XGBOOST and Multitemporal DETER Data for Deforestation Forecasting

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Abstract

This paper reports research that is part of a project to combat deforestation in the Brazilian Amazon rainforest by developing an online system designed to forecast deforestation risk over the short term, spanning 2 to 4 weeks. This online platform aims to empower stakeholders with timely data, facilitating proactive conservation and intervention strategies to safeguard the Amazon rainforest. We built a multitemporal database that compiles weekly deforestation alerts from the DETER project, forming our analysis's backbone. Utilizing the XGBOOST regression algorithm, we have crafted a predictive model that identifies areas within the Amazon at imminent risk of more intensive deforestation. Preliminary results reveal an RMSE of 0.29 for predicting areas under deforestation risk, as validated against early alert data from 2020 to 2023. Our work advances environmental monitoring by focusing on a spatial resolution of 25 km x 25 km, providing accessible, near real-time information on deforestation risks.

1. Introduction

Deforestation in the Amazon rainforest represents nowadays one of the most important environmental threats. According to data from PRODES Monitoring System (INPE, 2022) conducted by INPE, deforestation rates in the Amazon rose to an alarming rate of 27 thousand km² in 2004. Efforts from government and civil society managed to reduce these rates between 2004 and 2014, starting, however, an increasing trend since 2015, which was intensified since 2019, driven by a combination of factors.

The Brazilian National Institute for Space Research (INPE), in collaboration with the Brazilian Institute for Environment and Renewable Natural Resources (IBAMA), launched the TerraBrasilis Situation Room (INPE, 2024a) in 2020. The platform integrates data from DETER (Near Real-time Deforestation Detection System) and BD Queimadas (active fire in vegetation) into deforestation and degradation indicators. These indicators are spatialized into different spatial units of analysis, such as cells, municipalities, or states, and can be observed and analyzed at different time intervals. The platform now includes information about the risk of imminent deforestation and has been used as an important tool to direct repression teams' actions to areas with the highest probability of imminent deforestation.

Following this line, we started a collaborative project in 2023, leveraging state-of-the-art machine learning technologies to develop a forecasting model to surpass the accuracy of currently used methods. The new model is being designed to be spatially explicit, incorporating data on forest degradation and deforestation from the DETER System (INPE, 2022) and a wide range of socio-political and economic factors to produce monthly deforestation risk maps.

The new method's intended gain is the ability to generate forecasts for the near future, specifically for periods between 15 and 30 days. This contrasts with most conventional models, which typically provide forecasts annually.

The previous system, still in use, employs a model based on the Maximum Entropy (MaxEnt) (Phillips et al., 2006) approach, recognized for its effectiveness in ecological and geographic modeling. However, moved by the complexity of the deforestation process, we are exploring more sophisticated regression models to improve our system's accuracy and predictive efficiency.

Another initiative is the PrevisIA project, which focuses on predictive analytics to combat deforestation in the Brazilian Amazon. This initiative, developed by Imazon in collaboration with Microsoft and Fundo Vale, utilizes monthly satellite data to monitor forest degradation. Based on spatial statistics, their deforestation prediction model leverages historical deforestation data and various spatially distributed auxiliary variables, such as proximity to roads, rivers, topography, protected areas, and socioeconomic factors. By analyzing these variables, the model generates long-term deforestation risk estimates (12 months), predicting forest destruction within the following deforestation calendar year (PrevisIA, 2024).

This paper outlines the current state of our project through the presentation of our machine learning model's architecture. It elaborates on the database we have constructed to train this model and evaluates the system's performance throughout 2023. The model operates at a spatial resolution of 25 km, reflecting the latest advancements and findings within our ongoing research efforts.

The remainder of this paper is organized as follows: Section

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2 reviews related works, highlighting previous efforts in deforestation forecast and the use of machine learning techniques in environmental conservation. Section 3 details the methodology, including building the multitemporal database from DETER project alerts and the specifics of the XGBOOST regression algorithm employed in our model. Section 4 presents our experimental analysis, showing the model performance through numerical accuracy metrics and graphical representations. This section also discusses the importance of various data variables in increasing forecast accuracy. Section 5 concludes the paper with a summary of our findings and outlines future work to refine the model and expand its capabilities to predict better and mitigate deforestation in the Amazon and beyond.

2. Related Works

Recent scientific research has focused on forecasting deforestation, especially in the Amazon region. A paper published in 2016 (Aguiar et al., 2016) presents qualitative and quantitative land-use scenarios for the Brazilian Amazon, aiming to provide a more accurate projection of deforestation trends. The study projected land-use changes up to the year 2050.

Bezerra and coauthors (Bezerra et al., 2022) proposed land-use change scenarios for Brazil, aiming to model the interplay between global and regional drivers influencing deforestation and land-use changes across the country's diverse biomes until 2050.

Jaffe et al. (2021) (Jaffe et al., 2021) used integrated nested Laplace approximations (INLA-SPDE) to project deforestation over the next three years in the Brazilian Amazon, with spatial resolution up to 100 km x 100 km. His research has emphasized identifying key drivers of deforestation and evaluating forecasting models at varying scales through spatial lock-in cross-validation. This approach, while innovative, highlights a gap in the literature regarding short-term, high-resolution deforestation forecasts.

Previously, Souza and DeMarco (2018) (Souza and de Marco, 2018) developed a deforestation risk prediction model for the entire Brazilian Amazon using the Maximum Entropy (Maxent) modeling framework at a high spatial resolution of 10 kilometers. The aim was to forecast deforestation trends in the upcoming years. The same tool was used by Rojas et al. (2019) (Rojas et al., 2019) for the Peruvian Amazon. However, both initiatives (Souza and de Marco, 2018), (Rojas et al., 2019), and Jaffe(2021)(Jaffe et al., 2021) focused on longer-term predictions without addressing the need for short-term forecasting.

Dominguez et al. (2022) (Dominguez et al., 2022) proposed a machine learning model that combines dense neural networks and LSTM to forecast deforestation in the Brazilian Amazon from 2000 to 2020. Their model, which achieved an R-square score of 87.82%, also utilized data from the TerraBrasilis portal to make annual deforestation forecasts at the state level. Despite its high predictive accuracy, the model's annual forecasting timeframe and state-level spatial resolution do not meet the need for more immediate, granular forecasts.

These studies collectively highlight the progress in deforestation modeling through various computational techniques. However, they reveal a significant gap: the absence of models capable of delivering short-term, high-resolution deforestation forecasts. Our research addresses this gap by forecasting the risk of intensified deforestation biweekly at a 25km x 25km spatial resolution. Furthermore, a distinctive feature of our project is the development of an online platform that allows access to short-term deforestation risk assessments for any location within the Amazon forest. This platform not only enhances the accessibility and applicability of our findings but also represents a novel approach to engage the public and stakeholders in proactive deforestation monitoring and prevention efforts.

3. Methodology

3.1 Database Construction

The database construction for this study leverages the deforestation alerts generated by the DETER project. These alerts are derived from optical imagery captured by the WFI sensor aboard the CBERS-4, 4A, and Amazônia-1/INPE satellites. The DETER project categorizes deforestation into two primary types: clear-cutting, which involves completely removing primary vegetation, and degradation, defined as the gradual erosion of primary vegetation (INPE, 2022). For this research, our database exclusively incorporates alerts of clear-cut deforestation as identified by the DETER project, which were accessed via (INPE, 2024).

The model developed in this study aims to forecast imminent deforestation events, enabling authorities to allocate resources in anticipation of these occurrences optimally. We defined the temporal scope of our forecasts as a half-month period, referred to as a 'bi-week,' and spatially confined our analysis to areas encapsulated within 25 km^2 units, from now on termed 'cells.' Figure 1 illustrates the arrangement of these 25 km x 25 km cells across the Brazilian Amazon biome.

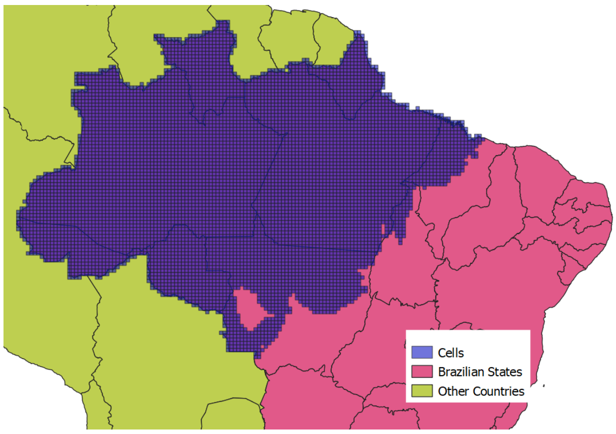

Figure 1. Cells distribution.

Our system selects a combination of static and dynamic variables. These variables are derived from DETER deforestation alerts and a range of socio-political, topographic and biophysical data potentially associated with deforestation trends. Additionally, we also introduced new features to capture temporal dynamics. Table 1 outlines all evaluated features.

3.2 XGBoost overview

In the current stage of our project, we selected the eXtreme Gradient Boosting (XGBoost) algorithm over more complex deep learning models for forecasting deforestation risk. This choice is primarily due to XGBoost's high performance on sparse data. Besides, XGBoost's scalability allows us to handle

Feature	Description	Unit	Temporality	Category	Source
ArDS	Deforestation alert area calculated for the bi-week	km²	Bi-weekly	Previous Deforestation	(INPE, 2024)
DeAr	Difference in deforestation alert area calculated between the reference bi-week and the previous one	km²	Bi-weekly	Previous Deforestation	(INPE, 2024)
AcAr	Cumulative deforestation alert area calculated up to the reference bi-week	km²	Bi-weekly	Previous Deforestation	(INPE, 2024)
CtDS	Deforestation alert count calculated for the bi-week	Alerts	Bi-weekly	Previous Deforestation	(INPE, 2024)
OcDS	Binary occurrence of deforestation alerts calculated for the bi-week	Binary	Bi-weekly	Previous Deforestation	(INPE, 2024)
XQ	Average of deforestation alert areas calculated for the four bi-weeks preceding the reference, considering a Queen contiguity neighborhood	km²	Bi-weekly	Previous Deforestation	(INPE, 2024)
XArDS	Average deforestation alert area calculated in previous years (*ArDS*) for the reference quarter	km²	Quarterly	Previous Deforestation	(INPE, 2024)
XDeDS	Average of the difference in deforestation alert area (*DeAr*) calculated in previous years for the reference quarter	km²	Quarterly	Previous Deforestation	(INPE, 2024)
ArDS_QN	*ArDS* for the N-th ($2 \leq N \leq 6$) most recent bi-week	km²	Biweekly	Previous Deforestation	(INPE, 2024)
NbQ	Number of the bi-week within the year (from 1 to 24)	Bi-week	Biweekly	Previous Deforestation	Generated
rodofic	Distance from cell to official roads	Meters	Static	Socioeconomic	(DNIT, 2022)
rodnofic	Distance from cell to unofficial roads	Meters	Static	Socioeconomic	(Imazon, 2012)
distrios	Distance from cell to rivers	Meters	Static	Geographic	(ANA, 2012)
distUrb	Distance from cell to urban areas	Meters	Static	Socioeconomic	(IBGE, 2017)
distport	Distance from cell to harbors	Meters	Static	Socioeconomic	(DNIT, 2022)
dvd	Vertical distance from cell to the closest drainage section	Meters	Static	Geographic	(Rennó et al., 2008)
EFAMS_APA	Percentage of the cell occupied with environmental protection areas	Ratio	Static	Socioeconomic	(MMA, 2022)
EFAMS_ASS	Percentage of the cell occupied with settlement	Ratio	Static	Socioeconomic	(INCRA, 2021)
EFAMS_CAR	Percentage of the cell occupied with rural properties	Ratio	Static	Socioeconomic	(SFB, 2023)
EFAMS_FPND	Percentage of the cell occupied with undesignated public forest	Ratio	Static	Socioeconomic	(MAPA, 2020)
EFAMS_TI	Percentage of the cell occupied with indigenous land	Ratio	Static	Socioeconomic	(FUNAI, 2021)
EFAMS_UC	Percentage of the cell occupied with conservation unit	Ratio	Static	Socioeconomic	(MMA, 2022)
EFAMS_IND	Percentage of the cell with unknown occupation	Ratio	Static	Socioeconomic	Generated

Table 1. Evaluated features.

extensive datasets characteristic of large areas like Amazon while providing the advantage of higher interpretability. This resource helps understand the predictors of deforestation and guide policy interventions. Unlike deep learning models, XGBoost requires less data for accurate results and requires more modest computational resources.

Additionally, we commenced our analysis at a 25km x 25km spatial scale. This resolution balances data detail with availability and computational feasibility, addressing the challenges of analyzing high-resolution data across Amazon's vast expanse. This scale expedites model training and aligns with our goal to identify broad deforestation patterns, offering insights directly applicable to policy and management strategies.

XGBoost, developed by Chen and Guestrin (Chen and Guestrin, 2016), is designed to perform efficiently across regression and classification tasks. XGBoost is an algorithm for building a committee of decision trees rooted in the gradient-boosting paradigm (Friedman, 2001). It amalgamates the predictive prowess of multiple decision trees to forge a singular, highly accurate, and robust forecasting model.

Central to the XGBoost framework is the principle of boosting, a method where each decision tree within the committee is specifically trained to address the residual errors propagated by the preceding trees. Following the deployment of a tree to make predictions, the discrepancies between these predicted values and the actual target outcomes are computed, delineating the errors. The next tree in the sequence is tailored to predict these residual errors rather than targeting the original outcomes, thereby learning from the prior tree's missteps.

This iterative enhancement cycle persists, with each subsequent tree honing in on the residual errors the cumulative preceding trees left unaddressed. Through this adaptive refinement, the model improves as each tree incrementally adds a corrective adjustment to the ensemble's predictive capability. The training of each tree is directed by the gradient optimization of a loss function, which quantitatively assesses the variance between the actual outcomes and the predictions, thus ensuring the model's continual trajectory toward heightened accuracy.

4. Experimental Analysis

This section describes the experiments conducted to assess the model's performance, covering the experimental protocol, dataset construction, variable selection, prediction accuracy, feature importance, and model comparisons. It concludes with a qualitative assessment using visual maps to illustrate the spatial accuracy of our predictions.

4.1 Experimental Protocol

For the experiments, we organized the dataset into three distinct sets: training, validation, and testing sets, which collectively span from January 2018 to December 2023. The training set included data from January 2018 to December 2020, and the validation set covered January 2021 to December 2021. The testing set, comprising data from January 2022 to December 2023, was used to evaluate the model's performance in predicting new, unseen data.

The objective was to estimate the area under deforestation alert every two weeks ahead. We used a variety of variables, as listed in Table1 for dynamic and static features, to make these predictions. For every cell and each two-week interval, we pair the current information (or "features") with the area under deforestation alert in the following two-week period. This pairing involves the current state of deforestation and other relevant information for a given area and time, aiming to predict the extent of deforestation alert for the next period.

The model employed the Pseudo-Huber error function (Huber, 1964) for robust regression, with key parameters set to a learning rate of 0.03, a maximum depth of 7, and subsampling rates for columns and rows at 0.7. Training stops after 50 epochs with no improvement in the RMSE measured on the validation set.

4.2 Results

4.2.1 Accuracy Figure 2 presents a hexbin scatter plot that graphically illustrates the relationship between predicted deforestation and reference data over a bi-weekly interval from January 2022 to December 2023. The axes are plotted on a logarithmic scale to provide a comprehensive view of the data distribution. The plot also uses color density to represent the count of observations within each bin, with yellow indicating a higher density, suggesting a close prediction-reference agreement. A dense concentration of points along the diagonal line and an RMSE of 0.29 indicate that the model performs well, often yielding predictions close to the actual values. However, divergence from the diagonal, particularly at higher reference values, points to potential limitations in the predictions or specific conditions that reduce the model's accuracy.

4.2.2 Feature Importance Evaluation Figure 3 illustrates the SHAP feature importance plot, which details the contribution of each feature to the forecasting model's output. The SHAP value, depicted on the horizontal axis, represents the magnitude and direction of a feature's impact on the model's predictions. Features on the vertical axis are ranked based on the mean absolute value of the SHAP values for each feature across all samples, with the length of each feature's spread in

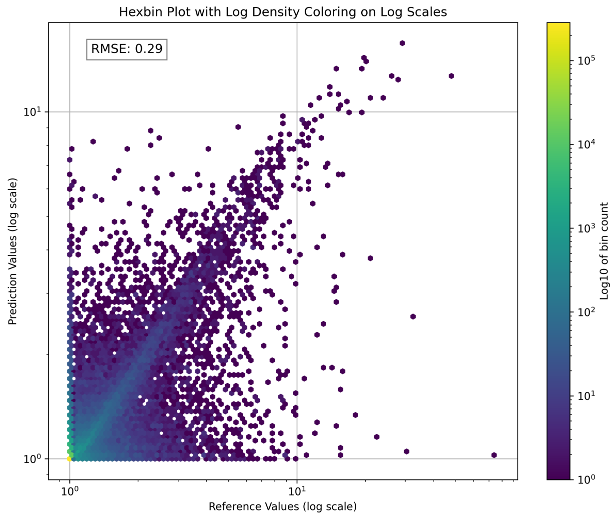

Figure 2. Hexbin Plot.

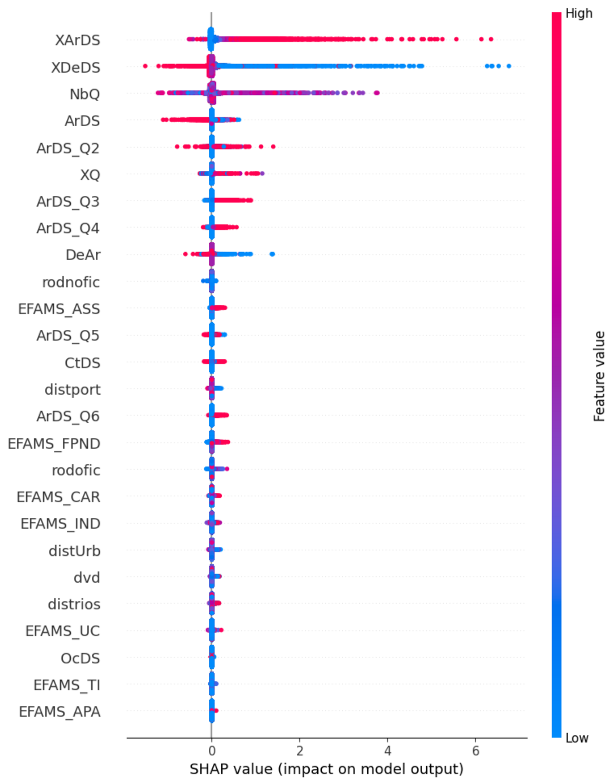

Figure 3. SHAP plot.

the plot corresponding to the variability of its impact. The coloring denotes the feature value, with red for high and blue for low values.

XArDS is depicted as the most important feature with a substantial positive impact on the model's output, with *XDeDS*, *NbQ*, and *ArDS* following in importance. This reveals that the model's predictive accuracy is influenced by recent deforestation areas (*ArDS*) and the aggregation of deforestation across different periods, particularly on a quarterly basis.

For features *XDeDS* and *DeAr*, a high difference in deforestation between the reference period and the preceding one tends to have a negative SHAP value. This trend suggests that the model could perceive sudden increases in deforestation as outliers, potentially leading to a conservative estimation of future deforestation areas when previous changes have been drastic.

Mixed impacts are observed for features like *ArDS_Q2*, *ArDS_Q3*, and *ArDS_Q4*, indicating that these features have varying contributions that may depend on the data context or reflect seasonal influences. Features such as *EFAMS.ASS*, *distport*, and *ArDS_Q5* are positioned closer to the center of the plot, suggesting they present a neutral or moderate influence on the model's predictions. On the contrary, features *EFAMS.TI* and *EFAMS.APA* exhibits the least impact on the model's output, pointing to a limited predictive role of static features related to land usage within the current model framework.

4.2.3 All Variables vs Most Important Variables Based on the SHAP feature importance plot, we trained a second model utilizing only the nine most significant variables, i.e., from *XArDS* to *DeAr* in Figure 3. These top-9 variables were identified as having the most substantial impact on the model's output, suggesting they possess the most predictive power necessary for accurate deforestation forecasting.

To empirically assess the performance of both models, we compared the RMSE values across different deforestation area bins. The findings from this comparative analysis are depicted in Figure 4. The RMSE is plotted on a logarithmic scale to facilitate the comparison.

Figure 4 shows that the simplified model, which uses just the nine most important variables (*Model Top-9*), matches the performance of the full model with all variables included (*Model All-Variables*). For low area (0, 1-2, 2-5 km^2), we observe that both models achieve low RMSE values, with 'Model Top-9' closely matching the performance of 'Model All-Variables.' As we progress to the moderate deforestation area bins, there are slight increases in RMSE for both models. However, the difference between the two models remains negligible. It is in the largest area bin, representing areas greater than 10 km^2, where we see a notable increment in RMSE for both models. This reflects the inherent challenge of forecasting larger-scale deforestation events accurately. Nonetheless, the *Model Top-9* continues to perform on par with *Model All-Variables*, suggesting the nine features capture the critical factors influencing deforestation even at this scale.

4.2.4 Qualitative assessment Figure 5 displays the reference map (top) and the forecast map (bottom) produced by the model using the nine most important variables for bi-week number 15, which corresponds to the first week of August 2022. Both maps use color gradients to indicate the magnitude of deforestation, with yellows and reds representing higher deforestation activity and greens indicating lower levels. These colormaps were generated using QGIS software, employing a cumulative count cut method that considers the 1^{st} and 99^{th} percentile of the data from both the reference and the forecast, which effectively eliminates the extremes in the dataset to focus on the most consistent data points.

Both maps show similar overall geographic distributions of deforestation, suggesting that the forecasting model is reasonably successful at capturing the spatial patterns of deforestation. There are clusters of higher deforestation (indicated by red spots) on both maps, and these clusters appear to be in similar locations, further indicating a good spatial agreement between the forecast and the reference. Some differences can be observed in the density and distribution of the high-deforestation areas, with the reference map showing more extensive red areas than the forecast map. This could imply that while the model can identify where deforestation is likely to occur, it might be less sensitive to detecting the full extent of deforestation within these areas. This could result from the model's limitations in handling outliers or extreme values in the data.

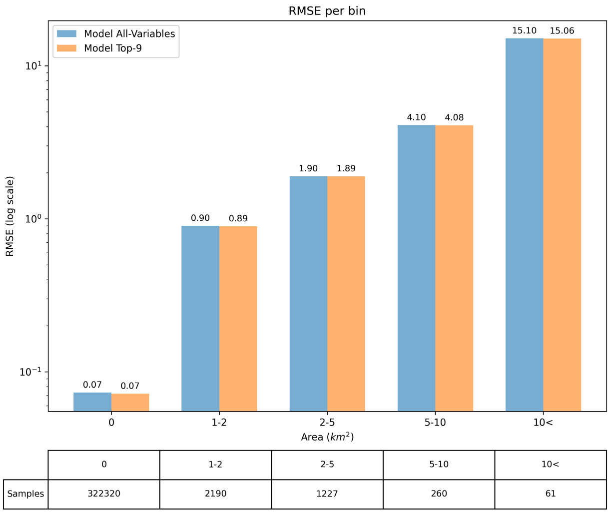

Figure 4. RMSE values for different deforestation area bins.

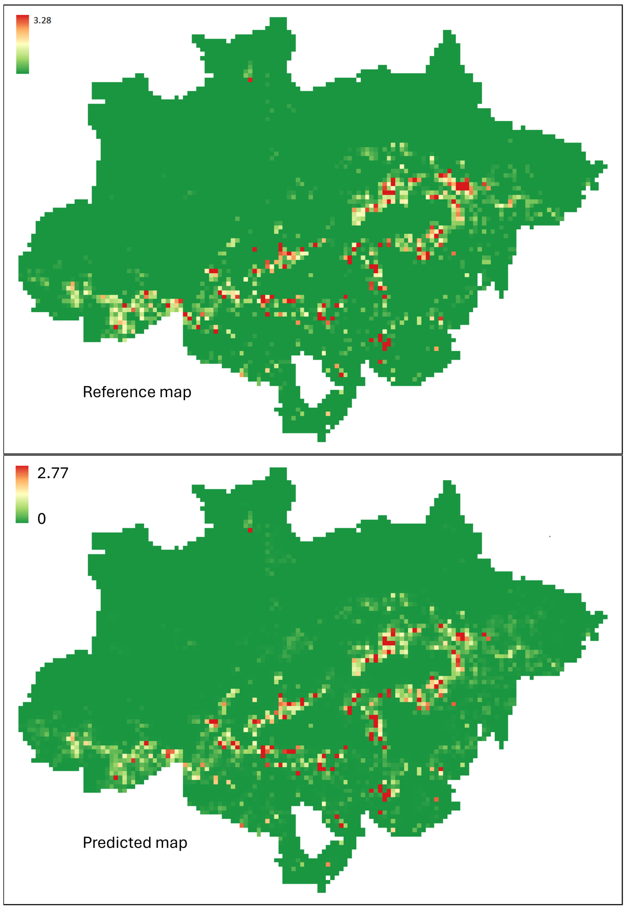

Figure 5. Refrence map (top) and forecast map (bottom) for bi-week number 15, i.e., first week of August 2022.

5. Conclusions and Future Works

In this research, we unveiled a model to predict the immediate risk of deforestation within the Amazon rainforest. This model, crafted by harnessing a comprehensive, weekly updated database from the DETER project and applying a regression algorithm powered by XGBOOST, marks an advancement in our grasp of deforestation trends across a 25km x 25km grid.

The research stressed the importance of blending dynamic and static factors—ranging from sociopolitical to geographical elements—to enhance the precision of deforestation forecasts. T

Nonetheless, our study has its limitations. The spatial resolution selected, while suitable for wide-ranging analysis, might not capture the nuances of smaller-scale deforestation occurrences.

Moving forward, the initiative aims to refine the model's forecasting abilities. This will involve integrating data with better resolution and applying more advanced machine-learning techniques. We also plan to broaden the scope of variables that influence deforestation rates. The ultimate objective is crafting a tool that not only predicts deforestation with higher accuracy but also serves as a practical instrument for forest conservation efforts, thereby aiding in the preservation of the Amazon rainforest and helping to curb global climate change.

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