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Land-use dynamics influence estimates of carbon sequestration potential in tropical second-growth forest

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Abstract

Many countries have made major commitments to carbon sequestration through reforestation under the Paris Climate Agreement, and recent studies have illustrated the potential for large amounts of carbon sequestration in tropical second-growth forests. However, carbon gains in second-growth forests are threatened by non-permanence, i.e. release of carbon into the atmosphere from clearing or disturbance. The benefits of second-growth forests require long-term persistence on the landscape, but estimates of carbon potential rarely consider the spatio-temporal landscape dynamics of second-growth forests. In this study, we used remotely sensed imagery from a landscape in the Peruvian Amazon to examine patterns of second-growth forest regrowth and permanence over 28 years (1985–2013). By 2013, 44% of all forest cover in the study area was second growth and more than 50% of second-growth forest pixels were less than 5 years old. We modeled probabilities of forest regrowth and clearing as a function of landscape factors. The amount of neighboring forest and variables related to pixel position (i.e. distance to edge) were important for predicting both clearing and regrowth. Forest age was the strongest predictor of clearing probability and suggests a threshold response of clearing probability to age. Finally, we simulated future trajectories of carbon sequestration using the parameters from our models. We compared this with the amount of biomass that would accumulate under the assumption of second-growth permanence. Estimates differed by 900 000 tonnes, equivalent to over 80% of Peru's commitment to carbon sequestration through 'community reforestation' under the Paris Agreement. Though the study area has more than 40 000 hectares of second-growth forest, only a small proportion is likely to accumulate significant carbon. Instead, cycles between forest and non-forest are common. Our results illustrate the importance of considering landscape dynamics when assessing the carbon sequestration potential of second-growth forests.

1. Introduction

Recent studies have highlighted the potential for carbon mitigation from rapid biomass recovery in regrowing tropical forests (Poorter *et al* 2016). In Latin America alone, second-growth forests could offset 21 years of the region's emissions from fossil fuels and other industrial processes (Chazdon *et al* 2016). Carbon sequestration through reforestation (including active restoration and natural regeneration) comprises a major contribution in many countries' Intended Nationally Determined Contributions (iNDCs) to emissions reductions in the UN Framework Convention on Climate Change (UNFCCC). However, carbon sequestration in forests can be temporary, since forests are always at risk of being

cleared or otherwise disturbed. Though the UNFCCC recognizes the risk of non-permanence and reversal of carbon gains from reforestation (UNFCCC 2014), estimates of potential benefits from second-growth forests typically consider just a snapshot of a landscape, without explicit analysis of the spatio-temporal dynamics of second-growth forest regrowth and clearing.

The carbon benefits and other services associated with tropical second-growth forests require the forests persist long-term (Chazdon *et al* 2009). Accumulating biomass equivalent to 90% that of old-growth forest takes a median time of 66 years (Poorter *et al* 2016). Long-term persistence of second-growth forest allows long-lived species and old-growth taxa to regenerate, enhancing long-term carbon storage and conservation value (Liebsch *et al* 2008, Chazdon *et al* 2009). Therefore, an estimate of the amount of second-growth forest in a region or the amount of land available for reforestation is not enough to quantify these benefits. Predictions of the likelihood of forest regrowth and persistence and an understanding of their drivers are necessary as well.

Drivers of forest regrowth range from global macroeconomic conditions to local management strategies, and vary across scales. Commodity prices, demand for agricultural and forest products, and other global macroeconomic drivers influence rates of deforestation and regrowth (Aide *et al* 2013, Lambin and Meyfroidt 2011, Grau and Aide 2008). At national scales, forest transition theory describes the shift from net deforestation to net increase in forest cover that has occurred in many countries as their economies have developed (Mather 1992). Mechanisms for forest transitions include agricultural intensification and adjustment to land quality, shortages of forest products, or demographic shifts such as rural-to-urban migration and associated remittances (Mather 1992, Meyfroidt and Lambin 2011, Hecht *et al* 2006). However, forest transitions can reverse (Jeon *et al* 2014). At sub-national scales, forest regrowth tends to occur first in regions with marginal suitability for agriculture (Rudel *et al* 2000, Asner *et al* 2009, Yackulic *et al* 2011). Within landscapes, forest regrowth is more likely far from roads (Rudel *et al* 2002) or closer to forest (Crk *et al* 2009, Sloan *et al* 2016). Finally, forest regrowth may be intertwined in local management strategies, particularly shifting cultivation (Rudel *et al* 2002), or may be influenced by land-tenure status (Robinson *et al* 2011).

Far less research has assessed if, when, and why second-growth forests persist. Most second-growth forests are not under formal protection, and rates of clearing of second-growth forest tend to be higher than old-growth forest (Heinimann *et al* 2007, Gutiérrez-Vélez *et al* 2011), though the probability of clearing tends to decline with increasing forest age (Helmer *et al* 2008, Etter *et al* 2005). Because regrowth tends to occur along forest margins (Asner *et al* 2009, Sloan *et al* 2016) and in small fragments (Helmer 2000), second-growth forests are highly vulnerable to fire (Alencar *et al* 2004, Armenteras *et al* 2013) and wind disturbance (Laurance and Curran 2008, Schwartz *et al* in review). Regrowth forests associated with shifting cultivation practices are unlikely to persist longer than the length of the fallow period, often as few as 5–7 years (Coomes *et al* 2000, Pinedo-Vasquez *et al* 1992). Furthermore, many drivers of regrowth are transitory. For example, commodity prices fluctuate and economic downturns affect the amount of remittances arriving in rural areas (Tilly 2011). These and other changes can lead to deforestation and shifts in land-use practices, affecting the likelihood that second-growth forests persist and influencing estimates of the carbon sequestration potential of second-growth forests.

In this study, we used remotely sensed imagery to examine annual patterns of second-growth forest development and permanence over 28 years (1985–2013) in a western Amazonian landscape. We investigate temporal variation in the amount of second-growth forest, and rates of forest regrowth and clearing. We also assess spatial variation in where second-growth forest develops and persists within the study landscape. Specifically, we ask:

1. How has the amount of second-growth forest in the study area changed over the last three decades?
2. What landscape factors are associated with forest regrowth?
3. What landscape factors are associated with clearing of second-growth forest?
4. How do estimates of carbon sequestration potential vary under different assumptions about second-growth forest persistence?

Better understanding the dynamics associated with second-growth forest development and persistence will allow more realistic estimation of the carbon potential of second-growth forest, and will allow managers interested in promoting forest regrowth to target efforts most effectively.

2. Materials and methods

2.1. Study area

This research focuses on an area of 215 800 ha near Pucallpa, the capital of the Ucayali region of Peru (figure 1). Elevation in the study area ranges from 136–180 m a.s.l., and slopes are gentle with 97.5% of the study area at a slope less than 9 degrees, and the maximum slope only 15 degrees. The landscape is a mosaic of forest (old-growth and naturally regenerating, plus a small number of forest plantations) surrounded by pastures, oil palm plantations, and smallholder farms. Pucallpa is connected to Lima, the

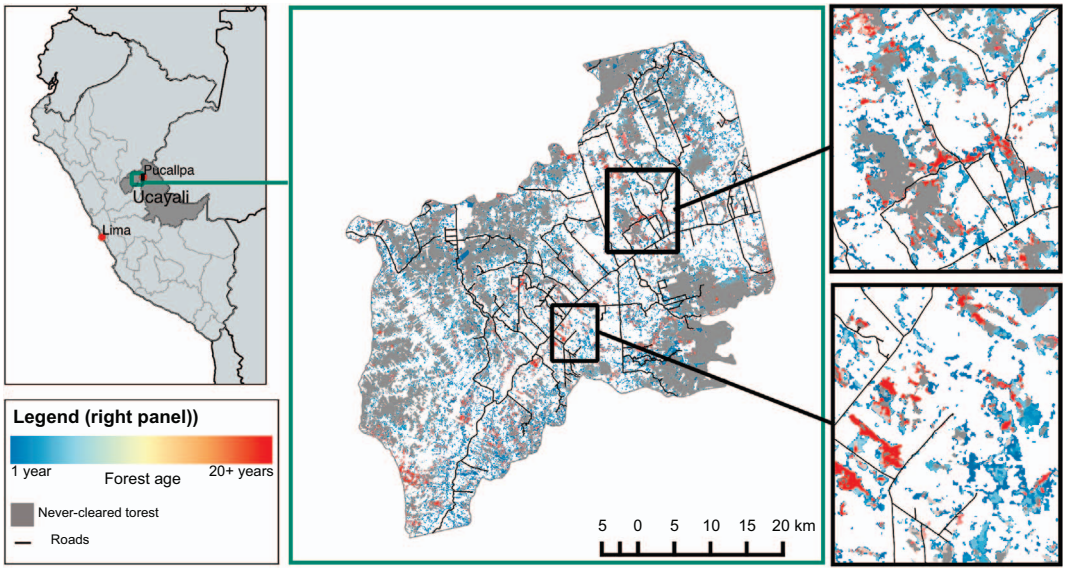

Figure 1. Location of study area in Peru, and location/extent of second-growth forest in study area in 2013.

capital city, by road, and has been an important transport center and a hotspot for in-migration, settlement, and land conversion since the 1960s. Recently, rural-to-urban migration has increased (Instituto Nacional Estadistica e Informatica 2009), which has been associated with cessation of cultivation on land owned by absentee landowners and an increase in fire activity in areas with high levels of landowner absenteeism (Uriarte *et al* 2012, Schwartz *et al* 2015). More recently, there has also been expansion of more intensive commodity crops, especially oil palm and cacao, in response to government policies incentivizing their cultivation, often into un-protected second-growth forest areas (Gutiérrez-Vélez *et al* 2011). Shifting cultivation is still a common form of smallholder production, with the typical fallow time being around 4–7 years (Pinedo-Vasquez *et al* 1992). The study area is in the midst of a transition from frontier clearing to small-scale farming and intensive agriculture, a common dynamic in some tropical landscapes (DeFries *et al* 2004). This region thus provides a useful example for considering second-growth forest dynamics in a changing tropical landscape.

2.2. Data collection

We developed a 28 year land cover time series with nearly annual Landsat data spanning from 1985–2013 (table S1). The classification differentiates between old-growth/high-biomass forest, young or low-biomass forest, pasture, fallow, oil palm and other land-cover types with an overall accuracy of 93%. Methods for the classification are detailed in Gutiérrez-Vélez and DeFries (2013) and in the supporting information.

Second-growth forest was defined as woody vegetation growing on land that was previously classified as non-forest at some point since 1985. Because we had nearly-annual land-cover data, forest age could be determined with high precision: second-growth forest age was determined as the number of years since a non-forest land cover type was replaced by forest. We identified regrowth events as a transition from non-forest to forest. To be classified as second-growth forest, we required that a pixel must have been classified as non-forest for at least two consecutive years prior, and that the new forest must have persisted for at least two consecutive years, to minimize the influence of random noise or classification error on our results.

We also used the land cover layers to generate a number of predictor variables (table 1). Predictor variables were related to either pixel position on the landscape (distance to roads, rivers, and settlements, distance to forest edge, forest patch size, and the amount of forest in the neighborhood around the pixel) or pixel history (forest age, number of years cleared before regrowth occurred, whether or not the pixel was ever classified as forest, table 1). Because the pixel size is 30 m, we cannot detect small forest patches less than 0.09 hectares. This limits the precision of the measurements of distance to forest edge, forest patch size, and the proportion of neighboring forests.

To develop a relationship between forest biomass and forest age, we collected data on above ground biomass in 30 field plots (Schwartz *et al* in revision, see SI available at stacks.iop.org/ERL/12/074023/mmedia). We identified the age of each plot using the land cover time series. Plots that were classified as forest for the entire study period were assigned an age of 30 years, which is a lower bound. We fit a linear model predicting biomass from log-transformed age, as the rate of biomass accumulation tends to slow with age (Poorter *et al* 2016, figure S1). The parameters from this model and their 95% confidence intervals were used to estimate biomass accumulated in second-growth forest pixels and associated uncertainty.

Table 1. Predictor variable descriptions, and results from the mixed effects models predicting forest regrowth in cleared areas and clearing of second-growth forest. n.a. indicates parameter not included in model, as some parameters (e.g. patch size, distance to edge) were relevant for only one of the models. Predictors were standardized to facilitate parameter comparison. Standard error values are in parentheses. Parameter significance: $^{***}p < 0.001$, $^{**}p < 0.05$, n.s. not significant.

R^2	Description	Regrowth	Clearing
R^2_{marginal}		0.31	0.22
$R^2_{\text{conditional}}$		0.64	0.35
Predictor		**Model parameters**	
Distance to road	Pixel distance to nearest road. Constant over time because historic roads maps were not available.	0.28 (0.05)***	−0.05 (0.01)***
Distance to river	Pixel distance to nearest river or stream. Constant over time.	0.01n.s.	−0.02 (0.01)**
Distance to settlement	Pixel distance to nearest settlement. Constant over time because historic data on the existence or location of settlements unavailable.	−0.18 (0.04)***	−0.01n.s.
Proportion of forest in neighborhood	Amount of forest (old growth and second growth) in a 30 × 30 pixel window around focal pixel	1.56 (.04)***	−0.11 (0.01)***
Ever forest	Binary variable variable for whether the pixel was ever previously classified as forest before time t.	0.50 (.10)***	n.a.
Distance to edge	For forest pixels, the distance to the nearest forest edge.	n.a.	−0.60 (0.02)***
Clear length	Number of consecutive years that pixel was classified as non-forest before regrowth event.	n.a.	0.3 (0.01)**
Patch size	For forest pixels, the size of the forest patch in which the pixel was located.	n.a.	0.15 (0.01)***
Age	Number of consecutive years classified as forest, up to and including present year (log-transformed).	n.a.	2.48 (0.04)***
Age^2	Quadratic log-transformed age.	n.a.	−2.17 (0.04)***

2.3. Statistical analysis

2.3.1. *Modeling forest regeneration*

Prior studies have assessed the factors that drive forest regrowth at patch (Sloan *et al* 2016) and landscape scales (Carreiras *et al* 2014). We analyzed regrowth and clearing at the level of individual pixels, in order to understand fine-scale variation in drivers of regrowth and clearing, and because regrowth and clearing in the study area rarely happen at the scale of entire forest patches but rather occur at the scale of hectares or smaller. To assess the factors associated with forest regrowth, we first sampled pixels every 600 m from a regular grid overlaid across the study area; this sampling scheme facilitates computation and avoids spatial autocorrelation. Pixels classified as non-forest were included in analyses, with the response variable determined as whether or not that pixel transitioned into forest (i.e. regrew) in the subsequent year. Sampled pixels that were always classified as forest during the 28 year time-series were not included in analysis. Ultimately, a total of 54 718 pixel-years were included in analysis, from 4223 unique pixels. We used the *R* package 'lme4' (Bates *et al* 2015) to fit generalized linear mixed effects models to assess what landscape characteristics best predicted forest re-growth. Fixed effects covariates are listed in table 1, and pixel ID and year were both included as random effects to account for year-to-year variation and repeated measures of individual pixels. Predictors were scaled by subtracting the mean and dividing by the standard deviation to facilitate model interpretation (Gelman and Hill 2006). To ensure that spatial autocorrelation did not bias our results, we tested for spatial autocorrelation in the residuals by calculating Moran's *I*. To assess goodness of fit, we calculated marginal and conditional R^2 values using the *R* package MuMIn, and compared predicted probability of regrowth with the proportion of pixels that did regrow (figure S2).

2.3.2. *Modeling second-growth forest permanence*

To analyze the degree to which second-growth forests persist and the factors associated with persistence, we sampled one pixel from every new second-growth forest patch greater than 1 ha for all years. For each sampled pixel, we tracked the fate of the pixel (whether it persisted as second-growth forest, or was cleared) for each year until the pixel was classified as non-forest, or until the end of the study period, whichever came first. This resulted in a total of 142 487 pixel-years included in analysis, from 19 805 unique pixels. We fit generalized linear mixed effects models including random effects for year and pixel ID, to account for repeated measures of individual pixels, and scaled predictors as described above. Predictors included variables related to pixel position and pixel history (table 1). We tested for spatial autocorrelation and assessed goodness of fit using the same procedures described above.

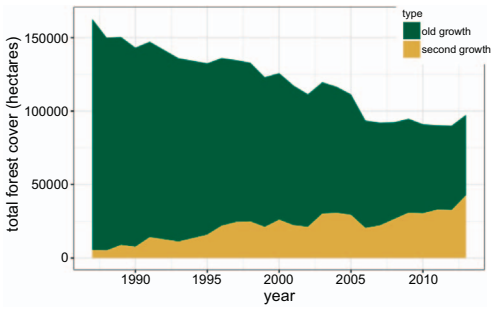

Figure 2. Forest cover in the study area (hectares) from 1985–2013.

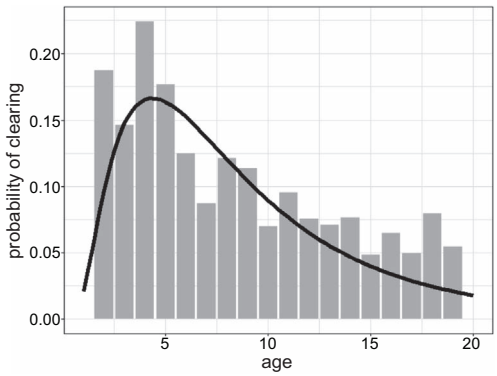

Figure 3. Predicted probability of clearing vs. age based on the coefficients from the model of second-growth forest clearing. Bars represent proportion cleared in different age classes in 2010.

2.3.3. Simulating future forest regrowth trajectories

To assess how estimates of carbon sequestration potential vary under different assumptions of second-growth forest persistence, we simulated future forest regrowth trajectories from the end of the study period until 2050. For each annual time step from 2013 to 2050, we recalculated predictor variables. Distance to road, river, and settlement were assumed to remain constant over time for pixels, because projections for how the location or number of these features will change over time are not available. Then, we calculated the probability of regrowth (for non-forest cells) or the probability of clearing (for the second-growth forest cells) using the model parameters from the models described above. Because we were interested specifically in dynamics surrounding regrowth forest, we assumed all 'old-growth' pixels (i.e. pixels that were never detected as a non-forest land cover class) remained old growth forest throughout the simulation. However, we included old-growth forest pixels in our simulated landscapes so they would be factored in as forest for variables like distance to forest edge and proportion of neighborhood made up of forest. To calculate total second-growth forest biomass over time, we applied the parameters from the model of biomass vs. forest age to all second-growth forest pixels and summed across the landscape (SI). We compared these calculations to the amount of biomass that would accumulate on the landscape if the regrowth forest present in the landscape at the end of the observation period (2013) was assumed to persist and continue to accumulate biomass until 2050.

3. Results

3.1. Forest regrowth and clearing, 1985–2013

From 1985–2013, total forest cover decreased from 162 725 hectares to 97 455 ha (figure 2). By 2013, 42 756 hectares of second-growth forest were present in the study area, while only 54 698 ha of old growth remained (figure 2). Most of this forest was young, with 57.4% of second-growth forest less than 5 years of age, and only 4.3% over 20 years of age (figure S4).

The model of forest regrowth reproduced the patterns observed in the data, but slightly over-predicted forest regrowth ($R^2 = 0.64$, table 1, figure S2). Spatial autocorrelation in the model residuals was low (Moran's $I < 0.001$, $p < 0.05$). Both pixel position and pixel history were important for predicting forest regrowth (table 1). The proportion of neighboring forest around a focal pixel was the most important predictor of forest regrowth (table 1), suggesting that forest cover is contagious. Distance to nearest road and to nearest settlement were also important predictors of the probability of regrowth, with regrowth more likely to occur further from roads, but closer to settlements. Whether a pixel had previously been classified as forest was the second most important predictor of regrowth probability, with probability of regrowth higher for pixels that were previously classified as forest.

The model of second-growth forest clearing somewhat under-predicted clearing of second-growth forest (figure S3), but explained 35% of the variation in observed clearing (table 1). Spatial autocorrelation in residuals was low (Moran's $I = 0.02$, $p < 0.05$). Again, both pixel position and pixel history were significant predictors of the likelihood of clearing, but the relative importance of predictors differed from the model of regrowth. Age was the strongest predictor of clearing, with the probability of clearing first increasing with age, until peaking approximately at 5 years of age, and then declining steeply (figure 3). The number of years pixels remained cleared before regrowing was also an important predictor of clearing likelihood, with pixels that had been cleared for shorter periods of time more likely to persist as second-growth forest. As expected, second-growth forest pixels farther from forest edges were more likely to persist, but counter to expectations, pixels in larger patches were more likely to be cleared. Pixels far from roads and far from rivers were less likely to be cleared, but these effects were weak relative to other significant predictors.

3.2. Forest regrowth trajectories and biomass accumulation

Simulations of future forest regrowth trajectories predicted a further increase in the total cover of

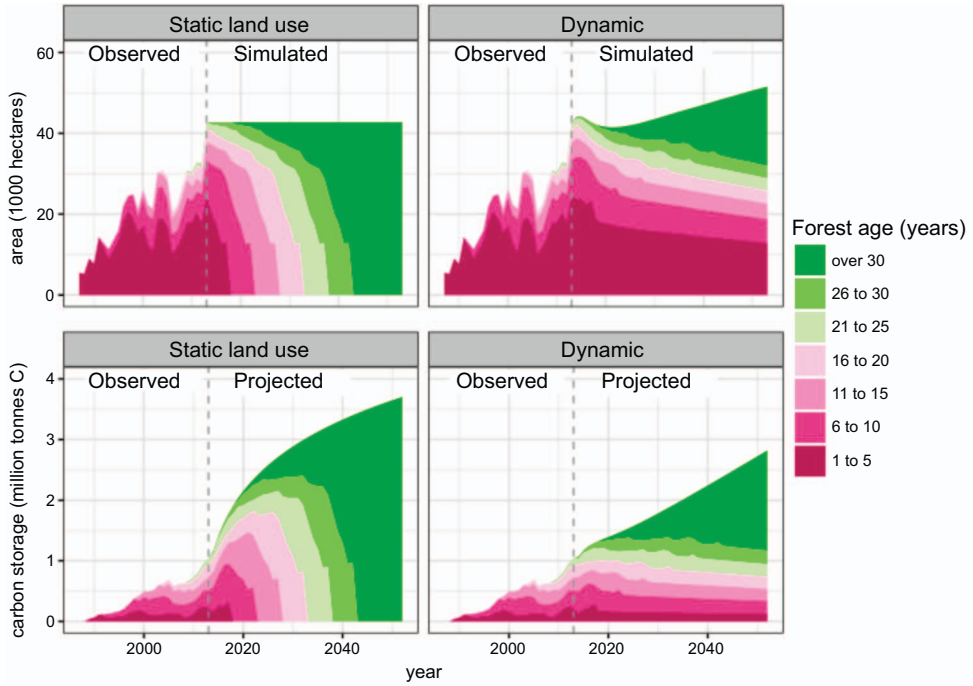

Figure 4. Observed and projected trajectories for area (top panels) and biomass (bottom panels) in different second-growth forest age classes (note: over 30 does not include old-growth forest). Left panels illustrate scenario in which all forest present in 2013 is presumed to persist and age until 2050 and right panel shows trajectories results from simulations using model parameters.

second-growth forest, from 42 756 hectares in 2013 to 50 636 hectares in 2050 (figure 2). However, 52% of second-growth forest in 2050 was still under 20 years old in our simulations, and only 35% was over 30 (figure 4). Our simulations predicted that by 2050, total carbon stored in second-growth forest in the study area was 2.724 million tonnes (CI = 0.300, 5.536, figure 4). Under the assumption that all second-growth forest on the landscape in 2013 persists and continues to age and accumulate carbon, but no new forest emerges, 3.649 (95% CI = 0.619, 6.614) million tonnes C are stored in the second-growth forest by 2050 (figure 5).

4. Discussion

Reforestation is frequently cited as a promising strategy for removing CO_2 from the atmosphere (van Vuuren *et al* 2013, Rhodes and Keith 2008), particularly in the humid tropics where second-growth forest can accumulate as much as 225 Mg biomass (113 Mg carbon) per hectare in just 20 years (Poorter *et al* 2016). Furthermore, forest cover is increasing in many countries as forest transitions take place, offering a cost-effective carbon mitigation strategy (Aide *et al* 2013, Meyfroidt *et al* 2010, Rudel *et al* 2005). Although reforestation is an attractive option, it is also risky: carbon sequestration from reforestation can be rapidly reversed because forests are inherently vulnerable to both natural and anthropogenic disturbance (Fuss *et al* 2014). Our study highlights the role that land-use and land-cover change play in influencing carbon sequestration potential of reforestation in tropical landscapes.

Peru estimates that community-based reforestation could provide up to 1.069 million tonnes CO_2 equivalent in emissions reductions (Peru 2015). We found that within our relatively small study area (0.16 of the area of Peru), estimates of carbon potential differed by nearly 925 000 tonnes of carbon depending on assumptions made about land-use change and disturbance. Similarly, Chazdon *et al* (2016) found that the degree of second-growth forest permanence could greatly reduce estimates of carbon sequestration across Latin America; for example, they estimated that 60% persistence would result in only 1.34 Pg C sequestration in Latin America versus 8.48 Pg under 100% persistence. Though there are more than 40 000 hectares of second-growth forest present in the study landscape, only a small proportion of that forest is likely to persist long enough to accumulate significant amounts of carbon. Instead, rapid cycles between forest and non-forest land-cover types are the norm. In a study in the Brazilian Amazon, Carreiras *et al* (2017 2014) found that most second-growth forest is very young, though some areas appear to have higher rates of permanence. As in our study, multiple clearing cycles and regrowth events were also common in their study landscapes (Carreiras *et al* 2014). Managing tropical landscapes for climate mitigation will require a deeper understanding of the factors that drive these dynamics within sites, and of the factors that explain variation in permanence across sites.

Regrowth and clearing varied considerably both temporally and spatially. Rates of regrowth and

clearing strongly fluctuated from year to year (figure 4). Large-scale processes, such as regional variation in climate and ecological conditions, land-use policies, and demographics, likely drive temporal fluctuations in rates of clearing and regrowth. Forest disturbance linked with climate conditions, specifically fire activity, could be an important driver of observed dynamics. The highest rate of clearing occurred in 2005, coincident with a severe drought and the highest levels of fire activity observed in the study area (figure S4, Fernandes *et al* 2011). Fire is commonly used for land management, and during dry years it frequently burns second-growth forest and can cause conversion to non-forest (Gutiérrez-Velez *et al* 2014).

Changes in land-use policies may also underlie temporal fluctuations in regrowth and clearing. For example, the Peruvian government has promoted oil palm cultivation in Ucayali since 1991 (Potter 2015), and oil palm is often planted in second-growth forest (Gutiérrez-Vélez *et al* 2011). Up to 42% of smallholder oil palm plantations in Ucayali have been abandoned due to crop disease and poor road access (Potter 2015), and abandoned oil palm plantations may convert to second-growth forest. Past rural development projects, such as those promoting pepper plantations, sugar cane, and rice may also have influenced fluctuations in second-growth forest cover and dynamics. However, land-use practices in the study area are particularly diverse and heterogeneous (Fujisaka and White 1998), so it may be difficult to distinguish the role of any particular policy or practice at the scale of the entire landscape.

Demographic changes and associated shifts in demand for forest products also influence forest dynamics in the study area. Pucallpa, the city adjacent to our study area, has rapidly grown since the 1960s (Padoch *et al* 2008). This growth has driven increased demand for cheap construction products, which has encouraged smallholder farmers who practice shifting cultivation to increase the size of their fallows and manage them to promote cheap and fast-growing timber species (Padoch *et al* 2008). These trees are harvested after four years of growth, which corresponds with the maximum probability of clearing occurring at about 4–5 years of age observed in our dataset.

The observed decline in probability of clearing with age is probably also influenced by changes in the way that people use and value forest with forest age. In a study nearby in the Peruvian Amazon, de Jong *et al* (2001) found that 27 percent of land owners intended to conserve at least some of their second-growth forest, often with the intention of extracting wood or non-timber forest products. Conservation plans were more common for older second-growth forest than for young forest. In our study area, once second-growth forests reach about 20 years of age the probability of clearing is low, suggesting that the economic or conservation value of second-growth forests increases with age.

Second-growth dynamics also vary spatially. Variables related to pixel remoteness were important, but not always in the direction expected. Pixels far from forest edges were less likely to be cleared. Regrowth was more likely and clearing less likely far from roads. Similarly, Rudel *et al* (2002) found that dynamics differed depending on distance to the road: close to roads, cyclical dynamics associated with swidden agriculture were common, while regrowth was more permanent far from roads. Surprisingly, regrowth was more likely close to settlements, possibly because shifting cultivation is more commonly practiced near settlements. However, there was no significant effect of distance to settlement on probability of clearing. This suggests that more permanent regrowth may be more common near settlements, possibly because people conserve some second-growth forest for ecosystem services beyond carbon (de Jong *et al* 2001). Also surprising was our finding that the probability of second-growth forest clearing increased with forest patch size. On the national and regional scales that are typically associated with forest transitions, increases in forest cover can result from scarcity of forest resources and forest cover (Rudel *et al* 2005). A similar dynamic, in which small forest patches are more protected because forest is locally scarce, might play out on a smaller scale within the study landscape, and could explain the fact that second-growth pixels in larger patches were more likely to be cleared than those in smaller patches.

The simulation results indicate that realistic scenarios of forest regrowth and clearing lead to much lower estimates of future carbon storage in the landscape. Our simulations predicted over 900 000 tonnes less carbon than the static land-use dynamics scenario, or 25% (figure 5). This is likely a conservative estimate of the discrepancy for several reasons. First, our models slightly over-predict regrowth and under-predict clearing (figures S2, S3). Furthermore, our models assume that when a pixel is forested, it continuously accumulates biomass and does not experience any disturbance other than clear-cutting, which results in being classified as non-forest. We do not consider variation in land-use history or in vulnerability to disturbance, important factors that affect rates and quantities of biomass accumulation. In the Amazon, the legacy of fire can reduce rates of carbon accumulation in second-growth forests (Zarin *et al* 2005). Fire is commonly used for clearing and agricultural management in our study area (Schwartz *et al* 2015) and might be an important factor influencing rates and quantities of biomass accumulation. Second-growth forests in our study area also tend to be highly fragmented and close to forest edges (Schwartz *et al* in revision). Fragmented forests are more susceptible to wind damage (Schwartz *et al* in revision) and forest edges tend to have lower biomass (Laurance *et al* 1997, Haddad *et al* 2015). In general, plot-based estimates of biomass accumulation rates

such as in this study may underestimate disturbance and morality, and therefore overestimate biomass accumulation (Fisher *et al* 2008, Chambers *et al* 2009, Di Vittorio *et al* 2014). This discrepancy might be particularly important in second-growth forests, which are more prone to disturbance. Finally, feedbacks with future climate change could affect successional trajectories and rates of biomass accumulation (Uriarte *et al* 2016, Anderson-Teixeira *et al* 2013). Still, our results illustrate the importance of considering land-use/land-cover change and landscape dynamics when considering the carbon sequestration potential of second-growth forest.

Because land-use dynamics vary across regions, the specific results of our study do not apply everywhere, but the approach and predictors we used are generalizable across landscapes. However, there are likely to be scale considerations when applying this approach, as decisions to clear or to allow regrowth are made on different scales in different settings. Landholding sizes differ across regions, and land-use decisions are also sometimes made on larger scales such as municipality, state, or national. In other areas, a more appropriate scale of analysis might be pixels (or even sub-pixels), individual landholdings, municipalities, or larger. Results from other scales might also facilitate different, and complementary, conclusions to those from finer scale analyses like this one; for example, analyses at the municipality scale might not yield a fine-scale understanding of how landscape position affects regrowth/clearing, but it could provide useful information for targeting land-use policies at the municipality level. Future studies of these dynamics would also benefit from the integration of socioeconomic data, such as land prices, land holding size, land tenure, and more detailed information about prior land use. Land tenure in particular can influence decisions about whether or not to clear or protect second-growth forest (Angelsen and Kaimowitz 1999, Robinson *et al* 2011), and spatially explicit data on landowner's tenure status could help elucidate some of the mechanisms behind regrowth/clearing dynamics.

5. Conclusions

Many countries, including Peru, have ambitious reforestation goals in their iNDCs. Peru predicts 1.069 million tonnes carbon sequestration via community reforestation (Peru 2015). Brazil plans 12 million ha reforestation (Brazil 2015), China plans 50–100 million ha reforestation, equivalent to 1 gigaton carbon (Fransen *et al* 2015), and India plans 5 million ha reforestation (100 million tonnes carbon, India 2015). These are non-trivial contributions to the carbon reductions these countries pledged under the Paris Climate Agreement, but the assumptions about land-use dynamics and methods to ensure second-growth forest permanence are not made clear in the iNDCs. Land-use dynamics reduced projected C storage potential by 25% in our study area; a similar discrepancy in China's estimates would lead to 250 million tonnes additional emissions. Looking to past dynamics of second-growth forests can help identify where second-growth forest is threatened by non-permanence and where to focus reforestation programs. Policies that promote management of young second-growth forests and enrichment planting of valuable timber species could reduce rates of clearing of young second-growth forests. Monitoring the fate of new second-growth forests will also be important to ensure that the carbon promise of second-growth forests can be achieved.

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References

Aide T M, Clark M L, Grau H R, López-Carr D, Levy M A, Redo D, Bonilla-Moheno M, Riner G, Andrade-Núñez M J and Muñiz M 2013 Deforestation and reforestation of Latin America and the caribbean 2001–2010 *Biotropica* **45** 262–71

Alencar A A C, Solórzano L A and Nepstad D C 2004 Modeling forest understory fires in an Eastern Amazonian landscape *Ecol. Appl.* **14** 139–49

Anderson-Teixeira K J, Miller A D, Mohan J E, Hudiburg T W, Duval B D and DeLucia E H 2013 Altered dynamics of forest recovery under a changing climate *Glob. Change Biol.* **19** 2001–21

Angelsen A and Kaimowitz D 1999 Rethinking the causes of deforestation: lessons from economic models *World Bank Res. Obs.* **14** 73–98

Armenteras D, González T M and Retana J 2013 Forest fragmentation and edge influence on fire occurrence and intensity under different management types in Amazon forests *Biol. Conserv.* **159** 73–9

Asner G P, Rudel T K, Aide T M, Defries R and Emerson R 2009 A contemporary assessment of change in humid tropical forests *Conserv. Biol.* **23** 1386–95

Bates D, Maechler M, Bolker B and Walker S 2015 Fitting linear mixed-effects models using lme4 *J. Stat. Software* **67** 1–48

Brazil 2015 Intended nationally determined contribution towards achieving the objective of the United Nations framework covention on climate change (http://www4.unfccc.int/ndcregistry/PublishedDocuments/Brazil%20First/BRAZIL%20iNDC%20english%20FINAL.pdf)

Carreiras J M B, Jones J, Lucas R M and Shimabukuro Y E 2017 Mapping major land cover types and retrieving the age of secondary forests in the Brazilian Amazon by combining single-date optical and radar remote sensing data *Remote Sens. Environ.* **194** 16–32

Carreiras M B, Jones J, Lucas R M and Gabriel C 2014 Land use and land cover change dynamics across the Brazilian Amazon: insights from extensive time-series analysis of remote sensing data *PLoS One* **9** e104144

Chambers J Q, Negrón-Juárez R I, Hurtt G C, Marra D M and Higuchi N 2009 Lack of intermediate-scale disturbance data prevents robust extrapolation of plot-level tree mortality rates for old-growth tropical forests *Ecol. Lett.* **12** 22–5

Chazdon R L *et al* 2016 Carbon sequestration potential of second-growth forest regeneration in the Latin American tropics *Sci. Adv.* **2** e1501639

Chazdon R L, Peres C A, Dent D, Shiel D, Lugo A E, Lamb D, Stork N E and Miller S E 2009 The potential for species conservation in tropical secondary forests *Conserv. Biol.* **23** 1406–17

Coomes O T, Grimard F and Burt G J 2000 Tropical forests and shifting cultivation: Secondary forest fallow dynamics among traditional farmers of the Peruvian Amazon *Ecol. Econ.* **32** 109–24

Crk T, Uriarte M, Corsi F and Flynn D 2009 Forest recovery in a tropical landscape: what is the relative importance of biophysical, socioeconomic, and landscape variables? *Landsc. Ecol.* **24** 629–42

DeFries R S, Foley J A and Asner G P 2004 Land-use choices: balancing human needs and ecosystem function *Front. Ecol. Environ.* **2** 249–57

Di Vittorio A V, Negrón-Juárez R I, Higuchi N and Chambers J Q 2014 Tropical forest carbon balance: effects of field- and satellite-based mortality regimes on the dynamics and the spatial structure of Central Amazon forest biomass *Environ. Res. Lett.* **9** 034010

Etter A, McAlpine C, Pullar D and Possingham H 2005 Modeling the age of tropical moist forest fragments in heavily-cleared lowland landscapes of Colombia *For. Ecol. Manage.* **208** 249–60

Fernandes K *et al* 2011 North Tropical Atlantic influence on western Amazon fire season variability *Geophys. Res. Lett.* **38** 1–5

Fisher J I, Hurtt G C, Thomas R Q and Chambers J Q 2008 Clustered disturbances lead to bias in large-scale estimates based on forest sample plots *Ecol. Lett.* **11** 554–63

Fujisaka S and White D 1998 Pasture or permanent crops after slash-and-burn cultivation? Land-use choice in three Amazon colonies *Agrofor. Syst.* **42** 45–59

Fuss S *et al* 2014 Betting on negative emissions *Nat. Clim. Change* **4** 850–3

Gelman A and Hill J 2006 *Data analysis using regression and multilevel/hierarchical models* (http://books.googlecom/books?id=c9xLKzZWoZ4C)

Grau H R and Aide M 2008 Globalization and land-use transitions in Latin America *Ecol. Soc.* **13** 16

Gutiérrez-Vélez V H and DeFries R 2013 Annual multi-resolution detection of land cover conversion to oil palm in the Peruvian Amazon *Remote Sens. Environ.* **129** 154–67

Gutiérrez-Vélez V H, DeFries R, Pinedo-Vásquez M, Uriarte M, Padoch C, Baethgen W, Fernandes K and Lim Y 2011 High-yield oil palm expansion spares land at the expense of forests in the Peruvian Amazon *Environ. Res. Lett.* **6** 44029

Gutiérrez-Velez V H, Uriarte M, Defries R, Pinedo-Vasquez M, Fernandes K, Ceccato P, Baethgen W and Padoch C 2014 Land cover change interacts with drought severity to change fire regimes in Western Amazonia *Ecol. Appl.* **24** 1323–40

Haddad N M *et al* 2015 Habitat fragmentation its lasting impact on earth's ecosystems *Sci. Adv.* **1** 1–9 (http://advances.sciencemag.org/content/1/2/e1500052.abstract)

Hecht S B, Kandel S, Gomes I, Cuellar N and Rosa H 2006 Globalization, forest resurgence, and environmental politics in El Salvador *World Dev.* **34** 308–23

Heinimann A, Messerli P, Schmidt-Vogt D and Wiesmann U 2007 The dynamics of secondary forest landscapes in the lower mekong basin *Mt. Res. Dev.* **27** 232–41

Helmer E H 2000 The landscape ecology of tropical secondary forest in montane costa rica *Ecosystems* **3** 98–114

Helmer E H, Brandeis T J, Lugo A E and Kennaway T 2008 Factors influencing spatial pattern in tropical forest clearance and stand age: Implications for carbon storage and species diversity *J. Geophys. Res.* **113** G02S04 (www.agu.org/pubs/crossref/2008/2007JG000568.shtml)

Instituto Nacional de Estadistica e Informatica 2009 *Perú: Migraciones Internas 1993-2007* (Lima: INEI) pp 1–166

Jeon S B, Olofsson P and Woodcock C E 2014 Land use change in New England: a reversal of the forest transition *J. Land Use Sci.* **9** 105–30

De Jong W, Freitas L, Baluarte J, Van de Kop P, Salazar A, Inga E, Melendez W and Germaná C 2001 Secondary forest dynamics in the Amazon floodplain in Peru *For. Ecol. Manage.* **150** 135–46

Lambin E F and Meyfroidt P 2011 Global land use change, economic globalization, and the looming land scarcity *Proc. Natl Acad. Sci.* **108** 3465–72

Laurance W F and Curran T J 2008 Impacts of wind disturbance on fragmented tropical forests: a review and synthesis *Austral Ecol.* **33** 399–408

Laurance W F, Laurece S G, Ferreira Leandro V, Merona Judy M R, Gascon C and Lovejoy T E 1997 Biomass collapse in amazonian forest fragments *Science* **278** 1117–8

Liebsch D, Marques M C M and Goldenberg R 2008 How long does the Atlantic Rain Forest take to recover after a disturbance? Changes in species composition and ecological features during secondary succession *Biol. Conserv.* **141** 1717–25

Mather A 1992 The forest transition *Area* **24** 367–79

Meyfroidt P and Lambin E F 2011 Global forest transition: prospects for an end to deforestation *Annu. Rev. Environ. Resour.* **36** 343–71

Meyfroidt P, Rudel T K and Lambin E F 2010 Forest transitions, trade, and the global displacement of land use *Proc. Natl Acad. Sci.* **107** 20917–22

Padoch C, Brondizio E, Costa S, Pinedo-Vasquez M, Sears R R and Siqueira A 2008 Urban forest and rural cities: multi-sited households, consumption patterns, and forest resources in Amazonia *Ecol. Soc.* **13** 2

Peru 2015 Intended nationally determined contribution from the Republic of Peru (http://www4.unfccc.int/ndcregistry/PublishedDocuments/Peru%20First/iNDC%20Per%C3%BA%20english.pdf)

Pinedo-Vasquez M, Zarin D and Jipp P 1992 Economic returns from forest conversion in the Peruvian Amazon *Ecol. Econ.* **6** 163–73

Poorter L *et al* 2016 Biomass resilience of neotropical secondary forests *Nature* **530** 211–4

Potter L 2015 *Managing Oil Palm Landscapes: A Seven-Country Survey of the Modern Palm Oil Industry in Southeast Asia* (Latin America and West Africa: CIFOR) (www.cifor.org/nc/online-library/browse/view-publication/publication/5612.html)

Rhodes J S and Keith D W 2008 Biomass with capture: negative emissions within social and environmental constraints: an editorial comment *Clim. Change* **87** 321–8

Robinson B, Holland M and Naughton-Treves L 2011 *Does secure land tenure save forests? CCAFS Working paper no. 7* (Copenhagen, Denmark) (www.ccafs.cgiar.org)

Rudel T K, Bates D and Machinguiashi R 2002 A Tropical Forest Transition? Agricultural change, out-migration, and secondary forests in the Ecuadorian Amazon *Ann. Assoc. Am. Geogr.* **92** 87–102

Rudel T K, Coomes O T, Moran E, Achard F, Angelsen A, Xu J and Lambin E 2005 Forest transitions: towards a global understanding of land use change *Glob. Environ. Change* **15** 23–31

Rudel T K, Perez-Lugo M and Zichal H 2000 When fields revert to forest: Development and spontaneous reforestation in post-war Puerto Rico *Prof. Geogr.* **52** 386–97

Schwartz N B, Uriarte M, Gutiérrez-Vélez V H, Baethgen W, DeFries R, Fernandes K and Pinedo-Vasquez M A 2015 Climate, landowner residency, and land cover predict local scale fire activity in the Western Amazon *Glob. Environ. Change* **31** 144–53

Sloan S, Goosem M and Laurance S G 2016 Tropical forest regeneration following land abandonment is driven by primary rainforest distribution in an old pastoral region *Landsc. Ecol.* **31** 601–18

Tilly C 2011 The impact of the economic crisis on international migration: a review *Work. Employ. Soc.* **25** 675–92

UNFCCC 2014 Land use, land-use change, and forestry (http://unfccc.int/land_use_and_climate_change/lulucf/items/3064.php)

Uriarte M, Lasky J R, Boukili V K and Chazdon R L 2016 A trait-mediated, neighbourhood approach to quantify climate impacts on successional dynamics of tropical rainforests *Funct. Ecol.* **30** 157–67

Uriarte M, Pinedo-Vasquez M, DeFries R S, Fernandes K, Gutierrez-Velez V, Baethgen W E and Padoch C 2012 Depopulation of rural landscapes exacerbates fire activity in the Western Amazon *Proc. Natl Acad. Sci.* **109** 21546–50

van Vuuren D P, Deetman S, van Vliet J, van den Berg M, van Ruijven B J and Koelbl B 2013 The role of negative CO_2 emissions for reaching 2 °C—insights from integrated assessment modelling *Clim. Change* **118** 15–27

Yackulic C B, Fagan M, Jain M, Jina A, Lim Y, Marlier M, Muscarella R, Adame P, DeFries R and Uriarte M 2011 Biophysical and Socioeconomic Factors Associated with Forest Transitions at Multiple Spatial and Temporal Scales *Ecol. Soc.* **16** art15 (http://www.ecologyandsociety.org/vol16/iss3/art15/)

Zarin D J *et al* 2005 Legacy of fire slows carbon accumulation in Amazonian forest regrowth *Front. Ecol. Environ.* **3** 365–9