforestation rates (Heilmayr et al. 2020).

In the current Brazilian policy discourse, different mechanisms to decrease deforestation rates are being discussed and implemented, accompanied by discussion on how to finance them. Forward-looking deforestation risk models provide an approach to identify drivers and dynamics, and areas that are more likely to be affected, enabling more informed decisions depending on prevailing economic pressures on natural forests (Rosa et al. 2017). Spatially explicit models can help identify risk areas for targeted policy responses. A deforestation warning system that jointly provides information on future deforestation pressures and where they are likely to manifest can improve the capacity of planning and performance of mechanisms to reduce deforestation.

2. Methods

We create a spatially explicit deforestation baseline and a policy scenario of increased protection in the Amazon forested areas. We first estimate a deforestation baseline that accounts for macroeconomic conditions (see Section 2.1.1, BAU) and, as an alternative, that uses a constant historical reference (see Section 2.1.2, HRL). We then allocate the total expected deforestation spatially (see Section 2.2) and simulate a policy scenario of increased governance in the Amazon by artifically altering the spatial allocation to represent increased forest protection in specific public land categories (see Section 2.3, GOV). The framework is divided into two main parts as illustrated in Figure 1: (i) model-based projections for the total expected amount of deforested area in the future, and (ii) the spatial allocation of deforestation.

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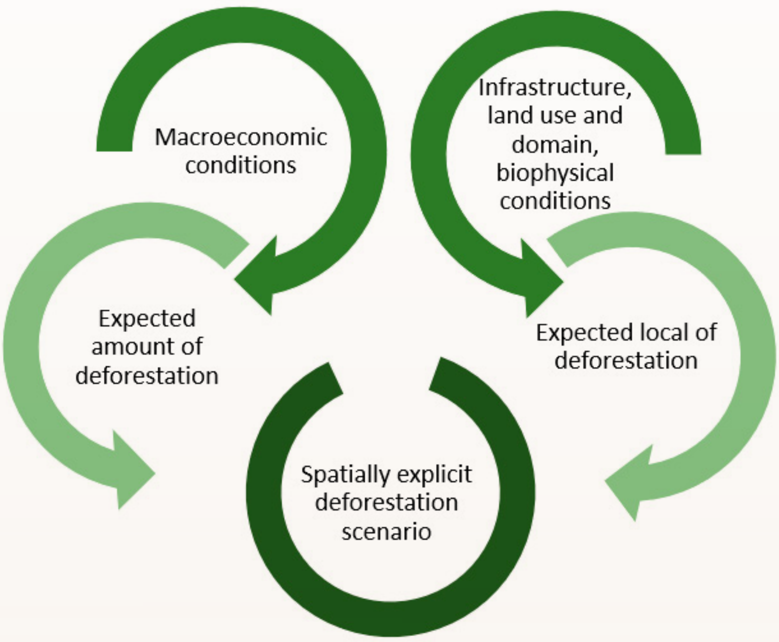

Figure 1. Modeling approach flowchart. On the left side, macroeconomic conditions determine the expected amount of deforestation. On the right side the spatial distribution of infrastructure, land use, land domain (tenure conditions), and biophysical conditions determine where it is more likely to observe deforestation. Both approaches together are used to create spatially explicit scenarios of expected yearly deforestation.

2.1 Quantification of deforestation

To quantify deforestation, we define the macroeconomic "business-as-usual" (BAU) baseline as the expected amount of deforestation based on the past relationship between deforestation and macroeconomic conditions, anchored in a macroeconomic projection. Details are available in Wang et al. 2023. Because of its widespread use, we also calculate the total amount of deforestation that would be projected based purely on historical deforestation trends (HRL), without using information from any variables other than past deforestation.

2.1.1 Business-as-usual (BAU) baseline[1]

The BAU baseline level of deforestation should represent the amount of deforestation we would expect to take place given exogenous, or at least predetermined, macroeconomic conditions. The BAU baseline should provide an estimate of deforestation not affected by policy efforts, so that it can serve as a counterfactual for scenario analysis and its residuals (observed deforestation minus baseline deforestation) can be interpreted as a result of policy actions. We know that policy efforts and interventions, such as the

[1] This subsection is adapted from Wang et al., 2023. Please refer to it for additional discussions, theoretical background and intermediate results.

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Amazon Soy moratorium or the updating of the forest code, have had significant impacts on the rate of deforestation. The key challenge is then to adequately account for past policy actions in the model fitting period, so as not to attribute the results of policy actions to macroeconomic conditions. We will first describe a full model that includes the policy process to develop the idea and clarify where we need to make simplifying assumptions to operationalize our model empirically.

Full model including policy. We denote with total deforestation in year t in the study area (here, the nine Brazilian states comprising the Legal Amazon, including Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, Tocantins, and parts of Maranhão). The full model treats total deforestation as a function of deforestation outcomes for the past three years, y_{t-p} , a set of K exogenous macroeconomic variables with up to *3* lags, x^k_{t-q}, as well as variables capturing past policy actions. Policies related to deforestation can occur either independently of macroeconomic conditions, π_d or be functions of macroeconomic conditions, π_m (x). We call the former independent policies and the latter macro-induced policies. The full model (1) below incorporates both processes additively.[2]

$$y_t = c + \sum_{p=1}^{P} \phi_p y_{t-p} + \sum_{k=1}^{K} \sum_{q=1}^{Q} \beta_q^k x_{t-q}^k + \gamma\pi_m(x_t) + \delta\pi_d + v_t \quad (1)$$

where:
y_t = Observed deforestation in year t
c = Constante
y_{t-p} = Lagged deforestation outcome in year t-p (with a maximum of P=3 lags)
x^k_{t-q} = Exogenous macroeconomic variables in year t and as lags in year t-q (with a maximum of Q=3 lags). Exogenous macroeconomic variables used are principal components of commodity prices and the real exchange rate.
$\pi_m(x_t)$ = macro-induced policies
π_d = independent policy d
v_t = residual in year t

The challenge arises from the macro-induced policies as omitting those means that our estimates of β^k_q would absorb their effects and we would attribute policy effects to macroeconomic factors. To consider how our results would be biased we differentiate between two cases where macro-induced policy changes are either positively correlated to macroeconomic factors or negatively correlated to macroeconomic factors. For ease of exposition, assume that an increase in x^k_{t-q} reflects macroeconomic conditions that increase deforestation pressure (for example an increase in global soy prices) and that an increase in $\pi_m(x)$ reflects policy changes that increase protection policies and decrease deforestation (for example tightened land use regulation). Procyclical macro-induced policy

[2] Note that under the assumption that independent policies and macroeconomic conditions are truly independent, omitting them in our estimation would lead to less precise estimates but would not bias our estimates of .

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actions are those where both effects move deforestation outcomes in the same direction. For example, if global commodity prices decrease $(x\downarrow)$ and hence deforestation pressure eases, governments may seize the opportunity to further tighten land use regulation $\left(\pi_m(x)\uparrow\right)$. This countercyclicality is reflected as $\partial\pi_m(x)/\partial x < 0$ The result is a larger reduction of deforestation than predicted from macroeconomic conditions alone. Conversely, macro-induced policy actions could be countercyclical, i.e. move deforestation outcomes in opposite directions. For example, an increase in commodity prices $(x\uparrow)$ would increase deforestation pressure but may also generate additional tax revenues for the government that could in turn be used to fund the forest police and combat illegal deforestation $\left(\pi_m(x)\uparrow\right)$. Here we would have $\partial\pi_m(x)/\partial x >$. A similar situation would occur if governments tightened deforestation to counteract an expected increase in deforestation pressure from projected increases in commodity prices.

Simplified model allowing for policy-induced level-shifts:
It is difficult to assess whether procyclical or countercyclical policy predominates in our estimation period and a strong assumption that such a pattern would remain unchanged in the future. Additionally, it is difficult to find proxies for the policy process $f\left(\pi_m(x)\right) + g\left(\pi_d\right)$, which renders estimating Model equation 1 infeasible. Instead, we adopt a simplified model common in the literature and represent a known policy action via a policy dummy variable $d_{t\geq s}$, which is one during and after the year when the relevant policy was introduced. This is in line with how previous literature has tried to capture policy effects when estimating the macroeconomic drivers of deforestation (e.g. Assunção, Gandour, Rocha 2015). We also restrict the number of lags for past deforestation and for the variables reflecting macroeconomic conditions to three. This yields our simplified model equation (2) below:

$$y_t = c + \sum_{p=1}^{3} \phi_p y_{t-p} + \sum_{k=1}^{K} \sum_{q=1}^{3} \beta_q^k x_{t-q}^k + \sum_{s\in T} \pi^s d_{t\geq s} + e_t \quad (2)$$

where:
y_t = Observed deforestation in year t
c = Constant
y_{t-p} = Lagged deforestation outcome in year t-p (with a maximum of P=3 lags)
x_{t-q}^k = VExogenous macroeconomic variables in year t and as lags in year t-q (with a maximum of Q=3 lags). Exogenous macroeconomic variables used are principal components of commodity prices and the real exchange rate.
$d_{t\geq s}$ dummy for policy d in year s, active for all years t > s
e_t = residual in year t

By not explicitly differentiating between $\pi_m(x)$ and $\pi_{d'}$ it is possible that our estimates for β^k_q (and π^s) suffer from omitted variable bias. An omitted procyclical deforestation policy would lead to an upward bias for β^k_q and hence the true deforestation baseline net of policy effects would be smaller than our forecast in absolute terms: $|y^0_t| - |\hat{y}_t| < 0$. If we use the difference between observed deforestation and estimated counterfactual deforestation, $y_t - \hat{y}_t$, as our measure of policy impact, then an omitted procyclical deforestation policy would mean that we underestimate the (cyclical) effect of policy. The reverse argument holds for an omitted countercyclical policy.

Given the lack of appropriate proxies and the brevity of data records, we have to rely on simple dummy variables, $d_{t \geq s}$, to estimate the relationship between macroeconomic conditions and deforestation β^k_q, that is net of any policy effects (as policy enters through our policy scenario). In this application, we allow for policy dummies in 2004 (Action Plan for the Prevention and Control of Deforestation in the Legal Amazon), 2009 (Zero Deforestation Cattle Agreement) and 2012 (updated Natural Vegetation Protection Law). Dummy variables could, in principle, be inserted to account for a reduction of policy efforts as well. In this model however, we only include policy dummies that represent increased policy efforts.

Estimation and data:

Model 2 above shows the estimated equation. Observed annual deforestation is taken from PRODES (TerraBrasilis, 2023), from 1999 to 2021, and is our outcome variable y_t. The model allows for the inclusion of up to three lags of observed deforestation. x^k_{t-q} are a set of exogenous variables that reflect macroeconomic conditions: the real effective exchange rate (REER) and principal components of global commodity prices (beef, coffee, soy bean, corn, sugar, soy oil, hardwood logs and iron ore) expressed in local currency. Table A1 in the appendix shows the first four principal components of commodity prices. Again, we allow for up to three lags because changes in macroeconomic conditions may be visible as observed deforestation only after some delay.

The combination of these variables and their lagged variants leaves many potential regressors. To keep the model tractable and its insights generalizable, we use a variable selection method (LASSO) to choose the most relevant predictors. The selected variables jointly explain about 90% of the observed deforestation between 1999 and 2021 (see Table 1).

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Table 1: Post-LASSO regression results. The results were obtained from fitting a linear regression model on the selected variables from the LASSO model. Hence, the standard errors are invalid and only serve an indicative purpose due to issues surrounding post selection inference. Note that a variable being selected by the LASSO does not imply that the variable is also statistically significant.

Group	Predictor	Lag	Coef.	S.E.	t-stat	p-val.	
	Deforestation	$t-1$	0.605	0.150	4.026	0.001	***
Macroeconomic	Δlog(REER)	$t-1$	-0.237	0.141	-1.677	0.114	
Commodities	Principal comp. 2	$t-1$	0.191	0.090	2.127	0.050	*
	Principal comp. 4	$t-1$	0.170	0.090	1.883	0.079	*
Dummies	2004 onwards	.	-0.028	0.053	-0.523	0.608	
	2009 onwards	.	-0.093	0.070	-1.333	0.202	
	2012 onwards	.	-0.004	0.060	-0.073	0.943	
	Constant	.	1.659	0.638	2.600	0.020	**
	R-squared	.	93.7%	.	.	.	.
	R-squared adj.	.	90.8%	.	.	.	.
	F-stat.	.	31.997	.	.	.	.
	Prob(F-stat.)	.	0.000	.	.	.	.
	Observations	.	23	.	.	.	.

Figure 2 shows expected deforestation (blue distributions) according to the model from 1999 until 2021 together with observed deforestation (green and red bars). The effects of the real effective exchange rate (REER) rising from its lowest point of 42 in 2004 and peaking at 109 in 2011,[3] are visible from the graph, as expected deforestation due to macroeconomic conditions decreased sharply. Note that there are still differences between observed and expected deforestation because our model does not account for all policy effects that may have managed to keep deforestation below expected levels (or have failed to do so).

[3] Note: the REER is indexed to 100 in 2020. See BIS Effective Exchange Rate Indices.

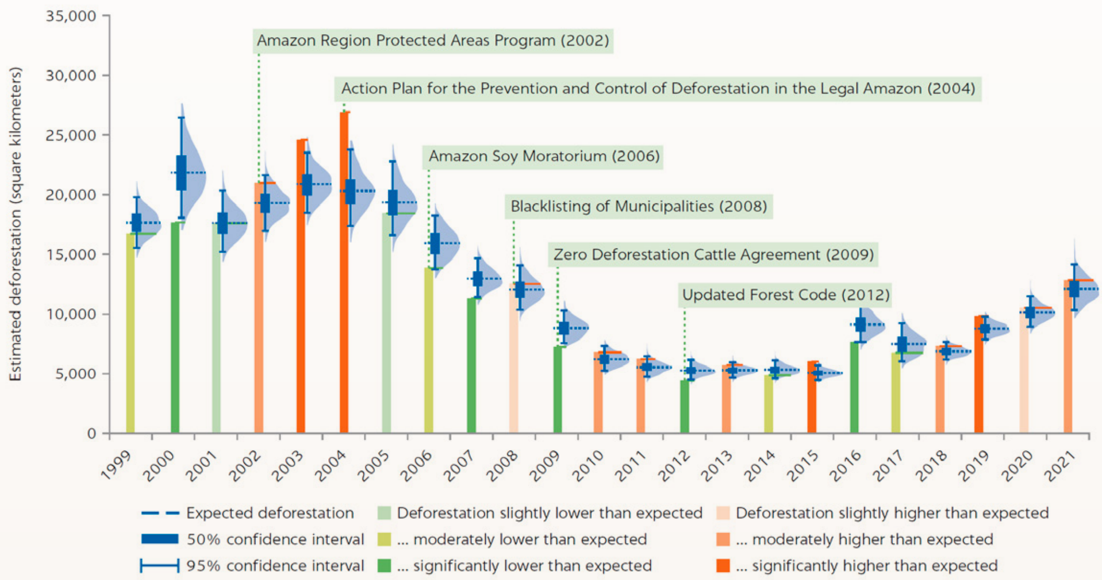

Figure 2. Observed deforestation from 1999 to 2021 are shown in the bars. The colors represent whether deforestation is lower or higher than expected according to the macroeconomic model. The blue distribution is the expected deforestation according to the model.

To construct a macroeconomic baseline for the total amount of deforestation in the near future, we use macroeconomic forecasts from the World Bank's Macro-Fiscal Model (MFMod) as discussed in (Burns et al., 2019).[4] Because these macroeconomic forecasts are only available up to three years into the future, we restrict our scenario to 2022-2025. The World Bank updates the three-year projections every six months and publishes them through the Macro Poverty Outlook series.[5] We used the coefficients from equation (1) with forecasted values for REER and global commodity prices to project deforestation from 2022 to 2025. Figure 3 shows the range of possible deforestation outcomes. For each year, we used the average value for the next steps of our analysis.

[4] We use the point estimates of the forecasts, thereby neglecting how uncertainty in macroeconomic forecasts would propagate to uncertainty in our deforestation estimates. Future research could address this by providing different scenarios, e.g. for strong or weak macroeconomic conditions.

[5] https://www.worldbank.org/en/publication/macro-poverty-outlook

Figure 3. The forecasts are formed by fitting the benchmarking model based on macroeconomic conditions (Equation 1) and using forecasted macroeconomic conditions to predict annual deforestation rates in Brazil's Legal Amazon. The average forecast (dark green line) represents the BAU scenario. The forecast intervals show the likelihood of alternative outcomes.

2.1.2 Historical Reference Level (HRL)

Due to its widespread use, we include the simplest way to construct a baseline for expected deforestation in our analysis as a comparison: assume that deforestation continues at the same rate as in the most recent year(s) with available data. For example, the Amazon Fund or CONAREDD+ / REDD+ forest reference levels use moving averages that get updated every five years. In our application, we only consider the near future until 2025, so, to apply this method, we assume that deforestation continues in 2022-2025 as in 2021 and 2022 (meaning 12,550 km^2 according to PRODES).

2.2 Spatial allocation of deforestation

The allocation of deforestation is a result of models that use the spatial distribution of cleared areas probability, and processes of expansion and creation of deforestation patches. The model was parameterized based on landscape changes occurring between 2017 and 2020. A list of variables is shown in Table 2 comprising environmental variables (both biological and physical-chemical), land domain, infrastructure, environmental regularization, socio-economic, and land use. The entire allocation model was implemented in the DINAMICA EGO platform (Soares-Filho et al., 2013, www.dinamica-ego.com).

We surveyed the literature for variables related to deforestation occurrence, culminating in 38 variables constructed and tested for deforestation dynamics. The relevance of the variables was tested for the Brazilian Legal Amazon as a whole, but also for two specific regions - one between the states of Acre, southwestern Amazonas, and northern Rondônia (also

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known as AMACRO), and another region between southern Pará and northern Mato Grosso. These regions are distinct in terms of physiognomies, physical-chemical factors, agricultural production, and socioeconomic characteristics, and thus bring about different relationships between native vegetation conversion and the explanatory variables. The variables selected to integrate the model are those presented in Table 2. They were selected based on the significance of deforestation dynamic and its lower correlation with other selected variables.

Table 2. Selected variables used to model probability of change. The region of interest is spread into the whole Amazon Biome, AMACRO (states of Acre, southwestern Amazonas, and northern Rondônia), and PA/MT (southern Pará and northern Mato Grosso).

Region of interest	Variable type	Variables
Amazon	Infrastructure	Distance to roads and branches (IMAZON Geo, 2023; DNIT, 2023)
Amazon	Infrastructure	Distance to urban areas (IBGE, 2023)
Amazon	Infrastructure	Distance to rural villages or settlements (IBGE, 2023)
Amazon	Land use	Distance to deforested areas in the last two years of the time series
Amazon	Environmental	Suitability for Agriculture (Pires, 2014)
Amazon	Environmental	Slope (SRTM, 2023)
Amazon	Land domain	Land tenure class (IPAM – internal material)*
AMACRO	Environmental	Carbon Density (MCTI, 2021)
MT/PA	Environmental	Terrain Altitude (SRTM, 2023)

* Rural Properties, Rural Settlements, Restricted Use Conservation Units, Sustainable Use Conservation Units, Non-Designated Public Forest, Indigenous Land - Homologated, Indigenous Land – Not homologated, Traditional Peoples and Communities, Other Public Lands, NoData

The probability of change was calculated by the Bayesian weights of evidence method (Bonham-Carter, 1994), using conditional probabilities to establish the relationship between presence/absence of change given the presence/absence of a given factor. The Weights of Evidence technique uses statistical relationships among the various layers of information (evidence) and known occurrences of deforestation (data-driven) to describe and analyze the interactions among the various spatial data (variables). When simulating scenarios of governance for which a certain area is expected to become more protected, the weights can be artificially modified to mimic the expected effects.

Finally, the simulation of changes is done by integrating the transition rates (quantification of deforestation) with the spatial probabilities of change. The cellular automata patcher and expander (Dinamica EGO software) are used to operate the allocation of quantified changes according to the probabilities obtained. The first creates new deforestation patches from a seeding mechanism (Leite-Filho et al., 2020), while the second expands pre-existing deforestation patches.

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The whole allocation model was applied for each municipality individually. The adherence of each variable presented in Table 2 was measured individually for each of them. Those variables that were not significant to the model for a certain municipality were excluded from the model applied to this same municipality. The results of the models for each municipality were compiled into a single result for the entire Amazon.

2.3 Governance (GOV) Scenario

Deforestation in the Amazon is related to both economic factors and governance issues. While the BAU baseline accounts for (macro)economic factors, we want to highlight the importance of governance through modelling policy scenarios. We develop an environmental governance scenario (GOV) showing possible deviations from the BAU baseline. Specifically, we model what would happen if all Non-Designated Public Forests (NDPFs) would be assigned to Conservation Units. We do this by altering the allocation model so that non-designated public forests (NDPF) receive the same deforestation weights of evidence as Conservation Units.

The GOV scenario influences the allocation of deforestation on the local level within each municipality. Whether it also decrease deforestation in the aggregate depends on the amount of deforestation that is displaced to neighbouring areas within the same municipality. The extent of leakage could be captured by a leakage elasticity. In this paper, we provide a range of possible scenario outcomes based on two extreme values for the leakage elasticity. First, a leakage elasticity of 1 assumes that all avoided deforestation in NDPFs is displaced within the municipality and total aggregate deforestation remains the same. We denote this variant of the governance scenario as GOVlq (lq=leakage). Second, a leakage elasticity of 0 assumes that no deforestation is displaced to other areas and the amount of deforestation in grid cells that are not NDPFs remains constant. This means that total aggregate deforestation will decrease proportional to the decrease in NDPFs. We denote this variant of the governance scenario as GOVdr (dr=decrease). Clearly, both extreme variants of the scenario are not realistic, but they illustrate the range of results from the implementation of a territorial public policy. Note that deforestation in NDPFs is not assumed to be zero in either variant of the scenario. Instead, other variables in NDPFs may be different from protected areas (e.g. distance to roads, settlements or previous deforestation) and exert sufficient deforestation pressure such that the model still simulates that some deforestation would occur in NDFPs, even after assigning them the same protection as conservation units. In such cases, the patcher and expander algorithms that allocate deforestation spatially are unable to allocate the amount of deforestation only outside of NDPFs, because expected deforestation rates are high and available forest patches are either not abundant enough or present even greater resistance to deforestation. Additionally, there has been some deforestation in protected areas historically, so the base deforestation probability for conservation units is also not 0.

2.4 Model Validation

We validated the model by comparing results from the macroeconomic BAU baseline (BAU) to the 2022 observed data using four metrics: (i) the amount of predicted and observed deforestation, (ii) the spatial similarity between observed and simulated maps according to different window sizes (fuzzy similarity method), (iii) the spatial agreement between observed and simulated maps in a 12km x 12km and 20 km x 20 km grid, and (iv) the analyzed agreement between observed and simulateds deforestation values on a municipality level.

We compared the amount of deforestation predicted by the BAU baseline and the amount of deforestation detected by PRODES in 2022 (TerraBrasilis, 2023). To obtain the overall mean spatial accuracy of simulated maps we have calculated spatial similarity between observed and simulated maps according to different window sizes, known as Fuzzy similarity method (Soares-Filho et al., 2013). This method accounts for commission and omission errors with window increasing from 1 cell (0.5 km spatial resolution) to 41 cells (20.5 km spatial resolution) (Silvestrini et al., 2011). Then, seeking to understand model accuracy on a local scale, we mapped spatial agreement in a 12 km x 12 km grid and a 20 km x 20 km grid by comparing deforestation detected by PRODES in 2022 and simulated deforestation. At a municipal level, we compared deforestation detected by PRODES in 2022 and simulated deforestation using both absolute values and proportional ones. The proportional values suggest the model's ability to capture deforestation dynamics even if the absolute amount of simulated deforestation is not the same. Finally, we compared the list of municipalities that were most deforested in simulated and observed maps.

3. Results and Discussion

3. 1 Prediction Accuracy of BAU Baseline

For 2022, our BAU baseline predicted a reduction in deforestation compared to the 2021 level, which we indeed observe in the data. However, while our BAU baseline predicted a deforested area of 9,619 km^2, true deforestation (according to PRODES[6]) was 12,695 km^2 in 2022 (TerraBrasilis, 2023). This is 32% more deforestation than estimated, likely reflecting weakened forest governance in 2022 and the years immediately before. Literature has pointed out that, indeed, Brazilian environmental policies have been weakened since 2016, effecting already protected areas and mainly Non-Designated Public Areas (Azevedo-Ramos et al., 2020; Carvalho et al., 2022; Coelho-Junior et al., 2022; Silva Junior et al., 2023).

[6] http://terrabrasilis.dpi.inpe.br/app/dashboard/deforestation/biomes/legal_amazon/rates

Overall mean spatial (fuzzy) similarity corresponded to 80% in a 12 x 12 km window size, and almost 90% in a 20 x 20 km, representing a good match between observed and simulated deforestation (see Appendix, Figure A2). Such pattern is also shown in Figure 4 with a significant portion of the map showing agreement between observed and simulated deforestation.

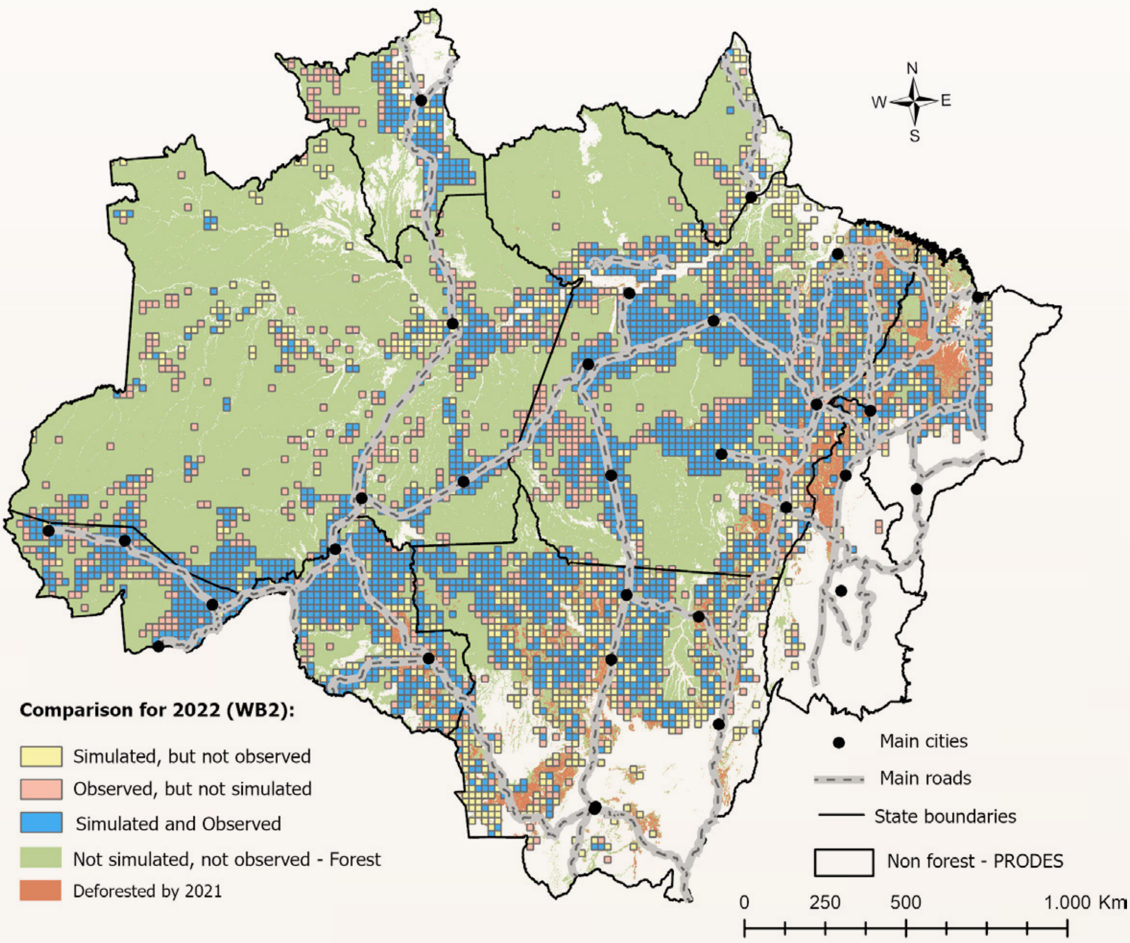

Figure 4. Spatial agreement in a 20 km x 20 km grid by comparing simulated (Macroeconomic BAU baseline) and observed (PRODES) deforestation in 2022

Local differences between observed and simulated deforestation are concentrated in the central area of the State of Amazonas (AM), in the northwest of the state of Roraima (RR), and in the southwest of the state of Pará (PA). We attribute this difference to two new dynamics which were likely not captured by our models due to the lag period between model calibration and scenario building. First, in the last two years, the forests in the interior of the State of Amazonas - the largest block of dense forest in the Amazon region - have experienced a significant increase in deforestation rates. These forests used to have negligible deforestation before 2020 but are quickly becoming a new deforestation

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frontier. Second, a new pattern of increasing deforestation emerged in protected areas and non-designated public forests (NDPF) in the states of Roraima and Pará (Alencar et al. 2022). Additionally, the increase in magnitude of deforestation in public areas is also a more recent dynamic (Alencar et al. 2022).

The 30 municipalities accounting for most deforestation summed up 61% of the total area deforested in the Brazilian Legal Amazon according to the observed deforestation by PRODES in 2022 (TerraBrasilis, 2023). Considering the absolute value of deforestation, these municipalities are mainly in the states of Amazonas (Apuí, Lábrea), Pará (Altamira, São Felix do Xingu) and Rondônia (Porto Velho). Most deforestation was also predicted in these 30 municipalities in the BAU scenario, including the top five municipalities in Amazonas, Pará and Rondônia. Additionally, 25 out these 30 municipalities are also presented in the group of most deforested municipalities in the baseline BAU and the GOV scenario. Still, difference between observed and simulated deforestation in the BAU baseline were higher than 50% in 13 municipalities – mainly in the states of Amazonas (Apuí, Lábrea, Manicoré, Nova Aripuanã), Pará (Itaituba, Portel) and Mato Grosso (Colniza, Nova Bandeirante).

3.2 Comparisons between BAU baseline and GOV scenario

The 2022 estimates highlight the strength of the macroeconomic BAU baseline relative to extrapolating historical values (the historical reference level, or HRL). The BAU accounts for the expected reduction in deforestation due to macroeconomic conditions that disincentivized deforestation and shows that, even though the amount of deforestation in 2022 (11,594 km^2) was lower than in 2021 (13,038km^2), weakened forest governance may have nevertheless led to higher-than-expected deforestation.

With a constant rate assumption, we would predict particularly poor deforestation outcomes from 2022 to 2025, accumulating almost 50,000 km^2. In comparison, the macroeconomic BAU baseline would accumulate 37,000 km^2 of deforested area by 2025 – 26% less than the historical reference level (Figure 5). Turning to the governance scenario, the expected accumulated deforestation between 2022-2025 ranges between 31,728 km^2 and 37,000 km^2, depending on whether we assume no or full leakage.

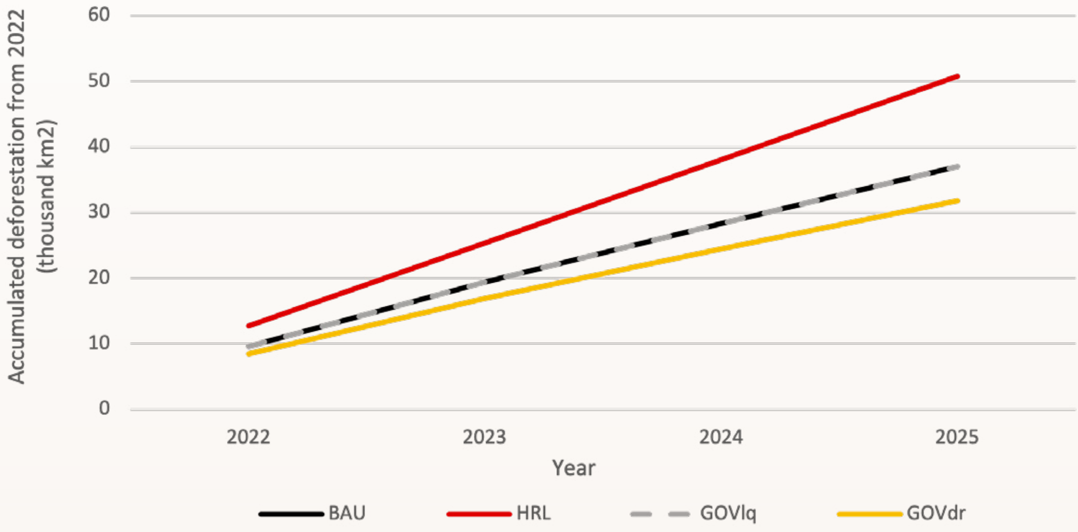

Figure 5. Deforestation accumulated from 2022 to 2025: Historical reference level (HRL), Macroeconomic Business as usual (BAU) and Governance with full leakage (GOVlq) and without leakage (GOVdr). There is no difference between BAU and GOVlq as they only differ in the allocation aspect.

The spatial distribution of simulated deforestation from 2022-2025 for all three models are shown in Figure 6. In general, the highest deforestation values (> 75 km^2 in a 400 km^2 cell) are more concentrated in central Pará (PA) and in southern Amazonas (AM), especially along the main roads. Lower values (< 25 km^2) were observed widespread along the border between Brazilian Amazon and Cerrado Biomes, region often called the Arc of Deforestation. This region is the oldest deforestation frontier in the Brazilian Amazon with highly fragmented forest. Thus, all the models simulated deforestation in small patches over the entire region.

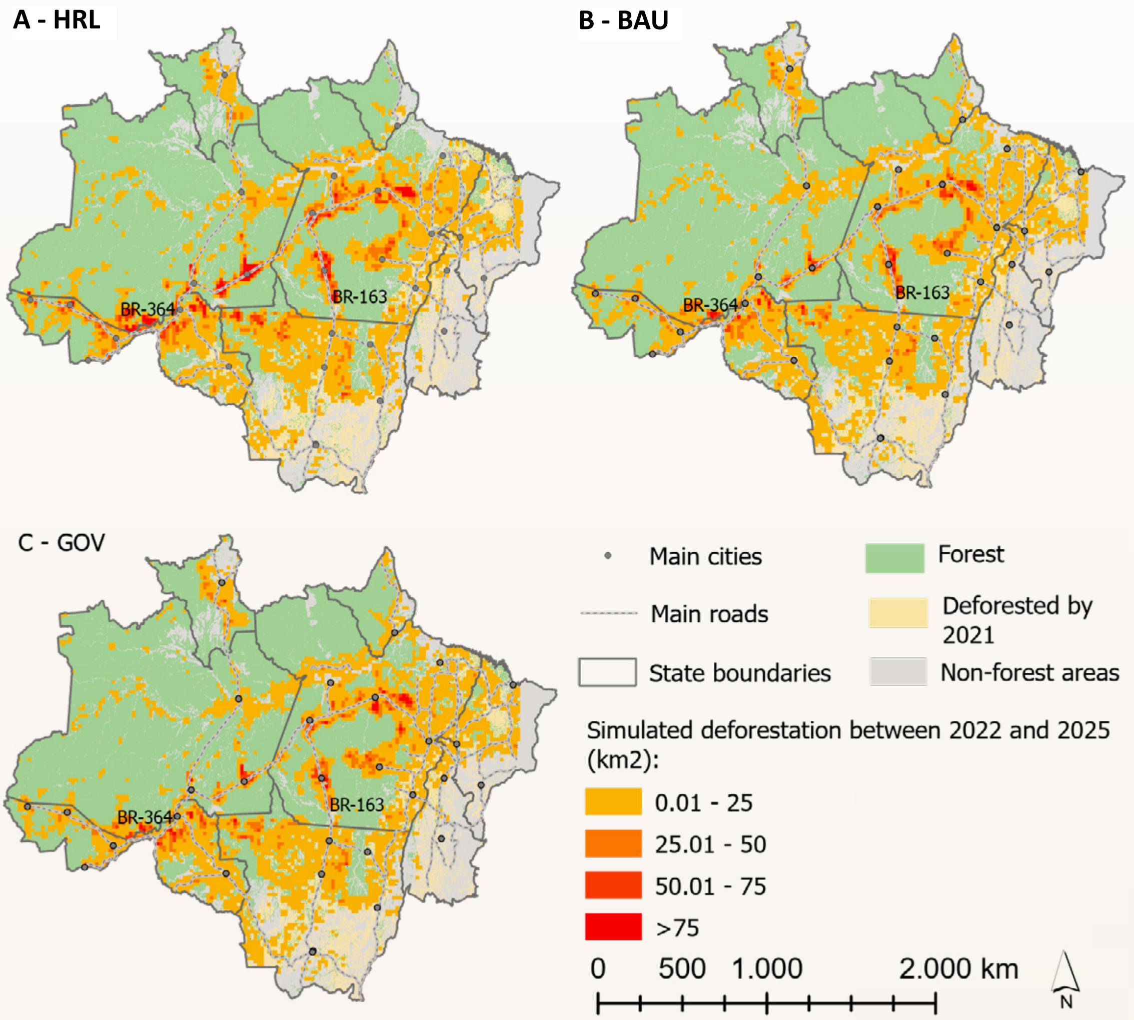

Figure 6. Simulated deforestation from 2022-2025 in grids of 20 x 20 km (400 km² cell) for each model: A) Constant rate assumption; B) Macroeconomics BAU baseline; C) Governance scenario (GOVlq).

In line with the larger accumulation of total deforestation, the constant rate projection also shows more grids with more than 75 km² of deforestation than the BAU baseline and GOV scenario. The differences between BAU and GOV can only be seen at local levels, especially along the BR-163 (south Pará) and BR-364 (south of Amazonas (AM), near Acre (AC) and Rondônia (RO) states). These are regions in which a significant amount of deforestation has occurred in non-designated public forests (NDPFs). Figure 7 shows an example of how the model simulates deforestation in all three different scenarios regarding NDPFs at a fine scale along BR 163, South Pará. With historical reference levels and the BAU baseline, NDPFs are deforested according to historical patterns, resulting in a deforested area of around 995 km² between 2022-2025 in the highlighted region (Figures 7A and 7C). In the scenario in which NDPFs are converted into protected lands, deforestation decreases to 553 km² in those areas (Figure 7B).

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Among public lands, the non-designated public forests (NDPF) were the most deforested in the constant rate projections and the BAU baseline, representing around 25% of total deforestation in the period. Such a pattern has been reported in the literature for the last years (Azevedo-Ramos et al., 2020, Alencar et al. 2022). The GOV scenario projects almost 57% less deforestation in NDPFs than the BAU baseline, when these areas are set to behave similarly to protected areas.

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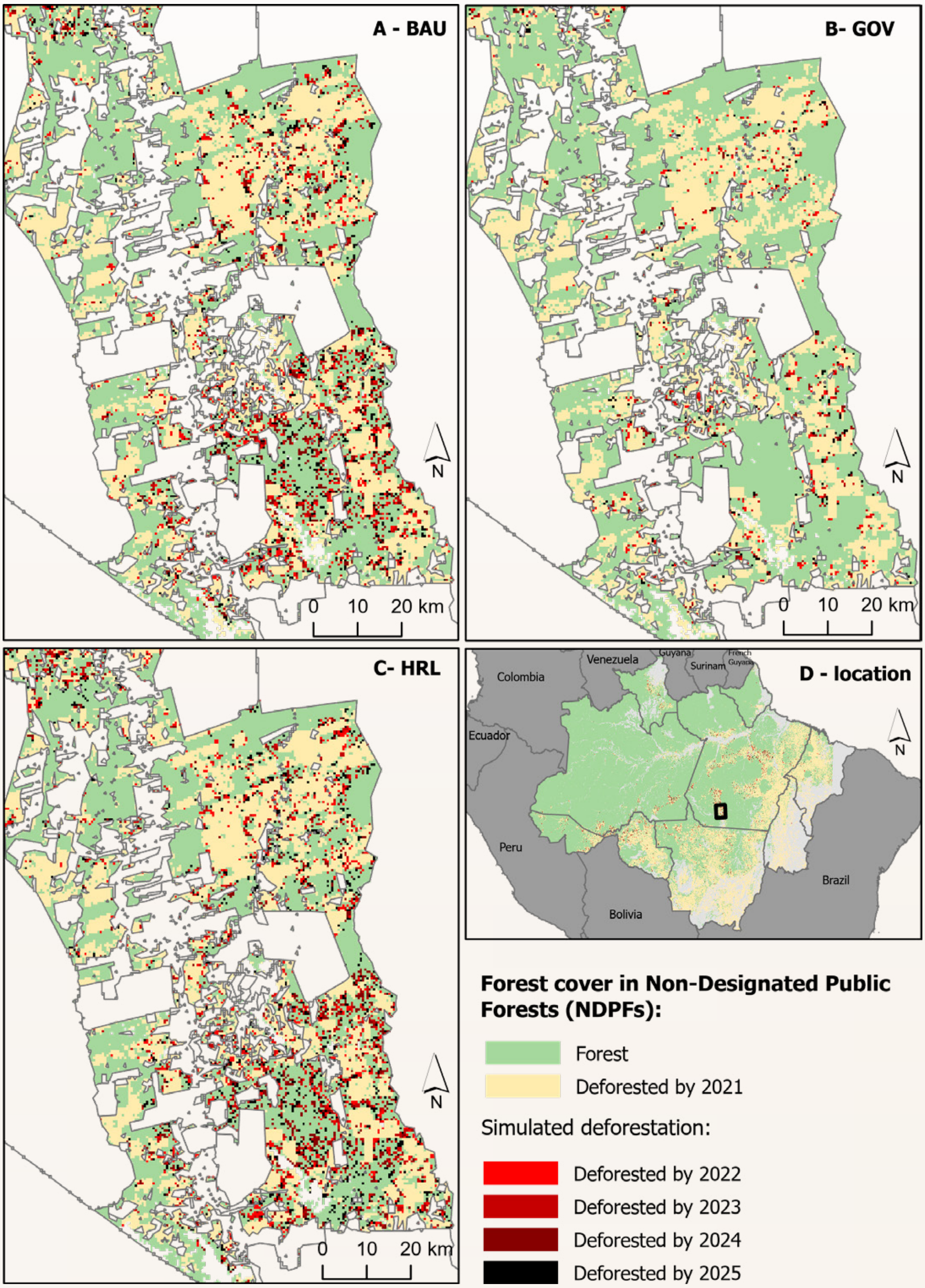

Figure 7. Deforestation in NDPF (non-designated public forests) in a zoom area in the southeast of Pará state among the models: A) Macroeconomic BAU baseline; B) Governance scenario; C) Historical Reference Level; D) location of the zoom area.

It is instructive to analyze which areas outside of NDPFs would see increased levels of deforestation when we make the (extreme) assumption that there is full leakage. This can help us understand unwanted side-effects of increased local protection and reveal where future deforestation patterns are likely to manifest. Full leakage means that total deforestation in the BAU baseline and the GOVlq scenario are the same, deforestation increases in other land tenure categories to offset the decrease in NDPFs. The classes with the largest increases in deforestation are rural settlements (42%), rural properties (21%), conservation units (14%), environmental protected areas (12%). Figure 8 shows the leakage distribution among these classes. Leakage into protected areas such as conservation units were observed in municipalities with already high deforestation pressure when those municipalities had NDPFs becoming more protected. Nevertheless, rural settlements and rural properties concentrated most of deforestation in all scenarios followed by NDPFs.

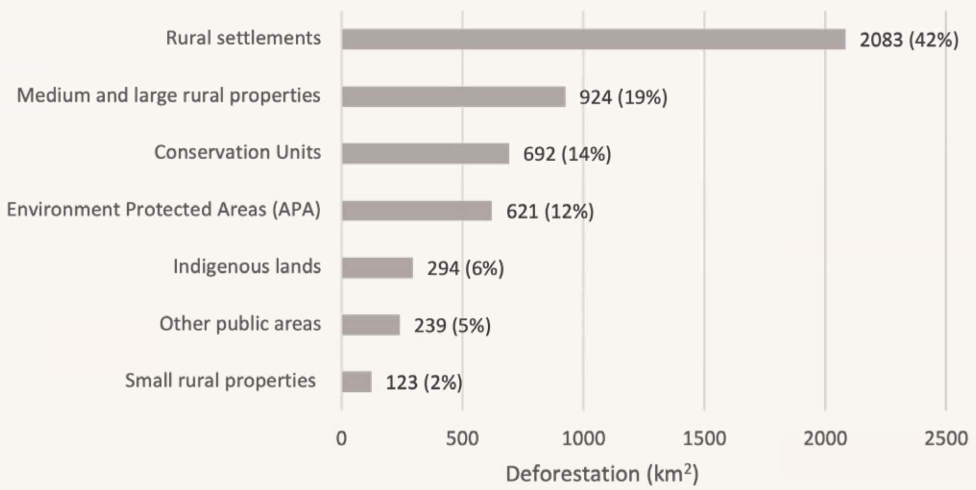

Figure 8. Leakage effect when increasing protection in non-designated public forests (NDPF) onto other land tenure classes. Numbers represent the area that would be deforested in this scenario for each land tenure class (km²).

4. Conclusion and Applications

Deforestation is a result of many interrelated factors, including socio-economic drivers, land-use policies, infrastructure development, and global market demands. Modelling the risk of deforestation enables us to better understand how different factors affect the spatial-temporal dynamics of this process. Predicting the quantity and where deforestation is more likely to occur in space is essential to build and implement effective mechanisms to avoid deforestation.

This study shows two important factors interfering in deforestation: macroeconomic cycles and governance in the form of designating public forests to protected areas.

Macroeconomic cycles can influence land-use decisions, resource allocation, and even the regulatory environment, impacting the overall risk of deforestation. Nevertheless, simulating scenarios in which public forest would be designated for protected areas shows how deforestation is reallocated compared to scenarios in which public forest remain undesignated. Such pattern of displacement, often called leakage, is expected when the overall drivers of deforestation are not addressed in tandem.

Future research could build on our initial results on deforestation leakage to better understand how microeconomic factors influence where leaked deforestation is most likely to occur. Here, Figure 8 provides a starting point to observe which land tenure categories absorb most of the (simulated) leakage. A better understanding of leakage effects would also help to inform policy discussions on how to best address and prevent deforestation from leaking from newly protected forests to neighboring areas. Additionally, estimating a leakage elasticity that depends on local microeconomic factors (e.g. road access and land tenure categories of neighbouring areas) and general equilibrium effects (e.g. reduced land supply and associated increases in deforestation pressures) could significantly narrow down the range of likely outcomes for any given policy scenario and improve upon our method of using two extreme assumptions of full or no leakage.

Section 2.1.1 shows, by means of a theoretical model, how policy intervention and macroeconomic conditions can be related. We operationalize this model for our analysis by including policy dummies, as is standard in the literature. However, we recognize the limitation of this approach in accounting for unobserved correlation in the timing and stringency of policy intervention with macroeconomic conditions and discuss possible biases at the end of Section 2.1.1. Future research could improve on our approach by identifying robust proxies for the policy process that contain more information than dummy variables.

Mechanisms to avoid deforestation approaching multiple parts of the intricated dynamics of deforestation are key to reduce ecosystem degradation and biodiversity loss. Different instruments to finance such mechanisms have been implemented such as certification and market-based initiatives, Payment for Ecosystem Services (PES), Reducing Emissions from Deforestation and Forest Degradation (REDD+), public and private funds. Almost all instruments enabling the implementation of mechanisms on a large scale are designed with a result-based approach. A refined version of models such as the one presented here could be used to support the computation of the performances within these mechanisms. A dashboard [https://forestatrisk.ipam.org.br] bringing all the results shown here is provided by IPAM and WB, where users can better analyze the difference between scenarios for specific regions through graphs and maps.

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Appendix

Table A1: Principal components of global commodity prices

The table shows the first four principal components of global commodity prices in Brazilian reals between 1996-2020 (annual frequency). The data was obtained from FRED, Federal Reserve Bank of St. Louis. Note that the LASSO variable selection model selected the second and fourth principal components for the analysis.

Principal component	1	2	3	4
Beef	0.3522	0.4019	-0.0203	0.5664
Corn	0.3641	-0.0979	-0.2659	-0.0701
Hard Logs	0.3586	0.3387	-0.1922	-0.0990
Coffee (Arabica)	0.3526	0.1899	0.4833	0.3263
Soybeans	0.3606	-0.0139	-0.4148	-0.1546
Sugar	0.3450	0.0784	0.6011	-0.6206
Soybeans Oil	0.3619	-0.1311	-0.3096	-0.2356
Iron Ore	0.3323	-0.8091	0.1706	0.3057
Explained variance	90.06%	93.46%	96.13%	97.97%

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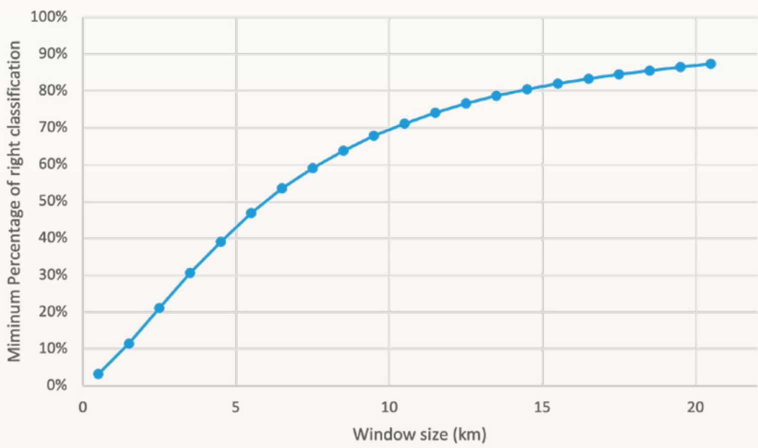
The figure shows the validation results of the spatial allocation algorithm, comparing observed deforestation and simulated deforestation in Brazil's Legal Amazon using PRODES data. The validation calculates the spatial similarity, following the Fuzzy similarity method (Soares-Filho et al., 2013).

Figure A2: *Validation of spatial simulation with different window sizes.*



Spatiotemporal deforestation model with leakage

The model described in equation (2) is on the country or regional level, which aims at modeling the effect of macroeconomic dynamics on deforestation on an aggregate level. In this section we describe how (2) could be reformulated to capture the effect on subnational entities along with spillover effects. This framework serves as a basis for discussion and future research.

Dynamic panel model

To simplify notation, let us extend (2) and then rewrite in vector notation, where represents a vector of deforestation values with typical value y_{it}, with i=1,...,N denoting the entity.[7] Moreover, without loss of generality, let us consider only one lag that is along with only one policy event effect.

$$y_{it} = \phi y_{it-1} + G_t^{\top}\delta_i + L_{it}^{\top}\gamma_i + \pi_{it} + e_{it} \quad (3)$$

Here, G_t is a vector of global factors, such as the real effective exchange rate or commodity prices, which may have entity-specific effects, δ_i. In contrast, L_{it} is a vector of entity-specific, local variables, such as population density or share of protected areas, with entity-specific effects γ_i. We also assume that policies, which may be relevant to more than one entity and period, will have time- and entity-specific effects, it π_{it}. Model (3) expresses idea that

[7] Entities could be administrative units, such as states or municipalities, or geographical units, such as 1km x 1km cells in a grid. The spatial distance matrix would be adjusted accordingly.

deforestation in a specific entity is both driven by global (G_t) and local (L_{it}) factors, and that the same factors may have heterogeneous effects (δ_i, γ_i).

We can express this more compactly as a vector-valued time series model.

$$y_t = \phi y_{t-1} + G_t^{\top}\delta + L_t^{\top}\gamma + \pi_t + e_t \quad (4)$$

To further simplify notation, we define an exogenous variable component that contains both global and local factors, that is $X_t^{\top}\beta = G_t^{\top}\delta + L_t^{\top}\gamma$. Consequently, the model (4) becomes

$$y_t = \phi y_{t-1} + X_t^{\top}\beta + \pi_t + e_t \quad (5)$$

Spatial modeling for leakage

The underlying assumption in models (3)-(5) has been that entities are isolated from each other. This is, however, far from reality, where neighboring regions experience spillover effects, or externalities in general. That is, the deforestation in region *i* may not only be driven by global and local factors, but also by spatial dependencies with a neighboring region *j*. We denote this distance between *i* and *j* as w_{ij}, which constitutes the *N*×*N* spatial dependency matrix *W*.

$$\begin{aligned} y_t &= \rho W y_t + \phi y_{t-1} + X_t^{\top}\beta + W X_t^{\top}\beta^* + \pi_t + W\pi_t^* + u_t \\ u_t &= \lambda W u_t + e_t \qquad\qquad e_t \sim N(0, \Sigma) \end{aligned} \quad (6)$$

The matrix *W* enters the model (6) through various channels. Not all channels are required to estimate the effect of interest. Nevertheless, we describe all components for the sake of generality.

- $\rho W y_t$: Contemporaneous spillovers due to deforestation in neighboring regions.
- $W X_t^{\top}\beta^*$: Contemporaneous (or lagged) spillovers due to global or local factors through neighboring regions.
- $W\pi_t^*$: Contemporaneous (or lagged) spillovers due to policies in neighboring regions.
- $\lambda W u_t$: Spatial dependency in the error structure

The inclusion of *W* is not only to model channels of interest but also to control for omitted variables and endogeneity issues that stem from spatial proximity. Spatial diagnostic tests, such as Moran's *I* or Lagrange Multiplier tests, should be conducted to identify which spatial components are most relevant. Note that the spatial autoregressive component $\rho W y_t$ renders the model nonlinear and requires maximum likelihood estimation methods. Moreover, while the model is written with annual data in mind, it is possible to estimate it on higher frequencies. In such cases, it would be insightful to allow the spatial dependency parameters ρ, β^*, λ to be time-varying, given that deforestation dynamics have a seasonal component. Appropriate state-space models and estimation methods exist in the literature. It is worth mentioning that the dependent variable can be deforestation rate itself or a probability of deforestation. This can be achieved by using a probit or logit transformation, which would yield results closer to the notion of "forest-at-risk". Finally, the distance matrix *W* usually refers to geographical distances. However, deforestation leakage is not always a function of distance. Anecdotal evidence points towards spillovers to comparable or similar regions, that can serve as a substitute whenever a target region is put under protection. In such cases, the *W* matrix would capture similarities rather than distances.