Landscape resistance index aiming at functional forest connectivity

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Abstract Resistance models may quantify the ability of the landscape to impede species' movement and represent suitable habitats. Moreover, the performance of resistance models parameterized by land-use/land cover attributes evidence that the integrity of the environments subject to urban sprawl is poorly understood. In this sense, the study assumed we could identify the forest functional connectivity in a landscape considering the disparity in the landscape mosaic. In this context, we sought to develop a landscape resistance index through structural equation modeling (SEM), supported by the criteria of heat emission, biomass, and anthropogenic barriers, obtained by remote sensing, called observed variables. The landscape studied in the Green Belt Biosphere Reserve of São Paulo has significant remnants of the Atlantic Forest, a biodiversity hotspot. However, our results indicated criteria variability in the landscape modeled through the SEM, obtaining a significant adjustment of the landscape resistance index, with comparative fit index (CFI) of 1.00 and root mean square error of approximation (RMSEA) of 0.00. The index reflects the resistance levels of the land use/land cover, expressed by the class interval, ranging from 0% (1.73) to 100% (493.88), with the highest values associated with the anthropized uses and forest isolation. Thus, our index based on environmental attributes reflects the structure of functional forest connectivity and offers a framework to design forest corridors across landscapes.

Keywords Structural equation model · Landscape structure analysis · Land use and land cover · Environmental criteria

Introduction

The land-use/land-cover (LULC) change, caused by the urbanized process, has been influenced biodiversity, ecosystem function, and regional climate (Choudhury et al., 2019). Also, they have directly affected the surface temperature, modifying the landscape radiative, physiological, and aerodynamic properties that control the surface water and energy balances (Rigden & Li, 2017).

Thus, urbanization transforms forest landscapes through the conversion of land use/land cover and fragmentation, influencing functional connectivity of the forest and, consequently, the conservation of species (Butsch & Heinkel, 2020).
From this perspective, functional connectivity considers the species’ biological reactions and estimates the ease with which the individual moves within the landscape units (Goodwin, 2003). Our study considers functional connectivity since urban sprawl characterizes our current landscape scenario well. The scenario consists of a non-forest matrix with forest fragments scattered across the landscape and support paths for species movement (Matos et al., 2019).

These environmental changes influence the occurrence, behavior, and species dispersion. Therefore, knowing the land-use/land-cover’s influences on species dispersion is essential for conserving the tropical forest. Mörtberg et al. (2013) found that the terrestrial surface is the basis for designing the species dispersal path, especially when overcoming the matrix resistance, and the species consider the landscape as a competitive space control of its territory. Thus landscape resistance was defined as the degree of ease or impediment to the movement of a specific species (Spear & Storfer, 2010).

According to Rudnick et al. (2012), resistance surfaces were developed from empirical data as gene flow, genetic distances, habitat use, and movement paths. However, they are also based on expert opinions concerning the ecology of focal species and their ability to cross landscapes, which has been the most used method (Cushman, Landguth, & Flather, 2013; Cushman, Wasserman, et al., 2013).

On the other hand, another focus of functional forest connectivity is landscape resistance surfaces modeling, aiming to accurately represent landscape features that act as conductor barriers to gene flow (Winiarski et al., 2020).

In this sense, we observed a significant number of studies using simulations to detail many landscape components that affect the functional connectivity analysis because they act on resistance surface, nature, and the relationship between surface and gene flow. These include the spatial scale and thematic resolution (Cushman & Landguth, 2010), the contrast in landscape resistance (Shirk et al., 2018), the sampling regimes (Olyer-McCance et al., 2013), and genetic imbalance (Zeller et al., 2016).

Multiple environmental variables, categorical or continuous, have been used for resistance surface modeling, such as the effects of elevation, presence of habitat, road resistance, LULC, and climatic conditions (Cushman, Landguth, & Flather, 2013; Cushman, Wasserman, et al., 2013; Gruber & Adamack, 2015; Peterman, 2018; Peterman et al., 2019; Row et al., 2017). Unfortunately, many inherent analytical issues, including spatial and genetic data, have resulted in poor performance, creating a fundamental challenge for modeling landscape strength surfaces (Winiarski et al., 2020).

This way, the researchers usually assign values to LULC, considering their resistance levels to the flow of matter and energy (Feng et al., 2011), recalling that the species’ focal movement is random (Liu et al., 2018). The intense subjectivity of this method and the lack of a theoretical framework related to the human activity disturbance on the landscape (i.e., on the LULC) have been criticized (Zhang et al., 2017).

Concerning the resistance surface, Belote et al. (2016) mentioned the approach based on the connection paths with a high level of integrity, avoiding barriers and natural vegetation considered highly modified. The paths are the least human-modified LULC, linking natural areas as protected areas and forest patches (Theobald et al., 2012).

According to Deng et al. (2018), an essential factor for assessing the environment is the heat exchange of water, measured by the land surface temperature (LST), which can be retrieved well by the atmospheric correction model from Landsat 8, and presents a significant increase with the impermeable surface, as mentioned by Silva et al., 2018; Rousta et al., 2018; Niu et al., 2019; Lin et al., 2018; Du et al., 2016.

Brose et al. (2012) observed a positive correlation between the surface temperature increase and the prey-predator interaction force due to their increased speeds, especially in heterothermic individuals. Also, they mentioned adverse effects for species persistence in complex food webs (Brose et al., 2012), especially when there are asymmetric responses to a temperature between predators and prey (Dell et al., 2014).

The temperature is vital in establishing the biological organization levels standard (Gibert et al., 2016). The metabolic ecology theory (MTE) and empirical data showed that the movement of an animal exhibits a multiple dependence between the temperature, with consequences for population dynamics and stability (Brown et al., 2004).

Therefore, it is essential to know the environmental pattern where the wildlife moves because several factors contribute to surface temperature variation, especially in urban sprawl areas. Among them, there are the morphological characteristics, the heat absorption,
storage, the increased heat convection (Gaur et al., 2018), the road orientation, the anthropogenic activities (Santos et al., 2017), the obstruction of wind by high buildings (Zhou & Chen, 2018), the energy balance, and the hydrological cycle (Silva et al., 2018).

Nascimento-Júnior (2017) complemented that urban sprawl can be characterized by socio-spatially unequal development and different degrees of environmental degradation. Furthermore, they can be revealed by nighttime reflectance intensity obtained from the Linescan Operating System (LOS) of the North American Defense Meteorological Satellite Program (Chen et al., 2016; Huang et al., 2014; Zhang et al., 2017).

The dichotomous classification between urban and rural space disregards the flow of people and scenarios that connect these environments though. Scenarios like the urban-rural transition are composed of scattered settlements and sparsely populated areas. Others are formed by the areas that have been gradually replaced by the natural condition, having less human influence and, consequently, denser natural vegetation (Benza et al., 2016).

Throughout these scenarios, LOS has registered variation in the surface temperature from areas under urban sprawl to those covered by native vegetation, following the order high-density urban area, low-density urban area, lawn, and the forest. Otherwise, the traditional Normalized Difference Vegetation Index (NDVI) showed an increase of value in the same sequence of LULC (Guha et al., 2018).

On the other hand, the soil reflectance in forest areas has shown fewer absorption rates than their canopy and, consequently, fewer temperature values than the agriculture and pastures (Shen et al., 2016), reducing the temperature (Wei et al., 2018).

Thus, when the focus is on the forested areas, the NDVI is commonly used to identify them, as well as their biomass and potential as a habitat for communities/species such as bees (Hoagland et al., 2018), grasshoppers (Shi et al., 2018), birds (Bonthoux et al., 2018), and large mammals (Ito et al., 2018; Johnson et al., 2018). These studies are supported by the robust correlation between plant biomass and active photosynthetic radiation absorption (Grossmann et al., 2018; Nandy et al., 2017).

Considered that LULC influence in vegetation corridors network regional, allowing the evaluation of the pasture use intensity (Gómez Giménez et al., 2017), the quantification of farmland abandonment (Estel et al., 2015), and the monitoring of potential protected rural areas (Weber et al., 2018).

Thus, the study was based on the hypothesis that we can identify the forest functional connectivity in a landscape, considering its representative land-use/land-cover attributes. Furthermore, considering that these attributes can express the disparity in the landscape mosaic regarding resistance to forest connectivity.

In this context, this study aimed to develop a landscape resistance index, which permits identifying the integrity of the environments, supporting the evaluation of the functional connectivity between forest fragments of landscapes under urban expansion.

**Material and methods**

**Study area**

The landscape studied (Fig. 1) is in the Green Belt Biosphere Reserve (GBBR) of São Paulo (SP), which is one of the largest cities in South America (IBGE, 2021b). Its main characteristic is the increasing urban sprawl, resulting in pressure in its surrounding area regarding conversion from agriculture to urban use.

According to the United Nations Educational, Scientific, and Cultural Organization (UNESCO, 2019), the Biosphere Reserve is a learning site for environmental protection, logistical provision for scientific research, and educational/sustainable use of natural resources. Considering the Biosphere Reserve as a place of excellence, it should support ways to solve human and environmental conflicts through the local and scientific communities (UNESCO, 2019).

The GBBR was considered of extreme importance for biodiversity conservation and to design an ecological corridor (MMA, 2021), considering that Atlantic Forest remnants cover 34.9% of its area (165099.25 ha), belonging to Ombrophilous Dense Forestry (IBGE, 2021a). Some remnants belong to Protected Area, such as the Cabreúva Environmental Protection Area (EPA) in the North, Morro Grande Forest Reserve (FR) in the South, and Itupararanga EPA in the Southwest (Fig. 1).

They are the most significant patches of the study area, with more than 300 ha, representing half our forest area (Table 1).
Other remnants are scattered through the matrix composed predominantly of vegetation in regeneration, unmanaged pastures (i.e., anthropic fields), and urban areas, which occupy 36.3% and 22.4%, respectively, of the total study. Furthermore, in the area, there are 3.4% of planted forests (Eucalyptus sp), 1.4% of farmlands, 1.0% water, and 0.6% of roads (highways and rural roads), as illustrated by the LULC map (Fig. 1).

![LULC map](https://qgis.org/en/site/)

**Fig. 1** Land use/land cover (LULC) and location of the studied landscape in the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil. Generated with Quantum GIS (version 3.16, https://qgis.org/en/site/)

| Class (ha) | NP (%) | Class (%) | Main characteristic | AREA (ha) | NEAR (m) | SHAPE |
|-----------|--------|-----------|--------------------|-----------|----------|-------|
| < 5       | 92.5   | 5.9       | 0.36* (± 0.79**)   | 17.80 (±42.46) | 1.15 (± 0.24) |
| 5 - 30    | 5.2    | 11.5      | 12.32 (±6.37)      | 107.67 (± 162.66) | 2.05 (±0.60) |
| 30 - 75   | 1.3    | 11.0      | 47.00 (±13.57)     | 57.57 (± 98.93) | 2.85 (±0.65) |
| 75 - 170  | 0.6    | 11.2      | 105.98 (± 24.89)   | 38.88 (±77.14) | 3.38 (± 0.82) |
| 170 - 300 | 0.3    | 10.4      | 244.71 (± 28.74)   | 21.56 (± 35.60) | 4.40 (±0.95) |
| > 300     | 0.2    | 50.0      | 1436.24 (± 2689.73) | 0.00 (± 0.00) | 6.50 (± 2.23) |

where NP, number of forest patches; Class (%), class percentage in landscape; AREA, habitat size; SHAPE, shape index; NEAR, distance of the nearest neighbor edge; *mean value; and **SD, standard deviation value
We generated this map (with 90%-accuracy) through the supervised classification method (Maximum Likelihood algorithm) of the CBERS 4-orbital images (MUX multispectral sensor, 20 m-spatial resolution).

Then, we followed with the digitalization-on screen of anthropized areas, including low and high-density urban areas. The first group comprises small urban agglomerations and farms characterized by horizontal, dispersed, and polycentric growth.

Conversely, the second group is formed by the significant urban areas. They were classified as a constraint, considering their low quality for functional connectivity, as they have a compact, vertical, and monocentric shape (Ojima, 2007).

Conceptual model

The landscape resistance index (LRI) was developed through structural equation modeling based on the maps of land surface temperature (LST), nighttime reflectance (Night), and inverted NDVI (NDVIinv).

These criteria represented, respectively, the physical (water and energy balance), anthropic (barriers effects), and biotic (vegetable biomass quality) attributes of the studied landscape. They indicate the way related with the least resistance in the landscape, based on the ecology integrity concept.

Thus, ecosystem integrity refers to a habitat that has not undergone an anthropic change. Nowadays, it is understood as a holistic and structural concept, focusing on natural variations to promote the conservation of native biodiversity (Keenleyside et al., 2012).

Therefore, the ecological systems that retain their native species and natural processes are, hypothetically, the most resistant and resilient to anthropogenic and natural stress (Woodley, 2010).

The criteria definition to support our index development considered the animal movement across the landscape, a complex process involving the local environment’s characteristics (Hooten et al., 2010). Furthermore, we considered that the barriers to animal movement and their preferred habitat as environmental covariables to assess animal behaviors (Hanks et al., 2015; Wilson et al., 2018).

In this sense, the LST map represents the areas where the energy and water balance were the most intense of the landscape, therefore, the most unfavorable to the gene flow. The Night map was used to identify anthropic barriers to gene flow. In the literature, the Night is considered effective in determining urban areas (Su et al., 2015; Zhou et al., 2014). Lastly, the NDVI is traditionally used to analyze vegetation vigor, considering that energy reflected in the red and near-infrared regions is inversely related. The result is directly proportional to the green biomass, represented by values closer to +1, indicating denser, moist, and well-developed vegetation (Gitelson et al., 2014).

The structural equation model used to obtain the LRI is described in Equation 1, normalized for 0 to 100% as indicated in Equation 2.

\[
LRI = (((factor \ LST \times \ LST) + error \ LST) + (factor \ NDVIinv \times NDVIinv) + error \ NDVIinv) + ((factor \ night \times night) + error \ night) \]

\[
LRI\% = \left( \frac{100}{Max \ LRI - Min \ LRI} \right) \times (LRI - Max \ LRI) + 100
\]

where factor loading and error are indicators obtained in the structural equation model for each observed variable; Max = value maximum; Min = value minimum. Thus, maximum values occur when all observed variables have a value of 255 bytes, while minimum values occur when all variables have a value of zero.

Using the Semplot package (R statistics program), we estimated the factors and errors considering a sample of 7620 points previously tested to correlation and normal distribution according to section 2.4.

The comparative fit index (CFI) calculates the relative fit of the observed model by comparing it with a base model (Byrne, 2013). The root mean square error of approximation (RMSEA) to assess how well the model fits a population and not just a sample estimated (Hair et al., 2009), as discussed in the specialized literature (Ullman, 2006).

For model adjustment, values greater than 0.90 for CFI and less than 0.10 for RMSEA were adopted as parameters proposed by Gama-Rodrigues et al. (2014). In addition, the factor loading must be statistically significant. According to Hair et al. (2009), an appropriate value should be greater than 0.50, being ideals greater
than 0.70. Also, according to the authors, construct reliability (CR) is a good convergent validity indicator. Values between 0.6 and 0.7 may be acceptable if other indicators are good. Nevertheless, for all measures to represent the construct, CR has to be greater than 0.70.

This way, modeling these variables, we obtained the landscape resistance index, which was our latent variable in the SEM context (Fig. 2).

**Structural equation modeling (SEM)**

Structural equation modeling (SEM) is a multivariate technique used to analyze a group of observed variables, following a holistic hypothesis previously established and having the ability to represent non-measurable variables, named latent variables or constructs (Grace et al., 2010).

While direct measures for abstract concepts such as “landscape resistance” may not exist, statistical methods can derive this value from other related variables. SEM uses confirmatory factor analysis (CFA) to estimate latent variables. These constructs are not directly observable in the data set but are derived from observed variables and can indicate causal relationships within the model. Thus, confirmatory factor analysis extracts the latent construction of other variables and shares the highest variance with related variables (Byrne, 2013).

This way, the landscape resistance index (LRI) constitutes the latent variable (dependent variable), which is a theorized and unobserved concept measured indirectly by the consistency analysis among multiple observed variables (independent variable), i.e., LST, Night, and NDVIinv. These indicators represent the theoretical concept response, including measurement error explanation (Hair et al., 2009).

According to Grace et al. (2010), the SEM also involves multiple regression problems using a path diagram. The unidirectional arrow indicates the cause-effect relationship between the variables (Fig. 2).

In general, the steps for building the model were the theoretical basis, model elaboration, collection

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**Fig. 2** Conceptual model used to obtain the landscape resistance index for the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil. Generated with Lucidchart online software (free version, http://www.lucidchart.com/pages/pt)
and preparation of variables, estimation, adjustment assessment, and discussion (Kaplan, 2009).

Observed variables

The observed variables selected for modeling the landscape resistance index were LST, Night, and NDVIinv.

The satellite images supported the production of the observed variables. LST used the thermal infrared, band 10 of the Landsat-8 (TIRS sensor), to determine our LULC terrestrial surface temperature. Their spatial resolution of 100 m was resampled to 20 m, the same as the LULC map.

The atmospheric band correction followed the available parameters on the United States Geological Survey website (USGS, 2019). This way, the later radiance value was converted to Kelvin temperature and then to degrees Celsius (°C), subtracting 273.15 K (Barsi et al., 2003).

The Night map constituted in the Night and Day Band (BND) of the Visible Infrared Imaging Radiometer Suite (VIIRS), which was provided by the Earth Observation Group (EOG) of the National Center for Environmental Information (NCEI). In this study, its 450 m-spatial resolution was downsized to 20 m. The available images were firstly filtered to exclude data affected by diffuse light, lightning, lunar illumination, and cloud cover addition though, and border bands were excluded, the so-called aggregation zones.

The NDVI was generated from CBERS-4 satellite images (MUX sensor, 20 m- spatial resolution). Thus, we multiplied NDVI by −1, using a raster calculator, to obtain NDVIinv, considering that values near −1 represent LULC with the most resistance to flow gene since they have less vegetable biomass.

Using a linear function, the LST, NDVIinv, and Night maps were normalized to a standard scale, ranging from 0 to 255 bytes. After, they were sampled considering 7620 points randomly distributed through the study area, with a minimum distance of 100 m among them, for modelling. This sample size corresponds to 20 times the statistical sampling required for a 95% confidence interval and 5% error.

Spatialization index

The LRI% spatialized in the Geographic Information System (GIS) supported different analyses. Firstly, on a continuous scale (%), we evaluated three scenarios, which were distribution (i) through our studied area, (ii) without the forest patches, and (iii) only inside these forest patches.

For the first scenario, the studied area was classified as a very low, low, medium, high, and very high level of resistance through the Jenk Natural Break method, an algorithm that maximizes similarity within classes and the distance between groups (Smith et al., 2020). Moreover, we analyzed the overlap between resistance and LULC classes.

Finally, we analyzed the relation between resistance and functional forest connectivity, considering the forest patches as the reference. The map of distance from forest fragment centroids was overlayed on the resistance classes map, and a sample grid (with 7620 points) of this product supported the statistical analysis.

In the statistic program, the distance data were log (x+1) transformed and applied the generalized linear model of binomial regression for each resistance class. For this, the presence (1) or absence (0) of the resistance class (dependent variable) was considered, depending on the distance from forest fragments centroids (independent variable).

Results

The environmental attributes maps (in 255 bytes) that supported the LRI modeling for the Green Belt Biosphere Reserve (SP, Brazil) are in Fig. 3.

Predominant values of NDVI and Night were represented by at most 50 bytes, which occupied 73% of our studied area on the first map and 93% on the second. The medium value on the NDVI map was 34.8 bytes (± 52.8), whereas the Night map was 12.1 bytes (± 39.8).

The LST was the variable with the greatest variability in the landscape, having 92.1% of our total area associated with values lower than 150 bytes (medium value: 68.8 and ± 63.7).

The LST was the variable with the greatest variability in the landscape, having 92.1% of our total area associated with values lower than 150 bytes (medium value: 68.8 and ± 63.7).

These attributes, i.e., observed variables in the model context, contributed to a significant adjustment of the landscape resistance index (LRI), with CFI of 1.00 and RMSEA of 0.00 (Fig. 4A).

This way, the factor loading obtained for the LST, Night and NDVIinv was respectively of 0.56 (error
Highlighting the significant adjustment that we obtained on the standardized assessment among these factor loadings (calculated by the model) and the sum of the points representing them.

The construct reliability (CR) of the model was 0.68, that is, considered adequate, despite presenting a great data variation in the intermediate values (between 400 and 800 points).

In this context, the SEM used to obtain the LRI is presented in Equation 3:

\[
\text{LRI} = ((0.80 \times \text{NDVI}_{\text{inv}}) + 0.37) + (0.57 \times \text{NIGHT}) + 0.68) + ((0.56 \times \text{LST}) + 0.68))
\]

This way, the resistance inside the forest patches is smaller than the matrix, although with different levels, as we also observed for the matrix components (urban areas, planted forest, farmlands, water, road, and anthropized fields).

Recalling that the urban areas refer to small urban agglomerations (low-density urban areas) and great urban areas (high-density urban areas), while anthropized fields are predominantly composed of vegetation in regeneration and unmanaged pastures.

Evaluating our study area in classes of resistance (Table 2), we obtained 36.3% of its total area classified as very low, 31.5% as low, 20.4% as a medium, 8.2% as high, and 3.6% as very high. In addition, we found a particular association with the native forest, high-density urban areas, and anthropized fields.

The native forest occupied 76% of the very low class, 23% of the low, and less than 2% of other classes. Otherwise, anthropized fields predominated in the low and medium classes, representing 55% and 62%. It was also the second use, with 36%, in the high class.

The most resistant land use of our landscape, represented by the high-density urban area, prevailed in the very high and high classes, occupying 92% and 51% of their respective total areas.

Table 2 also indicates the presence of planted forest in 7% of the very low class, in 3% of the low class, but it is associated with or close to the native forest or abandoned anthropized fields.

Regarding the resistance model analysis, aiming at the functional forest connectivity, our results indicated coherence between the occurrence of resistance classes and the distance of forest fragments from their respective centroids (Fig. 6). The frequency of high and very high resistance classes increased with the distancing from the patch’s centroids (Fig. 6D/E), while the very low and medium-class frequencies decreased (Fig. 6B/C). Conversely, very low resistance increased with the patch’s centroids’ distancing, reflecting the large forest patches in the studied area (Fig. 6A). Especially for those having more than 300 ha (Table 1), where there is a great distance between their centroid and edge, traversing great distances within the forest fragments.

Discussion

In the Green Belt Biosphere Reserve of São Paulo, the landscape studied supported the modeling of the landscape resistance index (Fig. 4A/B) through the selection criteria. The model evidences a positive correlation between the point sampled in the criteria maps and the factorial load convergence of the index.
Thus, we observed that the NDVIInv had greater significance for the composition of the index. Considering its high variability, we can say that the criteria influenced differently on LRI with NDVIInv showing the highest factor loading (n) and lowest error (error) among the three. While the Night and LST equally contributed to represent the latent effect implicit in the concept of landscape resistance and meeting the statistical parameters for a structural equation model.

In turn, the index reflects the resistance levels of the land use/land cover, expressed by the class interval, ranging from 0% (1.73) to 100% (493.88), with the highest values associated with the anthropized uses and forest isolation (Table 2, Fig. 6). This way, LRI supports the design of forest corridors through environmental with the lowest resistance. Therefore, the model assumes that the greatest resistance is correlated with the sum of the criteria’s factor loading, and intermediate resistance values can evidence potential environments for restoration and protection of habitats. (Equations 3 and 4).

Thus, insights are not limited to a few specific habitat patches. However, they are available in continuous and large-scale maps across the study region, indicating functional connectivity capability.

Terrestrial surface knowledge may accurately represent the impact of landscape resistance on species movements, according to Sinsch et al.’s (2012) literature analysis. However, it is also likely that a migrant specimen’s likelihood of successfully reproducing is impacted negatively by the high cost of dispersal over a poorer matrix habitat, which should be considered when making predictions about functional connectivity (Churko et al., 2020).

Consequently, the regions with the highest plant biomass, the lowest temperature on the land surface, and the lowest presence of anthropized areas meet the conceptual foundations. We obtained these results because our criteria represent the landscape attributes with intrinsical variability without requiring biological information from species, as proposed by other approaches to evaluating functional connectivity. Thus, through LRI, we decrease the subjectivity, which characterized some approaches based on focal species such as birds or mammals.

Differently, LRI models a continuous univariate surface and brings the multivariate characteristics of the studied landscape. Then, our index can be adjusted according to the landscape criteria. According to Vasudev et al. (2021), when dispersing, animals try some degree of non-ideal exploration of the landscape, have some knowledge about the surrounding landscape, and make movement decisions according to environmental information.

Human activities are directly associated with LULC alteration (Jiao et al., 2019). Several land-use concerns, including the loss of permanent cropland, irrational construction design, land pollution, and other related environmental difficulties, have been brought on by rapid socioeconomic development and urbanization processes (Li et al., 2017). Therefore,
the land-use/land-cover changes significantly impact regional landscape heterogeneity and composition.

Our results indicated that the index could reflect the resistance levels of the land use/land cover. In our study, regions occupied by anthropized uses and having isolated patches show the highest values for LRI. Otherwise, those areas centering the forest patches showed the lowest value (Fig. 5C).

According to Gracanin and Mikac (2023), connectivity for species is apparent, as the discontinuity of the landscape limits the intensity or existence of paths to movement. In this sense, when analyzing the functional connectivity in the continuity of the fuzzy logic and based on the observed variables, the LRI includes the landscape analysis in the territory’s management and planning. Modeling regional-scale connectivity is essential and valuable for conserving connectivity, habitat preservation, and conflict mitigation.

Thus, NDVI, LST, and Night were modeled to bring the main characteristics, considering their variability and importance to functional forest connectivity.

Traditionally, NDVI has differentiated land use/land cover (De Castro et al., 2018; Dong et al., 2016), including agriculture (Remelgado et al., 2020), pasture (Rickbeil et al., 2017), and forest (Mills et al., 2018). On the other hand, the rest and foraging animal behavior require specific environments (Abrahms et al., 2017) associated with LULC (Brown et al., 2017; Remelgado et al., 2019; Remelgado et al., 2020; Rickbeil et al., 2017).

Although the impacts of changes in land use/land cover are commonly evaluated as local or regional extinction of species, ecological processes operate at varied scales, i.e., a locally occurring species may suffer population decline elsewhere, making the analysis crucial for conservation.

In this sense, functional connectivity maps are good visual aids that are simple to use and intuitively allow users to identify regions within the distribution of each species where landscape resistance is high or low on a scale. The importance of fine-scale features that can help guide decisions about development and land use change, propose road crossings, or highlight sensitive circulation corridors that could benefit from protective measures (Churko et al., 2020).

Some studies have shown that animals moving in the landscape respond to environmental changes, mainly influenced by vegetation (Brown et al., 2017; Da Silveira et al., 2016; Remelgado et al., 2019), which can identify through the vegetation indexes (Pettorelli et al., 2011). Thus, navigation efficiency seems more significant when the environment’s high spatial correlation directs the animal movement (Bailey et al., 2018). This way, our result considered that NDVI values similar to forest fragments represented regions with less resistance to functional forest connectivity, which we call NDVIinv (Fig. 3A and Fig. 5).

Changes in the environment temperature influence the dynamics and function of the natural systems, affecting their ecological communities (Osmond et al., 2017). Results like this, in animal acclimatization or plasticity (Luhring & DeLong, 2017), have leading to the persistence or stability of the environmental system (Salt et al., 2017) and inducing animals to operate in ranges of thermal tolerance limits (Sunday et al., 2014). The main result is that the thermal restrictions (Broders et al., 2012) induce animal movement near the forest remnants or through shaded environments (Alston et al., 2020; McCann et al., 2016) to produce less metabolic heat.

In the same way, our criteria LST represent the temperature effects on the ecological processes (Fig. 3B). According to Delong (2012), temperature influences the animal movement across the landscape, and its variation influences the quality of the movement (Gibert et al., 2016; Pawar et al., 2016).

Remembering that the species persistence depends on the ability of the specimens to tolerate thermal changes in the landscape and on the thermal suitability of the habitat, which varies spatially according to the soil cover and surrounding vegetation (Robinson et al., 2013). Consequently, gradient thermal effects define how species select their habitat (Nowakowski et al., 2017).

Therefore, LST supported identifying the environments with a temperature similar to the forest fragment, assuming that these regions show the least resistance to functional forest connectivity (Fig. 3B and Fig. 5).

The variable Night expresses that the environment drives the species distribution (Alagador et al., 2012), under the principle that similar species dispersed in similar environments have similar integrity (Sawyer et al., 2011). The species movement is sensitive to the change in the landscapes (Krosby et al., 2015), though, causing resistance to the energy flow through
the matrix (Marulli & Mallarach, 2005) or barriers that affect intra behavior species-specific (Berger-Tal & Saltz, 2019).

Resulting from urban sprawl, the light pollution registered by Night gradually invades natural environments, and it generates excellent resistance to photosensitive species in habitats close to impact sources (Davies & Smyth, 2018; Gaston & Holt, 2018; Guetté et al., 2018). In this context, the nighttime reflectance supports the identification of modified environments (Levin & Zhang, 2017), considering a positive relationship among the anthropized and reflectance levels with resistance to functional forest connectivity (Fig. 3C and Fig. 5). Thus, the Night criterion differentiates the resistance in fragments close to urbanized areas from planted forests and fields in recovery.

This way, our criteria represented the landscape attributes such as the LULC, topography, and indicators of anthropogenic disturbance (Krishnamurthy et al., 2016; Mateo-Sánchez et al., 2015; Milanesi et al., 2017; Neumann et al., 2015; Milanesi et al., 2017; Wasserman et al., 2010). It is essential to remember that, while the landscape resistance is related to a point surface value, the connectivity is cumulative to movement across the dispersal surface (Cushman et al., 2014; Krishnamurthy et al., 2016). Thus, spatial correlations are fundamental to infer the dispersion capacity of species in the environment (Bajaru et al., 2020).

This information is essential for landscape planning, as efforts to conserve functional connectivity must protect forests that provide essential links between habitats and, simultaneously, invest efforts in the matrix to maintain or even improve the permeability of these lands to movement, thus ensuring their role in landscape-scale conservation of threatened and generalist species (Vasudev et al., 2021).

Another positive point of the index is that it reflects the resistance levels of the land use/land cover, expressed by the fixed class intervals, with the highest values associated with anthropized uses and forest isolation (Equations 3 and 4). There was the greatest dispersion of results in environments of moderate resistance, i.e., those in transition between forests and urban areas (Fig. 4B).

The model predictability for our landscape was 88% of resistance, having the greatest variability in the matrix (Fig. 5A/B). Thus, even in anthropized areas, the index supports the identification of microhabitats, identified by where the animals move and by a behavioral pattern (Peterman et al., 2014; Reding et al., 2013; Zeller et al., 2012). The predictability of resistance for forest fragments, which was 53%, shows this characteristic of reflecting heterogeneity inserted in the model through the criteria (Fig. 5C and Table 2). Hence, using the index, we can identify places where species can occupy or move in these environments, conferring characteristics of resilience or ecological resistance to the spatialization of landscape resistance (Moraes et al., 2018; Nimmo et al., 2015; Robinson et al., 2013).

In the same way, when we classified the landscape in classes of the index, we obtained the very low resistance environments associated with forest fragments (75.9%) while very high resistance regions with urban areas (91.9%). In the intermediate environments, there was a transition process from the natural to the urbanized LULC due to the increase in

| Table 2 | The LULC and resistance classes of the study area, located in GBBR-SP, Brazil |
|---------|----------------------------------|
| LULC Class | Very Low | Low | Medium | High | Very High |
|----------|---------|-----|--------|------|-----------|
| Anthropized Field | 13.8  | 55.2 | 61.7 | 35.7 | 4.8       |
| Native Forest | 75.9  | 22.6 | 1.7  | 1.3  | 0.0       |
| High Density Urban Area | 1.6   | 11.7 | 26.5 | 50.7 | 91.9      |
| Planted Forest | 6.9    | 2.6  | 0.6  | 0.0  | 0.0       |
| Farmlands | 0.5    | 2.2  | 1.9  | 0.8  | 0.0       |
| Others | 2.2    | 5.7  | 7.6  | 11.5 | 3.4       |
| TOTAL | 100    | 100  | 100   | 100  | 100       |
A

Very Low Resistance

B

Low Resistance

C

Medium Resistance

D

High Resistance

E

Very High
resistance, especially for anthropized fields, planted forests, and agriculture (Table 2).

In this sense, the reports that the landscape structure is only one component of the many affecting functional connectivities and that individuals can traverse inadequate habitats during dispersal corroborate the stratified analysis of the LRI (Baguette et al., 2013; Froidevaux et al., 2016; Melin et al., 2016). Thus, the resistance of the landscape can vary according to the dispersion capacity of the species (Liu et al., 2018) and the sensitivity to barriers (Breckheimer et al., 2014).

This coexistence structure between animals and anthropized environments is reported in the literature with carnivores, small mammals, and multispecies (Bajaru et al., 2020; Ceia-Hasse et al., 2017; Chapron et al., 2014; Ducci et al., 2015; König et al., 2020; Loveridge et al., 2017). In this perspective of heterogeneity of resistance in the landscape, the analysis of the LRI performance showed coherence and the increase of forest isolation (Fig. 6).

In this context, we obtained many environments associated with very low resistance due to the representativeness of the greatest forest fragments in our landscape (Table 1, 34.9%). As the resistance to movement in these patches is meager, we cannot affirm that the functional connectivity promotes the structuring of the local community in these regions (Lindenmayer et al., 2020; Poniatowski et al., 2016).

In the same way, there was an increase in the distance from the forest patches, proportional to the occurrence of regions with very high and high resistance (Fig. 6D/E). Regions, justly represented by urban areas and highways with low capacity for connectivity that performs species filtering, mediated by habitat characteristics, resulting in an unequal probability of species occurrence (Kurz et al., 2014; Salgueiro et al., 2021).

Thus, the proximity to the forest patches was one of the decisive factors in defining the resistance and occurrence of many areas. We can mention those occupied by anthropized fields (with different stages of regeneration), planted forests, and agriculture that showed low and medium resistance. Chazdon and Uriarte (2016) also observed this relation, reporting that places close to forest fragments had a rapid natural regeneration.

According to Dallabrida et al. (2019), the dynamics of the bush-tree component is not a spatially homogeneous process, having factors ecological, biotic, and abiotic influences on the demographic rates of the regenerative component and which will affect biodiversity conservation (Arroyo-Rodríguez et al., 2017).

In this approach, in intermediate resistance environments, sensory perception plays an essential role for the animal during movement across the landscape (Clarke et al., 2013). Recalling that the animals need the acquisition, interpretation, selection, and organization of sensory impressions to assign meaning to the surrounding environment, based on their respective life history and, for some animals, depending on their memory (Almeida et al., 2010).

As we improve models of animal movement and landscape resilience, our ability to shape holistic conservation at landscape scales and achieve conservation success is enhanced (Vasudev et al., 2021).

Conclusion

The study was developed for landscapes like our studied area, which has suffered from urban sprawl, although having a significant remnant of the Atlantic Forest, a biodiversity hotspot. Remnants that support ecological processes and species dispersion across the environment.

Our challenge was to identify the paths based on LULC resistance, aiming at the forest functional connectivity. Even more, considering landscape attributes instead of a species dispersion pattern. Attributes that we could model supported the landscape resistance index. In this study, they were modeled through the structural equation model, naming observed variables.

Thus, our observed variables are NDVIinv, Night, and LST, robustly determining the landscape resistance, aiming at functional forest connectivity. They have different influences on the landscape and, consequently, on the index, resulting in spatial heterogeneity associated with the movement across the landscape.
Hence, LRI supports the definition of fixed limits, reflecting LULC with different resistance. Regions classified as very low resistance were associated with forest fragments, very high to urban areas, and intermediate levels having a transition process from the natural to the urbanized LULC.

Finally, we can say that our criteria were sensible and efficient to represent the landscape characteristics in terms of their respective resistance, allowing the LRI production.

In this context, LRI provides a measure of landscape resistance supporting forest connectivity analysis. A measure that we can obtain for various landscapes considering their actual structure, independently of the fauna species that they have. So, LRI brings the actual landscape physical characteristics for the forest connectivity analysis.

This way, through the index we can plan actions to improve forest connectivity and years after quantifying the results.

Another point is related to the resistance level inside the forest patches. According to our results, LRI was sensible to represent the range from the edge to the central region of the remnants.

Lastly, we conclude that the index based on environmental attributes reflects the structure of functional forest connectivity and it is a resistance measure for landscapes. A measure that can be calculated for various landscapes to plan the design of forest corridors and after to evaluate the improve that action on the forest connectivity.

Author contribution Ivan Vanderley Silva: conceptualization, validation, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, visualization, and project administration. Roberta Averna Valente: writing—review and editing, conceptualization, validation, formal analysis, visualization, supervision, resources, and funding acquisition.

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Declarations

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