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Estimating optimal sampling area for monitoring tropical forest restoration

Vinícius Londe [a,*], J. Leighton Reid [b], Fabiano Turini Farah [c], Ricardo Ribeiro Rodrigues [c], Fernando Roberto Martins [d]

[a] Ecology Graduate Course, Institute of Biology, University of Campinas, Campinas, São Paulo, Brazil
[b] School of Plant and Environmental Sciences, Virginia Tech, Blacksburg, VA, United States
[c] Laboratory of Ecology and Forest Restoration, School of Agriculture "Luiz de Queiroz", University of São Paulo, Piracicaba, São Paulo, Brazil
[d] Department of Plant Biology, Institute of Biology, University of Campinas, Campinas, São Paulo, Brazil

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ABSTRACT

Although critical to evaluating success, monitoring is often neglected in ecological restoration. An important question is how much area should be sampled to adequately monitor restoration projects, particularly as projects become larger. We elucidate this issue by testing the following hypotheses: There is an optimal sampling area (OSA) that efficiently captures variation in the estimation of ecological indicators; The restoration intervention and forest type affect OSA; The OSA change over time as restoration projects age. Information on large-scale vegetation monitoring ($n = 374$) in the Brazilian Atlantic Forest was used to test our hypotheses. We studied moderately assisted recovery (MAR) and lightly assisted recovery (LAR) projects within three forest types (50.5-ha of sampling). The projects were between three months and seven years in age. We calculated the variance for 11 indicators and the proportion of a restoration site that was sampled. We performed segmented regressions to find the OSA. Across all indicators, OSA ranged from 0.25–2.16% for MAR and 0.24–4.67% for LAR. There was weak evidence that OSA was greater in LAR projects ($P = 0.052$) and semideciduous seasonal forest type ($P = 0.060$). OSA increased over time, reaching 4.0% of the project area for projects seven years in age. By knowing the OSA for a range of indicators, practitioners can plan for the minimum monitoring needed to evaluate the restoration trajectory confidently and avoid vague or erroneous conclusions. The restoration of large areas will mark this decade, and this study helps fill the knowledge gap on how to monitor them more effectively.

1. Introduction

Monitoring is critical to evaluate the trajectory and success of ecological restoration projects (DeLuca et al., 2010; Holl and Cairns, 2002). Monitoring is the phase of ecological restoration where restoration practitioners employ indicators (socio-cultural or ecological attributes) to evaluate if restoration objectives were met on schedule (Gann et al., 2019). Monitoring allows practitioners to identify shortcomings and take early corrective actions to prevent project failure (i.e., adaptive management) (Vallauri et al., 2005). Despite its importance, monitoring is frequently neglected in ecological restoration, limiting the potential for sustainability and knowledge sharing (Murcia et al., 2016). Moreover, when monitoring is performed it is often limited to short timespans, potentially missing important change as restoration projects mature (Nilsson et al., 2016).

Monitoring can also be neglected because there is a perception that it is too expensive — although very few studies have looked at the restoration costs, including monitoring (Wortley et al., 2013). Indeed, monitoring has its costs, and they are directly linked to the sampling effort. If practitioners set a reduced sampling effort to monitor ecological indicators (Viani et al., 2018), they might reduce the monitoring costs; however, they risk misdiagnosing restoration progress. On the other hand, practitioners can waste resources if they set a higher sampling effort than necessary (Viani et al., 2018). Identifying an optimal sampling area (OSA) would help restoration practitioners plan for the minimum monitoring needed to gauge the restoration trajectory confidently and avoid wasting scarce resources.

Sampling sufficiency is a fundamental assumption for statistical analyses and data validation (Quinn and Keough, 2002). However, few studies have attempted to identify the optimal sampling for restoration monitoring, particularly at large spatial scales and with multiple ecological indicators (Abella and Covington, 2004; Viani et al., 2018). Moreover, it is unclear whether the OSA varies among restoration interventions, vegetation types, or restoration project age.

* Corresponding author.
E-mail address: vlonde.ecologia@gmail.com (V. Londe).

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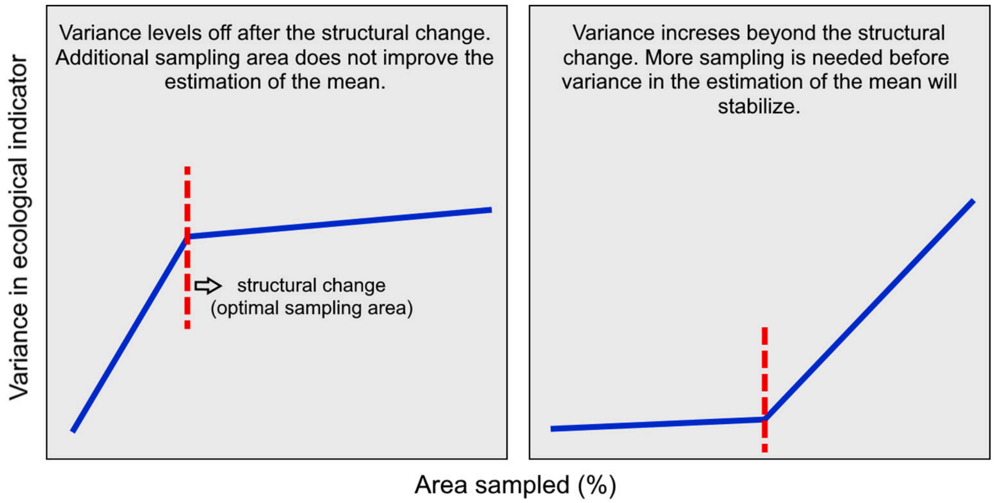

Fig. 1. Conceptual model of the optimal sampling area (OSA), the sampling area that efficiently captures most variance in an ecological indicator. The OSA can be thought of as an inflection point where variance in an ecological indicator stabilizes when a sufficient portion of a restored area has been sampled via monitoring (left). The shape of the function is critical; a breakpoint following by increasing variance indicates that a larger area of sampling is required before variance in the indicator will stabilize (right).

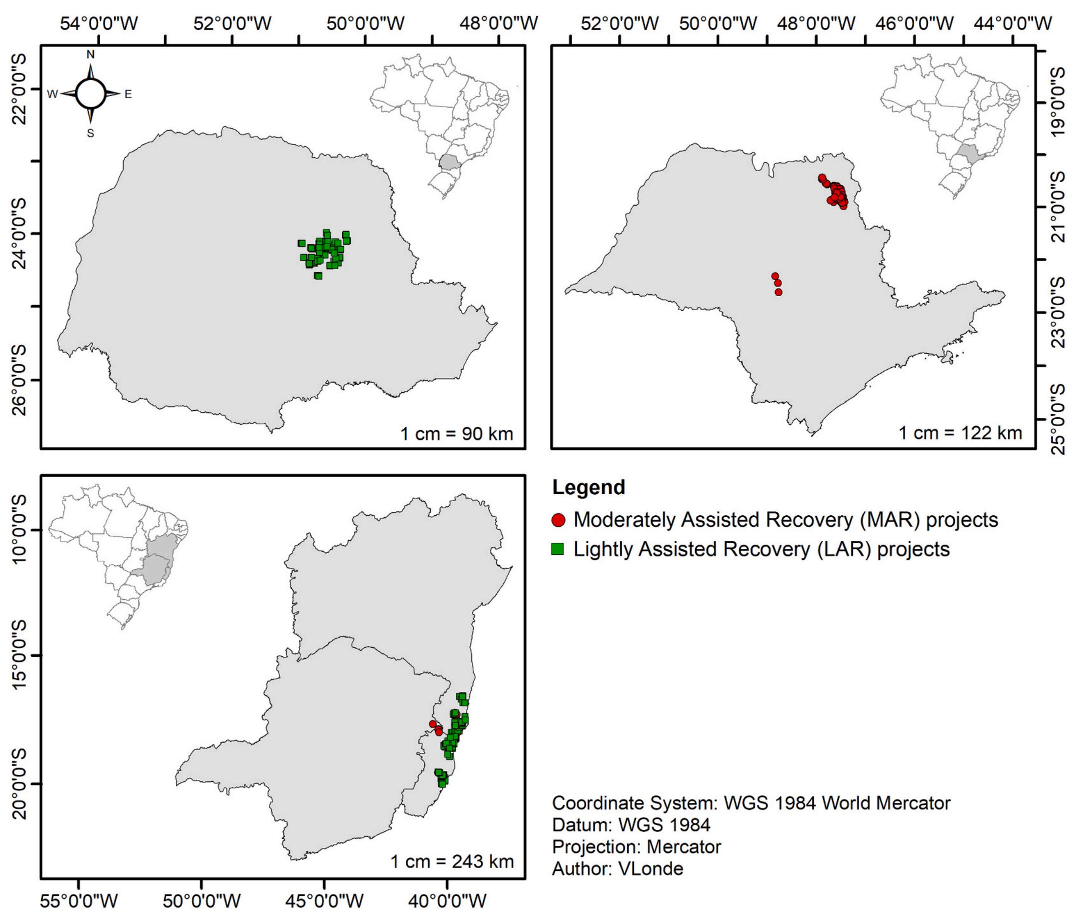

Fig. 2. Location of 374 forest restoration projects in five states within the Brazilian Atlantic Forest biome: Paraná (upper left), São Paulo (upper right), and northeast Minas Gerais, southern Bahia and northern Espírito Santo (lower left). Restoration interventions made in MAR projects were site preparation and tree planting. Interventions made in LAR projects were fencing the sites and protecting them after eucalypt and pine harvesting.

Here we estimated the OSA for a range of ecological indicators in restored tropical forests in the Brazilian Atlantic Forest biome. We tested the following hypotheses: (1) there is an OSA that efficiently captures variation in the estimation of ecological indicators in restoration projects; (2) restoration intervention and forest type affect OSA; (3) OSA change over time as restoration projects age. We predicted that (1) structural changes occur in the restoration outcomes and these changes indicate the OSA (Fig. 1); (2) the variance of the outcomes levels off after the structural change, meaning that no additional sampling area is needed to estimate the mean (Fig. 1); (3) naturally regenerating forests require more sampling effort as they may be more heterogeneous than tree plantings (Holl et al., 2013); (4) mixed rainforests require more sampling than semideciduous seasonal and dense rainforests due to environmental conditions (Vibrans et al., 2020); (5) the OSA increases with increasing age as older forests may have more spatial and temporal variation (Finegan and Delgado, 2000).

Table 1
Indicators used to monitor restoration projects in the Brazilian Atlantic Forest. Adapted from the Monitoring Protocol (2013).

Ecological indicator	Description
Grass cover (%)[1]	Amount of land covered by super dominant or invasive grass species
Canopy cover (%)	Amount of land shaded by the canopies of tree species. It was estimated through the line interception method (Canfield, 1941)
Mean canopy height (m)[2]	Mean canopy height measured with a clipper pole within a plot
Basal area (m^2 ha^{-1})	Sum of cross-sectional basal areas, obtained via measuring all branches of plants, including at least one branch with diameter at breast height (dbh) ≥ 4.77-cm
Tree density (stem ha^{-1})	Number of large size trees (dbh ≥ 4.77-cm) per hectare
Tree species richness (n)	Count of large sized tree species with dbh ≥ 4.77-cm present in the restoration zone
Regional tree species (%)[2] Zoochoric tree species (%)[2] Non-pioneer tree species (%)[2]	Proportion of species from planted or regenerating trees with dbh ≥ 4.77-cm
Density of regenerating species (stem ha^{-1})	Number of small-sized trees per hectare (height ≥ 0.5-m and dbh < 4.77-cm)
Regenerating species richness (n)[2]	Count of small-sized woody species with height ≥ 0.5-m and dbh < 4.77-cm

[1] This indicator was sampled into two or three 2-m^2 subplots within the 60-m^2, 100-m^2, or 120-m^2 plots.
[2] These indicators were not included in the monitoring protocol, but we estimated them from other indicators (except canopy height).

2. Material and methods

2.1. Study areas

The study was carried out in the Brazilian Atlantic Forest, a biodiverse but threatened biome, currently considered one of the most significant restoration hotspots in the Tropics (Brancalion et al., 2019). The Atlantic Forest once covered 1,315,460-km^2, but today it is reduced to about 11.4–16% of its original range (Ribeiro et al., 2009). Historically, the Atlantic Forest was a mosaic of dense and mixed rainforests (also known as Ombrophilous forests); deciduous and semideciduous seasonal forests; high-altitude grasslands, mangroves, and salt marshes (IBGE - Brazilian Institute of Geograph and Statistics, 2012).

Due to its high importance and degradation status, the Atlantic Forest has received large-scale restoration effort in recent decades (Rodrigues et al., 2009). One of these efforts is the Atlantic Forest Restoration Pact, a national public-private movement launched in 2009 to recover 15 million hectares of degraded areas by 2050 (Atlantic Forest Restoration Pact, 2021). Studies have estimated that about 1.40-Mha of degraded lands in the Atlantic Forest were under-recovery by 2020, indicating that ambitious restoration targets can be feasible (Crouzeilles et al., 2019).

We studied 374 restoration projects in five Brazilian states: 144 sites were moderately assisted recovery (MAR), and 230 sites were lightly assisted recovery (LAR) (Chazdon et al., 2021) (Fig. 2). Projects from the Paraná region are about 480-km apart from those of the São Paulo region and 1356.00-km from Bahia. Restoration sites fall into several unique vegetation types, including semideciduous seasonal forests (SSF) (between 20% and 50% of trees lose their leaves in the dry season), dense rainforests (DRF) (without a dry period), and mixed rainforests (MRF) (i.e., *Araucaria* forest (IBGE, 2012). Sites that fall exclusively into SSF amounted to 23%, sites into a mix of SSF and DRF were 40%, and DRF/MRF were 37%.

In MAR projects, saplings from 40 to 50 regional tree species were planted in 2- × 3-m or 3- × 3-m lines between January 2006 and September 2013. Grasses and other herbs were removed using glyphosate before planting. Soil pH was corrected using an average of 1-ton of limestone per hectare. The tree planting restoration intervention was applied in sites lacking potential for natural regeneration, e.g., in highly fragmented agricultural landscapes, mainly used for sugar cane cultivation. MAR projects were three months to 6.5 years old at the time of sampling and between 0.5- and 114.4-ha (mean 15.2-ha).

LAR was implemented between June 2007 and June 2012 in sites with potential for natural regeneration. These sites were mostly located in forested landscapes and surrounded by commercial eucalypt and pine plantations. Indeed, LAR was always implemented after harvesting eucalypt and pine. The sites were fenced and abandoned to promote natural regeneration. Natural regeneration after harvesting commercial plantations has proven to be an effective restoration intervention in the Brazilian Atlantic Forest (Brancalion et al., 2020). LAR projects were between two months and six years and eight months in age at the time of sampling, and between 0.5- and 111.2-ha in size (mean 4.4-ha).

2.2. Data collection

We monitored and evaluated the restoration projects from January 2011 to December 2015. The projects were monitored using a standard monitoring protocol, the Protocol for Monitoring Programs and Projects of Forest Restoration in the Atlantic Forest (Monitoring Protocol, 2013). Eleven indicators were used to monitor the canopy structure and ecological trajectory (phases I and II) of the restoration projects (Viani et al., 2017) (Table 1). These ecological indicators were chosen because they can be measured quickly in the field and represent three vital ecosystem attributes: structure, diversity, and functionality (Ruiz-Jaen and Mitchell Aide, 2005).

As the restoration projects had different sizes/areas, the sampling effort for monitoring them also varied. We used non-permanent plots of 60-m^2 and 100-m^2 to monitor the restoration projects at Paraná, 100-m^2 and 120-m^2 at São Paulo, and 100-m^2 at Bahia region (Fig. 2). The plots were randomly distributed using a simple random sampling design to capture the heterogeneity of each site. We allocated 1–4 plots in restoration projects of 0.5-ha; five plots in projects >0.5-ha and ≤1-ha; and five plots plus one plot for each additional hectare in projects greater than 1-ha (Monitoring Protocol, 2013). For example, to monitor a restoration area of 24-ha at Paraná with 60-m^2 plots, we used 28 plots (five plots for 1-ha plus 23 plots for 23 additional hectares). The total percentage of the area sampled in this example was 7% (1680-m^2). In total, we collected data from 5000 plots: 2820 in MAR projects and 2180 in LAR projects. The area sampled amounted to 30.3-ha in MAR projects and 20.2-ha in LAR projects (50.5-ha total).

We estimated canopy cover through the line interception method (Canfield, 1941) and canopy height with a clipper pole. We considered large-sized plants with diameter at breast height (dbh at 1.30-m) ≥ 4.77-cm and small-sized (regenerating) plants with dbh < 4.77-cm and height > 0.5-m. In MAR projects, we measured as regenerating only the plants found outside the planting lines (thus, the saplings planted were not counted as regenerating). Unlike most studies where the regenerating plants are measured in subplots (e.g., 1-m^2 plots), we counted and identified all regenerating plants within the large plots. We used subplots of 2-m^2 each to estimate the percentage of grass cover visually. We installed two subplots within the 60-m^2 plots and three subplots within the 100-m^2 and 120-m^2 plots.

We identified woody species in the field and collected botanical material from some specimens for further identification through literature consultations. In LAR projects, the eucalypt (regrowth) and pine trees were also measured if present in the plots. We classified the species according to their regionality (whether a species belonged to the regional floristic pool), dispersion mode (zoochoric and non-zoochoric), and successional stage (pioneer and non-pioneer) by consulting several sources (Horus Institute - Horus Institute for Environmental Conservation and Development, 2021; IPÊ - Instituto de Pesquisas Ecológicas [Ecological Research Institute], 2021; Lorenzi, 2016, 2020, 2021).

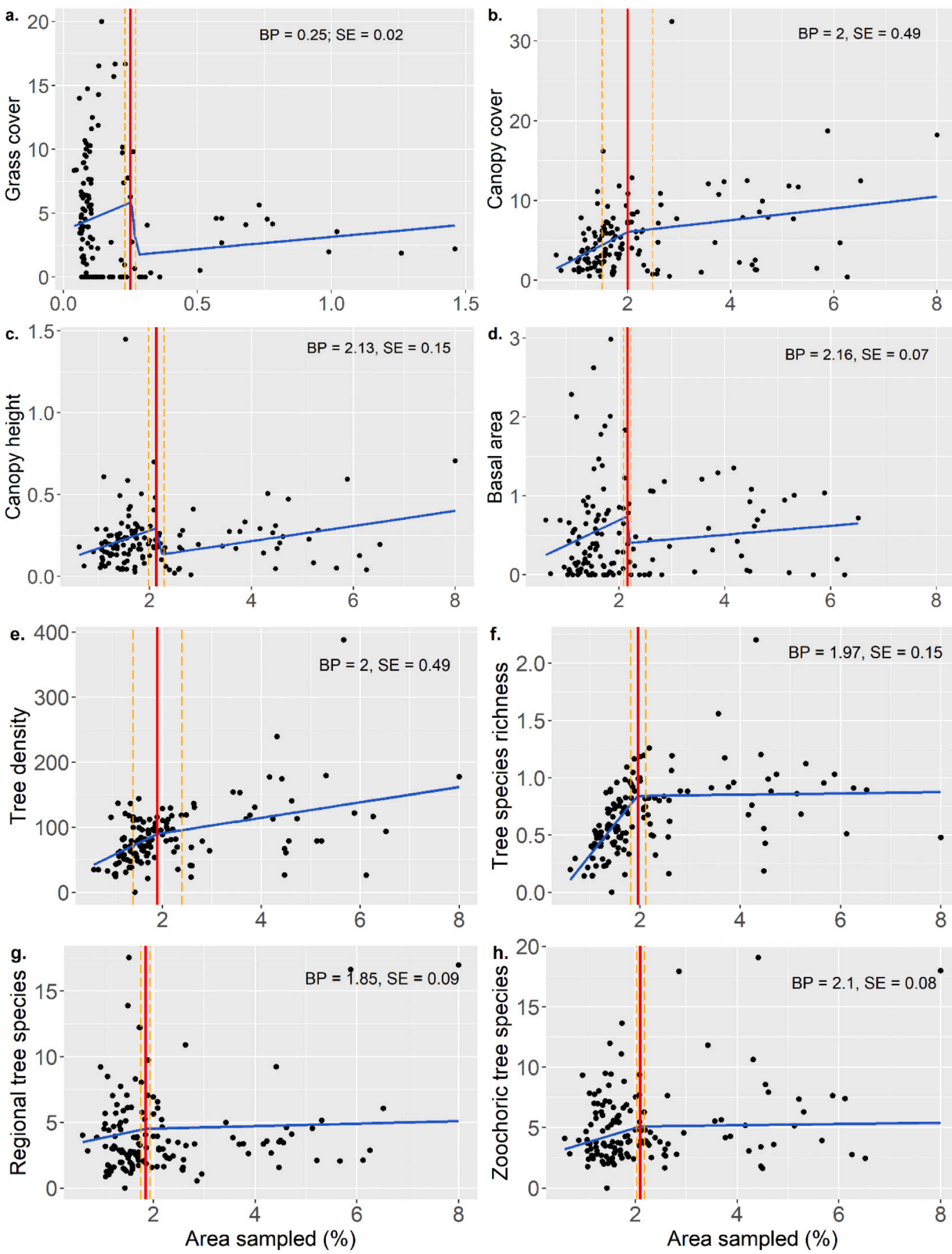

Fig. 3. Optimal sampling area (OSA; red line) for moderately assisted recovery (MAR) projects estimated from segmented regressions of variance in ecological indicators (standard error) against area of a restoration project that was sampled (%; blue line). Vertical dashed orange lines represent the standard error of the OSA. MAR projects (n = 144) are characterised by local site preparation and full tree planting (Chazdon et al., 2021). BP = breakpoint. SE = standard error. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.3. *Data analysis*

We started by calculating the percentage of the area sampled and standard error (the measure of variance) for each ecological indicator in each restoration project. For example, the project “Adorama” in São Paulo has 7.74-ha, and it was monitored using 12 120-m^2 plots, totalling 0.144-ha (or 1.86%) of the area sampled. Taking the indicator canopy cover as an example, we had a measure for each plot, so the mean was 17.1%, and the standard error was 4.08. We used the area sampled (e.g., 1.86%) and standard error (e.g., 4.08) to estimate OSA. We used the ‘DescTools’ package (Signorell et al., 2021) in the R environment (R Core Team, 2021) to perform these tasks.

Next, to test whether there is an OSA that efficiently captures variation while estimating the ecological indicators (H1), we fitted the data into segmented regression (or piecewise regression). Segmented regression models are “broken” models, where two or more lines are joined at unknown point(s), called breakpoint(s) or changepoint(s) (Toms and Lesperance, 2003). Breakpoints represent one or more values where the effect on the response variable changes in non-linear relationships, indicating structural changes in the data (Muggeo, 2003)

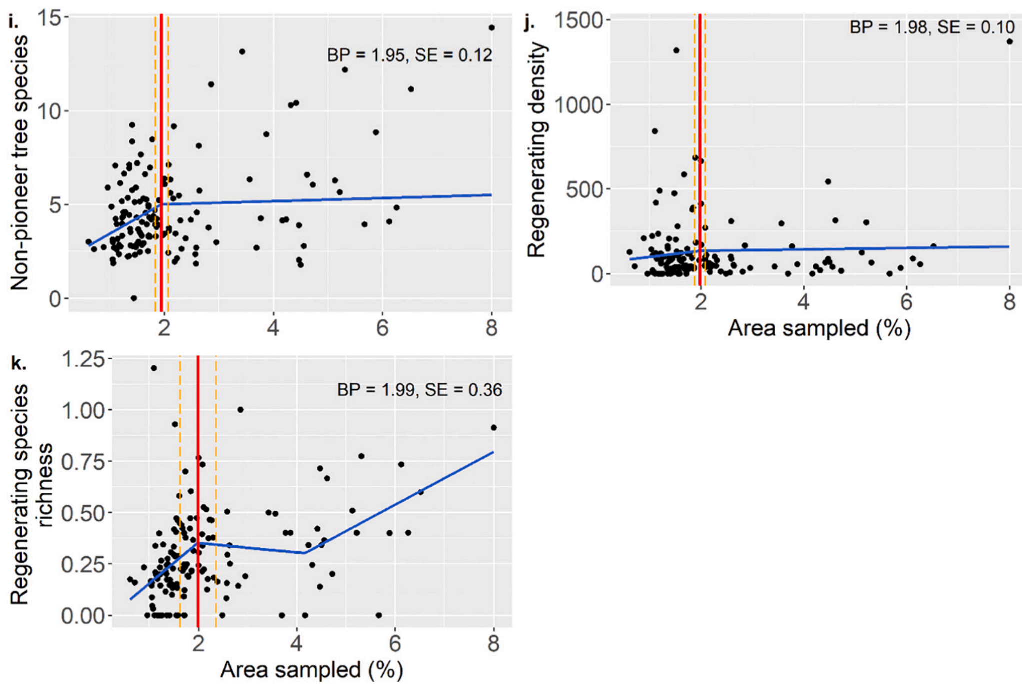

Fig. 3. (*continued*).

(Fig. 1 — vertical bar). Breakpoints split the data into two or more segments, and their occurrence can be gradual or abrupt (Topál et al., 2016). Breakpoints have previously been used to identify structural changes and thresholds in earth sciences and ecology (D'Amario et al., 2019; Toms and Lesperance, 2003; Topál et al., 2016).

We performed the segmented regressions using the percentage of the area sampled to predict the variation (standard error) in each ecological indicator. The regressions were performed according to the restoration intervention and forest type. We defined the starting values for some segmented models by observing the data distribution. We used the breakpoint to determine the OSA and the regression line's shape to find if the variance levelled off after the structural change. Segmented regressions were performed into the 'segmented' package (Muggeo, 2008), where we also tested for the number of breakpoints in the segmented relationship ('selgmented' function) and change in the slope (Davies' test). If more than one breakpoint was detected, we interpreted the first one as the OSA. (The second breakpoint was infrequent, occurring in six of 55 cases). The fitted data from the segmented model were used to build the regression lines in the graphics. We created the graphics using the 'ggplot2' package (Wickham, 2016).

We used the area sampled for each ecological indicator to test whether OSA varies among restoration interventions and forest types (H2). Normality was checked via the Shapiro-Wilk test and homogeneity of variances via F-test (restoration intervention data — two groups) and Bartlett test (forest type data — three groups). We also checked for influential values by performing Cook's distance tests. We performed a Kruskal-Wallis test to analyse the effect of restoration intervention (non-normal distribution and unequal variances) and a one-way ANOVA to test the effect of forest type. Significant outliers were not found for any variable (Cook's distance <1) (Quinn and Keough, 2002).

To test whether and how the OSA changes over time (H3), we divided the data according to years since project initiation, calculated the OSA, and performed nonlinear regressions. The data was divided into the following ages: 0–1, 1.1–2, 2.1–3, 3.1–4, 4.1–5, 5.1–6, 6.1–7 years since project initiation. Since the number of estimations of the sampling area and regressions would be high if calculated for all ecological indicators, we decided to investigate which indicators were uncorrelated and use them in the analyses. We used the variance calculated for each indicator to perform a rank-based (Spearman) correlation matrix. The assumption of multivariate normality was performed in the 'mvnormtest' package (Slawomir, 2012) and correlation matrix with significance levels (P-value <0.01) in the 'Hmisc' package (Harrell, 2021). We represented the results in a correlogram ('ggcorrplot' package) (Kassambara, 2019).

We calculated the OSA by age for the uncorrelated indicators (those with correlation coefficients <0.60 (Quinn and Keough, 2002)) and then fitted the data into nonlinear models due to the lack of linearity, even when data were log-transformed. The nonlinear models fitted were power, exponential, logarithmic, polynomial (quadratic), and hyperbolic (Logan, 2010). We choose the best fit nonlinear model to the data via BIC (Bayesian Information Criterion). Confidence intervals for fitted lines were predicted using Monte Carlo simulations into the 'nlraa' package (Miguez, 2022).

3. Results

The percentage of the area sampled ranged from 0.61% to 8.0% in MAR projects and 0.31% to 8.0% in LAR projects. For grass cover (sampled in subplots), the percentage of the area sampled ranged from 0.04% to 1.46% in MAR projects and 0.02% to 0.48% in LAR projects. Regarding the OSA, it ranged from 0.25% for grass cover to 2.16% for the basal area in MAR projects (Fig. 3). After the breakpoint (structural change), variance levelled off for all indicators in MAR projects. OSA ranged from 0.24% for grass cover to 4.67% for the basal area in LAR projects (Fig. 4). Variance also levelled off after the breakpoint estimation. There was weak evidence that OSA was greater in LAR projects than in MAR projects (median of 2.4 and 2.0, respectively) (Kruskal-Wallis: χ^2 = 3.76, df = 1, P = 0.052) (Fig. S1 — Supplementary material).

The OSA ranged from 0.07% to 6.08% in semideciduous seasonal forests (3.31 ± 1.53), 0.05% to 4.0% in dense rainforests (2.45 ± 1.23), and 0.23% to 4.0% in mixed rainforests (1.94 ± 1.08) (Table 2). However, there was weak evidence that OSA was greater in semideciduous seasonal forests than in dense rainforests and mixed rainforests (ANOVA: $F_{2, 29}$ = 3.10, P = 0.060) (Fig. S2 — Supplementary material).

Grass cover, canopy cover, regional (native) trees, zoochoric trees,

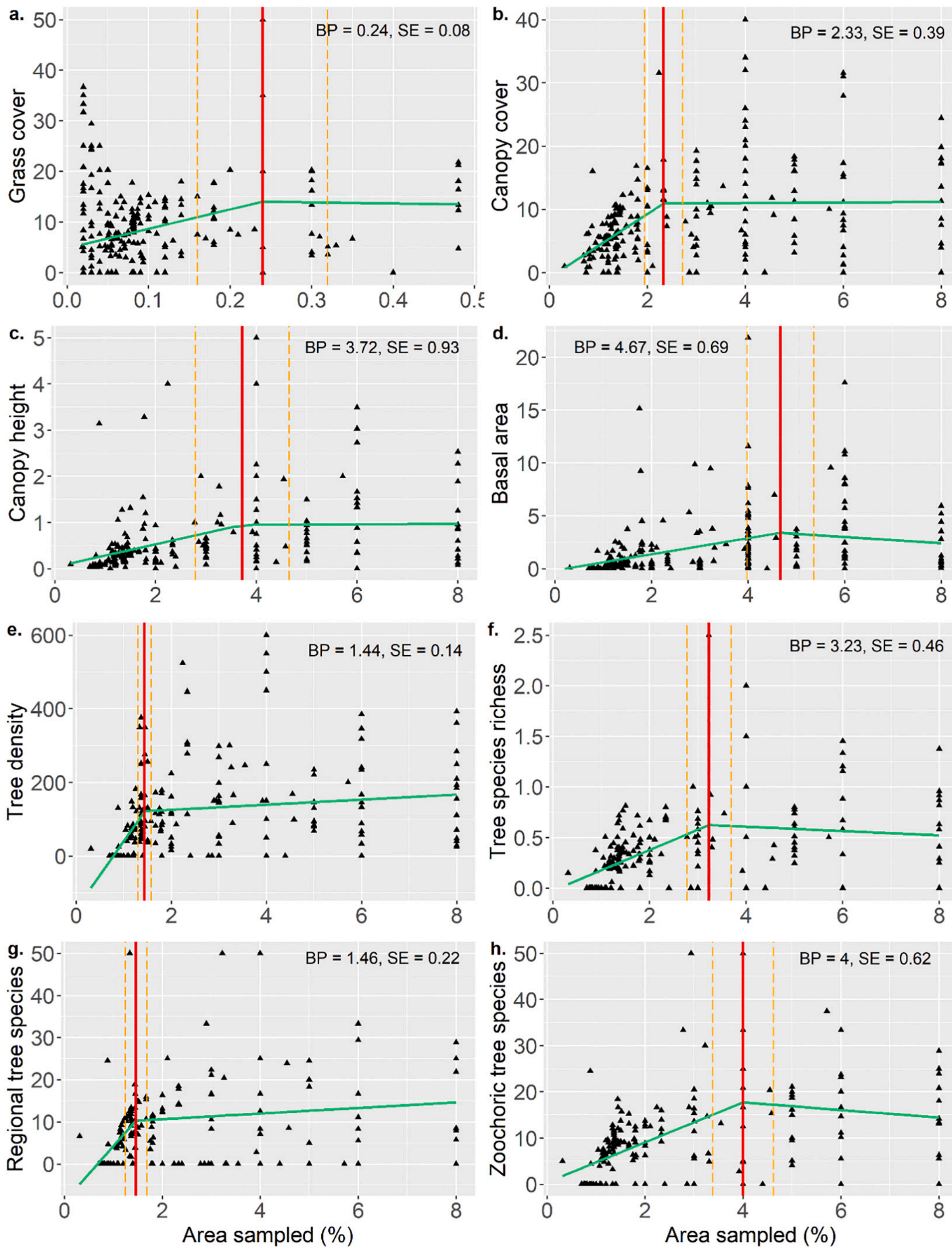

Fig. 4. Optimal sampling area (OSA; red line) for lightly assisted recovery (LAR) projects estimated from segmented regressions of variance in ecological indicators (standard error) against area of a restoration project that was sampled (%; green line). Vertical dashed orange lines represent the standard error of the OSA. LAR projects (n = 230) are characterised by natural regeneration after harvesting eucalypt and pine plantations (Chazdon et al., 2021). BP = breakpoint. SE = standard error. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and non-pioneer trees were uncorrelated with other indicators, and as such these were used to evaluate changes in OSA with increasing age of restoration projects (Fig. S3 — Supplementary material). Best-fit models were hyperbolic and quadratic, indicating that OSA changes as restoration projects mature, but that the direction of change varies among indicators (Table S1 — Supplementary material). While optimal sampling area diminished over time for grass cover, there was evidence that it increased for other indicators (except zoochoric trees), reaching 4.0% of the area to be sampled (Fig. 5).

4. Discussion

As investment in large-scale restoration ramps up, it is critical that planners and practitioners have ecologically adequate, cost-effective strategies for monitoring restoration success. Here, we have described a method for estimating the optimal sampling area (OSA) for ecological indicators in restoration projects and demonstrated the method using a large sample of restoration projects from southeastern Brazil. Historically, monitoring has been applied only sporadically, often due to a lack of funding (Bernhardt et al., 2007), with severe consequences for

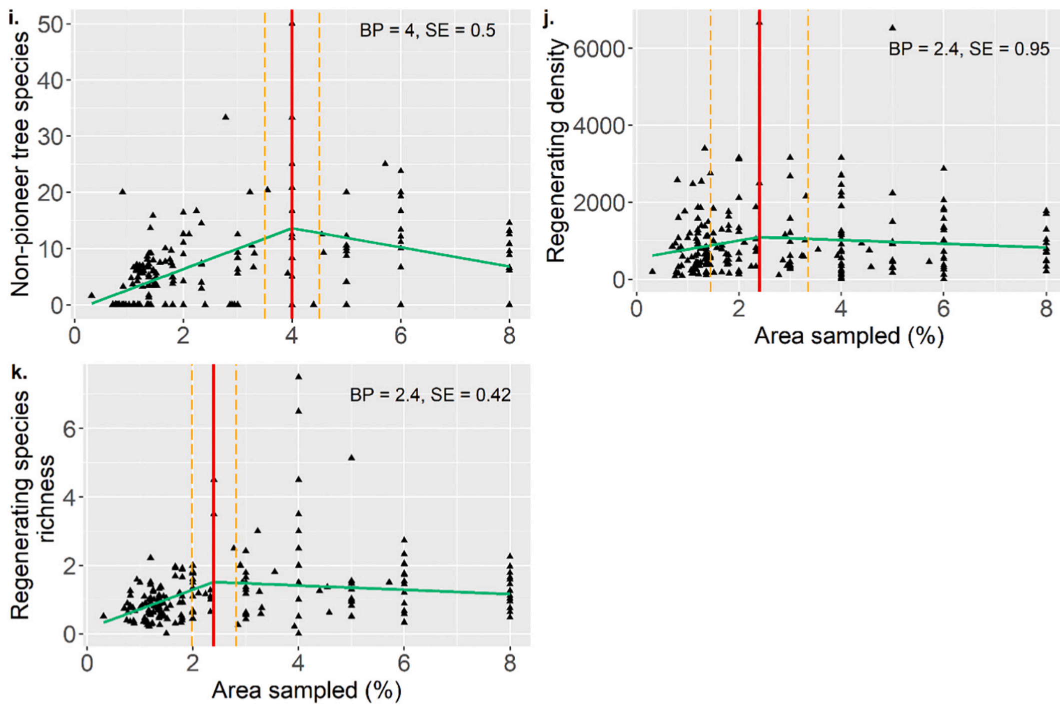

Fig. 4. (*continued*).

Table 2
The optimal sampling area (% ± SE) estimated for 11 ecological indicators and three forest types in the Brazilian Atlantic Forest.

Ecological indicator	Forest type		
	Semidecidual seasonal forest	Dense rainforest	Mixed rainforest
Grass cover	0.07 ± 0.02	0.05 ± 0.02	0.23 ± 0.04
Canopy cover	2.24 ± 0.55	2.32 ± 0.34	3.58 ± 0.42
Canopy height	4.00 ± 1.66	3.59 ± 0.71	1.57 ± 0.15
Basal area	6.08 ± 1.59	NA	1.5 ± 0.14
Tree density	2.86 ± 0.63	1.49 ± 0.14	1.44 ± 0.14
Tree species richness	2.71 ± 0.38	1.54 ± 0.14	1.41 ± 0.10
Regional tree species	4.28 ± 1.85	2.64 ± 0.68	4.00 ± 0.48
Zoochoric tree species	4.00 ± 0.68	4.00 ± 0.58	1.36 ± 0.20
Non-pioneer tree species	4.00 ± 0.53	4.00 ± 0.46	1.46 ± 0.18
Density of regenerating species	2.23 ± 1.02	2.40 ± 0.56	2.40 ± 0.64
Regenerating species richness	4.00 ± 0.72	2.47 ± 0.33	2.44 ± 0.45

NA = No breakpoint was estimated.

adaptive management and knowledge transfer. By developing OSAs for different indicators, regions, interventions, and stages of restoration projects, we expect that planning and implementing restoration monitoring will become more predictable and accessible for restoration programs globally.

The number of forest restoration assessments has increased in recent years, especially in South America (Gatica-Saavedra et al., 2017). However, we do not know if these restoration projects have been monitored adequately, i.e., if the spatial area monitored has been more or less than the optimal amount. The narrow standard errors we found around OSAs suggest that many restoration practitioners are monitoring either below or beyond the optimal amount, and this is probably the reality for many other restoration projects worldwide. Those monitoring larger areas than the optimal amount have had little risk of reaching wrong conclusions about the restoration trajectory as they achieved the sampling effort necessary to reach the asymptote of the sampling curve (Chao et al., 2009), but they could save money by scaling back the area sampled. In contrast, those sampling below the optimal area may reach false negative or positive conclusions about their projects' success, and they could improve their ability to adaptively manage restoration sites by increasing the spatial scale of their monitoring.

Studies evaluating ecological indicators at small spatial scales can underestimate scale-dependent effects and contribute to uncertainty about the importance of regional processes for community assembly and restoration success (Catano et al., 2021). Although our study includes a relatively small range of the area sampled (0.31 to 8.0%), variance levelled off after the breakpoint for all indicators, suggesting that the OSA represents an appropriately-sized monitoring area, at least for the ecological indicators used here. This is promising for large-scale restorations where the entire area remains a technical and logistical challenge.

Additionally, the optimal sampling area's estimation for several indicators allows the restoration practitioners to evaluate specific vegetation parameters or a set of them together. For instance, if one intends to monitor natural regeneration areas using species richness, density and height of trees — the most commonly used indicators for assessing forest composition and structure (Gatica-Saavedra et al., 2017) —, an optimal sampling area of 3.72% encompasses all of them.

We found evidence that MAR and LAR likely require similar spatial sampling scales, or perhaps slightly larger sampling areas in LAR. Large-scale studies have shown that many ecological indicators can be recovered in natural regeneration and tree planting areas within one decade or two (Londe et al., 2020). Perhaps because indicators can recover relatively rapidly in both interventions, the OSA is similar. A larger spatial scale could be required for interventions that promote spatial heterogeneity, such as applied nucleation (Holl et al., 2013). Future studies would be useful to evaluate the OSA for specific indicators and restoration interventions in different regions.

Also, contrary to predicted, we found evidence that OSA is similar between forest types. Recent studies have shown that more sample plots are necessary to achieve sample sufficiency in mixed rainforests than semideciduous seasonal and dense rainforests (Vibrans et al., 2020). However, the mentioned study was carried out in secondary and old-

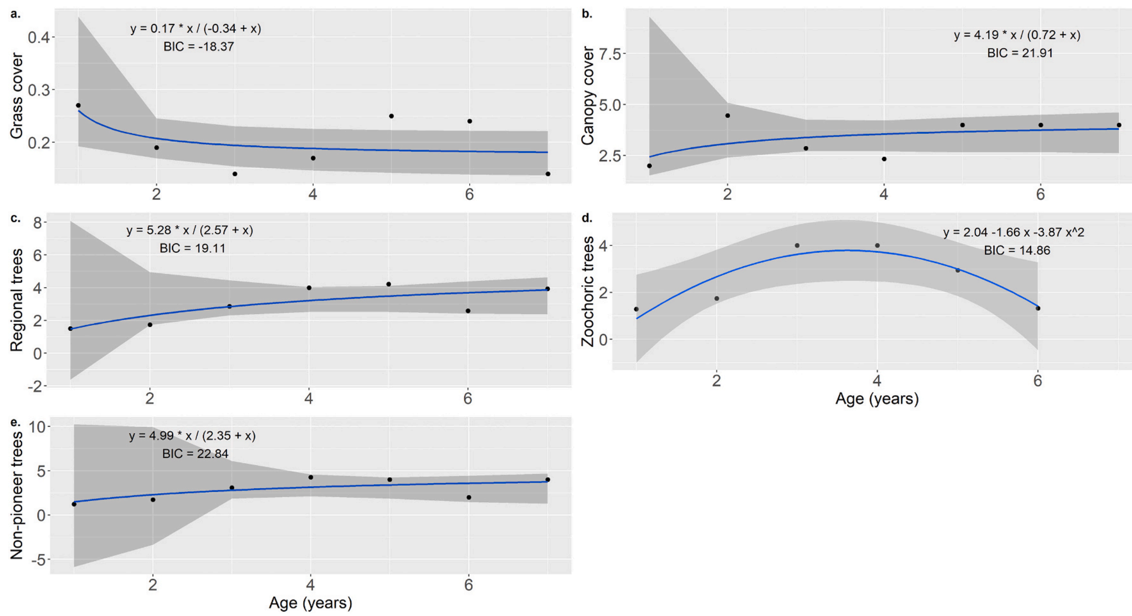

Fig. 5. Nonlinear relationships between optimal sampling area (OSA) and the age of restoration sites for five uncorrelated ecological indicators. Best-fit models were hyperbolic (a, c, d, e) and quadratic (b). The blue line represents the fitted function and shaded area the confidence interval at 95%. BIC = Bayesian Information Criterion. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

growth forest remnants. Recently restored forests tend to differ from older forests (reference ecosystems) in structure, composition and function (Londe et al., 2020; Toledo-Aceves et al., 2021; Williams-Linera et al., 2021). Even so, a broader evaluation of OSAs across ecosystem types (e.g., grasslands, deserts, mangroves) will likely find that optimal sampling area varies. The evidence of similarity in OSA among forest types in our study is likely related to the early successional stage and lower heterogeneity of MAR and LAR projects. As the restoration forests mature, it is expected that structural and floristic heterogeneity increase (Finegan and Delgado, 2000).

In this context, we can also understand why there was evidence that the OSA increased over time for some indicators. If older forests are more spatially heterogeneous in form and function, it makes sense that older restorations may require more sampling to capture their variability. For example, tree planting and applied nucleation can increase animal-dispersed seed heterogeneity at a local scale after a decade of restoration (Werden et al., 2021). However, we need more investigations over longer time scales to determine whether OSA shifts over time are meaningful for evaluating restoration success. Our sample size was restricted to up to seven years of age. For now, our findings suggest that OSA will stabilize by about 4.0% (the confidence intervals are narrower with increasing age), which is within the range of values we have estimated.

Finally, we provide some advice when monitoring very large-scale restoration projects. For example, it may be challenging to monitor 1000-ha restoration projects as the OSA should be of at least 20-ha. In such cases, we suggest that monitoring a smaller set of indicators or over a smaller area is still preferable to not monitoring at all. Restoration practitioners and land managers may also be able to combine field surveys with remote sensing to cover larger areas for a lower cost (Zahawi et al., 2015). Currently, there are several sensors and platforms useful to monitor restoration, but they are still little used (Camarretta et al., 2020). In all cases, monitoring should measure variables that correspond to the project's objectives (which will vary from project to project) and should have a clear plan for what to do with the data collected (Holl, 2020). All monitoring should aspire to be simple, inexpensive, safe, and replicable.

Data availability statement

The database is publicly available on Mendeley Data (doi: 10.17632/bwzrdtpkbc.1).

CRediT authorship contribution statement

Vinícius Londe: Conceptualization, Methodology, Formal analysis, Writing – original draft. **J. Leighton Reid:** Conceptualization, Methodology, Writing – review & editing. **Fabiano Turini Farah:** Investigation. **Ricardo Ribeiro Rodrigues:** Conceptualization, Writing – review & editing, Supervision. **Fernando Roberto Martins:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abella, S.R., Covington, W.W., 2004. Monitoring an Arizona ponderosa pine restoration: sampling efficiency and multivariate analysis of understory vegetation. Restor. Ecol. 12, 359–367. https://doi.org/10.1111/j.1061-2971.2004.00317.x.

Bernhardt, E.S., Sudduth, E.B., Palmer, M.A., Allan, J.D., Meyer, J.L., Alexander, G., Follastad-Shah, J., Hassett, B., Jenkinson, R., Lave, R., Rumps, J., Pagano, L., 2007. Restoring rivers one reach at a time: results from a survey of U.S. River restoration practitioners. Restor. Ecol. 15, 482–493. https://doi.org/10.1111/j.1526-100X.2007.00244.x.

Brancalion, P.H.S., Niamir, A., Broadbent, E., Crouzeilles, R., Barros, F.S.M., Almeyda Zambrano, A.M., Baccini, A., Aronson, J., Goetz, S., Leighton Reid, J., Strassburg, B. B.N., Wilson, S., Chazdon, R.L., 2019. Global restoration opportunities in tropical rainforest landscapes. Sci. Adv. 5, 3223–3226. https://doi.org/10.1126/sciadv.aav3223.

Brancalion, P.H.S., Amazonas, N.T., Chazdon, R.L., Melis, J., Rodrigues, R.R., Silva, C.C., Sorrini, T.B., Holl, K.D., 2020. Exotic eucalypts: from demonized trees to allies of tropical forest restoration? J. Appl. Ecol. 57, 55–66. https://doi.org/10.1111/1365-2664.13513.

Camarretta, N., Harrison, P.A., Bailey, T., Potts, B., Lucieer, A., Davidson, N., Hunt, M., 2020. Monitoring forest structure to guide adaptive management of forest restoration: a review of remote sensing approaches. New For. 51, 573–596. https://doi.org/10.1007/s11056-019-09754-5.

Canfield, R.H., 1941. Application of the line interception method in sampling range vegetation. J. For. 39, 388–394. https://doi.org/10.1093/jof/39.4.388.

Catano, C.P., Grman, E., Behrens, E., Brudvig, L.A., 2021. Species pool size alters species–area relationships during experimental community assembly. Ecology 102, e03231. https://doi.org/10.1002/ecy.3231.

Chao, A., Colwell, R.K., Lin, C.-W., Gotelli, N.J., 2009. Sufficient sampling for asymptotic minimum species richness estimators. Ecology 90, 1125–1133. https://doi.org/10.1890/07-2147.1.

Chazdon, R.L., Falk, D.A., Banin, L.F., Wagner, M., Wilson, S., Grabowski, R.C., Suding, K.N., 2021. The intervention continuum in restoration ecology: rethinking the active–passive dichotomy. Restor. Ecol. e13535 https://doi.org/10.1111/rec.13535.

Crouzeilles, R., Santiami, E., Rosa, M., Pugliese, L., Brancalion, P.H.S., Rodrigues, R.R., Metzger, J.P., Calmon, M., Scaramuzza, C.A.de M., Matsumoto, M.H., Padovezi, A., Chaves, R.B., Metzker, T., Fernandes, R.B., Scarano, F.R., Schmitt, J., Lui, G., Christ, P., Vieira, R.M., Senta, M.M.D., Malaguti, G.A., Benini, R.de M., Strassburg, B.B.N., Pinto, S., 2019. There is hope for achieving ambitious Atlantic Forest restoration commitments. Perspect. Ecol. Conserv. 17, 80–83. https://doi.org/10.1016/j.pecon.2019.04.003.

D'Amario, S.C., Rearick, D.C., Fasching, C., Kembel, S.W., Porter-Goff, E., Spooner, D.E., Williams, C.J., Wilson, H.F., Xenopoulos, M.A., 2019. The prevalence of nonlinearity and detection of ecological breakpoints across a land use gradient in streams. Sci. Rep. 9, 3878. https://doi.org/10.1038/s41598-019-40349-4.

DeLuca, T.H., Aplet, G.H., Wilmer, B., Burchfield, J., 2010. The unknown trajectory of forest restoration: a call for ecosystem monitoring. J. For. 108, 288–295. https://doi.org/10.1093/jof/108.6.288.

Finegan, B., Delgado, D., 2000. Structural and floristic heterogeneity in a 30-year-old Costa Rican rain forest restored on pasture through natural secondary succession. Restor. Ecol. 8, 380–393. https://doi.org/10.1046/j.1526-100X.2000.80053.x.

Gann, G.D., McDonald, T., Walder, B., Aronson, J., Nelson, C.R., Jonson, J., Hallett, J.G., Eisenberg, C., Guariguata, M.R., Liu, J., Hua, F., Echeverría, C., Gonzales, E., Shaw, N., Decleer, K., Dixon, K.W., 2019. International principles and standards for the practice of ecological restoration. In: Restor. Ecol, , Second edition27, pp. S1–S46. https://doi.org/10.1111/rec.13035.

Gatica-Saavedra, P., Echeverría, C., Nelson, C.R., 2017. Ecological indicators for assessing ecological success of forest restoration: a world review. Restor. Ecol. 25, 850–857. https://doi.org/10.1111/rec.12586.

Harrell Jr., F.E., 2021. Hmisc: Harrel Miscellaneous.

Holl, K.D., 2020. Primer of Ecological Restoration, 1st ed. Island Press, Washington, D.C.

Holl, K.D., Cairns Jr., J., 2002. Monitoring and appraisal. In: Perrow, M.R., Davy, A.J. (Eds.), Handbook of Ecological Restoration. Cambridge University Press, Cambridge, pp. 411–432. https://doi.org/10.1017/CBO9780511549984.

Holl, K.D., Stout, V.M., Reid, J.L., Zahawi, R.A., 2013. Testing heterogeneity–diversity relationships in tropical forest restoration. Oecologia 173, 569–578. https://doi.org/10.1007/s00442-013-2632-9.

Horus Institute - Horus Institute for Environmental Conservation and Development, 2021. Brazil invasive alien species database [WWW Document]. Horus Inst. Environ. Conserv. Dev. http://bd.institutohorus.org.br/www/. (Accessed 15 July 2021).

IBGE - Brazilian Institute of Geograph and Statistics, 2012. Manual técnico da vegetação brasileira (Technical manual of the Brazilian vegetation), 2nd ed. IBGE, Rio de Janeiro, Brazil.

IPÊ - Instituto de Pesquisas Ecológicas [Ecological Research Institute], 2021. Restauração: Árvores na Mata [Restoration: Trees in the Forest] [WWW Document]. Inst. Pesqui. Ecológicas [Ecological Res. Institute]. http://flora.ipe.org.br/. (Accessed 20 June 2016).

Kassambara, A., 2019. ggcorrplot: Visualization of a Correlation Matrix using "ggplot2.".

Logan, M., 2010. Biostatistical Design and Analysis Using R: A Practical Guide. Wiley-Blackwell, Chichester.

Londe, V., Turini Farah, F., Ribeiro Rodrigues, R., Roberto Martins, F., 2020. Reference and comparison values for ecological indicators in assessing restoration areas in the Atlantic Forest. Ecol. Indic. 110, 105928 https://doi.org/10.1016/j.ecolind.2019.105928.

Lorenzi, H., 2016. Árvores Brasileiras II: Manual de identificação e cultivo de plantas arbóreas nativas do Brasil (Brazilian Trees II: Identification and Cultivation Manual of Arboreal Plants Native to Brazil), 5th ed. Plantarum, Nova Odessa.

Lorenzi, H., 2020. Árvores Brasileiras I: Manual de identificação e cultivo de plantas arbóreas nativas do Brasil (Brazilian Trees I: Identification and Cultivation Manual of Arboreal Plants Native to Brazil), 8th ed. Plantarum, Nova Odessa.

Lorenzi, H., 2021. Árvores Brasileiras III: Manual de identificação e cultivo de plantas arbóreas nativas do Brasil (Brazilian Trees III: Identification and Cultivation Manual of Arboreal Plants Native to Brazil), 3rd ed. Plantarum, Nova Odessa.

Miguez, F., 2022. nlraa: Nonlinear Regression for Agricultural Applications.

Monitoring Protocol, 2013. Monitoring protocol for forest restoration programs and projects [WWW Document]. In: Atl. For. Restor. Pact.. https://www.pactomataatlantica.org.br/o-movimento/acervo/. (Accessed 14 July 2021).

Muggeo, V.M.R., 2003. Estimating regression models with unknown break-points. Stat. Med. 22, 3055–3071. https://doi.org/10.1002/sim.1545.

Muggeo, V.M.R., 2008. Segmented: An R Package to Fit Regression Models With Broken-line Relationships.

Murcia, C., Guariguata, M.R., Andrade, Á., Andrade, G.I., Aronson, J., Escobar, E.M., Etter, A., Moreno, F.H., Ramírez, W., Montes, E., 2016. Challenges and prospects for scaling-up ecological restoration to meet international commitments: Colombia as a case study. Conserv. Lett. 9, 213–220. https://doi.org/10.1111/conl.12199.

Nilsson, C., Aradottir, A.L., Hagen, D., Halldórsson, G., Høegh, K., Mitchell, R.J., Raulund-Rasmussen, K., Svavarsdóttir, K., Tolvanen, A., Wilson, S.D., 2016. Evaluating the process of ecological restoration. Ecol. Soc. 21, 41. https://doi.org/10.5751/ES-08289-210141.

Pact, Atlantic Forest Restoration, 2021. About the pact: The movement [WWW Document]. In: Pacto pela restauração da Mata Atlântica. https://www.pactomataatlantica.org.br. (Accessed 14 July 2021).

Quinn, G.P., Keough, M.J., 2002. Experimental Design and Data Analysis for Biologists. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511806384.

Ribeiro, M.C., Metzger, J.P., Martensen, A.C., Ponzoni, F.J., Hirota, M.M., 2009. The brazilian Atlantic Forest: how much is left, and how is the remaining forest distributed? Implications for conservation. Biol. Conserv. 142, 1141–1153. https://doi.org/10.1016/J.BIOCON.2009.02.021.

Rodrigues, R.R., Lima, R.A.F., Gandolfi, S., Nave, A.G., 2009. On the restoration of high diversity forests: 30 years of experience in the Brazilian Atlantic Forest. Biol. Conserv. 142, 1242–1251. https://doi.org/10.1016/j.biocon.2008.12.008.

Ruiz-Jaen, M.C., Mitchell Aide, T., 2005. Restoration success: how is it being measured? Restor. Ecol. 13, 569–577. https://doi.org/10.1111/j.1526-100X.2005.00072.x.

Signorell, A., et al., 2021. DescTools: Tools for Descriptive Statistics.

Slawomir, J., 2012. mvnormtest: Normality Test for Multivariate Variables.

Team, R.Core, 2021. R: A Language and Environment for Statistical Computing.

Toledo-Aceves, T., Trujillo-Miranda, A.L., López-Barrera, F., 2021. Tree regeneration in active and passive cloud forest restoration: functional groups and timber species. For. Ecol. Manag. 489, 119050 https://doi.org/10.1016/j.foreco.2021.119050.

Toms, J.D., Lesperance, M.L., 2003. Piecewise regression: a tool for identifying ecological thresholds. Ecology 84, 2034–2041. https://doi.org/10.1890/02-0472.

Topál, D., Matyasovszkyt, I., Kern, Z., Hatvani, I.G., 2016. Detecting breakpoints in artificially modified- and real-life time series using three state-of-the-art methods. Open Geosci. 8, 78–98. https://doi.org/10.1515/geo-2016-0009.

Vallauri, D., Aronson, J., Dudley, N., Vallejo, R., 2005. Monitoring and evaluating forest restoration success. In: Mansourian, S., Vallauri, D., Dudley, N. (Eds.), Forest Restoration in Landscapes. Springer-Verlag, New York, pp. 150–158. https://doi.org/10.1007/0-387-29112-1_21.

Viani, R.A.G., Holl, K.D., Padovezi, A., Strassburg, B.B.N., Farah, F.T., Garcia, L.C., Chaves, R.B., Rodrigues, R.R., Brancalion, P.H.S., 2017. Protocol for monitoring tropical forest restoration: perspectives from the Atlantic Forest restoration pact in Brazil. Trop. Conserv. Sci. 10, 1–8. https://doi.org/10.1177/1940082917697265.

Viani, R.A.G., Barreto, T.E., Farah, F.T., Rodrigues, R.R., Brancalion, P.H.S., 2018. Monitoring young tropical forest restoration sites: how much to measure? Trop. Conserv. Sci. 11, 1–9. https://doi.org/10.1177/1940082918780916.

Vibrans, A.C., De Gasper, A.L., Moser, P., Oliveira, L.Z., Lingner, D.V., Sevegnani, L., 2020. Insights from a large-scale inventory in the southern brazilian Atlantic Forest. Sci. Agric. 77, 2020. https://doi.org/10.1590/1678-992x-2018-0036.

Werden, L.K., Holl, K.D., Chaves-Fallas, J.M., Oviedo-Brenes, F., Rosales, J.A., Zahawi, R.A., 2021. Degree of intervention affects interannual and within-plot heterogeneity of seed arrival in tropical forest restoration. J. Appl. Ecol. 58, 1693–1704. https://doi.org/10.1111/1365-2664.13907.

Wickham, H., 2016. ggplot2: Elegant graphics for data analysis, 2nd ed. Use R! Springer-Verlag, Cham. https://doi.org/10.1007/978-3-319-24277-4.

Williams-Linera, G., Bonilla-Moheno, M., López-Barrera, F., Tolome, J., 2021. Litterfall, vegetation structure and tree composition as indicators of functional recovery in passive and active tropical cloud forest restoration. For. Ecol. Manag. 493, 119260 https://doi.org/10.1016/j.foreco.2021.119260.

Wortley, L., Hero, J.-M., Howes, M., 2013. Evaluating ecological restoration success: a review of the literature. Restor. Ecol. 21, 537–543. https://doi.org/10.1111/rec.12028.

Zahawi, R.A., Dandois, J.P., Holl, K.D., Nadwodny, D., Reid, J.L., Ellis, E.C., 2015. Using lightweight unmanned aerial vehicles to monitor tropical forest recovery. Biol. Conserv. 186, 287–295. https://doi.org/10.1016/J.BIOCON.2015.03.031.