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RESEARCH ARTICLE

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A new approach to map landscape variation in forest restoration success in tropical and temperate forest biomes

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Abstract

1. A high level of variation of biodiversity recovery within a landscape during forest restoration presents obstacles to ensure large-scale, cost-effective and long-lasting ecological restoration. There is an urgent need to predict landscape variation in forest restoration success at a global scale.
2. We conducted a meta-analysis comprising 135 study landscapes to predict and map landscape variation in forest restoration success in tropical and temperate forest biomes. Our analysis was based on the amount of forest cover within a landscape — a key driver of forest restoration success. We contrasted 17 generalized linear models measuring forest cover at different landscape sizes (with buffers varying from 5 to 200 km radii). We identified the most plausible model to predict and map landscape variation in forest restoration success. We then weighted landscape variation by the amount of potentially restorable areas (agriculture and pasture land areas) within the same landscape. Finally, we estimated restoration costs of implementing Bonn Challenge commitments in three specific temperate and tropical forest biome types in the United States, Brazil and Uganda.
3. Landscape variation decreased exponentially as the amount of forest cover increased in the landscape, with stronger effects within a 5 km radius. Thirty-eight per cent of forest biomes have landscapes with more than 27% of forest cover and showed levels of landscape variation below 10%. Landscapes with less than 6% of forest cover showed levels of variation in forest restoration success above 50%.
4. At the biome level, Tropical and Subtropical Moist Broadleaf Forests had the lowest (12.6%), whereas Tropical and Subtropical Dry Broadleaf Forests had the highest (22.9%) average of weighted landscape variation in forest restoration success.

Our approach can lead to a reduction in implementation costs for each Bonn Challenge commitment between US$ 973 Mi and 9.9 Bi.

5. *Policy implications*. Our approach identifies landscape characteristics that increase the likelihood of biodiversity recovery during forest restoration — and potentially the chances of natural regeneration and long-term ecological sustainability and functionality. Identifying areas with low levels of landscape variation can help to reduce the risks and financial costs associated with implementing ambitious restoration commitments.

KEYWORDS

biodiversity, forest landscape restoration, GIS, global restoration commitments, habitat loss, landscape ecology, meta-analysis, natural regeneration

1 | INTRODUCTION

Given high levels of deforestation and degradation of previously forested lands worldwide, together with serious threats from global climate change, several international and country-led efforts aim to boost forest and landscape restoration. To date, over 59 commitments have been pledged to restore 170 M ha of deforested lands by 2030 under international initiatives such as the Bonn Challenge and the New York Declaration on Forests (Chazdon et al., 2017). These initiatives are supported by national governments, investors, development banks, and bilateral and multilateral funders (Brancalion et al., 2017). They will require an estimated US$18–300 billion per year to be implemented (Ding et al., 2017). It is not clear how and when these funds will be available to restoration initiatives, but consensus exists that each dollar invested in restoration needs to be spent in the most ecologically and economically efficient way (Ding et al., 2017; Verdone & Seidl, 2017).

The cost-effectiveness of restoration (e.g. actions generating greatest socio-ecological benefit per unit of opportunity and/or implementation cost) can differ widely among restoration initiatives (Birch et al., 2010; Molin, Chazdon, Ferraz, & Brancalion, 2018) and methods (Brancalion, Campoe, et al., 2019). Measured outcomes can range from near-total success in achieving specific targets to complete failure (Crouzeilles, Curran, et al., 2016). Outcomes are strongly influenced by spatial variation in the ecological, biophysical and socio-economic characteristics of landscapes where forest restoration is implemented (Crouzeilles et al., 2017; Meli et al., 2017). Investors operating in different businesses usually avoid high-risk transactions, which likely constrains the flow of financial resources to restoration initiatives perceived as financially risky (Ding et al., 2017). Thus, the high level of unpredictability in biodiversity recovery in forests undergoing restoration (hereafter restoring forests) increases the risks associated with investments in ecological restoration programmes. This high level of unpredictability can constrain both long-term ecological sustainability and functionality, and expected multiple benefits of restoration for biodiversity, ecosystem services, and human well-being.

Here, we develop a new approach to predict and map landscape variation in forest restoration success in tropical and temperate forest biomes. Landscape variation emerges from comparisons of values of biodiversity recovery (measured through multiple ecological metrics for different taxonomic groups) between restoring and reference forests within different sampling sites in a landscape. Thus, our approach was developed by conducting a meta-analysis on biodiversity recovery (e.g. Crouzeilles, Curran, et al., 2016) for developing spatially explicit maps that predict landscape variation in forest restoration success based on ecological and/or socio-economic factors. Our map identifies landscapes in previously forested lands where restoration is most likely to foster biodiversity recovery towards levels typical of reference forest ecosystems. Our novel analysis opens new opportunities for policy-makers, entrepreneurs, practitioners and researchers to (a) establish forest landscape restoration targets and identify cost-effective priority areas for restoration, (b) improve regulations for biodiversity offsetting and (c) estimate implementation costs of forest restoration at a global scale. An important aspect of such an approach is estimating the effects of key ecological and/or socio-economic factors affecting landscape variation and predicting them at a global scale.

The amount of forest cover within a landscape is easily measured using global land cover databases, and it is a key ecological driver of the forest restoration processes (reviewed by Leite, Tambosi, Romitelli, & Metzger, 2013). Forest cover can act both as a source of seeds for re-colonization of native plant species and as a provider of critical habitat for seed dispersing animals (Chazdon, 2003; Helmer, Brandeis, Lugo, & Kennaway, 2008). Previous studies revealed that biodiversity recovery in restoring forests varies substantially depending on the amount of forest cover in the landscape (Crouzeilles & Curran, 2016). Therefore, such relationship could be used to map variation in forest restoration success of other landscapes.

We propose a new conceptual model for the expected relationship between the amount of forest cover in a landscape and landscape variation in forest restoration success (Figure 1). That is, in some landscapes, restoring forests are similar to the reference forests in terms of the levels of biodiversity supported (Klanderud et al.,

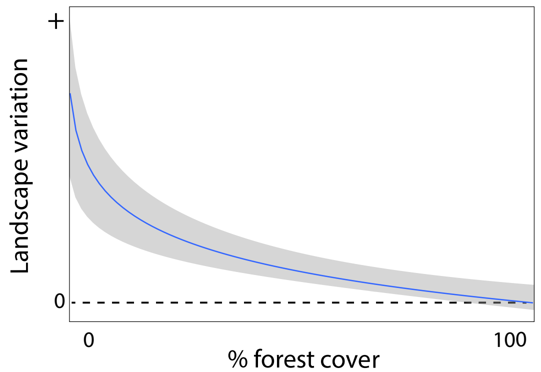

FIGURE 1 Conceptual model showing the expected relationship between the amount of forest cover (%) in a landscape and variation in forest restoration success. Landscape variation in forest restoration success is defined as the variation of biodiversity recovery in relation to the values found in the reference condition. Low variation occurs when restoring forests are consistently similar in the levels of biodiversity supported compared to the reference forests, whereas large variance in biodiversity recovery is associated with highly deforested landscapes and tends to occur due to the mixing of early and late successional species and non-native species, extinction of late successional species and lack of dispersers. The blue line represents the expected relationship between x and y variables and the grey area represents the confidence interval which tends to decrease for higher values of the amount of forest cover.

2010; implying low variation). In contrast, other landscapes exhibit high levels of variation in biodiversity recovery (Clarke, Rostant, & Racey, 2005; whereby the magnitude or even direction of the difference between restoring and reference forests is highly variable). Increasing variance in biodiversity recovery, in relation to reference conditions associated with highly deforested landscapes, tends to occur due to the (a) mixing of early and late successional species and non-native species, (b) potential local extinction of late successional species and (c) lack of dispersal of species or propagules into restoring forests (e.g. Crouzeilles & Curran, 2016; Holl & Aide, 2011).

In this study, based on a meta-analysis for tropical and temperate forest biomes and comprising 135 landscapes, we asked, *At which scale of effect does forest cover best predict the variation in restoration success within a landscape?* We used this result to map landscape variation in forest restoration success in tropical and temperate forest biomes. We also asked, *How does landscape variation change across major forest biomes and across countries?* We used the map of landscape variation in forest restoration success, combined with data on per ha forest implementation costs and opportunity costs, to estimate restoration costs of implementing Bonn Challenge commitments. We focused our estimates on three forest biome types and countries where restoration implementation costs were available: 15 M ha from USA in Temperate Broadleaf and Mixed Forests and Temperate Coniferous Forests, 1 M ha from Brazil's Atlantic Forest Restoration Pact in Tropical and Subtropical Moist Broadleaf Forests, and 1 M ha from Uganda in Tropical and Subtropical Dry Broadleaf Forests. By identifying landscapes with low variance in forest restoration success, our approach may assist in reducing the risks of failure in large-scale ecological forest restoration projects and facilitate the flow of financial investments needed to implement the ambitious restoration commitments planned at a global scale.

2 | MATERIALS AND METHODS

2.1 | Forest restoration database

Crouzeilles, Ferreira, and Curran (2016) built an extensive forest restoration database encompassing 269 original studies across 221 study landscapes (based on the geographic coordinates reported by the original studies) and which contains 4,645 quantitative comparisons between reference forests and degraded systems or restoring forests for biodiversity and vegetation structure. They defined reference forests as old-growth or less disturbed forest; degraded systems as different types of human land use (e.g. plantation or agriculture); restoring forests as passively or actively restoring native and non-native forests in their initial or secondary stage of succession; biodiversity as plants, mammals, birds, herpetofauna and invertebrates measured through ecological metrics (abundance, richness, diversity or similarity); and vegetation structure (cover, litter, density, height and biomass).

From this database, we selected original studies that included comparisons between reference and restoring forests for biodiversity and information on the time since restoration started. We used the last criterion to investigate whether our results were affected by the time since restoration started. In total, our analysis encompassed 135 study landscapes (Figure 2) and contained 2,063 quantitative comparisons between reference and restoring forests for the recovery of biodiversity (29.8% of the comparisons for birds, 29.2% for invertebrates, 24.2% for plants, 12.9% for mammals and 3.9% for herpetofauna). Data on species richness (39%) and abundance (37%) were more frequent than for species diversity and similarity (12% each), which are more sensitive ecological metrics to measure changes in community composition. Most of the study landscapes (79%) were located in Tropical and Subtropical Moist Broadleaf Forests (Figure 2), but we mapped the landscape variation in forest restoration success across all forest biomes. This was because Crouzeilles, Curran, et al. (2016) found no significant geographical variation in predictors of forest restoration success.

2.2 | Forest cover dataset

Crouzeilles and Curran (2016) built a forest cover data layer based on the recent 1 km resolution consensus land cover dataset, derived from combining three existing land cover products (GLC 2000, MODIS 2005 and ESA GlobCover 2008; Tuanmu & Jetz, 2014). This ‘reduced’ dataset avoids the influence of pre-2000 deforestation (product DISCover from 1995) and includes three land cover classes (evergreen/deciduous needleleaf trees, evergreen broadleaf trees and deciduous broadleaf trees) to represent the extent of forest vegetation within landscapes as robustly as possible. From this database, we calculated the percentage

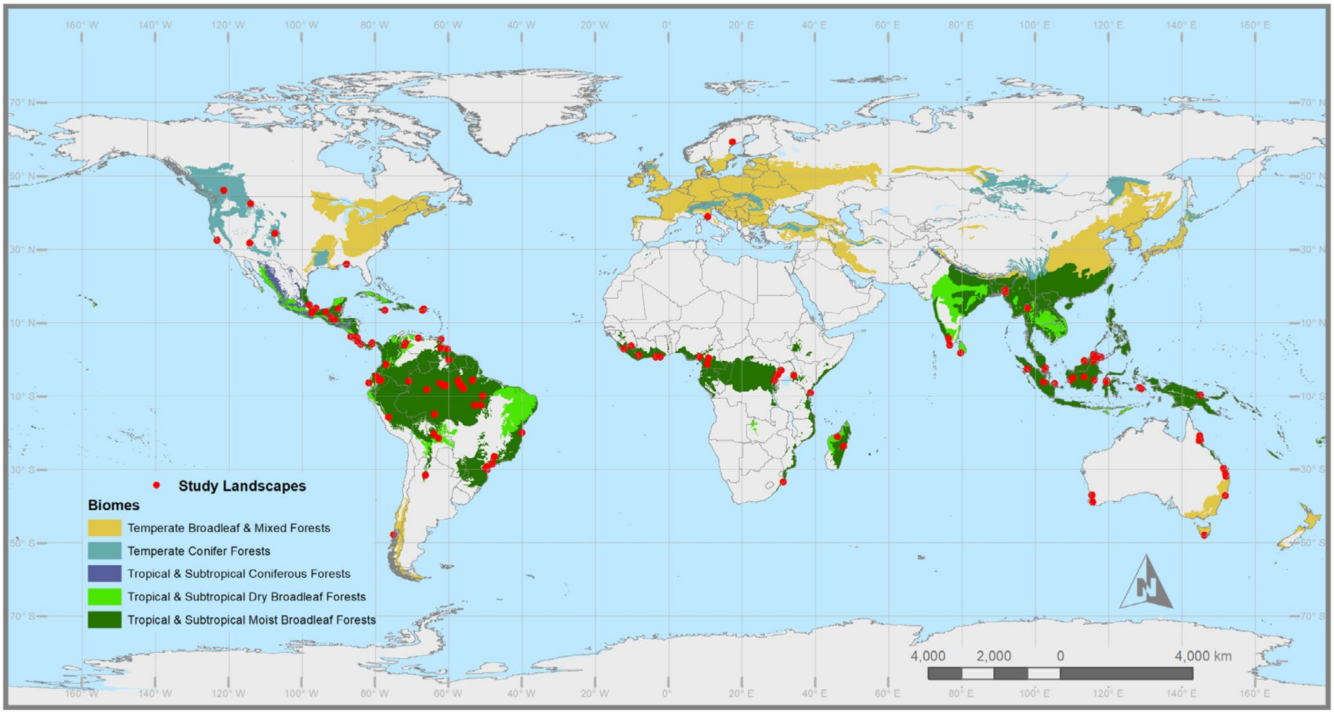

FIGURE 2 Map of 135 study landscapes across the five originally forested biomes. Study landscapes are represented by red dots.

of overall and continuous forest cover within eight different buffer sizes (with 5, 10, 25, 50, 75, 100, 150 and 200 km of radius) for the same study landscapes reported in the forest restoration database. Overall forest cover includes all forest remnants ≥9 ha, whereas continuous forest cover includes only 1 km pixels with a minimum percentage of 60% of forest cover. The lowest buffer size was 5 km radius because the median distance between sites within a study landscape was 5 to 3 km (M. Curran, unpublished data), whereas the largest buffer size is two orders of magnitude bigger than the lowest, following the recommendations of Jackson and Fahrig (2015).

2.3 | Response ratio variation

We used response ratios (*RR*; Hedges, Gurevitch, & Curtis, 1999) to measure the standardized mean effect size of comparisons between restoring and reference forests within the same study (such as a control–treatment experiment; Equation 1). Multiple *RRs* can be calculated within the same study landscape (e.g. multiple ecological metrics for different taxonomic groups within different sampling sites), but the amount of forest cover is the same within a given study landscape (for a given buffer size). Therefore, we developed an equation to estimate landscape variation in biodiversity recovery (measured through multiple response ratios within a landscape) relative to the 'full' restoration success within each study landscape (defined as *landscape variation in forest restoration success; LVFRS*). We calculated the difference between each measured *RR* for each taxonomic group (hereafter $RR_{m,t}$) in relation to the *RR* of the 'full forest restoration success' (RR_{frs}; which is obtained when restoring forests are equal to reference forests in terms of biodiversity value, hence RR_{frs} = 0) within the same study landscape (Equation 2):

$$RR_m = \ln\left(\frac{\bar{x}_{restored}}{\bar{x}_{reference}}\right) \quad (1)$$

$$RRV = \sum_{i=1}^{n} \frac{\left(RR_m - RR_{frs}\right)^2}{n-1} \quad (2)$$

where $RR_{m,t}$ is each measured response ratio, $\bar{x}$ is the mean value for a quantified ecological metric for biodiversity within all sampling locations of an original study representing either restoring or reference forests, RR_{frs} is the response ratio when both restoring and reference forests have the same quantitative value for biodiversity (RR_{frs} = 0), *n* is the number of response ratios within a study landscape, and *RRV* is the variance of $RR_{m,t}$ around the RR_{frs}. *RRV* depends upon the amount of forest cover in the landscape and it ranges from zero to positive values. Values close to zero are the desired outcome of restoration projects, that is, there is low variation of restoration outcomes in bringing biodiversity in a restoring forest back to the reference system state. To avoid extreme *RRs* that may affect modelling of *RRV*, we removed the highest and lowest 0.25% *RR* values from our database, which corresponds to *RRs* > 0.4 and *RRs* < −0.4, totalling 11 *RRs*.

2.4 | Model selection

We used an information theoretic approach (Akaike Information Criterion; Burnham & Anderson, 2002) to identify the buffer size within which the percentage of overall or contiguous forest cover best predicted landscape variation in forest restoration success. We compared 17 generalized linear models, with buffer size varying from 5 to 200 km (5, 10, 25, 50, 75, 100, 150 and 200 km radius) and with data on either continuous or overall forest cover, plus a null model. We modelled landscape variation in forest restoration success assuming a gamma distribution where the values were continuous and varying between 0 and positive infinite (Bolker, 2008). We log-transformed the percentages of overall and contiguous forest cover following Crouzeilles and Curran (2016) because these could be non-linearly related with landscape variation in forest restoration success. We avoided pseudo-spatial-auto-correlation using only one value of landscape variance per study landscape. For each model, we calculated the Akaike Information Criterion corrected for small samples (AICc), the ΔAICc as $AICc_i$ − minimum AICc, and the Akaike weight (w_i), which indicates the probability that the model *i* is the best model within the set. Finally, we also calculated an evidence ratio, which was used to compare the model's relative goodness of fit (w_1/w_j, where model 1 is the estimated best model and *j* indexes the rest of the models in the set; Burnham & Anderson, 2002). Models with $\Delta AICc_i < 2$ can be considered equally plausible, but we considered the top-ranked model only (i.e. lowest AICc and highest w_i). This was because we were interested in the model that best explained landscape variation in forest restoration success.

Many factors (e.g. climate and land use change) may affect landscape variation in forest restoration effectiveness for biodiversity (Spake & Doncaster, 2017), but the effects of such factors on landscape variation have not previously been studied. We therefore focused on the strong and recognized relationship between forest cover and landscape variation in forest restoration success (e.g. Crouzeilles & Curran, 2016). However, we also investigated whether landscape variation in forest restoration success was affected by either the number of response ratios within a study landscape (i.e. number of comparisons between restoring and reference forests for biodiversity) or the time since restoration started using Pearson regressions. We did not include both the number of response ratios and the time since restoration started in the model selection because we aimed to build a spatially explicit predictive model, that is, we needed to work only with variables that were predictable in space, which does not apply to sample size and time since restoration started.

2.5 | Mapping landscape variation in forest restoration success in tropical and temperate forest biomes

To define our study area, we considered only tropical and temperate forest biomes, based on a geospatial dataset (Dinerstein et al., 2017). We then used the updated version (2016) of the geospatial dataset from the 21st-century forest cover change between 2000 and 2012 (Hansen et al., 2013; updated version is available at Global Forest Watch, 2016) to map forested and non-forested areas. This dataset contains information on the amount of vegetation taller than 5 m in height within each 30 m pixel for the year 2000, as well as pixels subject to forest loss between 2001 and 2016. To obtain values for forest cover in 2016, we excluded forest loss pixels between 2001 and 2016 from the forest cover map of 2000. We resampled the forest cover map of 2016 to 1 km pixel size, the same resolution of the forest cover dataset from Crouzeilles and Curran (2016). That is, the amount of tree canopy cover within a 1 km pixel size was the mean of the tree canopy cover of all the 30 m pixels that fell within the 1 km pixel.

We masked non-restorable areas within the forest biomes. We considered non-restorable areas to be 1 km pixels with 100% of tree canopy cover, urban areas, water bodies as well as locations that were not previously forested (e.g. grasslands). We obtained data on 1 km pixels with 100% tree canopy cover from the forest cover map in 2016. We obtained data on urban areas and water bodies from the global CCI-LC map (ESA Climate Change Initiative, 2017). We also considered wetlands as non-restorable places because the restoration of wetlands demands different kinds of management than examined in this study. We obtained data on wetlands from GIEMS-D15 (Fluet-Chouinard, Lehner, Rebelo, Papa, & Hamiton, 2015; Prigent, Papa, Rossow, & Matthews, 2017).

We used the best fitting model from the model selection (see the Results section) to map landscape variation in forest restoration success (*LVFRS*). Thus, we calculated the percentage of forest cover surrounding each 1 km focal pixel within a buffer size of 5 km radius and then applied the global equation for each potential pixel to be restored, and the equations is as follows (Equation 3):

$$LVFRS = 1.37595 - 0.23498 * \log_{\text{natural}}\left(\begin{array}{l}\text{\% overall forest cover with a}\\ \text{buffer of 5 km radius} + 1\end{array}\right) \quad (3)$$

where the buffer size of 5 km radius was the top-ranked model to predict the effects of percentage of forest cover on landscape variation in forest restoration success. Finally, we standardized landscape variation in forest landscape restoration success (*SLVFRS*) to vary between 0% (minimum variation) and 100% (maximum variation; Equation 4):

$$SLVFRS = \frac{LVFRS - LVFRS_{\min}}{LVFRS_{\max} - LVFRS_{\min}} * 100 \quad (4)$$

When landscape variation is 100%, it means that restoration success for biodiversity is highly variable (i.e. unpredictable).

2.6 | Bonn challenge commitments as a case study

We used three Bonn Challenge commitments to show how our approach can be used to estimate implementation costs of forest restoration in different types of forest biomes. These are as follows: 15 M ha from USA in Temperate Broadleaf and Mixed Forests and Temperate Coniferous Forests, 1 M ha from Brazil's Atlantic Forest Restoration Pact in Tropical and Subtropical Moist Broadleaf Forests, and 1 M ha from Uganda in Tropical and Subtropical Dry Broadleaf Forests. Uganda committed 2.5 M ha of three types of native vegetation (forests, savannahs and grasslands) for restoration, but the largest areas are for forest restoration. We assumed at least 1 M ha of forests as our targeted area for restoration in Uganda.

To estimate the total implementation cost of each commitment, we made the following assumptions: (a) implementation cost is linearly positively related with the landscape variation in forest restoration success (i.e. restoration is more expensive in landscapes with higher variation in forest restoration success — this is a potential surrogate of the lower chances of natural regeneration and long-term ecological sustainability and functionality; e.g. Strassburg et al., 2019) and (b) the total restoration area pledged will be implemented within landscapes with either the lowest landscape variation or the lowest opportunity costs. Thus, implementation cost was estimated using (Equation 5):

$$\text{Inplementation cost} = SLVFRS * \text{US\$ full tree planting cost} \quad (5)$$

where *SLVFRS* is the standardized landscape variation, and full tree planting cost represents the most expensive method for active restoration. Implementation cost will be higher when the *SLVFRS* is lower. The per ha full tree planting cost was estimated to be (US$ mean ± standard deviation): 677 ± 363 in USA (Crawford County Conservation Districts, 2007; Stringer, 2009; Virginia Department of Forestry, 2018), 3,504 ± 915 in the Brazilian Atlantic Forest (Benini & Adeodato, 2017; Serviço Florestal Brasileiro, 2017) and 1,179 ± 439 in Uganda (Ministry of Water & Environment, 2016; Omeja et al., 2011; Omeja, Obua, Rwetsiba, & Chapman, 2012).

We estimated the reduced implementation cost of prioritizing natural regeneration when *SLVFRS* is low compared to the cost of implementing only full tree planting as the restoration method used to reach each target committed. We also estimated the total opportunity cost for each commitment when identifying landscapes with either the lowest landscape variation or lowest opportunity costs. Opportunity cost represents the cost of setting aside land for restoration instead of using it for other purposes. We calculated total opportunity cost based on Naidoo and Iwamura (2007).

3 | RESULTS

3.1 | At which scale of effect does forest cover best predict the variation in restoration success within a landscape?

Our top-ranked model explaining landscape variation in forest restoration success included the percentage of overall forest cover measured at a buffer size of 5 km (w_i = 0.4; Table 1 and Figure 3). The second-ranked model, which included the percentage of overall forest cover measured at a buffer size of 10 km radius, was equally plausible ($\Delta AICc_i$ = 1.09, w_i = 0.23). The evidence ratio of the top-ranked model was only 1.74 times higher than the second-ranked model, but 400 times higher than the null model, highlighting the importance of forest cover in explaining landscape variation in forest restoration success (Table 1). We selected the top-ranked model to build the map of landscape variation in forest restoration success (Table 1). If the second-ranked model was used, we would expect similar results, as variables included in the top-ranked and second-ranked models (percentage of forest cover at 5 km and 10 km radius,

TABLE 1 Performance of 17 models predicting the landscape variation in forest restoration success

Model	AICc	ΔAICc	w_i
Overall 5 km	206.33	0.00	0.40
Overall 10 km	207.42	1.09	0.23
Continuous 200 km	208.63	2.30	0.13
Overall 25 km	209.62	3.29	0.08
Continuous 150 km	209.7	3.38	0.07
Continuous 100 km	211.56	5.23	0.03
Overall 50 km	211.89	5.57	0.02
Continuous 75 km	213.88	7.55	0.01
Overall 75 km	214.51	8.18	0.01
Overall 100 km	215.95	9.63	0.00
Continuous 50 km	216.23	9.90	0.00
Continuous 25 km	216.92	10.59	0.00
Null	217.79	11.47	0.00
Continuous 10 km	218.31	11.98	0.00
Overall 150 km	219.25	12.92	0.00
Continuous 5 km	219.62	13.29	0.00
Overall 200 km	219.88	13.55	0.00

Note: Overall = percentage of overall forest cover, Continuous = percentage of continuous forest cover, km = km radius. A null model was also included for comparison. AICc = Akaike Information Criterion corrected for small ratio of sample size/number of parameters, ΔAICc = AICc − minimum AICc, w_i = Akaike weight.

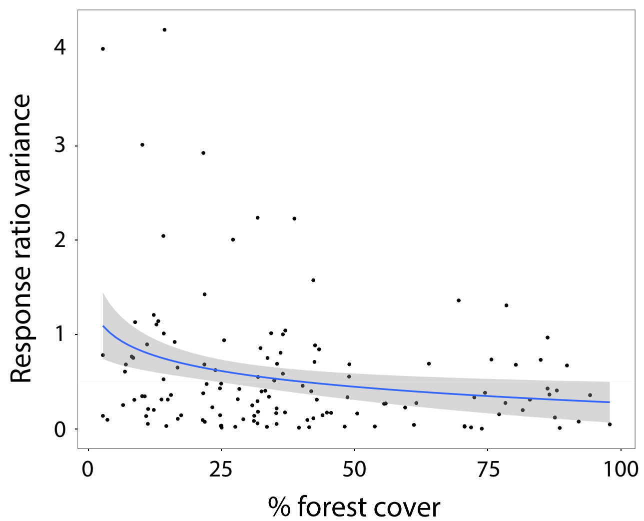

FIGURE 3 Relationship between landscape variation in forest restoration success for biodiversity and percentage of overall forest cover measured at a buffer size of 5 km radius (x-axis) for biodiversity. Points represent variation in forest restoration success obtained from all response ratios at each study landscape. Blue line = mean value and grey line = 95% confidence intervals.

respectively) were 98% correlated. We found that landscape variation in forest restoration success was neither affected by the sample size (Pearson's $r = .11$, $p = .19$) nor by the time since restoration started (Pearson's $r = -.02$, $p = .85$).

3.2 | How landscape variation change across major global forest biomes and across countries?

Landscape variation in forest restoration success ranged from <1 to 85% (0% = minimum variation and 100% = maximum variation; Figure 4). Landscapes (1 × 1 km pixel) with more than 27% of forest cover showed low levels of variation in forest restoration success (below 10%). Below this threshold level of forest cover, landscape variation increased substantially. Landscapes with less than 6% of forest cover showed high levels of variation in forest restoration success above 50%.

After weighting the landscape variation in forest restoration success by the amount of restorable areas within the same landscape (1 × 1 km pixel), Tropical and Subtropical Moist Broadleaf Forests had lower predicted average landscape variation (12.6%), whereas Tropical and Subtropical Dry Broadleaf Forests had higher landscape variation (22.9%) compared to the other biomes (see Table S1). At the country level, French Guiana had the lowest, (0.6%) whereas Somalia, the highest (56.9%) average of weighted landscape variation in forest restoration success (Table S2). Among the five countries with the largest areas potentially restorable (i.e. previously forested areas currently occupied by other land uses; China, Russia, Brazil, the United States and India; in descending order of availability), the United States has the lowest (14.8%) and India has the highest (40.3%) average of weighted landscape variation in forest restoration success (Table S2).

3.3 | Bonn challenge commitments as a case study

The total restoration cost (implementation and opportunity costs combined) of forest restoration varied among the three Bonn Challenge commitments used as case studies. In each region, we identified (a) the landscapes with lowest variation in forest restoration success and (b) the landscapes with lowest opportunity costs, to reach each committed target (Figure 5). These simulations aggregated both national-scale implementation costs and per ha opportunity costs assuming that less expensive restoration methods, such as natural regeneration, are prioritized for forest restoration implementation. Implementation costs based on full tree planting varied from US$ 216 Mi (±273 – 160 Mi) to 11 billion (±16 – 5 Bi).

When prioritizing landscapes with lowest landscape variation, our approach led to a reduction in implementation costs for each commitment from US$ 973 Mi (±1.3 Bi – 610 Mi) to 9.9 Bi (±15 – 4.6 Bi) below costs incurred either using full tree planting as the sole restoration method (Figure 5). Our approach also led to a reduction in implementation costs for each commitment from US$ 71 Mi (±97 – 44 Mi) to 1.3 Bi (±2.0 Bi – 600 Mi) when compared to prioritizing forest restoration in landscapes with lowest opportunity cost but based on full tree planting (Figure 5). That is, our solutions were 26% to 82% less expensive than solutions based on the lowest opportunity costs. On the other hand, our approach was from 12 Mi

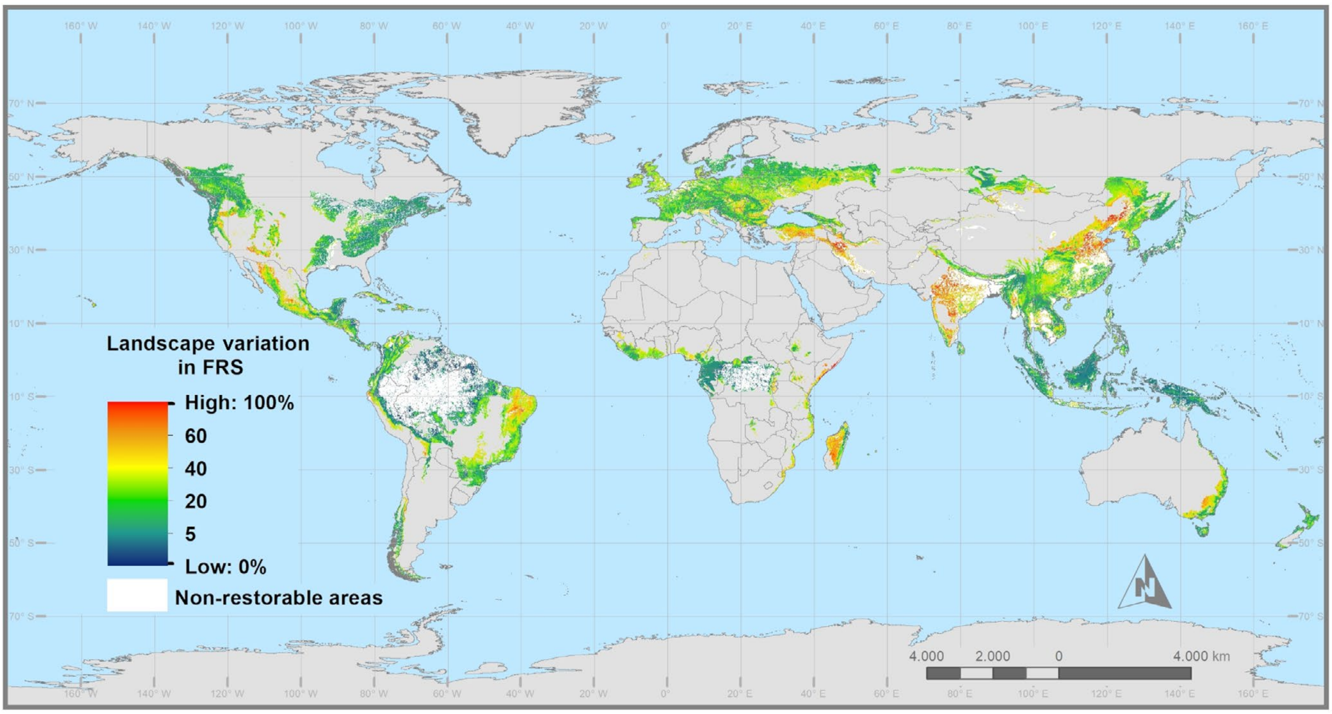

FIGURE 4 Map of landscape variation in forest restoration success (FRS) for the five forest biomes. Non-restorable areas are considered 1 km pixels with 100% of tree canopy cover, urban areas, water bodies, wetlands and areas that were not previously forested (e.g. grasslands).

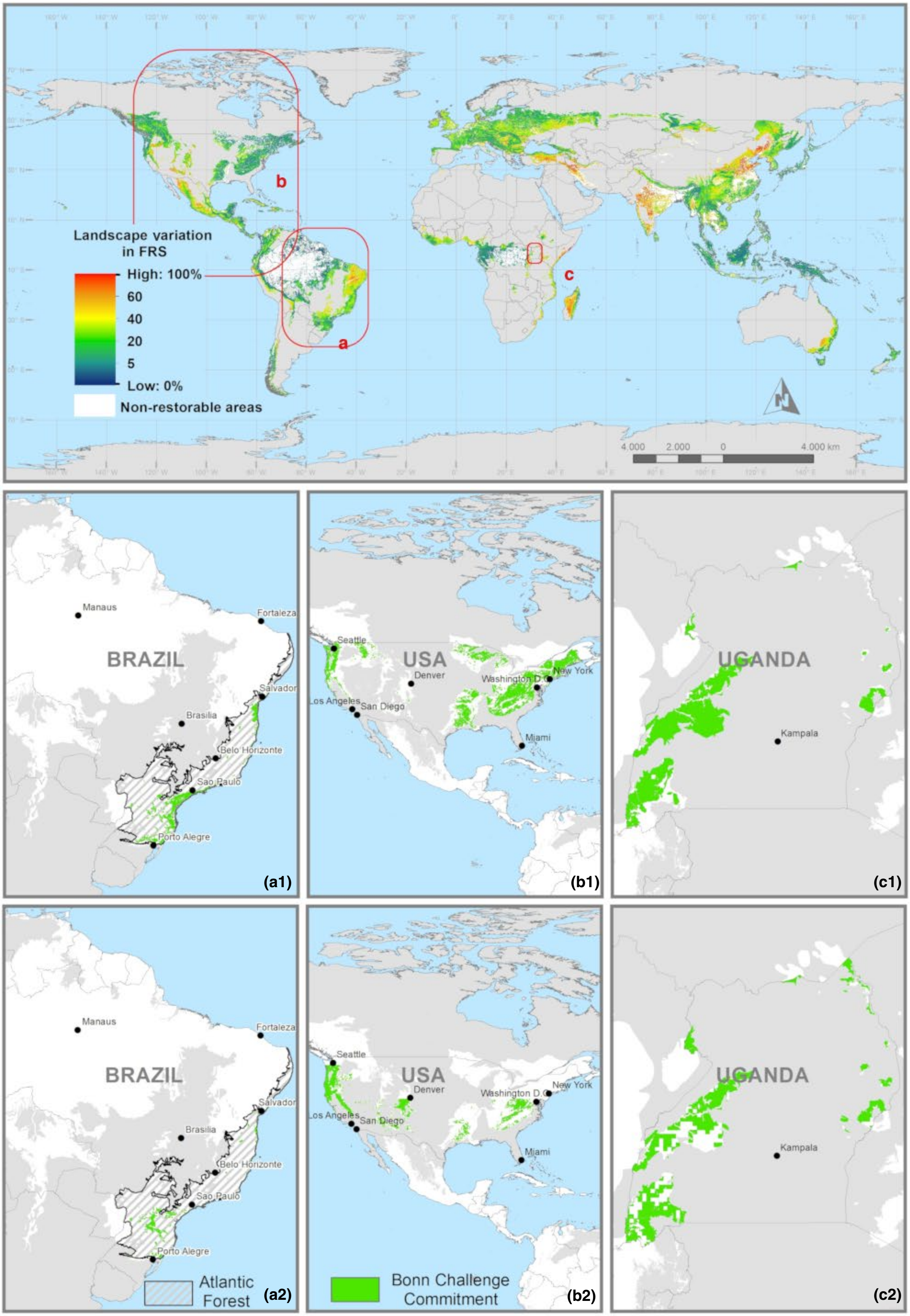
Landscape variation in FRS
High: 100%
60
40
20
5
Low: 0%
Non-restorable areas
a
b
c
4.000 2.000 0 4.000 km
BRAZIL
Manaus
Fortaleza
Salvador
Brasilia
Belo Horizonte
Sao Paulo
Porto Alegre
(a1)
USA
Seattle
Denver
Washington D.C.
New York
Los Angeles
San Diego
Miami
(b1)
UGANDA
Kampala
(c1)
Atlantic Forest
(a2)
Bonn Challenge Commitment
(b2)
(c2)

FIGURE 5 Three Bonn Challenge commitments used as case study to identify landscapes with lowest either landscape variation in forest restoration success (FLS) (a1, b1, c1) or opportunity costs (a2, b2, c2), to reach each committed target. These are (a) Atlantic Forest Restoration Pact with 1 M ha in Tropical and Subtropical Moist Broadleaf Forests, (b) USA with 15 M ha in Temperate Broadleaf and Mixed Forests and Temperate Coniferous Forests and (c) Uganda with 1 M ha in Tropical and Subtropical Dry Broadleaf Forests.

to 282 Mi more expensive in terms of opportunity cost than when identifying landscapes with lowest opportunity costs.

4 | DISCUSSION

As expected, landscape variation in forest restoration success in temperate and tropical forest biomes decreased exponentially as the amount of forest cover increased within a landscape. We found the strongest scale of effects was within a buffer size of 5 km radius — followed by an equally plausible model measuring forest cover at a buffer size of 10 km radius. That is, both restoration success (see Crouzeilles & Curran, 2016) and its variation in relation to the quantitative values of biodiversity found in reference systems are best predicted by forest cover within a buffer size (landscape) of 5 to 10 km in radius.

We mapped, for the first time, landscape variation in forest restoration success across major forest biomes, which is higher across countries than across the biomes. Landscapes where the forest cover has declined below 30% show increased landscape variation in forest restoration success. Nonetheless, the good news is that the forest biomes with larger potentially restorable areas are those with lower landscape variation in forest restoration success (Temperate Broadleaf and Mixed Forests, Temperate Conifer Forests, and Tropical and Subtropical Moist Broadleaf Forests). Despite the large amount of deforested land worldwide (Hansen et al., 2013; Lewis, Edwards, & Galbraith, 2015), 38% of the 172 countries (238 M ha) that had previously forested areas still have low levels (≤10%) of landscape variation in forest restoration success, on average (Table S2). Countries with marginally higher weighted landscape variation but more restorable areas also may be considered as no-regret targets for private restoration investments, such as Brazil and Russia (with 324 M ha restorable areas). Therefore, our new approach can help to identify landscapes with reduced risks of ecological forest restoration success, a critical first step to implementing large-scale, long-lasting and cost-effective forest restoration interventions.

Our robust methodological approach (including a new metric to measure variation in restoration outcomes) provides a novel template for developing predictive models and maps to better guide forest restoration investments and policies (see Molin et al., 2018). Other ecological and socio-economic variables that affect forest restoration at the landscape scale (e.g. Crouzeilles et al., 2017) also may result in similar patterns of variation in restoration outcomes, such as past disturbance, rural migration and precipitation. However, such potential variations have not yet been examined and are beyond the scope of this study. Future studies should explore whether these relationships can be meaningfully predicted and mapped. In our case, landscape variation in forest restoration success was not affected by higher levels of replication (i.e. number of response ratios within a study landscape), but it needs to be investigated in future studies using our approach. Although the approach developed here was applied on a global scale, it also can be easily replicable at smaller scales to solve local questions using on-the-ground comparisons of biodiversity recovery between restoring and reference forests.

It is important to note that the studies in our meta-analysis measured variation in forest restoration success under favourable landscape conditions, as publications on forest restoration may have a bias towards positive results (Reid, Fagan, & Zahawi, 2018). Moreover, not all restoration initiatives measure restoration success based on biodiversity responses and often focus on other outcomes such as ecosystem services provisioning, local livelihoods and financial returns. Nevertheless, our map is useful for guiding decision-making under several different circumstances, such as (a) prioritizing landscapes for restoration with a focus on recovery of biodiversity, (b) improving regulations on biodiversity offsetting and (c) estimating implementation costs of forest ecological restoration at the global scale. Complementarily, although other diverse outcomes may be specifically targeted by restoration programmes, biodiversity recovery is a pre-requisite for all restoration processes, as it is a surrogate of a myriad of contributions of restoration to people and nature.

4.1 | Helping to unlock investments in forest landscape restoration

Our approach may help unlock the flow of funds to implement the ambitious restoration commitments planned worldwide. For example, the financial feasibility of restoration is a critical criterion when identifying priority areas for cost-effective restoration (Brancalion, Niamir, et al., 2019; Strassburg et al., 2019). The financial feasibility of restoration is dependent on landscape variation in forest restoration success because risky restoration initiatives (with unpredicted outcomes) are unlikely to attract investors (Brancalion, Niamir, et al., 2019; Brancalion et al., 2017), may rely more heavily on public funds (Ding et al., 2017) and can have higher costs. Costly, labour-intensive interventions may be needed for kickstarting restoration processes and adaptive management interventions, potentially essential for safeguarding a favourable restoration trajectory. Identifying landscapes with low risks of restoration success can encourage greater restoration investments from the private sector in countries with lower average of weighted landscape variation, such as Suriname, French Guiana, Solomon Islands, Dominica and Palau (the top five countries; always with values <3%, Table S2). Alternatively, the public sector and governments may decide to spatially complement private investments in restoration that target less risky interventions and concentrate the bulk of their investments on restoration in more risky landscapes such as those in highly deforested areas. In these cases, restoration outcomes may focus less on biodiversity recovery, and more on improving local food security, the supply of ecosystem services (e.g. carbon storage, water quality, fuel wood or timber) and/or supporting local livelihoods (e.g. Strassburg et al., 2019).

4.2 | Supporting biodiversity offsetting with forest landscape restoration

The lack of a robust mechanistic understanding of landscape variation underpinning forest restoration success has precluded the use of restoration initiatives as a reliable operational approach to compensate for environmental degradation (e.g. biodiversity offsets; Budiharta et al., 2018; Maron et al., 2012; Moilanen, Teeffelen, Ben-Haim, & Ferrier, 2009). Thus, our map can be used to support and develop new regulations and policies for biodiversity offsetting, in which the total area to be restored can be weighted by values for landscape variation in forest restoration success. This weighting would require larger areas to be restored where landscape variation is higher, or prohibit compensatory restoration in areas with landscape variation above a given threshold. For example, several landscapes across countries (top five: Somalia, Seychelles, Iraq, Benin and Madagascar; in descending order) with high weighted landscape variation (>41%, Table S2) may be too risky to permit compensatory restoration. In these cases, halting and reversing deforestation above a given threshold in terms of amount of forest cover will facilitate recovery and reduce the risk of irreversible biodiversity decline (e.g. Pardini, Arruda Bueno, Gardner, Prado, & Metzger, 2010). It is critical to highlight, however, that our map does not account for species uniqueness and complementarity. Thus, biodiversity offsetting mechanisms must be supported by additional critical biodiversity data.

4.3 | Bonn challenge commitments as study cases

The restoration target in the Bonn Challenge is 350 M ha of restored forests by 2030, with 170 M ha within 59 commitments pledged to date (Bonn Challenge, 2018). Most of these commitments are based on a 'forest landscape restoration' approach, which aims to enhance the ecological functionality of deforested landscapes (Chazdon et al., 2017). Although achieving reference ecosystem levels of biodiversity is not the main focus of these programmes, biodiversity recovery will certainly play a central role in recovering diverse ecological functions (Kaiser-Bunbury et al., 2017; Strassburg et al., 2019). Landscapes with lower levels of variation in forest restoration success are more likely to be successfully restored as they are characterized by more forest cover in surrounding areas, which is a strong predictor of success (e.g. Crouzeilles & Curran, 2016; Leite et al., 2013). We have shown that the implementation costs of forest restoration could potentially be reduced by more than 80%–97% if our approach is adopted (i.e. identifying landscapes with lowest landscape variation) instead of the widely preferred use of full tree planting as a restoration method (Chazdon, 2014; Chazdon & Guariguata, 2016). Although our approach increases opportunity costs by US$ 12 Mi, 28 Mi and 282 Mi compared to prioritizing restoration in landscapes with lowest opportunity cost, these costs are compensated for by a reduction in implementation costs, which are US$ 121 Mi, 71 Mi and 1.3 Bi for Brazilian Atlantic Forest, Uganda and US commitments, respectively. These results highlight the importance of our map as a tool to help decision-makers overcome a critical barrier — identifying landscapes where low-cost restoration methods based on natural regeneration processes can be implemented for large-scale restoration (Chazdon & Guariguata, 2016).

5 | CONCLUSIONS

We found that variation in forest restoration success at the landscape scale was strongly associated with the forest cover remaining within the landscape. Ensuring the persistence of native forests (Reid et al., 2017) and integrating restoration with conservation practices and policies are key elements for forest restoration success. Four key recommendations arise from this study. First, it is essential to halt deforestation, particularly in areas where forest cover in the landscape declines below 30%. Second, commencing restoration on landscapes with low (<10%) levels of variation in forest restoration success may attract the levels of financial investment needed to fund large-scale restoration focused on biodiversity recovery. Third, restoration in areas with high landscape variation (>50%) will be costly and may not be effective for restoring native biodiversity. Nevertheless, landscape restoration initiatives in these areas can be vitally important for increasing the supply of a wide range of ecosystem services and improving socio-economic conditions. Therefore, restoration in these areas should be a planned process also considering other landscape factors to increase forest cover as a whole and consequently decrease the variation in forest restoration success. Fourth, given limited financial resources to invest in forest and landscape restoration, our results can help guide restoration efforts towards landscapes where restoration interventions will yield higher cost-effectiveness for biodiversity conservation.

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AUTHORS' CONTRIBUTIONS

R.C. conceived the idea and analysed the data; P.H.S.B. and M.S.F. considerably improved on it; F.S.B. and P.G.M. processed the geospatial analyses; R.L.C. led the writing with assistance from all other authors. All authors gave final approval for publication.

DATA AVAILABILITY STATEMENT

Data and R scripts available from the Dryad Digital Repository https://doi.org/10.5061/dryad.7cr627n (Crouzeilles et al., 2019).

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