Appendix S2: Landscapes land use and forest cover at different scales

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This appendix is a description of land uses in the focal landscapes together with the description of forest cover at both the local and the focal landscape scales. We present the baseline models for the selection of the best scale for the local forest cover variable for each dataset. For the local scale, we measured the percentage of forest cover within buffers of 400, 600 and 800 m around each sampling site. For the focaal landscape forest cover, we used the 2 km buffer around the landscape centroid.

1. Land use composition in landscapes

To clarify the differences in landscapes between regions and to show that these differences are in accordance with our categorical classification of high- and low-quality matrices for birds, we show in Figure S2.1 the composition of the main land use types per landscapes, and in Figure S2.2 and Table S2.1 the comparisons of land use types among the high- and low-quality regions.

We tested for differences in Shannon and Simpson diversity indexes using the percentage of land use types of the landscapes (Figure S2.3). We found larger diversity of land use types in high-quality matrix landscapes for both diversity indices, that is, more matrix heterogeneity in high-quality matrix landscapes.

We used Principal Coordinate Analysis (PCoA) to show the clear separation in land uses of landscapes from both regions (Figure S2.4). PCoA is more adequate than PCA given the nature of the data (sum up 100%, compositional data). We used gower distance tranformation to create a distance matrix among landscapes. Among the main land uses, landscapes in the low-quality region are more associated with larger proportions of pasture, eucalyptus plantations and urban areas to a lower extent, while landscapes in the high-quality region are more associated with larger proportions of coffee, sugar cane and lower proportions of pasture to a lower extend. The PCoA analysis also shows that forest cover variation is similar between regions and are not relevant in separating landscapes from both regions,i.e., the amount of forest cover among landscapes follows a similar gradient in both regions.

Although landscapes in the high-quality matrix region do have some proportion of pasture (mean 35.5% ± 10.2), this remains lower than the proportion of pasture in the low-quality matrix region (mean 46.9% ± 11.1). Moreover, as it can be seen in PCoA results (Figure S2.4), high-quality matrix landscapes are more negatively related to proportion of pasture when compared together with low-quality matrix landscapes.

Eucalyptus tree plantations represent the only arboreal matrix element in all 13 low-quality matrix landscapes and compose an average of 18% $\pm$ 8.7 of matrix cover, while high-quality landscapes have on average 2% $\pm$ 3.2 of eucalyptus in matrix cover but it is still present in 7 of the 10 landscapes. Although eucalyptus trees may, in principle, provide less edge effects as pastures and coffee plantations, it doesn't necessarily mean it is a high-quality matrix for birds. (Barros *et al.* (2019)) concluded that eucalyptus plantations at the same region of our low-quality matrix landscapes were matrices of lower quality because of intensive management including biocidal suppression of native understory vegetation. Such understory vegetation suppression results not only in resource poor environments, but in very simplified stratification with a limited amount of microhabitats required specially for understory and terrestrial species, allowing only a subset of more generalist species capable of using such areas (Jacoboski, Mendonça-Lima & Hartz (2016)). Moreover, eucalyptus plantations are also less perennial elements in the landscape with cycles of clearcut around 6-8 years (Rodrigues *et al.* (2019)). It means that eucalyptus plantations may not be necessarily equally high-quality matrices as initially supposed (Barros *et al.* (2019)), especially when compared with coffee plantations, which not only present a low-contrast physical structure, but also provide a variety of resources for different species yearlong, evidenced by high-rates of spillover movements from forest to them (Boesing, Nichols & Metzger (2018)).

Also note the high negative correlation among percentage of pasture and forest cover in Figure S2.5.

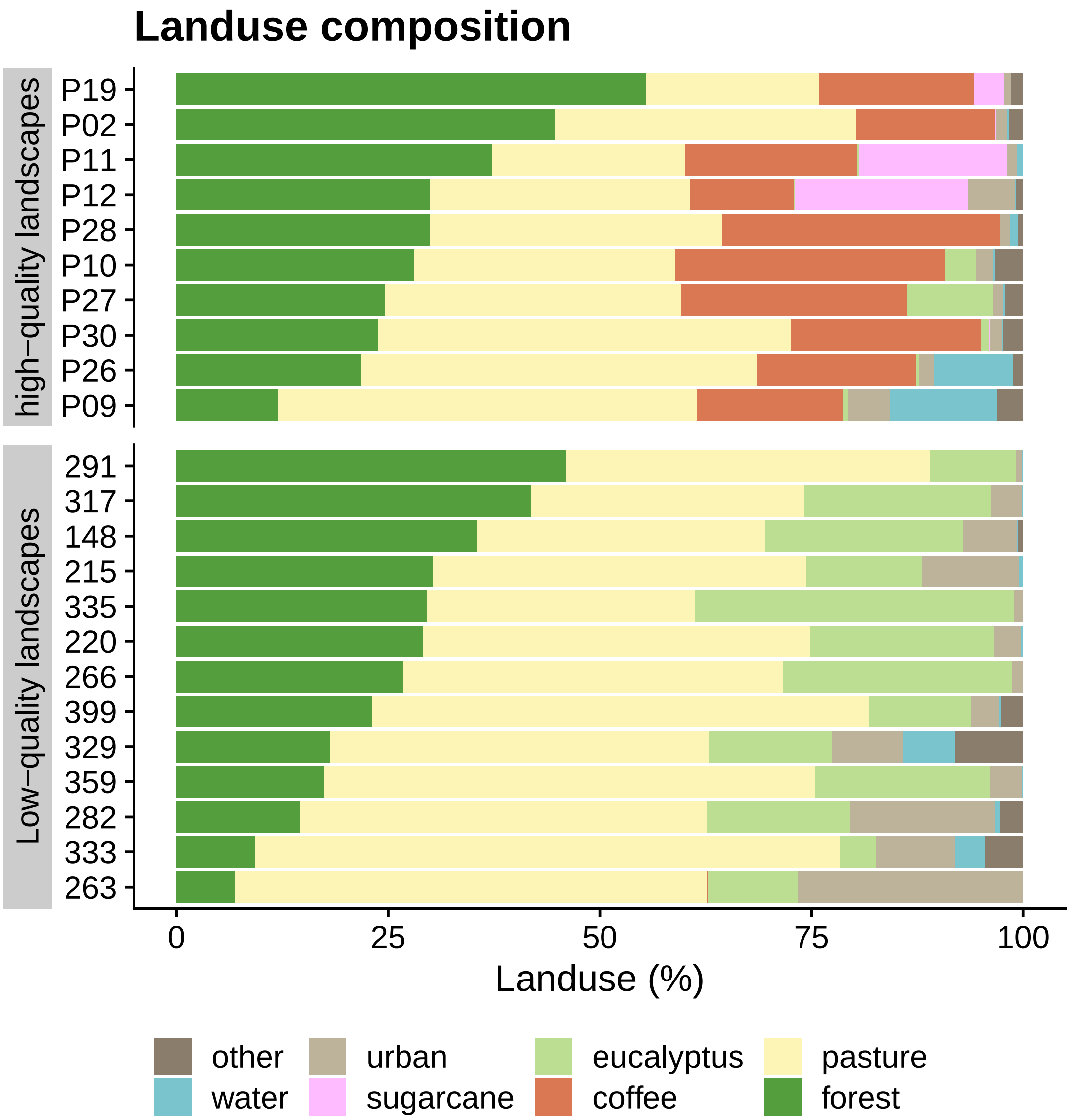

Figure S2.1: Percentage of the 8 main land use types per landscape in each region.

Table S2.1: Summary table of the land use percentages for landscapes in both regions of high- and low-quality matrix landscapes.

matrix	landuse	min	mean	sd	median	max
high_quality	forest	12.0	30.8	12.4	29.0	55.5
high_quality	pasture	20.4	35.5	10.2	34.7	49.5
high_quality	coffee	12.4	21.7	6.8	19.5	32.9
high_quality	eucalyptus	0.0	1.6	3.2	0.4	10.1
high_quality	sugarcane	0.0	4.2	7.9	0.0	20.6
high_quality	urban	0.8	2.1	1.7	1.4	5.5
high_quality	water	0.0	2.5	4.6	0.3	12.7
high_quality	other	0.0	1.6	1.1	1.5	3.4
low_quality	forest	6.9	25.3	11.9	26.8	46.0
low_quality	pasture	31.7	46.9	11.1	44.8	69.1
low_quality	coffee	0.0	0.0	0.0	0.0	0.0
low_quality	eucalyptus	4.3	18.1	8.7	16.9	37.7
low_quality	sugarcane	0.0	0.0	0.0	0.0	0.0
low_quality	urban	0.7	7.4	7.5	3.8	26.6
low_quality	water	0.0	0.9	1.9	0.1	6.2
low_quality	other	0.0	1.4	2.5	0.0	8.0

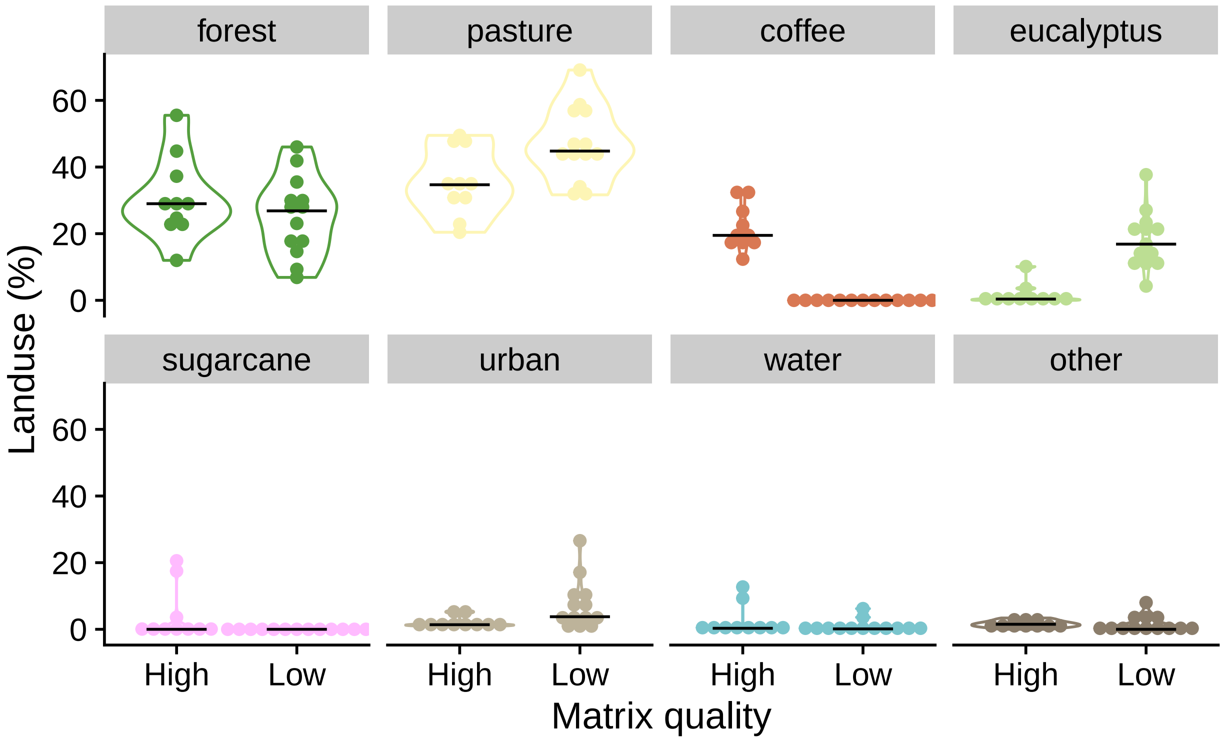

Figure S2.2: Proportions of landuse types among high- and low-quality landscapes

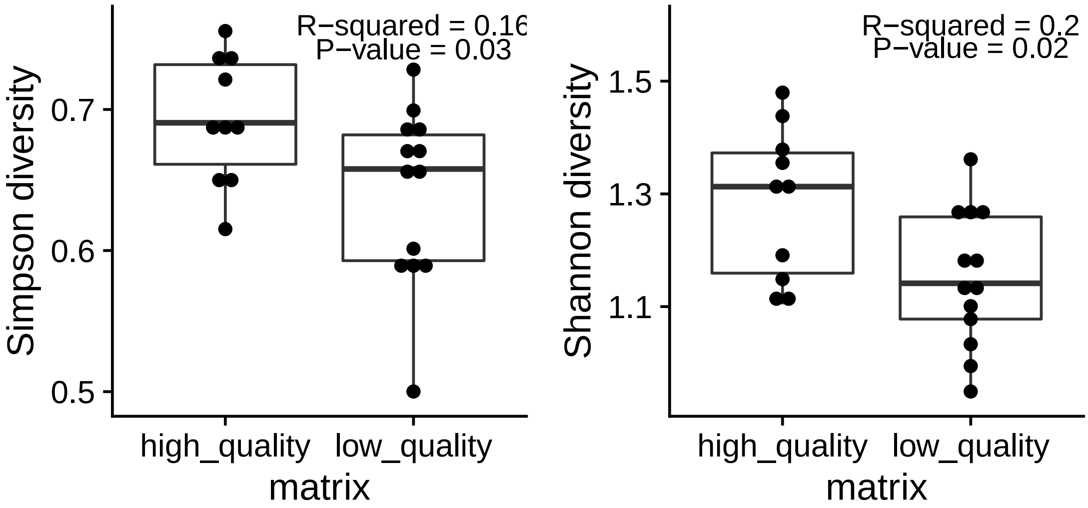

Figure S2.3: Simpson and Shannon diversity indexes for land uses in landscapes from both high- and low-quality matrix regions.

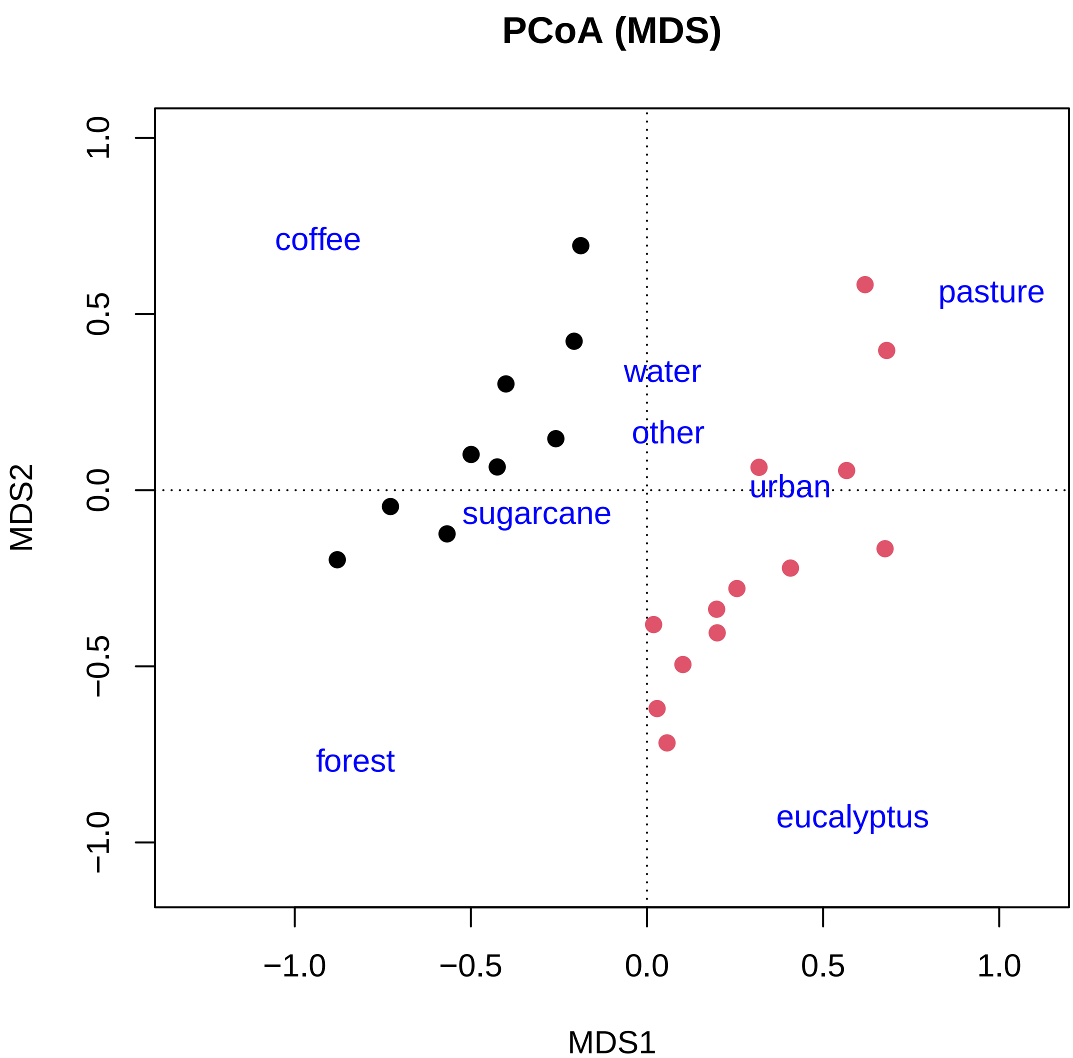

Figure S2.4: First 2 axes of the PCoA results for the composition of land use types among landscapes from the high-quality matrix (black dots) and low-quality matrix (red dots) regions.

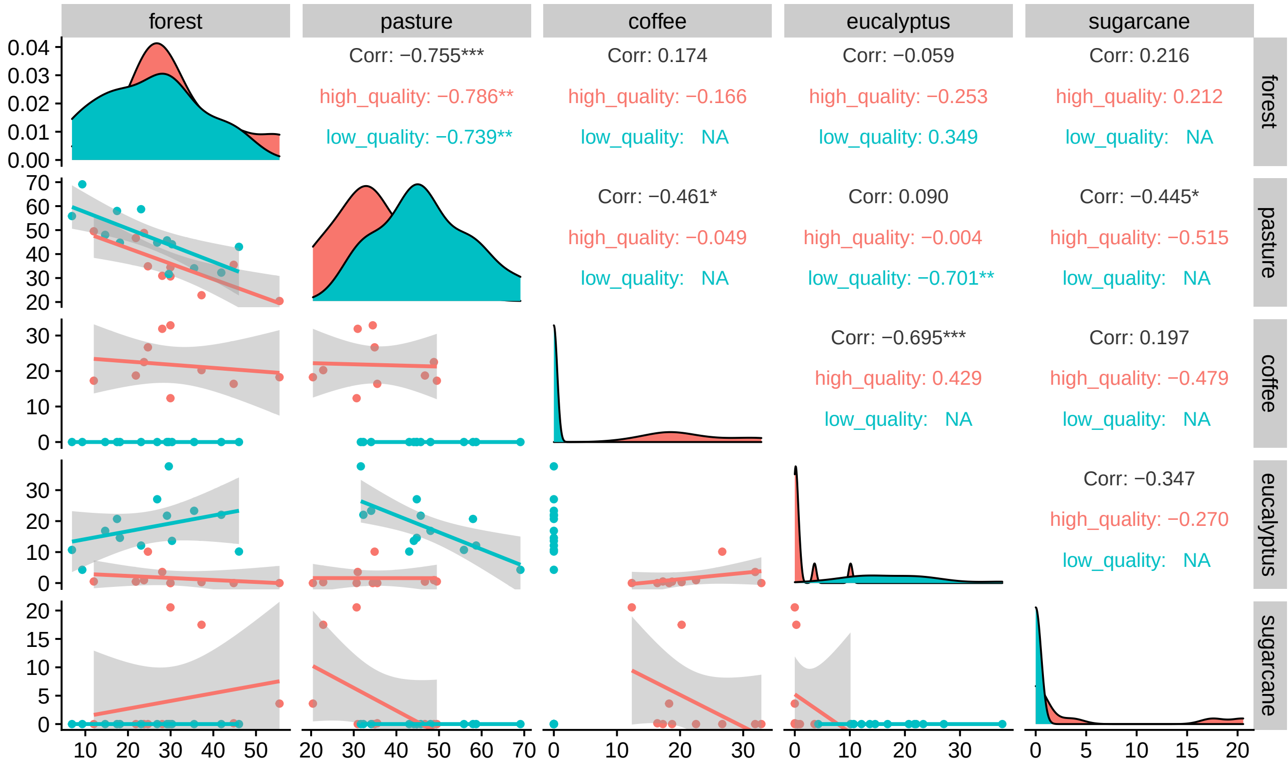

Figure S2.5: Correlation among percentages of landuse types.

2. Relationships among forest cover variables

We calculated Pearson correlation coefficients for forest cover variables in each matrix quality region (Figure S2.6). Also, we ploted the range of local forest cover (400 m) within the landscapes to see how local forest cover varies among landscapes in both regions (Figure S2.7).

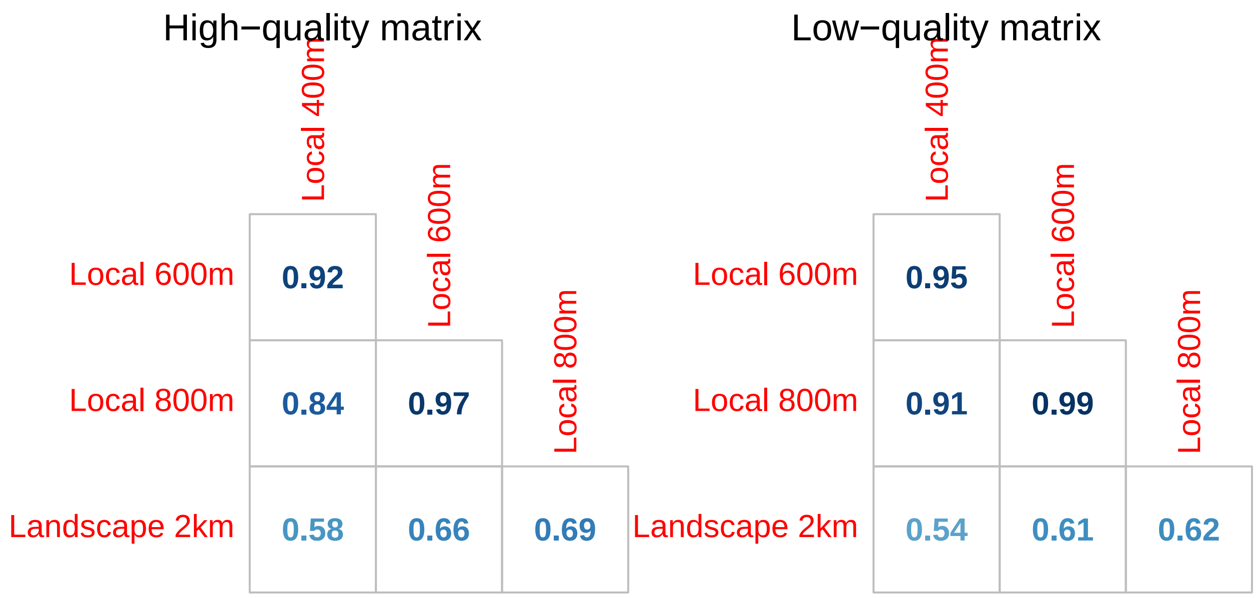

Figure S2.6: Correlations among forest cover variables in the high-quality (left) and low-quality matrix (right) landscapes.

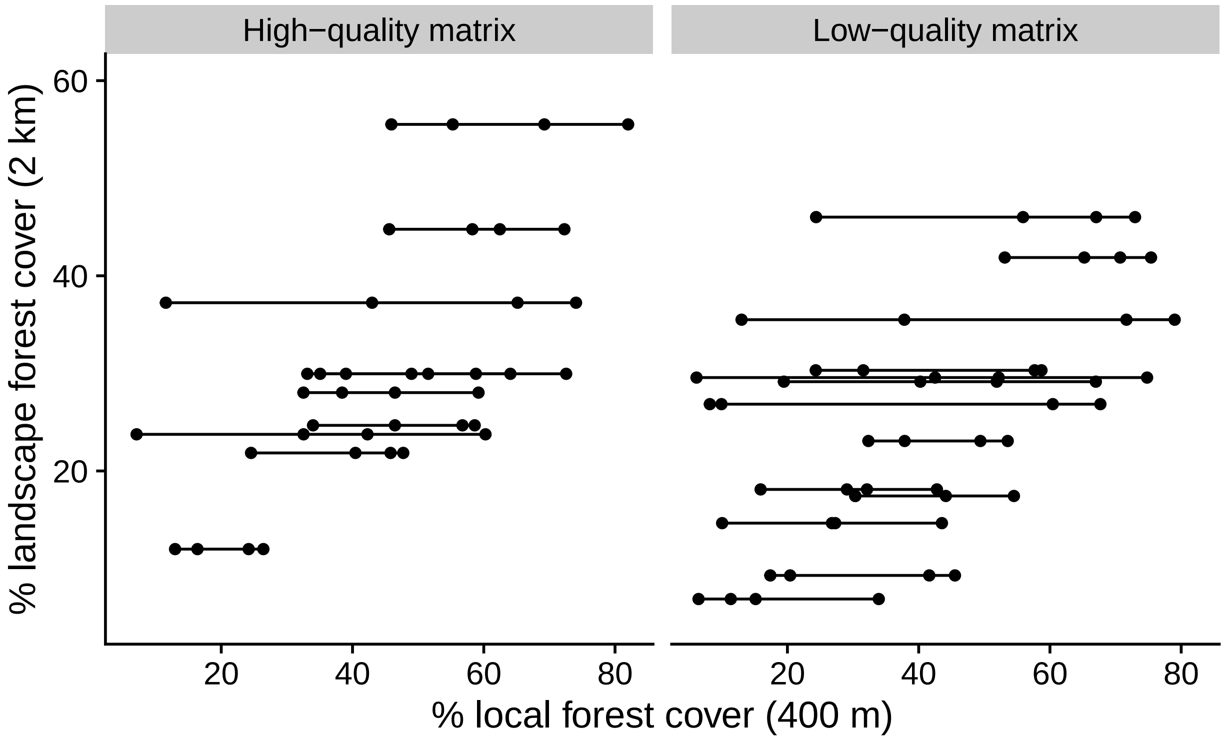

Figure S2.7: Range of local forest cover (buffer 400 m) within each landscape (buffer 2 km) for both landscapes with different matrix quality. Each line represent a landscape and the dots area the local forest cover for each sampling site.

3. Scale of effects for local forest cover

We ran different models with each local forest cover variable and selected the scale of effect using AIC model selection and the R^2 of the models. The models follow the specification presented in the paper (*Modeling* section), except that here we did not include trait variables, i.e. we only modeled the occurrence of species according to forest cover.

We used `lme4` package (Bates *et al.* (2015)) to perform a GLMM with binomial (proportion) distribution. An example of the code for each assemblage is as follows:

```
model <- glmer(cbind(occor, n.visit-occor) ~
                local.cover + (local.cover|sp) +
                (1|landscape:sp) + (1|site:sp) +
                (1|landscape) + (1|site),
                family=binomial, data=high.spe)
```

In Figure S2.8, we present the occurrence probability predicted for the models with different local forest cover scales for all the assemblages. Predictions were quite similar and decreased with forest cover for the specialists, especially in the low-quality matrix region, and increased or remained flat for the generalists.

Table S2.2: Overal and marginal r-squares and model comparisons with Akaike Information Criterion (AIC) for models with different local forest cover scales as predictor for the specialist and generalists species in both regions with different matrix qualities. For the terms see Table 1 (main text). dAIC is the difference in Akaike Information Criterion to the best model; df are the degrees of freedom.

								AIC	
Model	Total	fixed	env.sp	lands.sp	site.sp	lands	site	dAIC	df
Forest specialist species									
Low-quality matrix									
400m	64.3	7.5	42.9	6.2	3.3	1.0	3.4	0.00	9
600m	63.9	6.2	43.1	6.2	3.4	0.9	4.1	10.03	9
800m	63.9	6.0	43.0	6.3	3.5	1.0	4.1	18.08	9
High-quality matrix									
400m	56.6	1.3	44.3	7.5	1.8	0.7	1.1	0.00	9
600m	56.8	1.0	44.2	7.5	1.8	0.9	1.3	8.57	9
800m	56.6	0.6	44.3	7.4	1.9	0.9	1.4	12.40	9
Forest generalist species									
Low-quality matrix									
400m	46.6	0.1	39.7	3.5	2.5	0.0	0.9	0.00	9
600m	46.6	0.0	39.1	3.6	3.0	0.0	0.9	20.27	9
800m	46.5	0.0	39.0	3.6	3.0	0.0	0.9	22.54	9
High-quality matrix									
400m	44.1	0.0	37.0	2.2	3.6	0.6	0.7	11.24	9
600m	44.3	0.0	37.5	2.0	3.4	0.6	0.7	2.45	9
800m	44.3	0.1	37.5	2.0	3.5	0.6	0.7	0.00	9

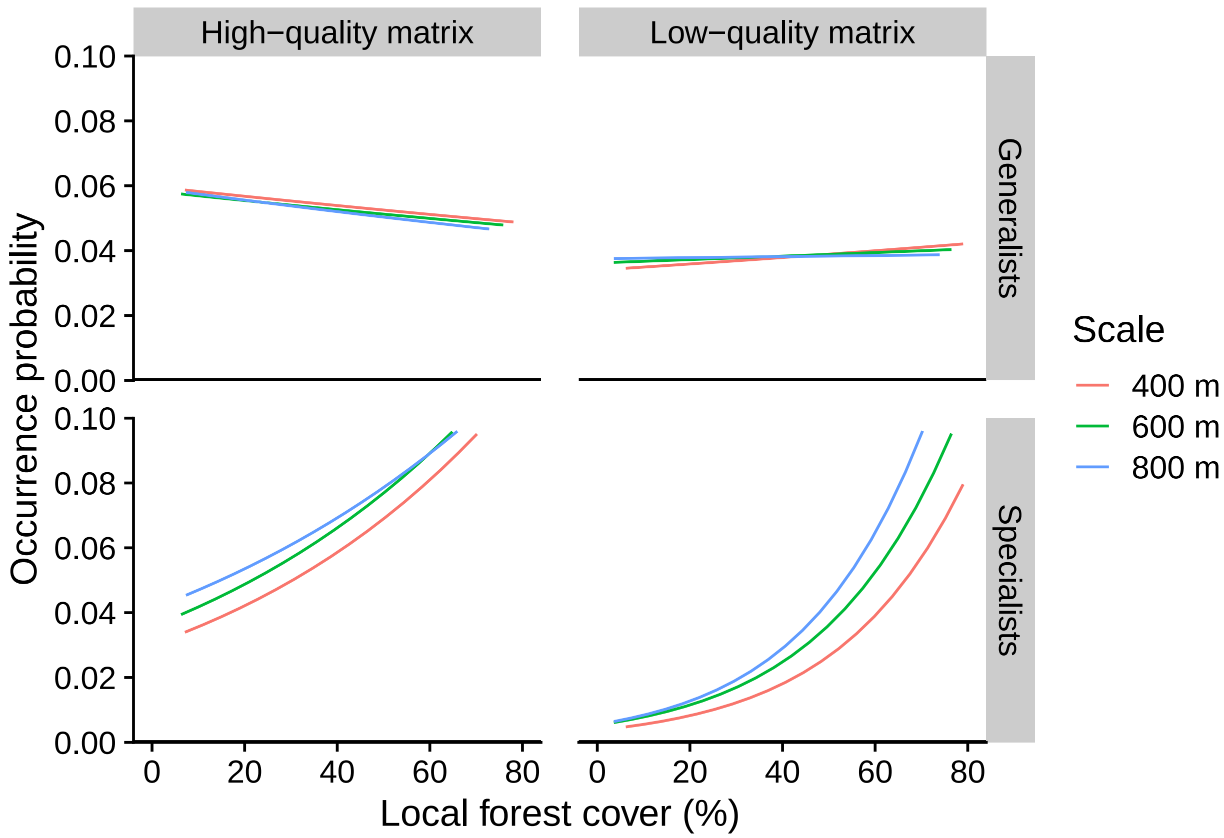

Figure S2.8: Predictions of the models with different local forest cover scales (lines) for specialists and generalists in both regions.

Residual correlations among species

We evaluated the residuals by Kendall correlations among species and among sites for the 400 m models using the predictions for site:sp random effects (Observation Level Random Effect), following the code provided by Miller, Damschen & Ives (2018). Codes for the species names are presented in the dataset available.

Below we show models residual correlation plots for the specialists in the high-quality matrix landscape. All the other assemblages presented similar results.

Range of species correlations: -0.41, 0.46.

Range of sites correlations: -0.25, 0.31.

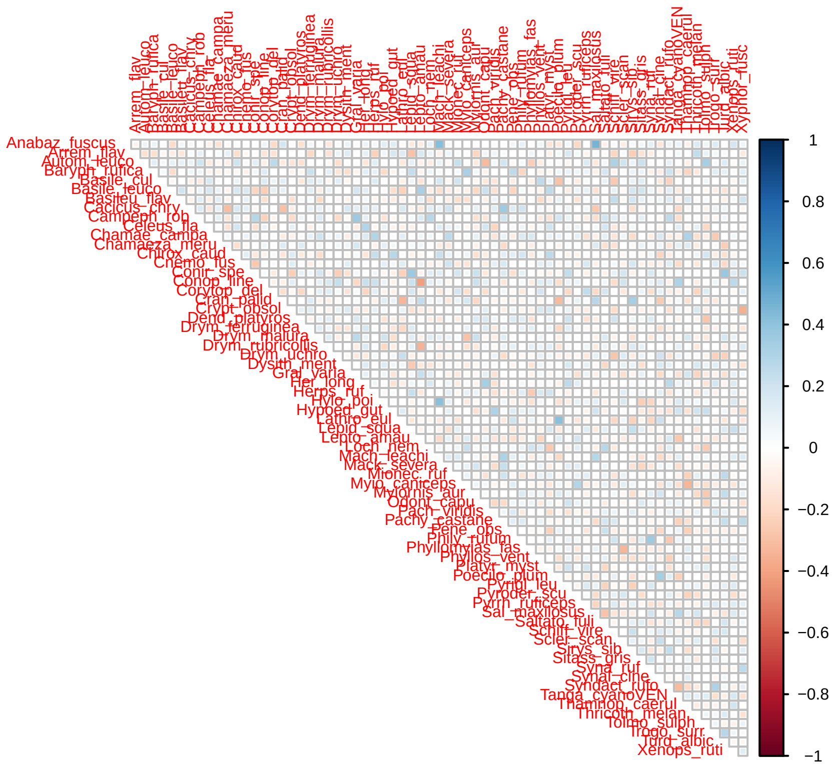

Figure S2.9: Species residual Kendall correlations for the specialist species in the coffee matrix region.

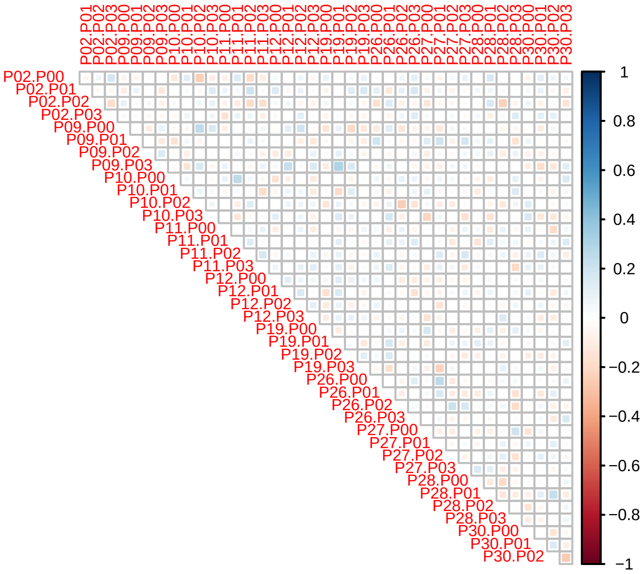

Figure S2.10: Sites residual Kendall correlations for the specialist species in the coffee matrix region.

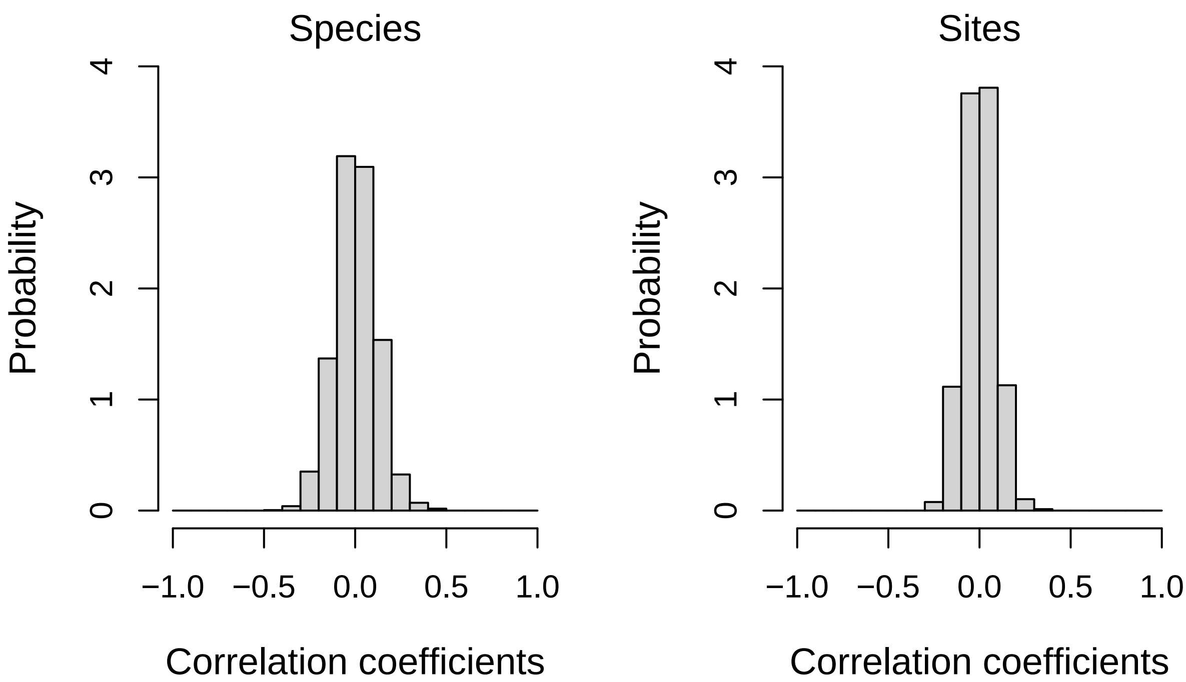

Figure S2.11: Histograms of the residual Kendall correlations for the specialists species in the coffee matrix region.

4. Including landscape forest cover

After selecting the local forest cover of 400 m radius buffer around each site for all datasets, we included the landscape forest cover (2 km radius buffer around the centroid of the landscape) in the model.

The R syntax example of this model area as follows:

```
model <- glmer(cbind(occor, n.visit-occor) ~
                   local.400 + landscape.2k +
```

Table S2.3: Variance Inflation Factor index for the variables of local forest cover and landscape forest cover.

	Local	Landscape
Specialists		
Coffee	1.26	1.26
Pasture	1.04	1.04
Generalists		
Coffe	1.13	1.13
Pasture	1.15	1.15

```
    (local.400 + landscape.2k |sp) +
    (1|landscape:sp) + (1|site:sp) +
    (1|landscape) + (1|site),
  family=binomial, data=high.spe)
```

Before analysing results, we evaluated possible colinearity between local and landscape forest cover using the Variance Inflation Factor with the code provided by John Lefcheck (https://jonlefcheck.net/2012/12/28/dealing-with-multicollinearity-using-variance-inflation-factors/). With VIF we found no evidence of collinearity between the forest cover scales (Table S2.3).

Predictions of the models are present in Figure S2.12. It is important to notice the differences in 20 and 40% landscape forest cover predictions for the specialists in the low-quality matrix.

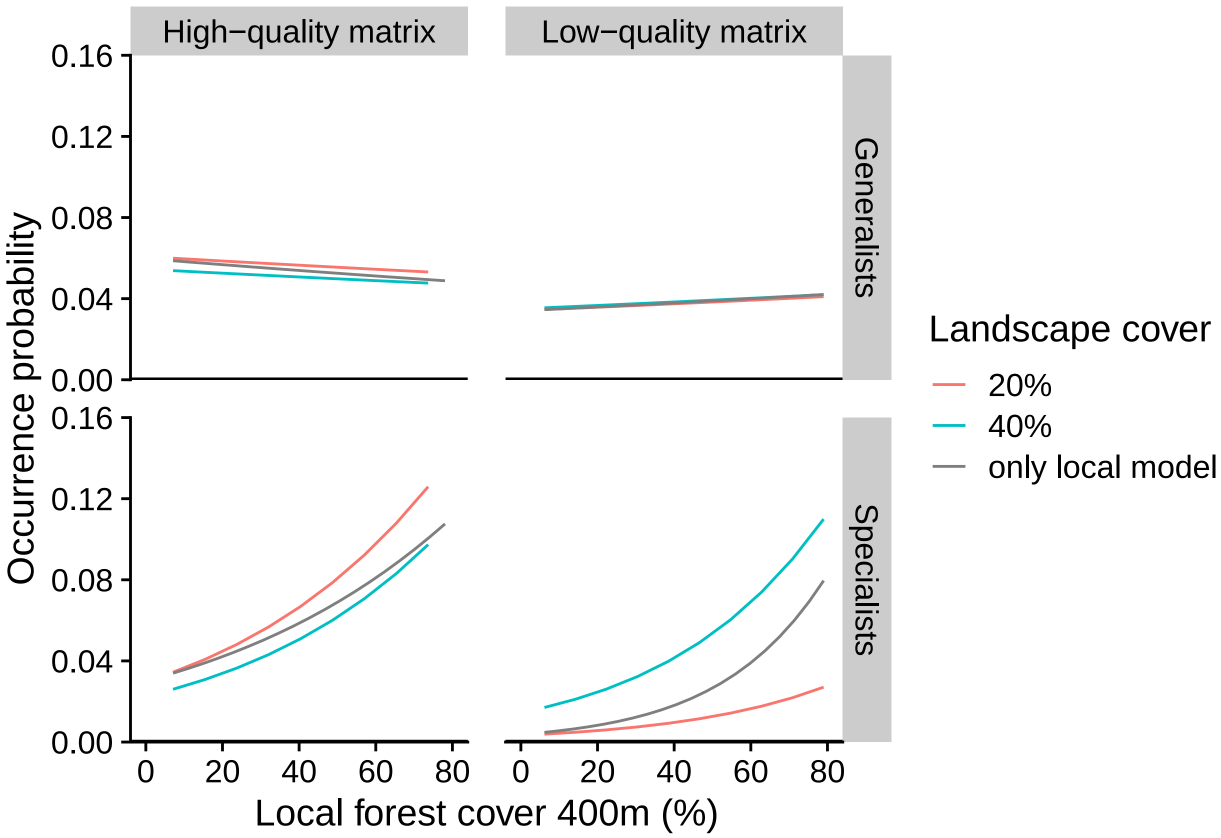

Figure S2.12: Predictions of the models without (gray lines) and with landscape forest cover scales (20 percent cover in red and 40 percent cover in blue lines) for specialists and generalists in both regions.

References

Barros, F.M., Martello, F., Peres, C.A., Pizo, M.A. & Ribeiro, M.C. (2019). Matrix type and landscape attributes modulate avian taxonomic and functional spillover across habitat boundaries in the Brazilian Atlantic Forest. *Oikos* **128**, 1600–1612.

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