

635 **Supporting information: methods:**

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637 Land cover classification

638 This study employed a land cover classification developed and validated in a previous  
639 study in our study area (Gutiérrez-Vélez and DeFries 2013). The original classification spanned  
640 10 years (2000-2010). It differentiates between high-biomass forest, low-biomass forest, and  
641 other land cover types, including oil palm, deforested, fallow, pasture, bare soil, and water, with  
642 overall accuracy of 93%. For a more detailed accuracy assessment see Gutierrez-Velez and  
643 DeFries (2013). We applied the same procedure and classification tree to additional images to  
644 complete a 30 year time series with 30x30 m pixel resolution. Specifically, we identified Landsat  
645 TM/ETM+ scenes from 1984-1999, and 2011-2013 (Table 1). All scenes were acquired as  
646 surface reflectance with atmospheric corrections from the Landsat CDR archive (USGS 2017)  
647 via USGS Earth Explorer (<http://earthexplorer.usgs.gov>). Scenes were radiometrically  
648 normalized to a reference image from the year 2000 using the iMAD algorithm (Canty and  
649 Nielsen 2008) and clouds and cloud shadows were masked using the Fmask band included in the  
650 surface reflectance product (Zhu and Woodcock 2012, Zhu et al. 2015, USGS 2017). We  
651 calculated the following band transformations for each image, for use in the classification  
652 procedure: 1) tasseled cap band transformations (brightness, greenness, third), 2) bare,  
653 vegetation, and shade fractions from spectral mixture analysis, and 3) NDVI. Finally, we applied  
654 the previously developed random forest classifier to the transformed bands and masked oil palm  
655 plantations with a previously developed map of oil palm in the study area (Gutierrez-Velez and  
656 DeFries 2013). To improve accuracy and predict land cover in data gaps or areas covered by  
657 clouds when possible, we applied a temporal filter to disallowed trajectories (cite). Remote  
658 sensing analyses were conducted in ENVI 4.8 (Exelis Visual Information Solutions).

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660 Field data collection and calculation of forest biomass

661 To establish the relationship between forest age and biomass accumulation, we used data  
662 from 30 field plots. In each plot, we measured all stems > 5 cm diameter at breast height (dbh).  
663 To determine plot level biomass, we used the following allometric equation developed for  
664 secondary forest species in the central Amazon (Nelson et al. 1999):

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$$\ln(\text{biomass}) = -1.9968 + 2.4128 * \ln(\text{DBH})$$

666 We scaled plot-level values to units of Mg/ha, and divided values by two so that estimates were  
667 in terms of kg C instead of kg biomass, under the assumption that C makes up 50% of biomass  
668 (Brown and Lugo, 1982). We found a highly significant relationship between biomass and forest  
669 age ( $R^2 = 0.517$ ,  $p > 0.001$ , Figure S1).

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671 References

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685 [https://landsat.usgs.gov/sites/default/files/documents/ledaps\\_product\\_guide.pdf](https://landsat.usgs.gov/sites/default/files/documents/ledaps_product_guide.pdf)  
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689 Zhu Z, Wang S and Woodcock C E 2015 Improvement and expansion of the Fmask algorithm:  
690 Cloud, cloud shadow, and snow detection for Landsats 4-7, 8, and Sentinel 2 images Remote  
691 Sens. Environ. 159 269–77 Online: <http://dx.doi.org/10.1016/j.rse.2014.12.014>  
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**Table S1: Landsat images used for classification (images for 2000-2010 were classified in Gutierrez Velez and DeFries 2013).**

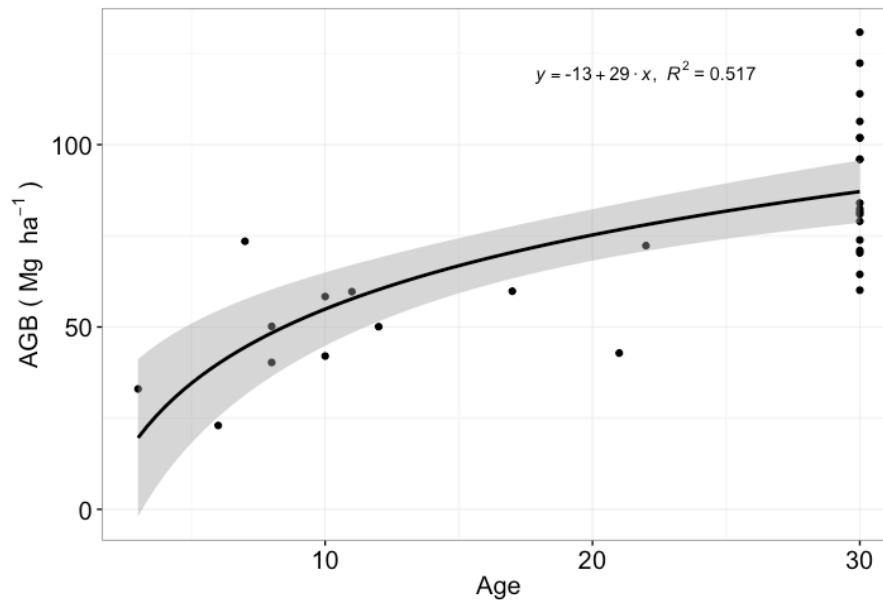
Year	Julian date	Satellite	Path/row
1985	195	Landsat TM	06-066
1985	218	Landsat TM	07-066
1987	185	Landsat TM	06-066
1987	96	Landsat TM	07-066
1988	204	Landsat TM	06-066
1988	211	Landsat TM	07-066
1989	190	Landsat TM	06-066
1989	221	Landsat TM	07-066
1990	225	Landsat TM	06-066
1990	216	Landsat TM	07-066
1991	164	Landsat TM	06-066
1991	219	Landsat TM	07-066
1993	192	Landsat TM	07-066
1993	217	Landsat TM	06-066
1995	207	Landsat TM	06-066
1995	262	Landsat TM	07-066
1996	265	Landsat TM	07-066
1996	114	Landsat TM	06-066
1997	180	Landsat TM	06-066
1997	251	Landsat TM	07-066
1998	247	Landsat TM	06-066
1998	142	Landsat TM	07-066
1999	218	Landsat TM	06-066
1999	233	Landsat ETM+	07-066
2000	189	Landsat TM	06-066
2000	244	Landsat TM	07-066
2001	215	Landsat TM	06-066
2001	182	Landsat TM	07-066
2002	250	Landsat TM	06-066
2003	141	Landsat ETM+	06-066
2003	4	Landsat TM	07-066
2003	236	Landsat ETM+	07-066
2004	216	Landsat TM	06-066
2004	31	Landsat TM	07-066
2005	186	Landsat TM	06-066
2005	209	Landsat TM	07-066
2006	221	Landsat TM	06-066
2006	148	Landsat TM	07-066

2007	184	Landsat ETM+	06-066
2007	183	Landsat ETM+	07-066
2008	195	Landsat TM	06-066
2008	227	Landsat TM	06-066
2008	202	Landsat TM	07-066
2009	181	Landsat TM	06-066
2009	156	Landsat TM	07-066
2010	184	Landsat TM	06-066
2010	332	Landsat TM	07-066
2011	203	Landsat TM	06-066
2011	226	Landsat TM	07-066
2013	208	Landsat OLI	06-066
2013	231	Landsat OLI	07-066

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**Figure S1: Relationship between AGB and age in 30 field plots.**



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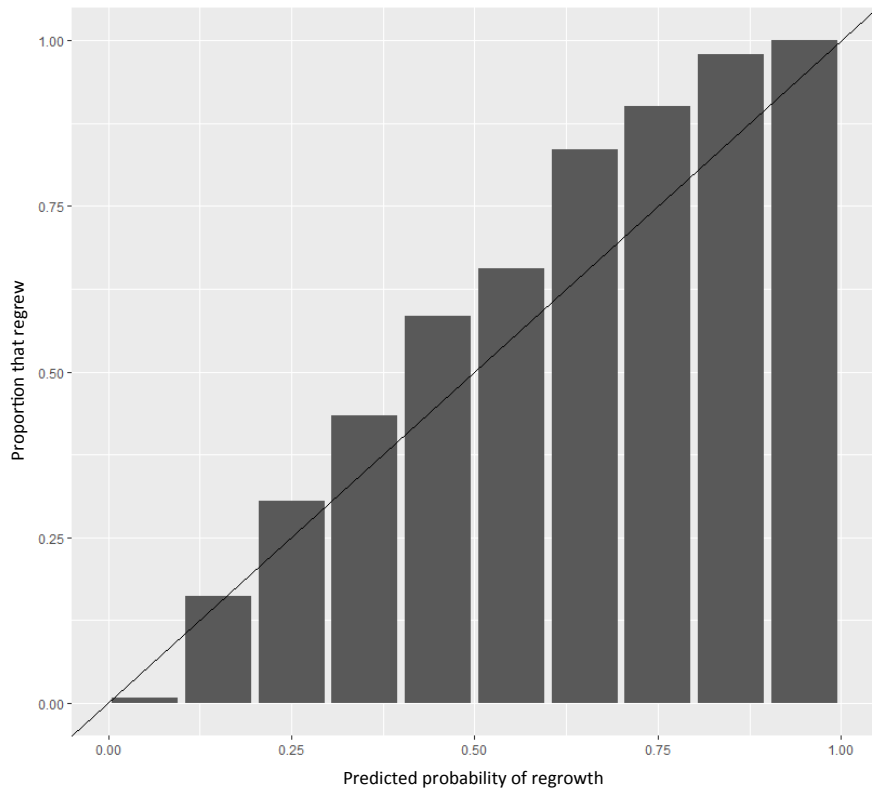
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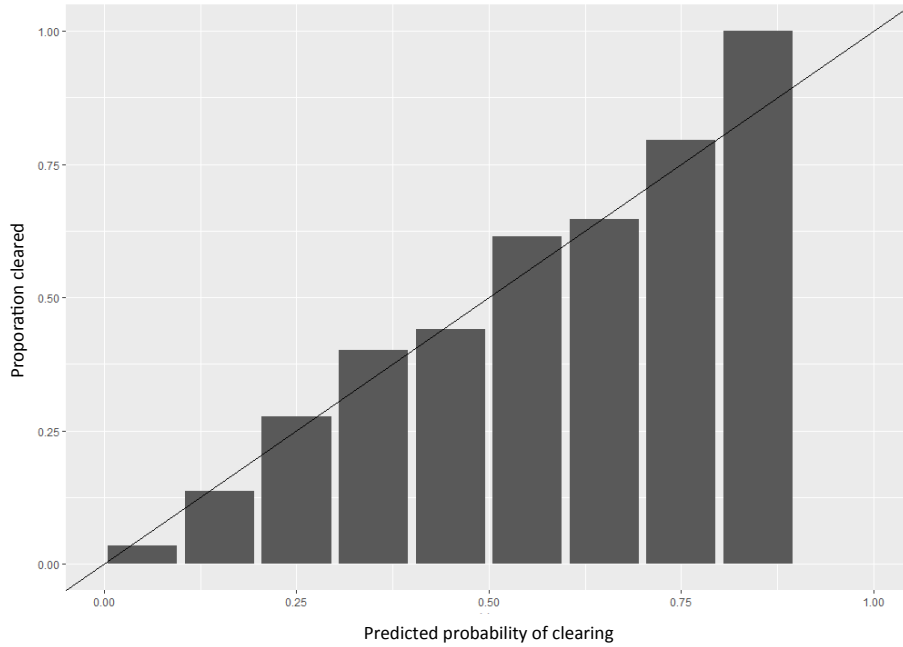
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Figure S2: Plot of proportion of pixels with predicted probability of regrowth that actually re-grew. The solid 1:1 line indicates the expected value for a model that perfect predicts probability of regrowth. Our model somewhat over-predicts regrowth.



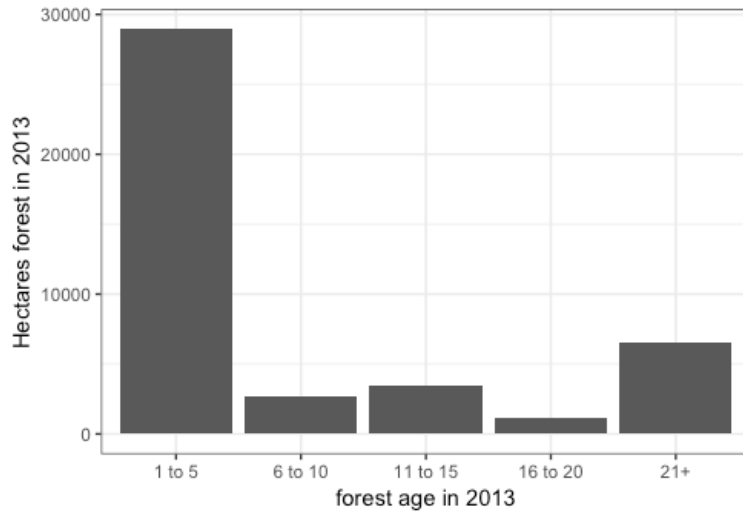
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704 Figure S3: Plot of proportion of second-growth forest pixels with predicted probability of  
705 clearing that were actually cleared. The solid 1:1 line indicates the expected value for a model  
706 that perfect predicts probability of clearing. Our model somewhat under-predicts clearing.



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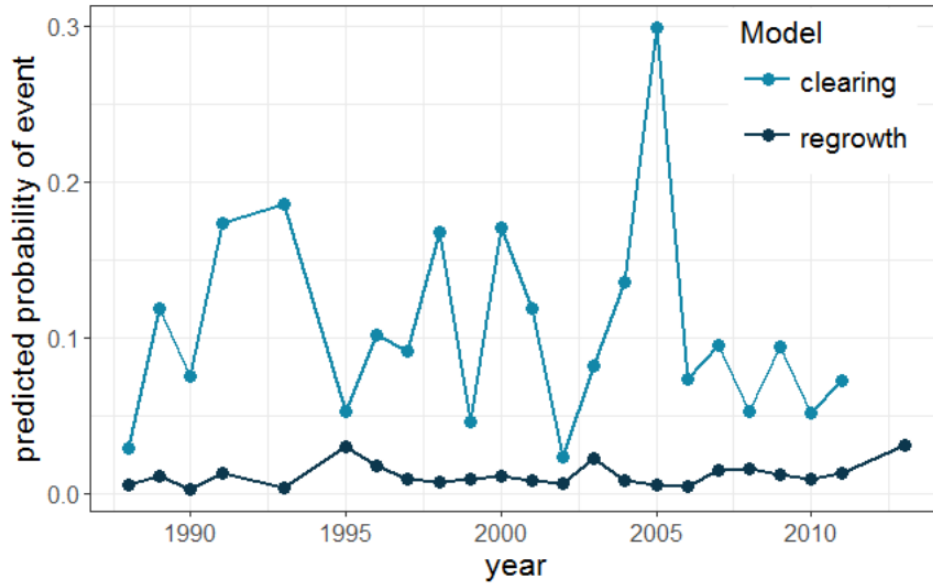
Figure S4: Distribution of forest ages in 2013.



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Figure S5: Inter-annual variability in probability of clearing and regrowth. Y-axis is the year-specific intercept from the mixed-effects models, i.e. the probability of event (forest regrowth, or second-growth forest clearing) at mean values for all predictors.



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