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The Forest Awakens: Amazon Regeneration and Policy Spillover [1]

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Abstract

Protecting and restoring natural ecosystems are critical cost-effective strategies to fight global climate change. Brazil holds vast amounts of degraded lands in tropical regions and, thus, has great potential to contribute to restoration-based carbon sequestration. However, by design, Brazil's innovative and successful satellite-based monitoring system focuses on combating primary forest loss, and does not detect the clearing of secondary vegetation. In this paper, we document the substantial growth in the area occupied by secondary vegetation in the Brazilian Amazon during 2004–2014, and investigate the extent to which that regeneration resulted from unanticipated spillover effects of law enforcement policy. Using large and rich pixel-level data over that time period, we find that increasing (by one standard deviation) the intensity of enforcement in a pixel's neighborhood increases regenerated area in that pixel by 6%. Counterfactual exercises suggest that improvements to the existing monitoring system could further contribute by augmenting total secondary vegetation cover by nearly 300 thousand hectares. This is the first study documenting positive spillover effects of command-and-control environmental policies, suggesting that such policies can have greater impacts on social welfare than previously thought.

Keywords: spillovers, regeneration, deforestation, monitoring and law enforcement

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1. Introduction

With the threat of climate change looming nearer, there is a pressing need for global action to mitigate the adverse effects of global warming (Greenstone and Jack, 2015; Nordhaus, 2019). Protecting and restoring natural ecosystems — especially tropical forests — are critical in any global strategy given their vital role, and their cost-effectiveness, in absorbing and stocking carbon (Stern, 2006; IUCN and Winrock, 2017; IPCC, 2018).[2] Indeed, ecosystem restoration figures prominently among the United Nations (UN) Sustainable Development Goals, and substantial efforts to regenerate forests worldwide are currently underway, with various degrees of success (Dave et al., 2017).

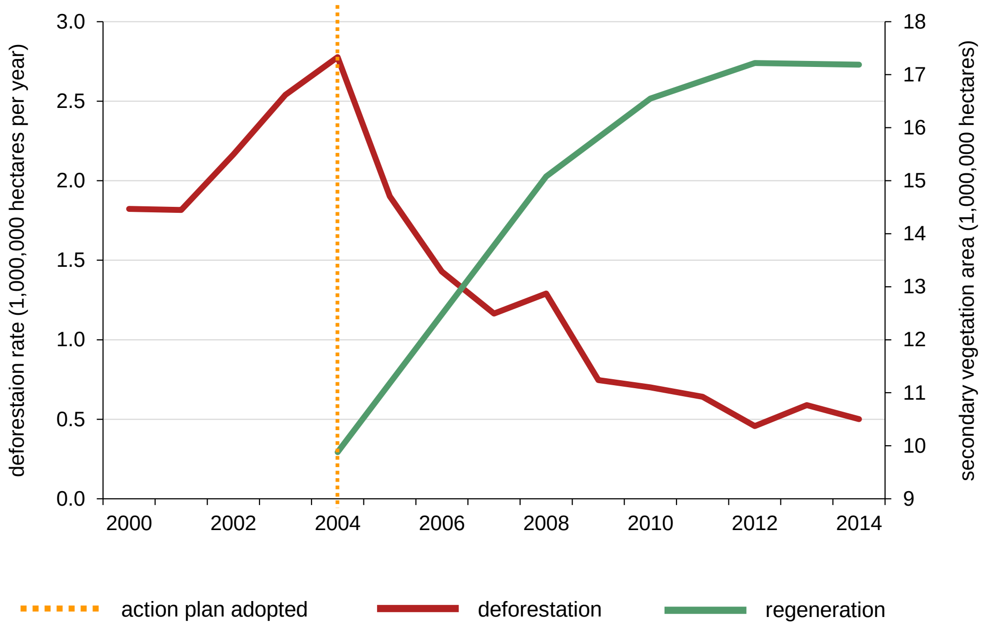
Brazil occupies a unique position in the global restoration scenario: It holds vast amounts of degraded and deforested lands within tropical ecosystems, with great potential for restoration-based carbon sequestration (Niles et al., 2002; Chazdon et al., 2016). In spite of this potential, tropical conservation efforts there have not been focused on promoting forest regeneration. Brazil's strategic measures focused on combatting primary forest loss during the last two decades; they were largely successful, directly contributing to a reduction in tropical clearing rates in the Amazon of more than 80% (Hargrave and Kis-Katos, 2013; Assunção et al., 2015; Burgess et al., 2018), drawing considerable attention from policy makers, academics, and the civil society. Yet another — no less remarkable — phenomenon occurred quietly during the same period (see Figure 1). The area covered by secondary vegetation in the Amazon increased by more than 70%, rising from less than 10 million hectares in 2004 to more than 17 million hectares ten years later (Inpe and Embrapa, 2016a). (Secondary vegetation is defined as vegetation that grows in areas that experienced clear-cut deforestation.) Thus, by 2014, nearly a quarter of the area historically cleared in the Brazilian Amazon already contained tropical forest regrowth.

That a phenomenon of this magnitude remained unnoticed seems unlikely; yet it is not an overstatement to claim that secondary vegetation was invisible from both policy and empirical perspectives. There were no policy efforts aimed at either promoting regeneration or protecting existing secondary vegetation (Casa Civil, 2004; MMA, 2009; MMA,2013). Remote sensing data on Amazon-wide regeneration were not available until the early 2010s, and — most importantly — Brazil's world-renowned satellite-based tropical forest monitoring systems, the key tools for effectively targeting Amazon law enforcement efforts, completely overlooked tropical regrowth.

This paper explores the unique empirical setting of Amazon regeneration, particularly its invisibility to monitoring systems, to assess the existence of policy spillovers. In light of the improvement in law enforcement capacity brought about by the adoption of satellite-based high-frequency monitoring of deforestation activity, it proposes two

[2] International Union for Conservation of Nature (IUCN) and Winrock International (2017) estimate that the restoration of 350 million hectares of degraded and deforested lands worldwide by 2030 has the potential to absorb 1.7 $GtCO_2$ per year, with approximately USD 170 billion in net annual benefits from watershed protection, improved agricultural yields and forest products.

Figure 1: Brazilian Amazon Deforestation and Regeneration, 2000–2014



Notes: The graph plots the Brazilian Amazon annual deforestation rate and total secondary vegetation cover, and marks the year the action plan was launched. Secondary vegetation is defined as that which grows in deforested areas. Data sources: PRODES/Inpe (deforestation), TerraClass/Inpe and Embrapa (secondary vegetation).

alternative mechanisms for how environmental law enforcement targeting the clearing of primary (never deforested) vegetation might affect tropical regrowth. Both mechanisms relate the perceived risk of engaging in an illegal activity and the demand for deforested area. Clearing tropical forest without due licensing/authorization is illegal in the Brazilian Amazon, but so is using the land in areas that have been illegally deforested. As such, if stricter law enforcement increases the perceived risk of getting caught and punished for an environmental infraction, potential offenders might respond by altering both forest clearing and land use practices. On the one hand, offenders might seek to evade enforcement by shifting their activities to areas that are less likely to be targeted (a problem known as "leakage"). In this scenario, instead of clearing primary forest and thereby risk getting caught by the monitoring system, offenders cut secondary forest and use these areas for production instead. Consequently, demand for previously deforested areas increases, and the extent of secondary vegetation decreases. On the other hand, enforcement might have a broad deterrence effect, causing offenders to give up on using deforested land altogether. With decreased demand for previously deforested areas, these areas are eventually abandoned, allowing a natural process of regeneration to take place and thereby increasing the extent of secondary vegetation. Hypothesized effects on regeneration in both displacement (the former) and deterrence (the latter) scenarios constitute policy spillovers, as enforcement exclusively targeted the loss of primary vegetation and was not aimed at influencing forest regrowth. Yet, which mechanism dominates and, in fact, whether enforcement affected regeneration at all remain to be answered empirically.

We investigate the potential relationship between law enforcement and secondary vegetation using a spatially explicit dataset covering the full extent of the Brazilian Amazon. Although satellite-based panel data on regeneration serve as the basis for dataset construction, we argue that the long-term cross-sectional difference in secondary vegetation area is less prone to measurement error than the time-series variation and is, thus, a preferable measure of the extent of regeneration. Because data on secondary vegetation are built from interpretation of satellite imagery, forest regrowth must be visible in the image. Yet, as imagery is inherently limited by the satellite's spatial resolution, it is plausible to expect that any given deforested area must accumulate sufficient natural biomass to be classified as secondary vegetation. Tropical regeneration is a time-consuming process that may take decades to occur in abandoned deforested areas (Alves et al., 1997; Aide et al., 2000; Guariguata and Ostertag, 2001), but data for secondary vegetation in the Amazon is only available for select years in the 2004 through 2014 period. Hence, to avoid noise from the time-series variation, we collapse the panel data into a cross-sectional ten-year difference in secondary vegetation coverage. However, we still use information on the persistence of secondary vegetation to build an arguably more robust measure of regeneration and thereby mitigate concerns regarding misclassification of degraded forest.

Based on this spatial cross-sectional setup, and using georeferenced deforestation alerts to capture law enforcement, the analysis tests whether cell-level changes in the extent of secondary vegetation are associated with the intensity of environmental enforcement in a cell's surroundings. Results support the existence of both policy and spatial spillovers — enforcement activity happening within 20km of a cell's surrounding had a significant impact on regeneration outcomes inside that cell. The spillover effect is sizable. An increase of one standard deviation in the intensity of neighborhood enforcement is estimated to increase the probability of cell-level expansion in secondary vegetation coverage by 11% of the sample mean, and to increase the area of secondary vegetation inside the cell by 6% of the sample mean. Counterfactual exercises show that feasible improvements to Brazil's tropical forest monitoring system could contribute to increase secondary vegetation cover by nearly 300 thousand hectares. The overall stability of estimated coefficients across the inclusion of controls for spatially explicit observables suggests that the proposed strategy adequately addresses concerns regarding omitted variable bias. Reverse causality is not a primary concern here given that regeneration does not affect enforcement by the design of the Brazilian monitoring system. We interpret these findings as evidence that deforestation-oriented enforcement affected regeneration via the deterrence mechanism, in which environmental offenders, once faced with a higher perceived risk of illegal activity, abandon the region they are operating in and thereby allow a natural process of forest regrowth to occur. This constitutes evidence of important and unanticipated policy spillovers. To the best of our knowledge, this is the first study documenting positive spillover effects of command-and-control environmental policies, suggesting that such policies may have greater impacts on social welfare than previously thought.

The analysis also documents important heterogeneity across proximity to local remaining primary forest cover. The spillover effect of law enforcement on regeneration appears to be largest in places that have undergone neither too much nor too little deforestation: in the former, forest clearings and non-forest land use are probably more consolidated, making abandonment and subsequent regrowth less likely; in the latter, there is still relatively little area for the forest to grow back in.

Related Literature. Our paper contributes first to an increasing number of studies that are making the case for the growing relevance of accounting for spillovers in the context of conservation policy impact evaluation (Baylis et al., 2016; Pfaff and Robalino, 2017). Several studies provide empirical evidence for the existence of conservation policy spillovers, but typically in contexts other than law enforcement. The most common examples are assessments of externalities from PES programs (Alix-Garcia et al., 2012, 2013; Jayachandran et al., 2017), and leakage or halo effects from protected territory (Herrera, 2015; Robalino et al., 2017). The literature assessing law enforcement under the action plan has largely focused on the policy's direct impacts on deforestation. Although stricter enforcement has been shown to have significantly reduced Amazon forest clearings (Hargrave and Kis-Katos, 2013; Assunção et al., 2019), it is the priority municipalities policy that, among all action plan efforts, has received most attention in the enforcement spillover literature. Results are mixed, with Cisneros et al. (2015) finding no evidence of the policy's deterrent effect on priority municipalities' neighbors, but both Andrade (2016) and Assunção et al. (2018) documenting significant reductions in non-priority municipalities located near priority ones. As far as we are aware, this is the first assessment of tropical regeneration as a spillover of action plan policies, and of law enforcement specifically. It is also the first study in the economic literature to explore the rich spatial data recently released on detailed classifications of land use in Amazon deforested areas.

This analysis also speaks to a growing literature on the importance of tropical regeneration. The environmental services provided by secondary vegetation have been widely documented. These include, but are not limited to, carbon sequestration, reestablishment of hydrological services, soil protection, and creation of ecological corridors for fauna and flora (Almeida et al., 2010; Caviglia-Harris et al., 2015; Uriarte and Chazdon, 2016; Crouzeilles et al., 2017; Tyukavina et al., 2017). This study contributes to this literature by shedding light on how policy influences regeneration in an empirical setting where this phenomenon is happening at scale.

Finally, an important disclaimer is in order: this work in no way claims that primary and secondary forests are biologically or ecologically equivalent, nor does it mean to argue that regeneration makes up for the devastation caused to the Brazilian Amazon over years of predatory deforestation. Rather, its goal is to shed light upon a phenomenon which is sizable, ongoing, and largely unknown. A better understanding of the remarkable growth in tropical regeneration could help inform decision-makers, shape future policy, and ultimately contribute to ongoing efforts for conserving the Amazon forest while promoting regional development.

The paper proceeds as follows: Section 2 describes the institutional context and proposes mechanisms through which, given this context, law enforcement could influence regeneration; Section 3 describes the data; Section 4 details the empirical strategy; Section 5 reports and discusses estimation results and counterfactual simulations; and Section 6 concludes with policy implications.

2. Institutional Context

In this section, we present the relevant background for the Brazilian Amazon, focusing on the institutional context and the introduction of satellite monitoring in 2004. We also discuss potential alternative mechanisms relating the monitoring system and forest regrowth.

The Brazilian Amazon accounts for two-thirds of the Amazon Rainforest and is itself a truly vast area, almost ten times the size of California. To date, around 20% of the Brazilian Amazon has been deforested — an area totaling over 700,000 square kilometers (which is larger than Texas.) Deforested areas are used mainly for agriculture: approximately two thirds of the cleared area comprises pasture, and around 6 percent is used for crops (Inpe and Embrapa, 2016a).

The Monitoring and Enforcement Systems. In 2004, the Brazilian federal government launched an ambitious plan to combat deforestation in the Amazon, the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). The cornerstone of the PPCDAm was a new satellite monitoring system, the System for Real-time Detection of Deforestation (DETER), developed by the Brazilian Institute for Space Research (INPE).[3] The adoption of DETER introduced near-real-time monitoring of forest disturbances, allowing Amazon clearings to be detected and acted upon in a more timely manner — as opposed to the previous system, fundamentally based upon land and air patrols (and limited in their effectiveness given the sheer extent of the area covered and risks posed to law enforcers). In the new system, INPE detects areas experiencing a loss of forest cover, in turn triggering DETER deforestation alerts for the immediate attention of law enforcers at the Brazilian Environmental Protection Agency (IBAMA), which then sends inspectors to the hot spots and penalizes offenders, by issuing fines or confiscating equipments, when appropriate.[4] Existing evidence suggests that this satellite-based system alone has had an important impact: estimated deforestation in the absence of the system in 2006–2016 would have been four times greater (Assunção et al., 2019). Indeed, Brazil's

[3]Several other conservation efforts were adopted under the PPCDAm framework, including: the strengthening of the regulatory environment concerning administrative sanctions for illegal deforestation; the identification of priority areas for differential action; the conditioning of rural credit concession upon compliance with environmental and land-titling requirements; and the the targeted expansion of protected areas.

[4]Created in 1989, IBAMA executes environmental policies and serves as the national police authority for the investigation and sanctioning of environmental infractions.

system for detecting tropical forest loss is now widely recognized as being at the forefront of national efforts to combat deforestation (Tyukavina et al., 2017).

Despite the important impacts of the system in preventing deforestation, the loss of secondary vegetation remained entirely invisible to DETER and, thus, to environmental authorities. This was partly due to a lack of available data. The country first started mapping Amazon deforestation the late 1980s. Since then, once an area of primary forest has been cleared, it is not revisited in future satellite imagery and becomes part of what is known as an accumulated deforestation mask. Through the early 2010s, Brazil had no system to track or measure Amazon-wide regeneration. The first map of tropical secondary vegetation, referring to land use in 2008, was only produced in 2012; it took another four years for data on 2004 and 2014 secondary vegetation cover to be released (see Online Appendix B.3 for details). More importantly, perhaps, was the fact that, in its first decade, the PPCDAm neither promoted regeneration, nor explicitly sought to protect existing secondary vegetation. Rather, it focused exclusively on combating the clearing of primary vegetation. It was designed to scan for signs of forest disturbance strictly outside the accumulated deforested area. Consequently, the loss of secondary vegetation is not accounted for in Amazon deforestation figures, nor does it trigger any forest clearing alerts in the DETER system.

Possible Channels. This institutional setting suggests two alternative mechanisms for a potential effect of deforestation-oriented law enforcement on regeneration. On the one hand, stricter monitoring and enforcement enabled by DETER might have displaced demand for cleared areas towards secondary forest — we henceforth refer to this as the displacement channel. Because the system used to target enforcement does not detect secondary deforestation, there is a lower chance of an offender getting caught and punished if clearing secondary versus primary vegetation. Hence, a potential offender seeking to use cleared land in the Amazon could attempt to elude monitoring by shifting his deforestation activities to regenerated areas. In this scenario, one would expect to see a decrease in the extent of secondary vegetation.

Three elements arguably favored this change in forest clearing behavior. First, the extent of secondary vegetation was already sizable in the mid-2000s (see Figure 1), providing ample supply of regenerated areas that were invisible to the monitoring system. Second, because secondary vegetation is typically sparser than primary forest, clearing these areas is likely easier and less costly. Finally, it could be argued that poorer soil quality) in areas covered by secondary forest would limit displacement towards previously cleared areas, due to lower expected gains from land use. This, however, is most relevant to crop farming, which covered less than 6% of the area historically cleared in the Brazilian Amazon through 2014 (Inpe and Embrapa, 2016a). With over two thirds of Amazon deforested areas being used as pasture, which demands less nutrients from the soil, it seems reasonable to expect that potential offenders would seek to minimize their chance of getting caught, even if at a relatively minor cost to production.[5]

On the other hand, because using illegally cleared areas in the Amazon is illegal in and of itself, stricter monitoring and enforcement might have broadly inhibited illegal activity and thereby lowered the demand for deforested areas — we henceforth refer to this as the deterrence channel. Cleared areas that are no longer in use are often abandoned. This reduces human interference in these areas and allows a natural process of regeneration to occur. In this case, one would expect to see an increase in the extent of secondary vegetation. An increase in the area covered by forest regrowth would also be expected if farmers hold inaccurate beliefs about the monitoring system, assuming DETER also monitors secondary forests in the Amazon.

3. Data and Descriptive Evidence

This section describes the key elements of dataset construction (Section 3.1) and presents descriptive statistics (Section 3.2). The Online Appendix provides a detailed account of the spatial setup (Appendix A), data sources (Appendix B), and variable construction (Appendix C).

3.1. Dataset Construction

We assembled a rich spatial dataset from a variety of publicly available sources. The area we consider is the Amazon biome, which is defined based on biophysical and ecological criteria.[6] We rasterized the Brazilian Amazon Biome at the 900 meters resolution. (A raster is a matrix data structure that represents a regular grid of cells.) That means that our grid is composed of 900m by 900m square cells; the total number of cells in our data is 5.2 million. Each cell in turn is subdivided into 30m by 30m square minicells, which allows us to calculate variables based on higher resolutions; e.g., shares of deforested area in a cell can be calculated by counting the number of deforested minicells. (See details in Online Appendix A.)

The baseline sample comprises all Amazon biome cells that contained strictly positive shares of deforestation (i.e., at least one deforested minicell) in 2003. We take that as the baseline year because the first year for which there are data on the extent of secondary vegetation is 2004 (see Section 2). Further, secondary vegetation, by definition, can only grow in areas that have been deforested — hence the need to restrict the sample to cells with strictly positive shares of cleared areas. Cells in which deforestation started in 2004 or later are not included in the analysis to mitigate both endogeneity concerns (as recent clearings trigger deforestation alerts, but also increase the potential area for forest regrowth)

[5] The case of Zona Bragantina, in eastern Pará state, indicates that the conversion of secondary forests into agricultural lands is not only a theoretical possibility, but a practical one. Vieira (2013) documents that, through 2008, the region saw reductions in both primary and secondary forest areas, alongside an increase in pasture areas in the 2000s. This anecdotal evidence supports the idea that the clearing of secondary forest areas can offer economically viable alternatives for agricultural production in the Brazilian Amazon.

[6] The Brazilian Amazon biome is entirely contained within the Legal Amazon, which in turn is a geopolitical administrative subdivision that encompasses the following states: Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins, as well as the western part of the Maranhão state.

and the chance of picking up on misclassified secondary vegetation (as degraded primary vegetation may be erroneously classified as secondary vegetation — see Appendix C for a detailed discussion).

In light of the role played by proximity to primary vegetation in the regeneration process, the extent of remaining primary vegetation in the cell at baseline is used as an additional selection criteria for the benchmark sample. Specifically, the literature on ecological and biophysical determinants of regeneration shows that proximity to primary forest is a key driver of tropical regeneration (Crouzeilles et al., 2016; Latawiec et al., 2016; Uriarte and Chazdon, 2016). Although an in-depth assessment of the underlying mechanisms behind this relationship are outside the scope of this paper, the importance of primary forests can be broadly summarized by their role as sources of seeds and as habitats for animals that disperse seeds, pollinators, and predators of pathogens that threaten forest development. Given this, a cell with a small amount of deforestation will likely contain more remaining primary vegetation, which typically favors tropical regrowth. Yet, on the other hand, a small amount of deforested land offers a relatively small area upon which secondary forest can grow. Because these effects pull the total amount of forest regrow in opposite directions, we take the *benchmark* sample as a subset of the *baseline* sample that is further restricted to cells containing at least 50% primary forest cover in 2004. (We provide robustness analysis by varying this fraction in the benchmark sample.)

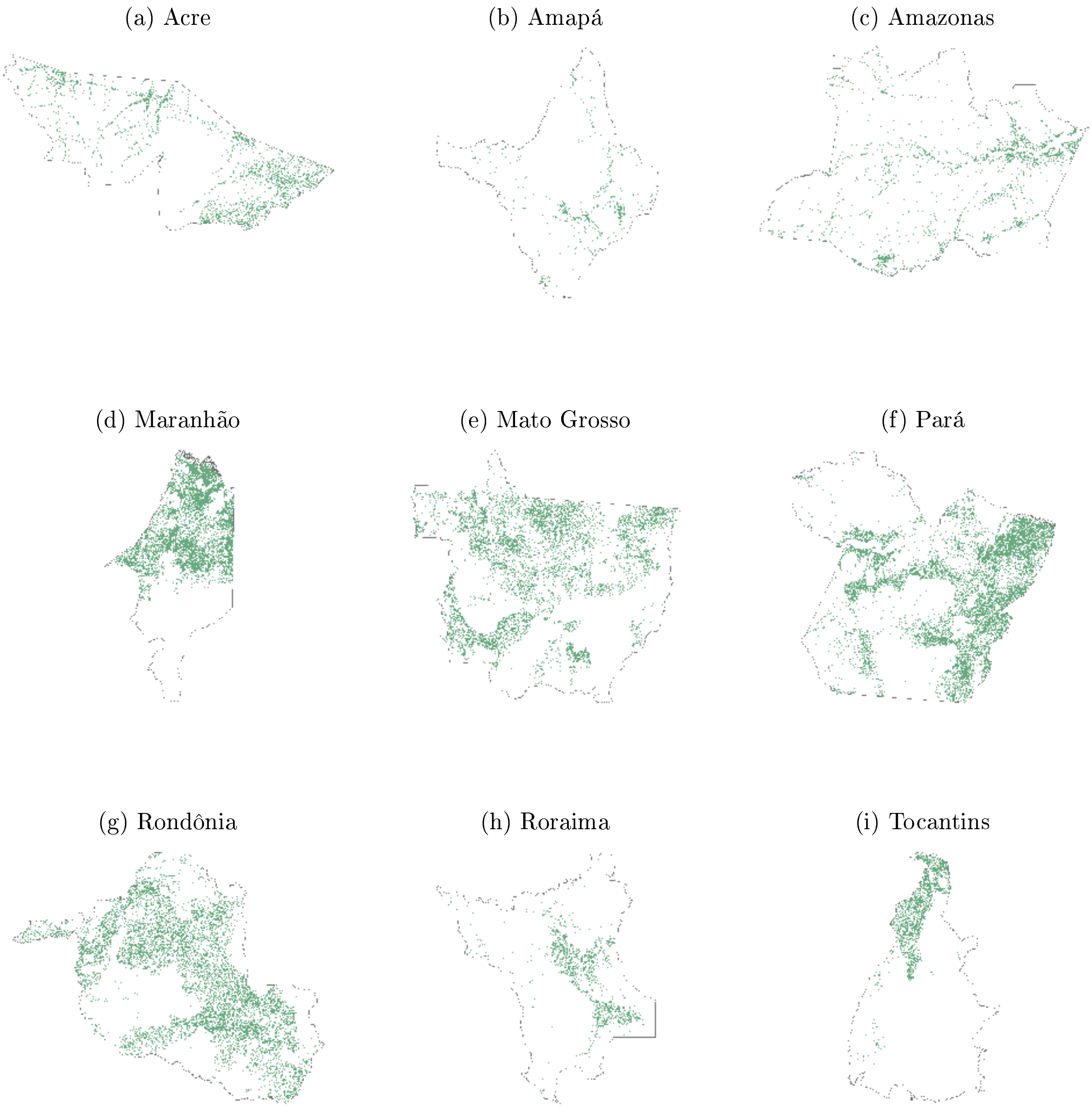
Next, we discuss the construction of the variables used in this study, together with the main data sources.

Secondary Vegetation. To measure secondary vegetation, one needs to identify first areas that experienced tropical forest loss. The Project for Monitoring Deforestation in the Legal Amazon (PRODES), established by INPE in 1988, provides georeferenced data on annual tropical deforested area. PRODES, however, does not register how land is used once an area is deforested. The TerraClass Amazônia, a joint effort between INPE and the Brazilian Enterprise for Agricultural Research (Embrapa), provides land use data for all deforested areas throughout the Brazilian Legal Amazon for select years from 2004 to 2014. The system identifies several land use categories, including forest regrowth, within the full extent of the PRODES accumulated deforested mask.[7] TerraClass defines secondary vegetation as areas that were once clear-cut, but currently contain trees and/or shrubs. It includes neither pasture under regeneration, nor commercial reforestation. This category therefore captures tropical regeneration. Figure 2 shows secondary vegetation mapped in each Amazon state in 2014.

Although TerraClass data has low rates of misclassified land use (Salum et al., 2011;

[7] The land use categories are: four types of pasture (grassy, shrubby, exposed soil, under regeneration); cropland (predominantly annual crops); secondary vegetation (detailed in what follows); reforestation (commercial forests of exotic species); urban; mining; mosaic of uses (where no single use can be discerned); and others (a residual category). If clouds, shadows cast by clouds, or smoke from fires obstruct visibility in imagery, the blocked area is classified as unobservable. See Almeida et al. (2016) for a full description of TerraClass classes and methodology.

Figure 2: Regeneration by Amazon State, 2014



Notes: The maps plot secondary vegetation area by Amazon state in 2014. States are not to scale across sub-figures. Because secondary vegetation patches are small at the sate-level scale, it is difficult to see the difference across years in print. Although available for other years, maps are therefore restricted to 2014 for illustrative purposes only. Data sources: TerraClass/Inpe and Embrapa (secondary vegetation); IBGE (states).

Almeida et al., 2010), the classification of forest regrowth is an empirically challenging endeavor. There are two main reasons for this — one inherent to the use of satellite imagery, the other a consequence of the design of Brazil's satellite-based systems. First, because data on secondary vegetation are built from interpretation of satellite imagery, regrowth must be visible in the image to be detected. As imagery is limited by the satellite's spatial resolution, it is plausible to expect that any given deforested area must accumulate sufficient natural biomass to be classified as secondary vegetation. Yet, tropical regeneration is a time-consuming process that may extend over decades.[8] It is therefore likely that areas that are already under regeneration may take several years to show up in satellite-based land use classification systems. (Short-term time-series variation in regeneration data derived from remote sensing is therefore prone to substantial measurement errors.)

Second, Brazil's land use classification system cannot distinguish degraded primary forest from actual secondary vegetation. The problem is that an area that has been sufficiently degraded and has lost enough biomass may be mis-classified as deforested (clear-cut) area by PRODES. It is then incorporated into PRODES deforested mask, making it available for classification under TerraClass. But since that area may continue to be just degraded forest (and so not put into agricultural use), TerraClass detects vegetation and classifies it as secondary vegetation. In this way, the total area covered by secondary vegetation may be overestimated in TerraClass. (See details in Appendix C.) This is particularly concerning in light of the increasing relevance of tropical degradation, as compared to clear-cut deforestation, in the Brazilian Amazon (Souza Jr. et al., 2013; Rappaport et al., 2018).

In light of this, we draw on the biophysical nature of forest processes to propose an alternative measure of secondary vegetation that is arguably less vulnerable to misclassification errors. While an area under regeneration typically sees an increase in biomass over time, degraded forests experiences the opposite trend. It is thus likely that, as degradation continues, a given area will eventually cease to look like secondary vegetation and will be classified in TerraClass according to some other use, like pasture. We therefore consider a more conservative measure of tropical regeneration, which we call "non-decreasing secondary vegetation". This measure only considers an area as containing tropical regrowth if it meets two criteria: (i) it has been classified as secondary vegetation for at least two consecutive TerraClass years, and (ii) once classified as secondary vegetation, it never ceases to be classified as secondary vegetation.[9] Importantly, non-decreasing secondary vegetation likely excludes fallow lands containing tropical regrowth, which are part of agricultural production cycles (Vieira et al., 2003; Perz and Walker, 2002). The classification applies to the 30m by 30m minicell, allowing for the calculation of shares of non-decreasing secondary vegetation in the 900m rater cells.

We also consider a second measure of regeneration for robustness: an indicator variable that equals 1 if the ten-year difference in the share of secondary vegetation in a cell is greater

[8]The literature indicates that natural regeneration following the abandonment of once agricultural lands extends over several decades before aboveground biomass, stem density, and species richness are restored to mature forest levels, with estimates ranging from 30 to 40 years (Aide et al., 2000; Chazdon, 2008). Although reestablishing plant composition of old-growth forest is likely to take centuries (Guariguata and Ostertag, 2001), empirical assessments of Brazilian Amazon regeneration indicate that, 18 years after abandonment, secondary vegetation biomass was roughly half that of primary forest (Alves et al., 1997).

[9]The classification algorithm detects permanence by using the full TerraClass time series, not just the beginning and end data points. The only exception to this rule is for areas in which satellite visibility is compromised by visual obstructions, as these do not indicate a change in land use, but a technical limitation in the imagery interpretation system.

than or equal to 0.1, and 0 otherwise. The indicator signals whether secondary vegetation expanded over at least one tenth of the cell during the sample decade, 2004–2014. (We also perform robustness analyses by varying the 10% threshold.)

DETER Alert System. We use the spatial distribution of forest clearing alerts from INPE's DETER system as a measure of the regional intensity of law enforcement. As DETER alerts are used to target law enforcement, the greater the intensity of alerts in a given area, the more likely it is that law enforcers will visit that area. (To the best of our knowledge, there is no available georeferenced data on enforcement deployment for the Brazilian Amazon.)

Monthly vector data on georeferenced alerts are rasterized at the 900m resolution, such that a cell will take on a value of 1 if it contains an alert and a value of 0 otherwise. Alert intensity is calculated as the total number of alert cells over the 2006 through 2013 period as a share of total neighborhood cell count. (Recall that 2006 is the year in which DETER became fully operational). See Appendix B.2 for further details.

Additional Variables. We complement the secondary vegetation and the DETER alert system datasets with additional variables that affect forest regrowth. All variables are either time-invariant, accumulated over the sample decade (2004–2014), or year-specific.

First, we consider municipality indicators (fixed-effects) to account for regional levels of regeneration, as affected by municipal initiatives and economic structure. Second, we incorporate more specific geographic location by taking into account the cell's latitude and longitude, thereby allowing for natural characteristics like soil quality, topography, and proximity to water, as well as proximity to roads and to major economic centers and ports. (In the data, latitude/longitude values refer to a cell's centroid.)

Third, weather variables account for average conditions that might favor or hinder tropical regeneration. Monthly data compiled by Matsuura and Willmott (2015) serve as the basis for building these variables. The authors use multiple sources of global weather data to calculate a regular georeferenced world grid of estimated temperature and rainfall over land. This database has been extensively used in the economic literature both to evaluate the impact of climate variables on economic outcomes and to provide relevant temperature and rainfall controls (Dell et al., 2014). We calculated average annual temperature and total annual rainfall from the monthly data for each Amazon cell.[10]

Fourth, clouds, shadows cast by clouds, and smoke from forest fires can all affect visibility in satellite imagery and thereby introduce error in observed land cover. We therefore consider "satellite visibility" as the share of cell area suffering from visual obstructions in 2004 and 2014. Fifth, to account for the area where secondary forest could grow, we compute the 2004 baseline cell-level accumulated deforestation, using the PRODES mask.

[10]Data points in the original dataset refer to grid nodes, not cells, such that average annual temperature and total annual rainfall are calculated from the monthly data for each Amazon grid node. Because the spatial resolution for this dataset is much lower than 900m, cell weather values are the 2006 through 2013 averages of all grid node values within 180km of each cell. This distance ensured all sample cells had non-missing weather data.

Table 1: Sample Deforestation and Regeneration

	Brazilian Amazon	baseline sample: primary forest ≥ 0	benchmark sample: primary forest ≥ 0.5
raster cell count (900m resolution)	—	1,157,648	403,191
deforested area, historical through 2003 (ha)	62,726,908	55,762,471	5,684,454
2004 secondary vegetation (ha)	9,671,861	9,307,164	1,995,152
2004 non-decreasing secondary vegetation (ha)	—	4,632,612	1,126,561
deforested area, historical through 2013 (ha)	74,261,876	63,690,094	10,322,528
2014 secondary vegetation (ha)	17,305,640	14,320,640	3,445,083
2014 non-decreasing secondary vegetation (ha)	—	9,607,376	2,399,001

Notes: The table reports total deforested and regenerated areas in the Brazilian Amazon, the baseline sample, and the benchmark sample. The baseline sample comprises all Amazon biome cells that contained non-null deforestation through 2003; the benchmark sample is a subset of this that is further restricted to cells that contained at least 50% primary forest cover in 2004. Areas for the Brazilian Amazon are calculated from vector data, while baseline and benchmark areas are calculated from the analysis' raster dataset. Non-decreasing secondary vegetation is a measure built for this empirical analysis (see Section 3.1) and has therefore not been computed for the full extent of the Brazilian Amazon. Data sources: PRODES/Inpe (deforestation); TerraClass/Inpe and Embrapa (secondary vegetation).

Finally, observed policy controls address other conservation efforts that could affect local regeneration and regional law enforcement. Annual spatial data on protected areas come from the Brazilian Ministry of the Environment (MMA), and on indigenous lands come from the Brazilian Native Peoples Foundation (FUNAI) and the Socioenvironmental Institute (ISA).[11] Throughout this analysis, an indigenous land is only regarded as protected when it has completed the declaration stage, at which point its spatial boundaries have been published via ordinance.[12] Protection status is captured by an indicator that flags whether a cell was under protection of any kind (indigenous lands, strictly protected areas, or protected areas for sustainable use) at any point from 2004 through 2014.

3.2. Descriptive Statistics

Table 1 summarizes deforestation and regeneration areas across the Brazilian Legal Amazon, the baseline sample, and the benchmark sample. Observed differences in areas across samples result from a combination of the following factors: (i) the Brazilian Legal Amazon is geographically larger than the Amazon biome; (ii) conversion from vector to raster data might result in area discrepancies due to loss of overlapping areas and spatial precision; and (iii) baseline and benchmark samples exclude cells with no deforestation by 2003. The table also shows that the total extent of non-decreasing secondary vegetation in

[11] FUNAI publicly releases spatial vector data for indigenous lands throughout the country. This dataset contains date variables for each of the indigenous territory recognition stages, enabling the construction of a georeferenced annual panel. Despite being the official source for information on indigenous lands in Brazil, the FUNAI dataset contains several occurrences of missing data for date variables. We address these gaps using information from ISA, which compiles its own historical record of the many recognition stages for indigenous territories. ISA data are publicly available online and were collected using a data-scrapping algorithm. The ISA-based dates fill in the gaps in FUNAI data, but never replace them.

[12] Chiavari et al. (2016) support this cutoff stage, stating that indigenous territories are only protected once they have been declared.

Table 2: Descriptive Statistics for Regression Variables

	Brazilian Amazon		benchmark sample	
	mean	std. dev.	mean	std. dev.
2004 secondary vegetation (% cell area)	0.0220	0.0865	0.0611	0.0862
2004 non-decreasing secondary vegetation (% cell area)	0.0109	0.0565	0.0345	0.0663
2014 secondary vegetation (% cell area)	0.0366	0.1167	0.1056	0.1274
2014 non-decreasing secondary vegetation (% cell area)	0.0243	0.0887	0.0735	0.1009
d=1 if 2004-2014 Δ secondary vegetation $\geq$ 0.1 cell area	0.0630	0.2430	0.2031	0.4023
2004-2014 Δ secondary vegetation	0.0146	0.0919	0.0445	0.1181
2004-2014 Δ non-decreasing secondary vegetation (% cell area)	0.0133	0.0605	0.0390	0.0785
alerts 5km neighborhood ring (% ring area)	0.0590	0.1920	0.1809	0.3067
alerts 10km neighborhood ring (% ring area)	0.0590	0.1576	0.1608	0.2372
alerts 20km neighborhood ring (% ring area)	0.0589	0.1327	0.1429	0.1881
alerts 50km neighborhood ring (% ring area)	0.0583	0.1039	0.1173	0.1321
alerts 100km neighborhood ring(% ring area)	0.0572	0.0819	0.0962	0.0985
2004 primary forest (% cell area)	0.7656	0.3853	0.7958	0.1512
total annual rainfall (mm)	2326.69	448.39	2182.20	368.65
average annual temperature (Celsius)	26.41	0.98	26.28	1.06
2004 unobservable TerraClass (% cell area)	0.0108	0.0820	0.0137	0.0553
2014 unobservable TerraClass (% cell area)	0.0070	0.0581	0.0146	0.0682
baseline accumulated deforestation (% cell area)	0.1318	0.3040	0.1742	0.1435
alert intensity (year average)	0.0590	0.3152	0.2216	0.5766
d=1 if protected	0.4879	0.4999	0.1922	0.3941

Notes: The table presents mean and standard deviations for variables used in the empirical analysis. Units are shown in parentheses; indicator variables are identified with "d=1".

the analytical sample is not only sizable, but actually represents a relevant share of secondary vegetation area recorded in TerraClass: in 2004, it amounted to 4.6 million hectares, or about 50% of secondary vegetation observed in the baseline sample; in 2014, it had increased to 9.6 million hectares, totaling 67% of secondary vegetation observed in the baseline sample. Because the baseline sample excludes cells that were first deforested in 2004 or later, secondary vegetation recorded in TerraClass for the baseline sample in 2014 totals about 14.3 million hectares, not the 17 million hectares observed for the entire Brazilian Amazon (see Figure 1).

Table 2 presents mean and standard deviations for variables used in the regression analysis, including statistics for the Amazon biome for comparison with the benchmark sample. The sample selection criteria implies higher average cell-level secondary vegetation coverage and neighborhood alert intensities. This is to be expected considering that cells that have never been deforested have, by definition, no secondary vegetation. Moreover, statistics for the full Amazon make no distinction between high and low deforestation pressure zones, whereas the benchmark selection of cells that had seen some deforestation but still contained primary forest area at baseline likely captures high-risk areas. Hence, although the benchmark sample might not be representative of the Brazilian Amazon as a whole from the perspective of descriptive statistics, it ensures the analysis is focused on areas that were actual candidates for seeing an impact of neighboring enforcement on local regeneration. Table 2 also indicates that the sample exhibits relevant cross-sectional variation.

Finally, descriptive statistics regarding changes in agricultural land use from 2004 through 2014 shed light on where regeneration was happening. In the baseline sample, 65% of cells where the expansion in secondary vegetation was greater than 10% saw a reduction in pasture area, and 50% of cells where non-decreasing secondary vegetation area grew saw this same reduction. In the benchmark sample, the analogous figures are 45% and 35%, respectively. Cropland, however, saw a reduction in only a tiny fraction of cells across samples. These statistics are aligned with official Amazon-wide transitions across TerraClass categories, which indicate that 33% of pasture and virtually 0% of cropland in 2004 contained regeneration in 2014 (Inpe and Embrapa, 2016b). Thus, the expansion of secondary vegetation appears to have occurred, in its vast majority, over pasture areas.

4. Empirical Strategy

In this section, we set out a framework that underlies our approach to studying the impact of environmental law enforcement on tropical regeneration, and discuss our identification strategy.

Our empirical strategy takes advantage of the spatial structure of the data. We test whether enforcement in a cell's neighborhood affects regeneration outcomes inside the cell. If the estimated impacts are large, they serve as evidence of policy spillovers, to the extent that enforcement during the period of interest was directed at primary forest loss, and not aimed at either promoting or protecting secondary vegetation. Furthermore, they also capture spatial spillovers, as they capture the effect of enforcement in one locality on regeneration outcomes in another.

The unit of observation is a cell in the Brazilian Amazon biome that experienced strictly positive deforestation by 2003; that is the baseline sample. Our main equation of interest is:

$$regeneration_i = \sum_{n \in \partial i} \beta_n enforcement_{n,i} + X_i'\theta + \varepsilon_i, \tag{1}$$

where $regeneration_i$ measures tropical forest regrowth in cell i over a certain time period; n is a neighborhood of cell i, and ∂i is a set of different neighborhoods of i; for each neighborhood $n \in \partial i$, $enforcement_{n,i}$ measures law enforcement intensity in that neighborhood during the same time period; X_i is a vector of control variables for location, weather, satellite visibility, baseline deforested area, and observed conservation policies; and ε_i is the cell-level idiosyncratic error.

We consider two measures of forest regeneration, as presented in Section 3.1. The first one is the "non-decreasing secondary vegetation," which measures the total change in tropical regrowth as a share of cell area over the period 2004–2014, recalling that it satisfies by construction the restriction that once a subregion of the cell (minicell) is classified as secondary vegetation, it never ceases to be classified as secondary vegetation during that period. The second measurement is a probability-based measure: it is an indicator that signals whether secondary vegetation expanded over at least 10% of the cell area during the decade, 2004–2014. As explained in Section 3.1, we focus on long-term cross-sectional differences in secondary vegetation coverage because short-term variation in satellite-based regeneration data is prone to measurement error. We consider the decade 2004–2014 because regeneration has been measured only over this period in the TerraClass data.

For each cell, multiple neighborhoods $n \in \delta i$ are formed by concentric rings of increasing diameter around it (see Appendix A for details.) Larger neighborhoods do not contain smaller ones, and the cell itself is excluded from the smallest neighborhood. All cells within a given neighborhood are weighted equally. To establish the catchment area, or reach, of potential spillover effects, we consider concentric rings of diameters 5km, 10km, 20km, 50km, and 100km.[13] (Recall that our grid is composed of 900m by 900m square cells.)

The intensity of law enforcement in each neighborhood, $enforcement_{n,i}$, is calculated as total number of DETER alerts from 2006 through 2013 as a share of neighborhood area. A region with greater alert intensity is under greater deforestation pressure, and also more likely to be targeted by enforcement personnel. While deforestation may push for broader clearing, inspection by enforcement personnel may deter activities that entail forest loss. (Recall that there exists no spatially explicit data of inspections on land.) Coefficients β_n therefore capture the average forest regrowth response to enforcement occurring increasingly further away. Negative coefficients $\beta_n < 0$ indicate that spillovers occur via the displacement channel, in which demand for cleared land shifts towards regenerated areas, while positive coefficients $\beta_n > 0$ lend support to the deterrence channel, in which previously cleared areas are abandoned and left to regenerate. The proposed strategy does not determine that alerts should exclusively capture one or the other; rather, it serves as an empirical test for which of these opposing forces prevail in practice.

The key identification assumption here is that DETER alerts in neighbor cells do not correlate with unobservable factors affecting regeneration in a given cell. The fact that Amazon regeneration is invisible to the satellite monitoring system provides support for that assumption, as it eliminates the risk of there being reverse causality between forest regrowth in an cell and alerts in its surroundings. Tackling omitted variable bias in this specification is however less straightforward. As previously discussed, cross-sectional time-difference data is more suitable to capture the response of a time-consuming process like regeneration. This, however, prevents the use of cell-level fixed effects to control for relevant time-invariant unobservable factors, making estimation more vulnerable to omitted variable bias. The

[13] In the hot spot policing literature, an intervention's catchment area is that within which spillovers occur (Braga et al., 1999; Braga and Bond, 2008; Taylor et al., 2011; Blattman et al., 2017). Although there are different ways to model spillovers, this literature often defines catchment areas as one fixed-width ring or several concentric rings (with increasing radii) around a given region.

proposed strategy mitigates this by including a host of cell-level controls (discussed in the next paragraph). Although we cannot directly test whether potential sources of bias have been fully accounted for in the benchmark specification, the stability of estimated coefficients across the gradual inclusion of controls suggests that the analysis' main findings do not suffer from significant bias (see Section 5.1).

Next, we discuss briefly the controls variables, X_i. They are either time-invariant, accumulated over the sample decade, or year-specific. First, we include municipalities fixed-effects. Second, we add a flexible function of the cell's latitude and longitude coordinates (a quadratic polynomial). This saturated specification controls for more specific geographic factors not captured by municipality fixed-effects such as soil quality, topography, proximity to water, to roads, and to economic centers. It further adjusts for local levels of regeneration, and also addresses spatial dependence across cells in the same region. Weather variables (rainfall and temperature) account for conditions that might favor or hinder tropical regeneration; the satellite visibility controls for errors caused by obstructions blocking visual access to the Earth's surface in satellite imagery. We also include the cell's total area cleared in 2003, as regeneration can only grow in deforested areas.[14] The last set of controls addresses conservation policies that might also contribute to regeneration. Policy controls include an indicator flagging whether the cell was protected at any point during the sample decade, as protection promotes isolation from human interference, and the total number of times the cell itself contained an alert, which serves as a measure of the intensity of local clearing activity.

5. Empirical Results

This section starts by empirically testing the existence and reach of environmental law enforcement in a cell's neighborhood on regeneration outcomes inside the cell. It then follows with robustness checks that use alternative thresholds for defining dependent variables and benchmark samples, as well as tests for additional controls. To shed light on aggregate impacts, the section closes with counterfactual exercises that explore variations in monitoring technology.

5.1. Main Results: Policy Spillovers

If environmental law enforcement targeting primary deforestation affects tropical regeneration via either displacement or deterrence mechanisms, enforcement in one locality should significantly impact regeneration elsewhere. Table 3 presents estimated coefficients under the inclusion of increasingly distant neighborhoods to establish the catchment area,

[14] An alternative specification would not control for initial levels of deforestation in a cell, but instead calculate the dependent variable as the change in the share of forest regrowth on the deforested cell area, at the beginning and end of the sample period. However, this leads to endogeneity problems related to the evolution of deforested areas, as opposed to isolated impacts on regeneration. For these reasons, we opt for a dependent variables as shares of cell area (not deforested area) and we control for the baseline extent of deforestation.

or reach, of this potential spillover effect. Column 1 starts with only the nearest 5km neighborhood, and columns 2 through 5 gradually add regressors for enforcement intensity in 10km, 20km, 50km, and 100km neighborhoods, respectively. Coefficients in Panel A capture the impact of enforcement on the indicator variable flagging whether the 2004 through 2014 difference in secondary vegetation area was equal to or greater than one tenth of cell area, and can therefore be interpreted as differences in the probability of seeing regeneration expand over a minimum cell area threshold. Coefficients in Panel B capture the 2004 through 2014 difference in non-decreasing secondary vegetation area as a share of cell area, and can therefore be interpreted as actual area effects. All columns include the full set of cell-level controls: location (municipality, saturated longitude/latitude), weather (temperature, precipitation), satellite visibility (visual obstructions in satellite imagery in 2004 and 2014), baseline deforested area (accumulated deforestation through 2003), and observed conservation policy (protected territory status, DETER alerts). Results indicate that cell regeneration is significantly affected by enforcement activity located within 20km, but not farther. This holds for both dependent variables, which also exhibit fairly stable coefficients across columns.

Identification of the proposed empirical strategy ultimately depends on adequately controlling for potential sources of bias (see Section 4). In light of this, Table 4 reports estimated coefficients for an uncontrolled specification (column 1), as well as for the gradual inclusion of five sets of controls: location (column 2), weather (column 3), satellite visibility (column 4), baseline deforested area (column 5), and observed conservation policy (column 6). Results show that it is important to control for location, including both municipality and a saturated function of cell centroid coordinates, as expected. Reassuringly, coefficients are largely stable across the inclusion of additional controls, lending support to the proposed identification strategy. Beyond location controls, the baseline deforested area control is that which affects estimated coefficients most markedly. This is consistent with the fact that the extent of existing deforestation at baseline captures an important aspect of potential regeneration.

Henceforth, the analysis focuses on the specification with the full set of controls (Table 4, column 6). Estimated coefficients point towards significant spillovers, with environmental law enforcement targeting loss of primary vegetation having had a positive impact on tropical regeneration — more intense enforcement activity in a cell's neighborhood was associated with both a greater probability of seeing cell-level growth in secondary vegetation coverage, and a larger expansion in non-decreasing secondary vegetation at the cell level. The spillover effect is sizable. An increase of one standard deviation in the intensity of neighborhood enforcement increases the probability of cell-level regeneration expansion by 11% of the sample mean, and increases the area of secondary vegetation inside the cell by 6% of the sample mean.

Figure 3 provides graphical representations of estimated coefficients for this benchmark specification: sub-figure (a) plots point estimates and the associated 95% confidence interval for coefficients from Table 4, Panel A; sub-figure (b) is analogous for Panel B. The graphs help

Table 3: Catchment Area for Law Enforcement Spillover on Regeneration

	(1)	(2)	(3)	(4)	(5)
Panel A: P(Δ secondary vegetation ≥ 0.1 cell area)					
alerts 5km	0.0489***	0.0203***	0.0216***	0.0216***	0.0216***
	(0.0032)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
alerts 10km		0.0537***	0.0271***	0.0272***	0.0272***
		(0.0051)	(0.0062)	(0.0062)	(0.0062)
alerts 20km			0.0532***	0.0519***	0.0519***
			(0.0072)	(0.0079)	(0.0080)
alerts 50km				0.0042	0.0045
				(0.0115)	(0.0121)
alerts 100km					-0.0018
					(0.0188)
R-squared	0.1208	0.1211	0.1212	0.1212	0.1212
Panel B: Δ non-decreasing secondary vegetation (% cell area)					
alerts 5km	0.0035***	-0.0001	0.0001	0.0001	0.0001
	(0.0006)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
alerts 10km		0.0068***	0.0030**	0.0030**	0.0030**
		(0.0010)	(0.0012)	(0.0012)	(0.0012)
alerts 20km			0.0076***	0.0075***	0.0077***
			(0.0014)	(0.0016)	(0.0016)
alerts 50km				0.0002	-0.0004
				(0.0022)	(0.0023)
alerts 100km					0.0038
					(0.0036)
R-squared	0.1403	0.1404	0.1404	0.1404	0.1405
number of observations	403,191	403,191	403,191	403,191	403,191
controls					
municipality	yes	yes	yes	yes	yes
coordinates (lon, lat, lon^2, lat^2, lon*lat)	yes	yes	yes	yes	yes
weather	yes	yes	yes	yes	yes
satellite visibility	yes	yes	yes	yes	yes
baseline accumulated deforestation	yes	yes	yes	yes	yes
observed conservation policy	yes	yes	yes	yes	yes

Notes: The table reports OLS coefficients for Equation 1 (Section 4). The dependent variable differs across panels: an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage ≥ 0.1 of cell area) in Panel A; non-decreasing secondary vegetation expansion (the 2004 through 2014 difference in non-decreasing secondary vegetation coverage as a share of cell area) in Panel B. Reported independent variables are neighborhood alert intensities (2006 through 2013 total alert area as a share of total neighborhood area). Maximum neighborhood size increases from 5km (column 1) through 100km (column 5). The no/yes markers in bottom rows indicate the inclusion of the following sets of cell-level controls: (i) location: municipality, saturated function of cell longitude/latitude; (ii) weather: average annual temperature, total annual precipitation; (iii) satellite visibility: visual obstructions in satellite imagery in 2004 and 2014; (iv) baseline deforested area: accumulated deforestation through 2003; and (v) observed conservation policy: protected territory status, alert intensity. The cross-sectional sample is built from 2004 through 2014 panel data. It includes all 403,191 Amazon biome cells that contained non-null deforestation through 2003 and at least 50% primary forest cover in 2004. Standard errors are robust to heteroskedasticity. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

illustrate that the estimated spillover effects are not linear in distance to law enforcement. For both probability- and area-based dependent variables, the impact grows in magnitude from

Table 4: Law Enforcement Spillover on Regeneration

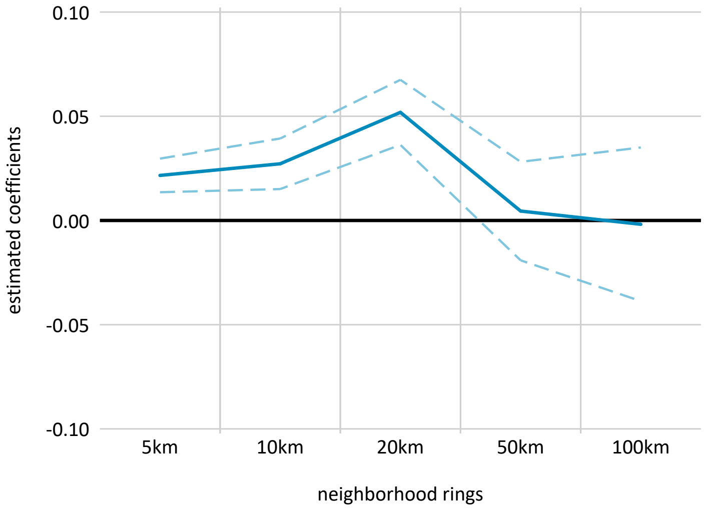
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: P(Δ secondary vegetation ≥ 0.1 cell area)						
alerts 5km	0.0034	0.0136***	0.0136***	0.0180***	0.0282***	0.0216***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0041)
alerts 10km	0.0188***	0.0246***	0.0246***	0.0252***	0.0257***	0.0272***
	(0.0063)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0062)
alerts 20km	0.0540***	0.0630***	0.0628***	0.0622***	0.0540***	0.0519***
	(0.0080)	(0.0080)	(0.0080)	(0.0080)	(0.0079)	(0.0080)
alerts 50km	-0.0165	0.0250**	0.0241**	0.0294**	0.0077	0.0045
	(0.0110)	(0.0121)	(0.0121)	(0.0121)	(0.0120)	(0.0121)
alerts 100km	0.0105	0.0085	0.0092	0.0171	0.0024	-0.0018
	(0.0108)	(0.0189)	(0.0191)	(0.0190)	(0.0188)	(0.0188)
R-squared	0.0012	0.0679	0.0679	0.0975	0.1212	0.1212
Panel B: Δ non-decreasing secondary vegetation (% cell area)						
alerts 5km	-0.0063***	-0.0058***	-0.0058***	-0.0041***	-0.0021***	0.0001
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
alerts 10km	0.0026**	0.0036***	0.0036***	0.0037***	0.0038***	0.0030**
	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
alerts 20km	0.0095***	0.0095***	0.0093***	0.0091***	0.0075***	0.0077***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
alerts 50km	-0.0012	0.0042*	0.0028	0.0037	-0.0005	-0.0004
	(0.0021)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
alerts 100km	0.0058***	0.0039	0.0022	0.0064*	0.0035	0.0038
	(0.0020)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
R-squared	0.0005	0.0741	0.0744	0.1164	0.1404	0.1405
number of observations	403,191	403,191	403,191	403,191	403,191	403,191
controls						
municipality	no	yes	yes	yes	yes	yes
coordinates (lon, lat, lon^2, lat^2, lon*lat)	no	yes	yes	yes	yes	yes
weather	no	no	yes	yes	yes	yes
satellite visibility	no	no	no	yes	yes	yes
baseline accumulated deforestation	no	no	no	no	yes	yes
observed conservation policy	no	no	no	no	no	yes

Notes: The table reports OLS coefficients for Equation 1 (Section 4). The dependent variable differs across panels: an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage ≥ 0.1 of cell area) in Panel A; non-decreasing secondary vegetation expansion (the 2004 through 2014 difference in non-decreasing secondary vegetation coverage as a share of cell area) in Panel B. Reported independent variables are neighborhood alert intensities (2006 through 2013 total alert area as a share of total neighborhood area). The no/yes markers in bottom rows indicate the inclusion of the following sets of cell-level controls: (i) location: municipality, saturated function of cell longitude/latitude; (ii) weather: average annual temperature, total annual precipitation; (iii) satellite visibility: visual obstructions in satellite imagery in 2004 and 2014; (iv) baseline deforested area: accumulated deforestation through 2003; and (v) observed conservation policy: protected territory status, alert intensity. The cross-sectional sample is built from 2004 through 2014 panel data. It includes all 403,191 Amazon biome cells that contained non-null deforestation through 2003 and at least 50% primary forest cover in 2004. Standard errors are robust to heteroskedasticity. Significance: *** p<0.01, ** p<0.05, * p<0.10.

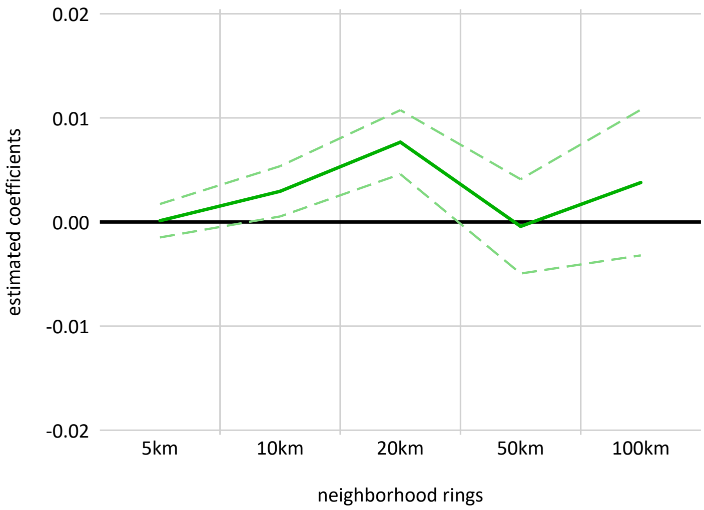
the smallest 5km neighborhood through 20km, and then drops back to insignificance. This pattern suggests that proximity to recent forest clearing activity might play an important role in tropical regeneration. Regions that are very close to deforestation alerts are probably more exposed to human interference and are thus at greater risk of seeing forest disturbances. Regrowth in these regions is less likely, as captured by the smaller coefficient for the 5km neighborhood. As distance to intense clearing activity increases, there is an increase in the

Figure 3: Law Enforcement Spillover on Regeneration

(a) P(Δ secondary vegetation $\geq$ 0.1 cell area)



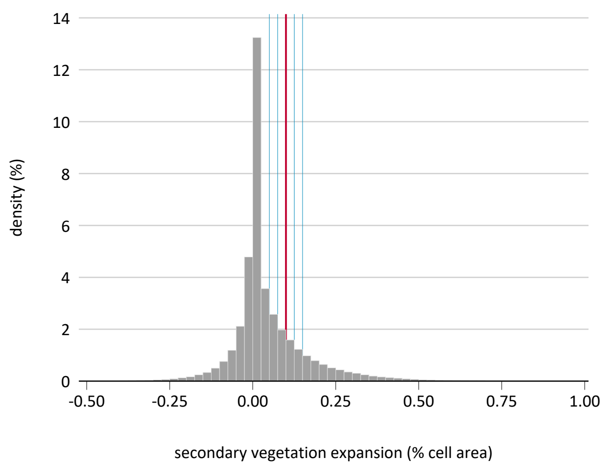
(b) Δ non-decreasing secondary vegetation (% cell area)



Notes: The graph plots estimated OLS coefficients for the benchmark specification (Table 4, column 6). The dependent variable differs across sub-figures: an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage $\geq$ 0.1 of cell area) in sub-figure (a); non-decreasing secondary vegetation expansion (the 2004 through 2014 difference in non-decreasing secondary vegetation coverage as a share of cell area) in sub-figure (b). The sample includes all 403,191 Amazon biome cells that contained non-null deforestation through 2003 and at least 50% primary forest cover in 2004. Solid lines indicate point estimates, and dashed lines indicate 95% confidence intervals.

probability of seeing secondary vegetation expansion and, notably, also an observed increase in the actual area of non-decreasing secondary vegetation. This latter result is particularly important in the sense that it mitigates concerns that probability-based specifications are erroneously capturing an increase in degraded primary forest, which could arguably occur at higher rates near recent forest clearing activity. Although it seems plausible that very close proximity to deforestation hot spots would inhibit regeneration, and that tropical regrowth would gradually increase as abandoned areas are further away from human interference, results do not currently offer an explanation for why this spillover effect suddenly disappears beyond 20km. This finding merits further empirical investigation, both from the perspective

Figure 4: Density Histogram for Difference in Secondary Vegetation Area



Notes: The figure plots the density histogram for the 2004 through 2014 difference in secondary vegetation extent as a share of cell area. The vertical lines represent the five alternative cutoffs for constructing an indicator that flags whether this difference met a minimum threshold. The bold red line indicates the benchmark threshold of 10% of cell area; the regular blue lines indicate the different thresholds used in robustness specifications (5%, 7.5%, 12.5%, and 15%).

of understanding the underlying spatial dynamics and from that of identifying specificities in the Amazon empirical setting that could explain the observed phenomenon.

Overall, results support the existence of both policy and spatial spillovers. Findings can be interpreted as evidence that the deterrence channel is driving this effect. The presence of stricter enforcement regionally inhibits illegal activity, leading potential offenders to reduce their demand for deforested land. As cleared areas are abandoned, their exposure to human interference decreases, and a natural process of regeneration takes place.

5.2. Robustness: Alternative Dependent Variables and Samples

Results presented thus far seem consistent with a regional deterrence effect from law enforcement contributing to the abandonment and regeneration of deforested lands. However, as the definition of the benchmark probability-based dependent variable and sample are based on set cutoff values, this section tests whether the findings are robust to variations in these thresholds. All robustness specifications reproduce the benchmark specification (Table 4, column 6) and always include the full set of controls. Estimated coefficients are reported in both table and plot formats.

To mitigate potential noise in original data, the probability-based dependent variable is built to capture a minimum mass of secondary vegetation expansion. The benchmark cutoff value of 10% of cell area sets a fairly stringent requirement for minimum regeneration expansion. Figure 4 portrays the density histogram for the 2004 through 2014 difference in secondary vegetation extent as a share of cell area, alongside benchmark and robustness cutoff values for dependent variable construction. The histogram shows that this benchmark cutoff successfully excludes much of the minor — but still positive — variations in area growth, which would otherwise count as actual expansion. The first robustness test uses

Table 5: Robustness – Alternative Dependent Variables

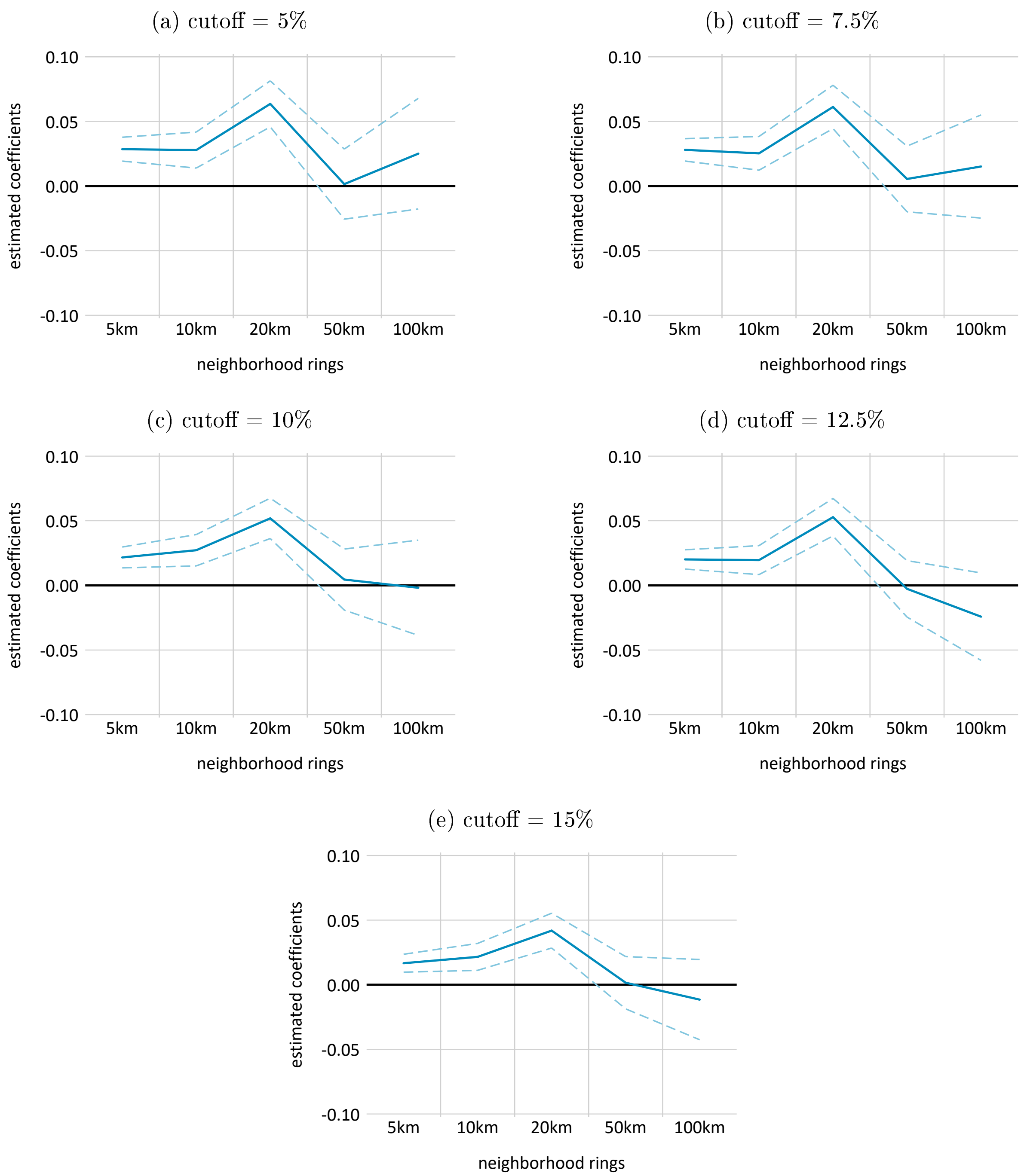
	(1)	(2)	(3)	(4)	(5)
dependent variable cutoff:	5%	7.5%	10%	12.5%	15%
P(Δ secondary vegetation ≥ cell area cutoff value (in column headings)					
alerts 5km	0.0285***	0.0280***	0.0216***	0.0201***	0.0167***
	(0.0047)	(0.0044)	(0.0041)	(0.0038)	(0.0035)
alerts 10km	0.0278***	0.0253***	0.0272***	0.0196***	0.0216***
	(0.0071)	(0.0067)	(0.0062)	(0.0057)	(0.0053)
alerts 20km	0.0636***	0.0612***	0.0519***	0.0528***	0.0419***
	(0.0091)	(0.0086)	(0.0080)	(0.0074)	(0.0069)
alerts 50km	0.0015	0.0055	0.0045	-0.0027	0.0016
	(0.0138)	(0.0130)	(0.0121)	(0.0111)	(0.0103)
alerts 100km	0.0251	0.0151	-0.0018	-0.0242	-0.0115
	(0.0218)	(0.0204)	(0.0188)	(0.0173)	(0.0158)
R-squared	0.1163	0.1204	0.1212	0.1185	0.1141
number of observations	403,191	403,191	403,191	403,191	403,191
controls					
municipality	yes	yes	yes	yes	yes
coordinates (lon, lat, lon^2, lat^2, lon*lat)	yes	yes	yes	yes	yes
weather	yes	yes	yes	yes	yes
satellite visibility	yes	yes	yes	yes	yes
baseline accumulated deforestation	yes	yes	yes	yes	yes
observed conservation policy	yes	yes	yes	yes	yes

Notes: The table reports OLS coefficients for Equation 1 (Section 4). The dependent variable is an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage ≥ a set cutoff value in terms of cell area). Each column refers to one such cutoff value: 5% in column 1; 7.5% in column 2; 10% in column 3 (benchmark); 12.5% in column 4; and 15% in column 5. Reported independent variables are neighborhood alert intensities (2006 through 2013 total alert area as a share of total neighborhood area). The no/yes markers in bottom rows indicate the inclusion of the following sets of cell-level controls: (i) location: municipality, saturated function of cell longitude/latitude; (ii) weather: average annual temperature, total annual precipitation; (iii) satellite visibility: visual obstructions in satellite imagery in 2004 and 2014; (iv) baseline deforested area: accumulated deforestation through 2003; and (v) observed conservation policy: protected territory status, alert intensity. The cross-sectional sample is built from 2004 through 2014 panel data. It includes all 403,191 Amazon biome cells that contained non-null deforestation through 2003 and at least 50% primary forest cover in 2004. Standard errors are robust to heteroskedasticity. Significance: *** p<0.01, ** p<0.05, * p<0.10.

different cutoff values for defining the probability-based dependent variable. Table 5 presents estimated coefficients for cutoff values set at 5%, 7.5%, 10% (the benchmark threshold), 12.5%, and 15%. For ease of comparison, Figure 5 plots point estimates and associated 95% confidence intervals for each of these values. Results are robust across alternative thresholds, with the intensity of law enforcement significantly increasing the probability of cell-level secondary vegetation expansion above these minimum thresholds throughout. The non-linear relationship, with effects increasing through the 20km neighborhood and disappearing for larger rings, also remains robust.

The second set of robustness checks restores the dependent variable cutoff to its benchmark value and, instead, explores how results hold across different cutoff values for sample definition. Proximity to remaining primary forest typically favors tropical regrowth (see Section 4). At the same time, if a cell has seen little deforestation, it actually has a

Figure 5: Robustness – Alternative Dependent Variables



Notes: The graphs plot estimated OLS coefficients for robustness specifications using alternative cutoff values for the probability-based dependent variable (Table 5). The dependent variable is an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage $\geq$ a set cutoff value in terms of cell area). Each sub-figure refers to one such cutoff value: 5% in sub-figure (a); 7.5% in sub-figure (b); 10% in sub-figure (c) (benchmark); 12.5% in sub-figure (d); and 15% in sub-figure (e) The sample includes all 403,191 Amazon biome cells that contained non-null deforestation through 2003 and at least 50% primary forest cover in 2004. Solid lines indicate point estimates, and dashed lines indicate 95% confidence intervals.

relatively small area upon which secondary forest can grow. Because these effects pull in opposite directions, the benchmark sample comprises cells that had non-null deforestation through 2003 and contained at least 50% primary forest cover in 2004. Alternative cutoff values for minimum primary forest cover at baseline could potentially capture cells with

Table 6: Deforestation and Regeneration Across Alternative Samples

	baseline primary forest minimum (share cell area)				
	10%	25%	50%	75%	90%
raster cell count (900m resolution)	666,563	556,833	403,191	250,122	135,225
deforested area, historical through 2003 (ha)	18,856,377	12,398,219	5,684,454	1,774,051	413,821
2004 secondary vegetation (ha)	4,828,339	3,595,704	1,995,152	772,163	214,229
2004 non-decreasing secondary vegetation (ha)	2,542,601	1,942,371	1,126,561	463,468	135,992
deforested area, historical through 2013 (ha)	26,055,487	18,766,705	10,322,528	4,361,201	1,590,435
2014 secondary vegetation (ha)	7,584,578	5,820,556	3,445,083	1,505,182	523,993
2014 non-decreasing secondary vegetation (ha)	5,245,999	4,045,630	2,399,001	1,037,194	346,579

Notes: The table summarizes deforestation and regeneration areas across alternative samples used in robustness checks. The baseline sample includes all Amazon biome cells that contained non-null deforestation in 2003; alternative samples are further restricted to cells that met a minimum threshold for primary forest cover in 2004 (benchmark cutoff of 50%).

different predominant effects. The tested values are 10%, 25%, 50% (the benchmark threshold), 75%, and 90%. Table 6 provides descriptive statistics for deforestation and regeneration areas across benchmark and robustness samples, as defined by minimum primary forest area at baseline. As expected, the lower the minimum primary forest requirement, the more accumulated deforestation the sample has seen.

Table 7 presents estimated coefficients across alternative samples for the probability-based dependent variable in Panel A, and the area-based dependent variable in Panel B. Again, Figures 6 and 7 plot point estimates and associated 95% confidence intervals for the five alternative cutoff values using probability- and area-based dependent variables, respectively. Results are generally robust across alternative thresholds for both dependent variables. However, as the minimum primary forest area moves towards the extremes of the distribution, there is variation in the shape of the distance-based relationship between law enforcement and regeneration. This points towards important heterogeneity across cells in the baseline sample. Cells that held less primary vegetation at baseline might have experienced deforestation at earlier dates and therefore have more consolidated land use in cleared areas. The significantly negative coefficients for law enforcement in the 5km neighborhood for samples that include these consolidated areas might indicate that, locally, potential offenders do displace their demand for deforested land to areas containing secondary vegetation. In contrast, cells with very large primary forest cover in 2004 have a higher chance of being located in the agricultural expansion frontier and thus of being intrinsically different in terms of their potential for recent and future clearings. Despite this heterogeneity, the overall patterns of estimated coefficients across alternative samples generally follow the benchmark.

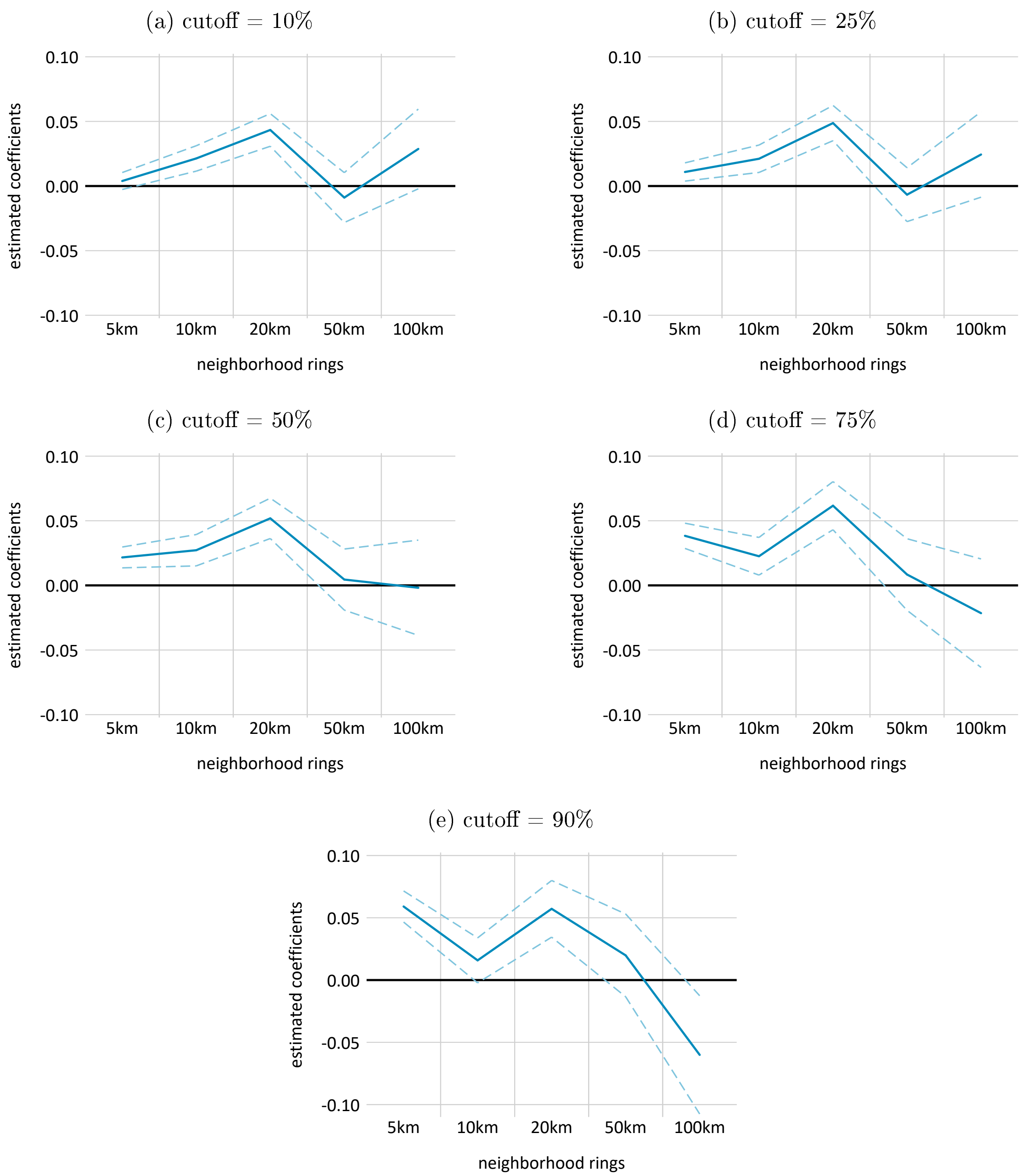
Overall, robustness checks corroborate the interpretation that, when significant, law enforcement has a positive spillover effect on regeneration in near vicinities — at least in areas that have seemingly not experienced advanced consolidation in use of deforested lands.

Table 7: Robustness – Alternative Samples

	(1)	(2)	(3)	(4)	(5)
sample selection cutoff:	10%	25%	50%	75%	90%
Panel A: P(Δ secondary vegetation ≥ 0.1 cell area)					
alerts 5km	0.0039	0.0109***	0.0216***	0.0384***	0.0591***
	(0.0033)	(0.0036)	(0.0041)	(0.0050)	(0.0064)
alerts 10km	0.0214***	0.0211***	0.0272***	0.0225***	0.0158*
	(0.0050)	(0.0054)	(0.0062)	(0.0074)	(0.0092)
alerts 20km	0.0434***	0.0487***	0.0519***	0.0617***	0.0572***
	(0.0064)	(0.0070)	(0.0080)	(0.0095)	(0.0116)
alerts 50km	-0.0089	-0.0067	0.0045	0.0084	0.0198
	(0.0099)	(0.0106)	(0.0121)	(0.0141)	(0.0170)
alerts 100km	0.0287*	0.0244	-0.0018	-0.0215	-0.0600**
	(0.0157)	(0.0168)	(0.0188)	(0.0214)	(0.0242)
R-squared	0.1140	0.1184	0.1212	0.1130	0.0924
Panel B: Δ non-decreasing secondary vegetation (% cell area)					
alerts 5km	-0.0041***	-0.0030***	0.0001	0.0046***	0.0069***
	(0.0007)	(0.0007)	(0.0008)	(0.0010)	(0.0013)
alerts 10km	0.0039***	0.0033***	0.0030**	0.0004	-0.0002
	(0.0011)	(0.0011)	(0.0012)	(0.0015)	(0.0019)
alerts 20km	0.0072***	0.0078***	0.0077***	0.0079***	0.0064***
	(0.0014)	(0.0015)	(0.0016)	(0.0018)	(0.0024)
alerts 50km	-0.0041*	-0.0028	-0.0004	0.0006	0.0023
	(0.0021)	(0.0022)	(0.0023)	(0.0026)	(0.0033)
alerts 100km	0.0079**	0.0064*	0.0038	0.0017	-0.0036
	(0.0033)	(0.0034)	(0.0036)	(0.0039)	(0.0048)
R-squared	0.1529	0.1534	0.1405	0.1092	0.0828
number of observations	666,563	556,833	403,191	250,122	135,225
controls					
municipality	yes	yes	yes	yes	yes
coordinates (lon, lat, lon^2, lat^2, lon*lat)	yes	yes	yes	yes	yes
weather	yes	yes	yes	yes	yes
satellite visibility	yes	yes	yes	yes	yes
baseline accumulated deforestation	yes	yes	yes	yes	yes
observed conservation policy	yes	yes	yes	yes	yes

Notes: The table reports OLS coefficients for Equation 1 (Section 4). The dependent variable differs across panels: an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage ≥ 0.1 of cell area) in Panel A; non-decreasing secondary vegetation expansion (the 2004 through 2014 difference in non-decreasing secondary vegetation coverage as a share of cell area) in Panel B. The spatial samples are defined as Amazon biome cells that contained non-null deforestation through 2003 and met a minimum cutoff value for primary forest cover in 2004. Each column refers to one such cutoff value: 10% in column 1; 25% in column 2; 50% in column 3 (benchmark); 75% in column 4; and 90% in column 5. Reported independent variables are neighborhood alert intensities (2006 through 2013 total alert area as a share of total neighborhood area). The no/yes markers in bottom rows indicate the inclusion of the following sets of cell-level controls: (i) location: municipality, saturated function of cell longitude/latitude; (ii) weather: average annual temperature, total annual precipitation; (iii) satellite visibility: visual obstructions in satellite imagery in 2004 and 2014; (iv) baseline deforested area: accumulated deforestation through 2003; and (v) observed conservation policy: protected territory status, alert intensity. The cross-sectional sample is built from 2004 through 2014 panel data. Standard errors are robust to heteroskedasticity. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Figure 6: Robustness – Alternative Samples, Probability-Based Outcome

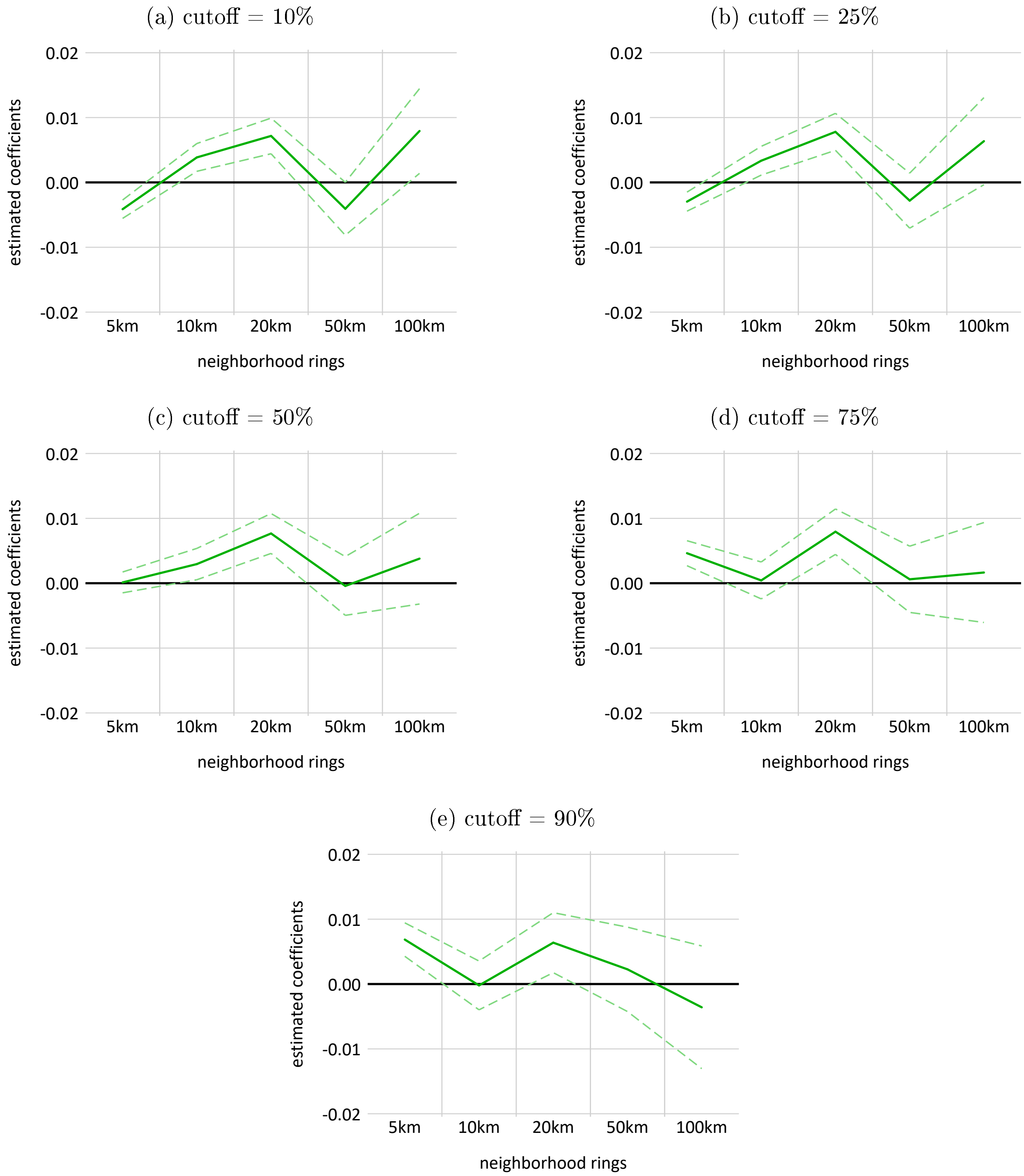


Notes: The graphs plot estimated OLS coefficients for robustness specifications using alternative cutoff values for sample definition (Table 7, Panel A). The dependent variable is an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage ≥ 0.1 of cell area). The samples are defined as Amazon biome cells that contained non-null deforestation through 2003 and met a minimum cutoff value for primary forest cover in 2004. Each sub-figure refers to one such cutoff value: 10% in sub-figure (a); 25% in sub-figure (b); 50% in sub-figure (c) (benchmark); 75% in sub-figure (d); and 90% in sub-figure (e). Solid lines indicate point estimates, and dashed lines indicate 95% confidence intervals.

5.3. Robustness: Additional Controls

The benchmark specification includes cell-level controls for location, weather, satellite visibility, baseline deforested area, and observed conservation policy. The set of robustness checks presented in Table 8 takes a closer look at controls. It starts by assessing estimated

Figure 7: Robustness – Alternative Samples, Area-Based Outcome



Notes: The graphs plot estimated OLS coefficients for robustness specifications using alternative cutoff values for sample definition (Table 7, Panel B). The dependent variable is non-decreasing secondary vegetation expansion (the 2004 through 2014 difference in non-decreasing secondary vegetation coverage as a share of cell area). The samples are defined as Amazon biome cells that contained non-null deforestation through 2003 and met a minimum cutoff value for primary forest cover in 2004. Each sub-figure refers to one such cutoff value: 10% in sub-figure (a); 25% in sub-figure (b); 50% in sub-figure (c) (benchmark); 75% in sub-figure (d); and 90% in sub-figure (e). Solid lines indicate point estimates, and dashed lines indicate 95% confidence intervals.

coefficients for the most endogenous set of benchmark controls, observed conservation policy (column 1), and then tests the robustness of results to the inclusion of additional controls that capture the cell's distance (in 100 kilometers) to the following: nearest road (column 2); nearest paved road (column 3); nearest municipality with population $\geq$ 20,000 (column 4);

and nearest waterway (column 5).

Results for the benchmark specification indicate that estimated coefficients for the policy controls flip signs across Table 8 panels. While protection reduces and local enforcement increases the probability of secondary vegetation expansion in a cell, they have the opposite effect on the extent of non-decreasing secondary vegetation. This can be explained by the inherent difference between these two outcome variables. As the probability-based dependent variable does not distinguish between remaining primary vegetation and actual secondary vegetation (see Section 4), estimated coefficients might mix effects that pull in opposite directions — protection is expected to increase regeneration, but decrease degradation and deforestation; greater alert intensity inside a cell indicates more intense clearing activity at the local level, which is expected to limit regrowth capacity but also capture a greater risk of degradation and deforestation. Interpreting these coefficients for the probability-based dependent variable can therefore be misleading. Thus, results for the area-based dependent variable are expected to more accurately capture the impact of these conservation policies on regeneration. Indeed, coefficients for protection are positive, although insignificant, and those for alert intensity are negative. This reinforces the idea that isolation favors regeneration, and that close proximity to deforestation activity significantly curbs regeneration.

The remaining columns of Table 8 include controls for the cell's distance to transport infrastructure, more populated municipalities, or waterways. Each of these could be interpreted as a measure of the cell's exposure to human interference. Estimated coefficients for neighborhood enforcement remain highly stable in magnitude and significance across specifications for both dependent variables. These findings lend further support to the benchmark specification, whose results do not appear to be driven by omitted variables.

5.4. Counterfactual Exercises: Monitoring Capacity

The evidence shows that regional law enforcement significantly promoted regeneration at the cell level. Yet, interpreting the magnitude of this effect when looking at a raster cell is not straightforward. To shed light on how these effects map onto aggregate sample impacts, if at all, this section presents two counterfactual exercises. In each exercise, the benchmark specification (Table 4, column 6) is used to predict outcomes under a different hypothetical scenario, and the total variation in non-decreasing secondary vegetation is calculated by adding predicted areas across sample cells. Instead of looking at two outcomes of interest, as in the regression analyses, counterfactual exercises are restricted to areas of non-decreasing secondary vegetation. This implies that counterfactual estimates are conservative to the extent that they only account for variation in a subset of observed regeneration.

The first counterfactual scenario builds on the idea of enhanced monitoring of forest clearing activity. Satellite-based measuring (PRODES) and monitoring (DETER) systems have different spatial resolutions (see Appendices B.1 and B.2). While DETER provides high-frequency information with low resolution, PRODES only generates annual data but at higher resolution. Thus, it is to be expected that the detected areas of forest disturbance differ

Table 8: Robustness – Additional Controls

	(1) benchmark	(2) all roads	(3) paved roads	(4) large pop	(5) water
Panel A: P(secondary vegetation expansion >= 10% of cell area)					
alerts 5km	0.0216***	0.0218***	0.0220***	0.0216***	0.0224***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
alerts 10km	0.0272***	0.0276***	0.0276***	0.0272***	0.0284***
	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0062)
alerts 20km	0.0519***	0.0523***	0.0521***	0.0519***	0.0568***
	(0.0080)	(0.0080)	(0.0080)	(0.0080)	(0.0080)
alerts 50km	0.0045	0.0004	0.0014	0.0049	0.0057
	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)
alerts 100km	-0.0018	-0.0119	-0.0132	-0.0020	0.0021
	(0.0188)	(0.0189)	(0.0190)	(0.0188)	(0.0188)
d=1 if protected	-0.0086***	-0.0070***	-0.0063***	-0.0085***	-0.0066***
	(0.0018)	(0.0019)	(0.0019)	(0.0018)	(0.0018)
alert intensity	0.0041***	0.0040***	0.0041***	0.0041***	0.0040***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
distance to header variable		-0.0131***	-0.0105***	-0.0070	-0.0352***
		(0.0022)	(0.0015)	(0.0044)	(0.0024)
R-squared	0.1212	0.1213	0.1213	0.1212	0.1217
Panel B: non-decreasing secondary vegetation expansion (cell share)					
alerts 5km	0.0001	0.0002	0.0002	0.0001	0.0002
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
alerts 10km	0.0030**	0.0030**	0.0030**	0.0030**	0.0031**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
alerts 20km	0.0077***	0.0078***	0.0077***	0.0077***	0.0084***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
alerts 50km	-0.0004	-0.0014	-0.0009	-0.0004	-0.0002
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
alerts 100km	0.0038	0.0014	0.0019	0.0038	0.0044
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
d=1 if protected	0.0002	0.0006	0.0006	0.0002	0.0005
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
alert intensity	-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0015***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
distance to header variable		-0.0031***	-0.0018***	0.0002	-0.0054***
		(0.0004)	(0.0003)	(0.0009)	(0.0005)
R-squared	0.1405	0.1405	0.1405	0.1405	0.1407
number of observations	403,191	403,191	403,191	403,191	403,191
controls					
municipality	yes	yes	yes	yes	yes
coordinates (lon, lat, lon^2, lat^2, lon*lat)	yes	yes	yes	yes	yes
weather	yes	yes	yes	yes	yes
satellite visibility	yes	yes	yes	yes	yes
baseline accumulated deforestation	yes	yes	yes	yes	yes

Notes: The table reports OLS coefficients for Equation 1 (Section 4). The dependent variable differs across panels: an indicator for secondary vegetation expansion (d=1 if the 2004 through 2014 difference in secondary vegetation coverage $\geq$ 0.1 of cell area) in Panel A; non-decreasing secondary vegetation expansion (the 2004 through 2014 difference in non-decreasing secondary vegetation coverage as a share of cell area) in Panel B. Reported independent variables are neighborhood alert intensities (2006 through 2013 total alert area as a share of total neighborhood area) and select controls. The benchmark specification (column 1) reproduces that of Table 4, column 6, but with reported coefficients for observed policy controls. Additional controls capture distance (in 100 kilometers) to the following: nearest road (column 2); nearest paved road (column 3); nearest municipality with population $\geq$ 20,000 (column 4); and nearest waterway (column 5), as indicated in column headers. The no/yes markers in bottom rows indicate the inclusion of the following sets of cell-level controls: (i) location: municipality, saturated function of cell longitude/latitude; (ii) weather: average annual temperature, total annual precipitation; (iii) satellite visibility: visual obstructions in satellite imagery in 2004 and 2014; and (iv) baseline deforested area: accumulated deforestation through 2003. The cross-sectional sample is built from 2004 through 2014 panel data. It includes all 403,191 Amazon biome cells that contained non-null deforestation through 2003 and at least 50% primary forest cover in 2004. Standard errors are robust to

Table 9: Recorded Areas in Monitoring and Measuring Systems

year	detected area DETER (ha)	detected area PRODES (ha)	detection share DETER/PRODES
2006	491,457	1,091,857	45%
2007	816,888	1,150,637	71%
2008	438,735	1,336,129	33%
2009	224,019	643,061	35%
2010	266,439	635,751	42%
2011	204,710	574,122	36%
2012	277,758	446,873	62%
2013	305,376	542,452	56%
total	**3,025,380**	**6,420,882**	**47%**

Notes: The table presents total area recorded for the Brazilian Legal Amazon in deforestation monitoring (DETER) and measuring (PRODES) systems, as well as the ratio between these areas.

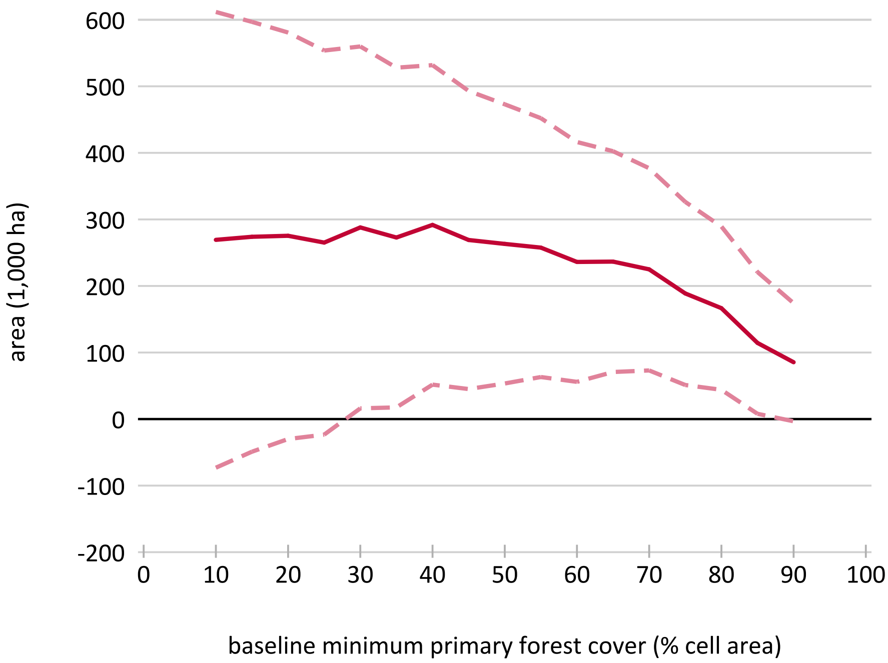
across systems, with PRODES systematically recording a larger total area of forest loss.[15] Table 9 shows that this was, in fact, the case. Despite large variability across years (likely due to variation in satellite visibility), the area recorded as DETER alerts is, on average, less than half that of PRODES. In light of this, the first hypothetical scenario boosts the monitoring system by allowing it to detect every deforestation patch detected in the measuring system. In practice, this means that every 900m raster cell that had held non-null PRODES deforestation increment from 2006 through 2013 also held a DETER deforestation alert.

Figure 8a plots the difference in the total area of non-decreasing secondary vegetation in counterfactual and observed scenarios. Each data point in the graph refers to a different sample, as defined by the minimum baseline primary forest cover. Counterfactual totals are systematically positive across samples, indicating that enhanced monitoring would have increased the area of non-decreasing secondary vegetation in the Amazon. For the benchmark sample, this increase totals about 280 thousand hectares and is statistically significant. Samples with lower thresholds for primary forest have roughly equal point estimates, but larger confidence intervals. This suggests that the cells with greater primary forest cover at baseline in these samples are driving the results. This finding appears to be aligned with the discussion that greater sample heterogeneity contributes to greater variability in outcomes under less stringent minimum primary forest requirements. As these requirements increase, the counterfactual point estimate decreases in size, although it remains substantial. To better contextualize this magnitude, Figures 8b and 8c present counterfactual area differences as shares of observed deforested and regenerated areas,

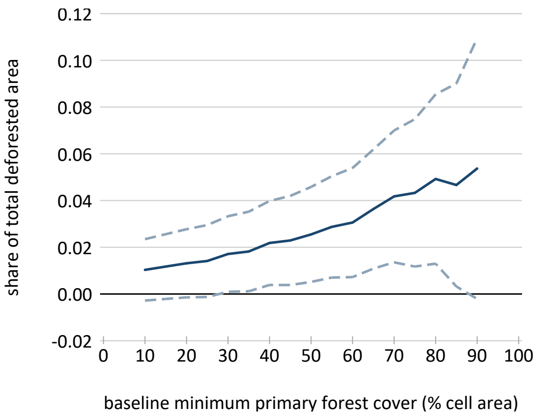
[15] Another potential source of difference in observed areas across systems is that PRODES only detects clear-cut deforestation, while DETER is capable of detecting forest degradation. In isolation, this could result in a larger observed area of disturbance via DETER. However, this potential advantage is likely undermined by DETER's significantly poorer resolution — during the sample period, DETER could only detect disturbances larger than 25ha, while PRODES detected clearings larger than 6.25ha.

Figure 8: Counterfactual Exercise – Enhanced Monitoring System

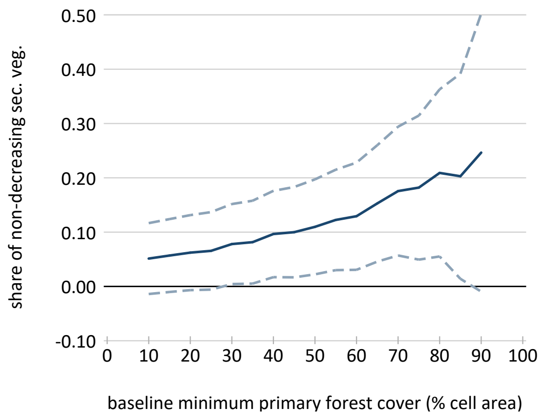
(a) absolute area



(b) as share of deforested area



(c) as share of regenerated area

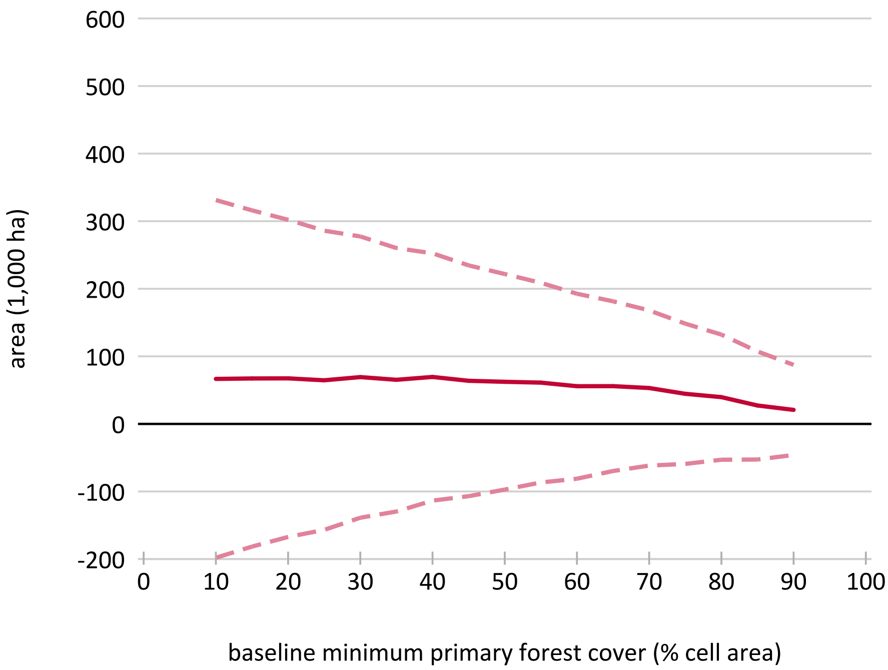


Notes: The figure illustrates the difference in total area of non-decreasing secondary vegetation in the counterfactual and observed scenarios. The counterfactual is a hypothetical scenario in which the deforestation monitoring system detected and issued alerts for all forest clearings that were recorded in the deforestation measuring system (2006 through 2013 increment). Alternative samples, plotted along the horizontal axis, are defined as Amazon biome cells that contained non-null deforestation through 2003 and met a minimum cutoff (axis) value defined in terms of primary forest cover in 2004. Solid lines indicate counterfactual estimates, and dashed lines indicate 95% confidence intervals. Results are shown as: total sample area in sub-figure (a); share of observed 2014 sample deforestation in sub-figure (b); and share of observed 2014 sample regeneration, as captured by the extent of non-decreasing secondary vegetation, in sub-figure (c). Counterfactual scenarios are built using results from the benchmark specification (Table 4, column 6) and setting the alert area equal to the observed deforested area (see Table 9).

respectively. Under the hypothetically enhanced monitoring system, non-decreasing secondary vegetation in the benchmark sample would have expanded over an additional 3% of total deforested area. This represents growth of more than 10% of recorded non-decreasing secondary vegetation area. For samples with greater minimum primary forest areas, these shares increase substantially, but so do confidence intervals.

This exercise is particularly informative considering that Brazil recently adopted a new

Figure 9: Counterfactual Exercise – No Monitoring System



Notes: The figure illustrates the difference in total area of non-decreasing secondary vegetation in the observed and estimated counterfactual scenarios. The counterfactual is a hypothetical scenario in which there was no deforestation monitoring system (no DETER alerts). Alternative samples, plotted along the horizontal axis, are defined as Amazon biome cells that contained non-null deforestation through 2003 and met a minimum cutoff value (axis value) defined in terms of primary forest cover in 2004. Solid lines indicate counterfactual estimates, and dashed lines indicate 95% confidence intervals. Results are shown as total sample area. Counterfactual scenarios are built using results from the benchmark specification (Table 4, column 6) and setting the alert area equal to zero.

monitoring system, DETER-B, which can detect areas of forest disturbance as small as 1ha and provide more detailed information on activity within these areas (Diniz et al., 2015) — an improvement that, by far, outperforms the enhancement proposed in the counterfactual scenario. Results suggest that this new system could make significant contributions to promote Amazon regeneration.

The second, and last, counterfactual exercise proposes a diametrically opposite hypothetical scenario. In it, there is no monitoring system to issue alerts and target law enforcement, such that alert intensities in all neighborhoods are set to zero. As before, Figure 9 plots the difference in the total area of non-decreasing secondary vegetation, but now the counterfactual estimate is deducted from observed totals. Although point estimates are positive across all samples, suggesting that the existence of the monitoring system promoted expansion in non-decreasing secondary vegetation, they are also systematically insignificant.

6. Final Remarks

This paper's analysis has policy implications that are both relevant and timely. From an Amazon conservation perspective, it indicates that potentially substantial policy impacts remained unaccounted for in PPCDAm effectiveness evaluations. Incorporating these impacts into policy design could significantly affect targeting and cost-benefit considerations.

Moreover, from a broader perspective, results are particularly salient in light of growing awareness regarding the need for global action to reconcile environmental and development goals. Central to this effort is the restoration of ecological integrity in degraded and deforested areas, due to its potential to mitigate climate change while improving human well-being. The emergence of international initiatives like the Bonn Challenge, which aims to restore 150 million hectares by 2020 and 350 million hectares by 2030 worldwide, attests to the mounting interest of the international community in promoting restoration at scale. Governmental commitments undertaken in the form of Nationally Determined Contributions (NDC) under the UNFCCC signal countries' recognition of the part they play in the pursuit of a shared interest. Brazil's NDC sets a target of reducing greenhouse gas emissions to more than 35% below its 2005 levels by 2030, partly by restoring/reforesting 12 million hectares of forest countrywide. As an endeavor of unprecedented magnitude in the country, restoration at scale poses significant practical challenges. Knowledge regarding what contributed to the remarkable expansion of Amazon secondary vegetation, particularly in a context of heightened vulnerability for regrowth, could catalyze regeneration and thereby help Brazil achieve its environmental commitments.

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Appendices

In this Online Appendix, we provide further information about data sources and the construction of key variables used in the empirical analysis.

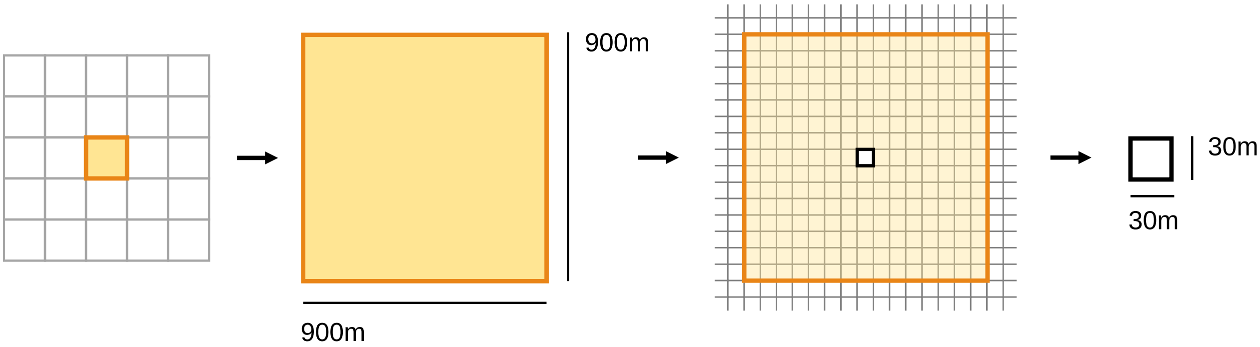
A. Spatial Setup

A raster is a matrix data structure that represents a regular grid of cells. For a given variable of interest taking on a range of possible values, each raster cell can hold one, and only one, value. Georeferenced rasters contain spatial information that associate it with a well defined region of the world's surface: (i) the coordinate reference system, which determines the origin and set of spatial axes to be used with geographical coordinates; (ii) the spatial extent, which defines the minimum and maximum limits of the area covered by the raster; and (iii) the spatial resolution, which sets raster cell size and thereby, given (i) and (ii), determines the number of rows/columns in a raster. In georeferenced rasters, each cell holds a specific position in space, as marked by the coordinates of that cell's centroid. This enables the recovery of spatial relationships, such as the distance between two cells. Moreover, it allows for the tracking of the same cell across different rasters, as long as all share the same coordinate reference system, extent, and spatial resolution.

The coordinate reference system used for dataset construction is the unprojected 1969 South American Datum (SAD69). All mentions of metric distances are metric equivalences of measures actually in degrees. The spatial resolution is set at 900m, such that the raster unit is a square raster cell with an area of 81ha. Construction of variables stated as shares of cell area are based on georeferenced rasters with the higher 30m resolution. Typically, each of the 900m cells contains 900 of the 30m minicells, though the existence of spatial boundaries may result in lower minicell count in frontier cells. Shares are always calculated in terms of total cell-specific minicell count. Each minicell is associated with its respective parent cell using an indexation algorithm. Figure A1 depicts cells, minicells, and the relationship between them. Cell neighborhoods refer to the areas covered by concentric rings of increasing diameter around the cell. Larger neighborhoods do not contain smaller ones, and the cell itself is excluded from the smallest neighborhood. Figure A2 illustrates raster cell neighborhoods. All cells within a given neighborhood are weighed equally, despite variation in distance to and direction from the central cell.

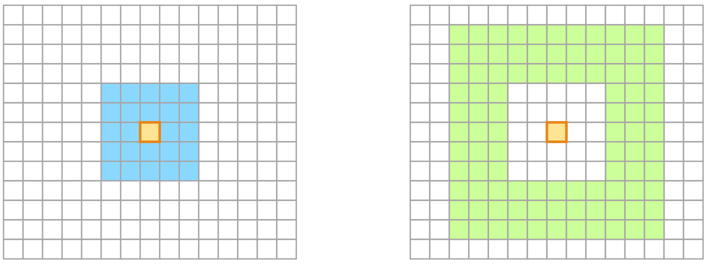
As explained in the main text, the area we consider in the analysis is the Amazon biome, which is defined based on biophysical and ecological criteria. The Brazilian Amazon biome is entirely contained within the Legal Amazon, which in turn is a geopolitical administrative subdivision that encompasses the following states: Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins, as well as the western part of the Maranhão state. The Amazon biome is entirely contained within the Legal Amazon, but is defined based on biophysical and ecological criteria. IBGE provides vector data indicating spatial boundaries for both. When rasterized at the 900m resolution, the Brazilian Legal Amazon and Amazon biome territories contain about 6.3 and 5.2 million cells, respectively.

Figure A1: Raster Grid, Cell, and Minicell



Notes: The figure illustrates the basic structure of the raster data used in the empirical analyses. The grid is composed of 900m by 900m square cells, which, in turn, subdivides into 30m by 30m square minicells. The cells and minicells in the figure are not drawn to scale.

Figure A2: Raster Cell Neighborhoods



Notes: The figure illustrates raster cell neighborhoods, as determined by concentric rings of increasing diameter around the cell. Larger neighborhoods do not contain smaller ones, and the cell itself is excluded from the smallest neighborhood.

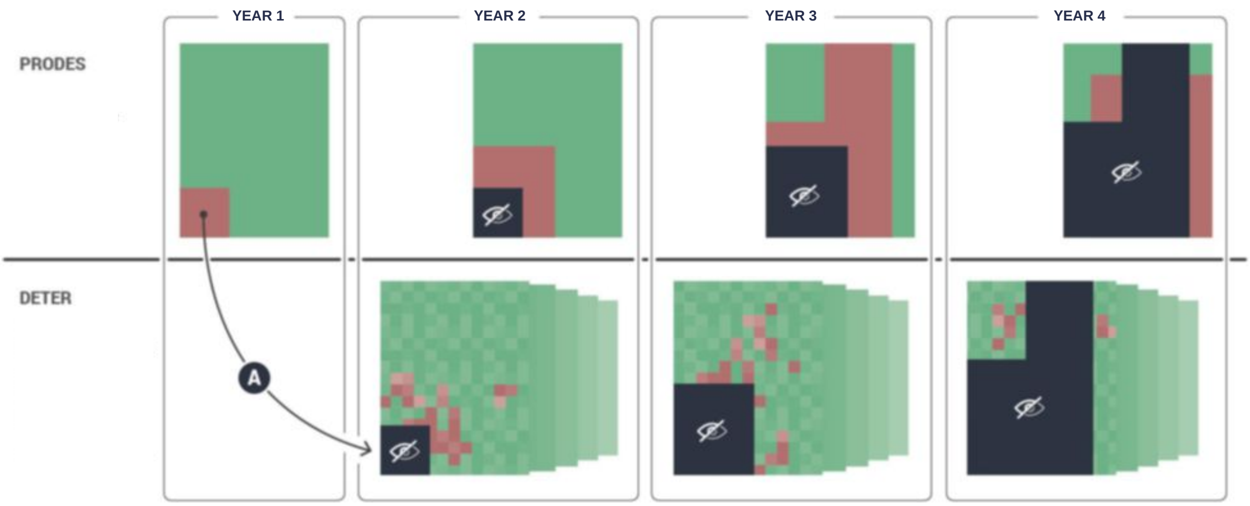
B. Data Sources

The country has used satellite imagery to map and quantify Amazon deforested area since the late 1980s. Today, it operates three different remote sensing-based programs for the Amazon. The programs interact, but each serves a specific goal: (i) measure annual tropical deforestation; (ii) monitor tropical forest disturbance; and (iii) classify land use in deforested areas, including secondary vegetation.

B.1. Measuring Deforestation

The Project for Monitoring Deforestation in the Legal Amazon (PRODES), established by the Brazilian National Institute for Space Research (Inpe) in 1988, provides georeferenced data on annual tropical deforested area. The system detects forest clearings by comparing, for any given area, satellite imagery from years $t-1$ and t to detect changes in land cover. When an area is identified as deforested in satellite imagery, it is classified as part of that year's deforestation increment; as of the following year, it is taken as accumulated deforestation and is not revisited. Accumulated deforestation is known as the "PRODES mask". The top panel in Figure B1 presents a conceptual illustration of how PRODES works: in year 1, the system maps and records deforested area; in year 2, the system no longer looks for clearings

Figure B1: Satellite Systems for Detecting Forest Disturbances



Notes: The figure presents a conceptual illustration of how satellite-based PRODES and DETER systems operate at an annual basis. The top panel refers to PRODES: in year 1, the system maps and records deforested area; in year 2, the system no longer looks for clearings inside this area, but maps and records new patches of cleared forest outside it; as of year 3, the process repeats itself. PRODES data is annual. The bottom panel refers to DETER: in year 1, the system takes input from PRODES (region A); in year 2, the system looks for signs of disturbance in forest areas outside the PRODES mask and issues deforestation hot spot alerts accordingly; at the end of year 2, PRODES will either confirm or reject deforested status for these areas, and only those that are confirmed are incorporated into the PRODES mask; in year 3 and beyond, the process repeats itself, with DETER always looking for signs of forest disturbance in forest areas outside the mask. DETER alerts are forwarded to law enforcement daily, but data is made publicly available in monthly aggregates. Both PRODES and DETER are built to only capture loss of primary tropical vegetation.

inside this area, but maps and records new patches of cleared forest outside it; in year 3 and beyond, this process repeats itself, with total deforested area through the previous year being incorporated into the PRODES mask and the system looking for new deforestation outside this mask. This setup has two important consequences. First, PRODES only detects the clearing of primary vegetation (forest that has never been cut down). Second, and relatedly, it is an incremental system, such that, for each year of data, it provides information on newly deforested areas, but never reclassifies previously cleared areas. This implies that the PRODES mask is, by construction, non-decreasing in area.

The system classifies land cover throughout the full extent of the Brazilian Legal Amazon into five categories of mutually-exclusive classes: forest (standing primary vegetation), deforestation, bodies of water, non-forest (areas that have never been covered by tropical vegetation), and residue (a minor residual category). Only tropical forest areas can ever be deforested, as PRODES is not technically fit to compute the clearing of other types of vegetation. Although the Brazilian Legal Amazon is mostly covered by tropical forest, some areas, particularly those outside the Amazon biome, are naturally covered by savanna-like *cerrado* vegetation — these areas are classified as non-forest in PRODES and are not accounted for in official Amazon deforestation statistics. Because clouds, shadows cast by clouds, and smoke from fires obstruct visibility in satellite imagery, some areas might be classified into a sixth category: non-observable areas. Actual land cover in these areas is only classified once the visual obstruction clears.

PRODES was created, and is still used, to calculate the Amazon-wide deforestation rate. While the deforestation increment measures total visible deforested area, the deforestation rate accounts for an estimate of cleared forest areas that were partially or entirely blocked from view during remote sensing. The rate thereby attempts to more closely capture the speed at which the Amazon was cleared, while the increment reflects when the cleared area became known to authorities.[16] Only the deforestation increment is made available as spatial data.

PRODES uses imagery from Landsat class satellites with a spatial resolution of 20 to 30m. When the system was implemented, technical limitations restricted detection to deforestation patches larger than 6.25ha. Today, although smaller patches are detected, processed, and forwarded to environmental authorities, public data are restricted to patches larger than 6.25ha to preserve comparability across the time series. In addition, the system only detects areas that have been clear-cut, so selective logging and forest degradation are not included. Deforested area measured by PRODES has been validated both internally, via Inpe-led field-based accuracy evaluations (Adami et al., 2017), and externally, via third-party independent interpretation of satellite imagery (Souza Jr. et al., 2013; Turubanova et al., 2018). Cross-validations only refer to clear-cut deforestation, as PRODES does not detect tropical degradation. As expected, analyses that account for degradation estimate larger areas of affected forest (Souza Jr. et al., 2013; Tyukavina et al., 2017).

Inpe annually releases updates to the PRODES series in vector format, such that year t data contain a spatial history of all areas deforested through that year and their associated year of deforestation. However, deforestation years do not refer to calendar years. To minimize cloud cover and thereby maximize visibility of the Earth's surface, satellite images from the Amazon dry season are typically used. Hence, for a given year t, PRODES measures deforestation that happened from August of the previous year $(t-1)$ through July of that year (t). The datasets in this analysis are built to fit this August-through-July window. For simplicity, we refer to this time frame simply as "year" throughout the analyses.

PRODES vector data are currently available through 2016, but the historical spatial series is only comparable through 2014. This is because, in 2015, Inpe implemented a mask shift — a non-linear spatial displacement to adjust for inaccuracies that accumulated over time. Unfortunately, during this procedure, the full history of clearings prior to 2013 was collapsed and all areas cleared until then became aggregated under the 2012 year reference. As restricting the sample to the post-2012 period would result in the loss of seven years of law enforcement data, the analyses use pre-shift PRODES data. This sets 2014 as the sample's final year.

[16] See Inpe (2013) for a detailed account of PRODES methodology and deforestation rate estimation details.

B.2. Monitoring Deforestation and Degradation

DETER is a satellite-based system, developed and operated by INPE, that provides near real-time identification of forest clearing activity. Like PRODES, DETER compares current satellite images with earlier ones, scanning for changes in forest land cover. Upon detection, potential forest disturbances map onto georeferenced alerts signaling areas of forest clearing activity. These alerts are sent to the environmental law enforcement authority and serve as the basis for targeting Amazon law enforcement.

DETER builds on the PRODES system to the extent that it only scans for forest disturbances outside the PRODES mask. The bottom panel in Figure B1 illustrates the procedure: DETER needs year 1 input from PRODES (deforested area in year 1, labeled A in the figure); in year 2, the system looks for signs of disturbance in forest areas outside the PRODES mask and issues deforestation hot spot alerts accordingly; at the end of year 2, PRODES will either confirm or reject deforested status for these areas, and only those that are confirmed are incorporated into the PRODES mask; in year 3 and beyond, the process repeats itself, with DETER always looking for signs of forest disturbance in forest areas outside the mask.

DETER covers the full extent of the Brazilian Legal Amazon, but only detects signs of disturbance in areas classified as forest in PRODES; again, *cerrado* areas are not included. It originally used images from the MODIS sensor on the Terra satellite, which has a spatial resolution of 250m. The system can therefore only detect forest clearings larger than 25ha. This relatively poor spatial resolution was compensated by both increased temporal frequency (the satellite revisits any given area within the Brazilian Legal Amazon daily) and the ability to detect not only clear-cut deforestation, but also forest degradation. Since 2015, INPE has operated DETER alongside DETER-B. The new system also serves to issue georeferenced alerts for recent forest degradation and deforestation activity, but it detects changes in land cover in patches larger than 1ha, albeit at lower temporal frequency (Diniz et al., 2015).

Despite its high frequency, DETER data is aggregated at a monthly basis for public release in vector format. DETER was implemented in 2004, but remained in experimental mode through mid-2005. Thus, although a few months of data are available for 2004 and early 2005, consistent remote sensing data on DETER alerts only starts in the second half of 2005. The first year of DETER data is therefore set at 2006 throughout the empirical analyses.

Monthly vector data on georeferenced alerts are rasterized at the 900m resolution, such that a cell will take on a value of 1 if it contains an alert and a value of 0 otherwise. Missing months in vector data indicate that no alerts were issued by DETER in that month. And there are a few occurrences of biweekly data, particularly in earlier DETER years. For a month with two deforestation alert datasets, we overlay the biweekly data to calculate total alert area for that month, as per INPE's recommendation. In practice, the rasterization algorithm assigns value 1 to a cell only if its centroid is contained within a polygon in the vector data. Because deforestation alerts can be as small as 25ha and the raster cells have an area of 81ha, running the algorithm on the raw vector resulted in the loss of a large amount of alerts. We therefore created a 1km buffer around all alerts and only then rasterized the alert-plus-buffer vector data, thereby ensuring that if a cell fell within 1km of an alert, it would be assigned value 1 during rasterization. For simplicity, we refer to this alert-plus-buffer area simply as the alert area throughout the analysis. Alert intensity is calculated as the total number of alert cells over the 2006 through 2013 period as a share of total neighborhood cell count.

B.3. Mapping Land Use in Deforested Areas

As PRODES and DETER are land cover classification systems, they provide information on whether natural phenomena covering the Earth's surface have undergone change. Yet, once an area is deforested, whatever happens within that area is regarded as land use. TerraClass Amazônia, a joint effort between INPE and the Brazilian Enterprise for Agricultural Research (Embrapa), provides land use data for all deforested areas throughout the Brazilian Legal Amazon. The system identifies eleven different land use categories: four types of pasture (grassy, shrubby, exposed soil, under regeneration); cropland (predominantly annual crops); secondary vegetation (detailed in what follows); reforestation (commercial forests of exotic species); urban; mining; mosaic of uses (where no single use can be discerned); and others (a residual category).[17] If clouds, shadows cast by clouds, or smoke from fires obstruct visibility in imagery, the blocked area is classified as unobservable. For a given year, TerraClass provides current land use data within the full extent of the PRODES mask; that is, within deforested area accumulated through the previous year. It is thus an accumulated, not an incremental, dataset that allows for the identification of transitions across different land uses over time.

TerraClass defines secondary vegetation as areas that were once clear-cut, but currently contain trees and/or shrubs. It includes neither pasture under regeneration, nor commercial reforestation. This category therefore captures tropical regeneration. (Figure 2 in the main text shows secondary vegetation mapped in each Amazon state in 2014.) Although land use data are now available for 2004 and biannually from 2008 through 2014, they were not processed and released in chronological order. TerraClass 2008 was the first to be released, but only in 2012. Data for 2010 and 2012 followed, and data for 2004 and 2014 were simultaneously released in mid-2016.

As TerraClass uses the same Landsat imagery as PRODES, it has a spatial resolution of 30m. The data are publicly released in both vector and raster formats at the same original spatial resolution, such that there is no loss of information from operating in either format.[18] In light of this, and because vector data for secondary vegetation are extremely heavy and computationally demanding, datasets for this analysis use TerraClass raster data.

[17] See Almeida et al. (2016) for a full description of TerraClass classes and methodology.

[18] This is not the case for PRODES, for which raster data are available, but only at lower spatial resolution.

C. Measuring Secondary Vegetation

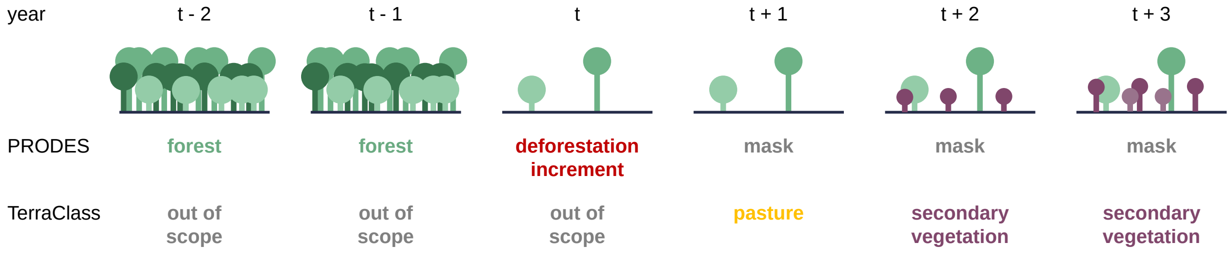
As explained in the main text, the classification of secondary vegetation is empirically challenging for two reasons. First, because data on secondary vegetation are built from interpretation of satellite imagery, regrowth must be visible in the image to be detected, which requires that any given deforested area must accumulate sufficient natural biomass to be classified as secondary vegetation, a process that may extend over decades (Alves et al., 1997; Aide et al., 2000; Guariguata and Ostertag, 2001; Chazdon, 2008). It is therefore likely that areas that are already under regeneration may take several years to show up in satellite-based land use classification systems, while short-term time-series variation in regeneration data are likely to suffer from serious measurement errors.

Second, Brazil's land use classification system cannot distinguish degraded primary forest from actual secondary vegetation. This is best understood with the help of a simplified illustration of how on-the-ground realities map onto satellite imagery-based land use categories. Figure C1 represents scenarios for a given area under correct classification and misclassification of secondary vegetation. It indicates how this area is classified under PRODES and TerraClass in each of these scenarios over time. Consider a forested area in the correct classification scenario (Figure C1a). While left intact (through year $t-1$ in this example), tropical vegetation is classified as forest in PRODES. In year t, it suffers clear-cut deforestation and falls under the deforestation increment PRODES category. Starting in year $t+1$, the area is part of the PRODES mask, and is henceforth classified in the TerraClass system. Suppose the area deforested in year t was used as pasture for one year after cleared and then abandoned, allowing regrowth. TerraClass therefore classifies the area as pasture in year $t+1$ and as secondary vegetation from year $t+2$ onwards. This is taken to be correct classification of tropical regeneration, because it captures vegetation that has grown in areas that were once clear-cut.

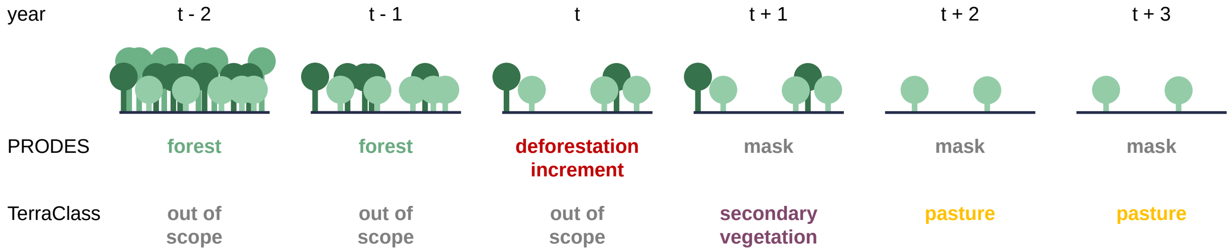
Now take an alternative scenario in which the forested area is not left intact, but rather suffers degradation over time through year $t-1$ (Figure C1b). However, because PRODES only detects clear-cut deforestation, early and medium stages of degradation are classified as forest in PRODES. The crucial difference in this scenario is that, in year t, the area has not suffered clear-cut deforestation. Instead, it has been sufficiently degraded and has lost enough biomass to look like a deforested area in satellite imagery, at which point it is classified as deforestation increment in PRODES. Again, from year $t+1$ onward, PRODES incorporates this area into its mask, making it available for classification under TerraClass. In year $t+1$, because TerraClass detects vegetation in the deforested area, the remaining (but degraded) primary forest is classified as secondary vegetation. Indeed, this is consistent with the TerraClass definition for secondary vegetation category — areas that were once clear-cut, but currently contain trees and/or shrubs. The misclassification in TerraClass occurs due to the fact that the area was never clear-cut, thereby violating the assumption that whatever vegetation found in it is tropical regrowth. This is regarded as a misclassification in quantifying regeneration, because it can overestimate the area covered

Figure C1: Satellite-Based Classification of Regeneration

(a) correct classification: actual secondary vegetation



(b) misclassification: degraded primary vegetation



Notes: The figure represents alternative scenarios for correct classification and misclassification of secondary vegetation in satellite imagery. It provides both PRODES and TerraClass categories for a given area over time in each of these scenarios. Panel (a) portrays correct classification. While left intact (through year $t-1$ in this example), tropical vegetation is classified as forest in PRODES. In year t, it suffers clear-cut deforestation and falls under the deforestation increment PRODES category. Starting in year $t+1$, the area is part of the PRODES mask, and is henceforth classified in the TerraClass system. Suppose the area deforested in year t was used as pasture for one year after cleared and then abandoned, allowing regrowth. TerraClass therefore classifies the area as pasture in year $t+1$ and as secondary vegetation from year $t+2$ onwards. In this case, the secondary vegetation classification actually captures vegetation that has grown in areas that were once clear-cut — it is therefore correctly classified. Panel (b) portrays misclassification. The vegetation is not left intact, but rather suffers degradation over time through year $t-1$. Yet, because PRODES only detects clear-cut deforestation, early and medium stages of degradation are classified as forest in PRODES through year $t-1$. In year t, when it has been sufficiently degraded and has lost enough biomass to look like a deforested area in satellite imagery, it is classified as deforestation increment in PRODES. Again, from year $t+1$ onward, PRODES incorporates this area into its mask, making it available for classification under TerraClass. In year $t+1$, because TerraClass detects vegetation in the deforested area, the remaining (but degraded) primary forest is classified as secondary vegetation. This is consistent with the TerraClass definition for secondary vegetation category — areas that were once clear-cut, but currently contain trees and/or shrubs. The misclassification in TerraClass occurs due to the fact that the area was never clear-cut, thereby violating the assumption that whatever vegetation found in it is tropical regrowth.

by secondary vegetation. This is particularly concerning in light of the increasing relevance of tropical degradation, as compared to clear-cut deforestation, in the Brazilian Amazon (Souza Jr. et al., 2013; Rappaport et al., 2018).

In light of this, we draw on the biophysical nature of forest processes to propose an alternative measure of secondary vegetation that is arguably less vulnerable to misclassification errors. While an area under regeneration typically sees an increase in biomass over time, one under degradation sees the opposite trend. It is thus likely that, as degradation continues, a given area will eventually cease to look like secondary vegetation and will be classified in TerraClass according to some other use, like pasture. In Figure C1b, this is shown starting in year $t+2$. Considering that the permanence of secondary vegetation status differs across scenarios of correct versus incorrect classification,

Figure C2: Non-decreasing Secondary Vegetation Classification Algorithm

TerraClass category					minicell classified as non-decreasing secondary vegetation in ... ?	
2004	2008	2010	2012	2014	2004	2014
sec. veg.	sec. veg.	sec. veg.	sec. veg.	sec. veg.	yes	yes
sec. veg.	sec. veg.	unobserved	unobserved	sec. veg.	yes	yes
forest	forest	sec. veg.	sec. veg.	sec. veg.	no	yes
forest	sec. veg.	unobserved	unobserved	sec. veg.	no	yes
forest	sec. veg.	unobserved	unobserved	unobserved	no	yes
pasture	pasture	sec. veg.	sec. veg.	sec. veg.	no	yes
sec. veg.	sec. veg.	pasture	pasture	pasture	no	no
sec. veg.	sec. veg.	pasture	pasture	sec. veg.	no	no
forest	pasture	sec. veg.	sec. veg.	pasture	no	no
forest	sec. veg.	unobserved	unobserved	pasture	no	no
forest	forest	forest	forest	sec. veg.	no	no

Notes: The figure presents possible land use classification histories at the raster minicell level over time and indicates how the decision algorithm classifies non-decreasing secondary vegetation minicell status in 2004 and 2014 based on this history. Land use categories refer to the 30m raster minicell. "Sec. veg." stands for secondary vegetation; pasture is used here merely as an example of a non-regeneration land use category that would be visible in satellite imagery, but the algorithm applies to all observable non-regeneration categories.

we use it as the basis for building a more conservative measure of tropical regeneration, which we call "non-decreasing secondary vegetation". This measure only considers an area as containing tropical regrowth if it meets two criteria: (i) once classified as secondary vegetation, it never ceases to be secondary vegetation; and (ii) it has been classified as secondary vegetation for at least two consecutive TerraClass years. The first criteria aims at avoiding the misclassification depicted in Figure C1b. The only exception to this rule is for areas in which satellite visibility is compromised by visual obstructions, as these do not indicate a change in land use, but a technical limitation in the imagery interpretation system. Thus, unobservable is the only non-regeneration TerraClass category that does not break secondary vegetation permanence. The second criteria sets a stringent filter for regeneration by ignoring all areas that have no panel history of regeneration status and can therefore not be duly assessed in terms of permanence. Non-decreasing secondary vegetation areas are regarded as such from the first time they appear as secondary vegetation. The classification algorithm detects permanence by using the full (five-year) TerraClass time series to construct indicator variables that capture whether the 30m raster minicell contained non-decreasing secondary vegetation in 2004 and 2014.[19] Figure C2 summarizes the history-based decision algorithm.

[19]The age of secondary vegetation could also be used as a measure of the likelihood of an area classified as secondary vegetation being actual regeneration versus degraded primary vegetation. To the best of our knowledge, these data are not available for the Brazilian Amazon.

Although the assessment of forest regrowth looks at the 2004 through 2014 cross-sectional difference in the extent of secondary vegetation, classification of non-decreasing secondary vegetation is based on high-resolution raster minicell data spanning the complete TerraClass historical series, and not just sample beginning and end data points. Moreover, because temporal permanence is the key classification criteria, non-decreasing secondary vegetation likely excludes fallow lands containing tropical regrowth. This increases the likelihood that the proposed measure capture secondary vegetation that grows as a result of the abandonment of deforested areas, and not as part of an agricultural production cycle (Vieira et al., 2003; Perz and Walker, 2002). Hence, if a minicell is classified as non-decreasing secondary vegetation, there is a greater chance that it actually does contain tropical regeneration. In this sense, non-decreasing secondary vegetation measure is a more stringent and, thus, more conservative definition for regeneration.