


Management intensification maintains wood production over multiple harvests in tropical *Eucalyptus* plantations

DEVIN E. MCMAHON ^{1,4} AND ROBERT B. JACKSON^{1,2,3}

¹Department of Earth System Science, Stanford University, 473 Via Ortega, Stanford, California 94305 USA

²Woods Institute for the Environment, Stanford University, 473 Via Ortega, Stanford, California 94305 USA

³Precourt Institute for Energy, Stanford University, 473 Via Ortega, Stanford, California 94305 USA

Citation: McMahon, D. E., and R. B. Jackson. 2019. Management intensification maintains wood production over multiple harvests in tropical *Eucalyptus* plantations. *Ecological Applications* 00(00):e01879. 10.1002/eap.1879

Abstract. Plantation forestry, in which trees are grown as a crop, must maintain wood production over repeated harvest cycles (rotations) to meet global wood demands on a limited land area. We analyze 33 yr of Landsat observations across the world's most productive forestry system, *Eucalyptus* plantations in southeastern Brazil, to assess long-term regional trends in wood production. We apply a simple algorithm to time series of the vegetation index NIRv in thousands of *Eucalyptus* stands to detect the starts and ends of rotations. We then estimate wood production in each identified stand and rotation, based on a statistical relationship between NIRv trajectories and inventory data from three plantation companies. We also compare *Eucalyptus* NIRv with that of surrounding native vegetation to assess the relative influence of management and environment on plantation productivity trends. Across more than 3,500 stands with three complete rotations between 1984 and 2016, modeled wood volume decreased significantly between the first and second rotation, but recovered at least partially in the third; mean wood volumes for the three rotations were 262, 228, and 247 m³/ha. This non-linear trend reflects intensifying plantation management, as rotation length decreased by an average of 15% (decreasing wood volume per rotation) and NIRv proxies of tree growth rates increased (increasing volume) between the first and third rotation. However, NIRv also increased significantly over time in unmanaged vegetation around the plantations, suggesting that environmental trends affecting all vegetation also contribute to sustaining wood production. Management inputs will likely continue to be important for maintaining wood production in future harvests.

Key words: intensification; land use; near-infrared from vegetation; plantation forestry; remote sensing; time series; wood production.

INTRODUCTION

As humans demand more goods and services from the world's ecosystems, agriculture and native vegetation compete for finite land (Lambin and Meyfroidt 2011). Industrial plantation forestry increases wood production per unit land area by growing trees as a crop, often in vast blocks of a single tree species and age cohort. Plantations currently supply more than 30% of the world's lumber and wood fiber on less than 1.5% of the world's forested land (Indufor 2012, FAO 2015) and may spare more biodiverse ecosystems from logging or conversion to annual crops by shrinking the land base needed to provide wood (Byerlee et al. 2014, Heilmayr 2014). In addition, continued plantation expansion, particularly in the tropics and subtropics (Payn et al. 2015), could

increase the terrestrial carbon sink and provide energy and chemical feedstocks for a low-carbon economy (Kraxner et al. 2013, Langholtz et al. 2016). Plantations established on degraded land may also connect fragmented habitats and control erosion (Brockerhoff et al. 2008, Chazdon 2008).

Despite these benefits, researchers and practitioners have questioned the ecological sustainability of plantation forestry (Poore and Fries 1985, Parrotta 1999, Gonçalves et al. 2008). Plantations can deplete surface and groundwater (Jackson et al. 2005, Mendham et al. 2011, Laclau et al. 2013) and soil nutrients (Berthrong et al. 2009, 2012, Leite et al. 2010, Deng et al. 2017) over time and relative to other vegetation types, potentially limiting future plant growth. Long-term productivity may also decline due to harvest-related soil compaction or erosion (Cambi et al. 2015, Guillaume et al. 2015), accumulation of pests and pathogens (Wingfield et al. 2013), or the inability of plantation species to cope with environmental changes such as increasing precipitation variability (Payn et al. 2015). Further,

Manuscript received 15 August 2018; revised 10 December 2018; accepted 14 February 2019. Corresponding Editor: Xiangming Xiao.

⁴E-mail: mcmahond@stanford.edu

the management of vast monocultures can exclude local human communities from land, resources, and decision-making, so biophysical sustainability has important social and political ramifications (Kröger and Nylund 2012, Fox and Castella 2013, Lyons and Westoby 2014).

Sustainable plantation forests should produce wood over multiple harvest cycles (rotations) without degrading the land. However, the slow growth of trees has historically hindered analysis of long-term sustainability within established plantations (Evans 2001). Prior studies have used forestry company records to identify sustained or increasing wood production (Fox 2000, Nissim et al. 2013), inter-site variation (Harwood and Nambiar 2014), or a general decrease in production between first and second rotations, which can be subsequently mitigated through changes in management (O’Hehir and Nambiar 2010). The scope of these studies is limited by access to forestry companies’ inventory data. Here, we apply models based on company data to region-wide, freely available remote sensing observations to track individual plantation management units (stands) over three or more rotations and assess trends in plantation production across time and space.

We implement this approach in southeastern Brazil, site of the world’s most productive plantation forests. *Eucalyptus* stands cover 5.6 million hectares in Brazil and are harvested approximately every seven years, primarily for short-lived wood products such as pulp and paper, particleboard, and charcoal used in steelworks (Ibá 2016). Globally, *Eucalyptus* is planted on approximately 20 million hectares across six continents, and land managers worldwide may look to the Brazilian industry as a model for future forestry (Booth 2013, Brockerhoff et al. 2013). Since the 1960s, changes in genetics and management have increased tree growth rates; the most productive stands now yield more than 80 m³ wood·ha⁻¹·yr⁻¹ (Gonçalves et al. 2013, IBÁ 2016).

The sustainability concerns associated with plantations in general are amplified in these intensive systems established on highly weathered soils (Laclau et al. 2010). For example, plantation operators and *Eucalyptus* researchers at a 2016 meeting on soil science and sustainability (Telêmaco Borba, Paraná, Brazil) posited that production is now declining as the same areas are repeatedly harvested. However, this hypothesis had not to our knowledge been tested at the regional scale. Here, we quantify long-term trends in vegetation productivity for individual plantation stands across the region. We address the following questions: (1) How well do simple models based on remotely sensed vegetation indices predict harvestable wood volume, and what elements of the time series are important in these predictions? (2) Has wood production declined with successive rotations on the same units of land? (3) How important is management in determining production trends, relative to environmental changes?

To answer these questions, we build on decades of studies using time series of vegetation indices derived

from satellite imagery to model primary productivity (Tucker 1979, Paruelo et al. 1997), tree growth (Wang et al. 2004), and plantation wood production (le Maire et al. 2011, Liu et al. 2014, Dube et al. 2015). We also use time series of satellite observations to map plantations on the landscape (Dong et al. 2013, Qiao et al. 2016) and to identify harvest and subsequent forest regrowth (DeVries et al. 2015). Unlike previous studies, we leverage the computing resources of the Earth Engine platform (Gorelick et al. 2017) to access the full data archive from Landsat satellites 5, 7, and 8, allowing us to identify planting and harvest dates in thousands of stands, compare vegetation index trends between plantations and native vegetation, and estimate wood production over successive harvests.

METHODS

Study area

The study covers approximately 22,000 km² in Minas Gerais, the Brazilian state with the largest planted area of *Eucalyptus* (IBÁ 2016), corresponding to seven Landsat scenes (Fig. 1; Appendix S1: Table S1). The southeastern portion of the study region is characterized by semi-deciduous Atlantic Forest, with mean annual precipitation between approximately 1,000 and 1,500 mm and elevation 200–1,100 m (Danielson and Gesch 2011, Funk et al. 2014). Much of the native vegetation has been cleared since European colonization began in 1500 (Ribeiro et al. 2009). *Eucalyptus* was first planted in this region in the 1860s, and plantations have proliferated since the late 1960s (Gonçalves et al. 2013), often on former pastures. Approximately 81% of the stands we studied in this biome are owned by one vertically integrated cellulose and paper company, and an unknown but substantial proportion had undergone several rotations prior to 1984.

The northwest of the region, further inland, is characterized by savanna-like Cerrado vegetation with varying canopy cover. Mean annual precipitation is also approximately 1,000–1,400 mm, with less than 2% falling in the driest three months. Elevation ranges from 600 to 1,200 m, with *Eucalyptus* often planted on plateaus. The Brazilian government incentivized settlement and crop establishment in this region primarily in the 1960s and 1970s. *Eucalyptus* was established at large scales beginning in the 1980s to supply charcoal for railroads and steel manufacturing, as well as pulp and other wood products, and continues to expand in the region (Klink and Moreira 2002, IBÁ 2016).

Both the Cerrado and the Atlantic Forest are biodiverse regions with highly fragmented remnants of native vegetation adapted to low-nutrient mineral soils (Silva et al. 2006, Ribeiro et al. 2009). Plantations are established primarily on deep, weathered Oxisols (Latossolos in the Brazilian soil classification system), with high clay and iron content and low concentrations of major plant

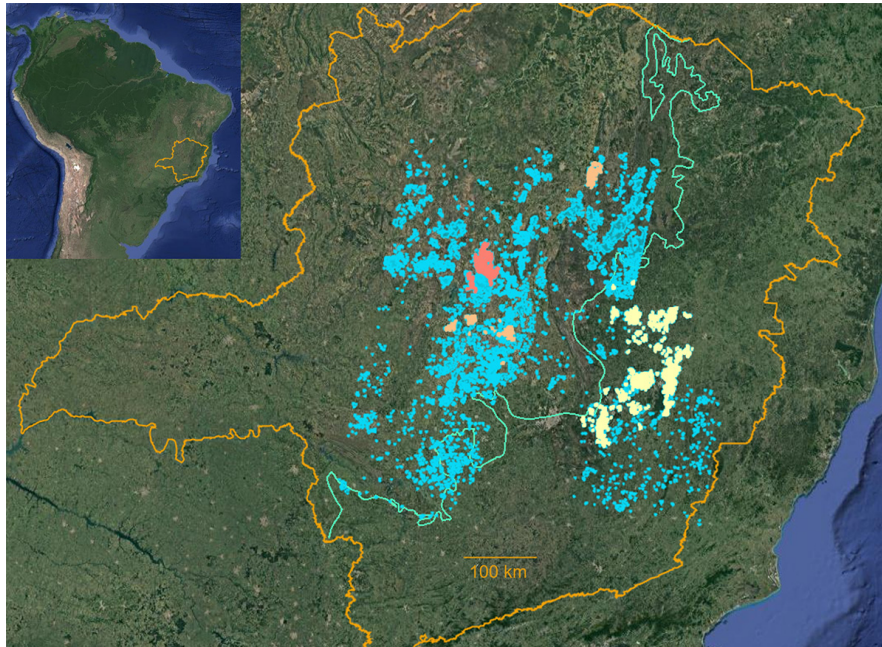


FIG. 1. The study region occupies the interior of Minas Gerais state (gold outline). Blue spots represent 1,745 areas encompassing stands and surrounding native vegetation. Red, orange, and yellow areas indicate stands from three plantation companies, whose primary products are charcoal for steelworks, wood for various industries, and cellulose pulp and paper, respectively. The green line represents the approximate boundary between the Cerrado, to the west, and the Atlantic Forest. Satellite imagery from TerraMetrics 2008, accessed via Earth Engine (3 May 2018); biome border from IBGE (Brazilian Institute of Geography and Statistics), accessed via mapforenvironment.org (27 April 2018); state border from IBGE, accessed via gmaps.com (24 April 2018).

nutrients and organic matter. Other plantation soils include Inceptisols (Cambissolos) and Entisols (Neossolos), also with generally low levels of exchangeable nutrients (Filho and Schaefer 2010).

Eucalyptus in this region is generally grown in rotations of five to seven years. Stands are clear-cut at the end of the rotation and may be allowed to resprout from stumps for one or two additional rotations (i.e., coppiced). More frequently, however, the stumps are killed and greenhouse-grown clonal sprouts are planted between the former rows. The most common clones are hybrids of *E. urophylla* × *grandis*; hybrids with *E. camaldulensis* and, occasionally, pure *grandis* or *urophylla* (Gonçalves et al. 2013).

Agricultural inputs to the plantations generally include nitrogen, phosphorus, potassium, agricultural lime, and micronutrients; plantations are not irrigated. Chemical pesticides are used to control competing vegetation, ants, and fungal pathogens for the first 2–3 yr after planting. These treatments are generally not applied following canopy closure, although formicide application continues annually in some regions (L. Vergütz and C. Afonso, *personal communication*).

Land cover classification

Plantation stands were identified from recent Landsat images, using the Random Forests machine learning

algorithm in Earth Engine and manually delineated training polygons (Appendix S1). Three wood-producing corporations, Cenibra, Gerdau, and Plantar, provided geospatial data files indicating the boundaries for 8,631 current eucalypt stands. Where available, we used these known boundaries in place of the classification results. In total, the algorithm identified approximately 8,500 stands outside the boundaries of the company-delineated stands. The median area of all stands was 17.3 ha, with a 95% interval from 2.3 to 74.2 ha (company-delineated stands smaller than 2 ha were excluded). The mean user's accuracy of the stand classification (i.e., the probability that a pixel classified as *Eucalyptus* in 2016 actually represented *Eucalyptus*) exceeded 85% (Appendix S1).

To separate the effects of forest management from other possible drivers of vegetation index trends, we compared the vegetation index values of *Eucalyptus* stands to those of adjacent patches (within 900 m of a cluster of stands) of non-crop, non-eucalypt woody vegetation identified by the Random Forests classification, with a mean user's accuracy of 79% prior to additional filtering of pixels and patches (Appendix S1). We also extracted vegetation index time series for similar vegetation >8 km from plantations, using the same annual compositing methods as for *Eucalyptus*, in order to assess possible effects of plantation management on adjacent native vegetation.

Time series extraction

For each plantation stand, we assembled a time series from 1984 to 2016 of the “near-infrared from vegetation” (NIRv) index (Badgley et al. 2017). NIRv is calculated as

$$\left(\frac{\text{NIR} - \text{red}}{\text{NIR} + \text{red}} \right) \times \text{NIR} \quad (1)$$

where NIR and red are the reflectance values in the near-infrared (760–900 nm) and red (630–690 nm) bands, respectively. This index is similar to the commonly used normalized difference vegetation index (NDVI), which has previously been used along with stand age to accurately predict wood volume in clonal *Eucalyptus* (Marsden et al. 2010, le Maire et al. 2011), as well as in process-based wood production models with species-specific biomass partitioning (Coops and Waring 2001, Nightingale et al. 2008). Compared to NDVI, NIRv saturates less in dense canopies and correlates better with eddy-flux measurements and sun-induced fluorescence estimates of annual primary productivity, including in forests (Badgley et al. 2017).

NIRv measurements were derived from Landsat missions 5, 7, and 8. We used the Collection 1 Landsat surface reflectance products, pre-processed using the LEDAPS atmospheric correction model (Landsats 5 and 7) or the LaSRC model (Landsat 8; USGS 2017a,b). We collected all Landsat images overlapping *Eucalyptus* stands and filtered out cloudy pixels using the internal CFMASK algorithm (Foga et al. 2017). For each year (1984–2016) and for each pixel in a *Eucalyptus* stand, we selected the Landsat images corresponding to the 90th, 75th, and 50th percentile NIRv, creating three mosaic images per year. We then averaged the values of NIRv in each mosaic over all pixels within a stand, so that each stand has three NIRv observations per year (99 in total). The three percentile classes were selected from a range of possible percentiles to exclude clouds, shadows, and erroneous NIRv maxima, while suggesting the range of

intra-annual variation in NIRv. For many stands, we could not reliably obtain more than three unique cloud-free observations per year, even with the mosaic approach. Each observation within each stand was assigned the most common (mode) date of acquisition among the pixels contributing to the mosaic for that stand, so that the stand’s NIRv observations could be placed on a timeline with concurrent observations of adjacent native vegetation (Fig. 2). Preliminary analyses showed no consistent difference in NIRv values retrieved from the different satellites within one week in a given vegetation patch, so we used the three satellites interchangeably.

To compare time series of *Eucalyptus* and native vegetation NIRv, we collected NIRv values for each native vegetation patch at each observation date in the Landsat archive, averaging all cloud-free pixels. For each stand, we identified all native vegetation patches within 900 m of that cluster of stands, with the same elevation (binned in 100-m increments), and with the same soil type as the target stand (Appendix S1). For each NIRv observation in the target stand, we then calculated the average NIRv value of these native patches on the same nominal observation date, weighted by the number of cloud-free pixels within each patch. This allowed us to calculate the difference in NIRv between contemporaneous observations of each stand and comparable native vegetation.

We applied a set of heuristics to the time series of the difference in NIRv between each stand and its paired native vegetation in order to identify the starts and ends of rotations, based on the higher NIRv of mature *Eucalyptus*, and the lower values of clear cuts, relative to native vegetation (Fig. 2). Comparing plantations to unharvested native vegetation eliminates the need for a calibration period with no harvests against which to detect changes in canopy cover, as required by common methods such as the BFAST algorithm (Verbesselt et al. 2010). Code used to detect rotations, and links to Earth Engine code for land cover classification and time series export, is available from the Stanford Digital Repository (see *Data Availability*). The rotation identification and

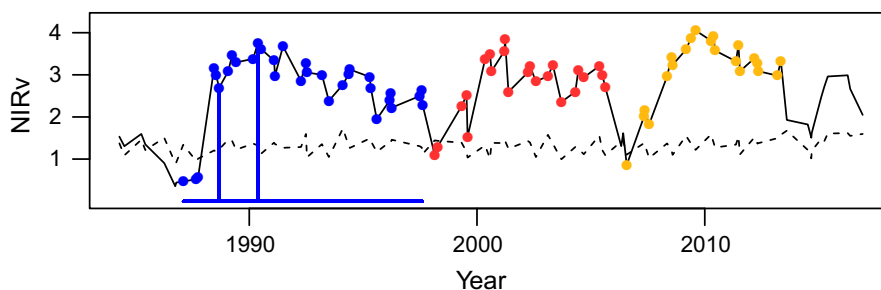


FIG. 2. Example NIRv time series, indicating three identified rotations and the three predictors of wood volume used in our model. The solid line shows *Eucalyptus* NIRv (3 observations/yr), dashed line shows corresponding native vegetation NIRv for each observation, and blue, red, and yellow points show the first, second, and third rotations since 1984. Blue lines indicate the rotation length, peak NIRv, and median NIRv of the first two years. NIRv scale is divided by 1,000 on figure axes for neatness, relative to values in linear models (Table 2).

all statistical analyses were performed in R version 3.3.0 (R Core Team 2016).

Our algorithm identified at least one complete rotation in 16,378 stands, of which approximately 38% were in the Atlantic Forest region and the rest in the Cerrado (Table 1). For 986 stands for which the year of planting or resprouting was known from company data and occurred prior to 2014, the rotation-finding algorithm correctly identified the rotation start date to within one year in 86% of stands (90% for replanted stands; 76% for resprouts, in which the canopy tended to close too fast for a harvest to be detected). In a random sample of 500 stands with at least two identified rotations, the algorithm detected the same harvest dates as visual interpretation of the time series in approximately 63% of stands and misidentified the start or end date of a rotation in another 13% (mean error in rotation length, relative to visual interpretation, was -0.4 yr with standard deviation 2.5 yr, $n = 63$ stands). In 19% of stands, the algorithm identified a rotation when the NIRv trajectory did not differ sufficiently from the surrounding vegetation to visually indicate *Eucalyptus* (i.e., a false rotation, usually due to variation in the NIRv of the vegetation preceding *Eucalyptus*), and in 6% appeared to miss an actual rotation. Further changes to the algorithm did not substantially improve these statistics, due to the substantial variation in NIRv patterns across stands and rotations.

Relationship between NIRv and Eucalyptus wood production

We used recent wood volume data from ~700 stands operated by the three companies to derive statistical relationships between NIRv time series and *Eucalyptus* wood production, similar to the approach taken in prior work on more homogeneous stands with more frequent observations (Marsden et al. 2010, le Maire et al. 2011). Wood volume, the relevant metric of production for industrial plantations, was calculated by the companies from annual or pre-harvest inventories at the stand level, and clone-specific allometric equations.

Using best-subsets regression to minimize model Bayesian Information Criterion (Lumley and Miller 2017), we selected a simple linear model of final wood volume as a function of three biologically important

aspects of the NIRv time series (see *Results*). Adding additional terms to the model improved the fit to the training data (i.e., further reduced BIC), but introduced correlated terms with opposing coefficients, even when a strong L1 constraint was applied using the lasso2 package (Lokhorst et al. 2014); it also produced a weaker fit to withheld test data, or yielded unrealistic wood volumes when extrapolated to the entire data set.

Trends in production: statistical methods

We analyzed trends in wood production over the first three rotations of stands with three or more complete rotations since 1984. We excluded stands in which the third rotation started after 2009 (seven years, or a standard rotation length, before the end of the time series) to avoid biasing our sample toward unusually short third rotations, although including these stands did not alter the direction of trends in wood volume or its predictors. While some rotations are truly more than twice as long as the industry standard (i.e., >14 yr), such long rotations may also indicate that the rotation detection algorithm missed a harvest, or may display age-related growth dynamics not captured in our training data. We therefore also excluded stands with any rotation longer than 14 yr from subsequent analysis, although including these stands did not significantly alter the trends in wood volume or rotation length reported in Results.

Preliminary analysis of variance found significant differences in modeled wood volume (square-root transformed) between rotations ($F_{2,10,764} = 369.8$), between biomes ($F_{1,10,764} = 2053.9$), and in the interaction of biome and rotation ($F_{2,10,764} = 109.6$); all $P < 2 \times 10^{-16}$). We subsequently analyzed each biome separately. We used Welch's nonparametric one-way analysis of variance and Games-Howell multiple comparisons, as implemented in the oneway function of the userfriendly-science package in R (Peters 2018), to compare mean wood volume between rotations within each biome, making our analysis robust to deviations from normality and heteroscedasticity of variance. By the same methods, we also analyzed trends in the predictors of modeled wood production, such as peak NIRv (see *Results* for description of the predictors), over successive rotations.

Drivers of wood production: statistical methods

We investigated the contribution of environmental trends affecting all vegetation over time to the observed trends in *Eucalyptus* productivity, which might otherwise be attributed to plantation management. To do this, we calculated the difference in NIRv between each stand and its paired native vegetation at each time point. We used linear models with an interaction between NIRv type (*Eucalyptus*, native, or difference between the two) and year to compare the trends in average annual values for the three types and assess the contribution of native vegetation trends to *Eucalyptus* NIRv trends in each biome.

TABLE 1. Rotations identified in each biome.

Rotations since 1984	Number of stands		
	Atlantic forest	Cerrado	Total
1	1,161	3,988	5,149
2	1,841	3,813	5,654
3	2,548	2,070	4,618
4	586	331	917
5	21	19	40

We then investigated the relationship of plantation and native vegetation NIRv to possible drivers, including temporal variables such as annual precipitation and atmospheric CO₂ concentration and spatial variables such as elevation and soil class (Appendix S1). We used Spearman’s ranked correlations and Random Forests variable importance (Hapfelmeier et al. 2014, Hothorn et al. 2015) to evaluate the potentially nonlinear relationships between productivity variables and possible drivers. To separate the spatial and temporal variation of precipitation and NIRv, we calculated annual anomalies for each stand as in Eq. 1. For precipitation, we considered mean anomalies of the last one, two, or three years, either annually, or in the first two years or the whole length of each rotation. Correlations between vegetation productivity and these anomalies were generally weak (magnitude of Spearman’s rho < 0.1), and their contribution to a Random Forests model that represented our predicted wood volume metric as a function of environmental variables was negligible; we do not discuss these factors in detail.

RESULTS

Question 1: How well do simple models based on remotely sensed vegetation indices predict harvestable biomass, and what elements of the time series are important in these predictions?

The model that best represents wood volume as a function of biologically meaningful components of the NIRv time series includes three terms: rotation length, rotation peak NIRv, and median NIRv of the first two years of the rotation (Table 2, Fig. 2). Our model is not able to represent the full scope of the variation in wood volumes ($R^2 = 0.36$, RMSE = 52.1 m³/ha), likely due to differences between *Eucalyptus* clones in biomass partitioning between leaves and wood, as well as variation in soil and microclimate between stands. Although the available training data do not include stands older than 10 yr or planted before 2000, the model produces reasonable wood volumes when extrapolated to all identified rotations (Fig. 3).

Question 2: Has wood production declined with successive rotations on the same units of land?

In the 3,590 stands with at least three complete rotations between 1984 and 2016, modeled wood volume showed a nonlinear trend, with the lowest volume in the second rotation ($P < 0.0001$, Welch’s one-way ANOVA and Games-Howell test for each biome). Median change in wood volume within a stand was –12% in the Atlantic Forest and –18% in the Cerrado. Wood volume increased in the third rotation, equaling the first-rotation volume in the Cerrado ($P = 0.272$, $n = 1,258$), but only partially recovering in Atlantic Forest stands (rotation 3 volume < rotation 1 volume, $P < 10^{-5}$, $n = 2,332$; Fig. 4a). Mean third-rotation volumes were 256 m³/ha

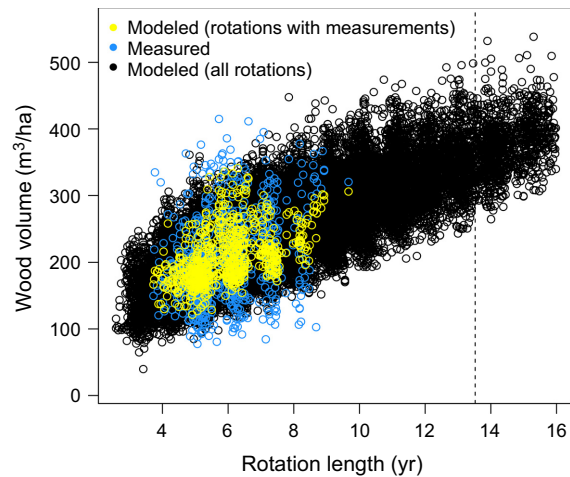


FIG. 3. Modeled and measured wood volumes per rotation plotted against rotation length to demonstrate the extent to which the model captures the variation among stands. The model is trained on inventory data for 707 stands (blue circles). Assuming that the model holds over time and for longer rotations, the relationship between the distributions of the yellow circles (modeled values) and the measured blue circles should reflect the relationship between the black circles (modeled values for all identified rotations) and the true wood volume produced in each rotation. The x-axis is truncated at 16 yr; 95% of detected rotations were shorter than 13.5 yr (dashed line).

TABLE 2. Components of wood volume model.

Predictor (units)	Biological significance	Coefficient	SE	t	P(> t)
Rotation length (months)	time trees are allowed to accumulate wood	1.510	0.160	9.45	$<2 \times 10^{-16}$
Maximum NIRv (arbitrary scale, 95% range 2,081–4,577)	proxy of maximum primary productivity, generally at canopy closure	0.0464	0.0058	7.99	5.55×10^{-15}
Median NIRv of first 2 yr	primary productivity prior to canopy closure, when NIRv is most correlated with wood production	0.0265	0.0039	6.78	2.61×10^{-11}
Intercept (m ³ /ha)	NA	–0.010	0.174	–5.77	1.17×10^{-8}

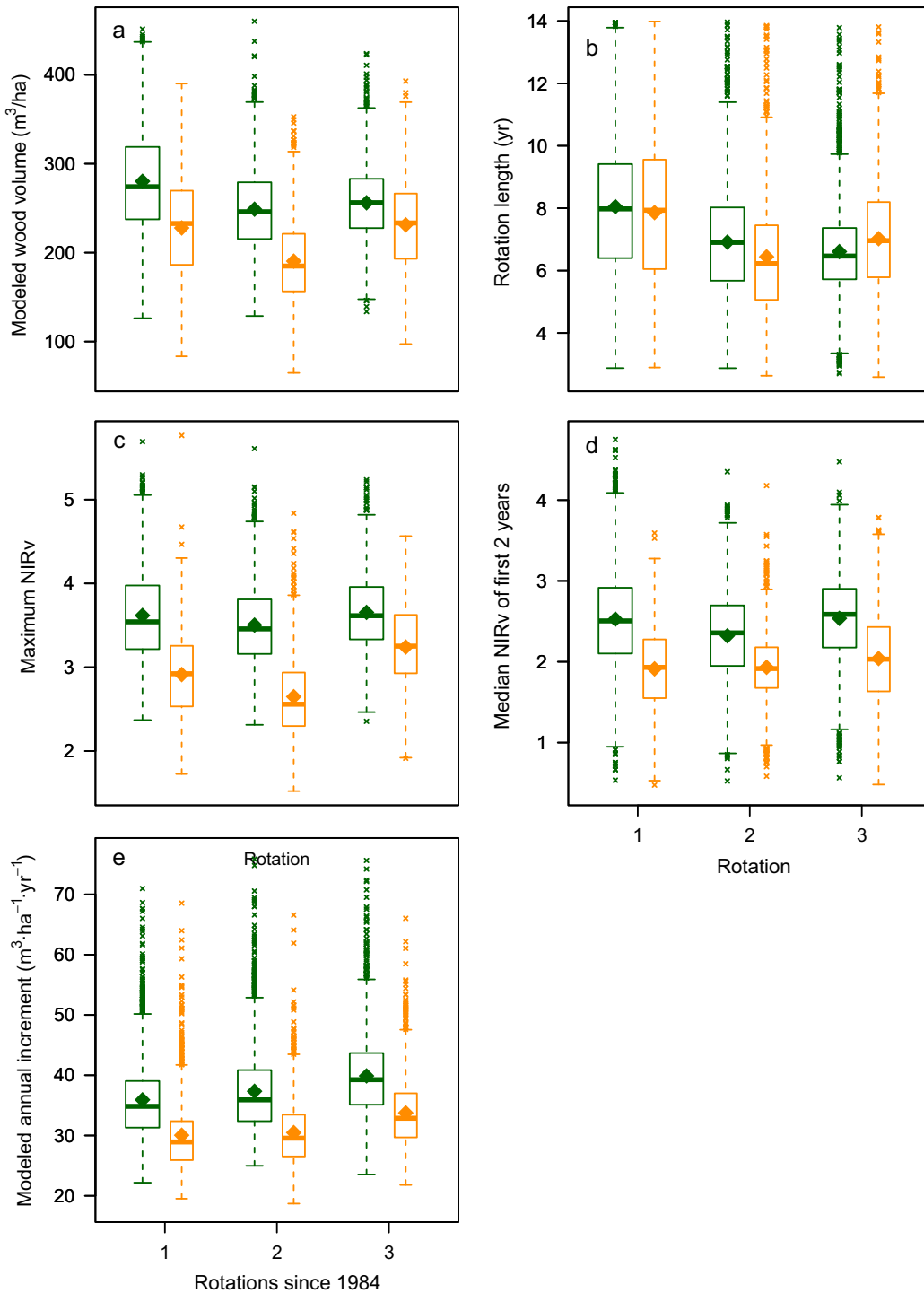


FIG. 4. (a) Modeled wood volume generally decreased, then recovered in the 3,590 stands with at least three complete rotations since 1984, due to (b) decreases between the first and third rotations in rotation length and increases in productivity rates as (c, d) represented by NIRv. (e) Mean annual increment (the quotient of panels a and b) increased in each rotation. The magnitude of these trends differed between the Atlantic Forest (green boxes, 2,332 stands) and the Cerrado (orange boxes, 1,258 stands; significant biome-rotation interactions in ANOVA, $P < 10^{-15}$). NIRv is unitless; surface reflectance from USGS data product (used in the wood volume model) has been divided by 1,000 for neatness. Boxes represent the 25th to 75th quantiles, dark lines show medians, diamonds show means, and whiskers extend to the most extreme data point within 1.45 times the box length (equivalent to the 95% interval in the case of normally distributed data).

in the Atlantic Forest and 231 m³/ha in the Cerrado, 9% lower and 2% higher than mean volumes in the first rotation, respectively.

Dividing modeled wood volume by rotation length, we observe an increase in annual productivity in successive rotations ($P < 10^{-5}$ for all comparisons). Between rotations 1 and 3, the mean annual increment increased from 36.0 to 40.6 m³·ha⁻¹·yr⁻¹ in the Atlantic Forest region and 30.1 to 33.8 m³·ha⁻¹·yr⁻¹ in the Cerrado, comparable to the reported industry average of 36 m³·ha⁻¹·yr⁻¹ for 2015 (IBÁ 2016). Wood density varies between clones; assuming a density of 511 kg/m³ (average of five literature values; Gominho et al. 2001, Couto et al. 2013, Sharma et al. 2015), this corresponds to a third-rotation mean annual wood production of 17.3–20.4 Mg/ha, or 9–10 Mg C·ha⁻¹·yr⁻¹ if wood is ~50% carbon. For comparison, annual C uptake for secondary Neotropical forests in the first 20 yr of regrowth ranges from 1 to 11 Mg C·ha⁻¹·yr⁻¹, with a mean of 3 Mg C·ha⁻¹·yr⁻¹ (Poorter et al. 2016).

In stands with three or more rotations, rotation length decreased between the first and second rotation ($P < 10^{-5}$) by an average of 14 months (Atlantic Forest; 95% confidence interval 12.0–15.3 months) or 17 months (Cerrado, 14.5–19.6 months), decreasing by another 3.7 months (2.2–5.1 months) in the third rotation in the Atlantic Forest region but increasing again by an average of 7 months (CI 4.8–9.1) in the Cerrado ($P < 10^{-5}$; Fig. 4b).

Peak plantation NIRv in both biomes was greatest in the third rotation and lowest in the second, although the third-rotation increase was greater in the Cerrado (Fig. 4c; $P < 10^{-5}$ for all comparisons except rotation 3 vs. 1 in Atlantic Forest, where $P = 0.036$). The trend was similar for the median NIRv of the first two years of each rotation; rotations 1 and 3 were statistically equivalent for this metric in the Atlantic Forest ($P = 0.86$), as were rotations 1 and 2 in the Cerrado ($P = 0.60$), indicating similar rates of canopy closure in those rotations (Fig. 4d).

We hypothesized that plant stresses that accumulate during and between rotations, such as water or nutrient depletion (Laclau et al. 2010, Mendham et al. 2011), would reduce NIRv at the end of the rotation, especially after multiple rotations. To test this hypothesis, we analyzed trends in the ratio of the mean NIRv of the last two years of each rotation to the rotation peak NIRv, as this ratio would decrease in the case of late-rotation NIRv declines. Rather than decreasing in successive rotations, the ratio was negatively correlated to rotation length (Spearman's rho = -0.44), such that it increased with each successive rotation in the Atlantic Forest and followed the pattern: rotation 1 < 3 < 2 in the Cerrado ($P < 10^{-5}$ for all comparisons). This correlation suggests that NIRv decreases with age following canopy closure, as observed in stands with known wood volume (Appendix S1: Fig. S2), but also suggests that trees are generally harvested before late-rotation stresses can

further reduce productivity. This additional metric therefore supports our finding that wood production does not decline with successive harvests.

Question 3: How important is management, relative to broader environmental changes, in determining production trends?

Unlike rotation length, which depends solely on management decisions, annual productivity in plantations may also depend on environmental factors affecting all vegetation, such as precipitation and atmospheric CO₂. Interestingly, we observed clear increases in the NIRv of both *Eucalyptus* and native vegetation over time, especially in the last decade of the time series (Fig. 5). For native vegetation around stands with three or more rotations in both biomes, NIRv increased significantly in each successive rotation, rather than decreasing during the second rotation as in the plantations ($P < 10^{-5}$ for all differences except rotation 2 vs. 1 in Atlantic Forest, $P = 0.007$, Games-Howell comparison). Native vegetation NIRv showed a significant linear relationship with year (linear mixed-effects model with random intercept for each stand, $P < 10^{-5}$, 116,907 observations in 3,543 groups, $R^2 = 0.69$). Annual NIRv also increased in native vegetation located at least 8 km from any stand, which is unlikely to be affected by plantation management (linear mixed-effects model, $n = 708$ vegetation patches, $R^2 = 0.74$). Annual native vegetation NIRv increased at the same rate in both biomes (Appendix S1: Table S2). However, in the Cerrado, plantation NIRv increased much faster than that of native vegetation, while the two trajectories were only slightly different in the Atlantic Forest ($P = 0.0008$, Appendix S1: Table S2).

Since the early 2000s, plantations have expanded into areas with lower mean native vegetation NIRv (Fig. 6). These areas also tend to be further west, warmer, and flatter, with a more pronounced dry season, characteristic of the Cerrado region. *Eucalyptus* in these regions is still able to achieve high NIRv values, though lower, on average, than for the Atlantic Forest in the same year (Appendix S1: Table S2).

DISCUSSION

We modeled wood volume in successive harvest cycles over thousands of *Eucalyptus* stands in southeastern Brazil and determined that decreasing rotation length and increasing plantation growth rates, as represented by the NIRv index, combined to generally sustain wood production over three rotations. In both the Atlantic Forest and Cerrado biomes, wood production decreased between the first and second rotations, by an average of 8%. However, continued increases in productivity as represented by NIRv, beyond the increases observed in unmanaged vegetation, allowed wood production to recover in the third rotation in the Cerrado. In the generally older Atlantic Forest plantations, continued

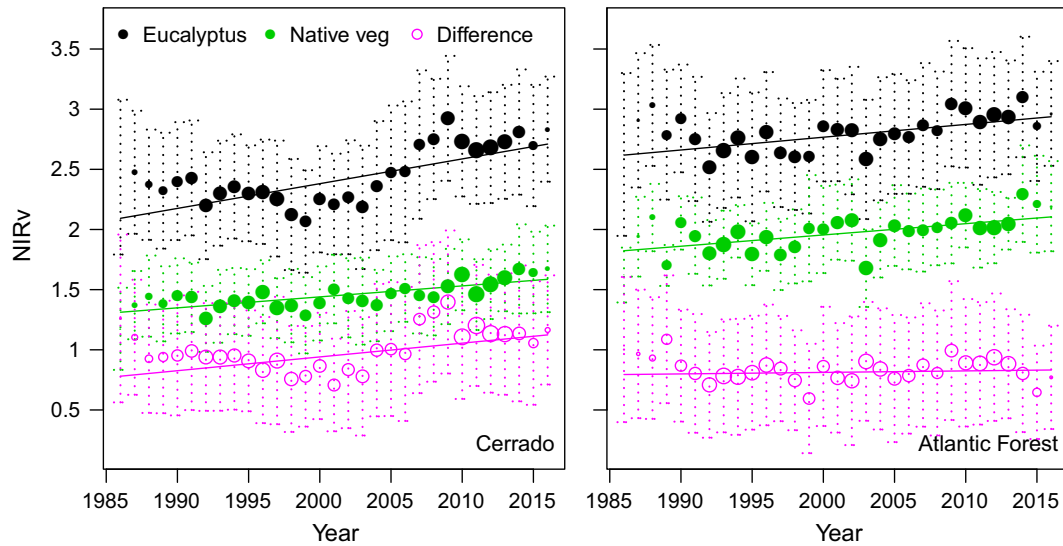


FIG. 5. NIRv increases over time in plantation stands with at least three rotations and in the native vegetation around these stands. Increases are larger in the Eucalyptus (black) than in the native vegetation (green), as indicated by the increasing difference between Eucalyptus and native NIRv for a given stand and date (open pink), particularly in the Cerrado. Points indicate mean NIRv (unitless) for each year, and bars indicate one standard deviation of the annual values across stands. NIRv observations are only included after the second year of each rotation to remove low pre-canopy closure values; point sizes represent the proportion of the 1,258 Cerrado stands or 2,332 Atlantic Forest stands included in each year. Solid lines represent linear model fits of NIRv vs. year, weighted by number of stands per year.

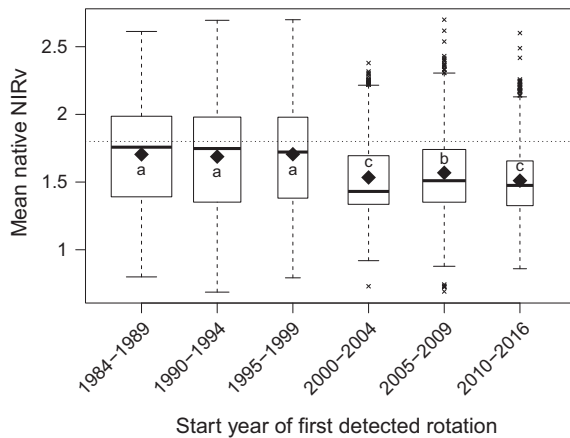


FIG. 6. Eucalyptus has expanded into Cerrado areas with less productive native vegetation, particularly in the 2000s. See Fig. 4 for box plot descriptions. Box widths represent number of stands established in each time period. Boxes with different letters have significantly different means (Games-Howell test). Horizontal line at 1.8 denotes the approximate boundary between Cerrado and Atlantic Forest native vegetation mean NIRv over 33 yr.

decreases in rotation length and modest NIRv increases led to incomplete recovery of production in the third rotation. In both biomes, recent management practices appear adequate to sustain high rates of wood production, at least when coupled with regional increases in vegetation productivity.

Rotation length and NIRv early in rotation roughly predict stand-level wood production

A wood volume model based on rotation length derived from segmenting NIRv time series into harvest cycles, together with the peak and median pre-canopy closure NIRv of each cycle, was able to predict 36% of the variance in final wood volume for the available training data. We extrapolated this model in space and time to examine regional trends in wood production. Similar conceptually simple models based on rotation length and NIRv at the beginning of the rotation may also predict wood production in other short-rotation forestry systems where the pre-canopy closure period is important in determining tree growth and final wood production.

More complex models, such machine-learning approaches incorporating many remotely sensed variables or ancillary measurements, can provide more accurate estimates of wood volume or stand biomass than our method is able to produce (Baghdadi et al. 2014, Xi et al. 2016, Dube et al. 2017). The strengths of our model are its simplicity, requiring only NIRv data as inputs, and the biological basis for each term included, which increases our confidence in the model’s applicability to stands and years beyond the available training data. The correlation between NIRv and wood volume is strongest before the canopy closes, about two years after planting, during which time the young trees increase leaf and stem biomass at similar rates (Borges 2009, le Maire et al. 2011). After canopy closure, wood volume

increases near-linearly until harvest for typical rotation lengths, while the leaf area observed by satellites typically declines (le Maire et al. 2011; F. Gomes, *unpublished data* [Appendix S1: Fig. S2]). Our model therefore incorporates the most informative parts of the NIRv time series of each rotation: rotation length and metrics of the peak and pre-peak growth rates. As multidecadal time series become available from additional remote sensing platforms, such as MODIS or repeated Lidar measurements, more sophisticated analyses of multi-rotation trends will be possible.

We note that the observed decreases in rotation length and increases in NIRv after the first rotation may be magnified by errors in the rotation delineation. Compared to visual inspection of NIRv time series, 17% of 500 stands had errors in the length of a rotation, with a mean error of 0.5 yr too long (0.7 yr too long in first and second rotations, 0.9 yr too short in the third). An error in rotation length of one year corresponds to 18 m³/ha for a given pre-peak and peak NIRv (Table 2). In addition, 9% of the 500 stands had a falsely detected first rotation in which low NIRv suggested that *Eucalyptus* had not yet been established in that stand; fewer than 1% of stands had a falsely detected second or third rotation. However, the magnitude and frequency of these errors are not sufficient to drive the observed trends in rotation length and NIRv, which are consistent with our knowledge of changing management practices.

Monitoring change in vegetation productivity over multiple rotations requires detecting multiple harvest and recovery periods from a few cloud-free observations per year, so we expected our rotation delineation algorithm to be less accurate than methods that look for a single deforestation or harvest event, or use higher temporal resolution data over a shorter time period (Verbeselt et al. 2010, le Maire et al. 2011, Dutrieux et al. 2015). Prior work attempting to identify multiple harvest and regrowth cycles also achieved an accuracy of <80% for sites that lacked a multi-year “calibration” period without harvests (DeVries et al. 2015), as in our approach.

Independent of rotation detection, predicting wood production in individual stands is complicated by differences in canopy structure and biomass partitioning between sites and genotypes. A project comparing the performance of *Eucalyptus* clones across environmental gradients in Brazil found large variation in production both within a clone across sites and between clones within a site (Binkley et al. 2017). We attempted to incorporate this inter-clonal and inter-site variability by training the model on stands with a wide range of production: 77–415 m³/ha of final wood volume or 11.5–66.8 m³·ha⁻¹·yr⁻¹ (33.2 ± 9.22 m³·ha⁻¹·yr⁻¹ [mean \pm SD]). Our training data include stands from three companies across two biomes, with one company providing wood volume data for 45 clones. The near six-fold range in wood volume easily encompasses the increase that would be expected over time based on

productivity increases reported by the Brazilian *Eucalyptus* industry, from 26 m³·ha⁻¹·yr⁻¹ in 1990 to 36 m³·ha⁻¹·yr⁻¹ in 2015 (Gonçalves et al. 2013, IBÁ 2016). This range suggests that the variability in wood production within the training set of stands will encompass the variability in the region over time, despite the lack of data from stands established prior to 2000.

Trends in wood production reflect management intensification and its possible limits

Across all stands in the region, we did not observe sustained declines in wood production with successive harvests. Instead, we observed three major trends in the NIRv time series from which we modeled production: decreasing rotation length, primarily between the first and second rotations; increasing peak-of-rotation, pre-peak, and annual NIRv, particularly in the last 10 yr; and increasing NIRv in adjacent native vegetation. These patterns combine to yield a nonlinear trend in which wood volume declines from the first to the second rotation, but recovers in the third rotation (Fig. 4). Our remote sensing analysis reflects the reported increase in industry-average annual growth rates of plantation *Eucalyptus* between the 1990s and 2010s. These increases have been driven primarily by development of new hybrid clones better adapted to site conditions and pathogens, but also by increased fertilizer inputs, less destructive site preparation (abandonment of tilling and slash burning in favor of subsoiling within rows), and new methods of managing pests and pathogens (Gonçalves et al. 2013, IBÁ 2016). Our findings are also consistent with reports from slower-growing forestry systems of a general “second-rotation decline” and possible recovery as management intensity increases to compensate for adverse effects of harvests on site quality (Evans 2001, O’Hehir and Nambiar 2010).

In the Atlantic Forest region, NIRv increased only slightly faster in plantations than in the adjacent forest, in contrast to the Cerrado (Fig. 5), and third-rotation wood volume was slightly less than in the first rotation. Our analysis therefore suggests that management is no longer rapidly increasing wood production in this biome. This may be because after three or more rotations (as noted, many Atlantic Forest stands were first planted prior to 1984), management is well adapted to the region and no further intensification is necessary, or because intensification is required just to maintain production.

If the observed decreases in rotation length suggest continued management intensification, production may be declining per rotation and per unit input, challenging economic if not ecological sustainability. In one plantation company, nitrogen inputs increased from 12 to 26 kg N/ha per rotation after 2011, while in another, nitrogen inputs increased from 7.5 kg/ha in the 1990s to 48 kg/ha in 2016–2017, and potassium inputs from 6 to 270 kg/ha (C. Afonso and H. Lourenço, *personal communication*). While these inputs are less than for

common annual crops in the region, fertilizer application may represent a significant operating cost in plantations (Franco et al. 2015, Martins et al. 2015, Matsuura et al. 2017). Fertilization beyond current application rates does not typically increase production following canopy closure (Stape et al. 2010, da Silva et al. 2013, de Gazola et al. 2015, Pulito et al. 2015). Fertilizer is generally applied only in the first 2–3 yr of the rotation, and companies have investigated consolidating into a single application per cycle (da Silva et al. 2013). Labor and machinery costs, organic matter removals, and soil disturbance associated with planting and harvest are of course confined to the ends of each rotation. Thus, while our findings suggest sustained wood production over multiple harvests, this sustainability is contingent on maintaining or increasing external inputs.

As demand for biomass grows and competition for arable land increases, plantation forests continue to expand in regions with lower native vegetation productivity, such as the Cerrado and the current Brazilian plantation frontier of Mato Grosso do Sul (IBÁ 2017). As these plantations mature, it will be important to monitor whether increases in productivity reach a plateau, as in the Atlantic Forest, such that NIRv follows the same trajectory in plantations as in native vegetation. We note that the observed NIRv increases in Cerrado-region plantations could be exaggerated if stands with especially low productivity in the 2010s were misclassified as native vegetation and excluded from the analysis. However, wood volume, NIRv, and their trends did not differ significantly between Cerrado-region stands identified by image classification and those identified by companies (Appendix S1). Overall, NIRv increased substantially across more than 1,000 Cerrado-region *Eucalyptus* stands over successive harvests, suggesting the potential for management to maintain and increase productivity. Collaborative research at regional and pan-tropical scales will continue to be important in minimizing the ecological and economic costs of plantation production (Nambiar et al. 2004, Binkley et al. 2017, Silva et al. 2018).

Environmental trends also contribute to plantation productivity, but additional data are needed to identify drivers of increasing NIRv across vegetation types

Despite intensive management within *Eucalyptus* stands, general increases in vegetation productivity throughout the region may also be important in sustaining wood production. We propose several possible causes for the general increases in NIRv we observed: satellite changes, precipitation trends, fertilization by increased CO₂ or nutrient deposition, and protection from disturbance.

As in all long-term remote sensing analyses, drift in satellite calibration or switches between sensors could lead to spurious trends in vegetation indices. However, large-scale “greening” has been observed across sensor

platforms, despite inconsistencies between and within sensors (de Jong et al. 2011, Tian et al. 2015, Zhang et al. 2017). We use the most recent surface reflectance products (USGS 2017a,b), developed to address sensor-continuity issues as discussed in (Roy et al. 2016), and NIRv shifts do not appear to coincide with satellite launches.

We hypothesized that annual precipitation would be positively correlated with both native vegetation and *Eucalyptus* NIRv, as *Eucalyptus* in the region responded strongly to water availability (Stape et al. 2010), and precipitation is more variable between years than other controls such as temperature and nutrient availability. The plantation industry attributes declining average annual *Eucalyptus* productivity since 2013 to abnormal rainfall, as well as expansion of plantations into harsher environments (IBÁ 2016, 2017). We observed expansion into areas of less productive native vegetation (Fig. 6), but annual precipitation was very weakly correlated with annual mean NIRv in both native vegetation (Spearman’s $\rho = -0.07$, annual NIRv anomaly vs. anomaly in precipitation of last three years) and plantation NIRv ($\rho = -0.05$, excluding the first two years of each rotation). The highest annual NIRv values in native vegetation tend to occur in the drier-than-average 2010–2016 period. A possible explanation is that when the wet season is less cloudy, vegetation growth is less limited by light availability, so photosynthesis, NIRv, and productivity may increase. Alternatively, NIRv could be decoupled from carbon fixation in drought-stressed plants (Yang et al. 2018). Changes in NIRv since 2013 do not strongly affect our wood volume analysis, as the peak of most analyzed rotations occurs prior to 2013.

Recent increases in NIRv of both *Eucalyptus* and native vegetation could also be due to increasing atmospheric CO₂ concentrations. Elevated CO₂ increased the productivity of young *Eucalyptus* and Atlantic Forest species in greenhouse experiments (Ghannoum et al. 2010, de Oliveira et al. 2012), and atmospheric CO₂ has contributed significantly to increased carbon uptake in other biomes (Fernández-Martínez et al. 2017). Atmospheric deposition of nitrogen, projected to increase in southeastern Brazil based on increasing fossil fuel and agricultural emissions (Phoenix et al. 2006), could also increase productivity, even in fertilized plantations, where deposition may help balance nitrogen inputs with removals in harvested biomass.

Alternatively, NIRv could increase in native vegetation near plantations due to protection against disturbances such as logging and fires. Brazilian landowners are mandated to maintain a portion of their land under native vegetation cover (Lei Ordinária n° 12.651/2012), and plantation companies have a substantial stake in demonstrating environmental preservation (Veracel Cellulose 2016). However, native vegetation patches at least 8 km removed from any *Eucalyptus* stand exhibited similar NIRv trends to those of the native vegetation around the *Eucalyptus*, suggesting that plantation-mediated

revegetation is not a primary driver of native vegetation greenness. Local data on each of these factors over time are needed to help determine which factors drive NIRV trends, and whether they will continue to boost productivity in the future.

Management intensification—shorter harvest cycles, increasing inputs, and more rapid tree growth—and general increases in plant growth appear to have sustained high wood production over several harvests in the plantation forests of southeastern Brazil. However, the influence of management in increasing plantation productivity, relative to trends that also affect native vegetation, may be diminished in the most recent rotations in the Atlantic Forest region. In both the Atlantic Forest and the Cerrado biomes, fertilizer, machinery use, and other inputs may be increasing per unit of wood production as management intensifies. Sustaining high rates of wood production in tropical plantation forests will likely require continued investment in genetic and chemical inputs to supplement regional plant productivity trends.

ACKNOWLEDGMENTS

We thank the NUTREE research group at the Federal University of Viçosa, particularly Leonardus Vergütz, for discussing this work and facilitating access to plantation data. We thank the plantation-owning companies Cenibra, Gerdau, and Plantar, and particularly Carlos Afonso, Francisco Gomes, and Guilherme Jesus for providing stand boundary and wood volume data, and Helton Lourenço of Veracel for fertilizer input data. We thank Jean-Paul Laclau and Guericq le Maire for their helpful feedback on the study and the relationships between vegetation indices and wood production. We also thank Christopher Field, Eric Lambin, and the Jackson lab group for their comments on the manuscript, Philip Broderick for statistical support, and George Azzari for Earth Engine guidance. We thank Xiangming Xiao and three anonymous reviewers for their suggestions to improve the manuscript. This work was funded by the School of Earth, Energy, and Environmental Sciences and a Stanford Interdisciplinary Graduate Fellowship, and we thank the Stanford Woods Institute for the Environment for their support of the project. The authors declare no conflict of interest.

LITERATURE CITED

- Badgley, G., C. B. Field, and J. A. Berry. 2017. Canopy near-infrared reflectance and terrestrial photosynthesis. *Science Advances* 3:1–6.
- Baghdadi, N., G. Le Maire, I. Fayad, J. S. Bailly, Y. Nouvellon, C. Lemos, and R. Hakamada. 2014. Testing different methods of forest height and aboveground biomass estimations from ICESat/GLAS data in eucalyptus plantations in Brazil. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7:290–299.
- Berthrong, S. T., E. G. Jobbágy, and R. B. Jackson. 2009. A global meta-analysis of soil exchangeable cations, pH, carbon, and nitrogen with afforestation. *Ecological Applications* 19:2228–2241.
- Berthrong, S. T., G. Piñeiro, E. G. Jobbágy, and R. B. Jackson. 2012. Soil C and N changes with afforestation of grasslands across gradients of precipitation and plantation age. *Ecological Applications* 22:76–86.
- Binkley, D., O. C. Campoe, C. Alvares, R. L. Carneiro, Í. Cegatta, and J. L. Stape. 2017. The interactions of climate, spacing and genetics on clonal Eucalyptus plantations across Brazil and Uruguay. *Forest Ecology and Management* 405:271–283.
- Booth, T. H. 2013. Eucalypt plantations and climate change. *Forest Ecology and Management* 301:28–34.
- Borges, J. S. 2009. Parametrização, calibração e validação do modelo 3-PG para eucalipto na região do Cerrado de Minas Gerais. Federal University of Viçosa, Viçosa, Minas Gerais, Brazil.
- Brockerhoff, E. G., H. Jactel, J. A. Parrotta, C. P. Quine, and J. Sayer. 2008. Plantation forests and biodiversity: Oxymoron or opportunity? *Biodiversity and Conservation* 17:925–951.
- Brockerhoff, E. G., H. Jactel, J. A. Parrotta, and S. F. B. Ferraz. 2013. Role of eucalypt and other planted forests in biodiversity conservation and the provision of biodiversity-related ecosystem services. *Forest Ecology and Management* 301:43–50.
- Byerlee, D., J. Stevenson, and N. Villoria. 2014. Does intensification slow crop land expansion or encourage deforestation? *Global Food Security* 3:92–98.
- Cambi, M., G. Certini, F. Neri, and E. Marchi. 2015. The impact of heavy traffic on forest soils: A review. *Forest Ecology and Management* 338:124–138.
- Chazdon, R. L. 2008. Beyond deforestation: restoring forests and ecosystem services on degraded lands. *Science* 320:1458–1460.
- Coops, N. C., and R. H. Waring. 2001. Estimating forest productivity in the eastern Siskiyou Mountains of southwestern Oregon using a satellite driven process model, 3-PGS. *Canadian Journal of Forest Research* 31:143–154.
- Couto, A. M., P. F. Trugilho, T. A. Neves, T. de P. Protásio, and V. A. de Sá. 2013. Modeling of basic density of wood from *Eucalyptus grandis* and *Eucalyptus urophylla* using nondestructive methods. *Cerne* 19:27–34.
- Danielson, J. J., and D. B. Gesch. 2011. Global multi-resolution terrain elevation data 2010. U.S. Geological Survey Open-File Report 2011-1073, 26 p. <https://doi.org/10.3133/ofr20111073>
- da Silva, P. H. M., F. Poggiani, P. L. Libardi, and A. N. Gonçalves. 2013. Fertilizer management of eucalypt plantations on sandy soil in Brazil: Initial growth and nutrient cycling. *Forest Ecology and Management* 301:67–78.
- de Gazola, R. N., S. Buzetti, M. C. M. T. Filho, R. P. Dinalli, M. L. T. de Moraes, T. de S. Celestrino, P. H. M. de Silva, and E. Dupas. 2015. Doses of N, P and K in the cultivation of eucalyptus in soil originally under Cerrado vegetation. *Semina: Ciências Agrárias* 36:1895–1912.
- de Jong, R., S. de Bruin, A. de Wit, M. E. Schaepman, and D. L. Dent. 2011. Analysis of monotonic greening and browning trends from global NDVI time-series. *Remote Sensing of Environment* 115:692–702.
- Deng, Q., D. E. McMahon, Y. Xiang, C.-L. Yu, R. B. Jackson, and D. Hui. 2017. A global meta-analysis of soil phosphorus dynamics after afforestation. *New Phytologist* 213:181–192.
- de Oliveira, E. A. D., A. U. Approbato, J. R. Legracie, and C. A. Martinez. 2012. Soil-nutrient availability modifies the response of young pioneer and late successional trees to elevated carbon dioxide in a Brazilian tropical environment. *Environmental and Experimental Botany* 77:53–62.
- DeVries, B., M. Decuyper, J. Verbesselt, A. Zeileis, M. Herold, and S. Joseph. 2015. Tracking disturbance-regrowth dynamics in tropical forests using structural change detection and Landsat time series. *Remote Sensing of Environment* 169:320–334.
- Dong, J., X. Xiao, B. Chen, N. Torbick, C. Jin, G. Zhang, and C. Biradar. 2013. Mapping deciduous rubber plantations through integration of PALSAR and multi-temporal Landsat imagery. *Remote Sensing of Environment* 134:392–402.

- Dube, T., O. Mutanga, E. M. Abdel-Rahman, R. Ismail, and R. Slotow. 2015. Predicting Eucalyptus spp. stand volume in Zululand, South Africa: an analysis using a stochastic gradient boosting regression ensemble with multi-source data sets. *International Journal of Remote Sensing* 36:3751–3772.
- Dube, T., M. Sibanda, C. Shoko, and O. Mutanga. 2017. Stand-volume estimation from multi-source data for coppiced and high forest *Eucalyptus* spp. silvicultural systems in KwaZulu-Natal, South Africa. *ISPRS Journal of Photogrammetry and Remote Sensing* 132:162–169.
- Dutrieux, L. P., J. Verbesselt, L. Kooistra, and M. Herold. 2015. Monitoring forest cover loss using multiple data streams, a case study of a tropical dry forest in Bolivia. *ISPRS Journal of Photogrammetry and Remote Sensing* 107:112–125.
- Evans, J. 2001. Biological sustainability of productivity in successive rotations. *Forest Plantations Thematic Paper 2*. Forestry Department. FAO, Rome, Italy.
- FAO. 2015. Global forest resources assessment 2015. FAO, Rome, Italy.
- Fernández-Martínez, M., et al. 2017. Atmospheric deposition, CO₂, and change in the land carbon sink. *Scientific Reports* 7:1–13.
- Filho, E. I. F., and C. E. G. R. Schaefer. 2010. Mapa de solos do estado de Minas Gerais. Fundação Estadual do Meio Ambiente, Belo Horizonte, Brazil.
- Foga, S., P. L. Scaramuzza, S. Guo, Z. Zhu, R. D. Dilley, T. Beckmann, G. L. Schmidt, J. L. Dwyer, M. J. Hughes, and B. Laue. 2017. Cloud detection algorithm comparison and validation for operational Landsat data products. *Remote Sensing of Environment* 194:379–390.
- Fox, T. R. 2000. Sustained productivity in intensively managed forest plantations. *Forest Ecology and Management* 138:187–202.
- Fox, J., and J. C. Castella. 2013. Expansion of rubber (*Hevea brasiliensis*) in mainland Southeast Asia: What are the prospects for smallholders? *Journal of Peasant Studies* 40:155–170.
- Franco, A. L. C., M. R. Cherubin, P. S. Pavinato, C. E. P. Cerri, J. Six, C. A. Davies, and C. C. Cerri. 2015. Soil carbon, nitrogen and phosphorus changes under sugarcane expansion in Brazil. *Science of the Total Environment* 515–516:30–38.
- Funk, C. C., P. J. Peterson, M. F. Landsfeld, D. H. Pedreros, J. P. Verdin, J. D. Rowland, B. E. Romero, G. J. Husak, J. C. Michaelsen, and A. P. Verdin. 2014. A quasi-global precipitation time series for drought monitoring: U.S. Geological Survey Data Series 832. U.S. Geological Survey, Reston, Virginia, USA.
- Ghannoum, O., N. G. Phillips, J. P. Conroy, R. A. Smith, R. D. Attard, R. Woodfield, B. A. Logan, J. D. Lewis, and D. T. Tissue. 2010. Exposure to preindustrial, current and future atmospheric CO₂ and temperature differentially affects growth and photosynthesis in *Eucalyptus*. *Global Change Biology* 16:303–319.
- Gominho, J., J. Figueira, J. C. Rodrigues, and H. Pereira. 2001. Within-tree variation of heartwood, extractives and wood density in the eucalypt hybrid urograndis (*Eucalyptus grandis* × *E. urophylla*). *Wood and Fiber Science* 33:3–8.
- Gonçalves, J. L. M., J. L. Stape, J.-P. Laclau, J.-P. Bouillet, and J. Ranger. 2008. Assessing the effects of early silvicultural management on long-term site productivity of fast-growing eucalypt plantations: the Brazilian experience. *Southern Forests* 70:105–118.
- Gonçalves, J. L. de M., et al. 2013. Integrating genetic and silvicultural strategies to minimize abiotic and biotic constraints in Brazilian eucalypt plantations. *Forest Ecology and Management* 301:6–27.
- Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore. 2017. Remote Sensing of Environment Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*. 202:18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Guillaume, T., M. Damris, and Y. Kuzyakov. 2015. Losses of soil carbon by converting tropical forest to plantations: erosion and decomposition estimated by d13C. *Global Change Biology* 21:3548–3560.
- Hapfelmeier, A., T. Hothorn, K. Ulm, and C. Strobl. 2014. A new variable importance measure for random forests with missing data. *Statistical Computing* 24:21–34.
- Harwood, C. E., and E. K. S. Nambiar. 2014. Productivity of acacia and eucalypt plantations in Southeast Asia. 2. Trends and variations. *International Forestry Review* 16:249–260.
- Heilmayr, R. 2014. Conservation through intensification? The effects of plantations on natural forests. *Ecological Economics* 105:204–210.
- Hothorn, T., K. Hornik, C. Strobl, and A. Zeileis. 2015. Package “party”: A laboratory for recursive partitioning. <http://party.R-forge.R-project.org>
- IBÁ. 2016. Indústria Brasileira de Árvores (Brazilian Tree Industry) annual report 2016. IBÁ, São Paulo, Brazil.
- IBÁ. 2017. Indústria Brasileira de Árvores (Brazilian Tree Industry) annual report 2017. IBÁ, São Paulo, Brazil.
- Indufor. 2012. Strategic review on the future of forest plantations. Indufor, Helsinki, Finland.
- Jackson, R. B., E. G. Jobbágy, R. Avissar, S. B. Roy, D. J. Barrett, C. W. Cook, K. A. Farley, D. C. le Maitre, B. A. McCarl, and B. C. Murray. 2005. Trading water for carbon with biological carbon sequestration. *Science* 310:1944–1947.
- Klink, C. A., and A. G. Moreira. 2002. Past and current human occupation, and land use. Pages 69–88 in Oliveira, P. S. and R. J. Marquis editors. *The Cerrados of Brazil: ecology and natural history of a Neotropical Savanna*. Columbia University Press, New York City, New York, USA.
- Kraxner, F., et al. 2013. Global bioenergy scenarios – Future forest development, land-use implications, and trade-offs. *Biomass and Bioenergy* 57:86–96.
- Kröger, M., and J. E. Nylund. 2012. The conflict over Veracel pulpwood plantations in Brazil – Application of ethical analysis. *Forest Policy and Economics* 14:74–82.
- Laclau, J.-P., et al. 2010. Biogeochemical cycles of nutrients in tropical Eucalyptus plantations: main features shown by intensive monitoring in Congo and Brazil. *Forest Ecology and Management* 259:1771–1785.
- Laclau, J.-P., E. A. da Silva, G. Rodrigues Lambais, M. Bernoux, G. le Maire, J. L. Stape, J.-P. Bouillet, J. L. M. Gonçalves, C. Jourdan, and Y. Nouvellon. 2013. Dynamics of soil exploration by fine roots down to a depth of 10 m throughout the entire rotation in *Eucalyptus grandis* plantations. *Frontiers in Plant Science* 4:243.
- Lambin, E. F., and P. Meyfroidt. 2011. Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences USA* 108:3465–3472.
- Langholtz, M. H., B. J. Stokes, and L. M. Eaton. 2016. 2016 billion-ton report: Advancing domestic resources for a thriving bioeconomy. U.S. Department of Energy, Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA.
- Lei Ordinária no 12.651/2012 (Forest Code of 2012). 2012. Brasília, Distrito Federal, Brazil.
- le Maire, G., C. Marsden, Y. Nouvellon, C. Grinand, R. Hakamada, J. L. Stape, and J.-P. Laclau. 2011. MODIS NDVI time-series allow the monitoring of *Eucalyptus* plantation biomass. *Remote Sensing of Environment* 115:2613–2625.

- Leite, F. P., I. R. Silva, R. F. Novais, N. F. De Barros, and J. C. L. Neves. 2010. Alterations of soil chemical properties by eucalyptus cultivation in five regions in the Rio Doce Valley. *Revista Brasileira de Ciência do Solo* 34:821–831.
- Liu, L., D. Peng, Z. Wang, and Y. Hu. 2014. Improving artificial forest biomass estimates using afforestation age information from time series Landsat stacks. *Environmental Monitoring and Assessment* 186:7293–7306.
- Lokhorst, J., B. Venables, B. Turlach, and M. Maechler. 2014. lasso2: L1 constrained estimation aka 'lasso'. <https://cran.r-project.org/package=lasso2>
- Lumley, T., and A. Miller. 2017. leaps: regression subset selection. <https://cran.r-project.org/package=leaps>
- Lyons, K., and P. Westoby. 2014. Carbon colonialism and the new land grab: Plantation forestry in Uganda and its livelihood impacts. *Journal of Rural Studies* 36:13–21.
- Marsden, C., G. le Maire, J. L. Stape, D. Lo Seen, O. Roupsard, O. Cabral, D. Epron, A. M. N. Lima, and Y. Nouvellon. 2010. Relating MODIS vegetation index time-series with structure, light absorption and stem production of fast-growing Eucalyptus plantations. *Forest Ecology and Management* 259:1741–1753.
- Martins, M. R., C. P. Jantalia, J. C. Polidoro, J. N. Batista, B. J. R. Alves, R. M. Boddey, and S. Urquiaga. 2015. Nitrous oxide and ammonia emissions from N fertilization of maize crop under no-till in a Cerrado soil. *Soil and Tillage Research* 151:75–81.
- Matsuura, M. I. S. F., F. R. T. Dias, J. F. Picoli, K. R. G. Lucas, C. de Castro, and M. H. Hirakuri. 2017. Life-cycle assessment of the soybean-sunflower production system in the Brazilian Cerrado. *International Journal of Life Cycle Assessment* 22:492–501.
- Mendham, D. S., D. A. White, M. Battaglia, J. F. McGrath, T. M. Short, G. N. Ogden, and J. Kinal. 2011. Soil water depletion and replenishment during first- and early second-rotation *Eucalyptus globulus* plantations with deep soil profiles. *Agricultural and Forest Meteorology* 151:1568–1579.
- Nambiar, E. K. S., J. Ranger, A. Tiarks, and T. Toma, editors. 2004. Site management and productivity in tropical plantation forests. *In Proceedings of Workshops in Congo July 2001 and China February 2003*. Center for International Forestry Research, Bogor Barat, Indonesia.
- Nightingale, J. M., M. J. Hill, S. R. Phinn, I. D. Davies, A. A. Held, and P. D. Erskine. 2008. Use of 3-PG and 3-PGS to simulate forest growth dynamics of Australian tropical rainforests. I. Parameterisation and calibration for old-growth, regenerating and plantation forests. *Forest Ecology and Management* 254:107–121.
- Nissim, W. G., F. E. Pitre, T. I. Teodorescu, and M. Labrecque. 2013. Long-term biomass productivity of willow bioenergy plantations maintained in southern Quebec, Canada. *Biomass and Bioenergy* 56:361–369.
- O'Hehir, J. F., and E. K. S. Nambiar. 2010. Productivity of three successive rotations of *P. radiata* plantations in South Australia over a century. *Forest Ecology and Management* 259:1857–1869.
- Parrotta, J. A. 1999. Productivity, nutrient cycling, and succession in single and mixed-species plantations of *Casuarina equisetifolia*, *Eucalyptus robusta*, and *Leucaena leucocephala* in Puerto Rico. *Forest Ecology and Management* 124:45–77.
- Paruelo, J. M., H. E. Epstein, W. K. Lauenroth, and I. C. Burke. 1997. ANPP estimates from NDVI for the central grassland region of the United States. *Ecology* 78:953–958.
- Payn, T., J. M. Carnus, P. Freer-Smith, M. Kimberley, W. Kolbert, S. Liu, C. Orazio, L. Rodriguez, L. N. Silva, and M. J. Wingfield. 2015. Changes in planted forests and future global implications. *Forest Ecology and Management* 352:57–67.
- Peters, G. 2018. userfriendlyscience: quantitative analysis made accessible. <http://doi.org/10.17605/osf.io/txequ>
- Phoenix, G. K., et al. 2006. Atmospheric nitrogen deposition in world biodiversity hotspots: The need for a greater global perspective in assessing N deposition impacts. *Global Change Biology* 12:470–476.
- Poore, M. E. D., and C. Fries. 1985. The ecological effects of eucalyptus. *FAO Forestry Papers*. FAO, Rome, Italy.
- Poorter, L., et al. 2016. Biomass resilience of Neotropical secondary forests. *Nature* 530:211–214.
- Pulito, A., et al. 2015. Available nitrogen and responses to nitrogen fertilizer in Brazilian eucalypt plantations on soils of contrasting texture. *Forests* 6:973–991.
- Qiao, H., M. Wu, M. Shakir, L. Wang, J. Kang, and Z. Niu. 2016. Classification of small-scale Eucalyptus plantations based on NDVI time series obtained from multiple high-resolution datasets. *Remote Sensing* 8:117.
- R Core Team. 2016. R: a language and environment for statistical computing. R Core Team, Vienna, Austria. www.R-project.org
- Ribeiro, M. C., J. P. Metzger, A. C. Martensen, F. J. Ponzoni, and M. M. Hirota. 2009. The Brazilian Atlantic Forest: How much is left, and how is the remaining forest distributed? Implications for conservation. *Biological Conservation* 142:1141–1153.
- Roy, D. P., V. Kovalsky, H. K. Zhang, E. F. Vermote, L. Yan, S. S. Kumar, and A. Egorov. 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Remote Sensing of Environment* 185:57–70.
- Sharma, S. K., S. R. Shukla, S. Shashikala, and V. S. Poornima. 2015. Axial variations in anatomical properties and basic density of Eucalypt urograndis hybrid (*Eucalyptus grandis* × *E. urophylla*) clones. *Journal of Forestry Research* 26:739–744.
- Silva, J. F., M. R. Fariñas, J. M. Felfili, and C. A. Klink. 2006. Spatial heterogeneity, land use and conservation in the Cerrado region of Brazil. *Journal of Biogeography* 33:536–548.
- Silva, L. N., P. Freer-Smith, and P. Madsen. 2018. Production, restoration, mitigation: a new generation of plantations. *New Forests* 1–16. <https://doi.org/10.1007/s11056-018-9644-6>
- Stape, J. L., et al. 2010. The Brazil Eucalyptus Potential Productivity Project: Influence of water, nutrients and stand uniformity on wood production. *Forest Ecology and Management* 259:1684–1694.
- Tian, F., R. Fensholt, J. Verbesselt, K. Grogan, S. Horion, and Y. Wang. 2015. Evaluating temporal consistency of long-term global NDVI datasets for trend analysis. *Remote Sensing of Environment* 163:326–340.
- Tucker, C. J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* 8:127–150.
- USGS. 2017a. Landsat 8 Surface Reflectance Code (LaSRC) product guide. Version 8.0. A new Product Guide with the same title was released December 2018, Sioux Falls, SD, USA, Version 1.0. https://prd-wret.s3-us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/atoms/files/LSDS-1368_%20L8_Surface-Reflectance-Code-LASRC-Product-Guide.pdf
- USGS. 2017b. Landsat 4-7 surface reflectance (LEDAPS) product guide. Version 1.0, Sioux Falls, SD. https://prd-wret.s3-us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/atoms/files/LSDS-1370_L4-7_Surface%20Reflectance-LEDAPS-Product-Guide.pdf
- Veracel Cellulose. 2016. Sustainability report 2016: base year 2015. Veracel Celulose, São Paulo, Brazil
- Verbesselt, J., R. Hyndman, G. Newnham, and D. Culvenor. 2010. Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment* 114:106–115.

- Wang, J., P. M. Rich, K. P. Price, and W. D. Kettle. 2004. Relations between NDVI and tree productivity in the central Great Plains. *International Journal of Remote Sensing* 25:3127–3138.
- Wingfield, M. J., J. Roux, B. Slippers, B. P. Hurley, J. Garnas, A. A. Myburg, and B. D. Wingfield. 2013. Established and new technologies reduce increasing pest and pathogen threats to Eucalypt plantations. *Forest Ecology and Management* 301:35–42.
- Xi, X., T. Han, C. Wang, S. Luo, S. Xia, and F. Pan. 2016. Forest above ground biomass inversion by fusing GLAS with optical remote sensing data. *ISPRS International Journal of Geo-Information* 5:45.
- Yang, J., H. Tian, S. Pan, G. Chen, B. Zhang, and S. Dangal. 2018. Amazon droughts and forest responses: Largely reduced forest photosynthesis but slightly increased canopy greenness during the extreme drought of 2015/2016. *Global Change Biology* 24:1919–1934.
- Zhang, Y., C. Song, L. E. Band, G. Sun, and J. Li. 2017. Reanalysis of global terrestrial vegetation trends from MODIS products: Browning or greening? *Remote Sensing of Environment* 191:145–155.

SUPPORTING INFORMATION

Additional supporting information may be found online at: <http://onlinelibrary.wiley.com/doi/10.1002/eap.1879/full>

DATA AVAILABILITY

Data and code are available from the Stanford Digital Repository at <https://purl.stanford.edu/vj220jy6262>