Appendix 2: Landscapes Landuse and forest cover at local and landscape scale

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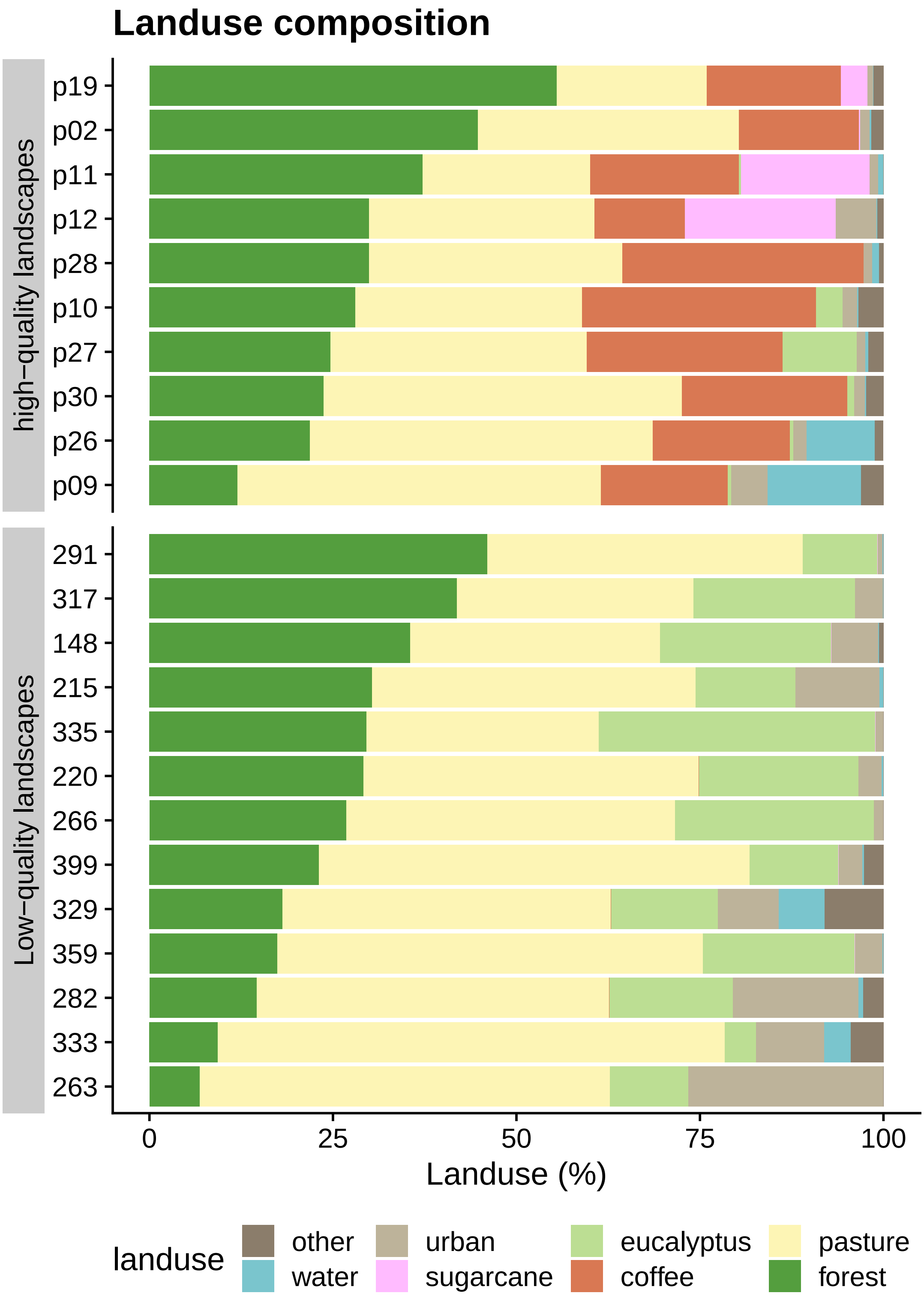
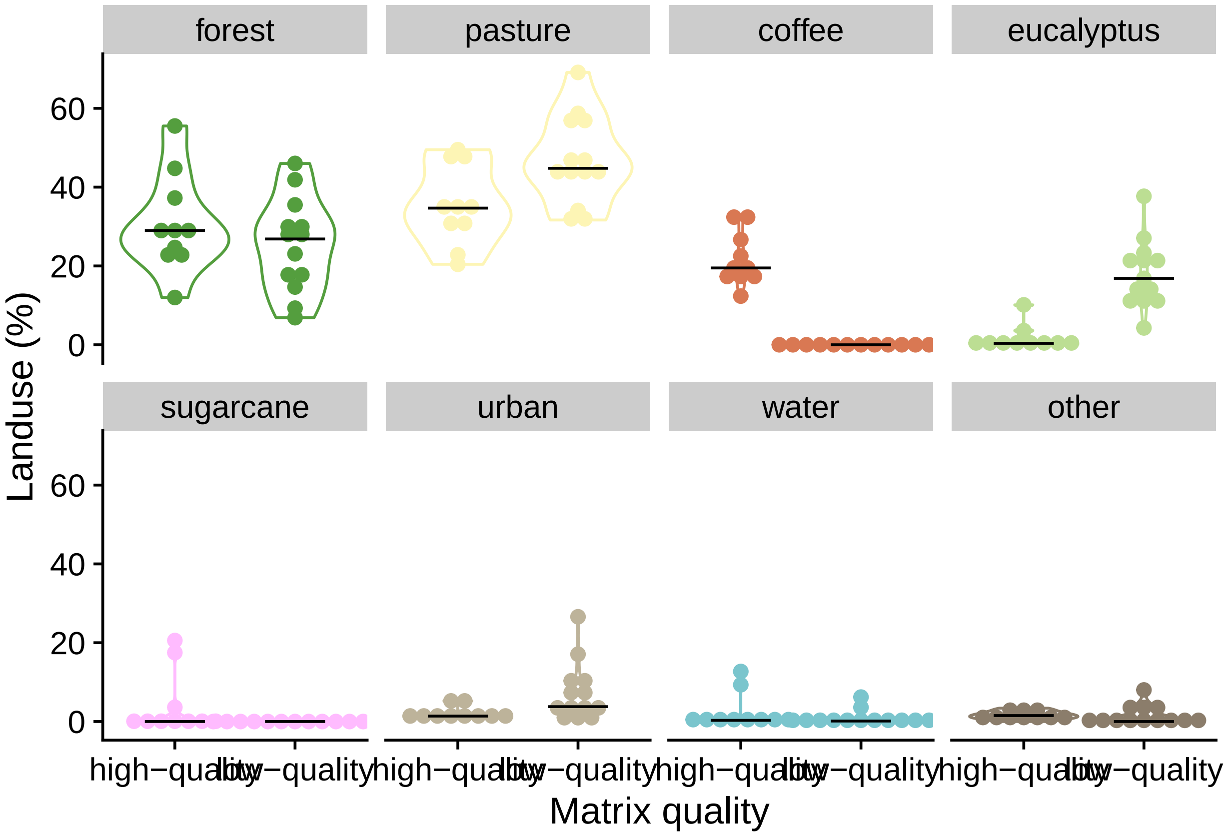
This appendix is a description of the landuse and matrix of the landscapes, togethe with a more specific description of forest cover variables at both local and landscape scales. We present the baseline models for the selection of the best scale for the local forest cover variable for each dataset. For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

1. Landuse and matrix description in landscapes

Percentage of each landuse type per landscape



Proportions of landuse types among high- and low-quality landscapes

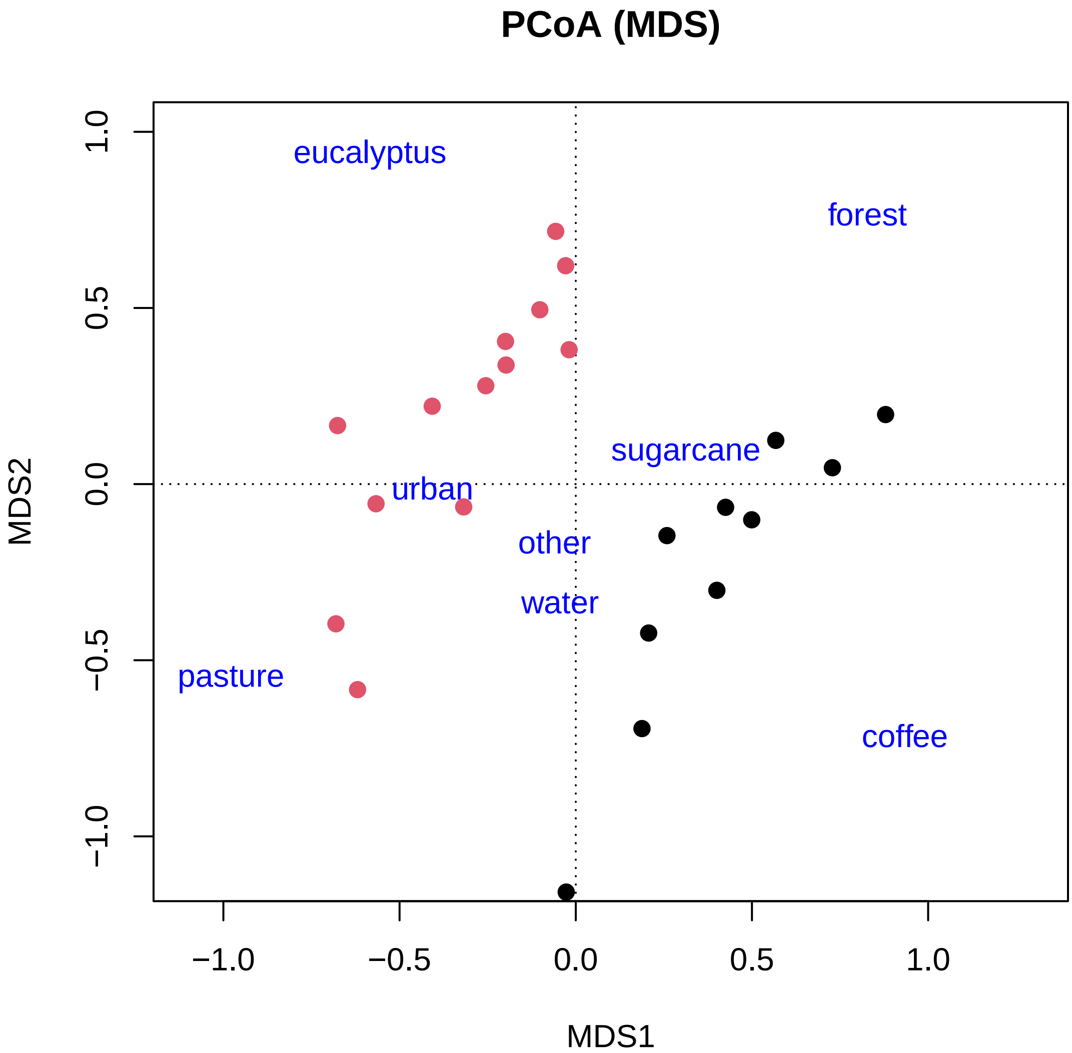


Summary table

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

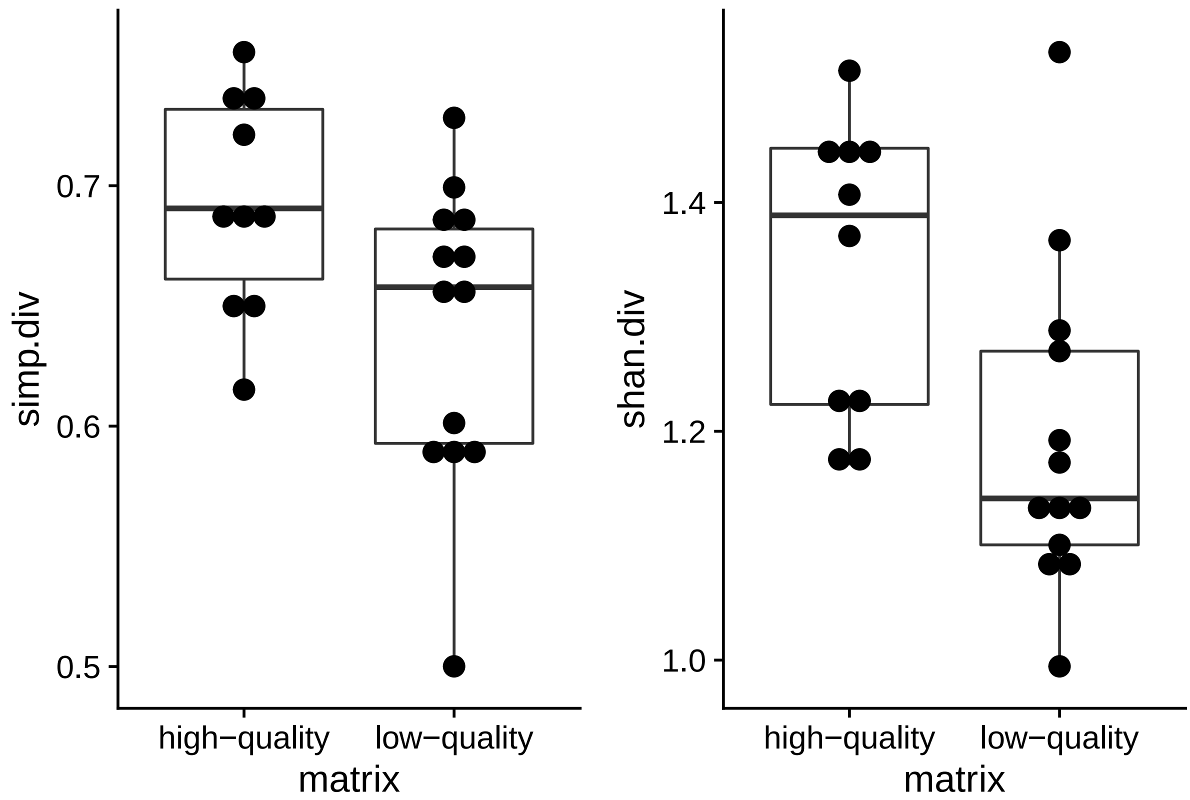
Principal Coordinate Analysis

To compare landuse matrices in both high- and low-quality landscapes, we performed a Principal Coordiante analysis with the proportions of each landuse type. - PCoA is more advisable given the nature of the data (sum up 100%, compositional data), we used gower distance tranformation to create a distance matrix among landscapes



Landuse heterogeneity - diversity index

Comparing matrix



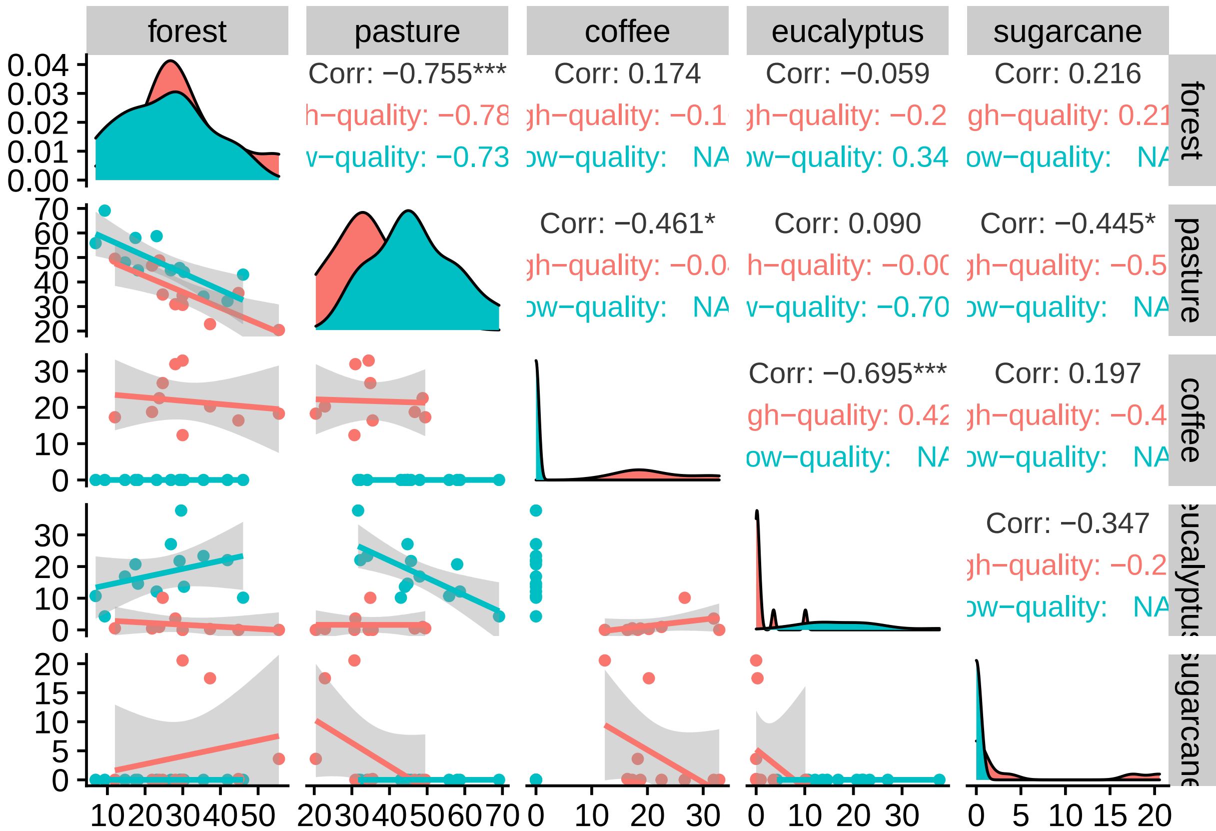
Testing differences in diversity indexes between matrix quality

```
##
## Call:
## lm(formula = simp.div ~ matrix, data = landuse)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.13997 -0.04294  0.01388  0.04218  0.08816
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.69288    0.01761  39.353   <2e-16 ***
## matrixlow-quality -0.05281    0.02342  -2.255   0.0349 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.05568 on 21 degrees of freedom
## Multiple R-squared:  0.1949, Adjusted R-squared:  0.1566
## F-statistic: 5.085 on 1 and 21 DF,  p-value: 0.03494
```

```
##
## Call:
## lm(formula = shan.div ~ matrix, data = landuse)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.19609 -0.10582 -0.01792  0.09598  0.34078
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          1.34359    0.04329  31.036   <2e-16 ***
## matrixlow-quality -0.15295    0.05758  -2.656   0.0148 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1369 on 21 degrees of freedom
## Multiple R-squared:  0.2515, Adjusted R-squared:  0.2158
## F-statistic: 7.055 on 1 and 21 DF,  p-value: 0.01478
```

Correlation among proportions of landuse types



2. Relationships among forest cover variables

We calculated Pearson correlation coefficients for forest cover variables in each matrix quality region (Figure S2.1). 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 S2.2).

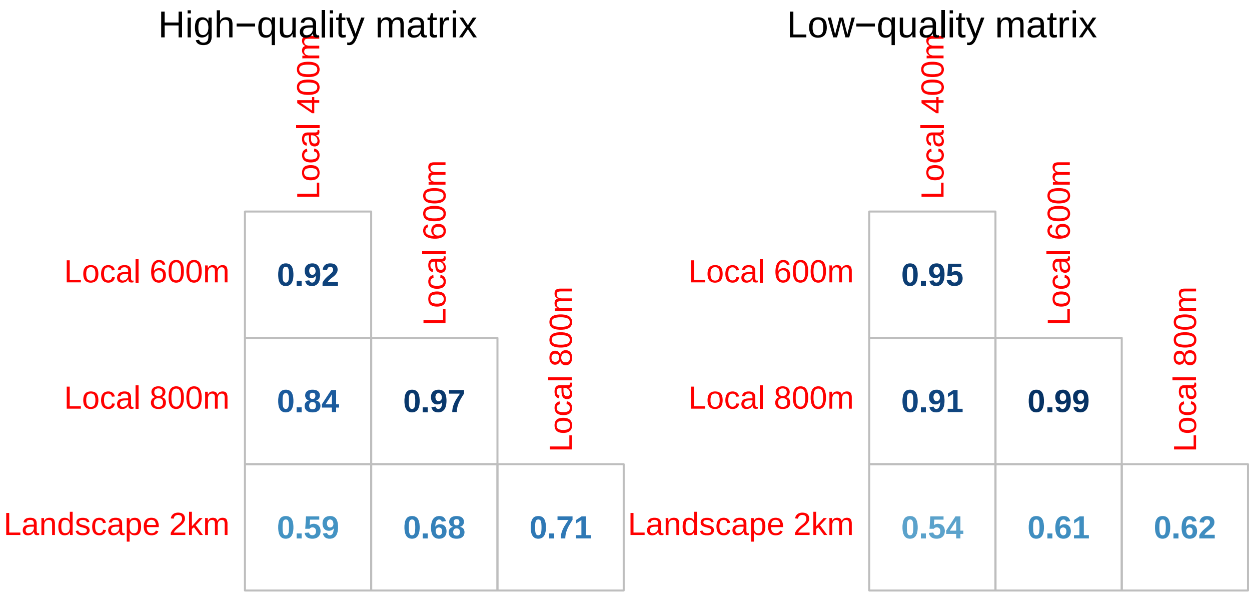


Figure S2.1: Correlations among forest cover variables in the high-quality (left) and low-quality matrix (right) landscapes.

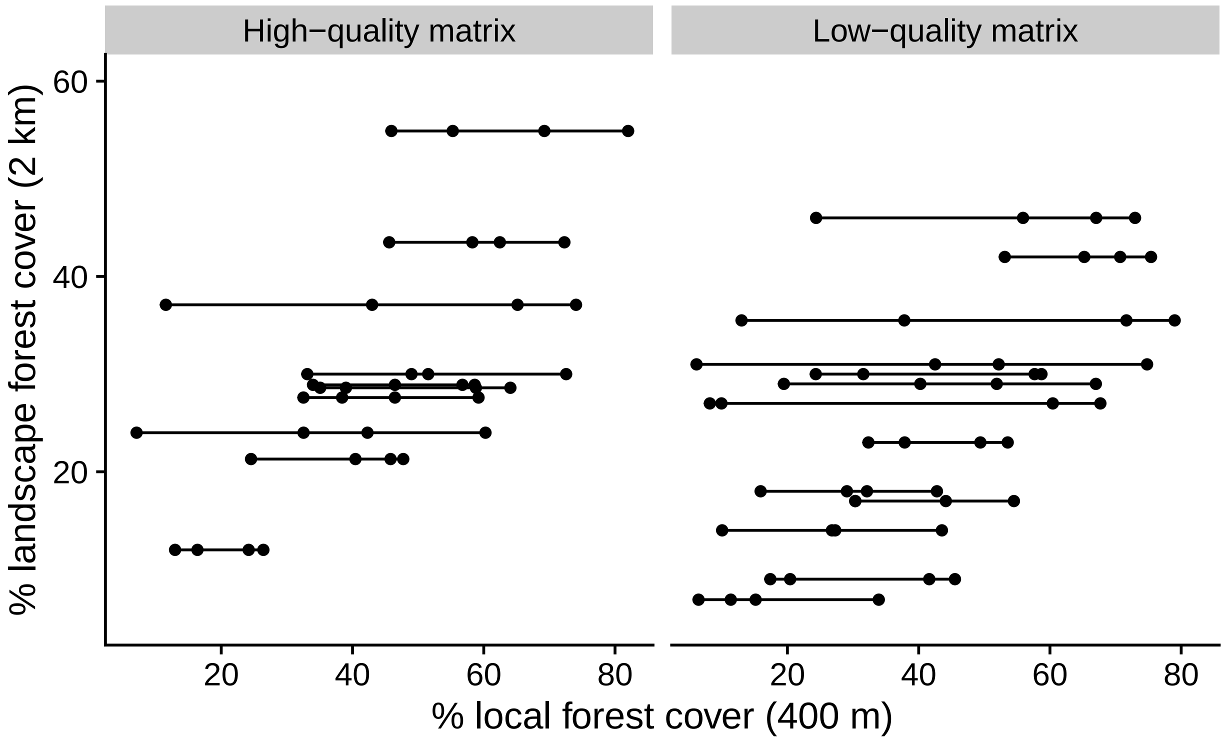


Figure S2.2: Range of local forest cover (buffer 400 m) within each landscape (buffer 2 km) for both landscapes with different matrix quality. Each line represent a landscape and the dots area the local forest cover for each sampling site.

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

Table S2.1: 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

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 S2.3, 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.

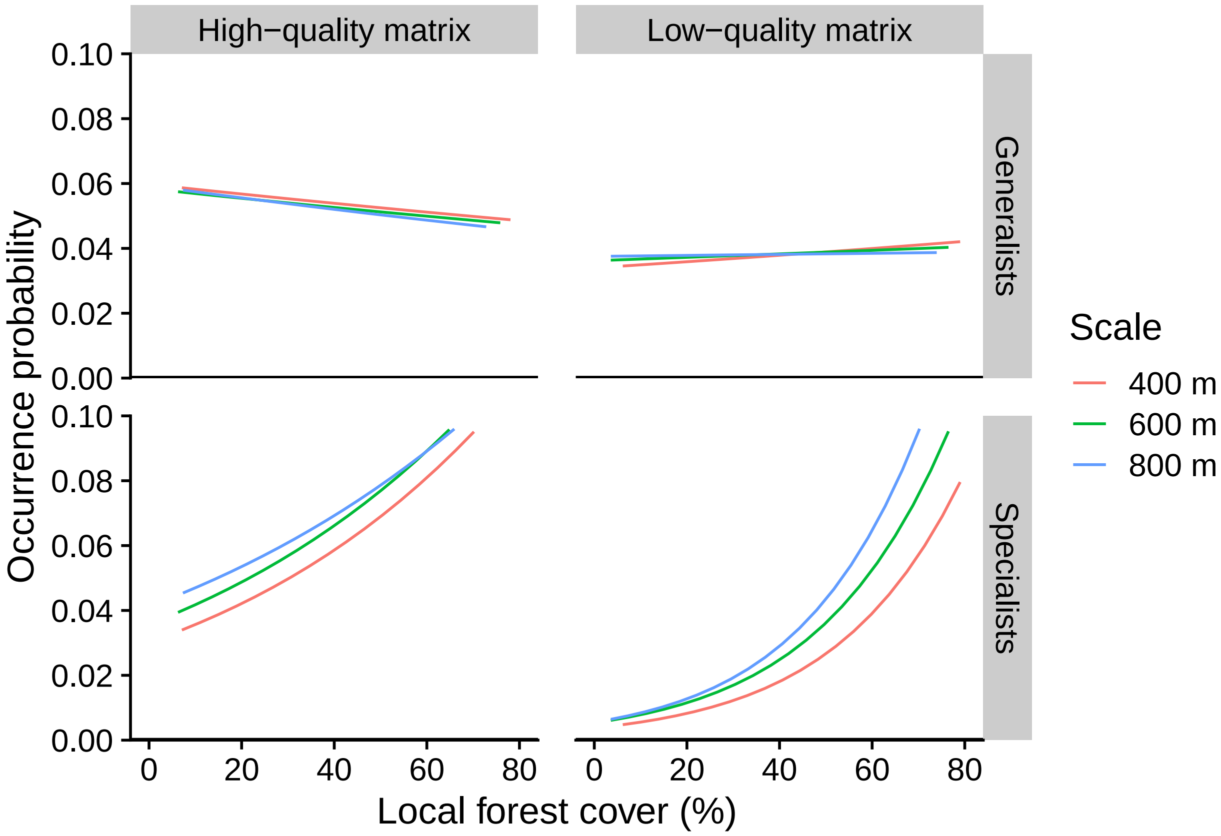


Figure S2.3: Predictions of the models with different local forest cover scales (lines) for specialists and generalists in both regions.

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.

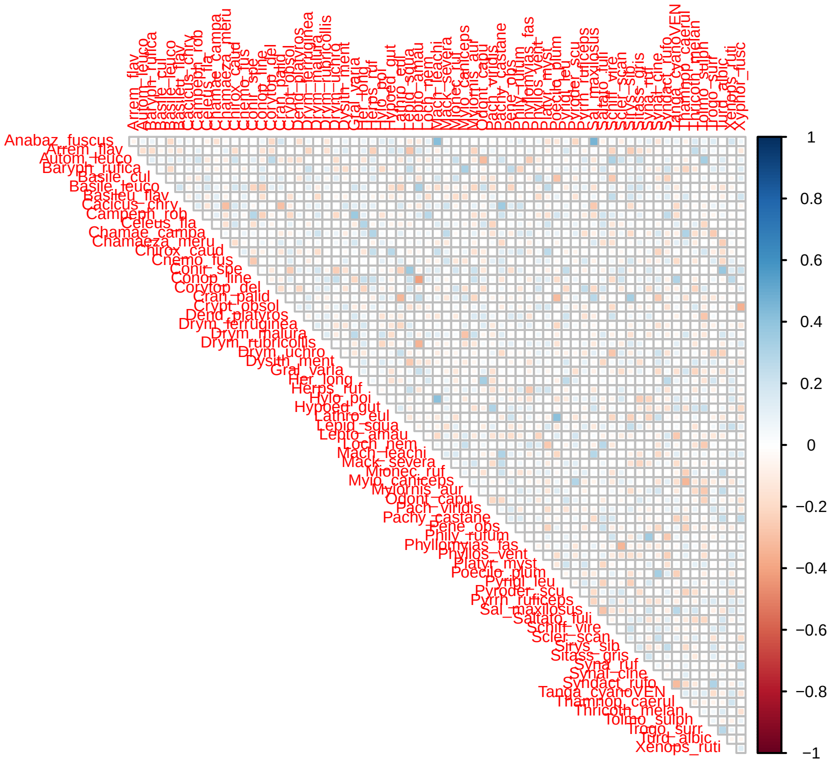


Figure S2.4: Species residual Kendall correlations for the specialist species in the coffee matrix region.

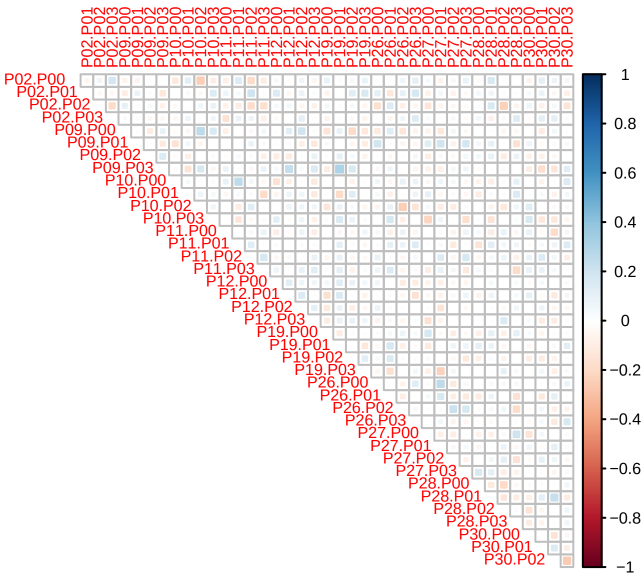


Figure S2.5: Sites residual Kendall correlations for the specialist species in the coffee matrix region.

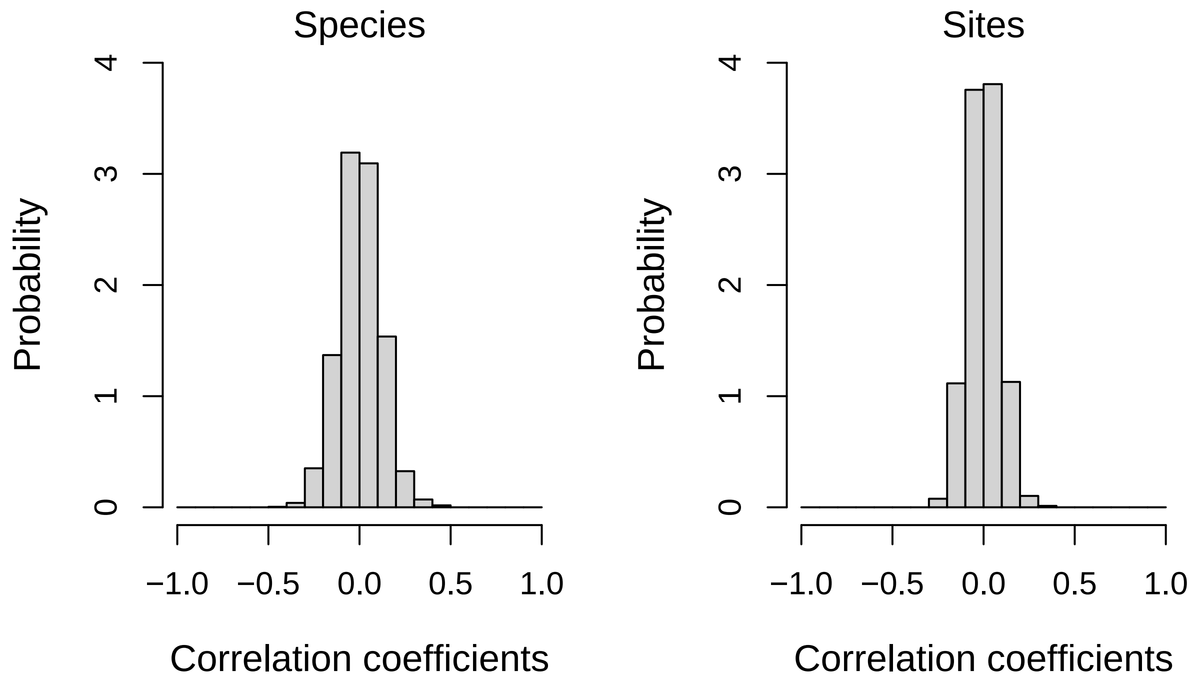


Figure S2.6: Histograms of the residual Kendall correlations for the specialists species in the coffee matrix region.

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 +
                   (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 S2.2).

Predictions of the models are present in Figure S2.7. It is important to notice the differences in 20 and 40% landscape forest cover predictions for the specialists in the low-quality matrix.

Table S2.2: 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

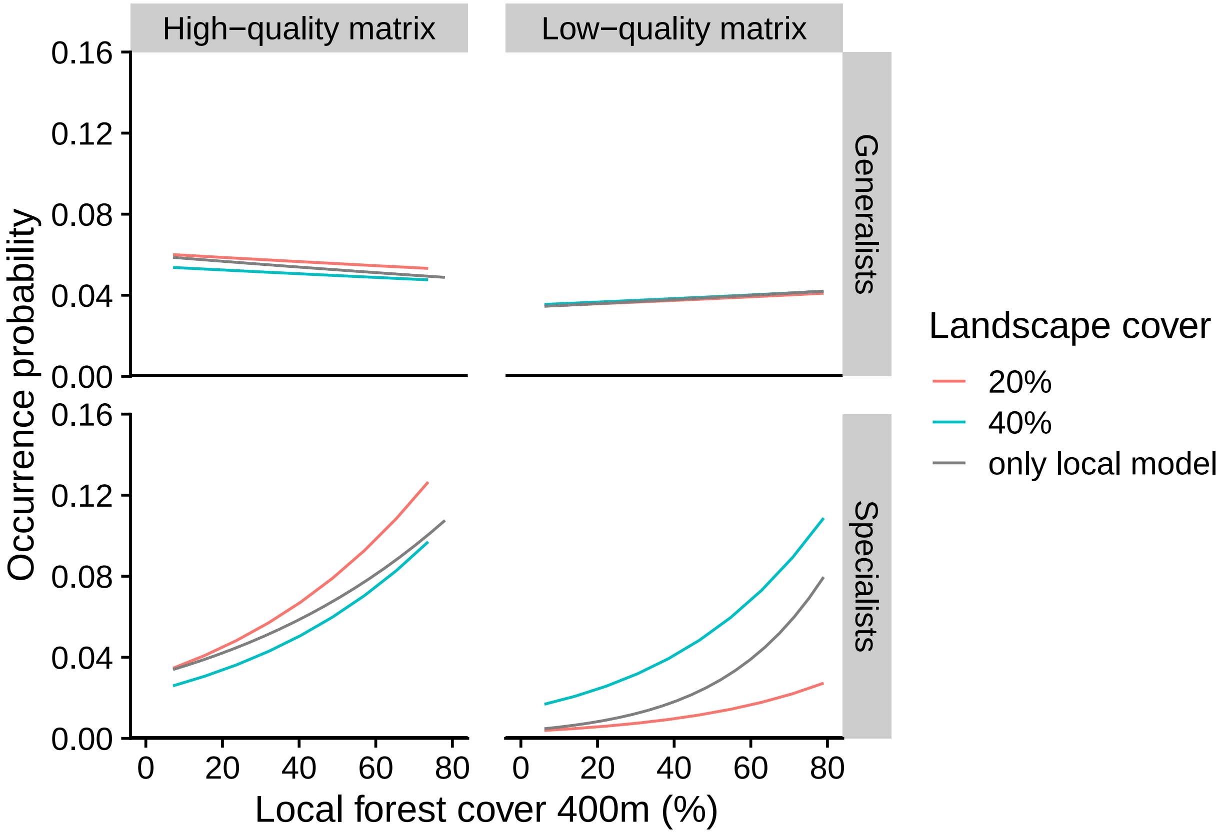


Figure S2.7: Predictions of the models without (gray lines) and with landscape forest cover scales (20 percent cover in red and 40 percent cover in blue lines) for specialists and generalists in both regions.

References

Bates, D., Mächler, M., Bolker, B. & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software* **67**, 1–48.

Miller, J.E.D., Damschen, E.I. & Ives, A.R. (2018). Functional traits and community composition: A comparison among community-weighted means, weighted correlations, and multilevel models. *Methods in Ecology and Evolution* **0**.