What Drives Deforestation and What Stops It? A Meta-Analysis

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Introduction

Forests provide a wealth of public services and private goods, including carbon storage, biodiversity habitat, water filtration, storm mitigation, disease suppression, timber and nontimber products, wild foods and medicines, and recreation (Raven 1988; Foley et al. 2005; van der Werf et al. 2009; Food and Agriculture Organization 2010; Myers et al. 2013). However, other land uses, including cropland, pasture, mining, and urban areas, frequently offer greater private economic returns. As a result, land users often prefer the private benefits of these other land uses to the public benefits of forests, thus leading to deforestation levels that are above the social optimum. The rate of global forest loss is both rapid (125,000 km^2/year between 2001 and 2012) and increasing (by 2,000 km^2/year) (Hansen et al. 2013).

In response to public concern about the benefits of forests that are lost due to deforestation, a variety of policies have been implemented that are aimed at slowing deforestation. For example, forested countries have designated protected areas (e.g., national parks or nature reserves), increased enforcement of forest laws, and established programs of payments for ecosystem services (PES). Consumer countries have restricted imports of illegally harvested tropical timber, and private supply chain actors have introduced eco-labeling, certification, and sustainable sourcing measures. At least three United Nations (U.N.) conventions, including the Framework Convention on Climate Change (UNFCCC), the Convention on Biological Diversity (CBD), and the Convention to Combat Desertification (UNCCD), are focused in part on slowing deforestation, as are the U.N. Sustainable Development Goals. The development of an international payment mechanism under the UNFCCC for reducing the 10 to 15 percent of global greenhouse gas emissions resulting from deforestation and forest

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degradation (REDD+) (van der Werf et al. 2009; Intergovernmental Panel on Climate Change 2014) has increased global attention on tropical deforestation.

Land users' decisions to convert land from forest to agriculture, pasture, or mining are influenced by a number of factors, or "drivers." The biophysical characteristics of land, such as slope, elevation, wetness, and soil suitability, influence the types of economic activity that different lands can support. The market demand for agricultural and timber commodities, reflected through prices, affects the revenues that can be gained from exploiting forests or converting them to agriculture. Characteristics of the built environment, such as roads and towns, influence the costs of transporting goods to market. The households or communities making land use decisions vary in their social, economic, cultural and demographic characteristics. Moreover, their decisions are made within the context of varying ownership and management rights—ranging from protected public lands, to open access commons, to leased concessions, to privately owned land with varying degrees of tenure security—and varying levels of war, violence, and corruption.[1] These drivers of deforestation interact in ways that are often complex. For example, fertile agricultural soil invites deforestation directly, and also encourages the construction of roads, which spurs further deforestation. Moreover, the causality can run in both directions. For example, while growing populations can increase demand for deforestation, more deforested land can also support a greater population.

Research on how these various drivers influence deforestation and which policies can most effectively stop or slow the rate of deforestation can provide important information to policymakers seeking to reduce deforestation (e.g., UNFCCC 2013). In particular, spatially explicit econometric analyses are especially well suited to the challenge of disentangling the influences of the multiple factors that drive deforestation. Spatially explicit econometric studies first overlay data on deforestation and potential driver variables that have been mapped to specific locations (i.e., that are spatially explicit). They then use statistical (i.e., econometric) tests to analyze the relationship between each driver variable and deforestation, controlling for the influence of other potentially confounding variables.[2]

The number of spatially explicit econometric studies of the drivers of deforestation has grown rapidly since 1996, when the first such study was published in a peer-reviewed journal (Turner et al. 1996).[3] In fact, by 2013, 121 spatially explicit econometric studies of the drivers of deforestation had been published in peer-reviewed academic journals, spanning multiple disciplines, including environmental sciences (55 studies), economics (32 studies), geography (22 studies), policy and management (7 studies), and development (5 studies). The goals of these studies ranged from understanding the determinants of historical deforestation, to anticipating which locations were under greatest threat of future deforestation, to comparing quantitative models for analyzing land use change, to evaluating or designing policies for slowing deforestation. The publication of spatially explicit econometric studies of the drivers of deforestation has accelerated in the last 10 years due to the increased policy attention on REDD + (since 2005), the free availability of deforestation data from the Landsat satellite

[1]Some authors have categorized the drivers of deforestation as proximate or underlying (Geist and Lambin 2002), while others have categorized them as biophysical, social, or economic (Chowdhury 2006).

[2]Note that we refer to these studies as "spatially explicit econometric studies" rather than "spatial econometric studies," because the majority of these studies do not account for spatial interactions between adjacent sites.

[3]See figure 1 in the online supplementary materials for information about the increase in the number of studies between 1996 and 2013.

(since 2008), and the increased sophistication and decreased cost of Geographic Information Systems and statistical packages for performing econometric analyses.

There have been numerous previous reviews of the drivers of deforestation. Some have covered a broad range of factors (Angelsen and Kaimowitz 1999; Geist and Lambin 2002; Chomitz 2007; Rudel et al. 2009; Angelsen and Rudel 2013; Pfaff, Amacher, and Sills 2013); others have focused on a single policy question such as the effectiveness of protected areas (Joppa and Pfaff 2010; Miteva, Pattanayak, and Ferraro 2012), the effectiveness of payments for ecosystem services (Pattanayak, Wunder, and Ferraro 2010; Miteva, Pattanayak, and Ferraro 2012), or the existence of an "environmental Kuznets curve for deforestation" (Choumert, Combes-Motel, and Dakpo 2013). However, to date, no review has used quantitative metrics to compare the relative influence of different drivers of deforestation.

We seek to fill this gap by presenting the results of a systematic and quantitative meta-analysis of what drives deforestation and what stops it. To this end, we constructed a comprehensive database of all spatially explicit econometric studies of the drivers of deforestation published in peer-reviewed academic journals between 1996 and 2013. We then used this database to identify driver variables for which many statistical analyses from many studies consistently found the same direction of influence on deforestation, as well as those driver variables for which the findings of studies did not agree. Like previous reviews of the drivers of deforestation, we sought to distinguish robust relationships from spurious correlations or outlying results, reconcile seemingly contradictory findings across studies in order to draw general conclusions, and identify variation across regions. Unlike previous reviews, however, we have generated statistics on the consistency with which driver variables are associated with higher or lower rates of deforestation across many individual regression analyses and studies. These quantitative statistics inform our own qualitative synthesis, which we present here.

The remainder of the article is organized as follows. We describe our methodology in the next section. This is followed by a presentation of the results of our meta-analysis, which is followed by a discussion of sensitivity analysis and caveats. Based on these results, we draw general conclusions about what drives deforestation, suggest effective policies to stop it, and identify priorities for future research.

Methodology

In this section we describe how we screened studies for inclusion in our database and how we constructed the database.

Criteria for Including Studies in the Database

In order to identify candidate studies to potentially include in our database, we conducted an extensive literature search of keywords related to our subject.[4] Candidate studies identified by the keyword search were included in the database only if they met the following five criteria:

[4]Specifically, we searched the Institute for Scientific Information (ISI) Web of Knowledge, Proquest, the EBSCO E-Journals Database, and Google Scholar. See table 1 in the online supplementary materials for a complete list of keywords searched. We also identified candidate studies using the literature review sections of other articles already included in the database, as well as expert feedback on an earlier version of this article (Ferretti-Gallon and Busch 2014).

(1) The study was published as an article in a peer-reviewed academic journal. Thus we excluded working papers (e.g., Kerr et al. 2002), book chapters (e.g., Brown, Iverson, and Lugo 1993), and nonacademic reports (e.g., Lambin 1994). We excluded three published studies that we could not access electronically and seven articles that were published after December 31, 2013. Application of this criterion resulted in 226 candidate studies.
(2) The dependent variable in the study was a direct indicator of either forest cover or forest cover loss.[5] We excluded indirect indicators of deforestation such as the expansion of agricultural land (e.g., Chomitz and Gray 1996). We did not distinguish between natural forests and plantations beyond the definitions applied in the original studies. Application of this criterion eliminated 24 studies, leaving 202 candidate studies.
(3) Forest cover or forest cover loss was remotely sensed (i.e., obtained from satellite or aircraft) and spatially referenced (i.e., mapped). To limit the scope of the database to consistent and comparable land use change data, we excluded studies in which forest cover was determined based on household surveys (e.g., Godoy, Groff, and O'Neill 1998). We also excluded cross-national studies that were based on tables of deforestation data that countries self-reported to the U.N. Food and Agriculture Organization's Forests Resources Assessments (e.g., Ehrhardt-Martinez 1998). Application of this criterion eliminated 30 studies, leaving 172 candidate studies.
(4) The article included at least one table presenting the results of a multivariate econometric analysis. We included both multivariate regression analyses and multivariate matching analyses.[6] Application of this criterion eliminated 51 studies, leaving 121 candidate studies.
(5) The econometric model of forest cover loss included at least one anthropogenic variable (e.g., roads or commodity prices). We excluded ecological studies of the natural spatial dynamics of shifting forest edges (e.g., Banfai and Bowman 2007). Because such studies were already excluded using the previous criteria, no further studies were eliminated.

Constructing the Database

Based on our literature search and selection criteria, we included 121 studies in the database.[7] Together, these studies contain 592 econometric analyses and 6,117 coefficients on 1,480 explanatory variables (with 1,228 unique names). To the best of our knowledge, the database comprehensively covers the literature since its inception (1996–2013).

First, for every coefficient on every explanatory variable in every results table in every study, we coded the sign and significance of the variable's association with deforestation (i.e.,

[5]Regressions with forest cover gain as the dependent variable were included only in our sensitivity analyses, which we describe later.
[6]Multivariate regression analyses estimate the correlation of independent variables with deforestation while controlling for the influence of other independent variables. Multivariate matching analyses compare the rate of deforestation in policy-affected areas to the rate of deforestation in unaffected areas with comparable observable characteristics.
[7]For a complete list of the studies, see table 2 in the online supplementary materials. For summary statistics, see table 3 in the online supplementary materials.

"negative and significant," "not significant," or "positive and significant" at the 95 percent confidence level). Where the dependent variable was related to forest cover or avoided deforestation (rather than deforestation), we inverted the coded sign.[8]

Next, we assigned the 1,228 uniquely named explanatory variables to 40 categories. For example, variables named "Elevation," "Altitude," and "Above 1,500 meters" in the studies were all assigned to the "Higher elevation" category. We inverted the coded signs on coefficients as necessary in order to polarize all relationships between driver variables and deforestation in the same direction. For example, within the category "Nearer to roads," the sign for the variable "Distance from roads" was inverted. For some categories we were unable to polarize variables (e.g., "Soil classes" of "Acrisols," "Lithosols," "Gleyic soil," and so forth). We excluded from our analysis (but not from our database) those categories that we were unable to polarize (e.g. "Soil class," "Forest type," "Land use type") and those categories for which there were fewer than forty regression results (e.g., "Presence of females," "Use of fuelwood," "Off-farm employment," "Erosion"). We also excluded variables that were not easily categorized, as well as interaction terms. As a result, we included 25 categories, comprised of 851 uniquely named explanatory variables and 4836 coefficients, in the analysis.[9]

Finally, for each category we determined whether the driver variables in that category were consistently associated with higher rates of deforestation, lower rates of deforestation, or neither. We produced one statistic at the individual regression level. Because the individual regression analyses in a study may not have been fully independent, we produced a second statistic at the study level.[10] For variables that had a consistent association with deforestation at the regression level but not the study level, we consider the evidence for these variables to be preliminary until confirmed by more studies, and we explicitly note such cases in the text.

Key Findings of the Meta-Analysis

This section presents the results of our meta-analysis. Specifically, we found that six drivers were consistently associated with higher deforestation at both the regression level and the study level (roads, urban areas, population, soil suitability, agricultural activity, and proximity to agriculture), three drivers were consistently associated with higher deforestation at the regression level but not the study level (agricultural price, proximity to cleared land, and rural income support), four drivers were consistently associated with lower deforestation at both the regression level and the study level (slope, elevation, protected areas, and poverty), and four drivers were

[8]We did not compile information on point estimates because this would require comparing very different metrics within meta-variables (e.g., "elevation (m)" versus "elevation > 1500 m"; "rice price" versus "change in bean price"), as well as comparing the results of different statistical tests. We included squared terms (e.g., U-shaped relationships were coded with one "positive and significant" variable and one "negative and significant" variable to reflect that such relationships are positive over some portion of their range and negative over others).

[9]For the study-by-study categorization of variables, see the accompanying open-access database online.

[10]At the individual regression level, we counted the number of times outputs from regression (or matching) analyses were negative and significant, not significant, or positive and significant. At the study level, we counted the number of times the plurality of outputs from regression (or matching) analyses were negative and significant, not significant, or positive and significant. At both the individual regression level and the study level, we considered the driver variable to be consistently associated with deforestation if the fraction (associated with more deforestation)/(associated with less deforestation + associated with more deforestation) was significantly different from 0.5 in a two-tailed t-test at the 95 percent confidence level.

consistently associated with higher deforestation at the regression level but not the study level (law enforcement, PES, presence of indigenous peoples, and wetness).[11]

We have organized our presentation of the results around five groups of driver variables, which are ordered roughly from the group that is most exogenous to the group that is most endogenous to land users' decision to deforest: biophysical characteristics, market demand for commodities, built infrastructure, demographic and socioeconomic characteristics, and ownership and management rights.[12]

Biophysical Characteristics

Variables related to the biophysical characteristics of the land (e.g., slope, elevation, wetness, soil suitability, distance to water) were included in 101 of the studies in our database, and most of these biophysical variables had consistent associations with deforestation. Specifically, deforestation was consistently lower at higher elevations and on steeper slopes and consistently higher on soil that was more suitable for agriculture. Wetter areas were consistently associated with lower deforestation at the regression level but not the study level. However, proximity to water was not consistently associated with either higher or lower deforestation.

Biophysical characteristics can influence the deforestation decision through agricultural productivity, accessibility, and clearing costs. Perhaps because biophysical variables are exogenous to the deforestation decision (within the static timeframe of most studies[13]), biophysical variables were almost never the primary focus of a spatially explicit econometric study. The only exception was Chomitz and Thomas (2003), who found that wetter areas of the Amazon experienced less deforestation because of their lower agricultural potential rather than because of their lower accessibility.

Market Demand for Commodities

The market demand for commodities had divergent effects on deforestation. Variables related to agriculture were consistently associated with more deforestation, while variables associated with timber production were not consistently associated with more or less deforestation.

Agriculture

Most clearing of forest land in the developing world is for agriculture and pasture (Hosonuma et al., 2012). Thus it should come as no surprise that three of the nine categories of variables consistently associated with higher deforestation are related to agriculture: greater agricultural activity, greater proximity to agriculture, and, at the individual regression level, higher agricultural prices. Agricultural prices are strongly influenced by global markets and therefore are mostly exogenous to local deforestation, but local agricultural activity is more endogenous to the local area of deforestation. Deforestation was found to be associated with higher commodity prices in Indonesia (Gaveau et al. 2009; Wheeler et al. 2013) and Brazil (Hargrave and Kis-Katos 2012), and with greater potential agricultural revenue in Costa Rica (Pfaff et al. 2007b) and

[11]See Appendix figure 1, Appendix figure 2, and table 4 in the online supplementary materials for details.
[12]Note that driver variables that are more endogenous to deforestation generally require more sophisticated methods to prove causality.
[13]In the longer term, deforestation can affect soil quality and weather patterns (Lawrence and Vandecar 2015).

Indonesia (Busch et al. 2012). However, there are many forms of agriculture, and the effects were found to vary; for example, across mechanized agriculture, small-scale agriculture, and cattle ranching in Bolivia (Müller 2012). Moreover, the interactions between these different forms of agriculture can be complex. For example, the encroachment of mechanized agriculture on existing pastures was found to shift pasture activity toward the forest frontier in Brazil (Arima et al. 2011).

Timber

One might expect timber variables to also be consistently associated with higher deforestation. However, neither higher timber prices nor greater timber activity was consistently associated with either higher or lower deforestation. This mixed relationship between timber variables and deforestation suggests that in some cases the economic returns that forests provide through timber harvest may be delaying a more rapid conversion of these forests to other uses, even though logging activity is often associated with the construction of new roads in remote areas, which can lead to deforestation later.

There are several caveats to the findings concerning timber variables. First, satellites used to detect large-scale deforestation may not detect all of the fine-scale forest degradation caused by logging. Second, plantation forests may be directly replacing more biodiverse and carbon-rich natural forests. Third, logging, like agriculture, is not a uniform activity, and logging practices vary in terms of their sustainability, as in Ecuador (Lopez, Sierra, and Tirado 2010). Finally, the relationship between "working forests" (e.g., logging concessions, timber plantations, shade-grown coffee, agroforestry) and forest cover may be dynamic, with a slowing of deforestation as forest management associations consolidate, as in Ethiopia (Takahashi and Todo 2012), or a rebound in deforestation following a swing in relative prices in favor of nonforest commodities, as in Mexico (Ellis et al. 2010).

Built Infrastructure

Variables related to built infrastructure (e.g., proximity to roads, proximity to urban areas) were among the first studied (Nelson and Hellerstein 1997) and the most studied (i.e., in 93 studies). Lands situated nearer to roads and urban areas were consistently associated with higher deforestation. Built infrastructure can increase deforestation by lowering transportation costs to markets (Cropper, Puri, and Griffiths 2001), by making frontier land more accessible to new migrants, and by enabling the transformation of remote economies from local subsistence agriculture to market-oriented farming systems (Mertens and Lambin 2000). The location of large cities and highways is likely to be exogenous to land use decisions during the static timeframe of most studies, while the expansion of smaller local roads and settlements is more likely to be endogenous to local clearing decisions. Over a long enough time horizon, the locations of medium or even large roads and cities may be influenced by trends in land use patterns. While the proximity to roads and cities was consistently associated with lower forest cover, there were exceptions. For example, proximity to cities was found to increase the presence of shade-grown coffee in Mexico (Blackman et al. 2008) and El Salvador (Blackman, Ávalos-Sartorio, and Chow 2012) and green space for urban residents in China (Gong 2013). And Getahun et al. (2013) found that regions in Ethiopia that were more integrated with cities were less reliant on clearing for subsistence agriculture because they had more economic alternatives. Although there is agreement in the literature that new roads in remote forested areas have led to deforestation, it remains unclear whether road improvements in regions that had substantial prior clearing attracted development away from those regions that had more forest remaining, thereby reducing regional deforestation (Pfaff et al. 2007a; Weinhold and Reis 2008; Deng et al. 2011).

Locations nearer to previously cleared land were consistently associated with greater deforestation at the regression level but not the study level. However, it is unclear whether this resulted more from increased access and reduced clearing costs or the omission of variables that were correlated with a greater likelihood of deforestation in adjacent locations.

Ownership and Management Rights

For variables related to ownership and management rights, their association with deforestation differed, with protected areas and law enforcement consistently associated with less deforestation and community management and land tenure security not consistently associated with either less or more deforestation.

Protected areas

Protected areas were examined in thirty-five of the studies and found to be consistently associated with lower deforestation. The key question examined by researchers has been whether the lower deforestation within protected areas is due to their legal status or their geographical remoteness (e.g., Nelson, Harris, and Stone 2001; Cropper, Puri, and Griffiths 2001). Although, on average, protected areas prevented deforestation that would have occurred otherwise, as in Brazil (Soares-Filho et al. 2010), studies in Costa Rica (Andam et al. 2008; Pfaff et al. 2009) and Indonesia (Gaveau et al. 2012) found that this effect was smaller than suggested by simple comparisons of protected and unprotected areas that do not control for land characteristics. This suggests that both geography and legal status contribute to lower deforestation within protected areas. Nelson and Chomitz (2011) found that multiple-use managed areas, where some extractive uses are allowed, had a greater impact on reducing deforestation than strictly protected areas. However, Ferraro et al. (2013) showed that this finding may be reversed when the fact that multiple-use areas may be under greater threat of deforestation in the absence of protection is considered.[14]

Law enforcement

Enforcement of forest protection laws on both private and public lands was also consistently associated with lower deforestation at the regression level but not the study level, as, for example, in the case of law enforcement preventing encroachment into a national park by coffee growers in Sumatra (Gaveau et al. 2009) and heightened monitoring of the forest code by police in Brazil (Hargrave and Kis-Katos 2012). These results suggest that law enforcement can play a key role in reducing deforestation.

[14]For additional reviews of the effectiveness of protected areas in stopping deforestation, see Joppa and Pfaff (2010), Miteva, Pattanayak, and Ferraro (2012), and Nelson and Chomitz (2011).

Community Forest Management

Community forest management (communally owned land or management cooperatives) showed no consistent association with either higher or lower deforestation. This was the case for *ejidos*, an especially well-studied communal property arrangement in Mexico (e.g., Deininger and Minten 1999; Ellis and Porter-Bolland 2008; Barsimantov and Kendall 2012; Perez-Verdin et al). For example, some studies concluded that *ejidos* reduce deforestation through better forest governance (Barsimantov and Kendall 2012), while others suggested that *ejidos* increase deforestation by encouraging the expansion of cultivated lands and pasture (Rueda 2010).

Land Tenure Security

No consistent association was found between more secure land tenure (land ownership, legal title, or duration of occupancy) and either higher or lower deforestation. On the one hand, more secure property rights can reduce deforestation by increasing the present value of standing forests and discouraging the conversion of land to productive use as a way to reduce expropriation risk, as has been found in Brazil (Araujo et al. 2009), Haiti (Dolisca et al. 2007), and Malawi (Place and Otsuka 2001). Moreover, in Panama, more secure property rights for indigenous peoples were associated with lower deforestation (Nelson et al. 2001). On the other hand, more secure land tenure has the potential to lead to more deforestation by encouraging greater investment in agriculture.

Demographic and Socioeconomics Characteristics

Demographic and socioeconomic characteristics, such as poverty and income, and policies to influence income, such as rural income support and payments for ecosystem services, had differing associations with deforestation.

Community Demographics

Most community demographic variables such as age, education, and property size were not consistently associated with either higher or lower deforestation.[15] The exception was the presence of indigenous peoples, which was consistently associated with lower deforestation at the regression level but not the study level.

Population

Population, which was included in fifty-five studies, showed a consistent association with greater deforestation. However, the causality of this relationship is difficult to interpret because of endogeneity (Rosero-Bixby and Palloni 1998). On the one hand, population can increase deforestation by increasing the supply of labor and the local demand for agricultural products. On the other hand, deforestation can increase population because more cleared land can support more people. We did not identify any studies that attempted to disentangle this endogeneity between population growth and deforestation. Additional factors complicate the relationship between population growth and deforestation. For example, Pfaff (1999) found

[15]See Vanwey et al. (2007) and Perez-Verdin et al. (2009) for evidence on Brazil and Mexico, respectively.

that in Brazil, the first migrants to a county had a greater impact on deforestation than later immigrants. DeFries et al. (2010) found that forest loss across forty-one countries was positively correlated with urban population growth and exports of agricultural products rather than with rural population growth.

Poverty and Income

Greater poverty was consistently associated with lower rates of deforestation. However, the results for changes in rural income over time were mixed. For example, Muller and Zeller (2002) and Gong (2013) found that rising incomes reversed the loss of forest cover in Vietnam and China, respectively. However, Li, Wu, and Deng (2013) found that rising income led to greater deforestation in China, while Sloan (2008), Zhao et al. (2011), and Vaca et al. (2012) did not find that rising income reversed deforestation in Panama, China, and Mexico, respectively.[16]

Rural Income Support

It can be difficult to disentangle whether greater wealth increases deforestation by allowing the purchase of more machines and the hiring of more laborers to clear land, or whether deforestation increases wealth through the returns to greater economic activity. The evidence is clearer when incomes are changed directly by rural income support programs, such as public loans, subsidies, or payments, that increase income independent of changes in forest cover. In such cases, increased income from rural support programs is consistently associated with increased rates of deforestation at the regression level but not the study level (see, e.g., Klepeis and Vance (2003) for evidence on Mexico). Alix-Garcia et al. (2013) examined the randomized rollout of a rural support program in Mexico and found that increased income raised the consumption of land-intensive goods and increased deforestation, especially in more remote communities.

Payments for Ecosystem Services

A different picture emerges when increases in income are tied directly to the maintenance of forest cover through PES.[17] PES were consistently associated with lower deforestation at the regression level but not the study level, although evidence to date comes from only five studies in two countries. More specifically, Sanchez-Azofeifa et al. (2007) and Robalino and Pfaff (2013) conducted nationwide studies of the early years of the PES program in Costa Rica and found little absolute reduction in deforestation over a 3-year period. These results were attributed to low overall rates of deforestation and evidence that payments were disproportionately made to lands with a lower threat of deforestation. In another study of Costa Rica, which focused on a region selected because of its higher rates of deforestation and better targeting of payments, Arriagada et al. (2012) found that PES produced a gain in forest cover over an 8-year period. Two studies of Mexico found that PES reduced deforestation

[16]For a broader meta-analysis of studies on the existence of an environmental Kuznets curve for deforestation, see Choumert, Combes-Motel, and Dakpo (2013).
[17]PES are voluntary transactions where a well-defined environmental service or a land use likely to secure that service is purchased from at least one provider, if and only if the service is actually provided (Wunder 2005). They are intended to internalize the public values of forests in private land use decisions.

both nationwide (Alix-Garcia et al 2012) and in the states of Michoacan and Mexico (Honey-Roses et al. 2011).[18]

Sensitivity Analyses and Caveats

In order to address potential problems of meta-analyses, such as biases, variations in quality across studies, or heterogeneous effects across studies, we conducted several sensitivity analyses.

Potential Sources of Bias

Potentially, the studies in a meta-analysis may be systematically biased toward geographical locations where the findings were extreme rather than representative (sample bias) or the review process for publication may have been biased toward supporting or refuting particular theories (publication bias). If such biases were persistent in the studies in our database, then the findings of our meta-analysis would also be biased. To examine the potential for sample bias and publication bias, we compared results for studies in which a variable was the primary focus versus studies in which that variable was included only as a control, with the idea that a discrepancy between the two might indicate persistent bias since control variables were assumed to be less likely to be characterized by bias.[19] Our results were robust across whether variables were included as the primary focus versus as a control,[20] which suggests the absence of systematic sample bias or publication bias in this literature. There was also no evidence that the studies in our database were persistently biased towards the publication of "more significant" results. In fact, variables that were the focus of a study were significant slightly less often (54 percent) than variables that were not the focus of a study (60 percent).

Another source of bias could arise if researchers systematically chose to study particular subregions within a country based on where an effect was thought to be more pronounced. To address this issue, we disaggregated results by the extent of the studies' coverage of the country in which they took place, with the assumption that local studies covering less than 10 percent of a country's area were more susceptible to this type of bias than national- or regional-scale studies. Our results were robust to whether analyses were site scale or national scale,[21] suggesting the absence of this type of bias.

Variations In Study Quality

As with any meta-analysis, we faced the challenge of variation in methodological quality across studies. As a proxy indicator for methodological quality, we disaggregated studies according to the discipline of the journal in which they were published, with the idea that because econometrics is a subfield of economics, the peer review of econometric issues was likely to have been

[18]For additional reviews of the effectiveness of PES in stopping deforestation, see Pattanayak, Wunder, and Ferraro (2010) and Miteva, Pattanayak, and Ferraro (2012).

[19]We coded a variable as the focus of a study if the title or abstract of the study mentioned inquiry into the effect of that variable on deforestation as a motivation for undertaking the study. Note that it is also possible that studies in which a variable was the primary focus may have been more careful in their design and analytical methods in order to generate credible results for that variable.

[20]For details, see table 4 in the online supplementary materials.

[21]For details, see table 5 in the online supplementary materials.

more stringent (on average) in economics journals than in journals of other disciplines.[22] Our results were robust across each discipline,[23] meaning that we were unable to identify any way in which variations in methodological quality systematically affected our findings.

Heterogeneous Effects

To examine the possibility that drivers may have had different effects in different locations, we disaggregated our results by region: Africa, Asia, and Latin America/Caribbean.[24] Results were robust across each region.[25] To examine the possibility that drivers of deforestation may have had different effects at different points along a "forest transition" from deforestation to reforestation (e.g., Angelsen and Rudel 2013), we compared the findings of regressions in which the dependent variable was either forest cover or forest cover loss with regressions on forest cover gain.[26] The results were mostly robust across dependent variables.[27] There were a few exceptions, however. For example, higher elevation and steeper slope were consistently associated with less deforestation and less reforestation, while greater population was consistently associated with more deforestation and more reforestation. This suggests that there may be important differences between the drivers of deforestation and the drivers of reforestation.

Caveats and Limitations

Although we conducted sensitivity analyses, there are some important issues that we were unable to address. First, our database included only eight multicountry studies. Thus, although we were able to compare the relative influence of various drivers across world regions, we were unable to examine the influence of specific countries or country-level variables on deforestation. Second, we excluded some potentially important drivers of deforestation that had not been studied using spatial data (e.g., mining, mills and processing facilities, corruption) as well as some that had been studied in only a very few instances (e.g., fuelwood collection, off-farm income opportunities). Thus our analysis of drivers of deforestation was not comprehensive. Third, although sophisticated techniques have been developed to test for and address spatial autocorrelation, that is, the degree to which a variable is correlated with itself across space (e.g., Li et al. 2013), more than half of the studies in our database did not report using any technique to test for or address spatial autocorrelation.[28] This means that the standard errors in our studies may have been systematically underestimated, potentially resulting in variables appearing to be more consistently significant than they are, although not affecting the direction of their effect on deforestation. Fourth, we were unable to produce statistics on the magnitude of effects, because of the wide variation across studies in both the independent variables included within each category and the dependent variables related to forest cover loss. This means that we are

[22]We did not use journal impact factor as a proxy for methodological rigor because of disparities in citation rates across disciplines (e.g., lower impact factors in economics journals relative to other disciplines).
[23]For details, see table 5 in the online supplementary materials.
[24]We did not disaggregate the results from other regions (for which there were only nine studies).
[25]For details, see table 6 in the online supplementary materials.
[26]Note that we did not include forest cover gain as the dependent variable in any other analyses.
[27]See table 6 in the online supplementary materials for details.
[28]Of the studies that reported addressing spatial autocorrelation, seventeen did so by sampling, while thirteen used a diagnostic test such as Moran's *I*. Only seven studies applied a weighting matrix (see table 3 in the online supplementary materials).

unable to quantify the relative impacts of different driver variables on deforestation. Finally, we only included econometric studies. When it comes to fully understanding complex phenomena at individual sites, qualitative case studies may offer superior or complementary evidence.

Concluding Discussion and Directions for Future Research

In this section we present our conclusions concerning what drives deforestation, suggest promising policy approaches to stopping deforestation, and propose directions for future research.

What Drives Deforestation?

Theories about what drives deforestation date back as far as Johann Heinrich von Thünen's quantitative spatial model, in which economic returns determine how land is allocated between forests and agriculture (von Thünen 1826). Economic returns diminish as transportation costs increase, which means that activities with relatively high transportation costs (e.g., dairy in von Thünen's original model) will be located closer to cities while activities with lower transportation costs (e.g., livestock grazing) will be located further away from cities.

The results of our meta-analysis suggest that economic returns continue to be a strong determinant of present-day patterns of deforestation. In particular, our meta-analysis shows that forests are more likely to be cleared in locations with higher economic returns to agriculture, due to either more favorable climatologic and topographic conditions or lower costs of clearing forest and transporting products to market. In locations with higher economic returns to forests, the use of forests may delay the conversion to agricultural use in the short term, although in the longer term such uses can degrade the forest or attract roads, which can encourage more clearing.

What Policies Stop Deforestation?

For decision makers seeking to reduce deforestation, our meta-analysis suggests a number of promising policy approaches. First, road networks can be planned to minimize their intrusion into remote forest areas. Second, protected areas can be targeted to highly threatened areas. Third, the strong and consistent effect of market demand for agricultural commodities on deforestation suggests that policies that can successfully insulate the forest frontier from the influence of high commodity prices have great potential to reduce deforestation. However, most of these types of policies (e.g., corporate supply chain commitments, certification schemes, moratoria on agricultural concessions, agricultural credit restrictions) had not been rigorously evaluated as of 2013, and thus we have not assessed them here. Fourth, while there is evidence that rural income support generally increases deforestation, there is also preliminary evidence that income support that is tied to preserving the forest resource (i.e., PES) can reduce deforestation if it is targeted to areas under greater threat of deforestation. Finally, there is preliminary evidence suggesting that policies related to stronger enforcement of forest laws and policies supporting the continued management of forests by indigenous peoples have the potential to reduce deforestation.

Some commonly suggested "win–win" approaches for reducing deforestation while meeting other societal goals are not supported by the results of our meta-analysis. This includes more secure land tenure and community forest management, which are not consistently associated with either lower or higher deforestation. There is also no consistent evidence that higher income slows deforestation. In fact, the reverse appears to be true—higher income is consistently associated with higher rates of deforestation.

Our findings are broadly consistent with those of previous reviews of the drivers of deforestation (Angelsen and Kaimowitz 1999; Geist and Lambin 2002 Chomitz 2007; Rudel et al 2009; Angelsen and Rudel 2013; Pfaff, Amacher, and Sills 2013).[29] However, there are a few noteworthy differences between our findings and those of previous reviews. Previous reviews disagreed about the role of timber as a driver of deforestation; we found no consistent association between timber and deforestation. Previous studies found either a positive or ambiguous association between poverty and deforestation; we found that greater poverty was consistently associated with lower deforestation. Finally, our meta-analysis examined a wider range of demographic variables than previous reviews. For example, our meta-analysis is the first to present empirical evidence of a consistent association between the presence of indigenous peoples and lower rates of deforestation.

Directions for Future Research

This meta-analysis has identified a number of gaps in the literature on drivers of deforestation, suggesting productive directions for future research. Fortunately the recent release to the public of annual globally consistent 30-m resolution data on forest cover change (Hansen et al. 2013) can help researchers close many of these gaps.

First, the geographical evidence base for our collective econometric understanding of deforestation consists largely of a few well-studied countries. In fact, more than half of the 121 studies in our database were from just six countries: Mexico, Brazil, Costa Rica, China, Indonesia, and Thailand. This geographical concentration is likely due to both the availability of data for these countries and policy interest. The number of spatially explicit econometric studies of land use change in North America, Eastern and Northern Europe, West and Central Africa, and Australia and New Zealand lags far behind these regions' share of forest cover and loss.[30] New global data should help close the evidence gap for understudied regions and countries.

Second, for a number of topics, the limited econometric evidence lags behind the growth in policy interest (e.g., PES, law enforcement, indigenous peoples, mining, and gender). Given the conclusion that agriculture is a consistent driver of deforestation, evaluation of interventions in the agricultural sector would be especially useful. Similarly, many potential large-scale drivers of deforestation (e.g., war, violence, corruption, the rule of law, openness to trade, and stage of economic development) have been studied using only cross-national data that is nonspatial and self-reported (Food and Agriculture Organization 2010). New globally consistent spatial data will also allow researchers to improve upon these earlier studies.

Third, nearly all studies in our database used data on changes in forest cover for time periods of 5 to 10 years. The recent availability of data on forest loss for time periods ranging from yearly to submonthly allows the application of more sophisticated panel econometric techniques (e.g., Vanwey et al. 2007; Weinhold and Reis 2008; Wheeler et al. 2013). Newly available data can be

[29]See Appendix figure 3 for a comparison.
[30]See table 7 in the online supplementary materials for details.

used to analyze not just where but when deforestation occurs in response to drivers such as roads or land management designations.

Fourth, relatively few studies have examined drivers of forest gain and almost no studies have examined drivers of forest degradation. Ongoing improvements in remote sensing can be expected to soon enable exploration of these forest changes as well. Improvements in remote sensing technology may also allow econometric studies to distinguish between changes in natural forest cover and changes in tree crop areas.

Finally, few spatially explicit econometric studies have conducted rigorous impact evaluations, and those that have have examined only protected areas, payments for ecosystem services, or rural income support. Experimental or quasi-experimental methods would be especially useful for evaluating the impact of endogenous variables such as poverty and population, as well as widely promoted interventions that were found to reduce deforestation in some cases but not consistently (e.g., land tenure security, community forest management). Thus we encourage future researchers to create randomized controlled experiments or to seek out natural experiments related to hypothesized drivers of deforestation and to combine evaluations of effectiveness with data on costs to compare the cost-effectiveness of alternative forest conservation policies.

Appendix

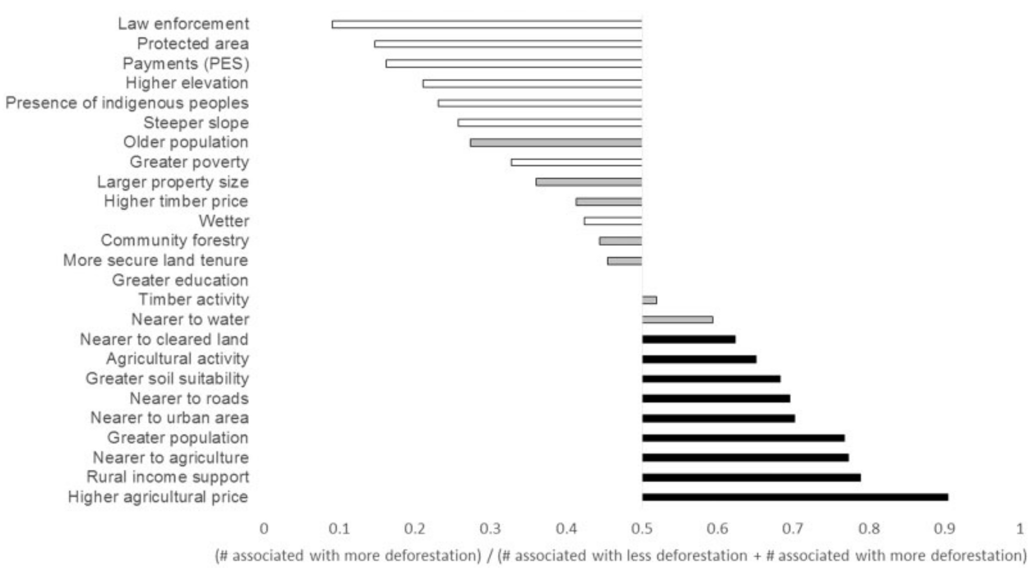

Figure A1 Consistency of association of driver variable with more or less deforestation (regression level)

Notes:The color of the bar indicates whether the driver variable is consistently associated with less deforestation (white), more deforestation (black), or neither (grey) across 592 statistical analyses. The association is considered to be consistent if the fraction (associated with more deforestation)/(associated with less deforestation + associated with more deforestation) is significantly different from 0.5 in a two-tailed *t*-test at the 95 percent confidence level. Categories containing fewer than forty observations are not displayed. For underlying data, see Figure 3 in the online supporting materials.

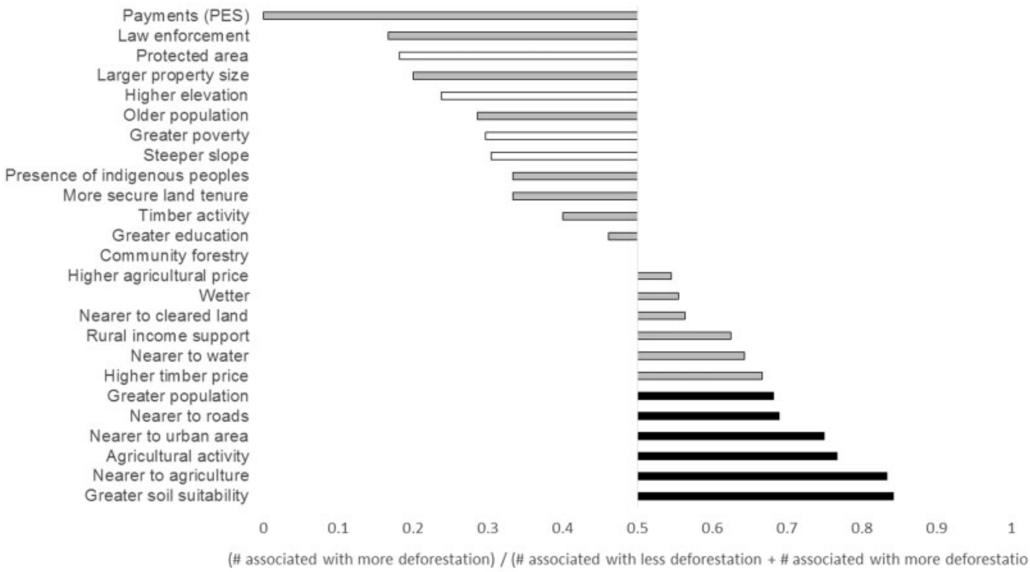

Figure A2 Consistency of association of driver variable with more or less deforestation (study level)
Notes:The color of the bar indicates whether the driver variable is consistently associated with less deforestation (white), more deforestation (black), or neither (grey) across 121 studies. The association is considered to be consistent if the fraction (associated with more deforestation)/(associated with less deforestation + associated with more deforestation) is significantly different from 0.5 in a two-tailed *t*-test at the 95 percent confidence level. Categories containing fewer than forty observations are not displayed. For underlying data, see Figure 3 in the online supporting materials.

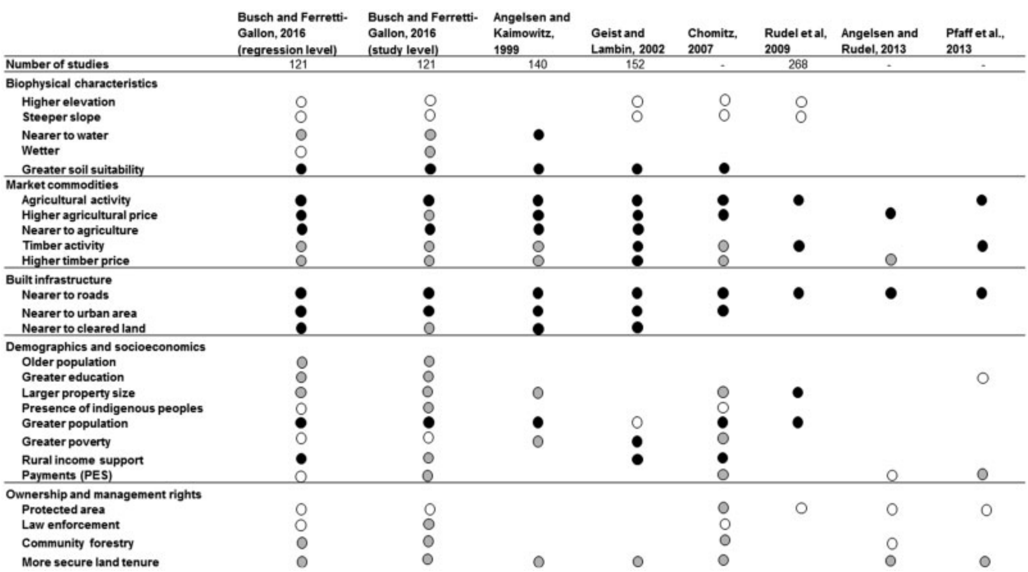

Figure A3 Comparison of findings from multiple reviews of drivers of deforestation
Notes:The color of the circle indicates whether the driver variable is associated with less deforestation (white), more deforestation (black), or neither (grey). Regression level refers to results from 592 statistical analyses. Study level refers to results from 121 studies.

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