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CENTRO DE CIÊNCIAS E TECNOLOGIAS PARA A SUSTENTABILIDADE
CAMPUS DE SOROCABA
PROGRAMA DE PÓS-GRADUAÇÃO EM
"PLANEJAMENTO E USO DE RECURSOS RENOVÁVEIS"

IVAN VANDERLEY SILVA

MULTICRITERIA EVALUATION FOR PRIORITIZING AREAS TO MAINTAIN FUNCTIONAL FOREST CONNECTIVITY

Sorocaba
Estado de São Paulo - Brasil
2022

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Tese apresentada ao Programa de Pós-graduação em Planejamento e Uso dos Recursos Renováveis - PPGPUR, UFSCar Campus Sorocaba, para obtenção do título de Doutor em “Planejamento e uso dos recursos renováveis”.

Orientação: Profa. Dra. Roberta Averna Valente.

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Comum e atual para muitos de nós, o texto lista os momentos difíceis de descrédito, desconfiança, descrença, ansiedade, frustação, desvalorização pessoal... e, também, as boas emoções, a esperança, gratidão, os acertos, resultados alcançados, a auto-estima, a vitória..., sentimentos e sensações que experimentamos nesse processo.

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EPÍGRAFE

"Uma ordem natural é uma ordem estável. Não existe a menor chance de que a gravidade deixe de funcionar amanhã, mesmo que as pessoas deixem de acreditar nela. Por sua vez, uma ordem imaginada está sempre sob a ameaça do colapso, porque depende de mitos, e os mitos desaparecem quando as pessoas deixam de acreditar neles. "

Yuval Noah Harari

RESUMO

VANDERLEY-SILVA, Ivan. Avaliação Multicriterial por priorização de áreas visando a manutenção da conectividade florestal funcional. Tese (Doutorado em “Planejamento e uso dos recursos renováveis”) – Centro de Ciências e Tecnologia para Sustentabilidade, Universidade Federal de São Carlos, Sorocaba, 137 f, 2022.

As diferenciações fisionômicas da paisagem são consequências da ocorrência e regularidade de perturbações antrópicas e naturais, de sua condição de resistência e capacidade de resiliência. Essas propriedades influenciam no funcionamento e na possibilidade de conectividade dos fragmentos florestais. Por ser um sistema socioecológico, a paisagem está exposta a constantes mudanças e exige gestão orientada para descrever seus complexos padrões e processos. Nesse contexto, a Avaliação Multicriterial (AMC), por apresentar a função de agregação espacial, é uma ferramenta adequada para a tomada de decisão, pois permite comparar, medir, avaliar e resolver diferentes critérios e cenários. Este estudo buscou a priorização de áreas, por meio da AMC, visando à conectividade florestal funcional em uma paisagem sob expansão urbana. A área estudada localiza-se na Reserva da Biosfera do Cinturão Verde da cidade de São Paulo, região sob pressão para a conversão de remanescentes florestais em uso urbano. Nesse cenário, utilizou-se da revisão da literatura, opinião de especialistas e técnicas estatísticas para definir um conjunto de critérios que representassem os atributos ambientais. Assim, proximidade aos fragmentos florestais, Índice de Resistência da Paisagem, proximidade à rede de drenagem, Índice Topográfico de Umidade e declividade são fatores que permitem identificar regiões onde há persistência dos fragmentos florestais e maior integridade da paisagem. Portanto, controlando a influência dos critérios, o modelo proposto apoia a priorização de áreas para conservação florestal, as quais dão suporte à conectividade funcional da estrutura florestal da paisagem e oferece suporte para o planejamento de programas de restauração florestal ou pagamento por serviços ecossistêmicos visando a conectividade funcional.

Palavras chaves: Estrutura da Paisagem, Índice de Resistência da Paisagem, Conectividade da paisagem, Corredor Ecológico, Expansão Urbana e Conservação Florestal.

ABSTRACT

VANDERLEY-SILVA, Ivan. Multicriteria decision analysis for prioritizing areas to maintain functional forest connectivity. Tese (Doutorado em “Planejamento e uso dos recursos renováveis”) – Centro de Ciências e Tecnologia para Sustentabilidade, Universidade Federal de São Carlos, Sorocaba, 137 f, 2022.

The physiognomic differentiations of the landscape are consequences of the occurrence and regularity of anthropogenic disturbances, condition of resistance, and capacity for resilience. These properties influence the functioning and the possibility of connectivity of forest fragments. As a socio-ecological system, the landscape constantly changes and requires oriented management to define its standards and processes. This way, Multicriteria Evaluation (MCE) is an adequate tool for decision-making, considering its function of spatial aggregation, which supports the comparison and evaluation of criteria and scenarios. Thus, the study prioritized areas aiming for functional forest connectivity in a landscape under urban sprawl through the MCE. The studied area is located in the Biosphere Reserve of the Green Belt of the city of São Paulo, a region under pressure to convert forest remnants into urban use. The criteria represented our landscape environmental attributes and were defined through literature review, expert opinion, and various statistical techniques. Thus, proximity to forest fragments, Landscape Resistance Index, proximity to the drainage network, Topographic Wetness Index, and slope were the criteria that allow the identification of regions with the persistence of forest fragments and greatest landscape integrity. Therefore, by controlling the influence of the criteria, the proposed model supports the prioritization of areas for forest conservation, which supports the functional connectivity of the landscape's forest structure and supports planning forest restoration programs or payment for ecosystem services aimed at functional connectivity.

Keywords: Landscape Structure, Landscape Resistance Index, Landscape Connectivity, Ecological Corridor, Urban Sprawl, and Forest Conservation.

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MULTICRITERIA DECISION ANALYSIS FOR PRIORITIZING AREAS TO MAINTAIN FUNCTIONAL FOREST CONNECTIVITY

1. INTRODUCTION

The importance of the native forest remnants and their connection has been highlighted in the context of the human pressures on natural environments associated with growing urban sprawl and their demand for ecosystem services, such as biodiversity and water resources. Recent estimates suggested that native forests occupy approximately 30% of the earth's surface and about 40% of these ecosystems are represented by tropical forests that still preserve an essential richness of regional flora and fauna (Keenan et al., 2015, Dahal et al., 2014).

Many of these forest remnants are in modified landscapes, whose complex composition of natural systems, associated with environmental damage, make them strategic for conservation and environmental preservation plans.

In this context, a significant challenge is understanding the mechanisms used by modified environments to maintain or restore the structure and processes that lead to forest connectivity. In the literature, several studies point to the importance of landscape composition and configuration, measured, and understood through traditional ecological metrics (Anhaia et al. 2012, Grise and Biondi, 2012, Su et al., al., 2011, Su et al., 2012, Cunha et al. 2014, Moraes, Mello, and Toppa, 2015).

The landscape metrics are easy to obtain and have been considered a possible indicator of biodiversity and environmental responses to maintain functional forest connectivity. When combined with environmental variables, they are an instrument sensitive to anthropogenic changes and can, for example, identify priority areas for forest conservation. Thus, the metrics can signal microclimates and habitats and indirectly interpret biodiversity conservation, pointing to adjustable monitoring criteria for changes in the landscape.

The measurement and determination of fluidity in the matrix is another area of landscape studies with wide gaps. Denied in the past, meeting the importance of altered environments is currently visible and relevant for the dispersion and maintenance of viable populations in the face of the expansion of anthropogenic barriers. In the scientific literature, the matrix connectivity potential is still a great deal topic. Studies rely on instruments based on habitat and movement genetics to determine dispersal capacity in the landscape. When combined with remote sensing and geoprocessing techniques, such studies enhance learning about functional forest connectivity.

Naturally, plans aimed at forest sustainability need to understand patterns of human pressure and depend on a theoretical base to assess the effectiveness of actions in highly modified environments and indicate which strategies value forest connectivity.

Concerning the spatialization of these effects, the cumulative human pressure maps are efficient because they are strong indicators of the collapse of modern natural populations, of the dispersal ability of a species, its invasive potential, biodiversity conservation planning, and connectivity in anthropized landscapes (Venter et al., 2016, Marull et al. 2015, Hand et al., 2014, Beans et al., 2012, Yackulic et al., 2011, Woolmer et al., 2008).

Given the need to balance social, economic, and ecological interests, prioritizing areas represents one effective and economic landscape management method. The basis for this support is the interaction and analysis of different information plans that point to promising natural areas.

In this context, the study area, located in the Biosphere Reserve of the Green Belt of the city of São Paulo (GRBB-SP), Brazil, is included between the Cabreúva Environmental Protection Area (EPA), the Morro Grande Forest Reserve, and the Itupararanga EPA, where essential fragments of the Dense Ombrophilous Forest remain. The landscape in this region suffers from a historical series of deforestation (Nobre et al., 2010), mainly in a diffuse way, in which fragments are suppressed by its borders, become smaller and smaller, and compromise connectivity (Leite, 2012). According to the authors, this growth occurred mainly through urban sprawl areas and the densification of areas occupied.

For Unesco (2019), the focus of the biosphere reserve is regional sustainability. Its objective is to allow the belt to be able, indefinitely, to ensure the conservation of biodiversity and the well-being of the population, providing ecosystem services and, on the other hand, harmonize the relationship and reduce the pressure of the city on its surroundings.

When faced with different scenarios, criteria, and interests, the ability to synthesize knowledge is essential to assist in decision-making. That capability is shown in Multicriteria Evaluation methods, which are based on participatory techniques and use specialists' different fields of understanding and experience to resolve conflicts and determine choices (Valente et al., 2017; Vettorazzi and Valente, 2016; Malczewski and Rinner, 2015).

Given this scenario, the study prioritized areas aiming for functional forest connectivity in a landscape under urban sprawl, through the Multicriteria Evaluation (MCE).

For a better understanding, we structure the document in three chapters, with the first entitled "Assessing environmental criteria to support forest connectivity under urban sprawl." This chapter evaluated the environmental criteria for prioritizing areas to obtain forest functional connectivity in a landscape subject to urban sprawl, understanding how the criteria are associated with the structural forest attributes represented by traditional landscape ecology metrics.

In this context, we diagnose the environmental variables mentioned in the literature as necessary for functional connectivity in forest fragments. Then, we opted for Canonical Correspondence Analysis (CCA) to direct the correlation between environmental variables as a function of landscape metrics. This procedure highlighted which variables have a theoretical basis, affect the forest structure, and be criteria for functional connectivity.

In the second chapter, entitled "Landscape resistance index aiming at functional forest connectivity," we developed a landscape resistance index, which allows the identification of the integrity of the environments, supporting the evaluation of the functional connectivity between forest fragments of landscapes under urban expansion.

The Landscape Resistance Index (LRI) was developed through the environment's integrity. The method uses ecological and habitat logic to determine the resistance to dispersion in the landscape. For this, the energy and water balance, represented by the temperature of the land's surface, the biomass concentration determined by the vegetation index (NDVI), and the anthropogenic barriers determined by nighttime reflectance were taken as a basis. The modeling was based on the Structural Equation, a statistical technique that explains the relationships between multiple observable and latent variables, such as landscape resistance.

In the third chapter, entitled "Functional connectivity supported by forest conservation in a landscape of urban sprawl, we sought to define Prioritize areas for forest conservation, aiming at functional connectivity in a landscape subject to urban expansion.

In the latter case, the knowledge acquired in the previous chapters was used to determine a set of criteria and, through Weighted Linear Combination, literature review, and experts' opinion, in the Multicriteria Evaluation, to identify priority areas for forest conservation aiming at forest connectivity functional facing the different land-use/land-cover.

REFERENCES

Anhaia, T. R. S. et al. A paisagem do Rio Pitangui em seu curso superior, no 1º Planalto Paranaense. **Raega (UFPR)**, Curitiba. v. 24, p. 134-148, 2012. https://doi.org/ http://dx.doi.org/10.5380/raega.v24i0.

Beans, C. M. et. al. Climate suitability and human influences combined explain the range expansion of an invasive horticultural plant. **Biological Invasions**, v. 14, p. 2067–2078, 2012. https://doi.org/10.1007/s10530-012-0214-0.

Cunha, E. R.; Bacani, V. M.; and Ayach, L. R. Geoprocessamento aplicado à análise da fragilidade ambiental. **Revista ANPEGE**, v. 9, n. 1, p. 89-105, 2013 https://doi.org/ 10.5418/RA2013.0912.0006.

Dahal, B. et al. Bird conservation values of off-reserve forests in lowland Nepal. **Forest Ecology and Management**, v. 323, p. 28-38, 2014.https://doi.org/10.1016/ j.foreco.2014.03.033.

Grise, M. M. and Biondi, D. The landscape structure analysis of National Park of Superagui, Paraná state and the buffer's zone. **Ciência Florestal**, v. 22, n. 1, p. 23-33. 2012 https://doi.org/10.5902/198050985076.

Hand, B. K. et. al. Assessing multi-taxa sensitivity to the human footprint, habitat fragmentation and loss by exploring alternative scenarios of dispersal ability and population size: a simulation approach. **Biodiversety Conservation**, v. 23, p. 2761–2779, 2014. https://doi.org/ 10.1007 / s10531-014-0747-x.

Keenan, R. J.; Reans, G. A.; Archad, F. et al.. Dynamics of global forest area: results from the FAO Global Forest Resources Assessment 2015. **Forest Ecology and Management**, v. 352, p. 9 – 20, 2015. https://doi.org/10.1016/j.foreco.2015.06.014.

Malczewski, J.; and Rinner, C. **Multicriteria Decision Analysis in Geographic Information Science**. Springer, 331p. 2015. https://doi.org/10.1007/978-3-540-74757-4.

Marull, J. et. al. Exploring the links between forest transition and landscape changes in the Mediterranean. Does forest recovery really lead to better landscape quality? **Agroforest System**, v. 89, n. 4, p. 709-719, 2015. https://doi.org/ 10.1007/s10457-015-9808-8.

Moraes, M. C. P.; Mello, K.; and Toppa, R. H. Análise da paisagem de uma zona de amortecimento como subsídio para o planejamento e gestão de unidades de conservação. **Revista Árvore**, v. 39, n. 1, p. 1-8, 2015. https://doi.org/10.1590/0100-67622015000100001.

Su, S., et. al. Characterizing landscape pattern and ecosystem service value changes for urbanization impacts at an eco-regional scale. **Applied Geography**, v. 34, p. 295-305, 2012. https://doi.org/ 10.1016 / j.apgeog.2011.12.001.

Su, S., et. al. Transformation of agricultural landscapes under rapid urbanization: a threat to sustainability in Hang-Jia-Hu region, China. **Applied Geography**, v. 31, p. 439-449, 2011. https://doi.org/10.1016/j.apgeog.2010.10.008.

Valente, R. A.; Petean, F. C. S.; and Vettorazzi, C. A. Multicriteria decision analysis for prioritizing areas for forest restoration. **Cerne**, v. 23, n. 1, p. 53-60, 2017. https://doi.org/10.1590/01047760201723012258.

Venter, O., et al. Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. **Nature Communication,** v. 7, 12558. https://doi.org/10.1038/ncomms12558.

Vettorazzi, C. A.; and Valente, R., A. Priority areas for forest restoration aiming at the conservation of water resources. **Ecological Engineering**, v. 94, p. 255-267, 2016. https://doi.org/10.1016/j.ecoleng.2016.05.069.

Woolmer, G et al. Rescaling the Human Footprint: A tool for conservation planning at na ecoregional scale. **Landscape and Urban Planning**, v. 87, p. 42-53, 2008. https://doi.org/10.1016/j.landurbplan.2008.04.005.

Yackulic, C. B. et al. Anthropogenic and environmental drivers of modern range loss in large mammals. **Proceeding of the National Academy of Science**, v. 108, p. 4024–4029, 2011. https://doi.org/10.1073/pnas.1015097108.

2. CHAPTER 1

ASSESSING ENVIRONMENTAL CRITERIA TO SUPPORT FOREST CONNECTIVITY UNDER URBAN SPRAWL

ABSTRACT

Establishing forest connectivity in landscapes under urban sprawl is essential for maintaining the ecological processes and ensuring biodiversity conservation. However, the major challenge is incorporating the ecological network in land-use/land-cover planning. This way, the main objective of the study was the evaluation of environmental criteria for prioritizing areas to obtain forest functional connectivity in a landscape under urban sprawl. The second objective was to understand how the criteria are associated with the structural forest attributes represented by traditional landscape ecology metrics. Based on the literature review, we defined the criteria to represent landscape feature such as the topographic, conflict, and biotic. The metrics used to characterize the forest structure were perimeter, shape index, and distance to the nearest neighbor. They were generated to a selected group of forest remnants, which represent the landscape forest structure. We assessed how the criteria are associated with the structural forest attributes by sampling the criteria and forest fragments maps (i.e., different maps representing the metrics-values) through the hexagon network. The statistical analysis used to evaluate these sampled values were The Moran Global (Moran I), Moran Local (LISA), and Canonical Correspondence Analysis (CCA). We found that the urban expansion process is diffuse, although it does not occur randomly in our landscape. The criteria slope, Topographic Wetness Index (TWI), distance from drainage network, distance from highways, distance from the low-density urban area, and distance from forest patches have characteristics that support this process. Furthermore, our results indicated a spatial autocorrelation among metrics and after, among metrics and these criteria. This way, through these criteria, we can identify regions where it is possible to have the persistence of forest fragments, even though in places under the impact of urban sprawl.

Keywords: Biodiversity conservation, Landscape ecology metrics, and Forest structural.

2.1 INTRODUCTION

The urban sprawl has been worldwide discussed in terms of its negative consequence as loss of natural habitat, forest fragmentation, and increased gene flow barriers, which has influenced the ecological connectivity of different species (Mimet et al., 2016; Semper-Pascual et al., 2018; Gavrilidis et al., 2019; Koprowska et al., 2020), one of the greatest threats to biodiversity conservation. (Scriven et al., 2019; Madadi et al. 2017).

Some studies showed that these consequences have already affected more than 50% of the worldwide landscapes (Watson, 2016; Tucker et al., 2018; Tabor et al., 2019) and that less than a third of the protected areas are appropriately connected (Saura et al., 2017).

The concern is ultimately motivated by uncertainties about knowing human activities can affect the ecosystem services functions (Dupras et al., 2016) and the maintenance of ecological processes, species dispersion, and specimen persistence in an altered environment (Yabsley et al., 2016).

Newbold et al. (2015) cited that the maintenance of forest functional connectivity is an essential component for biodiversity conservation in landscapes under urban sprawl, especially when the ecological network is incorporated into the land-use/land-cover planning (Huang et al., 2019; Grădinaru et al., 2017).

The importance of the theme has been highlighted in the literature, based on results that showed the connectivity analysis could support the effectiveness of forest conservation schemes (Ayram et al., 2016; Matos et al.2019; Almenar et al., 2019).

When the dispersion is low, the damages in the ecosystem services include changes in the carbon production and storage rates (Ziter, Bennet and Gonzalez, 2013), less resistance of communities to environmental fluctuations (Isbell et al., 2015), causing variation in the population and the aggregated biomass (Balvanera et al., 2014).

However, an important point related to the connectivity is that the decrease in its performance is not always linear to habitat loss and forest fragmentation, or both (Thompson et al., 2017; Semper-Pascual et al., 2018). This process is due to the presence of main habitats in the landscape dynamics or new paths to the species movement (Almenar et al. 2019), which can preserve the ecosystem functioning and stability (Wang and Loreau, 2016). Still, in function to the pattern and dispersion capacity of individuals (Bergsten and Zetterberg, 2013), who interact, in environments under urban sprawl, with the connectivity to support viable communities, which in turn can suffer from genetic selection and changes in allele frequency (Edelsparre et al., 2018).

According to Perky et al. (2018), the urban sprawl impacts distinct species due to their intrinsic resilience ability in different ways. This way, the functional connectivity modeling can be skewed if it is only based on one species (Almenar et al., 2019) and overestimated if we do not consider the response time to habitat loss and deforestation (Semper-Pascual et al., 2018).

In this context, contemporary models and indices have also been developed not only based on species but including environmental criteria, indicators, or parameters. An example is models based on the graph theory as the least-cost path analysis (Matos et al., 2019; Tarabon et al., 2019; Ribeiro et al. 2020) and circuit theory (Pelletier et al., 2017; Merrick and Koprowski, 2017; Koen, Bowman, and Ellington, 2019), as well as hybrids between least-cost path analysis and circuit theory (Monaco et al., 2020).

Other studies have been supported their decision based mainly on environmental criteria (Valente et al., 2017; Torrella et al., 2018; Balzotti et al., 2020), considering their ability to represent the landscape characteristics. Loro et al. (2016) mentioned that methods based on environmental criteria could introduce substantial variability in the evaluation process.

Zeller et al. (2012) pointed out that several criteria can support the connectivity analysis as relief shape, proximity among forest native remnants, drainage network, and urban areas.

Loro et al. (2016) highlighted the proximity among remnants because it is related to the species movement in the landscape, considering that variation in the proximities can modify the dispersion resistance of the species. Acevedo et al. (2011) suggested a criterion representing a sufficient distance from disturbance sources, considering their impact on the functional connectivity. Pays et al. (2012) also indicated the relief shape as an essential criterion since some animals prefer specific characteristics of the landscape relief.

Ibanez et al. (2014) emphasized the influence of environmental conditions for the connectivity, considering its correlation with landscape structure.

Conversely, we have the traditional landscape metrics, which have been used to evaluate changes in the composition and configuration (i.e., structure) of the landscape (McGarigal, 2013). For decades, the metrics were used to study processes such as habitat loss and forest fragmentation (Cheung et al. 2016) and evaluated impacts on abiotic and biotic functions (Lausch and Herzog, 2002).

Based on the landscape metrics, Uezu et al. (2005) studied the importance of fragment size and connectivity (structural and functional) on the occurrence and abundance of bird species. The study exemplified the potential of metrics to characterize the landscape structure, supporting analysis related to processes and their ability to provide information when they are associated with other methods.

Concerning these abilities, Schindler et al. (2013) and Senzaki and Yamaura (2016) cited the metrics as an adequate tool for identifying forest areas with high conservation value. In the same way, the representativeness of the forest fragments metrics was reported to evaluate the species dispersion and abundance pattern (Economo and Keitt, 2010), a species-area relation (Hammus and Von Nümers, 2008), the herbivores aggregation in the herd (Borthagaray, Arim, and Marquet, 2012), and the plant-pollinator interaction (Van Geert, Van Rossum, and Triest, 2009).

The major challenge is selecting an adequate metric set, which can be done through a literature review (Frank et al., 2013; Lechner et al., 2013). In the case of ecological analysis prevails the metrics of area, edge, and connectivity (Cheung et al., 2016; Senzaki and Yamaura, 2016; Schindler et al., 2015), that reflect the forest fragments characteristics in terms of biodiversity (Pereira et al., 2013).

However, some metrics do not bring sufficient information to relate them to the land-use and land-cover (LULC). Moreover, few studies have discussed the reason behind their selection and their relationships with the models resulting in metrics selection through subjective criteria (Lin et al., 2020).

The landscape under urban sprawl has characteristics distinct from rural landscapes, requiring precise methods, models, and criteria (Tarabon et al., 2020), which since factors as topography, slope, and urban policy affect the urban growth pattern differently over time (Akin and Erdoğan, 2020).

In this context, the main objective of the study was the evaluation of environmental criteria for prioritizing areas to obtain forest functional connectivity in a landscape under urban sprawl. The second objective was to understand how the criteria are associated with the structural forest attributes represented by traditional landscape ecology metrics.

2.2 MATERIAL AND METHODS

2.2.1 Study Area

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

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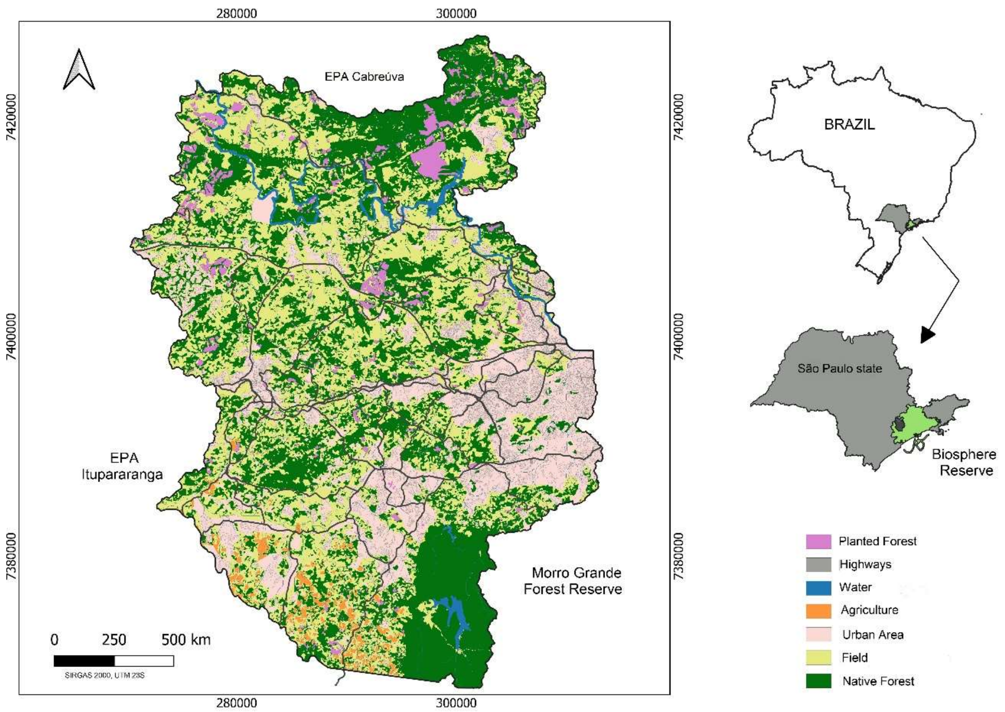


Fig.1 – Location and land-use/land-cover of the study area in the Green Belt Biosphere Reserve of São Paulo City, (GBBR-SP), Brazil.

The GBBR-SP region is an example of this situation, considering that its agricultural production has as leading destination São Paulo city. This way, the urban sprawl occurs in areas occupied initially by Atlantic Forest, affecting ecosystem services (ES) (González-García et al., 2019; Yuan et al., 2019) as the biodiversity (Newbold et al. 2015; Tabaron et al., 2020), water quality (Mello et al., 2020; Klink, Aversa, and Empinotti, 2019) and the forest connectivity (Almenar et al., 2019). Lembi et al. (2020) pointed out also the loss of matrix permeability as another negative effect of urban sprawl.

Studies have been conducted to minimize these adverse effects (Newbold et al. 2015; Ayram et al., 2016; Ribeiro et al. 2020) of the lack of forest connectivity and the importance of the GBBR areas. According to Unesco (2019), in these areas, human and environmental conflicts should be solved through the efforts of the local and scientific communities, aiming at the sustainable use of natural resources.

Urban-rural transitions characterize the study area; however, 34.9% of its area is (165099.25 ha) covered by Atlantic Forest (IBGE, 2012). Some remnants belong to the Protected Area 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). In this scenario, the studied area was significant for biodiversity conservation and to design an ecological corridor (MMA, 2019).

Other remnants are scattered through the matrix composed predominantly of pastures (i.e., anthropic fields) and urban areas that occupy 36.3% and 22.4%, respectively, of the total study. Furthermore, in the area, there is 3.4% of planted forests (Eucalyptus sp), 1.4% of farmlands, 1.0% water, and 0.6% of roads (highways and rural roads), as show Fig.1.

2.2.2 Conceptual Model

The conceptual framework model (Fig. 2) for our study area in GBBR-SP includes the environmental criteria and landscape ecology metrics at fragment level that were spatialized in the Geographic Information System (GIS).

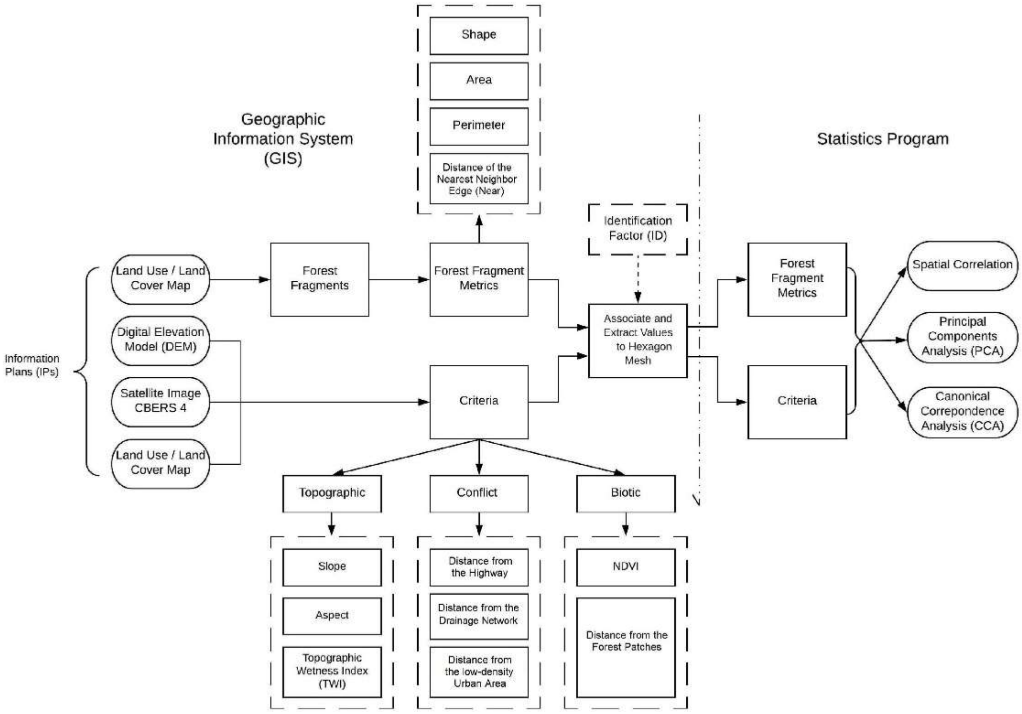


Fig. 2. Conceptual Model for the study area in the GBBR-SP, Brazil.

Environmental criteria were group according to the landscape characteristic as follow:

- Topographic: Slope, Aspect, and Topographic Wetness Index (TWI).
- Conflicts: Distance from highways (Highway), Distance from a drainage network (Drainage), and Distance from the low-density urban area (Urban); and
- Biotics: Normalized Difference of Vegetation Index (NDVI) and Distance from forest patches (Patch).

In the context of connectivity analysis, the database used to produce criteria and its justification will be described in the section below.

The landscape metrics used to characterize the forest structure were perimeter, shape index, and distance to the nearest neighbor (Near). They were generated to a selected group of forest remnants, which represent the landscape forest structure.

We assessed how the criteria are associated with the structural forest attributes by sampling the criteria and forest fragments maps (i.e., different maps representing the metrics-values) through the hexagon network.

The statistical analysis used to evaluate these sampled values were The Moran Global (Moran I), Moran Local (LISA), Principal Components Analysis (PCA), and Canonical Correspondence Analysis (CCA) (Fig. 2).

2.2.3 Criteria selection

The criteria were defined through the literature review from 2015 to 2019, using Scielo, Scopus, Web of Science, and Google Scholar platforms. We defined a combination of search terms with sufficient comprehensiveness to maximize the finding of environmental criteria since they represented the integration of forest functional connectivity and conservation principles.

Despite differences in terminology, the most mentioned criteria were related to forest cover, topography, water resources, urban area, highways, and soils (Table 1).

Table 1 – Environmental criteria for connectivity analysis, that were select from literature I the period from 2015 to 2019, for the study area in the GBBR-SP, Brazil.

Reference Study	Social	Biodiversity	Climate	Economic factors	Urban area	Forest cover	Agriculture	Highways	Water resources	Topographic	Land-use/land-cover	Soils
Ayram et al., 2016		x			x	x	x	x	x	x	x	
Curiel-Esparza et al., 2015				x	x	x		x	x	x	x	x
Fernádez and Morales, 2016						x					x	
Lakicev et al., 2014	x	x	x			x		x				
Mello et al., 2018					x	x	x	x		x		
Rincón, et al., 2019		x				x					x	
Santos et al., 2018					x			x	x	x	x	x
Silva et al., 2017									x	x	x	
Unda and Etter, 2019		x				x						
Vettorazzi and Valente, 2016								x	x		x	X

The selection of environmental criteria, among the most cited, considered: the study area characteristic; that it is under urban sprawl; the main justification of authors to use a criterion; and the criterion representativeness in terms of environmental characteristics.

This way, the selected criteria were slope, aspect, Topographic Wetness Index (TWI), distance from highways, drainage network, distance from low-density urban areas, Normalized Difference of Vegetation Index (NDVI), and distance from forest fragments. As mentioned in the conceptual model section, they were the group in topographic, conflicts, and biotics.

The first three criteria and the drainage network were produced from the Digital Elevation Model (DEM) of the study area, which was produced from the Shuttle Radar Topography Mission (SRTM) model (https://earthexplorer.usgs.gov/). The 10-m contour lines were extracted from the SRTM model (30m-spatial resolution) and interpolated (nearest neighbor method) with a 20m-spatial resolution to the new DEM integrates our geographic database. In the GIS environment, watershed and slope/aspect plug-ins were used to generate these criteria.

The other criteria were produced from features (i.e., highways, low-density urban areas, and forest patches) extracted from the land-use/land-cover map (Fig.1), which resulted from a supervised classification (Maximum Likelihood algorithm) of CBERS-4 satellite images (20m-spatial resolution). The map presents 90% accuracy, according to a field verification (in the 2019 year) based on 140 points randomly stratified across the study area.

This way, we obtained the Euclidian distance from highways, low-density urban areas, and forest patches, also calculating the NDVI from the last feature. The low-density urban areas are small agglomerations or farms characterized by horizontal, dispersed, and polycentric growth. Conversely, the highly dense urban areas were classified as constraints, considering their low quality for the support he functional connectivity, have a compact, vertical and monocentric shape (Ojima, 2007).

The NDVI index considers the relation between the energy reflected in the red and near-infrared wavelengths to represent the vegetation biomass. The index varies from -1 to +1, with the last value indicating vegetation denser, moist, and well-developed (Melo et al., 2011). We used NDVI to represent the forest vegetation vigor (Anatoly, Peng, and Huemmrich, 2014).

The principal component analysis (PCA) explained the organization and variability of criteria in the landscape. Thus, it was possible to confirm whether the selected criteria were sufficient to explain the forest structure.

2.2.4 Forest patches metrics

The metrics used to characterize a selected group of patches representing the landscape forest structure were area, perimeter, shape index, and distance to the nearest neighbor. According to Pereira et al., 2013; Mello, Toppa, and Cardoso-Leite, 2016; Palmero-Iniesta et al., 2020 these metrics also support the forest patches description in terms of connectivity and conservation.

Firstly, we divided the forest remnants into size classes, having similar areas (ha). The analysis guaranteed the representativeness of different-sized patches in the classes, excluding the specific categories composed only by the small patches (smaller than 5ha) or the largest (forest fragments bigger than 300ha).

After the patches selected were identified individuality in a map, used to calculate the metrics through the Vector-Based Landscape Analysis Tools Extension (V-Late) in the GIS environment.

The metrics values were associated with their respective patches to compose maps, representing their perimeters, shapes, and distances to their nearest neighbor.

2.2.5 Criteria and forest structure evaluation

We assessed how criteria are associated with the forest patches metric (representing the structural forest attributes) based on a hexagon network sampling (Fig. 3).

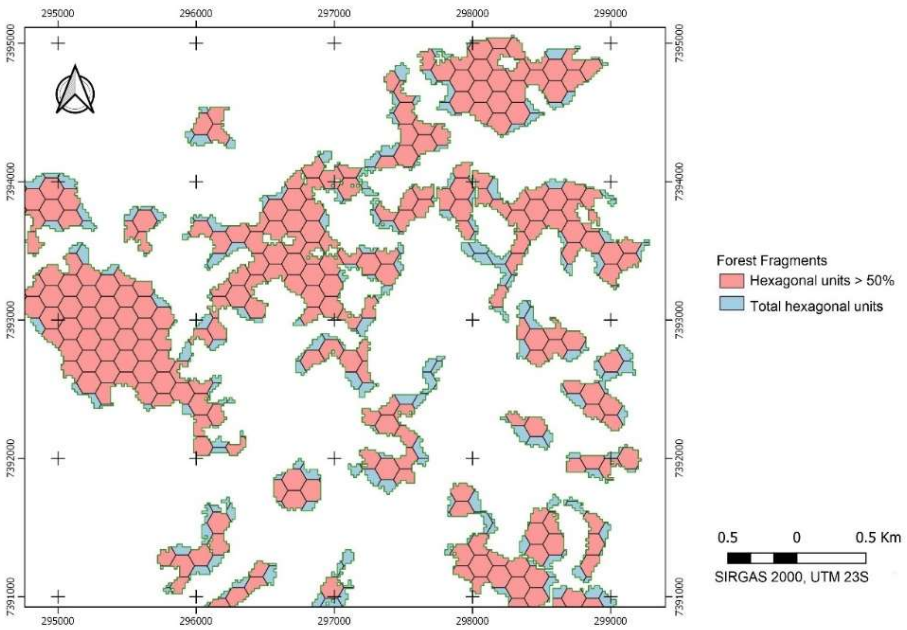


Fig. 3 – Forest patches and hexagonal network, used to evaluate criteria of the study area in the GBBR-SP, Brazil.

We sampled the maps of criteria and metrics through this network, considering hexagons that covered more than 50% of the patch size (Fig. 3.) As the size of the hexagon unit was 2 ha, at least two sample points by patch were obtained.

These sampled values supported the statistical analyses. Using Moran Global (Moran I) (Moran, 1950) and Moran Local (LISA) indexes (Anselin, 1995), we evaluated the spatial autocorrelation of the criteria, metrics, and finally, among the criteria and metrics.

For the two indexes, the significance level considered was $p < 0.05$, which was calibrated for the Euclidean distance from the average point of the sample space.

The canonical correspondence analysis (CCA) tested the hypothesis that the metrics can indicate the criteria importance rank to the forest functional connectivity, revealing these criteria influence under the forest patches.

The vegan package (R software) supported the canonical correspondence analysis after the pre-verification of multicollinearity for values greater than 5 (James et al., 2014) and the validation of product with $p < 0.05$ through permutation and ANOVA tests.

2.3 RESULTS

The environmental criteria, selected from the literature review (from 2015 to 2020), considering terms as forest functional connectivity, connectivity and forest conservation, and landscape subject to urban sprawl, are listed in Table 2.

Table 2 – Criteria importance for functional forest connectivity analysis, in the forest conservation context, according to literature review.

Feature	Criteria	Importance
Topographic	Aspect	Aspect has an effect on the diversity, regeneration, and structure of tropical and temperate forests worldwide (Wagner et al. 2020, Tiwari et al. 2020, Ou et al., 2020, and Hollunder et al. 2021). In the same way, the criterion can reveal sensitive places from a topographic perspective, that are especially the faces with minor moisture retention ability. Faces that should be cover by native vegetation, aiming to avoid problems as soil erosion (among others). This way, we think in the prioritization of these sensitivity regions to obtain forest functional connectivity, as a way to the maintenance of landscape feature.

Feature	Criteria	Importance
	Slope	It is the main criterion related to soil erosion, considering (Valladares et al., 2012). Since high slopes reduce human access, the criterion is an important physical attribute for forest regeneration. on the other hand, sloping land has less water and soil retention capacity, which can reduce the forest regeneration rate. These reasons could explain why elevation has a positive effect on the change rate of the forest cover, while the interaction between slope and elevation can have a significant negative effect (Li et al., 2013). Regions associated with high levels of slope have been indicated as susceptible to erosion processes, the criterion is highlighted in the literature related to soil erosion (Haidaraa et al. 2019)
	TWI	Wetlands are important ecosystems as they provide habitat for plants and animals and improve water quality (Guo et al., 2017). The topographic wetness index (TWI) is used to identify the saturated areas and to distinguish the reliefs where there are well-drained soils (O'Neil, Goodall and Watson, 2018). For this reason, topography shapes and restricts vegetations, causing a number of environmental conditions that are favorable to many communities and to the ecosystem process. This allows for the detection of patterns of species with different resource habitat requirements as correlated with attributes such as river valleys, mountainous regions and other varied topographies (Czarnecka, Rysiak and Chabudzinski, 2017).
Biotic	NDVI	NDVI is a robust metric for estimating forest cover and its development status, as it produces a strong estimate of the chlorophyll concentration in the leaf (Nagai et al., 2010). The richness of species increases with the vegetation structural heterogeneity and biomass. More complex stretches provide more resources and opportunities for microhabitat segregation (Wood et al., 2013).

Feature	Criteria	Importance
	Distance from Forest Patches	The distribution pattern of mature forests, combined with the disturbance, and replacement of old forests, can influence the dispersion of species, movement and processes at the population level and define whether species adapt or perish in altered forest ecosystems (Ruffell, Clout, and Didhan, 2017). Habitat reduction, with subsequent increased edge effects, changes the behavior of individuals and habitat use patterns, also reducing movement between fragments (Ramesh, Kalle and Downs, 2015). Proximity to nature reserve areas also affects how people perceive the importance of forest conservation. As they move away from core areas, the opportunities and level of anthropic disturbance increase (Deng et al., 2015).
Conflicts	Distance from the low-density urban area	In the urban expansion area, there is an increase for work and housing, a rapid regional economic development (Shiferaw et al., 2019), and a greater pressure on habitats and systemic services provided (Yuan et al., 2019). In particular, forest fragmentation caused by waterproofing surfaces threatens species and habitat (McDonald; Marcotulio and Guneralp, 2013). These threatens effect on the mobility of organisms, being a central factor in the ecosystem services provision (Mitchell, Bennett, and Gonzalez, 2013). The reduction in connectivity affects the regulation of ecological flows, which determines the effectiveness of preserved natural areas, observed through changes in focal species behavior and in the habitats preference (Ayram et al. 2019).
	Distance from Drainage Network	In Brazil, environmental legislation determines a minimum riparian zone along perennial watercourses within private properties or public areas (Brasil, 2012). This riparian vegetation continues offers an opportunity to establish an integrated network of forest remnants, which can serve as habitat and connectors at the regional or local scale, especially when reduced as sources that cause environmental degradation (Zimbres et al., 2018). The riverside areas are dynamic, biologically rich ecosystems, with a high content of nutrients, humidity and the presence of unique microclimates for species of invertebrates (Ramey and Richardson, 2017) terrestrial mammals (Zimbres et al., 2018) and birds (Mitchell et al., 2018).
	Distance from Highways	Disturbances caused by highways increase the forest patches edge effects, decreasing the fauna species presence (Avalos and Bermúdez, 2016). In addition, highways contribute to increased landscape

Feature	Criteria	Importance
		fragmentation, as they cut through continuous areas with high connectivity and create barriers to movement between habitats (Carvalho et al., 2015).

The group represents landscape features relating to their topography and biotic components that can support the prioritization of areas to obtain forest function connectivity in the forest conservation context. They also have characteristics representing conflicts for this objective, threatening the process (Fig. 4).

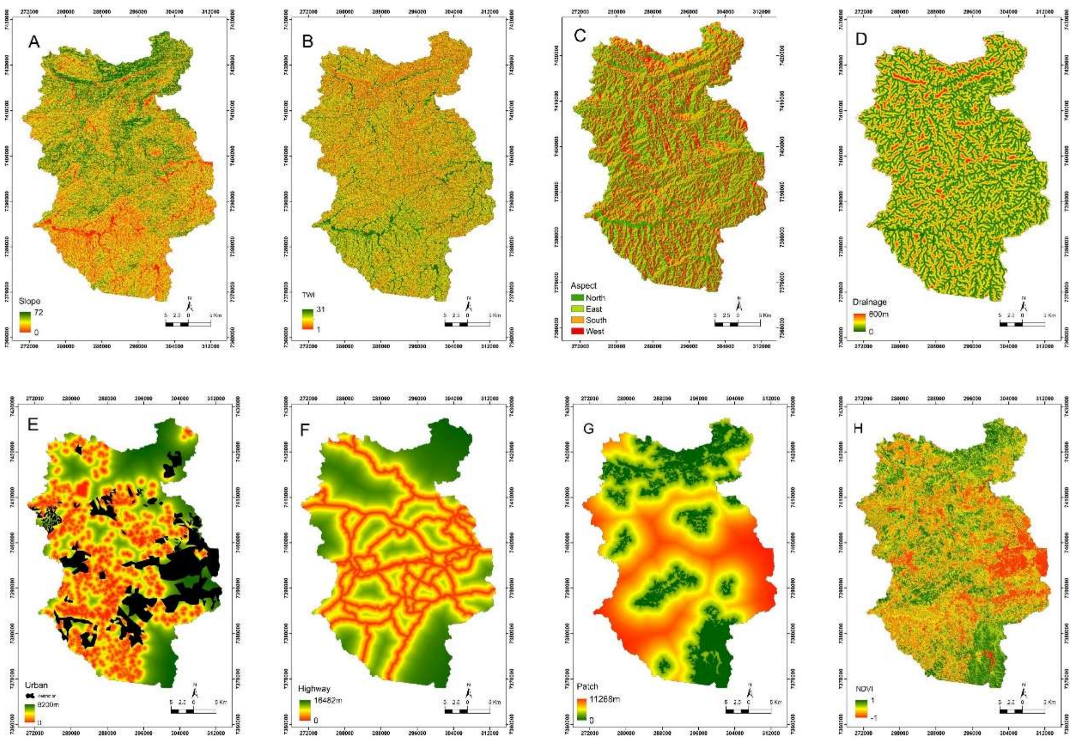


Fig. 4 Environmental criteria set produced for the study area in the GBBR-SP, Brazil. Where: (A) Slope – Slope; (B) TWI – Topographic Wetness Index; (C) Aspect – Aspect; (D) Drainage - Distance from the drainage network; (E) Urban - Distance from the low-density urban area; (F) Highway - Distance from the highway; (G) Patch - Distance from the forest patches; and (H) NDVI – Normalized Difference Vegetation Index.

According to the slope criterion (Fig. 4 A), approximately 91% of the study area showed declivity at most 20%. Nearly 47% of this total presented at most 8% of a declivity, and they are concentrated in the South region of the study area (Fig. 4 A).

The LISA index also appointed this concentration classifying the region by low-low, indicating the spatial proximity between lowest slope values (Fig. 5 A).

In this context, the slope was the criterion associated with the higher value of Moran Index (I = 0.457) among the topographic criteria (TWI=0.190 and Aspect = 0.292), indicating that its features have a spatial distribution significant positive (I > 0) (Fig. 5 ABC).

According to the LISA index results for the criterion, the study area was classified in 20% as high-high and 21% as low-low, having significant spatial autocorrelation.

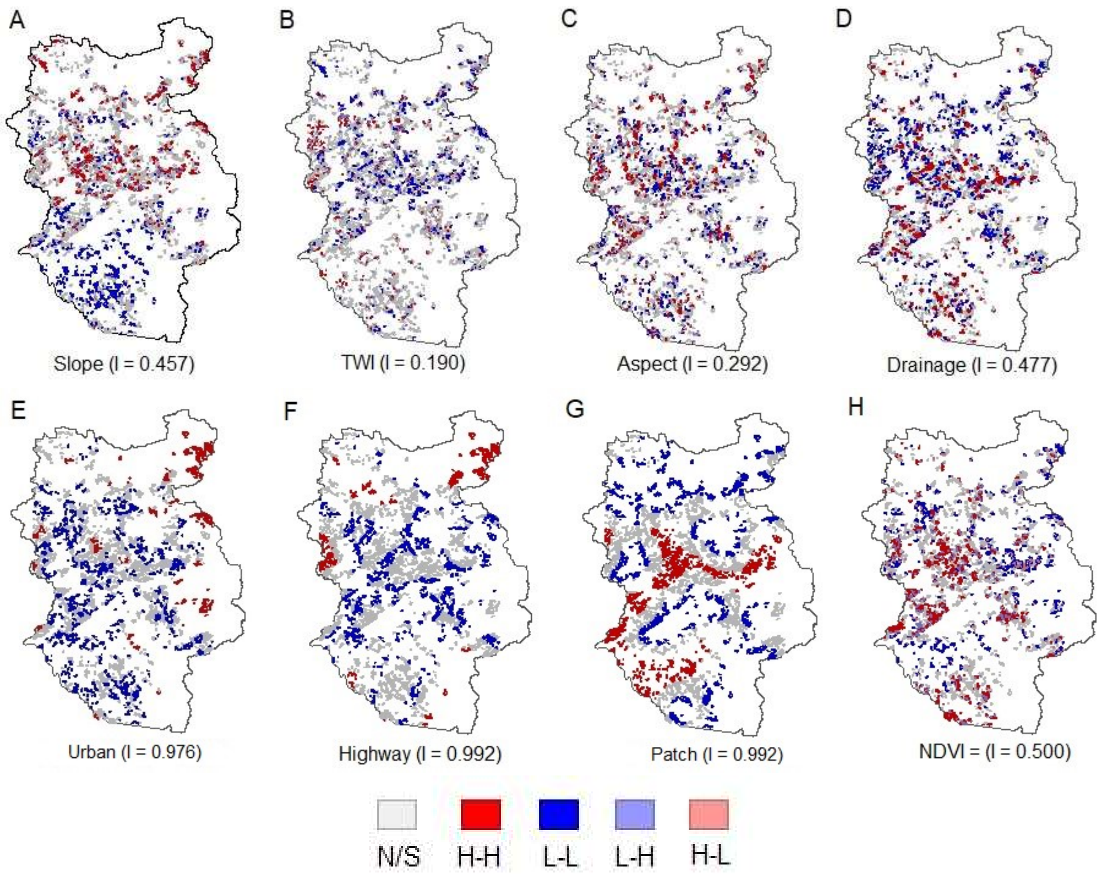


Fig. 5 Spatialization of the Moran Global (Moran I) and the Moran Local (LISA) indexes for the criteria: (A) Slope – Slope; (B) TWI – Topographic Wetness Index; (C) Aspect – Aspect; (D) Drainage - Distance from the drainage network; (E) Urban - Distance from the low-density urban area; (F) Highway - Distance from the highway; (G) Patch - Distance from the forest patches; and (H) NDVI – Normalized Difference Vegetation Index.

Where: N/S = Not Significant; H-H = High-High; L-L = Low-Low; L-H = Low-High; H-L = High-Low.

The TWI criterion (Fig. 4B) indicated the South region is also associated with high moisture-retention ability, with values varying from 12 to 27, which occupy 16% of the study area.

However, 62,2% of TWI values varied from 5 −12, spread across the study area. Thus, values between 5 – 7, 7 – 9, and 9 – 12 represent 42.8%, 14.3%, and 5.1%, respectively. The TWI values greater than 27 totaling less than 1% of the total, occurring only in the North (Fig. 4B).

Reflecting this spatial pattern of most features distributed randomly across the landscape, the Moran Index for TWI was 0.190, which was the lowest value obtained among the criteria (Fig. 5B).

In the same way, LISA did not identify regional grouping (Fig. 5B), except a tendency in the Central-North region because of the lowest TWI values. This region was classified as low-low (with 15.4% of spatial autocorrelation) (Fig. 5B). However, this tendency is not statistically significant, considering the great variability of the criterion features.

The Central-North region was associated with relief Heavily-Undulating (20 – 45%) and Hilly (> 45%) (Fig. 4AB), having a significantly positive spatial distribution (Fig. 5C). As mentioned, the LISA index indicated groupings in regions classified as high-high because of the high spatial correlations between near features (Fig. 5C).

The LISA index also showed groupings for the aspect criterion in the Central-North region classified as high-high (16.2%) and low-low (16.3%) (Fig. 5C), considering the predominance of faces oriented to east-west direction (Fig. 4C).

However, Fig. 4C illustrated these faces spread across the landscape and interact with others, resulting in a low value of Moran Index (I=0.292), as we observed for TWI. The east-west faces occupied 65.3% of the landscape, and the north-south faces 34.7% (Fig. 4C).

Similarly, the distance from the drainage network showed its watercourses spread over the landscape (Fig. 4D), obtaining the Moran index of 0.477. A value that was superior to TWI and aspect, which pointed to a positive autocorrelation in the spatialization of watercourses. Although with a low level, having only 18% classified as high-high and 23% as low-low (Fig. 5D).

The maximum distance from the drainage network was 800m, although values at the maximum of 200m from watercourses represented 56% of the total area and between 200-400m approximately 36% (Fig. 5D).

Based on the low-density urban areas and highways, the maximum distances obtained were, respectively, 8200 m and 16482 m, mainly in the function of the values present in the extremes of North and Southeast (Fig. 4E and Fig. 4F).

This way, those features presented more influence in the Central-to-South-west portion of the landscape, where we observed the great urban areas, which were classified as a restriction to functional connectivity because of their low quality. Due to these conflict features, the region was classified as low-low (LISA index), showing significant spatial autocorrelation of 41.5% for low-density urban areas and 41.4% for distance from the highway.

Consequently, this region has significant positive spatial autocorrelation with regions classified as high-high represented 14.0% (low-density urban area) and 16.8% (distance from highways) (Fig 5E and Fig 5F). However, the spatial autocorrelation of distance from the highway is slightly higher than the distance from low-density urban areas, considering their Moran index values of 0.992 and 0.976.

The urban areas and highways influenced the forest patches spatialization through the landscape, which presented 11268 m as the maximum distance among them (Fig. 4h).

That criterion showed a Moran index value of 0.992, reflecting the high and positive correlation among the distances from forest patches. Thus, the LISA index showed grouping with a high autocorrelation degree (29.2% of spatial correlation) in the landscape's central region, classified as high-high (Fig. 5h).

The high-high class indicates a place associated with a high probability of great distance values occurring near other places in the same condition. For the study, in the same region, the LISA index indicated the low-low (38.6% of spatial autocorrelation) groupings for the distances from low-density urban areas and highways (i.e., the concentration of places near to the features of the conflict).

This way, the spatial autocorrelation analysis indicated that the great distance from the forest patches occurred in places occupied by urban areas and highways.

Finally, Fig. 4g showed the NDVI index, having its highest values associated with the largest forest patches.

Although, its Moran Index was 0.50, indicating that the criterion has a minor autocorrelation degree than the criterion distance from the forest patch.

Fig. 5g illustrated the groupings detected through the LISA analysis classified as high-high (23.7% of spatial autocorrelation) and they were in similar regions of the distance from forest patches criterion. However, the spatial autocorrelation of this criterion is smaller than the last one.

Regarding the criteria variability, PCA analysis explained 42.6% of the data (Fig. 6). According to the first axis, the slope decreases as the distance from the drainage network decrease. Conversely, TWI and Aspect values increased (Fig. 6).

Fig. 6 showed in the second axis that, as the forest patches are coming toward the low-density urban areas and highways, there is a decrease in the distance value among forest patches and the NDVI index.

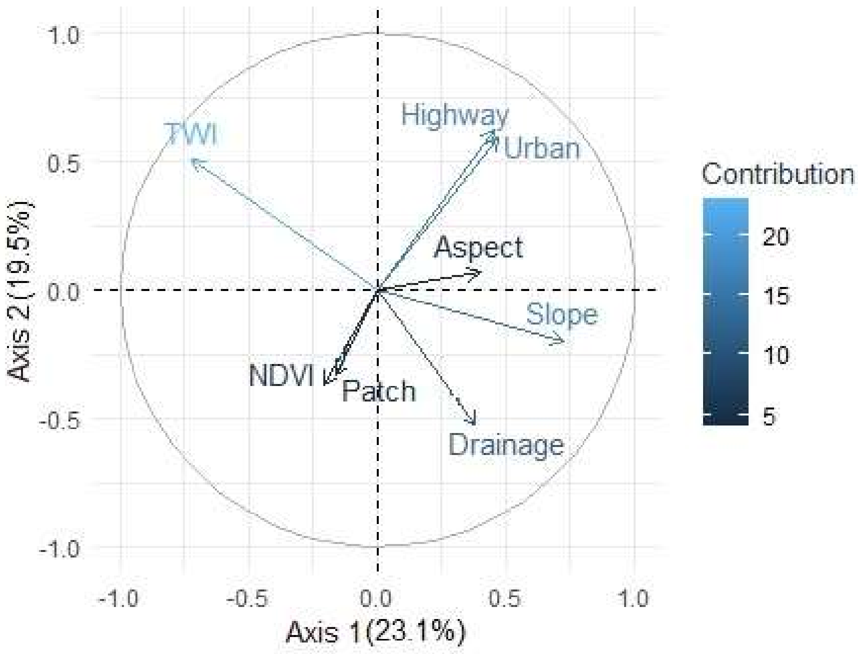


Fig.6. PCA analysis for the criteria variability evaluation for the study area in the GBBR-SP, Brazil.

Where: Slope – Slope; TWI – Topographic Wetness Index; Aspect – Aspect; Drainage - Distance from the drainage network; Urban - Distance from the low-density urban area; Highway - Distance from the highway; Patch - Distance from the forest patches; and NDVI – Normalized Difference Vegetation Index.

2.3.1 Forest structure evaluation

The study area has 57665.75 ha covered by 10428 Atlantic Forest remnants with sizes varying from 0.04 ha to 11248.31 ha.

According to Table 3, 92.4% of these remnants have less than 5 ha; however, they represented only 5.9% of the total native forest area.

Otherwise, we observed that 0.2% of the total patches (i.e., 21 patches) occupying 50% of the total forest area. Most of these local group belongs to three Protect Areas, located inside the study area, i.e., Cabreúva EPA and Morro Grande FR (Fig. 1).

Despite that, 7.3% of the remaining forests occupy 44.1% of the studied landscape and have sizes ranging from 5 ha to 300 ha. As predefined by this study, their size classes occupy a similar percentage of native cover (Table 3).

Table 3. Distribution of patches by size classes and the forest metrics values (mean and standard deviation) applied to forest structure evaluation of the study area in the GBBR-SP (Brazil).

Class (ha)	NP (%)	Area (%)	Forest patches metrics			
			Area (ha) Mean (SD)	Perim (m) Mean (SD)	Near (m) Mean (SD)	Shape Mean (SD)
< 5	92.4	5.9	0.36 (± 0.79)	277.90 (± 299.03)	17.80 (±42.46)	1.15 (± 0.24)
5 - 30	5.2	11.5	12.32 (±6.37)	2857.48 (±1301.65)	107.67 (± 162.66)	2.05 (±0.60)
30 - 75	1.3	11.0	47.00 (±13.57)	7814.90 (± 2366.13)	57.57 (± 98.93)	2.85 (±0.65)
75 - 170	0.6	11.2	105.98 (± 24.89	13933.64 (± 4035.25)	38.88 (±77.14)	3.38 (± 0.82)
170 - 300	0.3	10.4	244.71 (± 28.74)	26434.43 (± 6538.71)	21.56 (± 35.60)	4.40 (±0.95)
> 300	0.2	50.0	1436.24 (± 2689.73)	92797.11 (±107803.9)	0.00 (± 0.00)	6.50 (± 2.23)

Where: NP= number of forest patches; Area - habitat size; Perim – Habitat perimeter; Shape - shape index; Near - a distance of the nearest neighbor edge; Mean - mean value; and SD - standard deviation value.

The remnants belonging to the 5–30 ha class represented 5.2% of the total forest patches. The class with 30–75 ha represented 1.3%, followed by 75–170 ha representing 0.6%, and the patches with 170–300 ha accounted for 0.3%. Their mean patch sizes were, respectively, 12.32 (SD = ±6.37), 47.00 (SD = ±13.57), 105.98 (SD = ± 24.89), and 244.71 (SD = ±28.74), with the standard deviation values together increases the mean size (Table 3).

Similarly, the Perimeter and Shape metric values (mean and SD) increased as the patch sizes were increased (Table 3). The mean metrics values were, respectively, 2857.48m and 2.05 (5-30 ha), 7814.90m and 2.85 (30-75 ha), 13933.64m and 3.38 (75 -170 ha), and 26434.43m and 4.40 (170-300 ha).

Conversely, the value of the Near metric (mean and SD) decreased as the mean patch size increased. According to Table 3, the distance among forest patches was 107.67m (5-30 ha), 57.57m (30-75 ha), 38.88m (75 -170 ha), and 21.56m (170-300 ha).

According to the Moral Index (Fig. 7), the metrics presented significant and positive spatial autocorrelation. Although, the spatial autocorrelation of Near (1.000) was slightly higher than the Area (0.971), PERIM (0.968), and Shape (0.963).

Consequently, the LISA index indicated regions with spatial proximity between similar characteristics (Fig.7).

In the case of the Near metric (Fig. 7), we can highlight groupings classified as low-low in the central portion of the study area. They represented the concentration of areas with small distance values from forest patches.

We can highlight the small low-low groupings for the other metrics, representing the concentration of the smallest patches, characterized by the smaller perimeters and regular shapes (Fig. 7b-d).

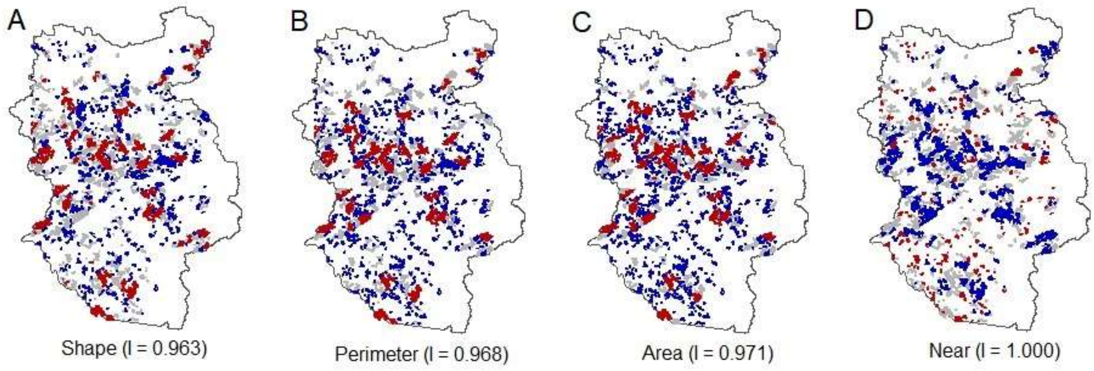


Fig. 7. Moran Index (I) and Local Spatial Autocorrelation (LISA) for Criteria for the study area in the GBBR-SP, Brazil.
Where: (A) Shape - shape index; (B) Perimeter – habitat perimeter; (C) Area - habitat size; and (D) Near - distance of the nearest neighbor edge;

2.3.2 Criteria and Forest Structure Analysis

The patches representing the forest structure of the study area were associated with criteria characteristics, as described in Table 4.

Our landscape presents 91% of the area with at most 20% of the slope, with a predominance of regions varying from 6.66%-17% (Slope mean = 11.83%; Fig. 4a). However, there are forest patches associated with relief plans (Slope minimum = 0.002%) as well as Heavily-Undulating (Slope maximum = 36.36%) (Table 4).

We defined the predominant pattern for the criterion based on its low standard deviation value. Table 4 also indicated TWI and NDVI in the same situation.

This way, regions associated with the forest patches showed TWI varying from 4.81 to 9.35 (TWI mean = 7.08). Values that integrated this more range frequently of moisture-retention ability were observed in the landscape (Fig. 4B).

Relating the aspect criterion, its mean value indicated a tendency of the patches to be placed on the East-West face (Aspect mean = 177.03). Although, the high variation value of standard deviation (SD) (Aspect SD = 70.67) cannot support the pattern definition for those regions.

We mainly consider its spatial pattern of the majority features distributed randomly across the landscape, indicated by the Moran Index (I =0.292) and the LISA index (Fig. 4 e 5C).

Otherwise, we can affirm that the part of forest remnants is at mostly 325.75 m from the watercourses (Table 4), but 92% of the landscape is less than 400 m from the rivers (Drainage mean = 199.27) (Fig.4 D).

The forest patches also presented a mean distance from the low-density urban area and highways of 829.44 m and 1680.86 m (Table 4), respectively. The conflict criteria maps (Fig.4 EF) indicated those features spread by the landscape with 71% of urban areas and 14% of the road at most 2000 m from the forest remnants.

However, these criteria maps presented the highest spatial autocorrelation (Moran I Urban =0.976 and Moran Highway I = 0.992) values among the criteria with groupings (LISA index) in the Central landscape region, representing the concentration of these features. The LISA index also indicated groups far from the central regions associated with high distances from the features, explaining these Standard Deviation values (Table 4).

Table 4. Variability of criteria characteristics for the forest patches of the study area in the GBBR-SP, Brazil.

Param	Slope (%)	TWI	Aspect	Drainage (m)	Urban (m)	Highway (m)	Patch (m)	NDVI
Min.	0.002	3.89	4.80	9.33	39.20	30.01	59.12	0.32
Max.	72.36	31.89	344.90	734.32	5843.36	13252.03	8542.66	0.69
Mean	11.83	7.08	177.03	199.27	829.44	1680.86	2440.01	0.58
SD±	5.17	2.27	70.67	126.48	878.10	1844.85	1671.40	0.03

Where: Slope - Slope; TWI - Topographic Wetness Index; Aspect - Aspect; Drainage - Distance from the Drainage Network; Urban – Distance from the low-density urban area; Highway - Distance from the highways; Patch - Distance from the forest patches; NDVI - Normalized Difference Vegetation Index; Param - Parameter; SD - Standard deviation value.

According to Table 4, the forest patches (Patch) showed a mean distance of 2440.01m. As the last two criteria (Urban and Highway), the mean values and standard deviation (Patch SD = 1671.40) values reflect the presence of the patches through the landscape (Fig. 4g). In the same way, the criterion presented the highest spatial autocorrelation values (Moran I = 0.992) among the criteria, supporting the concentration of remnants in the same regions of the landscape. The Near metric (Table 3) indicated values varying from 21.56 m to 107.67 m for patches grouped in similar size classes. Still, the minimum distance indicated in Table 4 was 59.12 m.

This way, the criterion reflected the forest patches scattered across the landscape, having a mean distance of 2440.01 m, but with some remnants near each other (Patch minimum = 59.12m).

The mean NDVI index of these patches varies from 0.55 to 0.61 (NDVI mean = 0.58), which was the minor range of standard deviation values among the criteria (Table 4). We obtained these values based on a hexagon network sampling, obtaining the NDVI values inside the patches.

The criterion map presented a Moran index of 0.500, indicating these small groupings. However, for the landscape prevailed its main characteristics, that is the low spatial autocorrelation (Fig. 4h).

Concerning the Canonical correspondence analysis (CCA), Fig. 8 illustrates that the forest patches metrics explain in 84.10% the criteria order.

The data variability was explained in 66% by axis 1 and 18.10 by axis 2. Through the first, we observed the greatest influence of the metrics Near and Perimeter. While in the second, the main ordering variables were Shape and Near. However, the Area variability was not significant (Fig. 8).

The CCA analysis (Fig. 8) also indicated that the forest patches perimeters values increase as the highways' distance increases. Conversely, the distance from the low-density urban areas decreases, and the distance among forest patches (Near) also decreases. Such a thing happens because low-density urban areas are composed of small urban agglomerations, which are scattered among the forest fragments.

In the same way, the aspect, TWI, NDVI, slope, and distance from the drainage network showed variation in their values associated with the metrics Shape and Perimeter. The criteria values decrease when the metrics decrease.

Finally, we observed a no-significant relation between the metric Area and the criterion distance from the forest patches.

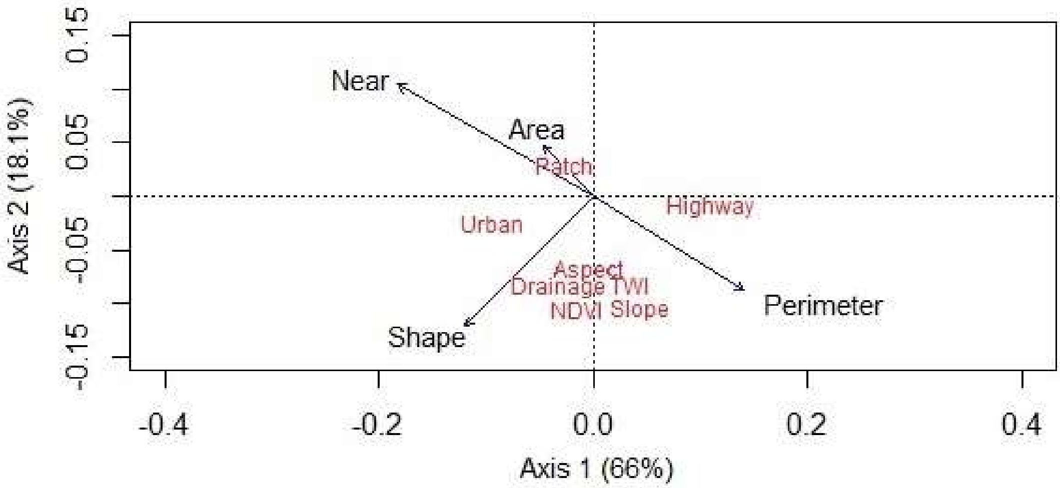


Fig. 8 - Canonical Correspondence Analysis (CCA) applied to the criteria according to fragment metrics of the study in the GBBR-SP, Brazil.

Where: Area - Habitat size; Perimeter – Habitat perimeter; Shape - Shape index; Near - Distance of the nearest neighbor edge; Slope – Slope; TWI – Topographic Wetness Index; Aspect – Aspect; Drainage - Distance from the drainage network; Urban - Distance from the low-density urban area; Highway - Distance from the highway; Patch - Distance from the forest patches; and NDVI – Normalized Difference Vegetation Index.

2.4 DISCUSSION

The environmental criteria that were selected through the literature review (Tables 1 and 2) represent essential characteristics of landscapes under urban sprawl in the context of prioritizing areas to obtain forest functional connectivity (Curiel-Esparza et al., 2015; Lakicev et al., 2016; Vettorazzi and Valente, 2016; Santos et al., 2018; Mello et al., 2018).

The topographic criteria have effects on drainage capacity (Loritz et al., 2019; Hojati and Mokarram, 2016), forest composition and structure (Jucker et al., 2018), habitat reduction and isolation (Zhang et al., 2018), and, consequently, on species patterns and richness (Li et al., 2019, Russo et al. 2016, and Keeley et al. 2016), which are necessary conditions for measuring forest connectivity.

The distance from the drainage network indirectly brings the concept and importance of riparian forests in maintaining forest connectivity (La Fuente et al., 2018). Considering that their place in the landscape along the river supports the flow among forest patches, which is commonly compromised by the expansion of urban infrastructure, producing barriers in the landscape (McRae et al., 2012), habitat loss (Alamgir et al., 2019), and changes in animal movement (Dickie et al., 2019).

The criteria have different importance for functional connectivity and forest conservation, representing a part of the process to obtain the main objective. The importance has been highlighted in the literature review (Table 2) (Ayram et al., 2016, Fernádez and Morales, 2016, Unda and Etter, 2019; Rincón et al., 2019).

This way, the criteria selection based on the literature review brings robustness to the study, considering that the set was previously evaluated in another research. It also eliminates the subjectivity that we bring to the project when experts opinion is required, considering the restricted number of people who contribute to the process (Silveira et al., 2014, Valente et al., 2017; Mello et al., 2018; Valente et al., 2021).

The important point is that the criteria selected for the study area in the GBBR-SP, Brazil, are not spatially correlated and do not have information overlap (Figs. 4 and 5). Thus, they can support prioritizing areas for functional connectivity.

Regarding criteria characteristics, we obtained 91% of the study area with at most of 20% of slope (Table 4 and Fig. 4A). This characteristic associated with the low variation of its standard deviation supports the definition of a spatial pattern for the criterion identified by the LISA index (I = 0.457) (Fig. 5A). Kane and John (2018) cited that topographical factors can determine land-use decisions by local communities, considering if the relief allows easy accessibility, there is an increase in deforestation (Bax et al., 2016) and a critical potential for natural regeneration (Molin et al., 2018).

Adams et al. (2014) complemented that tree growth and forest productivity can be affected by slope, TWI, and aspect due to influences on runoff and wind exposure. Thus, these factors allow the elaboration of forest connectivity models based on relief, as the species have different habitat requirements (Czarnecka et al., 2017).

Relating to the TWI criterion, we obtained approximately 62.1% of the total area varying from 5-12, including soils classified as well-drained (TWI of 4-5), moderately drained (TWI of 5-7), and poorly drained soils (TWI of 7-12) (Li et al., 2006). Approximately 43% of this total is associated with the moderately drained soils, contributing to the classification of these areas as low-low by LISA Index (Fig. 5B), since they are showed a scattered distribution through the landscape.

According to our results, regions associated with the 5-12 TWI range are also occupied by forest fragments, characterizing TWI as a heterogeneous criterion with the same value of Moran Index (I = 0.190) mentioned by Da Silva et al. (2019).

Similarly, the aspect was also defined as a heterogeneous criterion (Table 4) because our study area has a topographic divider of water flow and 65.3% of its area associated with East-West slopes facing (Fig. 4C). These facings are associated with forest patches groups (LISA index, Fig. 5C), the most regular landscape patches placed in faces with the lowest aspect values (CCA analysis, Fig. 8). Thus, it can be explained by the predominance of anthropic land use on the east landscape face (Victor et al., 2004).

Aspect reveals a tendency to coming toward the slope values because they came from DEM. However, we cannot establish a statistical and significant pattern between them. Adding that the criterion does not present a high spatial correlation, it cannot be considered adequate for a model of prioritization areas aiming for functional connectivity. The uncertainties justify this in connectivity analysis that the aspect can bring to the model.

According to our results, the aspect is the only environmental criterion not adequate for prioritizing forest functional connectivity in a landscape subject to the urban sprawl. For another way, the slope and TWI, the distances from forest patches, and drainage network criteria are essential to a model of the prioritization of areas subject to urban sprawl (Fig. 4 D).

The slope brings the topographic heterogeneity that influences the edaphic, hydrological, and climatic conditions landscape (Yang et al., 2016, Jucker et al., 2018, Féret and Asner, 2014, Chadwick and Asner, 2016, He et al., 2017, Lippok et al., 2014).

TWI evidences microclimates, indicating places with greater nutrient availability, better drainage, and a slight increase in soil temperature (Wylie et al., 2019). Some studies associated TWI with forest susceptibility to fire (Kim and Lee, 2018), forest productivity (Wylie, Woods, and Dech, 2019), species richness (Bourque and Bayat, 2015), survival rate, and mortality of trees (Bayat et al., 2019) and forest structuring, such as canopy height (Ediriweera et al., 2016) and above ground biomass accumulation (Muscarella et al., 2020).

In the same way, the distance from the drainage network corroborated our results because the rivers are homogeneously scattered through the study area. Spacialization that in turn, resulted in a high spatial autocorrelation of the criterion with values upper than the topographic criterion and that supported the cluster structuration in two regions (I = 0.477) (Fig. 4 and 5D). The first with the least distances among patches and watercourses (LL in LISA) and the second with the highest (HH) distances (Fig. 5D).

We also can highlight that the criterion results were predominately supported by the proximity to watercourses, the most critical region for the main objective. This way, an adequate name for the criterion is proximity to the drainage network instead of the distances from the drainage network. The name reflects the most important region for the criterion and becomes following the literature, wherein have been considering riparian forest corridors as the most suitable environment for forest connectivity (La Fuente et al., 2018, Zimbres et al., 2018).

While the watercourses are scattered through the landscape, the main features of the distance from the low-density urban area and highways criteria showed concentrated, mainly, in its Central-to-South-west portion (Fig 4E and Fig 4F). Due to the significant urban areas and roads, the forest patches cluster of these regions presented spatial autocorrelation classified as LL (Fig. 5E; I = 0.976 and Fig. 5F; I = 0.992). It is noted in Figure 4E that a restricted area was created over consolidated urban agglomerations to analyze only the effects of urban sprawl on forest remnants.

However, the features of criteria (roads and urban) and consequently their respectively distance maps showed an effect in the forest fragments spatialization. Around 71% of the forest patches are 2000 m from an urban area, and 86% are 2000 m from a road.

Anthropogenic disturbance in the landscape favors generalist species exploring environments, such as disturbed habitats (Magioli et al., 2019). Consequently, there is an increase in conflict factors, such as running over wildlife (Abra et al., 2021), predation of farm animals (McPherson et al., 2016), and lethal animal control (Blackwell et al., 2016), being essential to define the most beneficial actions of conservation planning and implementation (Abra et al., 2021).

Conflict features showed high spatial correlation (Fig 6), indicating that they can compose a unique criterion in future studies. A criterion that brings information related to the connectivity, since that urban areas and roads have crossed landscapes subject to urban sprawl, which have become one of the greatest threats to biodiversity conservation (Scriven et al., 2019; Madadi et al., 2017).

Kuang et al. (2014) cited that the urban expansion process and the relationship with forest fragmentation is an effect of worldwide verification, carried out on the scale of megacities, and due to the increase in the population living in urban areas (Angel et al., 2016). Thus, given that land-use can occur in many different patterns, metrics that consider the spatial arrangement of urban infrastructure can explain landscape fragmentation (Bar-Massada, Radeloff, and Stewart, 2014; Lin and Fuller, 2013).

In the same way, our findings indicated as essential the maintenance of the criterion distance from forest patches. We have forest patches supporting the native fauna and flora, especially those formed by patches with sizes greater than 300 ha (Table 4 and Fig. 4H). As we have mentioned, this group is formed by 21 patches, belongs to three Protect Areas located inside the study area, and occupies 50% of the total forest area. These forest patches are integrated with others, considering that the minor are scattered across the landscape (Table 3).

According to Magioli et al. (2019), the large and continuous habitats support populations with more complex trophic structures, acting as a source for biodiversity maintenance in modified habitats. Gibson et al. (2011) complemented that these habitats are essential refuges for wildlife, assuming their similarity to natural areas (i.e., without anthropic actions).

The Brazilian environmental legislation has encouraged the conservation of areas like patches greater than 300 ha. However, it is not enough to minimize the urban pressure effect (Romero et al., 2020). In our study areas, it is not only this group that has potential for connectivity in the studied landscape. We can include the medium-size group, highlighting the importance of the criterion distances from forest patches. Considering these close relations among the forest patches, we can suggest for the following studies the term proximity to forest remnants as proposed by Mello et al. (2018) and Valente et al. (2021).

Showing different behavior of other criteria, we have the NDVI, which represents the forest patches in terms of their status and quality (Fig. 4H), i.e., the conditions inside the remnants. Consequently, it is not a criterion that represents the conditions of the natural vegetation on the landscape, as our objective requires.

However, patches-level data are essential to support the decision-makers discussion, which guided us to include our second objective.

For the study area, the patches-level metrics showed coherent resultants, considering the proposed classes areas. The largest forest remnants showed great values of perimeter and shape than the slightest but minor values of distance among their components (Table 3).

Furthermore, the class areas support evaluating the spatial autocorrelation among metrics and after, among metrics and criteria.

The results were a high Moran index value for metrics (Fig. 7), which supported in their correspondence with the criteria since these results reflected that the external influences on the fragments did not occur randomly and that the criteria act on the landscape (with 84.1% of explanation in CCA, Fig. 8).

Different studies have shown the potential of the ecological metrics in the definition of areas for conservation, on analysis of sprawl urban and evaluation of the landscape structure (Schindler et al., 2013, De Jesus et al., 2015, Otero et al., 2015, Romero et al., 2018, and Lelli et al., 2019), corroborating with our results.

The CCA analysis (Fig. 8) also indicated that the reduction in the distance from low-density urban areas was associated with a reduction in the distance among forest fragments (NEAR). In comparison, the distance from highways was associated with an increase in perimeter and area of the forest patches.

According to Pirnat and Hladink (2018), new diffuse urban areas do not subject patches to significant changes in their habitat size, which tends to happen regardless of population changes (Organization of United Nations Habitat, 2016). Otherwise, the drier regions of the landscape, on the flatter terrains, near to the rivers, and facing to the east face were associated with our smallest and most regular patches that were isolated and presented the lowest NDVI values. Thus, in these landscape regions, the condition related to the urban infrastructure and topography were favorable to human occupation, as also observed by Torres et al. (2016).

2.5 CONCLUSION

This study evaluated environmental criteria for prioritizing forest functional connectivity in a landscape subject to urban sprawl.

Our results indicated that we obtained robust criteria through the literature review, decreasing the intrinsic subjectivity commonly associated with their definition in the participatory technique context. Criteria set composed by slope, TWI, distance from drainage network, distance from highways, distance from a low-density urban area, and distance from forest patches. Also, they are not spatially correlated or have information overlap.

In this context, these criteria support the identification of regions where it is possible to have the persistence of forest fragments, even though in places under the impact of urban sprawl.

Conversely, we concluded that aspect and NDVI (originally selected) are not adequate criteria for our objective. The first showed a heterogeneous behavior through the landscape, revealing a tendency toward the slope values because both came from Digital Elevator Model. The second reflects the patches' quality instead of their potential for forest connectivity.

In this context, we can affirm that the selected criteria reflect the forest structure of landscapes under urban sprawl. Furthermore, they support identifying areas near watercourses with the greatest moisture retention potential and associated with the deep slope. Areas covered by the great forest patches are the most irregular and connected of the study area.

In this sense, places far from the highways reflect areas with more preserved forest structure characteristics. However, large and connected forest fragments are close to low-density urban environments in areas under diffuse urban sprawl. Areas that are also essential for functional connectivity.

This way, our findings indicated a spatial autocorrelation among metrics and after, among metrics and criteria. Also, we obtained that the external influences on the fragments did not occur randomly and that the criteria act on the landscape.

Finally, our results reveal more suitable value ranges for each criterion in the environment under urban sprawl to indicate the occurrence of forest fragments, aiming for functional forest connectivity.

REFERENCES

Abra, F. D.; Huijser, M. P.; Magioli, M.; et al. An estimate of wild mammal roadkill in São Paulo state, Brazil. **Heliyon,** v. 7, n. 1, e06015, 2021. https://doi.org/10.1016/j.heliyon.2021.e06015.

Acevedo, P.; Real, R.; and Gortázar, C. Favorabilidad ecogeográfica para el corzo: distribución y abundancia. **Pirineos**, v. 166, p. 9–27, 2011. https://doi.org/10.3989/pirineos.2011.166001.

Adams, H. R.; Barnard, H. R.; and Loomis, A. K. Topography alters tree growth–climate relationships in a semi-arid forested catchment. **Ecosphere**, v. 5, n. 11, p. 1-16, 2014. https://doi.org/10.1890/ES14-00296.1.

Akin, A.; and Erdoğan, M. A. Analysing temporal and spatial urban sprawl change of Bursa city using landscape metrics and remote sensing. **Modelling Earth Systems and Environment**, v. 6, p.1331-1343, 2020. https://doi.org/10.1007/s40808-020-00766-.1.

Alamgir, M.; Campbell, M.J.; Sloan, S.; et al. High-risk infrastructure projects pose imminent threats to forests in Indonesian Borneo. **Sci Rep,** v. 9, 140, 2019. https://doi.org/10.1038/s41598-018-36594-8.

Almenar, J. B.; Bolowich, A.; Elliot, T.; et al. Assessing habitat loss, fragmentation and ecological connectivity in Luxembourg to support spatial planning. **Landscape**

and Urban Planning, v. 189, p. 335-351, 2019. https://doi.org/10.1016/j.landurbplan.2019.05.004.

Anatoly G.; Peng, Y.; and Huemmrich, K. F. Relationship between fraction of radiation absorbed by photosynthesizing maize and soybean canopies and NDVI from remotely sensed data taken at close range and from MODIS 250m resolution data. **Remote Sensing of Environment**, v. 147, p. 108-120, 2014. https://doi:10.1016/j.rse.2014.02.014.

Anselin, L. Local Indicators of Spatial Association – LISA. **Geographical Analysis**, v. 27, n. 2, p. 93-115, 1995. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

Avalos, G.; and Bermudez, E.. Effect of a major highway on the spatial and temporal variation in the structure and diversity of the avifauna of a tropical premontane rain forest. **Rev. Biol. Trop**, v. 64, n. 4, p. 1383-1399, 2016. http://dx.doi.org/10.15517/rbt.v64i4.21517.

Ayram, C. A. C.; Mendonza, M. E.; Etter, A.; et al. Habitat connectivity in biodiversity conservation: A review of recent studies and applications. **Progress in Physical Geography.** v. 40, n. 1, p. 7-37, 2016. https://doi.org/ 10.1177/0309133315598713.

Balvanera, P.; Siddique, I.; Dee, L.; et al. Linking Biodiversity and Ecosystem Services: Current Uncertainties and the Necessary Next Steps, **BioScience**, v. 64, n.1, p. 49–57, 2014. https://doi.org/10.1093/biosci/bit003.

Balzotti, C. S.; Asner, G. P.; Adkins, E. D.; et al. Spatial drivers of composition and connectivity across endangered tropical dry forests. **Journal Applied Ecology,** v. 57, n. 8, p. 1593-1604, 2020. https://doi.org/10.1111/1365-2664.13632.

Bar-Massada, A.; Radeloff, V. C.; and Stewart, S. I. Biotic and Abiotic Effects of Human Settlements in the Wildland–Urban Interface. **BioScience**, v. 64, n. 5, p. 429–437, 2014. https://doi.org/10.1093/biosci/biu039.

Bax, V.; Francesconi, W.; and Quintero, M. Spatial modeling of deforestation processes in the Central Peruvian Amazon. **Journal of Nature Conservation**, v. 29, p. 79-88, 2016. https://doi.org/10.1016/j.jnc.2015.12.002.

Bayat, M.; Ghorbanpour, M.; Zare, R.; et al. Application of artificial neural networks for predicting tree survival and mortality in the Hyrcanian forest of Iran. **Computers and Eletronics in Agriculture**, v. 164, 104929, 2019. https://doi-org.ez31.periodicos.capes.gov.br/10.1016/j.compag.2019.104929.

Bergsten, A.; and Zetterberg, A. To model the landscape as a network: A practitioner's perspective. **Landscape and Urban Planning**, v. 119, p. 35-43, 2013.https://doi.org/10.1016/j.landurbplan.2013.06.009.

Blackwell, B. F.; DeVault, T . L.; Fernández-Juricic, E.; et al. No single solution: application of behavioural principles in mitigating human–wildlife conflict. **Animal Behaviour,** v. 120, n. 2, p. 245-254, 2016 https://doi.org/10.1016/j.anbehav.2016.07.013.

Borthagaray, A. I.; Arim, M.; and Marquet, P. A. Connecting landscape structure and patterns in body size distributions. **Oikos**, v. 121, n. 5, p. 697-710, 2011. https://doi.org/10.1111/j.1600-0706.2011.19548.x.

Bourque, C. P. A.; Bayat, M. Landscape variation in tree species richness in northern Iran forest. **Plos one**, v. 10, n. 4, e0121172, 2015. https://doi.org/10.1371/journal.pone.0121172.

Brasil, Lei Federal nº 12651/2012, de 25 de maio de 2012. Dispõe sobre a proteção da vegetação native e dá outras providências. Available in http://www.planalto.gov.br/ccivil_03/_ato2011-2014/2012/lei/l12651.htm, Accessed on February 12, 2021.

Carvalho, F.; Carvalho, R.; Mira, A.; and Beja, P. Assessing landscape functional connectivity in a forest carnivore using path selection functions. **Landscape Ecology**, v. 31, p. 1021-1036, 2015. https://doi.org/10.1007/s10980-015-0326-x.

Chadwick, K. D.; and Asner, G. P. Tropical soil nutrient distributions determined by biotic and hillslope processes. **Biogeochemistry,** v.127, p. 273–289, 2016. https://doi.org/10.1007/s10533-015-0179-z.

Cheung, A. K. L.; Brierley, G.; and O'Sullivan, D. Landscape structure and dynamics on the Qinghai-Tibetan Plateau. **Ecological Modelling**, v. 339, p. 7-22, 2016. https://doi.org/10.1016/j.ecolmodel.2016.07.015.

Curiel-Esparza, J.; Gonzalez-Utrilla, N.; Canto-Perelo, J.; and Martin-Urilla, M. Integrating climate change criteria in reforestation projects using a hybrid decision-support system. **Environmental Research Letters**, v. 10, e094022, 2015. https://doi.org/10.1088/1748-9326/10/9/094022.

Czarnecka, B.; Rysiak, A.; and Chabudzinski, L. Topographic attributes and ecological indicator values in assessing the ground-floor vegetation patterns. **Biodiv. Res. Conserv**, v. 47, p. 9-22, 2017. https://doi.org/10.1515/biorc-2017-0010.

Da Silva, J. M. F.; Santos, L. J. C.; and Oka-Fiori, C. Spatial correlation analysis between topographic parameters for defining the geomorphometric diversity index: application in the environmental protection area of the Serra da Esperança (state of Paraná, Brazil). **Environ Earth Sci**, v. 78, 356, 2019. https://doi.org/10.1007/s12665-019-8357-2.

Deng, H.; Chen, Z.; Cao, H.; et al. Perceptions and attitudes of local residents on a nature reserve: a case study in Baimaxueshan National Natural Reserve. **International Journal of Sustainable Development and World Ecology**, v. 22, p. 165-170, 2015. https://doi.org/10.1080/13504509.2014.930361.

Dickie, M.; McNay, S. R.; Sutherland, G. D.; et al. Corridors or risk? Movement along, and use of, linear features varies predictably among large mammal predator and prey species. **Journal of Animal Ecology**, v. 89, n. 2, p. 623-634, 2019. https://doi.org/10.1111/1365-2656.13130.

Dupras, J.; Coll, F.; and Marrul, J., et al. The impacts of urban sprawl on ecological connectivity in the Montreal Metropolitan Region. **Historical Landscape Ecology Group**, v. 58, p. 61-73, 2016. https://doi.org/10.1016/j.envsci.2016.01.005.

Economo, E. P.; and Keit, T. H. Network isolation and local diversity in neutral metacommunities. **Oikos,** v. 119, n. 8, p. 1355-1363, 2010. https://doi.org/10.1111/j.1600-0706.2010.18272.x.

Edelsparre, A. H.; Shahid, A.; and Fitzpatrick, M. J. Habitat connectivity is determined by the scale of habitat loss and dispersal strategy. **Ecology and Evolution,** v. 8, n. 11, p. 5508-5514, 2018. https://doi.org/10.1002/ece3.4072.

Ediriweera, S.; Danaher, T.; and Pathirana, S. The influence of topographic variation on forest structure in two woody plant communities: a remote sensing approach. **Forest Systems**, v. 25, n. 1, e049, 2016. http://dx.doi.org/10.5424/fs/2016251-07123.

Féret, J. B.; and Asner, G. P. (2014). Microtopographic controls on lowland Amazonian canopy diversity from imaging spectroscopy. **Ecological Applications**, v. 24, p.1297–1310, 2014. https://doi.org/10.1890/13-1896.1.

Fernández, I. C.; and Morales, N. S. A spatial multicriteria decision analysis for selecting priority sites for plant species restoration: a case study from the Chilean biodiversity hotspot. **Restoration Ecology**, v. 24, n. 5, p. 599-608, 2016. https://doi.org/10.1111/rec.12354.

Frank, S.; Fürst, C.; Koschke, L.; et al. Assessment of landscape aesthetics—Validation of a landscape metrics-based assessment by visual estimation of the scenic beauty. **Ecological Indicators**, v. 32, p. 222-231, 2013. https://doi.org/ 10.1016/j.ecolind.2013.03.026.

Gavrilidis, A. A.; Nita, M. R.; Onose, D.; et al. Methodological framework for urban sprawl control through sustainable planning of urban green infrastructure. **Ecological Indicators**, v. 96, n. 2, p. 67-78, 2019. https://doi.org/10.1016/j.ecolind.2017.10.054.

Gibson, L.; Lee.; T. M.; Koh, L. P., et al. Primary forests are irreplaceable for sustaining tropical biodiversity. **Nature**, v. 478, n. 7369, p. 378-381, 2011. https://doi.org/ 10.1038/nature10425.

Gonzalez-Garcia, A.; Palomo, I.; Gonzalez, J. A.; et al. Quantifying spatial supply-demand mismatches in ecosystem services provides insights for land-use planning. **Land Use Policy**, v. 94, e104493, 2019. https://doi.org/10.1016/j.landusepol.2020.104493.

Grădinaru, S. R.; Iojă, C. I.; Pătru-Stupariu, I.; et al., Are Spatial Planning Objectives Reflected in the Evolution of Urban Landscape Patterns? A Framework for the Evaluation of Spatial Planning Outcomes" **Sustainability**, v. 9, n. 8, 1279, 2017. https://doi.org/10.3390/su9081279.

Guo, X.; Coops, N. C.; Gergel, S. E.; Bater, C. W.; Nielsen, S. E.; and Stadt, J. J. Integrating airborne lidar and satellite imagery to model habitat connectivity dynamics for spatial conservation prioritization. **Landscape Ecology**, v. 33, n. 3, p. 491-511, 2018. https://doi.org/10.1007/s10980-018-0609-0.

Haidara, I.; Tahri, M.; Maanan, M.; et al. Efficiency of Fuzzy Analytic Hierarchy Process to detect soil erosion vulnerability. **Geoderma**, v. 354, 113853, 2019. https://doi.org/10.1016/j.geoderma.2019.07.011.

He, S.; Zhong, Y.; Sun, Y. et al. Topography-associated thermal gradient predicts warming effects on woody plant structural diversity in a subtropical forest. **Sci Rep**, v. 7, 40387, 2017. https://doi.org/10.1038/srep40387.

Hojati, M.; and Mokarram, M. Determination of a topographic wetness index using high resolution digital elevation models. **European Journal of Geography**, v. 7, n.4, p. 41-52, 2016.

Hollunder, R. K.; Mariotte, P.; Carrijo, T. T.; et al. Topography and vegetation structure mediate drought impacts on the understory of the South American Atlantic Forest. **Science of the Total Environment**, v. 766, 144234, 2021. https://doi.org/10.1016/j.scitotenv.2020.144234.

Huang, C.; Huang, X.; Peng, C.; et al., Land use/cover change in the Three Gorges Reservoir area, China: Reconciling the land use conflicts between development and protection. **CATENA**, v. 175, p. 388-399, 2019. https://doi.org/10.1016/j.catena.2019.01.002.

Ibánez, I.; Katz, D. S. W.; Peltier, D.; and Wolf, S. Assessing the integrated effects of landscape fragmentation on plants and plant communities: The challenge of multiprocess-multiresponse dynamics. **Journal of Ecology**, v.102, n. 4, p. 882-895, 2014. https://doi.org/10.1111/1365-2745.12223.

IBGE – Instituto Brasileiro de Geografia e Estatística. **Mapa de Vegetação do Brasil**. Available in https://geoftp.ibge.gov.br/informacoes_ambientais/vegetacao/mapas/brasil/vegetacao.pdf. Accessed on march, 2021.

IBGE – Instituto Brasileiro de Geografia e Estatística. **São Paulo/SP**. Available in https://cidades.ibge.gov.br/brasil/sp/sao-paulo/panorama. Accessed on march, 2021.

Isbell, F. I.; Craven, D.; Connolly, J.; et al. Biodiversity increases the resistance of ecosystem productivity to climate extremes. **Nature**, v. 526, 574-577, 2015. https://doi.org/10.1038/nature15374.

Jesus, E. N. de; Ferreira, R. A.; Aragão, A. G.; et al., Estrutura dos fragmentos florestais da bacia hidrográfica do rio Poxim-Se, como subsídio à restauração ecológica. **Revista Árvore**, v. 39, n. 3, p. 467-474, 2015. https://doi.org/10.1590/0100-67622015000300007.

Jucker, T.; Bongalov, B.; Burslem, D. F. R. P.; et al. Topography shapes the structure, composition and function of tropical forest landscapes. **Ecology Letters**, v. 21, n. 7, p. 989-1000, 2018. https://doi.org/10.1111/ele.12964.

Kane, R.; and John, R. Topographical influence on recent deforestation and degradation in the Sikkim Himalaya in India; Implications for conservation of East Himalayan broadleaf forest. **Applied Geography**, v. 92, p. 85-93, 2018. https://doi.org/10.1016/j.apgeog.2018.02.004.

Keeley, A.T.H.; Beier, P.; and Gagnon, J. W. E. Estimating landscape resistance from habitat suitability: effects of data source and nonlinearities. **Landscape Ecol**, v. 31, p. 2151–2162., 2016. https://doi.org/10.1007/s10980-016-0387-5.

Kim, E. J.; and Lee, S. W. Structural Equation Model for Burn Severity with Topographic Variables and Susceptible Forest Cover. **Sustainability**, v. 10, n. 7, 2473, 2018. https://doi.org/10.3390/su10072473.

Klink, J.; Aversa, M.; and Empinotti, V. On contested water governance and the making of urban financialisation: Exploring the case of metropolitan São Paulo, Brazil. **Urban Studies**, v. 57, n. 1, 004209801984439, 2019. https://doi.org/ 10.1177/0042098019844390.

Koen, E. L.; Bowman, J.; and Ellington, E. H. Mapping landscape connectivity for large spatial extents. **Landscape Ecology**. v. 34, n. 2, p. 2421-2433, 2019. https://doi.org/10.1007/s10980-019-00897-6.

Koprowska, K.; Laszkiewicz, E.; and Kronenberg, J. Is urban sprawl linked to green space availability? **Ecological Indicator**, v. 108, 105723, 2020. https:// doi.org/10.1016/j.ecolind.2019.105723.

Kuang, W.; Chia, W.; Lu, D.; and Dou, Y. A comparative analysis of megacity expansions in China and the U.S.: Patterns, rates and driving forces. **Landscape and Urban Planning**, v, 133, p. 121-135, 2014. https:// doi.org/10.1016/j.landurbplan.2014.08.015.

La Fuente, B.; Mateo-Sánchez, M. C.; Rodriguez, G.; et al. Natura 2000 sites, public forests and riparian corridors: The connectivity backbone of forest green infrastructure. **Land Use Policy**, v. 75, p. 429-441, 2018. https://doi.org/10.1016/j.landusepol.2018.04.002.

Lakicev, M.; Srdjevic, Z.; Srdjevic, B.; and Zlatic, M. Decision making in urban forestry by using approval voting and multicriteria approval method (case study: Zvezdarska forest, Belgrade, Serbia). **Urban Forestry and Urban Greening**, v. 13, n. 1, p. 114-120, 2014. https://doi.org/10.1016/j.ufug.2013.11.001.

Lausch, A.; and Herzog, F.; Applicability of landscape metrics for the monitoring of landscape change: Issues of scale, resolution and interpretability. **Ecological Indicators**, v. 1, n. 2, p. 3-15, 2002. https://doi.org/10.1016/S1470-160X(02)00053-5.

Lechner, A. M.; Reinke, K.; Wang, Y.; and Bastin, L. Interactions between landcover pattern and geospatial processing methods: Effects on landscape metrics and classification accuracy. **Ecological Complexity**, v. 15, p. 71-82, 2013. https://doi.org/10.1016/j.ecocom.2013.03.003.

Lelli, C.; Bruum, H. H.; Chiarucci, A.; et al. Biodiversity response to forest structure and management: Comparing species richness, conservation relevant species and functional diversity as metrics in forest conservation. **Forest Ecology and Management**, v. 432, p. 707-717, 2018. https://doi.org/10.1016/j.foreco.2018.09.057.

Lembi, R. C.; Cronemberger, C.; Picharillo, C.; et al. Urban expansion in the Atlantic Forest: applying the Nature Futures Framework to develop a conceptual model and future scenarios. **Biota Neotrop**., e20190904, 2020. https://doi.org/10.1590/1676-0611-bn-2019-0904.

Li, N.; Chu, H.; Qi, Y.; et al. Alpha and beta diversity of birds along elevational vegetation zones on the southern slope of Altai Mountains: Implication for conservation. **Global Ecology and Conservation**, v. 19, e00643, 2019. https://doi.org/10.1016/j.gecco.2019.e00643.

Li, Y.; Viña, A.; Yang, W.; et al. Effects of conservation policies on forest cover change in giant panda habitat regions, China. **Land Use Policy**, v. 33, p. 42-53, 2013. https://doi.org/10.1016/j.landusepol.2012.12.003.

Lin, B. B.; and Fuller, R. A. FORUM: Sharing or sparing? How should we grow the world's cities? **Journal of Applied Ecology**, v. 50, n. 5, p. 1161-1168, 2013. https://doi.org/10.1111/1365-2664.12118.

Lin, J.; Li, X.; Li, S.; et al. What is the influence of landscape metric selection on the calibration of land-use/cover simulation models? **Environmental Modelling & Software**, v. 129, 10479, 2020. https://doi.org/10.1016/j.envsoft.2020.104719.

Lippok, D.; Beck, S. G.; Renison, D.; et al. Topography and edge effects are more important than elevation as drivers of vegetation patterns in a neotropical montane forest. **Journal of Vegetation Science**, v. 25, n. 3, p. 724-733, 2014. https://doi.org/10.1111/jvs.12132.

Loritz, R.; Jackisch, C.; Kleidon, A.; et al. A topographic index explaining hydrological similarity by accounting for the joint controls of runoff formation. **Hidrology and Earth System Sciences**, v. 23, n. 9, p. 3807-3821, 2017. https://doi.org/10.5194/hess-23-3807-2019.

Loro, M.; Ortega, E.; Arce, R. M.; et al. Assessing landscape resistance to roe deer dispersal using fuzzy set theory and multicriteria analysis: a case study in Central Spain. **Landscape Ecol. Eng**, v. 12, p. 41-60, 2016. https://doi.org/10.1007/s11355-015-0275-1.

Madadi, H.; Moradi, H.; Soffianian, A.; et al. Degradation of natural habitats by roads: Comparing land-take and noise effect zone. **Environ. Impact. Asses.**, v. 65, p. 147–155, 2017. https://doi.org/10.1016/j.eiar.2017.05.003.

Magioli, M.; Moreira, M. Z.; Fonseca, R. C. B.; et al. Human-modified landscapes alter mammal resource and habitat use and trophic structure. **PNAS,** v. 37, p. 18466-18472, 2019. https://doi.org/10.1073/pnas.1904384116.

Matos, C.; Petrovan, S. O.; Wheeler, P. M; et al. Landscape connectivity and spatial prioritization in an urbanising world: A network analysis approach for a threatened amphibian. **Biological Conservation**, v. 237, p. 237-247, 2019. https://doi.org/10.1016/j.biocon.2019.06.035.

McDonald, R. I.; Marcotulio, P. J.; and Guneralp, B. Urbanization and global trends in biodiversity and ecosystem services. In: Elmqvist T, Fragkias M, Goodness J, Güneralp B, Marcotullio PJ, McDonald RI, Parnell S, Schewenius M, Sendstad M, Seto KC, Wilkinson C (eds) **Urbanization, biodiversity and ecosystem services: Challenges and opportunities.** Springer, Netherlands, p. 32–52, 2013.

McGarigal, K. Landscape Pattern Metrics. **Encyclopedia of Environmetrics**, 2013. https://doi.org/10.1002/9780470057339.val006.pub2.

McPherson, S. C.; Brown, M.; and Downs, C.T. Diet of the crowned eagle (Stephanoaetus coronatus) in an urban landscape: potential for human-wildlife conflict? **Urban Ecosyst**., v. 19, p. 383–396, 2016. https://doi.org/10.1007/s11252-015-0500-6.

McRae, B. H.; Hall, S. A.; Beier, P.; et al. Where to Restore Ecological Connectivity? Detecting Barriers and Quantifying Restoration Benefits. **Plos One**, v. 7, n. 12, e52604, 2012. https://doi.org/10.1371/journal.pone.0052604.

Mello, K.; Costa, D. R.; Valente, R. A.; and Vettorazzi, C. D. Multicriteria Evaluation for Protected Area Definition Aiming at Water Quality Improvement. **Floresta e Ambiente**, v. 25, n. 3, e20160134, 2018. https://doi.org/10.1590/2179-8087.013416.

Mello, K.; Taniwaki, R. H.; Paula, F. R.; et al. Multiscale land use impacts on water quality: Assessment, planning, and future perspectives in Brazil. **Journal of Environmental Management,** v. 270, 110879, 2020. https://doi.org/10.1016/j.jenvman.2020.110879.

Mello, K.; Toppa, R. H.; and Cardoso-Leite, E.; Priority area for forest conservation in an urban landscape at the transition between Atlantic forest and Cerrado. **Cerne**, v. 22, n. 3, p. 277-288, 2016. https://doi.org/10.1590/01047760201622032172.

Merrick, M. J.; and Koprowski, J. L. Circuit theory to estimate natal dispersal routes and functional landscape connectivity for an endangered small mammal. **Landscape Ecol.**, v. 32, p.1163-1179, 2017. https://doi.org/10.1007/s10980-017-0521-z.

Mimet, A.; Clauzel, C.; and Foltête, J. C. Locating wildlife crossing for multispecies connectivity across linear infrastructures. **Landscape Ecology**, v. 31, n. 9, p. 1955-1973, 2016. https://doi.org/10.1007/s10980-016-0373-y.

Ministério do Meio Ambiente (MMA). Áreas prioritárias para conservação da biodiversidade brasileira. Available in http://areasprioritarias.mma.gov.br/1-atualizacao-das-areas-prioritarias. Accessed on March 8, 2021.

Mitchell, S. L.; Edwards, D. P.; Bernard, H. et al. Riparian reserves help protect forest bird communities in oil palm dominated landscapes. **Journal of Applied Ecology**, v. 55, n. 6, p. 2744-2755, 2018. https://doi.org/10.1111/1365-2664.13233.

Molin, P. G.; Robin, C.; Ferraz, S. F. B.; and Brancalion, P. H. S. A landscape approach for cost-effective large-scale forest restoration. **Journal of Applied Ecology**, v. 55, n. 6, p. 2767-2778, 2018. https://doi.org/10.1111/1365-2664.13263.

Muscarrela, R.; Kolyaie, S.; Morton, D. C.; et al., 2020. Effects of topography on tropical forest structure depend on climate context. **Journal of Ecology**, v. 108, n. 1, p. 145-159, 2020. https://doi.org/10.1111/1365-2745.13261.

Nagai, S.; Nasahara, K. N.; Muraoka, H.; et al. Field experiments to test the use of the normalized-difference vegetation index for phenology detection. **Agricultural and Forest Meteorology,** v. 150, n. 2, p. 152-160, 2010. https://doi.org/10.1016/j.agrformet.2009.09.010.

Newbold, T.; Hudson, L.; Hill, S.; et al. Global effects of land use on local terrestrial biodiversity. **Nature**, v. 520, p. 45–50, 2015. https://doi.org/10.1038/nature14324

O'Neil, G. L.; Goodall, J. L.; and Watson, L. T. Evaluating the potential for site-specific modification of LiDAR DEM derivatives to improve environmental planning-scale wetland identification using Random Forest classification. **Journal of Hydrology**, v. 559, p. 192-208, 2018. https://doi.org/10.1016/j.jhydrol.2018.02.009.

Ojima, R. Dimensões da urbanização dispersa e proposta metodológica para estudos comparativos: uma abordagem socioespacial em aglomerações urbanas brasileiras. **R. Brasileira de Estudos de População**, v. 24, n. 2, p. 277-300, 2007. https://doi.org/10.1590/S0102-30982007000200007.

Otero, I.; J. Marull, E.; Tello, G. L.; et al. Land abandonment, landscape, and biodiversity: questioning the restorative character of the forest transition in the Mediterranean. **Ecology and Society**, v. 20, n. 2, p. 7, 2015. http://doi.org/10.5751/ES-07378-200207.

Ou, Z.; He, S.; P. Q.; Peng, Y.; et al. Effects of vegetation restoration and environmental factors on understory vascular plants in a typical karst ecosystem in southern China. **Scientific Reports,** v. 10, 12011, 2020. https://doi.org/10.1038/s41598-020-68785-7.

Palmero-Iniesta, M.; Espelta, J. M.; Gordillo, J.; et al. Changes in forest landscape patterns resulting from recent afforestation in Europe (1990–2012): defragmentation of pre-existing forest versus new patch proliferation. **Animals of Forest Science**, v. 77, 43, 2020. https://doi.org/10.1007/s13595-020-00946-0.

Pays, O.; Fortin, D.; Gassani, J.; and Duchesne, J. Group dynamics and landscape features constrain the exploration of herds in fusionfission societies: the case of European Roe Deer, **Plos One**, v. 7, n. 3, e34678, 2012. https://doi.org/10.1371/journal.pone.0034678.

Pelletier, D.; Lapointe, M. E.; Wulder, M. A.; et al. Forest Connectivity Regions of Canada Using Circuit Theory and Image Analysis. **Plos One**, v. 12, n. 2, e0169428, 2017. https://doi.org/10.1371/journal.pone.0169428.

Pereira, H.M.; Ferrier, S.; Walters, M.; et al. Essential biodiversity variables. **Science,** v. 339, n. 80, p. 277–278, 2013. http://dx.doi.org/10.1126/ science.1229931.

Pirnat, J.; and Hladnik, D. The Concept of Landscape Structure, Forest Continuum and Connectivity as a Support in Urban Forest Management and Landscape Planning. **Forests**, v. 9, 584. https://doi.org/10.3390/f9100584.

Ramesh, T.; Kalle, R.; and Downs, C. T. Sex-specific indicators of landscapes use by servals: Consequence of living in fragmented landscapes. **Ecological Indicators**, v. 52, p. 8-15, 2015. https://doi.org/10.1016/j.ecolind.2014.11.021.

Ramey, T. L. and Richardson, J. S. Terrestrial Invertebrates in the Riparian Zone: Mechanisms Underlying Their Unique Diversity, **BioScience**, v. 67, n. 9, p. 808–819, 2017. https://doi.org/10.1093/biosci/bix078.

Ribeiro, M. P.; Mello, K.; and Valente, R. A. Avaliação da estrutura da paisagem visando à conservação da biodiversidade em paisagem urbanizada**. Ciência Florestal**, v. 30, n. 3, p. 819-834, 2020. https://doi.org/10.5902/1980509837683.

Rincón, V.; Velázquez, J.; Gutiérrez, J.; Sánchez, B.; et al. Evaluating European Conservation Areas and Proposal of New Zones of Conservation under the Habitats Directive. **Application to Spanish Territories. Sustainability**, v. 11, n. 2, 398, 2018. https://doi.org/10.3390/su11020398.

Romero, A. C.; Issii, T. M.; Pereira-Silva, E. F. L.; et al. Effects of urban sprawl on forest conservation in a metropolitan water source area. **Revista Árvore,** v. 42, n. 1, e420114, 2018. https://doi.org/10.1590/1806-90882018000100014.

Ruffel, J.; Clout, M. N.; and Didham, R. K.; The matrix matters, but how should we manage it? Estimating the amount of high-quality matrix required to maintain biodiversity in fragmented landscapes. **Ecography**, v. 40, n. 1, p. 171-178, 2017. htttps://doi.org/10.1111/ecog.02097.

Russo, I. R. M.; Sole, C. L.; Barbato, M.; et al. Landscape determinants of fine-scale genetic structure of a small rodent in a heterogeneous landscape (Hluhluwe-iMfolozi Park, South Africa). **Scientific Reports**, v. 6, 29168, 2016. https://doi.org/10.1038/srep29168.

Santos, A. R.; Silva, R. C. F.; Assis, L. C.; et al. Defining environmental conservation levels considering anthropic activity in the Uberaba River Basin protected area. **Revista Ambiente & Água**, v. 14, n. 1, e2279, 2019. https://doi.org/10.4136/ambi-agua.2279.

Saura, S.; Bastin, L.; Battistella, L.; et al. Protected area connectivity: Shortfalls in global targets and country-level priorities. **Biological Conservation**, v. 219, p. 53-67, 2018. https://doi.org/10.1016/j.biocon.2017.12.020.

Schindler, S.; VonWehrden, H.; Poirazidis, K.; et al. Performance of methods to select landscape metrics for modelling species richness. **Ecological Modelling**, v. 295c, p.107–112, 2015. https://doi.org/10.1016/j.ecolmodel.2014.05.012.

Schindler, S.; von Wehrden, H.; Poirazidis, K.; et al. Multiscale performance of landscape metrics as indicators of species richness of plants, insects and vertebrates, **Ecological Indicators**, v. 31, p. 41-48, 2013. https://doi.org/10.1016/j.ecolind.2012.04.012.

Scriven, S. A.; Carlson, K. M.; Hodgson, J. A.; et al. Testing the benefits of conservation set-asides for improved habitat connectivity in tropical agricultural landscape. **Journal of Applied Ecology**, v. 55, n. 10, p. 2274-2285, 2019. https://doi.org/10.1111/1365-2664.13472.

Semper-Pascual, A.; Macchi, L.; Sabatini, F. M.; et al. Mapping extinction debt highlights conservation opportunities for birds and mammals in the South Amercian Chaco. **Journal of Applied Ecology**, v. 55, n. 3, p. 1218-1229, 2018. https://doi.org/10.1111/1365-2664.13074.

Senzaki, M.; and Yamaura, Y.; Surrogate species versus landscape metric: does presence of a raptor species explains diversity of multiple taxa more than patch area? **Wetlands Ecology and Management**, v. 24, n. 4, p. 427–441, 2016. https://doi.org/10.1007/s11273-015-9469-4.

Shiferaw, H.; Bewket, W.; Alamirew, T.; et al. Implications of land use/land cover dynamics and Prosopis invasion on ecosystem service values in Afar Region, Ethiopia. **Science of the Total Environment**, v. 675, p. 354-366, 2019. https://doi.org/10.1016/j.scitotenv.2019.04.220.

Silva, V. A. M.; Mello, K. de; Vettorazzi, C. A.; Costa, D. R. da; and Valente, R. A. Priority Areas for Forest Conservation , Aiming at the Maintenance of Water resources, Through the Multicriteria Evaluation. **Revista Árvore**, v. 41, n. 1, e410119, 2017. https://doi.org/10.1590/1806-90882017000100019.

Tabor, G.; Ayran, C. A. C.; Garcia, L. C.; et al. Ecological connectivity: a bridge to preserving biodiversity. Frontiers 2018/19 Emerging Issues of Environmental Concern (Nairobi: United Nations. Environment Programme), p. 24–37, 2019.

Tarabon, S.; Bergés, L.; Dutoit, T.; et al. Maximizing habitat connectivity in the mitigation hierarchy. A case study on three terrestrial mammals in an urban environment. **J Environ Manage**, v. 1, p. 243-340, 2019. https://doi.org/ 10.1016/j.jenvman.2019.04.121.

Tarabon, S.; Calvet, C.; Delbar, V.; et al. Integrating a landscape connectivity approach into mitigation hierarchy planning by anticipating urban dynamics. **Landscape and Urban Planning**, v. 202, 103871, 2020. https://doi.org/10.1016/j.landurbplan.2020.103871.

Thompson, P. L.; Rayfield, B.; and Gonzalez, A. Loss of habitat and connectivity erodes species diversity, ecosystem functioning, and stability in metacommunity networks. **Ecography**, v. 40, n. 1, p. 98-108, 2017. https://doi.org/10.1111/ecog.02558.

Torrella, S. A.; Piquer-Rodriguez, M.; Levers, C.; et al. Multiscale spatial planning to maintain forest connectivity in the Argentine Chaco in the face of deforestation. **Ecology and Society**, v. 23, n. 4, 37, 2018. https://doi.org/10.5751/ES-10546-230437.

Torres, A.; Jaeger, J. A. G.; and Alonso, J.C. Multi-scale mismatches between urban sprawl and landscape fragmentation create windows of opportunity for conservation development. **Landscape Ecol,** v. 31, p. 2291–2305, 2016. https://doi.org/10.1007/s10980-016-0400-z.

Tucker M. A; Gaese, K. B.; Fagan, W. F.; et al. Moving in the anthropocene: global reductions in terrestrial mammalian movements. **Science**, v. 359, n. 6374, p. 466–469, 2018. https://doi.org/10.1126/science.aam9712.

Uezu, A.; Metzger, J. P.; and Vielliard, J. M. E. Effects of structural and functional connectivity and patch size on the abundance of seven Atlantic Forest bird species. **Biological Conservation**, v. 123, n. 4, p. 507-519, 2005. https://doi.org/10.1016/j.biocon.2005.01.001.

Unda, M.; and Etter, A. Conservation Opportunities of the Land Restitution Program Areas in the Colombian Post-Conflict Period. **Sustainability**, v. 11, n. 7, 2048, 2019. https://doi.org/10.3390/su11072048.

Union Nations Educations, Scientific and Cultural Organization (UNESCO), 2019. Biosphere Reserves. Available in https://en.unesco.org/biosphere. Accessed on November 20, 2019.

Valente, R. A.; Petean, F. C. S.; and Vettorazzi, C. A. Multicriteria decision analysis for prioritizing areas for forest restoration. **Cerne**, v. 23, n. 1, p. 53-60, 2017. https://doi.org/10.1590/01047760201723012258.

Valladares, G. S.; et al. Modelo multicritério aditivo na geração de mapas de suscetibilidade à erosão em área rural. Pesquisa. **Agropecuária Brasileira**, v. 47, n. 9, p. 1376-1383, 2012. http://doi.org/10.1590/S0100-204X2012000900023.

Van Geert, A.; Van Rossum, F.; and Triest, L. Do linear landscape elements in farmland act as biological corridors for pollen dispersal? **Journal of Ecology**, v. 98, n. , p. 178-187, 2009. https://doi.org/10.1111/j.1365-2745.2009.01600.x.

Vettorazzi, C. A.; and Valente, R., A. Priority areas for forest restoration aiming at the conservation of water resources. **Ecological Engineering**, v. 94, p. 255-267, 2016. https://doi.org/10.1016/j.ecoleng.2016.05.069.

Victor, R. A. B. M.; Neto, J. B. C.; Ab'Saber, A. N.; et al. Application of the Biosphere Reserve Concept to Urban Areas: The Case of São Paulo City Green Belt Biosphere Reserve, Brazil—São Paulo Forest Institute: A Case Study for UNESCO. **Urban Ecosphere and Society Partnership of Cities**, v. 1023, n. , p. 237-281, 2004. https://doi.org/10.1196/annals.1319.012.

Wagner, F. H.; Sanchez, A.; Aidar, M. P. M.; et al. Mapping Atlantic rainforest degradation and regeneration history with indicator species using convolutional network. **PLoS ONE,** v. 15, n. 2, e0229448, 2020. https://doi.org/10.1371/journal.pone.0229448.

Wang, S.; and Loreau, M. Biodiversity and ecosystem stability across scales in metacommunities. **Ecology Letters**, v. 19, n. 5, p. 510-518, 2016. https://doi.org/10.1111/ele.12582.

Watson J. E.; Shanahan, D. F.; Marco, M. D. Catastrophic declines in wilderness areas undermine global environment targets. **Current Biology**, v. 26, n. 21, p. 2929–2934, 2016. https://doi.org/10.1016/j.cub.2016.08.049.

Wood, E.; Pidgeon, A. M.; Radeloff, V. C.; Kueler, N. Image texture predicts avian density and species richness **PLoS ONE**, v. 8, n. 5, e63211, 2013. https://doi.org/10.1371/journal.pone.0063211.

Wylie, R. R. M.; Woods, M. E.; and Dech, J. P. Estimating Stand Age from Airborne Laser Scanning Data to Improve Models of Black Spruce Wood Density in the Boreal Forest of Ontario. **Remote Sensing,** v. 11, n. 17, 2022, 2019. https://doi.org/10.3390/rs11172022.

Yabsley, N. A.; Olds, A. D.; Connolly, R. M.; et al. Resource type influences the effects of reserves and connectivity on ecological functions. **Journal of Animal Ecology**, v. 85, n. 2, p. 437-444, 2015. https://doi.org/10.1111/1365-2656.12460.

Yang, Y.; Saatchi, S. S.; Xu, L.; Yu, Y.; Lefsky, A. M. et al. Abiotic controls on macroscale variations of humid tropical forest height. **Remote Sensing**, v. 8, n. 6, 494, 2016. https://doi.org/10.3390/rs8060494.

Yuan, Y.; Chen, D.; Wu, S.; et al. Urban sprawl decreases the value of ecosystem services and intensifies the supply scarcity of ecosystem services in China. **Science of the Total Environment**, v. 697, 134170, 2019. https://doi.org/10.1016/j.scitotenv.2019.134170.

Yuan, Y.; Chen, D.; Wu, S.; et al. Urban sprawl decreases the value of ecosystem services and intensifies the supply scarcity of ecosystem services in China. **Science of the Total Environment,** v. 20, 697, 134170, 2019. https://doi.org/10.1016/j.scitotenv.2019.134170.

Zeller, K. A.; McGarigal, K.; and Whiteley, A. Estimating landscape resistance to movement: a review. **Landscape Ecol**, v. 27, p. 777–797, 2012. https://doi.org/10.1007/s10980-012-9737-0.

Zhang, L.; Liu, S.; Sun. P.; and Wang, T. Using DEM to predict Abies faxoniana and Quercus aquifolioides distributions in the upstream catchment basin of the Min River in southwest China. **Ecology Indicator**, v. 69, p. 91–99, 2016. https://doi.org/ 10.1016/j.ecolind.2016.04.008.

Zhang, Z.; Zinda, J. A.; Yang, Z.; et al. Effects of topographic attributes on landscape pattern metrics based on redundancy ordination gradient analysis. **Landscape and Ecological Engineering,** v. 14, p. 67-77, 2018. https://doi.org/10.1007/s11355-016-0322-6.

Zimbres, B.; Peres, C. A.; Penido, G.; et al. Thresholds of riparian forest use by terrestrial mammals in a fragmented Amazonian deforestation frontier. **Biodiversity and Conservation**, v. 27, n. 11, p. 2815–2836, 2018. https://doi.org/10.1007/s10531-018-1571-5.

Ziter, C.; Bennett, E. M.; and Gonzalez, A. Functional diversity and management mediate carbon storage in small forest fragments. **Ecosphere**, v. 4, n. 7, p. 1 – 21, 2013. https://doi.org/10.1890/ES13-00135.1.

3. CHAPTER 2

LANDSCAPE RESISTANCE INDEX AIMING AT FUNCTIONAL FOREST CONNECTIVITY

ABSTRACT

The resistance surfaces have been developed from empirical data as gene flow, genetic distances, habitat use, and movement paths. Moreover, they are also based on expert opinions concerning the ecology of focal species and their ability to cross landscapes.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. It was developed through Structural Equation Modeling (SEM), supported by the criteria of Land Surface Temperature, Nighttime Reflectance, and Inverted Normalized Difference Vegetation Index (NDVI), which are called observed variables. The landscape studied in the Green Belt Biosphere Reserve of São Paulo has suffered from urban sprawl. It has significant remnants of the Atlantic Forest though, which is a biodiversity hotspot. Our results indicated criteria variability in the landscape, however, 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, the index based on environmental attributes reflects the structure of functional forest connectivity, supporting the planning design of forest corridors across landscapes.

Keywords: Structural Equation Model; Landscape Structure Analysis; Land use and Land cover; and Environmental criteria.

3.1 INTRODUCTION

The land-use/land-cover (LULC) change, caused by the urbanized process, has been influenced biodiversity, ecosystem function, and regional climate (Choudhury; Das and Das, 2018). 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 and Li, 2017).

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. The same authors argue that the species consider the landscape as a competitive space control of its territory. Thus, Spear and Storfer (2010) defined landscape resistance as a degree of facility or impediment to the movement of a specific species.

According to Rudnick et al. (2012), resistance surfaces have been developed from empirical data as gene flow, genetic distances, habitat use, and movement paths. Authors as Cushman et al. (2013) add that 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.

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, Peterman, and MacGarigal, 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 and Landguth, 2010), the contrast in landscape resistance (Shirk, Landguth, and Crushman, 2018), the sampling regimes (Olyer-McCance, Fedy, and Landguth, 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 et al. 2013, Gruber and 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, Perterman, and McGarigal, 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; Silva and Santos, 2018; Rousta et al., 2018; Niu et al., 2018; 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; Pawar and Sawage et al., 2013).

The temperature is vital in establishing the biological organization levels standard (Gilbert et al., 2016). The metabolic ecology theory 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, Eichenbaum, and Simonovic, 2018), the road orientation, the anthropogenic activities (Santos et al., 2017), the obstruction of wind by high buildings (Zhou and Chen, 2018), the energy balance, and the hydrological cycle (Silva; Silva and Santos, 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 (Huang et al., 2014; Chen et al., 2016; 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., 2018), 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; Beier and Lee, 2018), grasshoppers (Shi et al., 2018), birds (Bonthoux et al., 2018), and large mammals (Johnson et al., 2018; Ito et al., 2018). These studies are supported by the robust correlation between plant biomass and active photosynthetic radiation absorption (Grossman et al., 2018; Nandy et al., 2017).

Pettorelli et al. (2016) highlighted the biodiversity monitoring of the whole landscape patches and not only their forested area though. They considered that LULC influence in vegetation corridors network regional, allowing the evaluation of the pasture use intensity (Gomez-Gimenez et al., 2017), the quantification of farmland abandonment (Estel et al., 2015), and the monitoring of potential protected rural areas (Weber, Schaepman-Strub, and Ecker, 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 sprawl.

3.2 MATERIAL AND METHODS

3.2.1 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, 2021). 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, 2012). 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).

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).

Table 1. Main characteristics of the forest patches of the studied landscape in the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil.

Class (ha)	NP (%)	Area (%)	Forest patches metrics Area (ha) Mean (SD)	Perim (m) Mean (SD)	Near (m) Mean (SD)	Shape Mean (SD)
< 5	92.4	5.9	0.36 (± 0.79)	277.90 (± 299.03)	17.80 (±42.46)	1.15 (± 0.24)
5 - 30	5.2	11.5	12.32 (±6.37)	2857.48 (±1301.65)	107.67 (± 162.66)	2.05 (±0.60)
30 - 75	1.3	11.0	47.00 (±13.57)	7814.90 (± 2366.13)	57.57 (± 98.93)	2.85 (±0.65)
75 - 170	0.6	11.2	105.98 (± 24.89	13933.64 (± 4035.25)	38.88 (±77.14)	3.38 (± 0.82)
170 - 300	0.3	10.4	244.71 (± 28.74)	26434.43 (± 6538.71)	21.56 (± 35.60)	4.40 (±0.95)
> 300	0.2	50.0	1436.24 (± 2689.73)	92797.11 (±107803.9)	0.00 (± 0.00)	6.50 (± 2.23)

Where: NP= Number of forest patches; Area - Habitat size; Perim – Habitat perimeter; Shape - Shape index; Near - Distance of the nearest neighbor edge; Mean - Mean value; and SD - Standard deviation value.

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).

3.2.2 Conceptual Model

The Landscape Resistance Index 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.

The LST map was produced from a thermal infrared band of the Landsat-8, using the LULC of the studied area for reference. The Night is a product of the Night and Day Bands (NDB) of the Visible Infrared Imaging Radiometer Suite (VIIRS) and, the NDVIinv came from the near and infrared band of the CBERS-4.

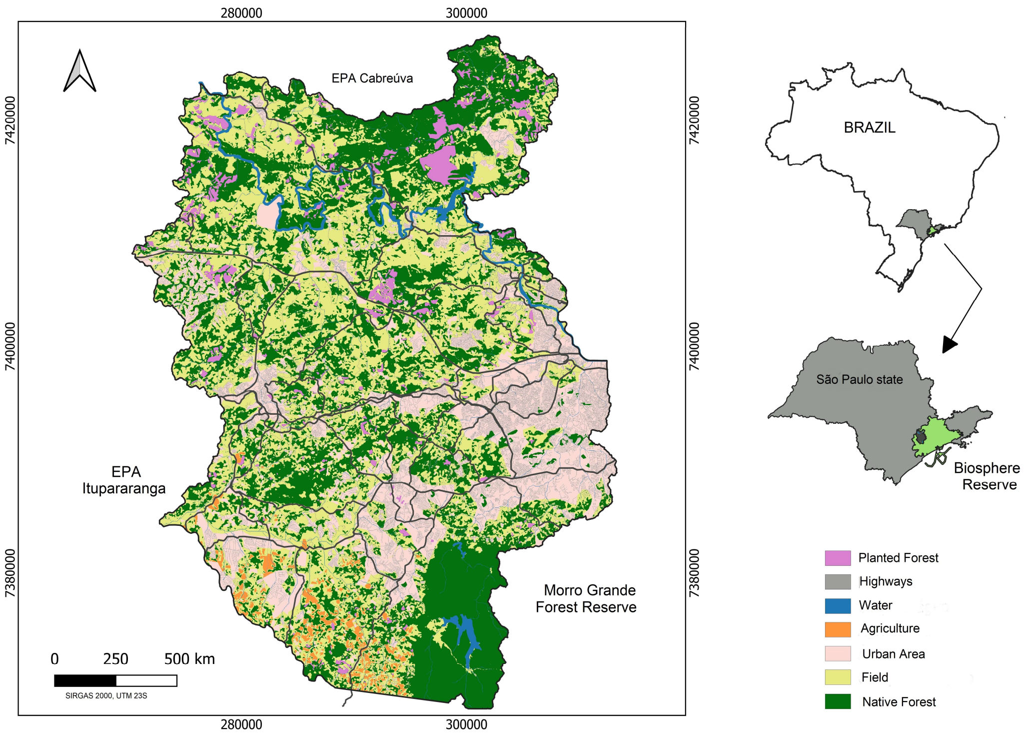


Fig. 1 – Land use/Land cover (LULC) and location of the studied Landscape in the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil.

The criteria maps were sampled using a Geographic Information System (7620 points randomly distributed) to support statistical analysis through Structural Equation Modeling (SEM), where criteria were inserted as observed variables.

This way, modeling these variables, we obtained the Landscape Resistance Index, which was our latent variable in the SEM context (Fig. 2).

3.2.3 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 represents non-measurable variables, named latent variables or constructs (Grace et al., 2010).

As mentioned, the observed variables were the maps of LST, Night, and NDVIinv to 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, 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).

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). 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 and preparation of variables, estimation, adjustment assessment, and discussion (Kaplan, 2008).

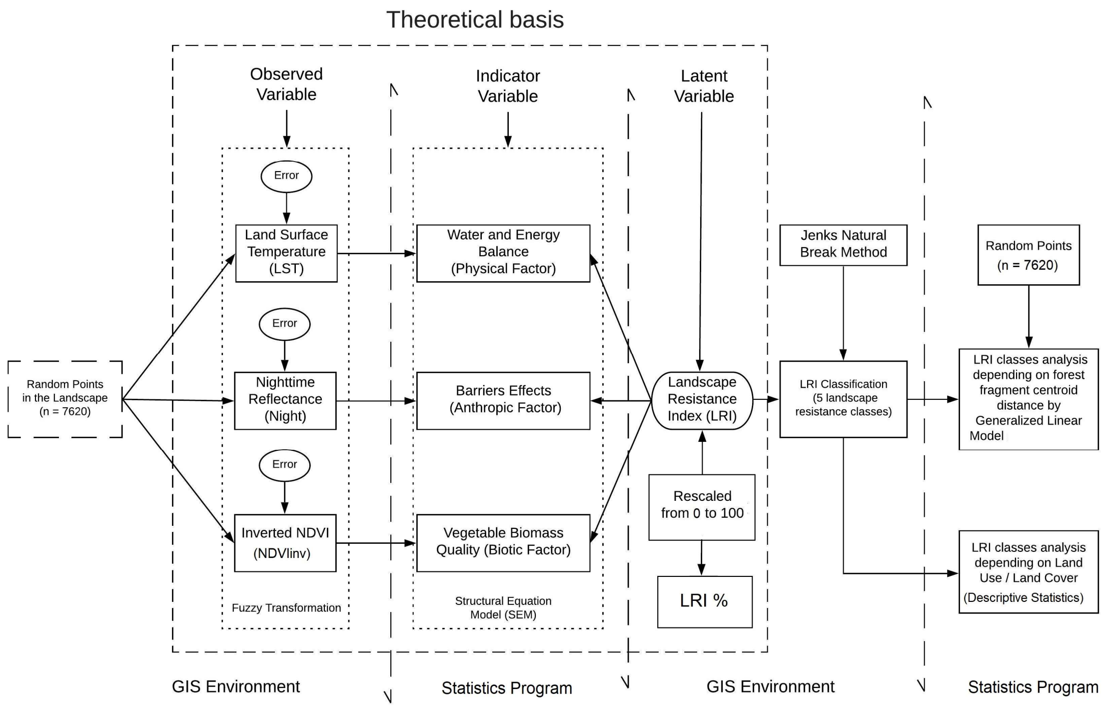


Fig.2 - Conceptual model used to obtain the Landscape Resistance Index (LRI) for the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil.

3.2.4 Observed Variables

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 assess animal behaviors (Hanks et al., 2015; Wilson et al., 2019).

This way, 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 20m, 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 (ºC), subtracting 273,15 K (Barsi, Barker, and Schott, 2003). 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 constituted in the Night and Day Band (NDB) 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 the literature, the Night is considered effective in determining urban areas (Su et al., 2015; Zhou et al., 2014), in this study, to identify anthropic barriers to gene flow. In the same way, its 450 m-spatial resolution was downsized to 20m. 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, 20m-spatial resolution). The index 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, Peng, and Huemmrich, 2014).

In this context, we multiplied NDVI by -1m, 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 100m among them. This sample size corresponds to 20 times the statistical sampling required for a 95% confidence interval and 5% error.

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

3.2.5 Landscape Resistance Index (LRI)

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

$$\textbf{(Eq. 1) } LRI = (((Factor\ LST*LST) + Error\ LST) + (Factor\ NDVIinv*NDVIinv) + Error\ NDVIinv)) + ((Factor\ Night*Night) + Error\ Night))).$$

$$\textbf{(Eq. 2) } LRI\% = (\left(\frac{100}{Max\ LRI - Min\ LRI}\right)*(LRI - Max\ LRI)) + 100$$

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 data previously tested to correlation and normal distribution.

The Comparative Fit Index (CFI) calculate the relative fit of the observed model by comparing it with a base model (Byrne, 2016). 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 (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.

3.2.6 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, Goodchild, and Longley, 2018). 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 (GLM) 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).

3.3 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).

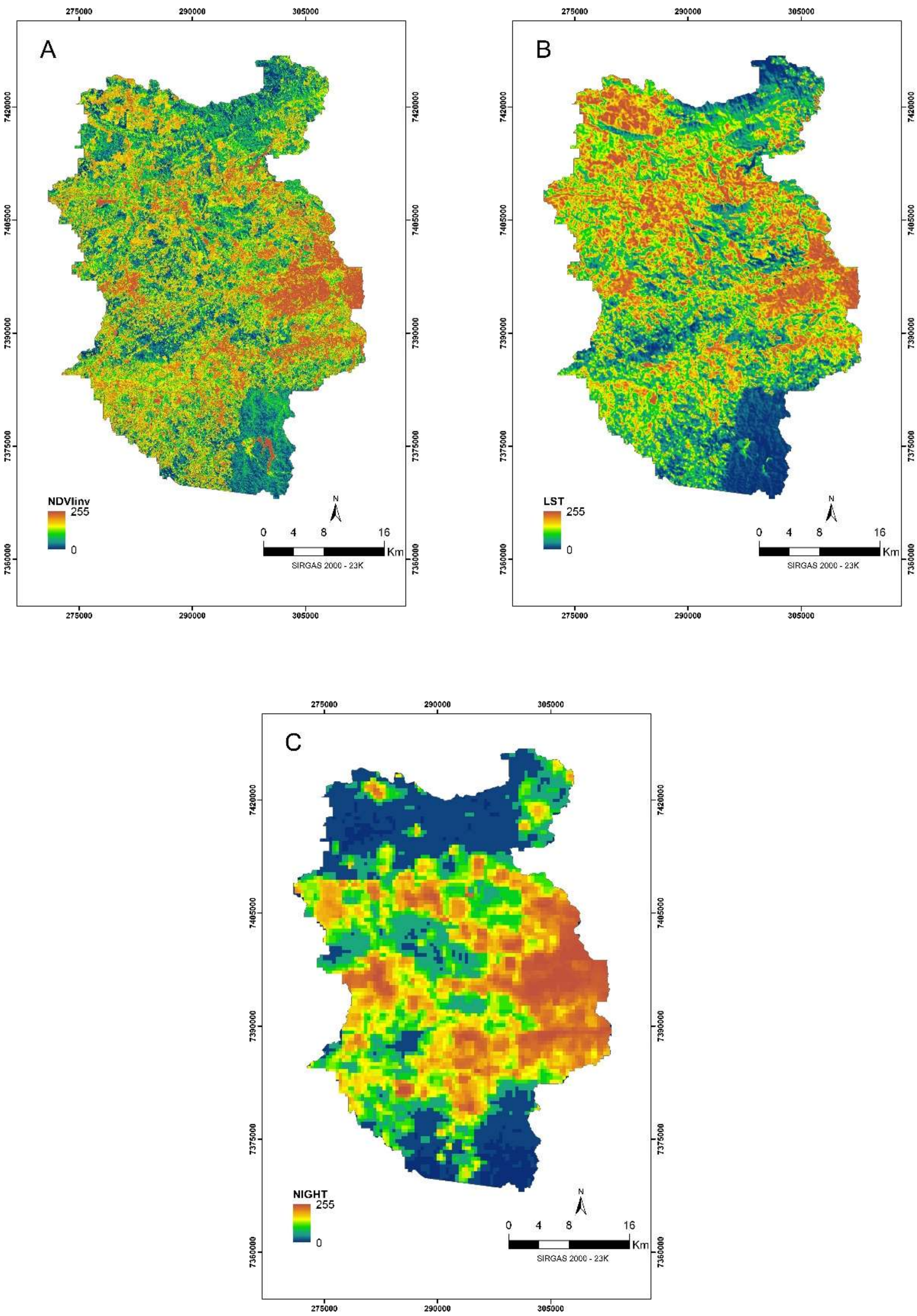


Fig. 3. Environmental attributes (in 255 bytes) for the study area in the GBBR-SP, Brazil: (A) Inverted NDVI, (B) Land Surface Temperature, and (C) Nighttime Reflectance.

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 = 0.68), 0.57 (error = 0.68), and 0.80 (error = 0.37). 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 (Fig. 4AB).

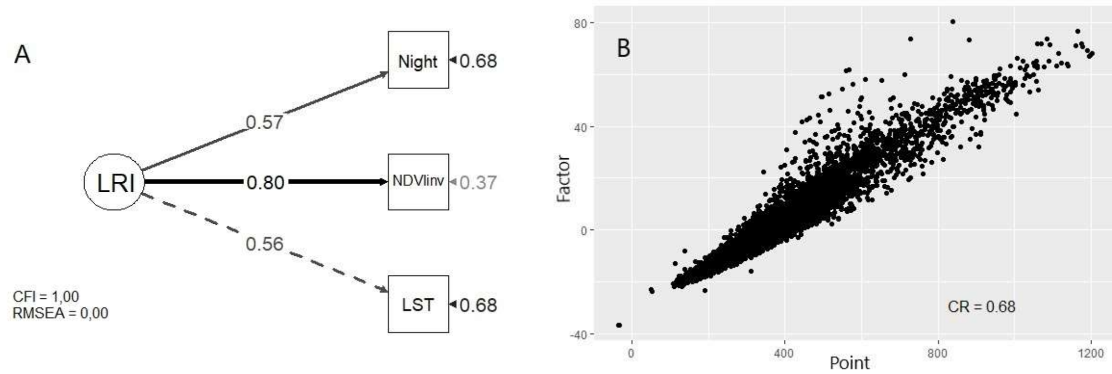


Fig.4 – Landscape Resistance Index for the studied area in the GBBR-SP, Brazil: (A) parameters and factor loadings modeled, and (B) model CR, based on the sum of the points representing the OV and their factor loadings.

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:

(Eq. 3) LRI =(((0.80*NDVIinv)+0.37)+(0.57*NIGHT)+0.68)+ ((0.56*LST)+0.68)))

Where: Inverted NDVI (NDVIinv), Nighttime Reflectance (Night), Land Surface Temperature (LST), and Landscape Resistance Index (LRI).

The model (Equation 3) resulted in an LRI ranging from 1.73 to 493.88 for our study area, justly reflecting the internal disparities of the matrix components in terms of resistance to genetic flow. These LRI threshold values are in the Equation 4 to normalize LRI from 0-100% (Fig. 5).

$$\textbf{(Eq. 4) LRI\% =(}\left(\frac{100}{492.15}\right)\textbf{*(LRI-493.88))+100}$$

Where: Landscape Resistance Index (LRI) and Landscape Resistance Index normalized for percentage (LRI%).

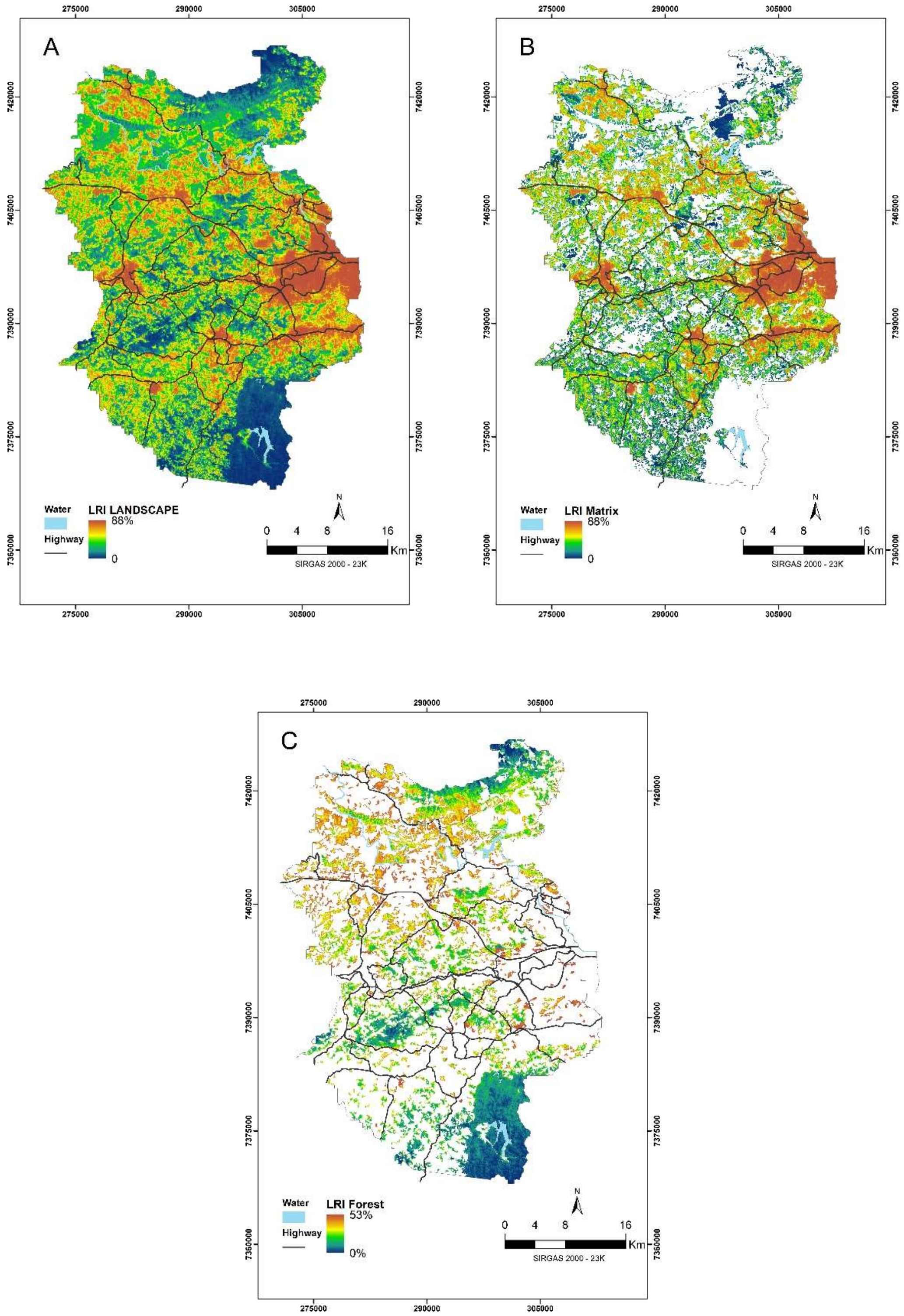


Fig. 5 - LRI% spatialized through the studied area (Fig. 5A), without the forest patches (Fig. 5B), and only inside these patches (Fig. 5C)..

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).

Considering 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, representing 92% and 51% of their respective total areas.

Table 2 also indicated 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.

Table 2 – The LULC and resistance classes of the study area, located in GBBR-SP, Brazil.

LULC Class	Resistance 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

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).

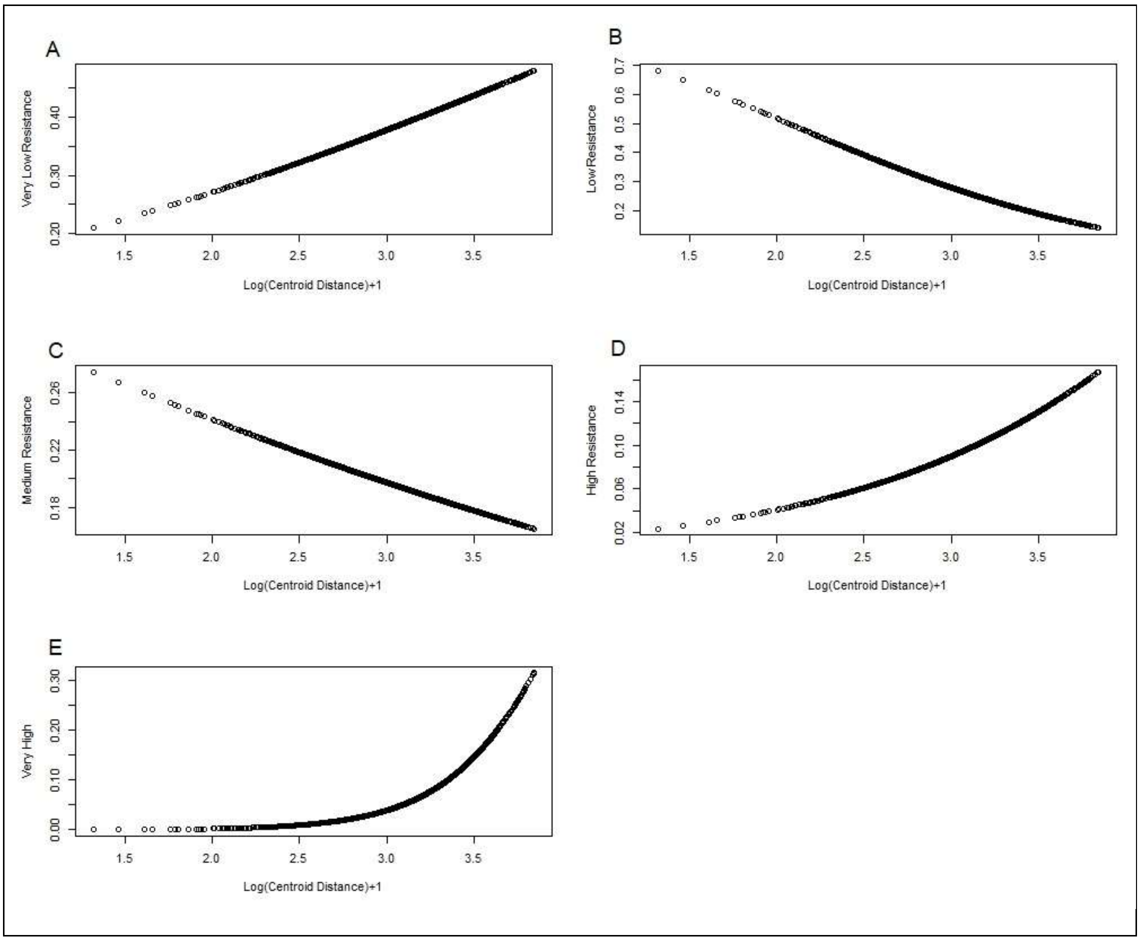


Fig.6 - Binomial regression Generalized Linear Model (GLM) for LRI resistance classes, depending on forest patches' distance from their centroids of the studied landscape, in the GBBR-SP, Brazil.

The frequency of high and very high resistance classes increased with the distancing from the patch’s centroids (Fig. 6D/E), while the low and medium-class frequencies decreased (Fig. 6 B/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.

3.4 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 (Equations 3 and 4).

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 their intrinsical variability, without requiring biologic information from species, as proposed by other approaches used to evaluate functional connectivity. Thus, through LRI, we decrease the subjectivity, which characterized some approaches based on focal species such as birds or mammals.

For example, Ribeiro et al. (2020), to define functional connectivity in an urbanized landscape (in the Atlantic Forest Biome), choose a bird species as a reference, using 100 m as the maximum value for dispersal distance. A value that was defined according to the literature as proposed by other studies based on graph theory. In anthropogenic landscape changes often characterized by habitat loss and reduced matrix quality, how the animal movements change in habitat open is not a well-known question (Da Silveira et al., 2016).

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.

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 concentering the forest patches showed the lowest value (Fig. 5C).

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

According to de Castro et al. (2018) and Dong et al. (2018), traditionally, NDVI has differentiated land use/land cover (LULC), including agriculture (Remelgado et al., 2018), pasture (Rickbeil et al., 2018), 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, Rickbeil et al., 2017, Remelgado et al., 2018, Remelgao, Wegmann, and Safi, 2019, Remelgado, Safi, and Wegmann, 2020).

Some studies have shown that animals moving in the landscape respond to environmental changes, mainly influenced by vegetation (Remegaldo, Wegamann, and Safi, 2019, Da Silveira et al., 2016, Brown et al., 2017), 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, Wallis, and Codling, 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 and 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 (Pawar et al., 2016, Gilbert et al., 2016).

Robinson et al. (2013) remembered 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, gradients thermal effects define how species select their habitat (Nowakowski et al., 2016).

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, Epps, and Brashares, 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 and Mallarach, 2005) or barriers that affect intra behavior species-specific (Berger-Tal and 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 (Guetté et al., 2018, Davies and Smyths, 2018, Gaston and Holt, 2018). In this context, the nighttime reflectance supports the identification of modified environments (Levin and Zhang, 2017), considering a positive relationship among the anthropized and reflectance levels with resistance to functional forest connectivity (Fig. 3C and Fig. 5).

This way, our criteria represented the landscape attributes such as the LULC and indicators of anthropogenic disturbance (Wasserman et al., 2010, Neumann et al., 2015, Mateo-Sánchez et al., 2015, Krishnamurthy et al., 2016, Milanesi et al., 2017). 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, Lewis, and Landguth, 2014, Krishnamurthy et al., 2016). Thus, spatial correlations are fundamental to infer the dispersion capacity of species in the environment (Bajaru et al., 2020).

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 micro-habitats, 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 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 (König et al., 2020, Chapron et al., 2014, Ceia-Hasse et al., 2017, Loveridge et al. 2017, Ducci et al., 2015, Bajaru et al. 2020). 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 (Poniatowski et al., 2016, Lindenmayer et al., 2020).

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 (Salgueiro et al., 2021, Kurz et al., 2014).

Thus, the proximity to the forest patches was one of the decisive factors for 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 influencing the demographic rates of the regenerative component and which will affect biodiversity conservation (Salami et al., 2014, Arroyo-Rodriguez 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, Almeida, and Almeida, 2010).

3.5 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.

REFERENCES

Abrahms, B., S. C.; Sawyer, N. R.; Jordan, J. W. et al. Does wildlife resource selection accurately inform corridor conservation? **Journal of Applied Ecology**, v. 54, p. 412–422, 2017. https://doi.org/10.1111/1365-2664.12714.

Alagador, D.; Triviño, M.; Cerdeira, J. O. et al. Linking like with like: optimising connectivity between environmentally-similar habitats. **Landscape Ecology**, v. 27, p. 291–301, 2012. https://doi.org/10.1007/s10980-012-9704-9

Almeida, M.; Almeida, A.; and Almeida, M. **Reeducação psiconeurológica**. 1ª Ed. Biblioteca 24 horas. São Paulo, 384p. 2010.

Alston, J. M.; Joyce, J. M.; Merkle, J. A.; et al. Temperature shapes movement and habitat selection by a heat-sensitive ungulate. **Landscape Ecology**, v. 35, p. 1961–1973, 2020. https://doi.org/10.1007/s10980-020-01072-y.

Arroyo-Rodríguez, V.; Melo, F.; Martinez-Ramos, M.; Bongers, F. et al. Multiple successional pathways in human-modified tropical landscapes: New insights from forest succession, forest fragmentation and landscape ecology research. **Biological Reviews**, v. 92, n. 1, p. 326–340, 2017. https://doi.org/10.1111/brv.12231.

Baguette, M.; Blanchet, S.; Legrand, D.; et al. Individual dispersal, landscape connectivity and ecological networks. **Biological Reviews,** v. 88, n. 2, p. 310–326, 2013. https://doi.org/10.1111/brv.12000.

Bailey, J.; Wallis, J.; and Codling, E. Navigational efficiency in a biased and correlated random walk model of individual animal movement. **Ecology**, v. 99, n. 1, p. 217-223, 2018. https://doi.org/10.1002/ecy.2076.

Bajaru, S.; Pal, S.; Prabhu, M.; et al. A multi-species occupancy modeling approach to access the impacts of land use and land cover on terrestrial vertebrates in the Mumbai Metropolitan Region (MMR), Western Ghats, India. **Plos One**, v. 15, n. 10, e0240989, 2020. https://doi.org/10.1371/journal.pone.0240989.

Barsi, J.; Barker, J. L.; and Schott, J. R. An Atmospheric Correction Parameter Calculator for a Single Thermal Band Earth-Sensing Instrument. " IGARSS 2003. **IEEE International Geoscience and Remote Sensing Symposium**. Proceedings (IEEE Cat. No.03CH37477), Toulouse, v. 5, p. 3014-3016, 2003. https://doi:10.1109/IGARSS.2003.1294665.

Belote, R. T.; Dietz, M. S.; McRae, B. H.; et al. Theobald DM, McClure ML, Irwin GH, et al. Identifying corridors among large protected areas in the United States. **PLoS ONE,** v. 11, n. 4, e0154223, 2016. https://doi.org/10.1371/journal.pone.0154223.

Benza, M.; Weeks, J. R.; Stow, D. A.; et al. A pattern-based definition of urban context using remote sensing and GIS. **Remote Sensing of Environment**, v. 183, p. 250-264, 2016. https://doi.org/10.1016/j.rse.2016.06.011.

Berger-Tal, O.; and Saltz, D. Invisible barriers: anthropogenic impacts on inter- and intra-specific interactions as drivers of landscape-independent fragmentation. **Philos Trans R Soc Lond B Biol Sci.**, v. 374, n. 1781, e20180049, 2019. https://doi.org/ 10.1098/rstb.2018.0049.

Bonthoux, S.; Lefèvre, S.; Herrault, P. A. et al. Spatial and Temporal Dependency of NDVI Satellite Imagery in Predicting Bird Diversity over France. **Remote Sens.**, v. 10, n. 7, 1136, 2018. https://doi.org/10.3390/rs10071136.

Breckheimer, I.; Haddad, N.; Morris, W. et al. Defining and evaluating the umbrella species concept for conserving and restoring landscape connectivity.

Conservation Biology, v. 28, p.1584–1593, 2014. https://doi.org/10.1111/cobi.12362.

Broders, H. G.; Coombs, A. B.; and McCarron, J. R. Ecothermic responses of moose (Alces alces) to thermoregulatory stress on mainland Nova Scotia. **Alces: A Journal Devoted to the Biology and Management of Moose,** v. 48, p. 53–61, 2012 .

Brose, U.;, Dunne, J. A.; Montoya, J. M.; et al. Climate change in size-structured ecosystems. **Phil. Trans. of the Royal Society B.**, v. 367, p. 2903-2912, 2012. http://doi.org/10.1098/rstb.2012.0232.

Brown, J. H.; Gillooly, J. F.; Allen, A. P.; et al. Toward a Metabolic Theory of Ecology. **Ecology Society of America**, v. 85, n. 7, p. 1771-1789, 2004. https://doi.org/10.1890/03-9000.

Brown, L. M.; Fuda, R. K.; Schtickzelle, N.; et al. Using animal movement behavior to categorize land cover and predict consequences for connectivity and patch residence times. **Landscape Ecology**, v. 32, p. 1657–1670, 2017. https://doi.org/10.1007/s10980-017-0533-8.

Brown, L. M., R. K.; Fuda, N.; Schtickzelle, H.; et al. Using animal movement behavior to categorize land cover and predict consequences for connectivity and patch residence times. **Landscape Ecology,** v. 32, p. 1657–1670, 2017. https://doi.org/10.1007/s10980-017-0533-8.

Byrne, B. M. **Structural equation modeling with AMOS: basic concepts, applications and programming**, 2ª edition. Routledge, 460p. 2016.

Ceia-Hasse, A.; Borda-de-água, L.; Grilo, C.; et al. Global exposure of carnivores to roads. **Global Ecology and Biogeography**, v. 26, n. 5, p. 592-600, 2017. https://doi.org/10.1111/geb.12564.

Chapron G.; Kaczensky, P.; Linnell, J. D. C.; et al. Recovery of large carnivores in Europe's modern human-dominated landscapes. **Science**, v. 346, p. 1517 – 1519, 2014. https://doi.org/10.1126/science.1257553.

Chazdon, R. L.; and Uriarte, M. Natural regeneration in the context of large-scale forest and landscape restoration in the tropics. **Biotropical**, v. 48, n. 6, p. 709-715, 2016. https://doi.org/10.1111/btp.12409.

Chen, Y.; Li, X.; Liu, X.; et al. Capturing the varying effects of driving forces over time for the simulation of urban growth by using survival analysis and cellular automata, **Landscape Urban Planning**, v. 152, p. 59-71, 2016. https://doi.org/10.1016/j.landurbplan.2016.03.011.

Choudhury, D.; Das, K.; and Das, A. Assessment of land use land cover changes and its impact on variations of land surface temperature in Asansol-Durgapur Development Region. **The Egyptian Journal of Remote Sensing and Space Science,** v. 22, n. 2, p. 203-218, 2018. https://doi.org/ 10.1016/j.ejrs.2018.05.004.

Clarke, A.; Taylor, K. I.; Devereux, B.; et al. From Perception to Conception: How meaningful objects are processed over time. **Cerebral Cortex**, v. 23, n. 1, p. 187–197, 2013. https://doi.org/10.1093/cercor/bhs002.

Cushman, S. A.; Landguth, E. L.; and Flather, C. H. Evaluating population connectivity for species of conservation concern in the American Great Plains. **Biodivers Conserv**., v. 22, p. 2583–2605, 2013. https://doi.org/10.1007/s10531-013-0541-1.

Cushman, S. A.; and Landguth, E. L. Scale dependent inference in landscape genetics. **Landscape Ecology**, v. 25, p. 967–979, 2010. https://doi.org/10.1007/s10980-010-9467-0.

Cushman, S. A.; Lewis, J. S.; and Landguth, E. L. Why Did the Bear Cross the Road? Comparing the Performance of Multiple Resistance Surfaces and Connectivity Modeling Methods. **Diversity**, v. 6, n. 4, p. 844-854, 2014. https://doi.org/10.3390/d6040844

Cushman, S. A.; Wasserman,T. N.; Landguth, E. L.; et al. Re-Evaluating Causal Modeling with Mantel Tests in Landscape Genetics. **Diversity**, v. 5, n. 1, p. 51-72, 2013. https://doi.org/10.3390/d5010051.

Da Silveira, N. S.; Niebuhr, B. B. S.; Muylaert, R. L.; et al. Effects of land cover on the movement of frugivorous birds in a heterogeneous landscape. **PLoS ONE**, v. 11, e0156688. https://doi.org/10.1371/journal.pone.0156688.

Dallabrida, J. P.; Silva, A. C.; Higuchi, P. L.; et al. Expansão da vegetação arbustivo-arbórea em áreas abertas alto-montanas adjacentes a fragmentos florestais, no Planalto Sul Catarinense. **Ciência Florestal**, v. 29, n. 1, p. 130-143, 2019.https://doi.org/10.5902/1980509825998.

Davies, T. W.; and Smyth, T. Why artificial light at night should be a focus for global change research in the 21st century. **Global Change Biology**, v. 2, p. 872–882, 2018. https://doi.org/10.1111/gcb.13927.

de Castro, A.; Six, J.; Plant, R.; et al. Mapping crop calendar events and phenology-related metrics at the parcel level by Object-Based Image Analysis (OBIA) of MODIS-NDVI time-series: a Case Study in Central California. **Remote Sens**., v. 10, 1745, 2018. https://doi.org/10.3390/rs10111745.

Dell. A. I.; Pawar, S.; and Savage, V. M. Temperature dependence of trophic interactions are driven by asymmetry of species responses and foraging strategy. **Journal of Animal Ecology**, v. 83, n. 1, p. 70-84, 2013. https://doi.org/10.1111/1365-2656.12081.

DeLong, J. P. Experimental demonstration of a 'rate-size' trade-off governing body size optimization. **Evolutionary Ecology Research**, v. 14, p. 343-352, 2012.

Deng, Y.; Wang, S.; Bai, X.; et al. Relationship among land surface temperature and LUCC, NDVI in typical karst area. **Scientific Reports**, v. 8, 641, 2018 https://doi.org/10.1038/s41598-017-19088-x.

Dong, J.; Xiao, X.; Menarguez, M. A.; et al. Mapping paddy rice planting area in northeastern Asia with Landsat 8 images, phenology-based algorithm and Google Earth Engine. **Remote Sens. Environ.**, v. 185, p. 142–154, 2016. https://doi.org/10.1016/j.rse.2016.02.016.

Du, H.; Wang, D.; Wang, Y.; et al. Influences of land cover types, meteorological conditions, anthropogenic heat and urban area on surface urban heat island in the Yangtze River Delta Urban Agglomeration. **Science of the Total Environmental**, v. 571, p. 461-470, 2016. https://doi.org/10.1016/j.scitotenv.2016.07.012.

Ducci, L.; Agnelli, P.; Di Febbraro, M.; et al. Different bat guilds perceive their habitat in different ways: a multiscale landscape approach for variable selection in species distribution modelling. **Landscape Ecology**, v. 30, p. 2147-2159, 2015. https://doi.org/10.1007/s10980-015-0237-x

Estel, S.; Kuemmerle, T.; Concepcion, P. C. A.; et al. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. **Remote Sensing Environmental**, v. 16, p. 312–325, 2015. https://doi.org/10.1016/j.rse.2015.03.028.

Feng, Y.; Luo, G.; Lu, L.; et al. Effects of land use change on landscape pattern of the Manas River watershed in Xinjiang, China. **Environ Earth Sci.,** v. 64, p. 2067–2077, 2011. https://doi.org/10.1007/s12665-011-1029-5.

Froidevaux, J. S. P.; Zellweger, F.; Bollmann, K.; et al. From field surveys to LiDAR: shining a light on how bats respond to forest structure. **Remote Sensing of Environment**, v. 175, p. 242–250, 2016.https://doi.org/10.1016/j.rse.2015.12.038.

Gama-Rodrigues, A. C.; Sales, M. V. S.; Silva, P. S. D.; et al. An exploratory analysis of phosphorus transformations in tropical soils using structural equation modeling. **Biogeochemistry**, v. 118, p. 453–469, 2014. https://doi.org/10.1007/s10533-013-9946-x.

Gaston, K. J.; and Holt, L. A. Nature, extent and ecological implications of night-time light from road vehicles. **The Journal of Applied Ecology**, v. 55, p. 2296–2307, 2018. https://doi.org/10.1111/1365-2664.13157.

Gaur A.; Eichenbaum M. K.; and Simonovic S.P. Analysis and modelling of surface Urban Heat Island in 20 Canadian cities under climate and land-cover change. **J Environ Manage**. V. 206, p. 145-157, 2018. https://doi:10.1016/j.jenvman.2017.10.002.

Gilbert, J. P.; Chelini, M. C.; Rosenthal, M. F.; et al., Crossing regimes of temperature dependence in animal movement. **Global Change Biology,** v. 22, n. 5, p. 1722-1736, 2016. https://doi.org/10.1111/gcb.13245.

Gitelson, A.; Peng, Y.; and Huemmrich, K. F. Relationship between fraction of radiation absorbed by photosynthesizing maize and soybean canopies and NDVI from remotely sensed data taken at close range and from MODIS 250 m resolution data. **Remote Sensing of Environment**, v. 147, p. 108-120, 2014. https://doi.org/10.1016/j.rse.2014.02.014.

Gomez-Gimenez, M.; Jong, R.; Peruta, R. D.; et al. Determination of grassland use intensity based on multi-temporal remote sensing data and ecological indicators. **Remote Sensing of Environment**, v. 198(C), p. 126-139, 2017. https://doi.org/10.1016/j.rse.2017.06.003.

Grace, J. B.; Anderson, T. M.; Olff, H.; et al. On the specification of structural equation models for ecological systems. **Ecological monographs**, v. 80, n. 1, p. 67-87, 2010. https://doi.org/10.1890/09-0464.1.

Grossmann, K.; Frankenberg, C.; Magney, T. S.; et al. PhotoSpec: A new instrument to measure spatially distributed red and far-red Solar-Induced Chlorophyll Fluorescence. **Remote Sensing of Environment**, v. 216, p. 311-327, 2018. https://doi.org/10.1016/j.rse.2018.07.002.

Gruber, B.; and Adamack, A. T. Landgenreport: A new r function to simplify landscape genetic analysis using resistance surface layers. **Molecular Ecology Resources**, v. 15, n. 5, p. 1172–1178, 2015. https://doi.org/10.1111/1755-0998.12381.

Guetté, A.; Godet, L.; Juigner, M. et al. Worldwide increase in Artificial Light At Night around protected areas and within biodiversity hotspots. **Biological Conservation**, v. 223, p. 97–103, 2018. https://doi.org/10.1016/j.biocon.2018.04.018.

Guha, S.; Govil, H.; Dey, A.; et al. Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy. **European Journal of Remote Sensing**, v. 5, p. 667-678, 2018. https://doi.org/10.1080/22797254.2018.1474494.

Hair, J. F.; Black, W. C.; Babin, B. J.; et al. **Análise Multivariada de Dados**. Porto Alegre: Bookman, 6 ª ed, 688p. 2009.

Hanks, E. M.; Hooten, M. B.; and Alldredge, M. W. Continuous-time discrete-space models for animal movement. **Annals of Applied Statistics**, v. 9, n. 1, p. 145-165, 2015. https://doi.org/10.1214/14-AOAS803.

Hoagland, S. J.; Beier, P.; and Lee, D. Using MODIS NDVI phenoclasses and phenoclusters to characterize wildlife habitat: Mexican spotted owl as a case study. **Forest Ecology and Management**, v. 412, p. 80-93, 2018. https://doi.org/10.1016/j.foreco.2017.12.017.

Hooten, M. B.; Johnson, D. S.; Hanks, E. M.; et al. Agent-based inference for animal movement and selection. **J. Agric. Biol. Environ. Stat**, v. 15, p. 523–538, 2010. https://doi.org/10.1007/s13253-010-0038-2.

Huang, Q.; Yang, X.; Gao., B.; et al. Application of DMSP/OLS Nighttime Light Images: A Meta-Analysis and a Systematic Literature Review. **Remote Sensing**, v. 6, n. 8, p. 6844-6866, 2014. https://doi.org/10.3390/rs6086844.

IBGE – Instituto Brasileiro de Geografia e Estatística. **Mapa de Vegetação do Brasil**. Available in https://geoftp.ibge.gov.br/informacoes_ambientais/vegetacao/mapas/brasil/vegetacao. pdf. Accessed on march, 2021.

IBGE – Instituto Brasileiro de Geografia e Estatística. **São Paulo/SP**. Available in https://cidades.ibge.gov.br/brasil/sp/sao-paulo/panorama. Accessed on march, 2021.

Ito, T. Y.; Sakamoto, S.; Lhagvasuren, B.; et al. Winter habitat of Mongolian gazelles in areas of southern Mongolia under new railroad construction: An estimation of interannual changes in suitable habitats. **Mammalian Biology**, v. 93, p. 13-20, 2018. https://doi.org/10.1016/j.mambio.2018.07.006.

Johnson, H. E.; Gustine, D. D.; Golden, T. S.; et al. NDVI exhibits mixed success in predicting spatiotemporal variation in caribou summer forage quality and quantity. **Ecosphere**, v. 9, n. 10, p. 1-19, 2018. https://doi.org/10.1002/ecs2.2461.

Kaplan, D., **Structural equation modeling: foundations and extensions**. Thousand Oaks: Sage Publications, 272p. 2008.

Keenleyside, K. A; Dudley, N.; Cairns, S.; et al. **Ecological restoration for protected areas: principles, guidelines and best practices**. IUCN, 2012.

König, H. J.; Kiffner, C.; Kramer-Schadt, S.; et al. Human – wildlife coexistence in a changing world. **Conservation Biology**, v. 34, n. 4, p. 786-794, 2020. https://doi.org/10.1111/cobi.13513.

Krishnamurthy, R.; Cushman, S. A.; Sarkar, M. S.; et al. Multi-scale prediction of landscape resistance for tiger dispersal in central India. **Landscape Ecology**, v. 31, p. 1355–1368, 2016. https://doi.org/10.1007/s10980-016-0363-0.

Krosby, M.; Breckheimer, I.; John Pierce, D.; et al. Focal species and landscape "naturalness" corridor models offer complementary approaches for connectivity conservation planning. **Landscape Ecology**, v. 30, p. 2121–2132, 2015. https://doi.org/10.1007/s10980-015-0235-z.

Kurz, D. J.; Nowakowski, A. J.; and Tingley, M. W. Forest-land use complementarity modifies community structure of a tropical herpetofauna. **Biological Conservation**, v. 170, p. 246-255, 2014. https://doi.org/10.1016/j.biocon.2013..12.027.

Levin, N.; and Zhang, Q. A global analysis of factors controlling VIIRS nighttime light levels from densely populated areas. **Remote Sensing of Environment**, v. 190, p. 366-382, 2017. https://doi.org/10.1016/j.rse.2017.01.006.

Lin, B. B.; Egerer, M. H.; Liere, H.; et al. Local- and landscape-scale land cover affects microclimate and water use in urban gardens. **Science of the Total Environment**, v. 610/611, p. 570-575, 2018. https://doi.org/10.1016/j.scitotenv.2017.08.091.

Lindenmayer, D. B.; Blanchard, W.; Foster, C. N.; et al. Habitat amount versus connectivity: an empirical study of bird responses. **Biological Conservation**, v. 241,108377, 2020. https://doi.org/10.1016/j. biocon.2019.108377.

Liu, C.; Newell, G.; White, M.; et al. Identifying wildlife corridors for the restoration of regional habitat connectivity: A multispecies approach and comparison of resistance surfaces. **PLoS ONE**, v. 13, n. 11, e0206071, 2018. https://doi.org/10.1371/journal.pone.0206071.

Loveridge, A. J.; Valeix, M.; Elliot, N. B.; et al. The landscape of anthropogenic mortality: how African lions respond to spatial variation in risk. **Journal of Apllied Ecology**, v. 54, n. 3, p. 815-825, 2016. https://doi.org/10.1111/1365-2664.12794.

Luhring, T. M.; and DeLong, J. P. Scaling from Metabolism to Population Growth Rate to Understand How Acclimation Temperature Alters Thermal Performance. **Integrative and Comparative Biology**, v. 57, n. 1, p. 103–111, 2017. https://doi.org/10.1093/icb/icx041.

Marulli, J.; and Mallarach, J. M. A GIS methodology for assessing ecological connectivity: application to the Barcelona Metropolitan Area. **Landscape and Urban Planning**, v. 71, p. 243-262, 2005. https:// doi.org/10.1016/j.landurbplan.2004.03.007.

Mateo-Sánchez, M. C.; Balkenhol, N.; Cushman, S.; et al. A comparative framework to infer landscape effects on population genetic structure: are habitat suitability models effective in explaining gene flow? **Landscape Ecology**, v. 30, p. 1405–1420, 2015. https://doi.org/10.1007/s10980-015-0194-4.

McCann, N. P.; Moen, R. A.; Windels, S. K.; et al. Bed sites as thermal refuges for a cold-adapted ungulate in summer. **Wildl Biol**., v. 22, p. 228–237, 2016. https://doi.org/10.2981/wlb.00216.

Melin, M.; Matala, J.; Mehätalo, L.; et al. Ecological dimensions of airborne laser scanning - analyzing the role of forest structure in moose habitat use within a year. **Remote Sensing of Environment**, v. 173, p. 238–247, 2016. https://doi.org/10.1016/j.rse.2015.07.025.

Milanesi, P.; Holderegger, R.; Bollmann, K.; et al. Three-dimensional habitat structure and landscape genetics: a step forward in estimating functional connectivity. **Ecology**, v. 98, n. 2, p. 393-402, 2017. https://doi.org/10.1002/ecy.1645.

Mills, E. C.; Poulsen, J. R.; Fay, J. M.; et al., Forest elephant movement and habitat use in a tropical forest-grassland mosaic in Gabon. **PLoS ONE**, v. 13, e0199387, 2018. https://doi.org/10.1371/journal.pone.0199387.

Ministério do Meio Ambiente (MMA). **Áreas prioritárias para conservação da biodiversidade brasileira.** Available in http://areasprioritarias.mma.gov.br/1-atualizacao-das-areas-prioritarias. Accessed on March 8, 2021.

Moraes, A. M.; Ruiz-Miranda, C. R.; Galetti, P. M.; et al. Landscape resistance influences effective dispersal of endangered golden lion tamarins within the Atlantic Forest. **Biological Conservation**, v. 224, p. 178-187, 2018. https://doi.org/10.1016/j.biocon.2018.05.023.

Mörtberg, U.; Haas, J.; Zetterberg, A.; et al. Urban ecosystems and sustainable urban development—analysing and assessing interacting systems in the Stockholm region. **Urban Ecosyst**., v. 16, p. 763–782, 2013. https://doi.org/10.1007/s11252-012-0270-3.

Nandy, S.; Singh, R.; Ghosh, S.; et al. Neural network-based modelling for forest biomass assessment. **Carbon Management**, v. 8, n. 4, p. 305-3017, 2017. http://dx.doi.org/10.1080/17583004.2017.1357402.

Nascimento-Júnior, L. Urbanização e cidade dispersa: implicações da produção do espaço urbano no Brasil, em Moçambique e na Austrália. **GEOUSP Espaço E Tempo (Online)**, v. 21, n. 2, p. 550-569, 2017. https://doi.org/10.11606/issn.2179-0892.geousp.2017.125392.

Neumann, J. E.; Price, J.; Chinowsky, P.; et al. Climate change risks to US infrastructure: impacts on roads, bridges, coastal development, and urban drainage. **Climatic Change**, v. 131, p. 97–109, 2015. https://doi.org/10.1007/s10584-013-1037-4

Nimmo, D. G.; Mac Nally, R.; Cunningham, S. C.; et al. Vive la résistance: reviving resistance for 21st century conservation. **Trends in Ecology & Evolution**, v. 30, n. 9, p. 516-523, 2015. https://doi.org/10.1016/j.tree.2015.07.008.

Niu, X.; Tang, J.; Wang, S.; et al. Impact of future land use and land cover change on temperature projections over East Asia. **Clim. Dyn.,** v. 52, p. 6475–6490, 2019. https://doi.org/10.1007/s00382-018-4525-4

Nowakowski, A. J.; Wating, J. L.; Whitfield, S. M.; et al. Tropical amphibians in shifting thermal landscapes under land-use and climate change. **Conservation Biology**, v. 31, n. 1, p. 96-105, 2016. https://doi.org/10.1111/cobi.12769.

Ojima, R. Dimensões da urbanização dispersa e proposta metodológica para estudos comparativos: uma abordagem socioespacial em aglomerações urbanas brasileiras. **R. Brasileira de Estudos de População**, v. 24, n. 2, p. 277-300, 2007. https://doi.org/10.1590/S0102-30982007000200007.

Olyer-McCance, S. J.; Fedy, B. C.; and Landguth, E. L. Sample design effects in landscape genetics. **Conserv. Genet**., v. 14, p. 275-285, 2013. https://doi.org/10.1007/s10592-012-0415-1.

Osmond, M. M.; Barbour, M. A.; Bernhardt, J. R.; et al. Warming-induced changes to body size stabilize consumer-resource dynamics. **American Naturalist**., v. 189, n. 6, p. 718-725, 2017. https://doi.org/10.1086/691387.

Pawar, S.; Dell, A. I.; Savage, V. M.; et al. Real versus artificial variation in the thermal sensitivity of biological traits. **American Naturalist**., v. 187, n. 2, p. 41-52, 2016. https://doi.org/10.1086/684590.

Peterman, W. E. Resistancega: An R package for the optimization of resistance surfaces using genetic algorithms. **Methods in Ecology and Evolution**, v. 9, n. 6, p. 1638–1647, 2018. https://doi.org/10.1111/2041-210X.12984.

Peterman, W. E.; Connette, G. M.; Semlitsch, R. D.; et al. Ecological resistance surfaces predict fine-scale genetic differentiation in a terrestrial woodland salamander. **Molecular Ecology,** v. 23, p. 2402–2413, 2014. https://doi.org/10.1111/mec.12747.

Peterman, W. E.; Winiarski, K. J.; Moore, C. E.; et al. A comparison of popular approaches to optimize landscape resistance surfaces. **Landscape Ecology**, v. 34, n. 9, p. 2197–2208, 2019. https://doi.org/10.1007/s10980-019-00870-3.

Pettorelli, N.; Owen, H. J. F.; and Ducan, C. How do we want Satellite Remote Sennsing to support biodiversity conservation globally? **Methods in Ecology and Evolution**, v. 7, n. 6, p. 656-665, 2016. https://doi.org/10.1111/2041-210X.12545.

Pettorelli, N.; Ryan, S. J.; Mueller, T.; et al. The Normalized Difference Vegetation Index (NDVI): Unforeseen successes in animal ecology. **Climate Reaserch**, v. 46, p. 15-27, 2011. https://doi.org/10.3354/cr00936.

Poniatowski, D.; Loffler, F.; Stuhldreher, G.; et al. Functional connectivity as an indicator for patch occupancy in grassland specialists. **Ecological Indicator**, v. 67, p. 735–742, 2016. https://doi.org/10.1016/j. ecolind.2016.03.047.

Reding, D. M.; Cushman, S.; Gosselink, T. E.; et al. Linking movement behavior and fin-scale genetic structure to model landscape connectivity for bobcats (Lynx rufus). **Landscape Ecology**, v. 28, p. 471–486, 2013. https://doi.org/10.1007/s10980-012-9844-y.

Remelgado, R. B.; Leutner, B.; Safi, K.; et al. Linking animal movement and remote sensing – mapping resource suitability from a remote sensing persperctive. **Remote Sensing in Ecology and Conservation**, v. 4, p. 211–244, 2018. https://doi.org/10.1002/rse2.70.

Remelgado, R. B.; Wegmann, M.; and Safi, K. From ecology to remote sensing: using animald to map land cover. **Remote Sensing in Ecology and Conservation**, v. 6, n. 1, p. 93-104, 2019. https://doi.org/10.1002/rse2.126.

Remelgado, R., B.; Wegmann, M.; and Safi, K. Rsmove – An R package to brigde remote sensing and movement ecology. **Methods in Ecology and Evolution**, v. 10, n. 8, p. 1212-1221, 2019. https://doi.org/10.1111/2041-210x.13199.

Ribeiro, M. P.; Mello, K.; and Valente, R. A. Avaliação da estrutura da paisagem visando à conservação da biodiversidade em paisagem urbanizada. **Ciência Florestal**, v. 30, n. 3, p. 819-834, 2020. https://doi.org/10.5902/1980509837683.

Rickbeil, G. J. M.; Hermosilla, T.; Coops, N. C.; et al. Barren-ground caribou (Rangifer tarandus groenlandicus) behaviour after recent fire events; integrating caribou telemetry data with Landsat fire detection techniques. **Glob. Change Biol.**, v. 23, p. 1036–1047, 2017. https://doi.org/10.1111/gcb.13456.

Rigden, A. J.; and Li, D. Attribution of surface temperature anomalies induced by land use and land cover changes. **Attribution of temperature anomalies**, v. 44, n. 13, p. 6814-6822, 2017. https://doi.org/10.1002/2017GL073811.

Robinson, N. M.; Leonard, S. W. J.; Ritchie, E. G.; et al. Review: Refuges for fauna in fire-prone landscapes: their ecological function and importance. **Journal of Applied Ecology**, v. 50, n. 6, p. 1321-1329, 2013. https://doi.org/10.1111/1365-2664.12153.

Rousta, I.; Sarif, M. O.; Gupta, R. D.; et al. Spatiotemporal Analysis of Land Use/Land Cover and Its Effects on Surface Urban Heat Island Using Landsat Data: A Case Study of Metropolitan City Tehran (1988–2018). **Sustainability**, v. 10, n. 12, p. 1-26, 2018. https://doi.org/10.3390/su10124433.

Row, J. R.; Knick, S. T.; Oyler-McCance, S. J.; et al. Developing approaches for linear mixed modeling in landscape genetics through landscape-directed dispersal simulations. **Ecology and Evolution**, v. 7, n. 11, p. 3751-3761, 2017. https://doi.org/10.1002/ece3.2825.

Rudnick, D.; Beier, P.; Cushman, S.; et al. The Role of Landscape Connectivity in Planning and Implementing Conservation and Restoration Priorities. **Issues in Ecology**, 2012.

Salami, B.; Higuchi, P. L.; Silva, A. C.; et al. Influência de variáveis ambientais na dinâmica do componente arbóreo em um fragmento de Floresta Ombrófila Mista em Lages, SC. **Scientia Forestalis**, v. 42, n. 102, p. 197-207, 2014. https://doi.org/10.5902/198050985081.

Salgueiro, P. A.; Valerio, F.; and Silva, C.; et al. Multispecies landscape functional connectivity enhances local bird species' diversity in a highly fragmented landscape. **Journal of Environmental Management**, v. 284, 112066, 2021. https://doi.org/10.1016/j.jenvman.2021.112066

Salt, J. L.; Bulit, C.; Zhang, W.; et al. Spatial extinction or persistence: landscape-temperature interactions perturb predator–prey dynamics. **Ecography**, v. 40, n. 10, p. 1177-1186, 2017. https://doi.org/10.1111/ecog.02378.

Santos, A. R.; Oliveira, F. S.; Silva, A. G.; et al. Spatial and temporal distribution of urban heat islands. **Science of the Total Environmental**, v. 605/606, p. 946–956, 2017. https://doi.org/10.1016/j.scitotenv.2017.05.275.

Sawyer, S. C.; Epps, C. W.; and Brashares, J. S. Placing linkages among fragmented habitats: do least-cost models reflect how animals use landscapes? **Journal Appl. Ecology**, v. 48, p. 668–678, 2011. https://doi.org/10.1111/j.1365-2664.2011.01970.x.

Shen, M.; Piao, S.; Chen, X.; et al. Strong impacts of daily minimum temperature on the green-up date and summer greenness of the Tibetan Plateau. **Global Change Biology**, v. 22, n. 9, 3057-3066, 2016. https://doi.org/10.1111/gcb.13301.

Shi, Y.; Huang, W.; Dong, Y.; et al. The influence of landscape's dynamics on the Oriental Migratory Locust habitat change based on the time-series satellite data. **Journal of Environmental Management**, v. 218, p. 280-290, 2018. https://doi.org/10.1016/j.jenvman.2018.04.028.

Shirk, A.; Languth, E. L.; and Cushman, S. A. A comparison of regression methods for model selection in individual-based landscape genetic analysisb. **Molecular Ecology Resources**, v. 18, n. 1, p. 55-67, 2018. https://doi.org/10.1111/1755-0998.12709.

Silva, J. S.; Silva, R. M.; and Santos, C. A. G. Spatiotemporal impact of land use/land cover changes on urban heat islands: A case study of Paço do Lumiar, Brazil. **Building and Environment**, v. 136, p. 279-292, 2018. https://doi.org/10.1016/j.buildenv.2018.03.041.

Smith, M. J.; Goodchild, M. F.; Longley, P. A.; et al. 2018. **Geospatial Analysis. A comprehensive guide to principles techniques and software tools**. 6º ed. Available in https://www.spatialanalysisonline.com/extractv6.pdf. Accessed in May 2020.

Spear, S. F.; and Storfer, A. Anthropogenic and natural disturbance lead to differing patterns of gene flow in the Rocky Mountain tailed frog, Ascaphus montanus. **Biological Conservation**, v. 143, n. 3, p. 778-786, 2010. https://doi.org/10.1016/j.biocon.2009.12.021.

Su, Y.; Chen, X.; Wang, C.; et al. A new method for extracting built-up urban areas using DMSP-OLS nighttime stable lights: a case study in the Pearl River Delta, southern China, **GIScience & Remote Sensing**, v. 52, n. 2, p. 218-238, 2015, https://doi.org/10.1080/15481603.2015.1007778.

Sunday, J. M.; Bates, A. E.; Kearney, M. R.; et al. Thermal-safety margins and the necessity of thermoregulatory behavior across latitude and elevation. **Proc Natl**

Acad Sci., v. 111, n. 15, p. 5610-5615, 2014. https://doi.org/10.1073/pnas.1316145111.

Theobald D. M.; Reed S. E.; Fields K.; et al. Connecting natural landscapes using a landscape perme-ability model to prioritize conservation activities in the United States. **Conserv Lett**., v. 5, p. 123–133, 2012. https://doi.org/10.1111/j.1755-263X.2011.00218.x.

Ullman, J. B. **Structural equation modeling**. In Tabachnick, B.G.& Fidell, L.S. (Eds.), Using multivariate statistics. Boston: Pearson, p. 653-771, 2006.

Union Nations Educations, Scientific and Cultural Organization (UNESCO). 2019. **Biosphere Reserves**. Available in https://en.unesco.org/biosphere. Accessed on November, 2019.

USGS. 2019. **Landsat Missions: Using the USGS Landsat8 Product**. U.S. Department of the Interior - U.S. Geological Survey. Available in https://www.usgs.gov/land-resources/nli/landsat/using-usgs-landsat-level-1-data-product. Accessed in September 2019.

Wasserman, T. N.; Cushman, S. A.; Schwartz, M. K.; et al. Spatial scaling and multi-model inference in landscape genetics: Martes americana in northern Idaho. **Landscape Ecology**, v. 25, p. 1601–1612, 2010. https://doi.org/10.1007/s10980-010-9525-7.

Weber, D.; Schaepman-Strub, G.; and Ecker, K.; Predicting habitat quality of protected dry grasslands using Landsat NDVI phenology. **Ecological Indicators,** v. 91, p. 447-460, 2018. https://doi.org/10.1016/j.ecolind.2018.03.081.

Wei, B.; Xie, Y.; Jia, X.; et al. Land use/land cover change and it's impacts on diurnal temperature range over the agricultural pastoral ecotone of Northern China. **Land Degradation & Development,** v. 29, n. 9, p. 3009–3020, 2018. https://doi.org/10.1002/ldr.3052.

Wilson, K.; Hanks, E. M.; and Johnson, D. Estimating animal utilization densities using continuous-time Markov chain models. **Methods in Ecology and Evolution**, v. 9, n. 5, p. 1232-1240, 2019. https://doi.org/10.1111/2041-210X.12967.

Winiarski, K. J.; Peterman, W.; and McGarigal, K. Evaluation of the R package 'resistancega': A promising approach towards the accurate optimization of landscape resistance surfaces. **Molecular Ecology Resources**, v. 20, n. 6, p. 1583-1596, 2020. https://doi.org/10.1111/1755-0998.13217.

Woodley, S. J. Ecological Integrity and Canada's National Parks. The George Wright Forum, v. 27, n. 2, p. 151-160, 2010. Avaliable in http://www.georgewright.org/272woodley.pdf. Accessed on March, 2020.

Zeller, K. A.; Creech, T. G.; Millette, K. L.; et al. Using simulations to evaluate Mantel-based methods for assessing landscape resistance to gene flow. **Ecology and Evolution**, v. 6, n. 12, p. 4115-4128, 2016. https://doi.org/10.1002/ece3.2154

Zeller, K.A.; McGarigal, K.; and Whiteley, A. R. Estimating landscape resistance to movement: a review. **Landscape Ecology,** v. 27, n. 6, p. 777–797, 2012. https://doi.org/10.1007/s10980-012-9737-0.

Zhang, L.; Peng, J.; Liu, Y.; et al. Coupling ecosystem services supply and human ecological demand to identify landscape ecological security pattern: A case study in Beijing–Tianjin–Hebei region, China. **Urban Ecosyst.,** v. 20, p. 701–714, 2017. https://doi.org/10.1007/s11252-016-0629-y.

Zhou, X.; and Chen, H. Impact of urbanization-related land use land cover changes and urban morphology changes on the urban heat island phenomenon. **Science of the Total Environmental**, v. 635, p. 1467-1476, 2018. https://doi.org/10.1016/j.scitotenv.2018.04.091.

4. CHAPTER 3

FUNCTIONAL CONNECTIVITY SUPPORTED BY FOREST CONSERVATION IN URBAN SPRAWL LANDSCAPE

ABSTRACT

The rapid transformation of natural environments is driven by urban sprawl for a growing human population, mainly characterized by peri-urbanization that threatens the conservation of important ecological species and processes. In this approach, the study's main objective was to identify priority areas for forest conservation, aiming at functional connectivity in a landscape under to urban sprawl. For this, we used the joint approach of Multicriteria Evaluation (MCE), literature review, and expert opinion. Thus, the selected criteria were proximity to forest fragments, Landscape Resistance Index (LRI), proximity to the drainage network, Topographic Wetness Index (TWI), and slope, aggregated through Weighted Linear Combination (WLC). Based on the results, the criteria's influence and importance were reflected in the values of 0-255 bytes range and associated with their priority levels. In the highest priority areas (37.3% of the landscape), values between 188 and 255 bytes were represented in 32% by proximity to forest fragments, 27% by the LRI, proximity to the drainage network amounted to 26%, TWI (8%), and slope (7%). The model supported our prioritization of areas for functional forest connectivity and brought the importance of our criteria set, controlling their respective influences. Thus, it can support planning for forest restoration and Payment for Ecosystem Services (PES) aimed at functional connectivity maintenance.

Keywords: Multicriteria Evaluation, Land-use/Land-cover, and Environmental Attributes.

4.1 INTRODUCTION

The urban sprawl process is a consequence of the growing population and has been causing a swift transformation of natural environments (Sekercioglu et al., 2015). On the other hand, this process drives peri-urbanization, an expressive characteristic of the ecosystem alterations.

According to Gibbs and Salmon (2015), more than 60% of terrestrial vegetation has been deforested or significantly modified through this process. Also, considering this urban sprawl tendency, UN (2019) estimated that 70% of the global population (about 6.3 billion) will be living in urban areas by 2050.

This way, urbanization transforms the forest landscapes through fragmentation and land-use/land-cover conversions, resulting in extensive metropolitan regions (Riad et al., 2020, Butsch and Heinkel, 2020, Simon et al., 2014), influencing the structural and functional forest connectivity and processes related, as species conservation.

Structural connectivity is related to the physical continuity among remnants, such as distances and corridors (Uezu et al., 2005). The functional considers the biological responses of species and estimates how easy it is for the individual to move through the landscape units (Goodwin, 2003). Our study considers this last connectivity since our present landscape scenario is well-marked by urban sprawl. Scenario composed of a non-forested matrix with many small forest patches scattered through the landscape and supporting the corridor for species movement (Matos et al., 2019).

In this scenario, biological processes are affected as individual dispersal, habitat colonization, and the structuring of population and metacommunities (Yabsley et al., 2016, Thiele et al., 2018, Tumas et al., 2018, Bajaru et al. 2020). Haddad et al. (2015) and Salgueiro et al. (2021) also mentioned the species association since they result from filtering habitat and landscape, increasingly dispersed and disconnected, making wildlife populations isolated in the remaining forest fragments.

The major challenge in landscapes under the sprawl process is forest conservation, defining priority habitats to support functional connectivity, especially when patches promote connectivity among Protected Areas (Ehlers-Smith et al., 2019, Coetzee, 2017).

Several studies have used a focal species to define these priority areas, thinking in designing the forest corridor (Costanza et al., 2020, Jenning et al., 2020, Meurant et al., 2020, Foster et al., 2017). However, urban sprawl has affected distinct species in different ways due to their intrinsic characteristics and resilience (Chambers et al., 2019).

In this sense, we focused on studies that used a model or simulation to identify the landscape characteristics, i.e., criteria, attributes, that influence the forest connectivity and support the identification or definition of ecological corridors (Auffret et al., 2017).

According to Vasudev et al. (2015), methods based on environmental criteria can introduce substantial variability in the evaluation process. Thus, Zeller et al. (2012) mentioned that several criteria support the connectivity analysis as relief shape, proximity among forest native remnants, drainage network, and urban areas.

Criteria representing resistance surfaces are also essential to support the functional connectivity since they bring landscape structure characteristics to the model (Rudnick et al.,2012; Cushman et al., 2014, Thiele et al., 2018).

In this way, the riparian zone is the main way of movement across matrixes with a greater level of resistance (Villalva et al., 2013; Carvalho et al., 2016). Still, they are wetlands and present dynamic characteristics and link the landscape in networks on a spatiotemporal scale that responds and adapt to anthropogenic disturbances (Bishop-Taylor et al., 2018, Allen, Gonzalles, and Parrott, 2020).

Topographic factors, in turn, play a limiting role in connectivity and dispersion, especially in steep terrain, as they make movement difficult even in the presence of preserved vegetation (Nali et al., 2020, Rio-Maior, et al., 2019, Hails et al., 2016, Torre et al., 2017). On the other hand, topographic heterogeneity harbors more diversified microclimates that increase the permeability of the landscape (Gaüzére et al., 2016). In this duality, the natural, historical characteristics that prevent the dispersal of species can often be more critical for connectivity than recent anthropogenic modification events (González-Serna et al., 2018).

Thus, the prioritization of areas involves criteria set representing characteristics that support the connectivity modeling.

The multicriteria evaluation (MCE) is a method for prioritizing areas already established for other areas of knowledge. It is a procedure that groups criteria with spatial distribution to obtain a final solution, supporting decision-making (Boroushaki, 2017). According to Valente et al. (2021), the differential of MCE is its ability to group criteria, considering the relative importance of criteria for the study's purpose.

Using distinct methods, MCE was employed for prioritization areas for landscape restoration (Li. et al. 2020, Valente et al., 2017, Lopes et al., 2020), identification of habitat for connectivity (Shanthala et al., 2016), determination of protected areas (Masoodi et al., 2016, Sumida and Valente, 2019) and sustainable urban sprawl (Shuaibu and Kara, 2019). These studies use a set of criteria and weights derived from expert knowledge in a spatial and participatory context (Wang et al., 2014, Malekmohammadi and Rahimi, 2014).

Esmail and Geneletti (2017) evaluated the use of different MCE methods applied to prioritize areas to nature conservation in 20 years (since 1996). They found a total of 86 studies with 24% related to conservation and landscape planning (e.g., Ferreti and Pomarico, 2013, Yang et al., 2019), and 21% to forest restoration and management (e.g., Valente and Vettorazzi, 2008, Orsi and Geneletti, 2010).

In these studies, considering the MCE method's ability and the hypothesis that we can support forest connectivity based on landscape characteristics, the study's main objective was to prioritize areas for forest conservation aiming at functional connectivity in a landscape subject to urban sprawl.

4.2 MATERIAL AND METHODS

4.2.1 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, 2021). 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 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 ecological corridor (MMA, 2021), considering that Atlantic Forest remnants cover 34.9% of its area (165099.25 ha) belongs to Ombrophilous Dense Forestry (IBGE, 2012). Some remnants belong to Protected Area 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).

Table 1. Main characteristics of the forest patches of the studied landscape in the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil.

Class	NP	Area	Forest patches metrics			
(ha)	(%)	(%)	Area (ha) Mean (SD)	Perim (m) Mean (SD)	Near (m) Mean (SD)	Shape Mean (SD)
< 5	92.4	5.9	0.36 (± 0.79)	277.90 (± 299.03)	17.80 (±42.46)	1.15 (± 0.24)
5 - 30	5.2	11.5	12.32 (±6.37)	2857.48 (±1301.65)	107.67 (± 162.66)	2.05 (±0.60)
30 - 75	1.3	11.0	47.00 (±13.57)	7814.90 (± 2366.13)	57.57 (± 98.93)	2.85 (±0.65)
75 - 170	0.6	11.2	105.98 (± 24.89	13933.64 (± 4035.25)	38.88 (±77.14)	3.38 (± 0.82)
170 - 300	0.3	10.4	244.71 (± 28.74)	26434.43 (± 6538.71)	21.56 (± 35.60)	4.40 (±0.95)
> 300	0.2	50.0	1436.24 (± 2689.73)	92797.11 (±107803.9)	0.00 (± 0.00)	6.50 (± 2.23)

Where: NP= Number of forest patches; Area - Habitat size; Perim – Habitat perimeter; Shape - Shape index; Near - Distance of the nearest neighbor edge; Mean - Mean value; and SD - Standard deviation value.

Other remnants are scattered through the matrix composed predominantly of vegetation in regeneration or 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).

We generated this map (having 90%-accuracy) through a supervised classification method (Maximum Likelihood algorithm) and digitalization of anthropized areas on the screen, based on the CBERS 4-orbital images (MUX multispectral sensor, 20 m-spatial resolution).

The anthropized areas include the low-density urban areas as well as the high-density. The first group is formed by small urban agglomerations or farms characterized by horizontal, dispersed, and polycentric growth. Thus, they were included in the analysis.

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

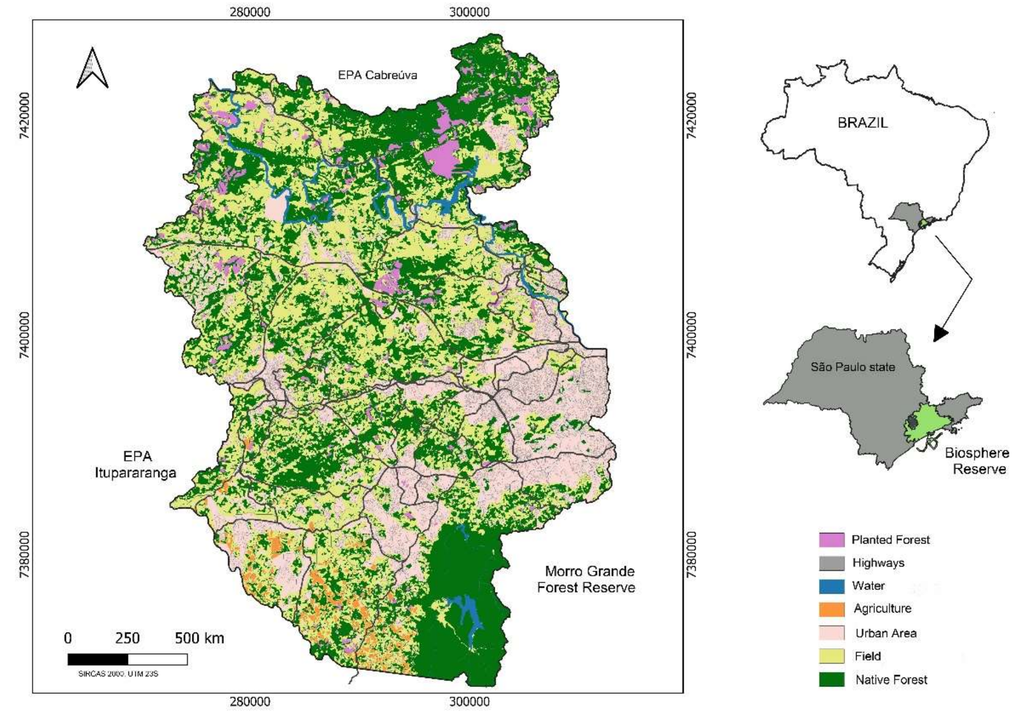


Fig. 1 - Land Use/Land Cover (LULC) and location of the study Landscape in the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil.

4.2.2 Conceptual Model

We generated the map of priority areas functional forest connectivity based on the following criteria that represent the landscape attributes: proximity to forest fragments, landscape resistance index, proximity to drainage network, topographic wetness index, and slope.

Based on the multicriteria evaluation (MCE) approach, the criteria selection considered the literature review and expert´s opinions. The Weighted Linear Combination method (WLC) supported their aggregation into a final map, following the previous steps of criteria normalization to a common scale (varying from 0-255 bytes) and defining their respective importance to our objective.

We classified the final maps in five classes of priorities for the sensitivity analysis and to evaluate the statistic correlation among the areas classified as the highest priority for forest connectivity and the location of forest fragments. Thus, criteria and priority maps in 255 bytes also supported some statistical analyses through samples (6448 points) extracted from them in a Geographic Information System environment.

The Dot Plot graphics permitted an evaluation of the histogram behavior (interval of variation, breaks, average value, etc.) of the maps and their values correlation. And we used cluster analysis to identify the LULC associated with the priority levels.

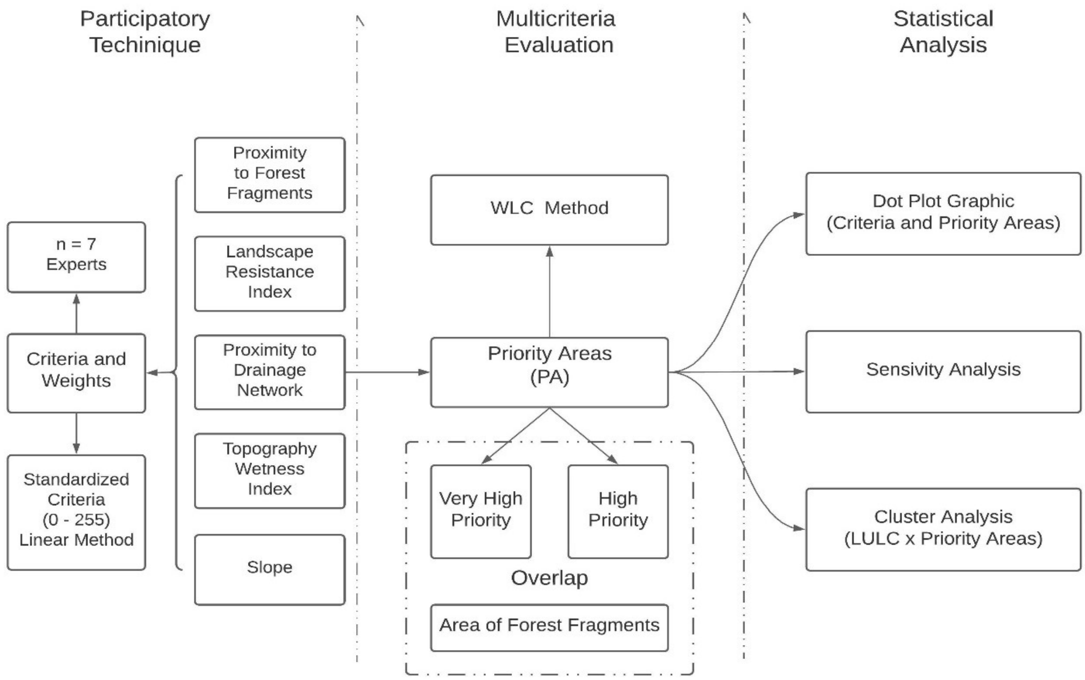


Fig. 2 – Conceptual model used to obtain the map of priority areas for the Green Belt Biosphere Reserve of São Paulo City (GBBR-SP), Brazil.

4.2.3 Criteria selection

The criteria represent the landscape attributes important for our study and fundamental in the decision-making process.

In our study, firstly, we defined the criteria based on a literature review from 2015 to 2021 through the platforms Scielo, Scopus, Web of Science, and Google Scholar. We defined a combination of search terms with sufficient comprehensiveness to maximize the finding of environmental criteria since they represented the integration of forest functional connectivity and conservation principles.

The most mentioned criteria, despite differences in nomenclatures, were related to forest cover pattern, topography, water resources, and land-use/land-cover (LULC) (Ayram et al., 2016, Curiel-Esparza et al., 2015, Fernández and Morales, 2016, Lakicev et al., 2014, Mello et al., 2018, Rincón, et al., 2019, Santos et al., 2018, Silva et al., 2017, Unda and Etter, 2019, and Vettorazzi and Valente, 2016).

After, we submitted these selected criteria to experts' evaluation in the context of the Participatory Technique approach (Pacetti et al., 2020). For this, we invited twelve experts to collaborate with the study. They represented Universities, Non-Governmental Organizations (NGOs), and managers of forest connectivity projects. According to

Camilo et al. (2015), few studies were based on expert opinion to assess the importance of conserving fragments and habitats.

Seven experts agreed to participate in the study. Thus, we shared the criteria with them through a google form, containing the project summary with the main objective of the research; the location of the study area and its land-use/land-cover map. Experts were free to agree with our criteria, delete, or add new criteria.

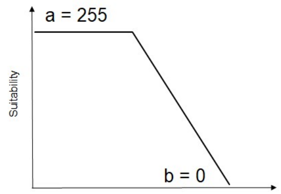
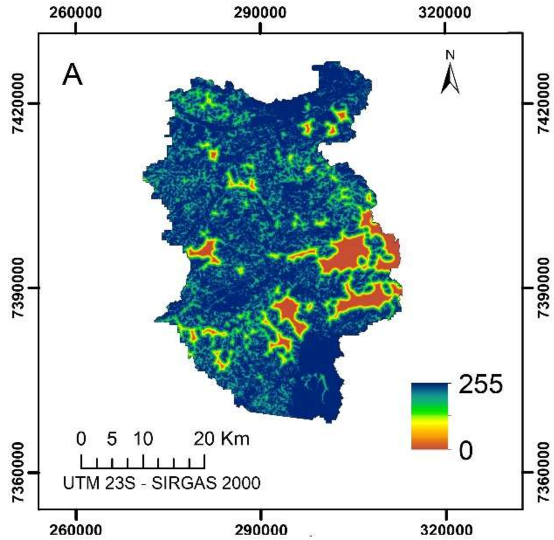
This way, we obtained the following criteria set, with the justification for their inclusion shown in Table 2:

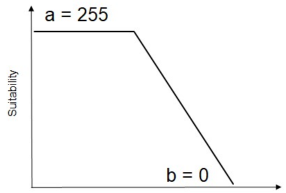
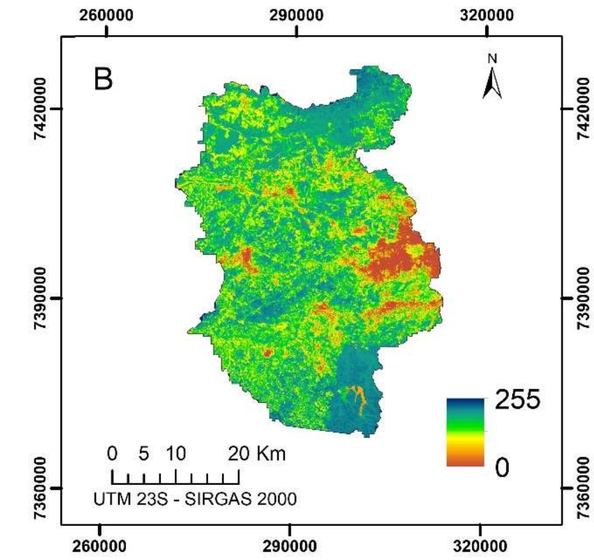
- Proximity to forest fragments: extracted from the land-use/land-cover map (Fig.1).
- Landscape Resistance Index: produced by Vanderley-Silva and Valente (2021b) through the Structural Equation Model (SEM), considering the attributes NDVIinv, Land Surface Temperature, and Nighttime Reflectance, which reflected the functional forest connectivity structure of our landscape.
- Proximity to the drainage network.
- Topographic Wetness Index (TWI); and
- Slope.

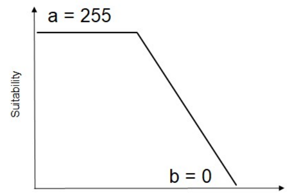
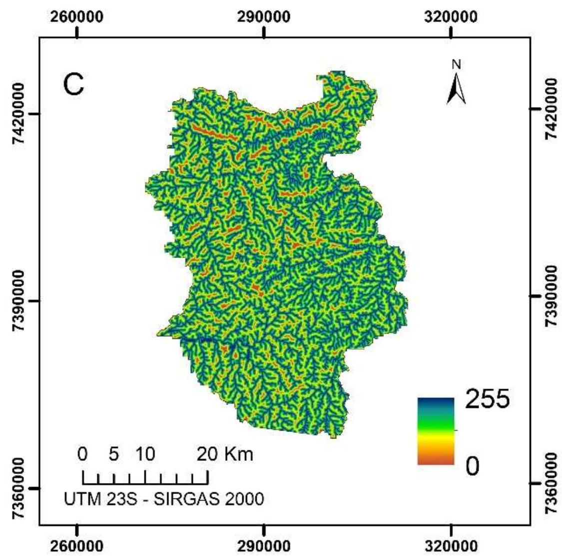
The last three criteria represented the physical and natural history characteristics of the landscape studied. These criteria were produced from the Digital Elevation Model (DEM) of the study area, which was produced from the Shuttle Radar Topography Mission (SRTM) model (https://earthexplorer.usgs.gov/). The 10-m contour lines were extracted from the SRTM model (30m-spatial resolution) and interpolated (nearest neighbor method) with a 20m-spatial resolution to the DEM integrated our geographic database. In the GIS environment, watershed and slope plug-ins were used to generate these criteria.

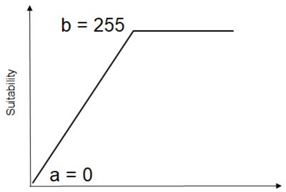
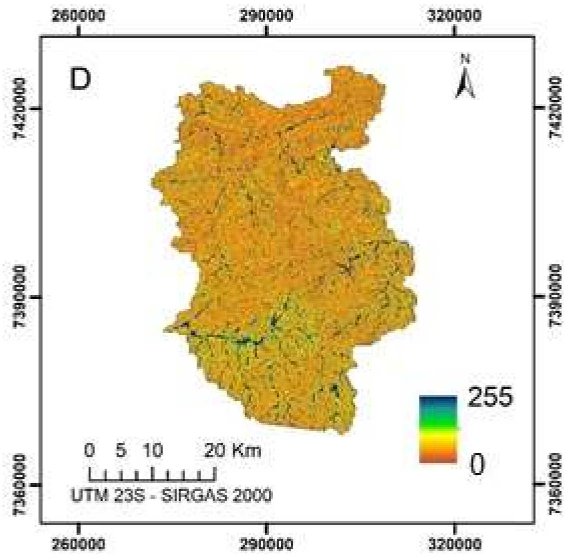
Table 2 also has the linear function used to criteria normalization to 0-255 bytes, respecting their importance to our study, i.e., maintaining a positive correlation between environmental attribute suitability and priority for forest functional connectivity. Thus, supporting the highest priority location close to forest fragments, drainage networks, areas of low resistance, regions with more significant moisture potential, and high slopes associated with the highest values (close to 255) on the standard scale. In this study, we also generated a constraints map containing water bodies, which are the areas where we cannot prioritize.

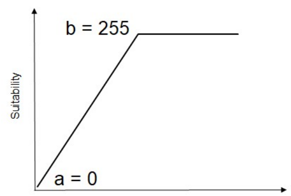
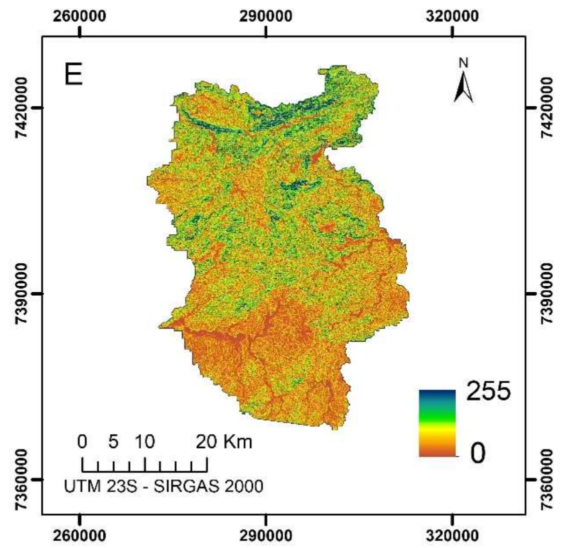
Table 2 – Criteria, defined in the context of Participatory Technique, for identifying priority areas for forest conservation, aiming at forest functional connectivity in the study area, located in GBBR-SP, Brazil.

Criteria	Justification	Values Originals/Standardization	Criteria maps
Proximity to Forest Fragments	Several studies emphasize the importance of forest fragments functioning as steps to maintain functional connectivity (Saura et al., 2013, Villard and Metzger, 2014, Piquer-Rodriguez, et al., 2015). Identifying priority forest patches to maintain connectivity and habitat quality enhances the potential for conservation as it delays collapse in areas subject to constant changes in land use and land cover (Albert et al., 2017). Because the probability of habitat colonization increases in landscapes with a more significant amount of forest cover (Scriven et al., 2019), the increase in distance between habitats causes a decrease in richness and recruitment of forest species or both (Lenoir et al., 2019). Therefore, the proximity between habitats would facilitate the movement of species (Krosky et al., 2018) and functional forest connectivity (Bastian et al., 2015).	Range 0 (a) - 3140.1m (b) Euclidean Distance 	

Criteria	Justification	Values Originals/Standardization	Criteria maps
Landscape Resistance Index	The land-use/land-cover change due to urban expansion has influenced the biodiversity, ecosystem function, and regional climate (Choudhury, Das, and Das, 2018). 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 and Li, 2017). According to Mörtberg et al. (2013), the terrestrial surface is the basis for designing the species dispersal path, especially when overcoming the matrix resistance. The species consider the landscape as a competitive space control of the coverage. 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 several modified. The paths are the least human-modified LULC, linking natural areas as protected areas and forest patches (Theobald et al., 2012). For methods based on habitat selection, landscape resistance is represented as an inverse function of environmental suitability. This way, high habitat importance is associated with low resistance and vice versa (Gao et al., 2017).	Range 1.7 (a) - 436.9 (b) 	

Criteria	Justification	Values Originals/Standardization	Criteria maps
Proximity to the drainage network	This riparian vegetation continues to offer an opportunity to establish an integrated network of forest remnants, which can serve habitats and connectors at the regional or local scale, especially when reduced sources that cause environmental degradation (Zimbres et al., 2018, Parsley et al., 2020, Covrrubias, González, and Gutiérrez-Rodriguez, 2021). Drainage networks often conserve the last forest remnants in altered landscapes (González et al., 2017). As riparian forests become smaller, disconnected from larger forest habitats, and degraded, their functional connectivity value is reduced (Fuente et al., 2018). Thus, wide corridors are preferred as conservation strategies to create connected habitats (Resasco, 2019). We also point out that most watercourses are not wide enough to serve as complete barriers to animal movement (Muñoz-Mendonza et al., 2017). In this sense, we consider a natural way for species dispersion along with riparian areas. The proximity to these environments would increase the forest functional connectivity capacity.	Range 0 (a) - 792.5m (b) Euclidean Distance 	

Criteria	Justification	Values Originals/Standardization	Criteria maps
Topographic Wetness Index	The vegetation present in wetlands has a high value for ecological and genetic connections between populations in a fragmented landscape (Zimbres et al., 2018). This ecosystem is influenced by surface runoff and groundwater discharges. In turn, moist soils present greater carbon saturation, promoting greater availability of nutrients and increased species richness (Kuglerová et al., 2014). In this context, the topographic moisture index (ITU) is used to identify saturated areas and to distinguish reliefs where soils are well-drained (O'Neil, Goodall and Watson, 2018), a method known to be sensitive to the resolution of the Digital Elevation Model (DEM) (Ågren et al., 2014). Thus, moisture indices can define patterns in vascular plant communities, being helpful to identify areas of interest for forest conservation (Echiverri and Macdonald, 2019). This study considered that places with more significant moisture potential were more favorable to forest functional connectivity. However, large bodies of water were considered a restriction for analysis.	Range 0 (a) – 30.1 (b) 	

Criteria	Justification	Values Originals/Standardization	Criteria maps
Slope	The slope of the land is an essential factor for human occupation, and globally, productive forests are located on slopes greater than 22º (Lundbäck et al., 2021). This criterion supports forest regeneration(Li et al., 2013) because steep slopes reduce human access. The razes act as reinforcement and anchorage of the soil in steep terrain, restricting the landslide (Kim et al., 2017, Shen et al., 2017) and serving as a refuge for forest remnants (Nüchel, Bocher, and Svenning, 2019).In this sense, the increase in slope was associated with more suitable environments for forest conservation. Consequently, they become environments with greater capacity to promote functional forest connectivity. According to Nüchel, Bocher, Svenning (2019), the association between slope and forest cover increases as population density increases, suggesting that the anthropogenic intensity of land use may influence the association.	Range 0 (a) – 70.2% (b) 	

4.2.4 Criteria importance

The criteria importance is expressed by the factor weights in the MCE context and calculated through the Pairwise Comparison Method, developed by Saaty (1977), in the Analytical Hierarchical Process (AHP).

In this context, we compared the criteria two-by-two, considering the experts' opinion and the continuous 9-point scale with the value one (1) indicates that two criteria are "equally" important and the value nine (9) implies that one criterion is "extremely" more important than the other (Saaty, 2008). The values integrated a pairwise matrix, where the factor weights (Table 3) were determined by normalizing the eigenvector, which is associated with the maximum eigenvalue of the (reciprocal) ratio matrix (Vettorazzi and Valente, 2016).

The matrix consistency is expressed by the consistency rate (CR) and considered adequate for values less than 0.10 (Saaty, 1980).

Table 3 – Factor weight and Consistency Rate (CR) for prioritization of areas for forest conservation aiming at forest functional connectivity in the study area in the GRBB-SP, Brazil.

Criterion	Factor weight (*fw*)
Proximity to forest fragmentation	35.45
Landscape Resistance Index (LRI)	32.56
Proximity to drainage network	14.75
Topographic Wetness Index (TWI)	9.58
Slope	7.66
CR = 0.03	100.00

4.2.5 Criteria aggregation

The Weighted Linear Combination (WLC) method supported our criteria aggregation into a final map. According to Malczewski and Rinner (2015), the method was developed by Voodg (1983) and is the most popular of the MCE.

Through WLC, a criterion is multiplied (pixel by pixel) by its respective weight, and after, it is aggregated jointly with others through a sum of the results (eq. 1).

$$S = \sum fwi.xi$$

Where, S = Adequacy; *fwi* = factor weight i; and *x*i = criterion score on factor i (Drobne and Lisec, 2009).

Finally, we evaluated the histogram of the priority areas map to identify homogeneous regions, i.e., classes of priority. We obtained ten classes based on geometric range classification, which associated two by two resulted in five priority levels for functional forest connectivity: very low, low, moderate, high, and very high.

The geometric interval is obtained when, for a class, the sum of squares of its components is minimized, ensuring that each range has approximately the same number of values and that the change between intervals is consistent (ESRI, 2016).

4.2.6 Decision-making support process validation

The validation process involved several analyses, beginning with the sensitivity analysis, which assessed the criteria importance in the decision-making process, remarking the impact of deleting a criterion on the final map. This tool can guide calibration and verification and support prioritizing efforts to reduce uncertainty (Pianosi et al., 2016).

For this, a criterion was eliminated (one at a time); the pairwise matrix reorganized (keeping the importance among other criteria); the factor weights recalculated (observing CR), and criteria were aggregated in a new map, also reclassified in five classes.

After, we compared the group of maps (without one criterion) with the final (original criteria) in terms of percentage of classes areas.

In this context, the sensitivity analysis also supported the definition of the adequate criteria and final maps for prioritization forest functional connectivity in our study area.

Previously, the influence of the criteria on the landscape was also evaluated. This procedure identifies the factor's dominance order and ensures expert opinion and the ecological logic established during modeling.

The following statistical analyses supported the samples grids of 6448 points extracted from original maps (criteria and final in 255 bytes).

Thus, the Dot Plot graphics were created to identify similar regions across the sampled values (Cabanettes and Klopp, 2018). So, using the graphics, we highlighted the occurrences, breaks, and inversions among the maps of priority areas and criteria at the same point.

The third analysis based on the maps categorized assessed the overlap among the highest priorities classes (i.n., high and very high) and the forest fragments with at least 5 ha (eq. 2).

$$\text{Eq. 2 Overlap>5ha} = \frac{\text{Intersection of high and very high priority classes x Forest fragments area >5ha}}{\text{Forest fragments area >5ha}}$$

The cluster analysis was created to identify the LULC associated with the priority levels. However, the LULC map was first sampled (1000 points per class), and the same grid was used to new sampled in the priority map (255 bytes).

In the statistical program, we use the hierarchical grouping method through different distance measures (Euclidean, Maximum, Manhattan, Canberra, Minkowski) and grouping (Ward.D, Single, Complete, Average, Centroid). From the cophenetic correlation coefficient ($R^2 = 0.95$), the Canberra distance was chosen as a dissimilarity measure and the average link as a clustering measure, according to Eq. 3 and 4.

Pearson's correlation between the elements of the dissimilarity matrix (matrix of distance between LULC, obtained from the original data, that is, map of priority areas) and the elements are called the cophenetic correlation coefficient. The cophenetic matrix (of the distance between LULC, obtained from the dendrogram). This coefficient can be used to assess the consistency of the clustering pattern in hierarchical methods, with values close to 1 indicating better representation (Barroso and Arte, 2003).

Eq. 3 Canberra distance $dij = \sum_{i=1}^{n} \frac{|xi-yi|}{|xi+yi|}$; Eq. 4 Average linkage $d(R,Q) = d(\bar{R}-\bar{Q})$

Where: where $\bar{R}$ and $\bar{Q}$ are respectively the centroids of the R and Q groups and d (R, Q) is the distance between them.

The Canberra distance is very sensitive to slight variations, as it considers the absolute difference in the values of the characteristics, divided by their absolute sum (Emran and Ye, 2001).

4.3 RESULTS

The priority areas for forest conservation aiming at the forest functional connectivity for our study area in the Green Belt Biosphere Reserve (SP, Brazil) are in Fig. 3.

The map represents the integration of criteria defined through the Participatory Technique (PT) when the experts pointed out the proximity to forest fragments as the most important criterion to our objective.

In the same way, the WLC method justly permitted that they bring to the map their respective importance defined in the PT context and expressed by the factor weights (fw). In our study, experts classified the landscape resistance index as the second important criterion, followed by the proximity to drainage network, topographic wetness index, and slope.

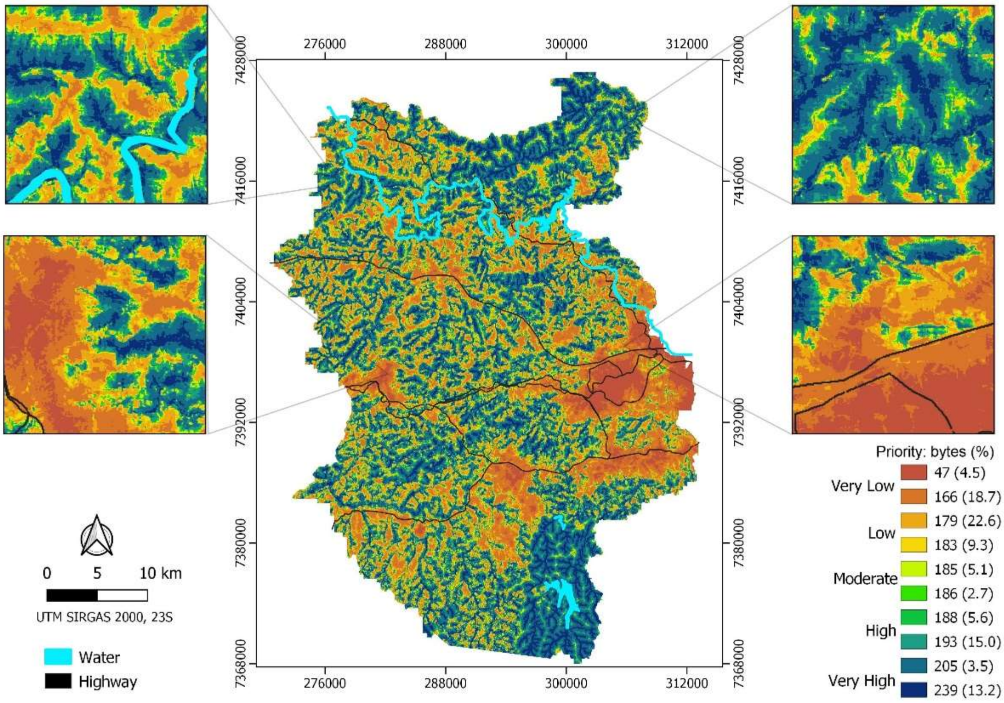


Figure 3 - Priority areas for functional forest conservation functional connectivity, through the WLC, at GBBR-SP, Brazil.

However, they also bring their influence, which in our study follows the same ranking of fw, since the map represents the most influence criterion (i.e., proximity to forest fragments) showed a high frequency of values near 255 bytes. According to Fig. 4. this criterion has 89,8% of its value occurrence between 229.5 and 255 bytes. The second influent criterion showed a concentration of value (81%) between 153 and 255 bytes; the third, 88% of its values between 153 and 229.5 bytes; and slope with 88% of values at most 76.5 bytes. Otherwise, the topographic wetness index (TWI) map was the least influential criterion, having a high frequency (around 76%) of values at between 25.5 and 51 bytes.

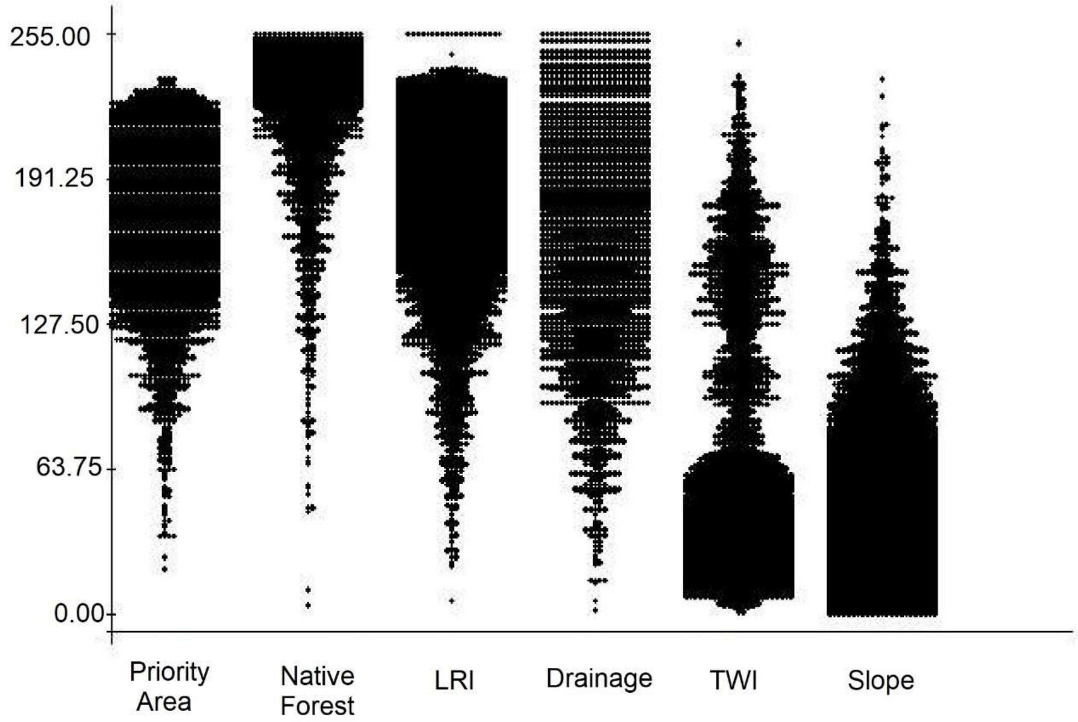


Figure 4 – Intervals of priority areas and criteria in the study area at GBBR-SP, Brazil.

Based on these results, we can say that the criteria influence and importance are reflected in the concentration of their values in the 0-255 bytes scale and their association with the priority levels.

The priority map showed 31.9% of the studied area as low priority, 23.2% as low, 20.6% as high, 16.7% as very high, and 7.8% as a medium priority (Fig. 3).

Thus, the areas that firstly require action sum 37.3% and showed the highest values of the three criteria most important and influence also with the highest values in the 255 bytes. Otherwise, these regions presented major values of slope and TWI represented by the lowest values in the 255 bytes-scale.

In these priority areas, 32% is represented by the criterion Proximity to Forest Fragments (Native Forest), followed by Landscape Resistance Index (LRI) with 27%, proximity to the drainage network (Drainage) denoted 26%, finally, Slope and TWI, with 8% and 7% respectively.

An important point related to the proximity maps is that their concentration values (near 255 bytes) result from their features scattered through our landscape. Their respective fw control this influence, resulting in prioritization, according to the experts proposed.

The sensitivity analysis reflected the adequation of these proximity maps in the process and the other criteria and their perspectives fw (Fig. 5).

Through the analysis, we obtained that the elimination of proximity to forest fragments map favored the increment of regions classified as low priority, which occupied 47.3%. When we disregard the proximity to the drainage network, we favor the regions of high priority, which occupied 43.1%.

When we excluded the LRI map, favored regions with a medium priority occupied 41.8% of the studied area. Lastly, eliminating the slope and TWI criteria favored the highest priorities regions, which represented 49.7% and 56.5% of the landscape, in this scenario.

Considering the sensitivity analysis results, we maintained the original criteria and fw, which support our prioritization of areas shown in Fig. 3. The consistency ratio (CR) obtained with the fw proposed was 0.03.

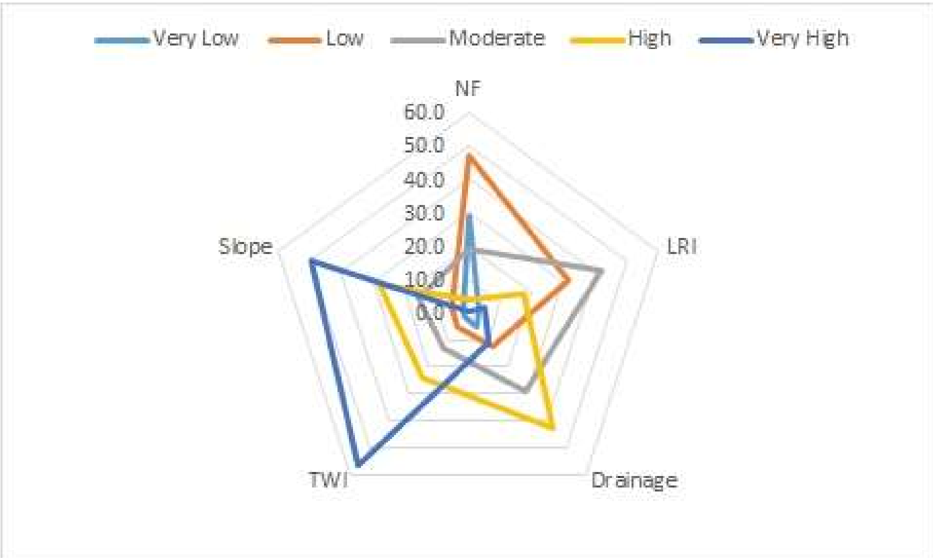


Figure 5. Sensitivity analysis applied to criteria and priority classes in the studied landscape in GBBR-SP, Brazil.

Where: Slope – the absence of slope; TWI – the absence of Topographic Wetness Index; Drainage – the absence of proximity to the drainage network; LRI – the absence of Landscape Resistance Index; NF – the absence of proximity to forest fragments.

In the priority map, regions near forest remnants were denoted and received high value (in 255 bytes scale), especially in regions with the condition of importance (also with the high value) for the other criteria. Thus, the fw controlled the criteria influence, resulting in a priority area that reflects all criteria. The map identified potential regions to integrate the ecological corridor and related to the drainage, forest remnants, low resistance to genic flux, high slope, and humidity.

Another important point is that the highest priorities classes overlapped in 86.22% with the forest remnants greater than 5 ha, with the very high class having 67,8% overlapping and the high class 18.42%.

We obtained these results through the cluster analysis between the priority and LULC classes. According to this analysis, there are three groups in our study area. The first was composed of native and planted forests, which also showed an association with the anthropized fields. The second is formed by agriculture and urban areas of low density and, the last, that bring the urban areas of high density (Fig. 6).

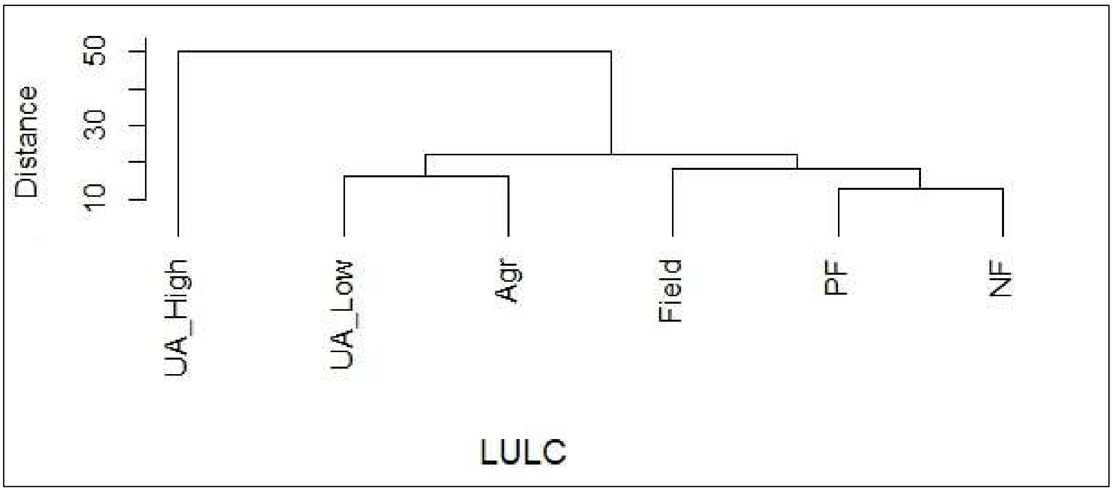


Figure 6 - Groups formed by land use and land cover from the map of priority areas for forest functional connectivity in the study area at GBBR-SP, Brazil.

Where: UA_High - High-density urban areas; UA_Low - Low-density urban areas; Agr - Agriculture; Field - Anthropised Fields; PF - Planted Forest; NF - Native Forest.

4.4 DISCUSSION

The model developed for the landscapes under urban sprawl supported our prioritization of areas for functional forest connectivity and brought the importance of our criteria set, controlling their respective influences.

The criteria represented our landscape attributes, and the factors weights defined through the experts and literature review integrated a matrix with an adequate consistency level. The criteria definition considers the literature review and, after taking into account the expert’s opinion to attribute their weights, is a new approach that decreases uncertainties related to the process because others preview studies available the criteria (Vanderley-Silva and Valente, 2021a).

Our study's consistency levels value reflects that the factors were aleatorily produced, as Saaty (1980) proposed through the pairwise comparison method because our value was minor than 0.10. The author who developed the method in the AHP context used this value as a reference, and they indicated the construction of a new matrix when the value is superior to 0.10, based on the criteria ranking importance predefined by experts.

This way, our factor weights are consistent, reflect the criteria important and control the proximities and LRI maps influence. Otherwise, the prioritization scenario could only be in function of these three maps, disregarding the importance of slope and TWI, which were essential to enhancing the spatialization of priority areas.

Valente et al. (2021) related the influence of maps composed of features scattered through the landscape, such as the forest patches and rivers. When these features are naturally close to each other, their distance values receive high importance (eg, values near 255 bytes) and dominate the landscape (Fig. 4). This way, the criterion has a strong influence because there are high values in any place on its map, i.e., according to the criterion, all landscape is a priority if their influence is not controlled.

In our study, the highest classes did not domain, corresponding to a specific region that sums around 37% of our total area (Fig. 3). The high and very high classes permit the planning of localized actions, for where we can designate economic resources in the planning stage. The economic resources and actions can bring to the study area to command, control instruments (based in Brazil legislation), and for voluntary action through Payment for Ecosystem Services (PES) (Valente et al., 2021, Bremer et al., 2019, Schirpke et al., 2018, Shepherd et al., 2016).

PES is a reality in Brazil, especially in priority regions under the Atlantic Forest domain, defined by law (Aza et al., 2021, Richards et al., 2020, Viani et al., 2018). The decision model we developed can benefit PES, which nowadays is selecting areas considering the voluntary adhesion of rural owners without considering the landscape characteristics important to the PES objective.

In the case of our regions with the highest priority, they are under the influence of the three most relevant criteria, i.e., have the influence of LRI and proximities maps, and still are in regions with a low resistance to species dispersion near forest patches, and rivers (Fig. 4).

In this scenario, we have the priorities areas in the riparian regions that are natural ways for different species in nature. The elongated shape of these fragments facilitates their proximity and supports their function as a corridor for different species (Issii et al., 2020, Matos et al., 2019). Furthermore, the Brazilian legislation considers some buffer of the riparian region as a protected region, where it is necessary to maintain the original vegetation.

Furthermore, these areas are near regions naturally covered by native forest, and we know that the amount of habitat is an important predictor of biodiversity (Evju and Sverdrup-Thygeson, 2016). Several studies pointed the threshold of 30% to 40% of coverage by forest as a relevant value for communities' conservation (Sans, Verón, and Paruelo, 2021, Yin, Leroux and He, 2017, Boesing, Nichols, and Metzger, 2017).

Conversely, plats regions with the low ability of soil saturation showed the lowest priority for forest conservation (Fig. 4). These regions are predominately located distant from the rivers, having high landscape resistance, reflecting an environment with a low ability for forest functional connectivity.

They are environment under the strong anthropic influence, where the absence of connectivity threatens species conservation (Santos et al., 2019), as it impedes movement, resource use, habitat colonization, and maintenance of plant gene flow (Tumas et al., 2018) and animals (Hilty, Lidicker, and Merenlender, 2006). Thus, habitats' spatial configuration and degree of isolation are important variables, especially in landscapes with few forest fragments (Rybicki and Hanski, 2013, Coudrain et al., 2014).

However, Fig 3. showed a transition between the highest and lowest priorities regions, classified as a medium priority, representing the minor percentage of our studied areas (near 10% of our studied area). This result is different from several studies that pointed to a tendency to obtain the predominance of medium priority associated with WLC since it is a method characterized by averages (Valente et al., 2021, Motlagh, Amrei, and Halimi, 2020, Argyriou et al., 2016, Gülci and Akay, 2015).

Firstly, we control this tendency through the knowledge of criteria weights and influence. Using WLC, the major of studies do not bring the criteria influence to the evaluation, and they work only with the importance pointed by experts. The consequence is that the WLC tendency predominates. However, when we bring this variable, we can control the criteria influence through the fw, respecting their ranking of importance, as proposed by Valente et al. (2021). The influence evaluation traditionally belongs to another MCE method, the OWA, an evolution of the WLC. However, some authors pointed that this variable could improve the WLC application, considering that the method is easy to apply and supports robust results.

Second, we evaluated the histogram tendency of the priority map, observing their clusters and break regions that result in the classes following its date tendency. The result is an improvement to the traditional breaks that traditionally result in maps classes with the same frequency, without significance.

Moreover, the sensibility analysis checked these results, indicating that the criteria with their respective weights adequately prioritize areas. Without the LRI criterion, there was an increment in the areas classified as a medium priority (Fig. 5) because it is the third influent criterion that balances the presence of the proximity's maps (the most influent and important criteria) and other criteria (the last important and influent).

Besides, LRI brings an essential theoretical component because it supports understanding several random species movements, considered only in an altered way (Thiele et al., 2018). So, LRI is a new perspective to landscape planning when the focus is species conservation.

Conversely, the highest priority areas naturally increased when we eliminated the least influent criteria (TWI and slope) (Fig. 5).

The two criteria show opposite behaviors in terms of spatialization and importance for forest connectivity. Even so, they bring robustness to the model because their respective priorities reflect sensitivity regions related to soil moisture and relief, indicating regions where uses of high intensity are inadequate and regions favorable for forest conservation (Nüchel, Bocher, and Svenning, 2019). For this reason, and even together representing only 17% of the criteria importance, sensitivity analysis indicated maintain them.

The cluster analysis corroborates our results, indicating the same location for the highest priority areas and forest remnants. This way, supporting the forest connectivity adequately since the urban areas of high density showed no clustered in the same regions. In the sequence, the low-density urban areas highlight the diffuse process of urban sprawl throughout the territory, represented by small farms and urban agglomerations. These anthropic interferences allocated among forest remnants can directly interfere with the dispersion or presence of specialist species sensitive to anthropic interference, an important factor for territorial planning.

In addition, we can highlight the agricultural and anthropogenic fields between the native forest remnants, both distinguished by the model and fundamental for the maintenance of functional forest connectivity (Fig.6) since they develop the connector paper between inadequate LULC for the dispersal of species, and the native forest remnants.

Authors as Thiele et al. (2018) and Oliveira-Junior et al. (2020) related the intensive land use with hostile environments and that the agriculture, arable fields, and pastures as an alternative for the species dispersion and migration.

Several studies have highlighted the opportunities related to pasture because they permitted species dispersion and migration. Besides that, there are opportunities related to them, as restoration with native vegetation, which is an advantage in landscapes urban under sprawl (Marcolin et al., 2021, Issii et al., 2020, Erbaugh et al., 2020, Mansourian et al., 2017).

Despite these actions being society's responsibility, decision-makers and public administrators are responsible for ensuring the implementation of public policies for landscape conservation and restoration (i.e., maintaining connectivity). That is because it is a challenging process, involves private areas, many stakeholders, authorities, and government institutions (Sans, Verón, and Paruelo, 2021).

In this context, we understood that functional connectivity has a dynamic and sustainable state, characteristic of shared landscapes, where wildlife and humans coexist under the governance of institutions, which must ensure the persistence of species in the long term, provide social legitimacy, and establish tolerable levels of risk (Carter and Linnel, 2016, König, et al., 2020).

This way, our model supports a holistic approach for forest functional connectivity based on landscape attributes. It can support the planning by indicating regions for actions based on command, control instruments, or the context of the voluntary program.

4.5 CONCLUSION

This paper presented a model based on the MCE method to prioritize areas for forest conservation, aiming at functional connectivity in a landscape subject to urban expansion.

The major challenge was structuring the criteria set, representing landscape under the urbanized process, that happened through the literature review followed by Participatory Technique.

The literature review reduces the uncertainties traditionally associated with this stage because we consider criteria previously evaluated in other studies. However, the experts' opinions validate the selection besides supporting the criteria' importance definition.

We concluded that interaction between authors and experts is a positive point for model construction, especially when several variables act on a process.

In this context, our major conclusion was that the proximity to forest remnants, proximity to drainage, LRI, slope, and TWI represents landscapes under urban sprawl, supporting obtaining a robust model.

Sensitivity analysis validated our model, indicating the different priorities for terrestrial reality. In this sense, high priority areas for functional connectivity are associated with native or planted forests and deserve attention for conservation and management plans for natural resources. In contrast, the low priority with urban areas (low or high density) should guide development and expansion plans.

Additionally, areas with moderate priority are linked with anthropized fields and agriculture, showing that the model evidences opportunities for forest restoration and Payment for Ecosystem Services (PES) aimed at functional connectivity maintenance.

REFERENCES

Ågren, A. M.; Lidberg, W.; Strömgren, M.; et al. Evaluating digital terrain indices for soil wetness mapping – a Swedish case study. Hydrol. **Earth Syst. Sci.**, v. 18, p. 3623-3634, 2014. https://doi.org/10.5194/hess-18-3623-2014.

Albert, C. H.; Rayfield, B.; Dumitru, M.; et al. Applying network theory to prioritize multispecies habitat networks that are robust to climate and land-use change. **Conservation Biology**, v. 36, n. 6, p. 1383-1396, 2017. https://doi.org/10.1111/cobi.12943.

Allen, C.; Gonzales, R.; and Parrott, L. Modelling the contribution of ephemeral wetlands to landscape connectivity. **Ecological Modelling**, v. 419, 108944, 2020. https://doi.org/10.1016/j.ecolmodel.2020.108944.

Argyriou, A. V.; Teeuw, R. M.; Rust, D.; et al. GIS multi-criteria decision analysis for assessment and mapping of neotectonic landscape deformation: A case study from Crete. **Geomorpholgy**, v. 253, p. 262-274, 2016. https://doi.org/10.1016/j.geomorph.2015.10.018.

Auffret, A. G.; Bullock, Y. R. J. M.; Hooftman, D. A., P.; Pakeman, R. J.; et al. Plant functional connectivity – integrating landscape structure and effective dispersal. **Journal of Ecology**. v. 105, n. 6, p. 1648-1656, 2017. https://doi.org/10.1111/1365-2745.12742.

Ayram, C. A. C.; Mendonza, M. E.; Etter, A.; et al. Habitat connectivity in biodiversity conservation: A review of recent studies and applications. **Progress in Physical Geography**, v. 40, n. p. 7-37, 2016. https://doi.org/ 10.1177/0309133315598713.

Aza, A.; Riccioli, F.; and Iacovo, D. Di. Optimising payment for environmental services schemes by integrating strategies: The case of the Atlantic Forest, Brazil. **Forest Policy and Economics,** v.125,102410, 2021. https://doi.org/10.1016/j.forpol.2021.102410.

Bajaru, S.; Pal, S.; Prabhu, M.; et al. A multi-species occupancy modeling approach to access the impacts of land use and land cover on terrestrial vertebrates in the Mumbai Metropolitan Region (MMR), Western Ghats, India. **Plos One**, v. 15, n. 10, p. 1-19, 2020. https://doi.org/ 10.1371/journal.pone.0240989.

Barroso, L. P. and Artes, R. **Análise multivariada Lavras.** UFLA,151p, 2003.

Bastian, O.; Grunewald, K.; and Khoroshev, A.V. The significance of geosystem and landscape concepts for the assessment of ecosystem services: Exemplified in a case study in Russia. **Landscape Ecology**, v. 30, p. 1145–1164, 2015. https://doi.org/10.1007/s10980-015-0200-x.

Belote, R. T.; Dietz, M. S.; McRae, B. H.; et al. Theobald DM, McClure ML, Irwin GH, et al. Identifying corridors among large protected areas in the United States. **PLoS ONE**, v. 11, n. 4, e0154223, 2016. https://doi.org/10.1371/journal.pone.0154223.

Bishop-Taylor, R.; Tulbure, M. G.; and Broich, M. Evaluating static and dynamic landscape connectivity modelling using a 25-year remote sensing time series. **Landscape Ecology**, v. 33, p. 625-640, 2018. https://doi.org/10.1007/s10980-018-0624-1.

Boesing, A. L.; Nichols, E.; and Metzger, J. P. Biodiversity extinction thresholds are modulated by matrix type. **Ecography**, v. 41, n. 9, p. 1520-1533, 2017. https://doi.org/10.1111/ecog.03365.

Boroushaki, S. Entropy-Based Weights for MultiCriteria Spatial Decision-Making. **Yearbook of the Association of Pacific Coast Geographers**, v. 79, p. 168–187, 2017. http://www.jstor.org/stable/26385014.

Bremer, L. L.; Farley, K. A.; and DeMaagd, N. Biodiversity outcomes of payment for ecosystem services: lessons from páramo grasslands. **Biodivers Conserv**., v. 28, p. 885–908, 2019. https://doi.org/10.1007/s10531-019-01700-3.

Butsch, C.; and Heinkel, S. Periurban Transformations in the Global South and Their Impact on Water-Based Livelihoods. **Water**, v. 12, n. 2, 458, 2020. https://doi.org/10.3390/w12020458.

Cabanettes, F.; and Klopp, C.; D-GENIES: dot plot large genomes in an interactive, efficient and simple way. **Bioinformatics and Genomics**, v. 6, e4958, 2018. https://doi.org/10.7717/peerj.4958.

Carter, N. H.; and Linnell, J. D. C.; Co-adaptation is key to coexisting with large carnivores. **Trends in Ecology and Evolution,** v. 31, p. 575– 578, 2016. Https://doi.org/10.1016/j.tree.2016.05.006.

Carvalho, F.; Carvalho, R.; Mira, A.; and Beja, P. Assessing landscape functional connectivity in a forest carnivore using path selection functions. **Landscape Ecology,** v. 31, p. 1021-1036, 2016. https://doi.org/10.1007/s10980-015-0326-x.

Chambers, J. C.; Allen, C. R.; and Cushman, S. A. Operationalizing Ecological Resilience Concepts for Managing Species and Ecosystems at Risk. **Frontiers in Ecology and Evolution**, v. 7, 241, 2019. https://doi.org/10.3389/fevo.2019.00241.

Choudhury, D.; Das, K.; and Das, A. Assessment of land use land cover changes and its impact on variations of land surface temperature in Asansol-Durgapur Development Region. **The Egyptian Journal of Remote Sensing and Space Science**, v. 22, n. 2, p. 203-218, 2018. https://doi.org/10.1016/j.ejrs.2018.05.004.

Coetzee, B. W. T. Evaluating the ecological performance of protected areas. **Biodiversity Conservation**, v. 26, p. 231-236, 2017. https://doi.org/10.1007/s10531-016-1235-2.

Costanza, J. K.; Watling, J.; Sutherland, R.; et al. Preserving connectivity under climate and land-use change: No one-size-fits-all approach for focal species in similar habitats. **Biological Conservation**, v. 248, 108678, 2020. https://doi.org/10.1016/j.biocon.2020.108678.

Coudrain, V.; Schüepp, C.; Herzog, F.; et al. Habitat amount modulates the effect of patch isolation on host-parasitoid interactions. **Frontiers in Environmental Science**, v. 30, n. 2, 27, 2014. https://doi.org/10.3389/fenvs.2014.00027.

Covrrubias, S.; González, C.; Gutierrez-Rodriguez, C. Effects of natural and anthropogenic features on functional connectivity of anurans: a review of landscape genetics studies in temperate, subtropical and tropical species. **Journal of Zoology**, v. 313, n. 3, p. 159-171, 2021. https://doi.org/10.1111/jzo.12851.

Curiel-Esparza, J.; Gonzalez-Utrilla, N.; Canto-Perelo, J.; and Martin-Urilla, M. Integrating climate change criteria in reforestation projects using a hybrid decision-support system. **Environmental Research Letters**, v. 10, e094022, 2015. https://doi.org/10.1088/1748-9326/10/9/094022.

Cushman, S. A.; Lewis, J.; and Landguth, E. L. Why Did the Bear Cross the Road? Comparing the Performance of Multiple Resistance Surfaces and Connectivity Modeling Methods. **Diversity**, v. 6, n. 4, p. 844-854, 2014. https://doi.org/10.3390/d6040844.

Drobne, S.; and Lisec, A. A. Multi-attribute Decision Analysis in GIS: Weighted Linear Combination and Ordered Weighted Averaging. **Informatica**, v. 33, p. 459–474, 2009.

Echiverri, L.; and Macdonald, S. E. Utilizing a topographic moisture index to characterize understory vegetation patterns in the boreal forest. **Forest Ecology and Management**, v. 447, p. 35-52, 2019. https://doi.org/10.1016/j.foreco.2019.05.054.

Ehlers-Smith, D. A.; Ehlers-Smith, Y. C.; and Downs, T. C. Promoting functional connectivity of anthropogenically-fragmented forest patches for multiple taxa across a critically endangered biome. **Landscape and Urban Planning**, v. 190, 103579, 2019. https://doi.org/10.1016/j.landurbplan.2019.05.010.

Emran, S. M.; and Ye, N. Robustness of Canberra metric in computer intrusion detection. **Quality and Reliability Engineering International**, v. 18, n. 1, p. 19-28, 2002. https://doi.org/10.1002/qre.441.

Erbaugh, J.T.; Pradhan, N.; Adams, J.; et al. Global forest restoration and the importance of prioritizing local communities. **Nature Ecology & Evolution,** v. 4, p. 1472–1476, 2020. https://doi.org/10.1038/s41559-020-01282-2.

Esmail, B. A.; and Geneletti, D. Multi-criteria decision analysis for nature conservation: A review of 20 years of applications. **Methods in Ecology and Evolution**, v. 9, n. p. 42-53, 2017. https://doi.org/10.1111/2041-210X.12899.

ESRI. Data classification methods. 2016. Available in: <https://pro.arcgis.com/en/pro-app/latest/help/mapping/layer-properties/data-classification-methods.htm >. Accessed on July, 9, 2021.

Evju, M.; and Sverdrup-Thygeson, A. Spatial configuration matters: a test of the habitat amount hypothesis for plants in calcareous grasslands. **Landscape Ecology**. v. 31, p. 1891-1902, 2016. https://doi.org/10.1007/s10980-016-0405-7.

Fernández, I. C.; and Morales, N. S. A spatial multicriteria decision analysis for selecting priority sites for plant species restoration: a case study from the Chilean biodiversity hotspot. **Restoration Ecology**, v. 24, n. 5, p. 599-608, 2016. https://doi.org/10.1111/rec.12354.

Ferretti, V.; and Pomarico, S. An integrated approach for studying the land suitability for ecological corridors through spatial multicriteria evaluations. **Environment, Development and Sustainability**, v. 15, p. 859– 885, 2013. https://doi.org/10.1007/s10668-012-9400-6.

Foster, E.; Love, J.; Rader, R.; et al. Integrating a generic focal species, metapopulation capacity, and connectivity to identify opportunities to link fragmented habitat. **Landscape Ecology**, v. 32, p. 1837–1847, 2017. https://doi.org/10.1007/s10980-017-0547-2.

Fuentes, B. de la.; Mateo-Sanchez, M. C.; Rodriguez, G.; et al. Natura 2000 sites, public forests and riparian corridors: The connectivity backbone of forest green infrastructure. **Land Use Policy**, v. 75, p. 429-441, 2018. https://doi.org/10.1016/j.landusepol.2018.04.002.

Gao, Y.; Ma, L.; Liu, J.; et al. Constructing Ecological Networks Based on Habitat Quality Assessment: A Case Study of Changzhou, China. **Scientific Reports**, v. 7, 46073, 2017. https://doi.org/10.1038/srep46073.

Gaüzére, P.; Princé, K.; Devictor, V. Where do they go? The effects of topography and habitat diversity on reducing climatic debt in birds. **Global Change Biology**, v. 23, n. 6, p. 2218-2229, 2016. https://doi.org/10.1111/gcb.13500.

Gibbs, H. K.; and Salmon, J. M.; Mapping the World's degraded lands. **Applied Geography**, v. 57, p.12-21, 2015. https://doi.org/10.1016/j.apgeog.2014.11.024.

González, E.; Felipe-Lucia, M. R.; and Bourgeois, B.; Integrative conservation of riparian zones. **Biological Conservation**, v. 211, p. 20 – 29, 2017. https://doi.org/10.1016/j.biocon.2016.10.035.

González-Serna, M. J.; Cordero, P. J.; and Ortego, J. Using high-throughput sequencing to investigate the factors structuring genomic variation of a Mediterranean grasshopper of great conservation concern. **Scientific Reports**, v. 8,13436, 2018. https://doi.org/10.1038/s41598-018-31775-x.

Goodwin, B. J. Is landscape connectivity a dependent or independent variable? **Landscape Ecology**, v. 18, p. 687–699, 2003. https://doi.org/10.1023/B:LAND.0000004184.03500.a8.

Gülci, S.; and Akay, A. E. Assessment of ecological passages along road networks within the Mediterranean forest using GIS-based multi criteria evaluation approach. **Environ. Monit. Assess.**, v. 187, 779, 2015. https://doi.org/10.1007/s10661-015-5009-1.

Haddad, N.; Brudvig, L.; Clobert, J.; et al. Habitat fragmentation and its lasting impact on Earth ecosystems. **Sci. Adv.**, v. 1, n. 2, e1500052, 2015. https://doi.org/10.1126/sciadv.1500052.

Hails, M.; Chytry, M.; and Horsák, M.; Exposure-related forest-steppe: A diverse landscape type determined by topography and climate. **Journal of Arid Environments**, v. 135, p. 75-84, 2016. https://doi.org/10.1016/j.jaridenv.2016.08.011.

Hilty, J.; Lidicker, W.; and Merenlender, A. **Corridor Ecology: The Science and Practice of Linking Landscapes for Biodiversity Conservation**. Washington, DC: Island Press, 2006.

IBGE – Instituto Brasileiro de Geografia e Estatística. 2012. **Mapa de Vegetação do Brasil**. Available in https://geoftp.ibge.gov.br/informacoes_ambientais/vegetacao/mapas/brasil/vegetacao.pdf. Accessed on march, 10, 2021.

Issii, T. M.; Pereira-Silva, E. F. L.; López de Pablo, C.T.; et al., Is There an Equivalence between Measures of Landscape Structural and Functional Connectivity for Plants in Conservation Assessments of the Cerrado? **Land**, v. 9, n.11, 459, 2020. https://doi.org/10.3390/land9110459.

Jennings, M. K.; Zeller, K. A.; and Lewison, R. L. Supporting Adaptive Connectivity in Dynamic Landscapes. **Land**, v. 9, n. 9, 295, 2020. https://doi.org/10.3390/land9090295.

Kim, J. H.; Fourcaud, T.; Jourdan, C.; Maeght, J.L.; et al. Vegetation as a driver of temporal variations in slope stability: The impact of hydrological processes. **Geophys. Res. Lett**, v. 44, p. 4897–4907, 2017. https://doi.org/10.1002/2017GL073174.

König, H. J.; Kiffner, C.; Schadt S. K.; et al. Human coexistence – wildlife in a changing world. **Conservation biology**, v. 34, n. 4, p. 786-794, 2020. https://doi.org/10.1111/cobi.13513.

Krosky, M.; Theobald, D. M.; Norheim, R.; et al. Identifying riparian climate corridors to inform climate adaptation planning. **PloS ONE**, v. 13, e0205156, 2018. https://doi.org/10.1371/journal.pone.0205156.

Kuglerová, L.; Ågren, A.; Jansson, R.; and Laudon, H. Towards optimizing riparian buffer zones: ecological and biogeochemical implications for forest management. **Forest Ecology Management**, v. 334, p. 74-84, 2014. https://doi.org/10.1016/j.foreco.2014.08.033.

Lakicev, M.; Srdjevic, Z.; Srdjevic, B.; and Zlatic, M. Decision making in urban forestry by using approval voting and multicriteria approval method (case study: Zvezdarska forest, Belgrade, Serbia). **Urban Forestry and Urban Greening**, v. 13, n. 1, p. 114-120, 2014. https://doi.org/10.1016/j.ufug.2013.11.001.

Lenoir, J.; Decocq, G.; Spicher, F.; et al., Historical continuity and spatial connectivity ensure hedgerows are effective corridors for forest plants: Evidence from the species–time–area relationship. **Journal of Vegetation Science**, v. 32, n. 1, e12845, 2021. https://doi.org/10.1111/jvs.12845.

Li, H.; Ma, Z.; Zhu, Y.; et al. Planning and prioritizing forest landscape restoration within megacities using the ordered weighted averaging operator. **Ecol. Indicat.**, v. 116, 106499, 2020. https://doi.org/10.1016/j.ecolind.2020.106499.

Lopes, T. R.; Moura, L. B.; Nascimento, J. G.; et al. Priority areas for forest restoration aiming at the maintenance of water resources in a basin in the Cerrado/Amazon ecotone, Brazil. **Journal of South American Earth Sciences**, v. 101, 102630, 2020. https://doi:10.1016/j.jsames.2020.102630.

Lundbäck, M.; Persson, H.; Häggström, C.; and Nordfjell, T. Global analysis of the slope of forest land. **Forestry**, v. 94, n. 1, p. 54–69, 2020, https://doi.org/10.1093/forestry/cpaa021.

Malczewski, J.; and Rinner, C. **Multicriteria Decision Analysis in Geographic Information Science**. Springer, 331p. 2015. https://doi.org/10.1007/978-3-540-74757-4.

Malekmohammadi, B.; and Rahimi, B. L. Ecological risk assessment of wetland ecosystems using multi criteria decision making and geographic information system. **Ecological Indicators**, v. 41, p. 133–144, 2014. https://doi.org/10.1016/j.ecolind.2014.01.038.

Mansourian, S.; Stanturf, J. A.; Adutwumwaa, M. A. et al. Forest Landscape Restoration: increasing the positive impacts of forest restoration or simply the area under tree cover? **Restoration Ecology**, v. 25, n. 2, p. 178-183, 2017. https://doi.org/10.1111/rec.12489.

Marcolin, F.; Lakatos, T.; Gallé, R.; et al. Fragment connectivity shapes bird communities through functional trait filtering in two types of grasslands. **Global Ecology and Conservation**, v. 28, e01687, 2021. Https://doi.org/10.1016/j.gecco.2021.e01687.

Masoodi, M.; Salmanmahiny, A.; Mohammadzadeh, M.; and Mirkarimi, S. H. Application of multi-criteria evaluation and GIS to ecotourism planning in protected areas (case study: MianKaleh wildlife refuge). **Journal of Natural Environment**, v. 69, n. 1, p. 211–229, 2016. https://doi.org/10.22059/JNE.2016.58637.

Matos, C.; Petrovan, S. O.; Wheeler, P. M.; et al. Landscape connectivity and spatial prioritization in an urbanising world: A network analysis approach for a threatened amphibian. **Biological Conservation**, v. 237, p. 237-247, 2019. https://doi.org/10.1016/j.biocon.2019.06.035.

Mello, K.; Costa, D. R.; Valente, R., A.; and Vettorazzi, C. D. Multicriteria Evaluation for Protected Area Definition Aiming at Water Quality Improvement. **Floresta e Ambiente**, v. 25, n. 3, e20160134, 2018.https://doi.org/10.1590/2179-8087.013416.

Meurant, M.; Gonzalez, A.; Doxa, A.; Albert, C. H.; et al. Selecting surrogate species for connectivity conservation. **Biological Conservation**, v. 227, p. 326-334, 2018. https://doi.org/10.1016/j.biocon.2018.09.028.

Ministério do Meio Ambiente (MMA). **Áreas prioritárias para conservação da biodiversidade brasileira**. Available in http://areasprioritarias.mma.gov.br/1-atualizacao-das-areas-prioritarias. Accessed on March 8, 2021.

Mörtberg, U.; Haas, J.; Zetterberg, A.; et al. Urban ecosystems and sustainable urban development—analysing and assessing interacting systems in the Stockholm region. **Urban Ecosystems**, v. 16, p. 763–782, 2013. https://doi.org/10.1007/s11252-012-0270-3.

Motlagh, M. G.; Amraei, B.; and Halimi, M. Evaluating the hazardous potential of the dieback of the Zagros Oak forests using the multi-criteria decision-making methods. **Arabian Journal of Geosciences**, v. 13, 995, 2020. https://doi.org/10.1007/s12517-020-05992-6.

Muñoz-Mendonza, C.; D'Elia, G.; Panzera, A.; et al. Geography and past climate changes have shaped the evolution of a widespread lizard from the Chilean hotspot. **Molecular Phylogenetics and Evolution**, v. 116, p. 157-171, 2017. https://doi.ogr/10.1016/j.ympev.2017.08.016.

Nali, R C.; Becker, G.; Zamudio, K. R.; Prado, C. P. A. Topography, more than land cover, explains genetic diversity in a Neotropical savanna tree frog. **Diversity and Distributions**, v. 26, n. 12, p. 1798-1812, 2020. https://doi.org/10.1111/ddi.13154.

Nüchel, J.; Bøcher, P. K.; and Svenning, J. C. Topographic slope steepness and anthropogenic pressure interact to shape the distribution of tree cover in China. **Applied Geography**, v. 103, p. 40–55, 2019. https://doi.org/10.1016/j.apgeog.2018.12.008.

O'Neil, G. L.; Goodall, J. L.; and Watson, L. T. Evaluating the potential for site-specific modification of LiDAR DEM derivatives to improve environmental planning-scale wetland identification using Random Forest classification. **Journal of Hydrology**, v. 559, p. 192-208, 2018. https://doi.org/10.1016/j.jhydrol.2018.02.009.

Ojima, R. Dimensões da urbanização dispersa e proposta metodológica para estudos comparativos: uma abordagem socioespacial em aglomerações urbanas brasileiras. **Revista Brasileira de Estudos de População**, v. 24, n. 2, p. 277-300, 2007. https://doi.org/10.1590/S0102-30982007000200007.

Orsi, F.; and Geneletti, D. Identifying priority areas for Forest Landscape Restoration in Chiapas (Mexico): An operational approach combining ecological and socioeconomic criteria. **Landscape and Urban Planning**, v. 94, p. 20–30, 2010. https://doi.org/10.1016/j.landurbplan.2009.07.014.

Pacetti, T.; Castelli, G.; Bresci, E. et al., Water Values: Participatory Water Ecosystem Services Assessment in the Arno River Basin, Italy. **Water Resources Management**, v. 34, p. 4527–4544, 2020. https://doi.org/10.1007/s11269-020-02684-4.

Parsley, M. B.; Torres, M. L.; Banerjee, S. M.; et al. Multiple lines of genetic inquiry reveal effects of local and landscape factors on an amphibian metapopulation. **Landscape Ecology**, v. 35, p. 319– 335, 2020. https://doi.org/10.1007/s10980-019-00948-y.

Pianosi, F.; Wagener, T.; Beven, K.; et al. Sensitivity Analysis of Environmental Models:a Systematic Review with Practical Workflow Environmental. **Modelling & Software**, v. 79, p. 214-232, 2016. https://doi.org/10.1016/j.envsoft.2016.02.008.

Piquer-Rodríguez, M.; Torella, S.; Gavier-Pizarro, G.; et al. Effects of past and future land conversions on forest connectivity in the Argentine Chaco. **Landscape Ecology**, v. 30, p. 817–833, 2015. https://doi.org/10.1007/s10980-014-0147-3.

Resasco, J. Meta-analysis on a decade of testing corridor efficacy: What new have we learned? **Current Landscape Ecology Reports**, v. 4, n. 3, p. 61-69, 2019. https://doi.org/10.1007/s40823-019-00041-9.

Riad, P.; Graefe, S.; Hussein, H.; et al. Landscape transformation processes in two large and two small cities in Egypt and Jordan over the last five decades using remote sensing data. **Landscape and Urban Planning**, v. 197, 103766, 2020. https://doi.org/10.1016/j.landurbplan.2020.103766.

Richards, R. C.; Petrie, R.; Christ, B.; et al. Farmer preferences for reforestation contracts in Brazil's Atlantic Forest. **Forest Policy and Economics**, v. 118, 102235, 2020. https://doi.org/10.1016/j.forpol.2020.102235.

Rigden, A. J.; and Li, D. Attribution of surface temperature anomalies induced by land use and land cover changes. **Geophysical Research Letters**, v. 44, n. 13, p. 6814-6822, 2017. https://doi.org/10.1002/2017GL073811.

Rincón, V.; Velázquez, J.; Gutiérrez, J.; et al. Evaluating European Conservation Areas and Proposal of New Zones of Conservation under the Habitats Directive. Application to Spanish Territories. **Sustainability**, v. 11, n. 2, 398, 2018. https://doi.org/10.3390/su11020398.

Rio-maior, H.; Nakamura, M.; Álvares, F.; et al. Designing the landscape of coexistence: Integrating risk avoidance, habitat selection and functional connectivity to inform large carnivore conservation. **Biological Conservation**, v. 235, p. 178-188, 2019. https://doi.org/10.1016/j.biocon.2019.04.021.

Rudnick, D.; Beier, P.; Cushman, S.; et al. The Role of Landscape Connectivity in Planning and Implementing Conservation and Restoration Priorities. Issue in Ecology. **Ecological Society of America,** v. 16**,** p. 1-20**,** 2012.

Rybicki, J.; and Hanski, I.; Species–area relationships and extinctions caused by habitat loss and fragmentation. **Ecology Letters**, v. 16, n. 1, p. 27-38, 2013. https://doi.org/10.1111/ele.12065

Saaty, T. L. A scaling method for priorities in hierarchical structures. **Journal of mathematical psychology**, v. 15, n. 3, p. 234-281, 1977. https://doi.org/10.1016/0022-2496(77)90033-5.

Saaty, T. L., 2008. Decision Making with the Analytic Hierarchy Process. **International Journal of Services Sciences**, v. 1, p. 83-98, 2008.

Saaty, T. **The Analytic Hierarchy Process**. McGraw-Hill, 1980, 287p.

Salgueiro, P. A.; Valeiro, F.; Silva, C.; et al. Multispecies landscape functional connectivity enhances local bird species' diversity in a highly fragmented landscape. **Journal of Environmental Management**, v. 284,112066, 2021. https://doi.org/10.1016/j.jenvman.2021.112066.

Sans, G. H. C.; Verón, S. R.; and Paruelo, J. M. Forest strips increase connectivity and modify forests' functioning in a deforestation hotspot. **Journal of Environmental Management**, v. 290,112606, 2021. https://doi.org/10.1016/j.jenvman.2021.112606.

Santos, A. R.; Silva, R. C. F.; Assis, L. C.; et al. Defining environmental conservation levels considering anthropic activity in the Uberaba River Basin protected area. **Revista Ambiente & Água**, v. 14, n. 1, e2279, 2019.https://doi.org/10.4136/ambi-agua.2279.

Santos, R. C.; Lima, M.; Silva-Junior, C. A.; and Battirola, L. D. Disordered conversion of vegetation committees connectivity between forest fragments in the Brazilian Legal Amazon. **Applied Geography**, v. 111, 102082, 2019. https://doi.org/10.1016/j.apgeog.2019.102082.

Saura S., Bodin Ö.; and Fortin M. J. Stepping stones are crucial for species' long-distance dispersal and range expansion through habitat networks. **Journal of Applied Ecology**, v. 51, n. 1, p. 171–182, 2013. https://doi.org/10.1111/1365-2664.12179.

Schirpke, U.; Marino, D.; Marucci, A.; et al. Positive effects of payments for ecosystem services on biodiversity and socio-economic development: Examples from Natura 2000 sites in Italy. **Ecosystem Services**, v, 34, part A, p. 96-105, 2018. https://doi.org/10.1016/j.ecoser.2018.10.006.

Scriven, S. A.; Carlson, K. M.; Hodgson, J. A.; et al. Testing the benefits of conservation set-asides for improved habitat connectivity in tropical agricultural landscapes. **Journal of Applied Ecology**, v. 56, n. 10, p. 2274-2285, 2019. https://doi.org/10.1111/1365-2664.13472.

Sekercioglu, Ç, H.; Loarie, S. R.; Oviedo-Brenes, F.; et al. Tropical countryside riparian corridors provide critical habitat and connectivity for seed-dispersing forest birds in a fragmented landscape. **Journal of Ornithology**, v. 156, Suppl. 1, p. S343-S353, 2015. Https://doi.org/10.1007/s10336-015-1299-x.

Shanthala, D. B. S.; Murthy, M. S. R.; Bijan, D.; et al. Identification of Potential Habitat Patches for Connectivity Using Weighted Linear Combination (WLC) and Integral Index of Connectivity (IIC) at East Godavari District, Andhra Pradesh, India. **Journal of the Indian Society Remote Sensing**, v. 44, p. 385–394, 2016. https://doi.org/10.1007/s12524-015-0508-7.

Shen, P.; Zhang, L. M.; Chen, H. X.; and Gao, L. Role of vegetation restoration in mitigating hillslope erosion and debris flows. **Engineering Geology**, v. 216, p. 122–133, 2017. https://doi.org/10.1016/j.enggeo.2016.11.019.

Shepherd, E.; Milner-Gulland, E.; Knight, A. T.; et al. Status and Trends in Global Ecosystem Services and Natural Capital: Assessing Progress Toward Aichi Biodiversity Target 14. **Conservation Letters**, v. 9, n. 6, p. 429-437, 2016. https://doi.org/10.1111/conl.12320.

Shuaibu, J. A.; and Kara, C. Evaluating suitability for sustainable urban growth of Abuja by using MCE and GIS. **International Journal of Advanced and Applied Sciences**, v, 6, n. 7, p. 68–76, 2019. https://doi.org/10.21833/ijaas.2019.07.009.

Silva, V. A. M.; Mello, K. de; Vettorazzi, C. A.; Costa, D. R. da; and Valente, R. A. Priority Areas for Forest Conservation, Aiming at the Maintenance of Water resources, Through the Multicriteria Evaluation. **Revista Árvore**, v. 41, n. 1, e410119, 2017. https://doi.org/10.1590/1806-90882017000100019.

Simon, D.; McGregor, D.; and Nsiah-Gyabaah K. The changing urban-rural interface of African cities: definitional issues and an application to Kumasi, Ghana. **Environment and Urbanization**, v. 16, p. 235–248, 2004. https://doi.org/10.1177/095624780401600214.

Sumida, S. S.; and Valente, R. A. Multicriterial evaluation in the definition of protected areas at the Piedade municipality, SP. **Revista Árvore (on-line)**, v. 43, p.1-12, 2019. https://doi.org/10.1590/1806-90882019000300007.

Theobald D. M.; Reed S. E.; Fields K.; and Soulé M. Connecting natural landscapes using a landscape perme-ability model to prioritize conservation activities in the United States. **Conserv Lett**, v. 5, p. 123–133, 2012. https://doi.org/10.1111/j.1755-263X.2011.00218.x.

Thiele, J.; Kellner, S.; Buchholz, S.; et al. Connectivity or area: what drives plant species richness in habitat corridors? **Landscape Ecology**, v. 33, p. 173–181, 2018. https://doi.org/10.1007/s10980-017-0606-8.

Torre, J. A. de La; Nuñez, J. M.; and Medelin, R. A. Habitat availability and connectivity for jaguars (Panthera onca) in the Southern Mayan Forest: Conservation priorities for a fragmented landscape. **Biological Conservation**, v. 206, p. 270-282, 2017. https://doi.org/10.1016/j.biocon.2016.11.034.

Tumas, H.R.; Shamblin, B.M.; Woodrey, M.; et al. Landscape genetics of the foundational salt marsh plant species black needlerush (Juncus roemerianus Scheele) across the northeastern Gulf of Mexico. **Landscape Ecology**, v. 33, p. 1585–1601, 2018. https://doi.org/10.1007/s10980-018-0687-z.

Uezu, A.; Metzger, J. P.; and Vielliard, J. M.E. Effects of structural and functional connectivity and patch size on the abundance of seven Atlantic Forest bird species. **Biological Conservation**, v. 123, n. 4, p. 507-519, 2005. https://doi.org/ 10.1016/j.biocon.2005.01.001.

Unda, M.; and Etter, A. Conservation Opportunities of the Land Restitution Program Areas in the Colombian Post-Conflict Period. **Sustainability**, v. 11, n. 7, 2048. https://doi.org/10.3390/su11072048.

Union Nations Educations, Scientific and Cultural Organization (UNESCO). **Biosphere Reserves**. Available in https://en.unesco.org/biosphere. Accessed on November 20, 2019.

United Nations, Department of Economic and Social Affairs, Population Division. **World Urbanization Prospects: The 2018 Revision.** (ST/ESA/SER.A/420). New York: United Nations, 2019.

Valente, R. A.; Mello, K.; Metedieri, J. F.; et al. A multicriteria evaluation approach to set forest restoration priorities based on water ecosystem services. **Journal of Environmental Management**, v. 285,112049, 2021. https://doi.org/10.1016/j.jenvman.2021.112049.

Valente, R. A.; Petean, F. C. S.; and Vettorazzi, C. A. Multicriteria decision analysis for prioritizing areas for forest restoration. **Cerne**, v. 23, p. 53-60, 2017. https://doi.org/10.1590/01047760201723012258.

Valente, R. O. A., and Vettorazzi, C. A., 2008. Definition of priority areas for forest conservation through the ordered weighted averaging method. Forest Ecology and Management, 256:1408-1417. https://doi.org/10.1016/j.foreco.2008.07.006.

Vanderley-Silva, I., and Valente, R. A., 2021a. Assessing Environmental Criteria to Support Forest Connectivity, 18 June 2021, PREPRINT (Version 1) available at Research Square [https://doi.org/10.21203/rs.3.rs-465496/v1].

Vanderley-Silva, I., and Valente, R. A., 2021b. Landscape Resistance Index Aiming At Functional Forest Connectivity, 25 June 2021, PREPRINT (Version 1) available at Research Square [https://doi.org/10.21203/rs.3.rs-640226/v1].

Vasudev, D., Fletcher, R.J., Goswami, V.R., and Krishnadas, M. 2015. From dispersal constraints to landscape connectivity: lessons from species distribution modeling. Ecography, 38:967-978. https://doi.org/10.1111/ecog.01306.

Vettorazzi, C. A., and Valente, R., A., 2016. Priority areas for forest restoration aiming at the conservation of water resources. Ecological Engineering. 94:255-267. https://doi.org/10.1016/j.ecoleng.2016.05.069.

Viani, R. A. G., Braga, D. P. P., Ribeiro, M. C., et al., 2018. Synergism Between Payments for Water-Related Ecosystem Services, Ecological Restoration, and Landscape Connectivity Within the Atlantic Forest Hotspot. Tropical Conservation Science. 11:1-9. https://doi.org/10.1177/1940082918790222.

Villalva P., Reto D., Santos-Reis M., Revilla E., and Grilo C. 2013. Do dry ledges reduce the barrier effect of roads? Ecological Enginnering. 57:143–148. https://doi.org/10.1016/j.ecoleng.2013.04.005.

Villard, M. A., Metzger, J. P. 2014. Beyond the fragmentation debate: a conceptual model to predict when habitat configuration really matters. J Appl Ecol 51(2):309–318. Https://doi.org/10.1111/1365-2664.12190.

Voogd, H., 1983. Multicriterial evaluation for urban and regional planning. London: Pion.

Wang, S. J., Ma, H., and Zhao, Y. B. 2014. Exploring the relationship between urbanization and the eco-environment—a case study of Beijing–Tianjin–Hebei region. Ecological Indicators, 45:171–183. Https://doi.org/10.1016 / j.ecolind.2014.04.006.

Wang, S., Zhao, M., Xeng, M., et al., 2020. Evaluation of the Effects of Forest on Slope Stability and Its Implications for Forest Management: A Case Study of Bailong River Basin, China. Sustainability. 12(6):6655. https://doi.org/10.3390/su12166655

Yabsley, N. A., Olds, A. D., Connolly, R. M., Martin, T. S. H., et al., 2015. Resource types influences the effects of reserves and connectivity on ecological functions. Journal of Animal Ecology. 82(2):437-444. https://doi.org/10.1111/1365-2656.12460 .

Yang, Y., Ren, G., Li, W., et al., 2019. Identifying transboundary conservation priorities in a biodiversity hotspot of China and Myanmar: Implications for data poor mountainous regions, Global Ecology and Conservation. e00732. https://doi.org/10.1016/j.gecco.2019.e00732.

Yin, D., Leroux, S. J., and He, F., Models and methods for identifying thresholds of habitat loss. Ecography. 40(1):131-143. Https://doi.org/10.1111/ecog.02557.

Zeller, K. A., McGarigal, K., and Whiteley, A., 2012. Estimating landscape resistance to movement: a review. Landscape Ecol. 27:777–797. https://doi.org/10.1007/s10980-012-9737-0.

Zimbres, B., Peres, C. A., Penido, G., et al., 2018. Thresholds of riparian forest use by terrestrial mammals in a fragmented Amazonian deforestation frontier. Biodiversity and Conservation. 27(11):2815–2836. https://doi.org/ 10.1007/s10531-018-1571-5.

5. GENERAL CONCLUSIONS

The study has a landscape under urban sprawl as studied area, located in an important economic region of São Paulo state and having Atlantic Forest remnants to support an ecological corridor.

Troughout the chapters, we describe the importance of selecting environmental criteria for maintaining functional connectivity, through forest conservation, for prioritizing spaces in the landscape under urban sprawl.

Our results indicate that we obtained a robust set of criteria through the literature review and, added to the opinion of experts, the subjectivity of the selection of criteria was reduced, reflecting the forest structure, and demonstrating that in the studied landscape, the external influences on the fragments forestry do not occur randomly. Thus, we concluded that the interaction between authors and experts is a positive point for model construction, especially when several variables act on a process.

In this context, a set of criteria composed of the slope, Topographic Wetness Index (TWI), distance from forest fragments, distance from the drainage network, distance from highway, and distance from low and high-density urban areas were analyzed and provided support for the identification of regions where the persistence of forest fragments is possible.

In this sense, the larger and more irregular forest fragments were located near watercourses, where higher soil moisture is associated with the deep slopes. At the same time, regions far from highways reflected areas with a forest structure with more preserved characteristics. Already, large and connected forest fragments are located close to low-density urban environments and under a diffuse process of urban sprawl.

Thus, we developed the Landscape Resistance Index (LRI) based on environmental integrity and previously defined concepts. The LRI showed adequate convergence of the observed variables NDVIInv, Night, and LST for the formulation of the resistance construct, resulting in spatial heterogeneity associated with the different LULC and occurrence of dispersion corridors.

In addition to fixed limits, the LRI associates low resistance with forest areas and high resistance with urban areas. In moderate fixed, we identified that anthropized fields and agricultural areas offer varied fluidity capacities compatible with movement through the landscape.

Given these findings, we can state that the best designation for the criteria for prioritizing areas through forest conservation for functional connectivity is proximity to forest fragments, proximity to drainage network, Landscape Resistance Index, Topographic Wetness Index, and slope.

Lastly, the sensitivity analysis validated the model generated based on MCE methods. The analysis indicates the terrestrial reality, in which the most priority areas are associated with native and planted forests and deserve attention from forest management and conservation plans. In contrast, low priority areas are associated with urban areas and should guide urban expansion plans. Already, areas classified as a moderate priority are linked with anthropized fields and agricultural areas, showing that the model offers clear opportunities for forest restoration and payment for Ecosystem Services (PES) programs to maintain functional connectivity.

Therefore, we demonstrate how it is possible to obtain a set of criteria that represent the landscape and adjustable according to forest structure through Canonical Correspondence Analysis. Already, our Structural Equation Model allows us to create an index with a theoretical base and locate regions of greater environmental relevance for landscapes under urban sprawl. Finally, the criteria selected, grouped, and conducted by the Multicriteria Evaluation method indicate forest fragments and other land-cover types favorable to functional connectivity, important for territorial planning.