Title: Understanding deforestation dynamics in Amazonian protected areas through land-use change models informed by conservation discourses

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Abstract
The Amazon Basin's agricultural frontiers – many of which overlap with protected areas (PAs) – experience deforestation for agriculture and pasture. Responses to PA deforestation require understanding the region-wide and PA-specific socio-environmental factors that increase forest conversion. Standard, quantitative approaches to land-use change (LUC) modeling may omit some factors, constraining understandings of and responses to deforestation. Dominant discourses about deforestation – promoted by government and conservation organizations – also shape deforestation responses. We integrated quantitative and qualitative analysis of deforestation dynamics into LUC models of three Amazonian PA complexes (Brazil's Jamanxim National Forest, Bolivia's Amboró and Carrasco National Parks, and Peru's Tambopata National Reserve and Bahuaja-Sonene National Park) to understand 1) the ability of conservation discourses to inform deforestation models and 2) region-wide and site-level factors related to deforestation. Our integrative methodology yielded better model performance than standard LUC modeling. From 2008-2018, forests on steeper slopes with higher population densities were less likely to convert, while forests surrounded by non-forest and closer to agriculture and fires had increased deforestation. Legal threats to Jamanxim's status increased deforestation likelihood, while in Amboró and Carrasco, payments for ecosystem services projects were associated with decreased deforestation. While dominant discourses sometimes aligned with LUC models' results (e.g., fires and increased deforestation), some factors commonly cited in deforestation discourses were not supported (e.g., REDD+ projects). Our results can inform forest management in our study sites and Amazon-wide, and emphasize the need for integrative approaches to operationalizing discourses in conservation science and practice, as the framing of deforestation shapes management responses.

Keywords: land-use change; forest loss; tropical forest; Amazon Basin; protected areas; conservation

1. Introduction

Forest conversion to agriculture occurs along agricultural frontiers throughout the Amazon Basin, with consequences for Indigenous communities, biodiversity, and ecosystem services (Ochoa-Quintero et al., 2015; Rorato et al., 2020; Xu et al., 2022). Agricultural frontiers are areas with active land use conversion for agriculture or livestock production (Browder et al., 2008; Schielein and Börner, 2018). While some policy interventions have successfully reduced forest clearing in the Amazon (Hänggli et al., 2023; Silva Junior et al., 2021), increasingly in the Amazon and around the world, areas of current and potential agricultural expansion overlap with areas of conservation priority, including protected areas (Dobrovolski et al., 2011; Hoang et al., 2023).

Protected areas (PAs) are a leading tool for reducing forest loss, and by 2022, they covered 25% of the Amazon region (RAISG, 2022), with an additional ~16% of land area in the nine countries that comprise the Amazon under some form of area-based conservation (Qin et al., 2024). These PAs have had varying impacts on deforestation. Amazonian PAs are diverse in their governance and the degree to which extractive activities are permitted, with consequences for forest cover (Jusys, 2018; Pfaff et al., 2015b, 2015a; Schleicher et al., 2017). Notably, despite the reductions in deforestation within PAs relative to unprotected forests in the Amazon, forest loss continues even within PA boundaries (Paiva et al., 2020), a trend mirrored worldwide (Wolf et al., 2021).

The precise land-use change pathways of agricultural frontiers vary with local environmental, socioeconomic, and policy contexts (Curtis et al., 2018; Hänggli et al., 2023). To understand deforestation dynamics in a particular place therefore requires understanding the spatial variation in socio-environmental drivers of forest conversion and variation in the strength of their effect on land use and land cover (Angelsen, 2007; Meyfroidt, 2016). Previous studies have compared deforestation trends and drivers, often using countries as the scale of analysis (Austin et al., 2017; Hänggli et al., 2023) or comparing individual sites within a country (Rosa et al., 2015). Across the Amazon, these analyses have identified common drivers of deforestation, such as proximity to roads or navigable rivers (Hänggli et al., 2023; Soares-Filho et al., 2006). Other factors have emerged at smaller spatial scales, such as oil palm expansion in Peru (Glinskis and Gutiérrez-Vélez, 2019) and oil exploration in the western Amazon (Finer et al., 2008). Despite regional- and national-level commonalities, the specific context of each individual PA also plays a role in determining the factors that contribute to land-use change within and around its boundaries, highlighting the importance of site-level land-use change analyses (Hänggli et al., 2023). Understanding the context-specific factors driving deforestation is important because it dictates effective solutions.

We use a mixed methods approach to compare factors related to forest conversion to agriculture in three case study sites across the Amazon Basin. While standard approaches to land-use change models typically draw on literature review and contextual, expert knowledge from land system science and conservation science to identify model variables, we integrate varied, context-specific factors into our land-use change models through an iterative approach that draws on both qualitative discourse analysis and literature review to identify appropriate model variables

(Kinnebrew et al., 2020). Previous work demonstrated that models that integrate variables derived through qualitative research methods with quantitative approaches have improved ability to predict deforestation in a PA in Brazil (Siegel et al., 2022). Here, we address the following research questions: 1) Do integrated methods better predict deforestation across multiple protected area complexes in the Amazon Basin, relative to land-use change models that do not integrate qualitative research approaches? 2) If so, what do integrative land-use change models tell us about the relative importance of different factors related to forest conversion to agriculture across protected area complexes with different geographic, socioeconomic, and political contexts? We thus aim to both inform deforestation modeling and to improve our understanding of deforestation dynamics in Amazonian PAs.

2. Methods

2.1. Study sites

We modeled land-use change in three Amazonian PA complexes: Brazil's Jamanxim National Forest, Bolivia's Amboró and Carrasco National Parks, and Peru's Tambopata National Reserve and Bahuaja-Sonene National Park (**Figure 1a**). The Jamanxim National Forest case study consists of a single PA, while the other sites comprise two or more adjacent PAs (**Figure 1b**). These sites have similar sizes (12,962-13,661 km^2), deforestation rates ranging from less than 1% (in Tambopata and Bahuaja-Sonene) to 3.6% (Jamanxim) from 2008-2018 (Kinnebrew et al., 2022), and varying deforestation dynamics and drivers (Killeen et al., 2007; Oliveira et al., 2007; Pinheiro et al., 2016; van Gils and Armand Ugon, 2006).

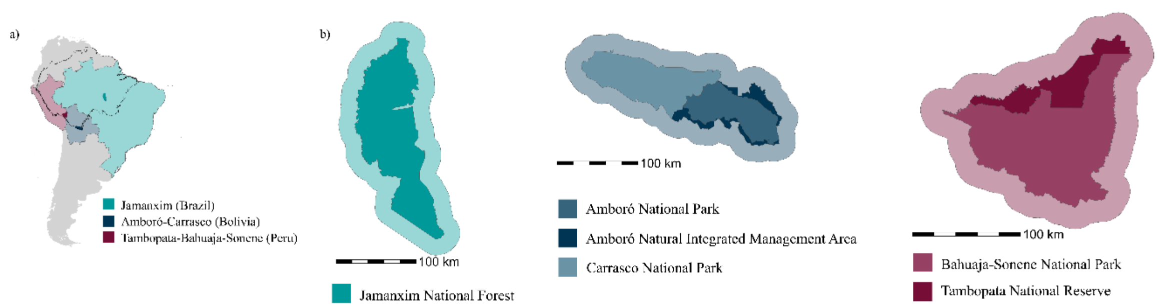

Figure 1. Map of the three case study sites. a) Location of the three case study sites within the Amazon Basin (black outline). b) Detailed map of the protected area complexes comprising each case study site, with a 20-kilometer buffer surrounding the protected area boundaries.

Jamanxim National Forest, in Pará, Brazil, was established in 2006 to address deforestation related to highway development. It has experienced deforestation through land-clearing for ranching, agriculture, and land speculation (Arima, 2016; Fearnside, 2005, 2001). Amboró National Park (established in 1984), Carrasco National Park (1991), and Amboró Natural Integrated Management Area (1995) (hereafter "Amboró-Carrasco") have experienced deforestation primarily for small-scale agriculture and ranching (Killeen et al., 2008; Müller et al., 2012; Romero-Munoz et al., 2019). Amboró-Carrasco also faces pressure from coca cultivation, hydrocarbon extraction, and a proposed hydropower dam (Romero-Munoz et al., 2019; UNODC, 2020). Tambopata National Reserve (established in 2000) and Bahuaja-Sonene National Park (1996) are in a globally recognized biodiversity hotspot (Myers et al., 2000).

Tambopata has a buffer zone with land use restrictions along its northern border (Weisse and Naughton-Treves, 2016). Prior to the mid-2000s, agricultural expansion drove forest loss in the region, but informal gold mining became a major factor beginning around 2006 (Scullion et al., 2014; Vuohelainen et al., 2012).

For all three sites, we modeled land-use change within the PAs and in 10- and 20-kilometer buffers around the PAs, to capture land-use change dynamics directly outside the PAs (Ewers and Rodrigues, 2008; Tesfaw et al., 2018). In the case of Tambopata-Bahuaja-Sonene, the buffer extended over the border between Peru and Bolivia. We cropped the buffer to only include the Peruvian portion because the sociopolitical factors identified in the discourse analysis vary by nation (Piquer-Rodríguez et al., 2021). We modeled deforestation from 2008 to 2018, ending our analysis before the beginning of Jair Bolsonaro's presidency in Brazil because his administration had a large impact on deforestation rates and conservation discourses (Barbosa et al., 2021; Pereira et al., 2020).

2.2. Land-use change maps

Our land-use change models used published land cover maps from 2008 and 2018 for each site (Kinnebrew et al., 2022). These maps were generated through supervised classification of cloud-free composites using pixels from Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 8 (OLI) Surface Reflectance datasets with 30 m resolution, using random forests. The maps identify forest, agricultural land and pastures, bare soil, built areas, wetlands, water, and in Amboró-Carrasco, deserts, with an overall accuracy rate of > 90% across the case study sites (Kinnebrew et al., 2022).

2.3. Land-use change modeling and projection

We used logistic regression to model the probability of conversion to agriculture for each forested pixel from 2008-2018, extracting pixel values along a 300-meter grid to avoid introducing spatial autocorrelation (Siegel et al., 2022). We performed all modeling in R (R Core Team, 2019). Logistic regression models facilitate interpretation of coefficient estimates, making them well suited to the dual goals of our analyses (Moulds et al., 2015). Following a methodological framework from Siegel et al. (2022), we created models for each site using different combinations of variables derived from an iterative process for integrating qualitative and quantitative methods. We selected variables using 1) a review of land-use change papers in the Amazon Basin (Appendix A), and 2) a qualitative discourse analysis of textual material addressing the causes of and solutions to forest conversion (Siegel et al., 2022; Appendix B). The discourse analysis identified deforestation discourses promoted by government and conservation actors: we coded management, policy, and advocacy documents, as well as gray literature at the park-, state-, and national-scale at each sites, using snowball sampling, legislative databases, and non-governmental organization (NGO) websites in English, Spanish, and Portuguese (**Table B.1**). We coded all documents in NVivo 12 (QSR International Pty Ltd., 2019), first using a set of predetermined themes identified from our review of Amazon land-use change models (e.g., physical and economic accessibility, suitability for agriculture, and protection status), and then adding emergent themes that arose through the coding process (e.g., land grabbing, state governance, and legal challenges to PAs) (**Table B.2**).

For each site, we built four models. The first used solely variables from the review of Amazonian land-use change literature (the LUC model), the second only used variables identified through discourse analysis (the DA model), the third model included all variables used in the LUC model and the DA model (the LUC and DA model), and the fourth model used the variables that emerged as statistically significant in the LUC model and qualitatively important through the discourse analysis (refined LUC and DA model) (**Figure 2**). The variables for the LUC model were the same across all sites and related to topography, accessibility to infrastructure and markets, agricultural suitability, human population characteristics, management status, and neighborhood effects (the proportion of surrounding pixels that were forested) (**Table 1**). The DA model variables varied across study sites, depending on the themes identified (**Table 1**; **Table C.1**). The models for Jamanxim differ from those in Siegel et al. (2022) due to minor changes in methodology to ensure comparability of the regression coefficients across case study sites. We compiled and standardized data from global, regional, and local datasets (**Table 1**), using the R packages *sf* (version 1.0-16), *raster* (version 3.6-26), and *lwgeom* (version 0.2-14) (Hijmans, 2019; Pebesma, 2019, 2018). To facilitate comparisons between study sites, we centered and scaled continuous variables.

While the variables for the LUC model were spatially explicit and quantitative or categorical, and thus straightforward to include in our models, additional steps were required to translate the discourse analysis themes into quantitative, spatially explicit proxies. For each theme, we attempted to develop a quantitative, spatial proxy using available data and published literature (Mallampalli et al., 2016; Siegel et al., 2022). As an illustration, sustainable development emerged as a theme mediating forest loss in Amboró-Carrasco and Tambopata-Bahuaja-Sonene: we used distance to ecotourism sites and the presence of PES programs and REDD+ projects as proxies for this theme. Some themes did not translate into spatial, quantitative proxies with available data; we did not include these themes in our models but integrated them into our interpretation of model results.

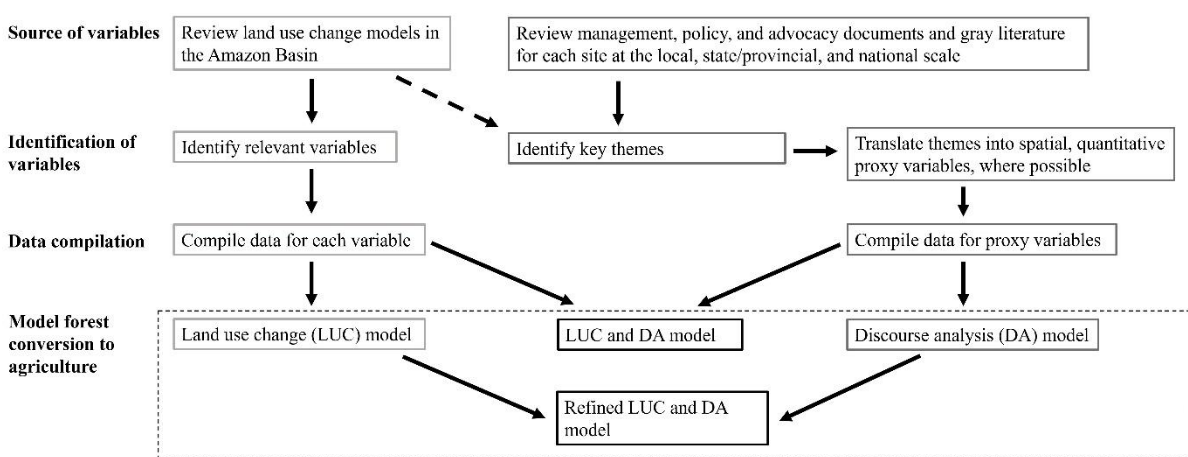

Figure 2. **Methods for identification of deforestation variables.** Overview of the methods used to identify and assemble the variables for the four logistic regression models created for each site: the land-use change (LUC) model, the discourse analysis (DA) model, the LUC and DA model, and the refined LUC and DA model.

To avoid multicollinearity, we assessed correlations between continuous variables and the variance inflation factor (VIF), using a final suite of variables for each model that minimized VIF and collinearity. Each model thus had a subset of the potential variables from Table 1. When faced with highly correlated explanatory variables, we selected which variable to retain in the model based on data quality and spatial resolution, the year of the data relative to our study period, and the expected strength of the variable's relationship to agricultural expansion (Siegel et al., 2022). **Table C.1** lists the variables included in each final model. Due to the strong emphasis on unauthorized mining in the Tambopata-Bahuaja-Sonene discourses, we ran a version of the refined LUC & DA model for Tambopata-Bahuaja-Sonene that included distance to unauthorized mining sites as an explanatory variable, despite its collinearity with other variables (**Table C.2**).

Table 1. Variables used in LUC models, including the LUC variables used for each case study site, and the site-specific DA variables, demonstrating the translation from qualitative theme to spatial and quantitative proxy variable.

LUC variables		
Variable	**Source**	**Case study sites(s)**
Elevation Slope Aspect	(Farr et al., 2007)	All
Distance to roads	("Open Street Map," 2019)	
Distance to rivers	(DIVA-GIS, 2019; GeoBolivia, 2009; OCHA, 2015a, 2015b)	
Distance to mines and mining concessions	(ANM, 2019; GeoBolivia, 2005; INGEMMET, 2021)	
Distance to cities	(GeoBolivia, 2013, 2002; IBGE, 2010; INEI, 2020)	
Crop suitability	(Zabel et al., 2014)	
Precipitation	(Funk et al., 2015)	
Soil moisture	(O'Neill et al., 2016)	
Population density	(GeoBolivia, 2013; IBGE, 2010; INEI, n.d.)	

Poverty rate		(GeoBolivia, 2015; IBGE, 2003; INEI, n.d.)	
Neighborhood effect		Derived from Kinnebrew et al. (2022)	
Management status		(UNEP-WCMC and IUCN, 2018)	
DA variables			
Theme	**Proxy variable**	**Source**	**Case study site(s)**
Physical accessibility, agricultural and land-clearing activity	Distance to agriculture	Derived from Kinnebrew et al. (2022)	All
	Distance to fires	(INPE, 2019)	
	Fire density	(INPE, 2019)	
Resource extraction	Distance to unauthorized mines	(RAISG, 2018)	All
Ranching	Head of cattle per km^2	(GeoBolivia, 2012; IBGE, 2017)	Jamanxim, Amboró-Carrasco
Legal challenges to protected areas	Protected area downgrading, downsizing and degazettement (PADDD)	(Conservation International and World Wildlife Fund, 2019)	Jamanxim, Tambopata-Bahuaja-Sonene
Infrastructure development	Distance to proposed railroads	(Ministério da Infraestrutura, 2019)	Jamanxim
	Distance to proposed dams	(ANEE, n.d.)	
Land tenure; settlements; land grabbing	Unallocated public land	(Imaflora and GeoLab, 2018)	Jamanxim
	Agricultural reform settlements	(INCRA, n.d.)	Jamanxim
	Land tenure	(INRA, 2016)	Amboró-Carrasco

	Distance to Indigenous communities	(COFOPRI, 2020)	Tambopata-Bahuaja-Sonene
Sustainable development	Distance to tourism	(Google Earth Pro, 2019; SERNAP, 2018)	Amboró-Carrasco, Tambopata-Bahuaja-Sonene
	Presence of PES programs	(Asquith, 2020)	Amboró-Carrasco
	Presence of REDD+ projects (medicinal plants, nut production, reforestation plots)	(SERFOR, 2019)	Tambopata-Bahuaja-Sonene
Enforcement capacity	Distance to control posts	(SERNANP, 2011)	Tambopata-Bahuaja-Sonene
Migration and settlement patterns	Location to the north or south of the geographic boundary from El Torno to Tablas Monte	Derived	Amboró-Carrasco

2.4. Model comparisons

We assessed model performance using Akaike information criterion (AIC) and analysis-of-variance (ANOVA) comparisons of model fit. To account for the different numbers of variables in the models, we used McFadden's adjusted pseudo R^2 to compare model performance for a given study site (Hebbali, 2020).

We compared the location of deforestation for agriculture predicted in 2018 by each model for each site to the actual observations of forest conversion. We used each logistic regression model to create a landscape representing each pixel's predicted probability of forest conversion to agriculture in 2008. Using these predicted probability maps and Monte Carlo simulations, we made 1000 projected landscapes in 2018 for each model, assuming no change in land cover for pixels that were non-forest in 2008. We used the observed forest loss area for each site to determine deforestation in the projected landscape by allocating forest loss to the pixels that converted most frequently across the simulations, until we reached the observed quantity of forest conversion. This resulted in a single predicted 2018 landscape for each model. The Monte Carlo simulations allowed us to predict which pixels would convert from forest to agriculture without relying on an arbitrary probability threshold for classifying converted vs. unconverted pixels. Comparing these predicted landscapes with the observed 2018 landscape in each site, we calculated quantity and allocation disagreement using the *diffeR* package (version 0.0-8) (Pontius Jr. and Santacruz, 2019; Pontius and Millones, 2011).

3. Results

3.1. Comparisons of model performance

Across all sites, models that included discourse analysis-derived variables along with more commonly used land-use change modeling variables explained the most variation in observed forest conversion to agriculture, as measured by McFadden's pseudo R^2 and AIC (**Table 2**). In Jamanxim, the refined LUC & DA model explained the most variation, explaining almost twice as much variation as the LUC model. In Amboró-Carrasco, the LUC & DA and refined LUC & DA models explained the most variation, followed by the DA model, then the LUC model, with less drop-off in variation explained than in Jamanxim. Per AIC, the refined LUC & DA model outperformed the LUC & DA model, but ANOVA analysis revealed no significant difference in performance between the two. In Tambopata-Bahuaja-Sonene, the LUC & DA model explained the most variation, followed closely by the refined LUC & DA model. The LUC model explained the least variation. Including distance to unauthorized mines did not yield significant improvements in model performance for Tambopata-Bahuaja-Sonene. The Tambopata-Bahuaja-Sonene models explained more variation than the other sites' models.

Table 2. Model performance metrics for the four models across the three case study sites. AIC values compare model performance within a given case study site. Allocation and quantity disagreements are reported as proportions.

Case study	Metric	LUC model	DA model	LUC & DA model	Refined LUC & DA model
Jamanxim	AIC	82567	66822	66044	62357
	McFadden's pseudo R^2 (%)	24.7	39.0	39.8	43.1
	Allocation disagreement	0	0	0	0
	Quantity disagreement	0.0256	0.0232	0.0226	0.0202
Amboró-Carrasco	AIC	62876	59373	56522	56506
	McFadden's pseudo R^2 (%)	31.1	34.9	38.1	38.1
	Allocation disagreement	0.0167	0.0001	0.0008	0.0113
	Quantity disagreement	0.0429	0.0511	0.0508	0.0456
Tambopata-Bahuaja-Sonene	AIC	2986	2538	2328	2331 (2329[a])

	McFadden's pseudo R^2 (%)	41.2	49.9	54.4	54.3 (54.4[a])
	Allocation disagreement	0.0011	0.0020	0.0012	0.0011 (0.0011[a])
	Quantity disagreement	0.0049	0.0044	0.0049	0.0049 (0.0049[a])

[a] Refined LUC & DA model when distance to unauthorized mines is included as a predictor variable

The different models' allocation (the proportion of difference between the predicted and observed maps caused by mismatch in the location of the pixels in each land cover class) and quantity (the difference in the proportion of pixels in each land cover category in the predicted and observed maps) disagreement was not as similar across the sites (**Table 2**). In Jamanxim, all models had negligible allocation disagreement, and the refined LUC & DA model had the lowest quantity disagreement. In Amboró-Carrasco, the DA model had the lowest allocation disagreement, but the LUC model had the lowest quantity disagreement. In Tambopata-Bahuaja-Sonene, the DA model had the highest allocation disagreement but the lowest quantity disagreement. The LUC model and refined LUC & DA models had the lowest allocation disagreement. Allocation disagreement was low across all sites, with the highest allocation disagreement in Amboró-Carrasco (mean of 0.007 across the four models). Quantity disagreement was similarly low in Tambopata-Bahuaja-Sonene (mean of 0.005) but higher in Jamanxim (mean of 0.023) and Amboró-Carrasco (mean of 0.048).

3.2. Site-level factors related to forest conversion to agriculture

Across Jamanxim models, forests on steeper slopes, at higher elevations, and further from agriculture, past fire perimeters, unauthorized mining, and proposed railroads had lower probability of converting to agriculture (**Tables C.3-C.6**). Forests with higher population densities also had lower conversion probability, while sites surrounded by a higher proportion of non-forest pixels were more likely to convert. Forested sites in the 10- and 20-km buffer outside Jamanxim National Forest were also more likely to convert, as were sites with greater fire densities and higher proportions of unallocated public land. Other variables' relationships with the likelihood of forest conversion varied across models.

In Amboró-Carrasco, forests on steeper slopes, at higher elevations, more distant from roads, rivers, mining concessions, cities, agriculture, past fire perimeters, and unauthorized mining sites always had lower probabilities of converting to agriculture (**Tables C.3-C.6**), as did forests within parcels enrolled in PES programs. Sites with higher crop suitability and a higher proportion of non-forest neighbors were more likely to convert, as were sites with higher fire density and formalized land tenure. Forests in the 10- and 20-km buffer outside the PA complex were also more likely to convert. Across the models, distance to tourism and precipitation did not have significant relationships with forest conversion. As in Jamanxim, there were also variables whose relationship with deforestation probability varied across the models (e.g., population density and poverty rate).

Across the models in Tambopata-Bahuaja-Sonene, forests located further from agriculture and fires were less likely to convert, while sites with higher crop suitability, a higher proportion of non-forest neighboring pixels, higher fire density, and presence of protected area downgrading, downsizing and degazettement (PADDD) proposals were more likely to convert. Distance to roads, cities, and unauthorized mining sites did not have significant relationships with forest conversion, nor did the locations of REDD+ projects. Other variables (e.g., elevation and distance to rivers, tourism sites and control posts) had differing relationships with deforestation across the models.

3.3. Cross-site comparisons

To compare factors related to forest conversion across the three sites, we focus on the LUC & DA model, as this was the best-performing model (with similar performance and variable relationships as the refined LUC & DA model). In all sites, the probability of forest conversion to agriculture from 2008-2018 increased as slope, population density, distance to agriculture, and distance to past fire perimeters decreased, and as fire density and the portion of non-forest surrounding pixels increased (**Figure 3, Table C.5**). Thus, forested areas with low human population density and flatter terrain, located closer to areas with higher fire activity and in proximity to existing agriculture or other non-forest land covers were more likely to convert. In Jamanxim and Amboró-Carrasco, forests located closer to roads and unauthorized mining sites had higher probability of conversion, while neither variable was included in Tambopata-Bahuaja-Sonene's model due to collinearity with other variables. When we ran a version of the refined LUC & DA model for Tambopata-Bahuaja-Sonene that intentionally included distance to unauthorized mining sites as an explanatory variable (due to the high importance this variable received in the discourse analysis), it did not have a significant relationship with forest conversion (**Table C.2**). The Supplementary Materials include tables with the coefficient estimates from all four models across all three sites (**Appendix C, Tables C.3-C.6**).

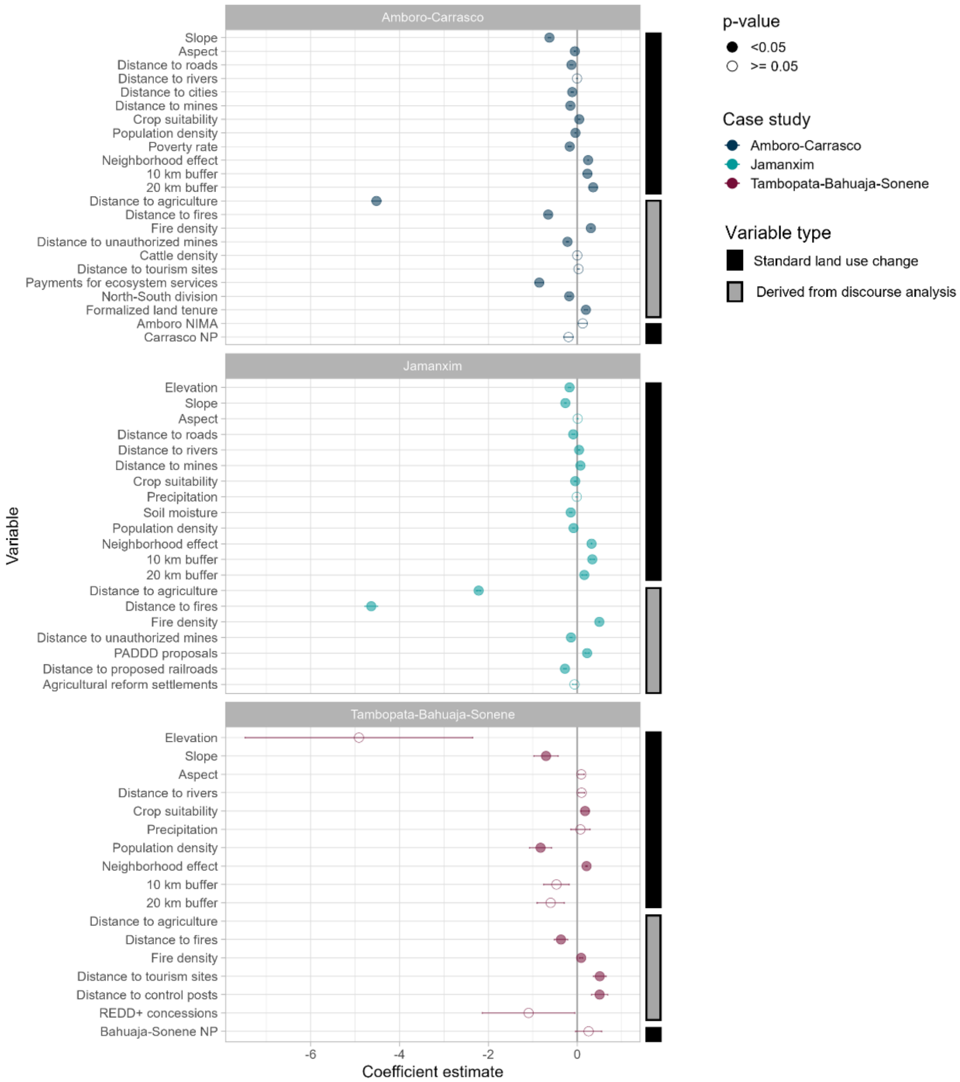

Figure 3. Relationships between explanatory variables and likelihood of deforestation. Coefficient estimates for the explanatory variables included in the LUC & DA model for the three sites, with their standard errors. All variables were scaled and centered. The coefficient estimate for distance to agriculture in Tambopata-Bahuaja-Sonene ($\beta = -81.3137 \pm 7.9017$, $p < 0.001$) is omitted for ease of visualization. Filled circles indicate statistically significant estimates ($p < 0.05$), while empty circles represent estimates with p-values ≥ 0.05. All coefficient estimate values reported in Table C.5.

The remaining variables had inconsistent relationships with forest conversion across the three sites. For example, in Jamanxim, forests closer to rivers had higher conversion probability, but the relationship was not significant elsewhere. In Jamanxim, forests located further from mining sites were also more likely to experience conversion, while the opposite pattern held for Amboró-Carrasco, and distance to mines was not included for Tambopata-Bahuaja-Sonene due to collinearity with other variables. In Amboró-Carrasco and Tambopata-Bahuaja-Sonene, sites with higher crop suitability had increased conversion probability, but this relationship was reversed in Jamanxim, where there is less spatial variation in crop suitability. And while forests located in the 10- or 20-km buffer outside of the PAs in Jamanxim and Amboró-Carrasco were more likely to convert than forests located within PA boundaries, no such relationship existed for Tambopata-Bahuaja-Sonene.

Some variables were only included in the model for a single site – due to lack of relative importance in the discourse analysis or collinearity with other variables – preventing cross-site comparisons. In Jamanxim, as soil moisture and distance from proposed railroads increased, probability of forest conversion decreased, while the presence of PADDD proposals was related to higher probability of conversion. PADDD proposals were also associated with increased deforestation likelihood in Tambopata-Bahuaja-Sonene in the refined LUC & DA model, but PADDD was not included as an explanatory variable in the LUC & DA model due to elevated VIF values. In Amboró-Carrasco, distance to cities, poverty rate, geographic location in the southern half of the study site, and enrollment in PES had negative relationships with forest conversion, while formalized land tenure was associated with increased conversion. Forests in Carrasco National Park had lower conversion probability than those in Amboró National Park. In Tambopata-Bahuaja-Sonene, sites located further from control posts had higher conversion likelihood.

4. Discussion

Our findings emphasize the limitations of large-scale and global modeling for understanding deforestation dynamics, as our models using only literature-derived land-use change variables had the poorest performance and missed context-specific factors, constraining the potential for tailored conservation responses. In contrast, models that integrated variables identified through qualitative discourse analysis best predicted forest conversion to agriculture across all sites, expanding on previous findings (Siegel et al., 2022) and highlighting the benefits of integrative methodologies for conservation science (Kinnebrew et al., 2020).

4.1. Insights for site-level and regional conservation

Identification of common factors related to deforestation can inform conservation interventions in PAs across the Amazon. While we cannot assume that the patterns observed in our case study sites hold uniformly across the region, the common trends across sites with diverse geographies and social, economic, and political contexts suggests that these factors – slope, fire activity, PADDD proposals, and proximity to roads, agriculture, and other non-forest land uses – may be important in other locations as well. However, some variables that are commonly included in Amazon land-use change models did not have consistent relationships with deforestation across the three sites, again illustrating the limitations of large- and global-scale analysis.

While our integrated models supported many of the relationships between explanatory variables and deforestation that would be predicted given existing literature and conservation discourses (Rosa et al., 2015, 2013; Soares-Filho et al., 2006), we observed some unexpected relationships. In all sites, higher population densities were associated with lower forest conversion probability; this may reflect the underlying data's coarse spatial scale, but it also aligns with findings that areas of the Brazilian Amazon where smallholder farmers have been replaced by ranchers and industrial farmers have both high deforestation rates and low population density (Tritsch and Le Tourneau, 2016).

In Amboró-Carrasco, areas with formalized land tenure had increased deforestation probabilities, reflecting the mixed evidence about the link between formalized land tenure and deforestation globally (Busch and Ferretti-Gallon, 2023): land tenure protects against encroachment and appropriation, but rightsholders may not choose land uses that align with conservation priorities (Robinson et al., 2018). In Jamanxim, forests located further from rivers and mining concessions had increased conversion probabilities, and neither proportion of unallocated public land nor presence of agricultural reform settlements had a significant relationship with forest conversion probability, contrary to our expectations (Pereira et al., 2022; Reydon et al., 2022). Finally, in Tambopata-Bahuaja-Sonene, forests located within the PAs or in REDD+ projects did not have reduced deforestation relative to unprotected or non-REDD+ forests. Distance to unauthorized mines was also not a significant explanatory variable, despite a strong emphasis on this dynamic in discourses and published literature (Asner and Tupayachi, 2017; Nicolau et al., 2019; Sánchez-Cuervo et al., 2020; Vuohelainen et al., 2012).

4.2. The role of discourses in explaining deforestation and constraining conservation responses

Analysis of conservation discourses identified significant regional and site-specific factors. Discourses across all sites stressed the role of fires in facilitating the spread of deforestation. In our models, we found that proximity to and high density of past fires were associated with increased likelihood of forest conversion, supporting dominant conservation discourses. The discourse analysis also identified PES programs and migration and settlement patterns as important factors in Amboró-Carrasco, proposed infrastructure and PADDD events in Jamanxim, and tourism and enforcement in Tambopata-Bahuaja-Sonene, and our models quantitatively supported these qualitative findings.

Our findings also demonstrate the potential for dominant conservation discourses to constrain our understanding of the drivers of and solutions to PA deforestation. The site-specific variables identified through the discourse analysis were not always quantitatively supported by our models. For example, in Amboró-Carrasco, the discourse analysis indicated that poverty was a driver of deforestation, but our models found the opposite relationship: higher poverty rates correlated to lower forest conversion (**Figure 3**). Conservation discourses associating the rural poor with deforestation are persistent and prevalent in the Amazon and beyond (Duraiappah, 1998; Peprah et al., 2017; Rai, 2019), even when data do not support these claims (Ravikumar et al., 2017). These discourses have shaped past policy responses, with ineffective and at times unethical outcomes (Green et al., 2022). Thus, while conservation discourses provide a window into potentially important factors related to deforestation in PAs, they may also reproduce power dynamics and recycle old tropes. We thus suggest that while qualitative methods and data can enrich land-use change modeling – and thus deepen our understanding of the drivers of and potential solutions to deforestation – quantitative modeling can in turn illuminate conservation discourses' oversights.

4.3. Limitations and nuances

There were additional, qualitatively significant themes that we identified through the discourse analysis that we were unable to integrate into our quantitative models. In some cases, this was due to lack of spatial variation in the themes across an individual site (e.g., agricultural policies, which apply at coarser spatial scales). Other themes lacked spatial, quantitative proxies with available data, as was the case for "level of local participation and inclusion" in Amboró-Carrasco and "lack of commodity traceability" in Jamanxim (**Table B.2**). In addition, there were scale mismatches for some variables in our models (e.g., cattle density, poverty rate, and population density were available at the municipal level, so the relationships between those variables and forest conversion may reflect municipal-level confounding variables). Finally, while we attempted to identify appropriate proxy variables to include the discourse analysis themes in the land-use change models, our ability to make this translation depended on data availability, so we were not always able to use the optimal proxy variable.

4.4. Conclusions
Through integration of qualitative analysis of conservation discourses with quantitative land-use change modeling, we identified factors related to deforestation in three protected areas in Amazonian agricultural frontiers. We found that land-use change models informed by qualitative discourse analysis better explained patterns of forest conversion to agriculture from 2008-2018 across a diverse region, highlighting the potential for conservation discourses to inform land-use change modeling and potential limitations of modeling at large spatial scales. Simultaneously, our results emphasize the need to critically consider dominant conservation discourses, as they may reflect the priorities of powerful actors rather than on-the-ground dynamics.

Supplementary materials
Appendix A: Land-use change literature in the Amazon
Appendix B: Discourse analysis methods
Appendix C: Models of land-use change in the three case study sites

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