UNIVERSIDADE FEDERAL DE SÃO CARLOS

CENTRO DE CIÊNCIAS E TECNOLOGIAS PARA A SUSTENTABILIDADE

CAMPUS DE SOROCABA

PROGRAMA DE PÓS-GRADUAÇÃO EM PLANEJAMENTO E USO DOS RECURSOS RENOVÁVEIS

MILTON VINÍCIUS MORALES

INTEGRATING LANDSCAPE ANALYSIS AND MULTICRITERIA DECISION-MAKING TO PRIORITIZE FOREST RESTORATION AREAS IN HUMAN-MODIFIED LANDSCAPES

Sorocaba

Estado de São Paulo – Brasil

2025

UNIVERSIDADE FEDERAL DE SÃO CARLOS

CENTRO DE CIÊNCIAS E TECNOLOGIAS PARA A SUSTENTABILIDADE

CAMPUS DE SOROCABA

PROGRAMA DE PÓS-GRADUAÇÃO EM PLANEJAMENTO E USO DOS RECURSOS RENOVÁVEIS

MILTON VINÍCIUS MORALES

INTEGRATING LANDSCAPE ANALYSIS AND MULTICRITERIA DECISION-MAKING TO PRIORITIZE FOREST RESTORATION AREAS IN HUMAN-MODIFIED LANDSCAPES

Tese apresentada ao Programa de Pós-Graduação em Planejamento e Uso dos Recursos Renováveis - PPGPUR, Universidade Federal de São Carlos - UFSCar, Campus Sorocaba, como requisito parcial para a obtenção do título de Doutor em Planejamento e Uso dos Recursos Renováveis.

Orientação: Profa. Dra. Roberta Averna Valente Botezelli Tolini

Sorocaba

Estado de São Paulo – Brasil

2025

Morales, Milton Vinícius

Integrating landscape analysis and multicriteria decision-making to prioritize forest restoration areas in human-modified landscapes / Milton Vinícius Morales -- 2025.
166f.

Tese de Doutorado - Universidade Federal de São Carlos, campus Sorocaba, Sorocaba
Orientador (a): Roberta Averna Valente Botezelli Tolini
Banca Examinadora: Milton Cezar Ribeiro, Ivan Vanderley Silva, Adriana Cavalieri Sais, Alexandre Camargo Martensen
Bibliografia

1. Manejo de bacias hidrográficas. 2. Análise multicriterial. 3. Ecologia da paisagem. I. Morales, Milton Vinícius. II. Título.

Ficha catalográfica desenvolvida pela Secretaria Geral de Informática (SIn)

DADOS FORNECIDOS PELO AUTOR

Bibliotecário responsável: Maria Aparecida de Lourdes Mariano - CRB/8 6979

UNIVERSIDADE FEDERAL DE SÃO CARLOS

Centro de Ciências e Tecnologias Para a Sustentabilidade
Programa de Pós-Graduação em Planejamento e Uso de Recursos Renováveis

Folha de Aprovação

Defesa de Tese de Doutorado do candidato Milton Vinícius Morales, realizada em 08/05/2025.

Comissão Julgadora:

Profa. Dra. Roberta Averna Valente Botezelli Tolini (UFSCar)

Prof. Dr. Milton Cezar Ribeiro (UNESP)

Prof. Dr. Ivan Vanderley Silva (Prefeitura de Barueri)

Profa. Dra. Adriana Cavalieri Sais (UFSCar)

Prof. Dr. Alexandre Camargo Martensen (UFSCar)

O Relatório de Defesa assinado pelos membros da Comissão Julgadora encontra-se arquivado junto ao Programa de Pós-Graduação em Planejamento e Uso de Recursos Renováveis.

AGRADECIMENTOS

É com imenso prazer que dedico estas linhas a agradecer a todos que, de diversas formas, estiveram comigo nesta árdua caminhada da pesquisa científica, sobretudo nesta última etapa de doutorado, que se iniciou no longínquo (ao menos para mim) ano de 2021.

Primeiramente agradeço aos meus familiares que sempre me incentivaram e motivaram a seguir meu caminho, meu pais, Milton e Silvana, por todo apoio e esforço que me dedicaram ao longo de toda a vida, a minha esposa e companheira Ana Beatriz, pelo seu apoio nestes anos e também pela paciência e compreensão, ao meu filho Miguel, por me inspirar todos os dias a seguir aprendendo e me esforçando, aos meus irmãos João (Jota) e Nicolas, pelo companheirismo, amizade, boa companhia e apoio em todos os momentos da minha vida e a minha tia Cecília (Tice), também por todo seu apoio e cuidado que teve e tem comigo e com minha família.

Agradeço à minha orientadora, Roberta, parte fundamental do resultado deste trabalho e da minha formação como pesquisador. Muito obrigado Roberta, tenho certeza que nossa parceria irá perdurar por longos anos. Agradeço a todo o corpo docente e técnico-administrativo da UFSCar Sorocaba e, em especial, do PPGPUR, bem como aos meus colegas de laboratório e grupo de pesquisa (Geoplan). Foi um prazer trabalhar com vocês nestes últimos anos.

Meus agradecimentos também a todos que me acolheram nas geladas terras Canadenses em minha estadia de 2024, especialmente aos meus supervisores de intercâmbio, Dra. Lenore Fahrig e Dr. Joseph Bennet, por todo o compartilhamento de conhecimento, ricas discussões e acolhimento, à todos os colegas do grupo de pesquisa GLEL (Gomatics and Landscape Ecology Laboratory) da Universidade de Carleton, as ricas discussões de sexta-feira do grupo seguida de uma passada no pub vão ficar sempre em minha memória. Também aos amigos que fiz nesta estadia, em especial à Noah, Dennis, David, Austin, Sammuel e Eammon, realmente espero que possamos nos encontrar novamente, seja acima ou abaixo da linha do Equador.

Devo agradecimentos também a alguns grandes amigos que fiz durante a vida, fundamentais para manter minha sanidade mental (ou perde-la comigo) nestes tempos em que vivemos. Nominalmente: Manoel, Ponex, Sarto, Victor, João Pedro, Caio Orru, Cainho, Julcimar (Jussara) e Alexis. A companhia de vocês, noites de boêmia e aprendizados compartilhados foi e é um alento em meio ao caos dos dias atuais.

Com muito carinho agradeço a Universidade Pública Brasileira, acostumada a trabalhar e persistir sob ameaças e ataques de diversas frentes, desde o velho grande capital até os mais recentes delírios negacionistas. A Universidade Pública no Brasil ainda nos resta como uma das únicas e mais democráticas formas de ascensão e ocupação de espaços. Mais do que isso, se mostra uma das nossas melhores chances para enfrentar as eminentes ameaças ambientais, humanitárias e geopolíticas dos tempos atuais e futuros. Assim, fica aqui meu reconhecimento e gratidão, a todos que fazem ciência de verdade no Brasil, e meu compromisso em lutar e defender a educação pública nacional.

Neste contexto, devo mencionar que o presente trabalho foi realizado com apoio da Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) via a conceção de bolsa de Doutorado e projeto de internacionalização PrInt, e da Fundação de Amparo à Pesquisa do Estado de São Paulo - FAPESP, via os projetos FAPESP n^{os} 2018/21612-8; 2023/08929-0; e 2024/17411-8. Assim, agradeço também estas duas importantes instituições de fomento à pesquisa no Brasil.

RESUMO

MORALES, Milton Vinícius. Integrando Análise da Paisagem e Tomada de Decisão Multicritério para Priorização de Áreas de Restauração Florestal em Paisagens Antropizadas. Defesa de Tese (Doutorado em Planejamento e Uso dos Recursos Renováveis) – Centro de Ciências e Tecnologia para Sustentabilidade, Universidade Federal de São Carlos, Sorocaba, 166 f, 2025.

O presente trabalho propõe uma abordagem integrada que alia análise de componentes ecológicos, antrópicos e biofísicos da paisagem com métodos de decisão multicritério para priorizar áreas de restauração florestal em paisagens modificados pelo uso humano. O estudo inicia com uma revisão sistemática da literatura (Capítulo I), a qual identifica e classifica os principais critérios espaciais utilizados em processos decisórios voltados para a restauração, ressaltando lacunas metodológicas e a necessidade de padronização na seleção e aplicação destes critérios. Posteriormente, uma análise espaço-temporal do Bacia do Rio Sarapuí (Capítulo II) revela dinâmicas de uso do solo e o fenômeno do rejuvenescimento da cobertura florestal, possibilitando a identificação de áreas com potencial para catalisar processos sucessórios e promover conectividade ecológica. Em seguida, o mapeamento da pegada humana (Capítulo III) integra aspectos ambientais e socioeconômicos, fornecendo um diagnóstico preciso das pressões antrópicas sobre a paisagem. Finalmente, o framework decisório proposto (Capítulo IV) consolida os resultados anteriores ao estruturar um método robusto e replicável, baseado em Análise Multicriterial (AMC), para a priorização de áreas de restauração, com potencial aplicação em políticas públicas e iniciativas de Pagamento por Serviços Ambientais. Os resultados demonstram que a convergência entre dados espaciais, análises de dinâmica ambiental e processos de decisão estruturados podem otimizar o direcionamento de investimentos e esforços para a efetiva restauração ecológica de ambientes degradados, contribuindo para a conservação da biodiversidade, mitigação das mudanças climáticas e promoção do desenvolvimento sustentável.

Palavras-chave: Restauração Florestal; Priorização de Áreas; Análise Multicriterial; Análise da Paisagem; Manejo de Bacias Hidrográficas.

ABSTRACT

MORALES, Milton Vinícius. Integrating Landscape Analysis and Multicriteria Decision-Making to Prioritize Forest Restoration Areas in Human-Modified Landscapes. Thesis Defense (Doctorate in Planning and Use of Renewable Resources) – Center for Science and Technology for Sustainability, Federal University of São Carlos, Sorocaba, 166 p, 2025.

This study proposes an integrated approach combining the analysis of the landscape's ecological, anthropical, and biophysical components with multicriteria decision-making methods to prioritize forest restoration areas in human-modified landscapes. The research begins with a systematic literature review (Chapter I) that identifies and categorizes the primary spatial criteria employed in decision-making processes for restoration, highlighting methodological gaps and the need for standardization in selecting and applying these criteria. Subsequently, a spatiotemporal analysis of the Sarapuí River Basin (Chapter II) reveals land-use dynamics and the phenomenon of forest cover rejuvenation, allowing for identifying areas with the potential to trigger successional processes and enhance ecological connectivity. Next, mapping the human footprint (Chapter III) integrates environmental and socioeconomic aspects, providing an accurate diagnosis of anthropogenic pressures on the landscape. Finally, the proposed decision framework (Chapter IV) consolidates the previous results by establishing a robust and replicable multicriteria decision analysis (MCDA) method for prioritizing restoration areas, with potential applications in public policies and Payment for Environmental Services initiatives. The findings demonstrate that the convergence of spatial data, environmental dynamics, and structured decision processes can optimize the allocation of investments and efforts for the effective ecological restoration of degraded environments, ultimately contributing to biodiversity conservation, climate change mitigation, and sustainable development.

Keywords: Forest Restoration; Area Prioritization; Multicriteria Analysis; Landscape Analysis; Watershed Management.

SUMMARY

INTRODUÇÃO

As ações de restauração florestal desempenham papel fundamental na regeneração ecológica de paisagens degradadas, contribuindo significativamente para a conservação da biodiversidade, mitigação das mudanças climáticas e manutenção dos serviços ecossistêmicos (S.E). Em biomas intensamente modificados como a Mata Atlântica e o Cerrado, a paisagem é comumente marcada por mosaicos complexos de usos do solo, nos quais remanescentes de vegetação nativa se encontram alocados em meio a áreas agrícolas, pastagens, infraestruturas e centros urbanos. Nesse cenário, o sucesso da restauração florestal está fortemente condicionado à capacidade das áreas restauradas de desempenharem funções estruturais e funcionais na paisagem, conectando e complementando os fragmentos remanescentes (Gama et al., 2013; Vettorazzi e Valente, 2016).

No entanto, planejar ações de restauração que efetivamente favoreçam a funcionalidade da paisagem constitui um grande desafio metodológico, sobretudo devido à multiplicidade de fatores biofísicos, ecológicos, climáticos e antrópicos que devem ser considerados (Höhl et al., 2020). A complexidade dessas interações exige abordagens capazes de integrar dados espaciais diversos, de modo a orientar decisões mais assertivas e eficientes.

Além dos desafios técnicos, há ainda limitações práticas e econômicas. A restauração florestal em larga escala demanda recursos humanos e financeiros substanciais, o que torna inviável a restauração integral de todas as áreas degradadas (Lamb, 2018). Assim, torna-se imperativa a adoção de estratégias que priorizem espacialmente as áreas com maior potencial de retorno ecológico e socioambiental, otimizando os esforços e investimentos.

Nesse contexto, abordagens baseadas em Análise Multicriterial (AMC) vêm se consolidando como ferramentas promissoras para apoiar processos decisórios no planejamento de ações de restauração. A AMC permite integrar múltiplos critérios espaciais com pesos ajustáveis conforme a importância relativa de cada fator para os objetivos do estudo (Drobne e Lisec, 2009; Esmail e Geneletti, 2018; Malczewski e Rinner, 2015). Quando bem estruturada, essa abordagem possibilita a geração de mapas de priorização robustos e replicáveis, que orientam a tomada de decisão de forma transparente e tecnicamente fundamentada.

Ainda assim, aplicações da AMC em contextos ambientais enfrentam limitações recorrentes, como o uso de conjuntos de critérios pouco representativos, a ausência de padronização na normalização dos dados espaciais e a escassa incorporação de critérios socioeconômicos (Esmail e Geneletti, 2018). Tais fragilidades podem comprometer a efetividade das decisões e reduzir a aplicabilidade dos resultados (Esmail e Geneletti, 2018). Dessa forma, uma priorização territorial eficaz exige não apenas rigor metodológico, mas também compreensão profunda das dinâmicas ecológicas envolvidas, conhecimento técnico dos critérios utilizados e sua tradução adequada em produtos cartográficos.

Diante disso, a presente pesquisa tem como objetivo contribuir para o aprimoramento das estratégias de restauração florestal em paisagens antropizadas, com foco na estruturação de processos decisórios espacialmente explícitos que incorporem tanto fundamentos conceituais quanto avanços tecnológicos na espacialização de fenômenos ambientais. A Tese foi organizada em quatro Capítulos, abordando de maneira integrada os principais desafios relacionados à definição de critérios espaciais, análise e representação da paisagem e estruturação do processo decisório no contexto da restauração florestal.

Assim, o primeiro capítulo apresenta uma revisão sistemática da literatura científica referente à processos decisórios estruturados no âmbito da Análise Multicriterial cujo o objetivo é a priorização de áreas para restauração florestal. Esta análise focou em identificar os critérios espaciais que efetivamente atuam para o sucesso das ações de restauração florestal e nas lacunas conceituais e técnicas a respeito da obtenção de critérios espaciais representativos da paisagem. Os resultados obtidos nesta meta-análise de processos decisórios para a restauração inspiraram os dois capítulos subsequentes que tratam de aspectos ecológicos e antrópicos da paisagem e sua importância na ciência da restauração, além de subsidiar a escolha do conjunto de critérios espaciais e sua respectiva ordem de importância no processo decisório desenvolvido no Capítulo IV.

Neste contexto, o Capítulo II realiza uma análise espaço-temporal da paisagem da Bacia do Rio Sarapuí, avaliando as dinâmicas do uso do solo, da cobertura florestal e a conectividade funcional entre fragmentos de habitat ao longo do tempo. Neste Capítulo um aspecto relevante à despeito das áreas de habitat foi revelado, o rejuvenescimento da cobertura florestal, alinhado à recentes resultados deste processo em análises de maiores escalas como nos trabalhos de Rosa et al., (2021), Dias et al., (2023) e Vancine et al., (2024).

Essa análise permitiu identificar áreas com maior potencial para catalisar processos sucessionais e contribuiu diretamente para a construção de um critério espacial orientado à conectividade ecológica.

No Capítulo III, a tese avança sobre a avaliação da pressão antrópica e de seus desdobramentos socioeconômicos a partir do mapeamento da pegada ecológica humana (*Human Footprint*) integrando os distúrbios ambientais e características socioeconômicas da ocupação humana no território. Neste capítulo adaptamos a metodologia desenvolvida por Sanderson et al. (2002) e posteriormente aprimorada em trabalhos como de Woolmer et al., (2008) e Venter et al., (2016) para uma escala compatível para o auxílio a tomada de decisão em nível de bacia hidrográfica.

Trata-se do primeiro mapeamento da pegada ecológica humana no território nacional excluídos os *datasets* globais como os de Venter et al., (2016) e Mu et al., (2022), e apresenta uma estrutura replicável para análises em escalas como as comumente utilizadas em bacias hidrográficas, visto que os citados *datasets* disponíveis são de baixa resolução e pensados para escalas globais de análise.

Por fim, o quarto Capítulo IV incorpora os resultados dos anteriores para a estruturação do processo decisório para a restauração florestal na bacia do rio Sarapuí. A partir da meta-análise conduzida no Capítulo I e das analises complementares locais e da produção dos critérios espaciais dos Capítulos II e III, desenvolvemos um framework robusto e replicável para a restauração florestal em paisagens antropizadas, com potencial de aplicação prática em políticas públicas e iniciativas de Pagamento por Serviços Ambientais (PSA).

Dessa forma, esta tese busca oferecer subsídios teóricos e metodológicos que contribuam para que a restauração florestal seja conduzida de forma mais estratégica, eficiente e contextualizada às dinâmicas ambientais e sociais da paisagem. Ao promover a integração entre critérios ecológicos, físicos e socioeconômicos no planejamento espacial da restauração, a pesquisa se alinha aos princípios da sustentabilidade, contribuindo para a conservação da biodiversidade, a regulação climática, a proteção de recursos hídricos e o fortalecimento da resiliência territorial. Esses elementos reforçam o papel da restauração ecológica como instrumento transversal na promoção do desenvolvimento sustentável, em consonância com os compromissos globais estabelecidos pela Agenda 2030 e seus Objetivos de Desenvolvimento Sustentável.

REFERÊNCIAS

Dias, T. da C., Silveira, L. F., e Francisco, M. R. (2023). **Spatiotemporal dynamics reveals forest rejuvenation, fragmentation, and edge effects in an Atlantic Forest hotspot, the Pernambuco Endemism Center, northeastern Brazil**. PLOS ONE, 18(9), e0291234. https://doi.org/10.1371/journal.pone.0291234

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

Esmail, B. A., e Geneletti, D. (2018). **Multi-criteria decision analysis for nature conservation: A review of 20 years of applications**. Methods in Ecology and Evolution, 9(1), 42–53. https://doi.org/10.1111/2041-210X.12899

Gama, V. F., Martensen, A. C., Ponzoni, F. J., Hirota, M. M., e Ribeiro, M. C. (2013). **Site Selection for Restoration Planning: A Protocol with Landscape and Legislation Based Alternatives**. Natureza and Conservação, 11(2), 158–169. https://doi.org/10.4322/natcon.2013.025

Höhl, M., Ahimbisibwe, V., Stanturf, J. A., Elsasser, P., Kleine, M., e Bolte, A. (2020). **Forest landscape restoration-What generates failure and success?** Forests, 11(9). https://doi.org/10.3390/F11090938

Lamb, D. (2018). **Undertaking large-scale forest restoration to generate ecosystem services**. In Restoration Ecology (Vol. 26, Issue 4, pp. 657–666). Blackwell Publishing Inc. https://doi.org/10.1111/rec.12706

Malczewski, J., e Rinner, C. (2015). **Multicriteria Decision Analysis in Geographic Information Science**. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-74757-4

Mu, H., Li, X., Wen, Y., Huang, J., Du, P., Su, W., Miao, S., e Geng, M. (2022). **A global record of annual terrestrial Human Footprint dataset from 2000 to 2018**. Scientific Data, 9(1). https://doi.org/10.1038/s41597-022-01284-8

Rosa, M. R., Brancalion, P. H. S., Crouzeilles, R., Tambosi, L. R., Piffer, P. R., Lenti, F. E. B., Hirota, M., Santiami, E., e Metzger, J. P. (2021). **Hidden destruction of older forests threatens Brazil's Atlantic Forest and challenges restoration programs**. Science Advances, 7(4). https://doi.org/10.1126/sciadv.abc4547

Vancine, M. H., Muylaert, R. L., Niebuhr, B. B., Oshima, J. E. de F., Tonetti, V., Bernardo, R., De Angelo, C., Rosa, M. R., Grohmann, C. H., e Ribeiro, M. C. (2024). **The Atlantic Forest of South America: Spatiotemporal dynamics of the vegetation and implications for conservation.** Biological Conservation, 291, 110499. https://doi.org/10.1016/j.biocon.2024.110499

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., e Watson, J. E. M. (2016). **Global terrestrial Human Footprint maps for 1993 and 2009**. Scientific Data, 3. https://doi.org/10.1038/sdata.2016.67

Vettorazzi, C. A., e 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

Woolmer, G., Trombulak, S. C., Ray, J. C., Doran, P. J., Anderson, M. G., Baldwin, R. F., Morgan, A., e Sanderson, E. W. (2008). **Rescaling the Human Footprint: A tool for conservation planning at an ecoregional scale**. Landscape and Urban Planning, 87(1), 42–53. https://doi.org/10.1016/j.landurbplan.2008.04.005

INTRODUCTION

Forest restoration efforts play a fundamental role in the ecological regeneration of degraded landscapes, contributing significantly to biodiversity conservation, climate change mitigation, and the maintenance of ecosystem services (E.S.). In highly modified biomes such as the Atlantic Forest and the Cerrado, the landscape is often composed of complex mosaics of land uses, in which remnants of native vegetation are interspersed with agricultural areas, pastures, infrastructure, and urban centers. In such contexts, the success of forest restoration is strongly conditioned by the capacity of restored areas to fulfill structural and functional roles in the landscape, connecting and complementing remaining forest fragments (Gama et al., 2013; Vettorazzi and Valente, 2016).

However, planning restoration interventions that effectively enhance landscape functionality poses a significant methodological challenge, primarily due to the multiplicity of biophysical, ecological, climatic, and anthropogenic factors that must be considered (Höhl et al., 2020). The complexity of these interactions requires approaches capable of integrating diverse spatial data to guide more accurate and efficient decision-making.

Beyond technical challenges, practical and economic limitations must also be addressed. Large-scale forest restoration requires substantial human and financial resources, making the full recovery of all degraded areas unfeasible (Lamb, 2018). Therefore, adopting strategies that spatially prioritize areas with the most significant potential for ecological and socio-environmental return becomes imperative, thereby optimizing efforts and investments.

In this context, Multi-Criteria Decision Analysis (MCDA) has emerged as a promising tool to support decision-making processes in restoration planning. MCDA allows for integrating multiple spatial criteria with adjustable weights according to the relative importance of each factor to the study's objectives (Drobne and Lisec, 2009; Esmail and Geneletti, 2018; Malczewski and Rinner, 2015). When well-structured, this approach enables the generation of robust and replicable prioritization maps, supporting transparent and technically sound decision-making.

Nonetheless, the application of MCDA in environmental contexts still faces recurring limitations, such as poorly representative criteria sets, lack of standardization in spatial data normalization, and limited incorporation of socioeconomic factors (Esmail and Geneletti, 2018). These weaknesses can compromise decision effectiveness and reduce the applicability of results. Thus, effective spatial prioritization requires methodological rigor and a deep understanding of ecological dynamics, technical knowledge of the criteria used, and their appropriate translation into cartographic products.

In light of this, the present research aims to contribute to improving forest restoration strategies in human-modified landscapes, focusing on developing spatially explicit decision-making processes that incorporate both conceptual foundations and technological advances in environmental spatialization. The thesis is organized into four chapters, which together address the main challenges associated with defining spatial criteria, landscape analysis and representation, and decision-making processes in forest restoration.

Chapter I presents a systematic review of the scientific literature on structured decision-making processes within MCDA aimed at prioritizing areas for forest restoration. This review focuses on identifying spatial criteria that effectively support restoration success and conceptual and technical gaps in representing landscape-relevant criteria. The findings of this meta-analysis informed the subsequent chapters, which address ecological and anthropogenic aspects of the landscape and their importance to restoration science. Also, they guided the selection of spatial criteria and their respective weights in the decision-making process developed in Chapter IV.

Chapter II presents a spatiotemporal analysis of the Sarapuí River Basin landscape, assessing land-use dynamics, forest cover, and functional connectivity between habitat patches over time. A noteworthy finding in this chapter concerns the rejuvenation of forest cover, consistent with recent large-scale observations reported by Rosa et al. (2021), Dias et al. (2023), and Vancine et al. (2024). This analysis made it possible to identify areas with more significant potential to catalyze successional processes and directly supported the development of a spatial criterion focused on ecological connectivity.

Chapter III advances the analysis of anthropogenic pressure and its socioeconomic implications by mapping the human footprint and integrating environmental disturbances with socioeconomic characteristics of human occupation in the territory. In this chapter, we adapted the methodology initially developed by Sanderson et al. (2002) and later refined in studies such as Woolmer et al. (2008) and Venter et al. (2016) to a watershed-scale framework appropriate for local decision-making. This represents the first mapping of the Human Footprint at the national level, excluding global datasets (e.g., Venter et al., 2016; Mu et al., 2022), and it provides a replicable structure for analyses at scales typically used in watershed planning, given that available global datasets are low resolution and intended for broader-scale assessments.

Finally, Chapter IV integrates the findings of the previous chapters to develop the decision-making framework for forest restoration in the Sarapuí River Basin. Building on the meta-analysis from Chapter I, the local analyses, and the spatial criteria developed in Chapters II and III, we propose a robust and replicable framework for forest restoration in human-modified landscapes, with practical application potential in public policies and Payment for Environmental Services (PES) initiatives.

In this way, the thesis seeks to provide both theoretical and methodological support to help ensure that forest restoration is implemented more strategically, efficiently, and in alignment with the environmental and social dynamics of the landscape. The research aligns with sustainability principles by promoting the integration of ecological, physical, and socioeconomic criteria into spatial restoration planning. It contributes to biodiversity conservation, climate regulation, water resource protection, and the strengthening of territorial resilience. These elements reinforce ecological restoration as a cross-cutting instrument for advancing sustainable development following the global commitments established under the 2030 Agenda and its Sustainable Development Goals (SDGs).

REFERENCES

Dias, T. da C., Silveira, L. F., and Francisco, M. R. (2023). **Spatiotemporal dynamics reveals forest rejuvenation, fragmentation, and edge effects in an Atlantic Forest hotspot, the Pernambuco Endemism Center, northeastern Brazil**. PLOS ONE, 18(9), e0291234. https://doi.org/10.1371/journal.pone.0291234

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

Esmail, B. A., and Geneletti, D. (2018). **Multi-criteria decision analysis for nature conservation: A review of 20 years of applications**. Methods in Ecology and Evolution, 9(1), 42–53. https://doi.org/10.1111/2041-210X.12899

Gama, V. F., Martensen, A. C., Ponzoni, F. J., Hirota, M. M., and Ribeiro, M. C. (2013). **Site Selection for Restoration Planning: A Protocol with Landscape and Legislation Based Alternatives**. Natureza and Conservação, 11(2), 158–169. https://doi.org/10.4322/natcon.2013.025

Höhl, M., Ahimbisibwe, V., Stanturf, J. A., Elsasser, P., Kleine, M., and Bolte, A. (2020). **Forest landscape restoration-What generates failure and success?** Forests, 11(9). https://doi.org/10.3390/F11090938

Lamb, D. (2018). **Undertaking large-scale forest restoration to generate ecosystem services**. In Restoration Ecology (Vol. 26, Issue 4, pp. 657–666). Blackwell Publishing Inc. https://doi.org/10.1111/rec.12706

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

Mu, H., Li, X., Wen, Y., Huang, J., Du, P., Su, W., Miao, S., and Geng, M. (2022). **A global record of annual terrestrial Human Footprint dataset from 2000 to 2018**. Scientific Data, 9(1). https://doi.org/10.1038/s41597-022-01284-8

Rosa, M. R., Brancalion, P. H. S., Crouzeilles, R., Tambosi, L. R., Piffer, P. R., Lenti, F. E. B., Hirota, M., Santiami, E., and Metzger, J. P. (2021). **Hidden destruction of older forests threatens Brazil's Atlantic Forest and challenges restoration programs**. Science Advances, 7(4). https://doi.org/10.1126/sciadv.abc4547

Vancine, M. H., Muylaert, R. L., Niebuhr, B. B., Oshima, J. E. de F., Tonetti, V., Bernardo, R., De Angelo, C., Rosa, M. R., Grohmann, C. H., and Ribeiro, M. C. (2024). **The**

Atlantic Forest of South America: Spatiotemporal dynamics of the vegetation and implications for conservation. Biological Conservation, 291, 110499. https://doi.org/10.1016/j.biocon.2024.110499

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., and Watson, J. E. M. (2016). **Global terrestrial Human Footprint maps for 1993 and 2009**. Scientific Data, 3. https://doi.org/10.1038/sdata.2016.67

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

Woolmer, G., Trombulak, S. C., Ray, J. C., Doran, P. J., Anderson, M. G., Baldwin, R. F., Morgan, A., and Sanderson, E. W. (2008). **Rescaling the Human Footprint: A tool for conservation planning at an ecoregional scale**. Landscape and Urban Planning, 87(1), 42–53. https://doi.org/10.1016/j.landurbplan.2008.04.005

1. CHAPTER I

THE ROLE OF SPATIAL CRITERIA IN ENHANCING FOREST RESTORATION ACTIONS: A SYSTEMATIC REVIEW

Abstract

Forest and landscape restoration is crucial for enhancing ecosystem integrity and services. However, achieving successful restoration outcomes presents significant methodological challenges and demands significant financial and human resources. Selecting appropriate restoration sites within the landscape determines forest restoration effectiveness. The restored habitats must complement existing ones by fulfilling structural and functional roles in the landscape. There are numerous approaches to prioritizing and selecting areas for restoration, often employing Multicriteria Decision Analysis (MCDA) approaches to address the spatial complexities influenced by diverse environmental, ecological, climatic, and anthropic landscape characteristics. The review identifies 59 distinct spatial criteria, systematically grouped into nine thematic categories: ecological, pedology, disturbances, water and hydrology, topography, climate, land use and land cover, socioeconomic, and protected areas. Through bibliometric analysis, we observed an increasing number of studies over time, with a strong regional concentration in tropical and subtropical biomes, particularly in Latin America. Despite the predominance of studies from Brazil, recent publications indicate a gradual expansion of MCDA-based approaches to other regions, such as the Mediterranean and semi-arid landscapes. Our findings highlight the growing complexity of spatial decision-making in forest restoration and emphasize the need for a more standardized approach to spatial criteria selection. This review provides critical insights into the methodological advances and geographic trends in restoration planning, offering a foundation for improving decision-support frameworks and guiding future research and conservation policies.

Keywords: Decision-Making Process; Ecological Restoration; Forest Restoration; Multicriteria Analysis; Priority Areas.

1.1. INTRODUCTION

Forest restoration plays an essential role in the landscape regenerative process by enhancing ecosystem integrity and services and offering a remedy to the historical impacts of habitat loss and forest fragmentation. Acknowledged as fundamental to mitigating climate change (Koch and Kaplan, 2022; Tuinenburg et al., 2022) and biodiversity loss (Barlow et al., 2016; Romanelli et al., 2022), forest restoration has gained increasing global attention in recent decades (Lamb, 2018), being subject in several commitments as the Bonn Challenge, that seeks to restore 350 million of hectares by 2030 (Bonn Challenge, 2014), the U.N. Convention on Biodiversity (CBD, 2011), that aimed to restore 15% of degraded ecosystems worldwide by 2020, and integrating the U.N Sustainable Development Goals (SDG, 2015), that the Goal 15 concerns to restore degraded landscapes to reach a “land-degradation neutral word” by 2030 (Lamb, 2018).

However, achieving the effectiveness of forest restoration remains a methodological challenge (Höhl et al., 2020). Overcoming obstacles such as land competition and resource scarcity requires evaluating a wide range of factors to ensure restored land persistence (Borda-Niño et al., 2020). This evaluation must encompass ecosystem complexity, landscape conditions, geomorphology, anthropic occupation patterns, climatic considerations, and the prevailing political and economic context (Höhl et al., 2020).

The restoration of ecological functionality in degraded ecosystems relies on the ability of restored habitats to complement existing ones effectively (Gama et al., 2013). However, determining which sites can be most effectively restored remains a significant gap in restoration science (Brancalion et al., 2016; Höhl et al., 2020; Lamb, 2018). Nonetheless, it is well-known that managing this gap involves catalyzing the ecological successional process (Borda-Niño et al., 2020), and promoting ecological function reestablishing while concurrently reducing implementation costs.

Determining appropriate sites for implementing forest restoration actions within a landscape requires addressing a decision problem that involves multiple variables interacting on a spatial and temporal scale. Multicriteria Decision Analysis (MCDA) is a valuable approach for dealing with spatial decision problems, which has proven to be highly effective in prioritizing and selecting sites for forest restoration (Mello et al., 2017; Valente et al., 2021).

MCDA-based approaches involve integrating and transforming geographical data (*inputs*) into well-informed decisions (*output*). Operationally, MCDA helps structure spatial decision problems, evaluate alternative options based on various criteria, explore trade-offs, formulate decisions, and assess their robustness (Drobne and Lisec, 2009; Esmail and Geneletti, 2018).

These approaches effectively use the landscape's biophysical and spatial aspects. However, the key challenge lies in expressing the preferences and needs of decision-makers, specialists, and affected communities using conceptually appropriate and spatially explicit criteria. The process results in a set of maps that seamlessly integrate into decision-making as decision factors (criteria and restrictions).

In the forest restoration context, spatial criteria are defined by maps that represent landscape characteristics conducive to successful forestry restoration actions. Characteristics that promote the protection or mitigation of soil and natural resources or facilitate the connection among forest remnants, performing essential structural and functional roles in the landscape. On the other hand, restrictions are also included, which bring characteristics that rule out the feasibility of forest restoration. These restrictions are often represented by land cover classes such as urban areas, surface water, or regions already covered by forests.

Selecting representative and effective spatial criteria for forest restoration is a complex task, often supported by extensive literature reviews (Cavalcante et al., 2022; Mendonça et al., 2022) or participatory techniques involving specialists and stakeholders to reach a consensus

(Lopes et al., 2020; Valente et al., 2017). Thus, criteria selection requires a comprehensive understanding of ecological aspects that drive successful restoration and anthropogenic factors that significantly influence the restoration's outcomes.

In this context, the success of forest restoration area prioritization depends on integrating scientific advances achieved in both MCDA-based approaches and forest's ecological succession knowledge. To address this knowledge gap, we systematically reviewed MCDA-based studies focused on selecting or prioritizing sites for forest restoration, emphasizing the spatial criteria used and the reasons for this choice. Our review centered around two specific questions: (a) *which spatial criteria are employed in MCDA-based approaches for selecting forest restoration sites?* (b) *what ecological concepts guide the choice of such spatial criteria?*

1.2. MATERIAL AND METHODS

Our research was conducted in two distinct stages. Firstly, we undertook a thorough systematic literature review, utilizing bibliometric tools to map out the structure and dynamics of the scientific field. Following this, we conducted a critical analysis of the selected papers, with a particular focus on methodology, spatial criteria, and ecological concepts.

Our focus was on studies employing MCDA approaches to define priority areas for forest restoration. According to Esmail and Geneletti (2018), MCDA approaches vary widely in terms of computational complexity, level of stakeholder engagement, time, and data availability. In-depth analyses on the theoretical foundations of these approaches and their integration with spatial analysis can be found in works such as those by Beinat and Nijkamp (1998), Malczewski and Rinner (2015), and Voogd (1982) .

Figure 1 illustrates the three main stages of the MCDA framework as outlined by Esmail and Geneletti (2018). The first stage, *Decision Context and Problem Structuring*, involves defining objectives, identifying alternatives, and establishing evaluation criteria. The second stage, *Analysis*, assesses the performance of the criteria set, applies weights to represent their relative importance (Saaty, 1980), aggregates the results, and performs sensitivity analyses to account for uncertainties. The final stage, *Decision*, integrates these results to rank or cluster the alternatives, supporting a transparent and informed selection process to address the proposed problem.

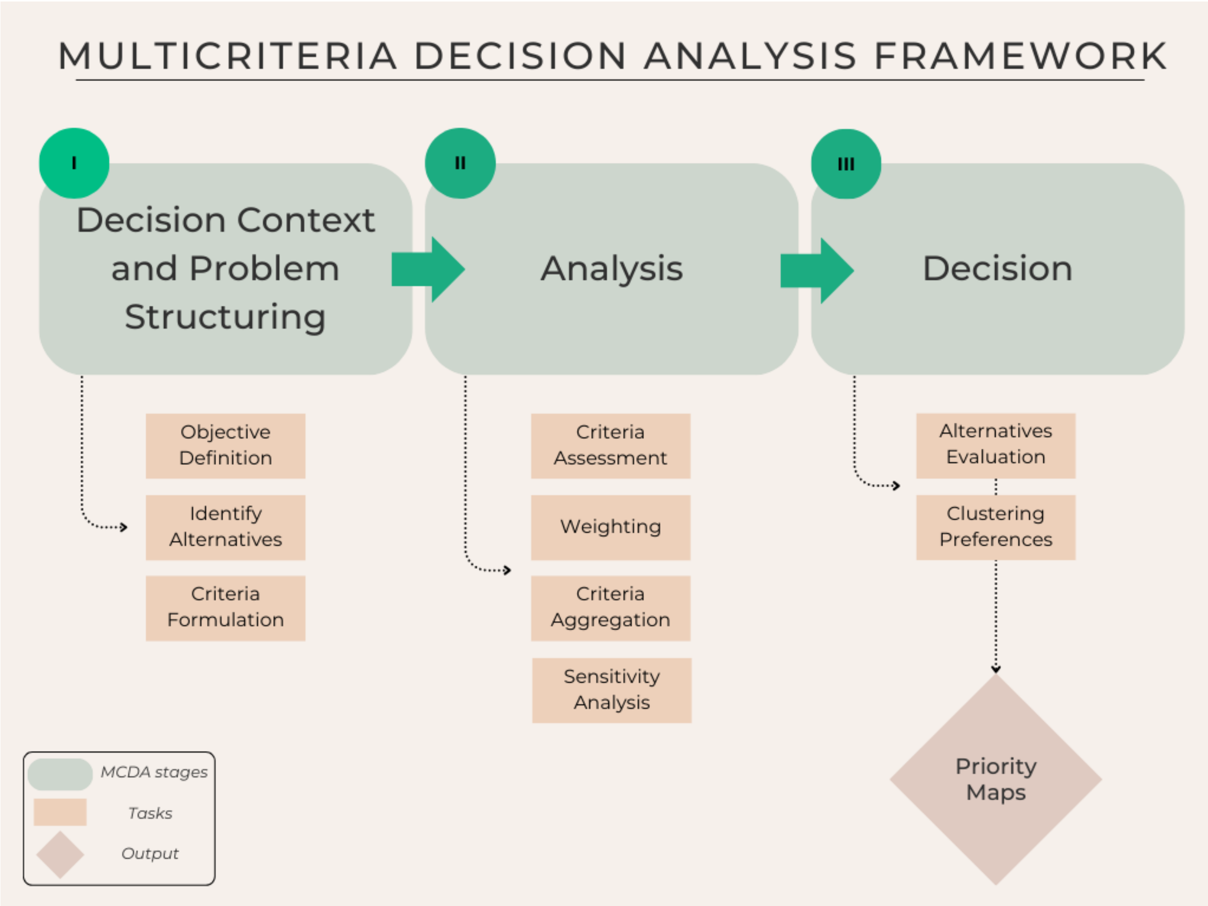


Figure 1 - A generalized scheme of the mains steps of a multi-criteria decision analysis approach (based on Malczewski and Rinner, 2015; Esmail and Geneletti, 2018).

The following items detail the procedures employed in our literature search and the analysis of the resulting database, focusing on articles that apply MCDA to the selection or prioritization of sites for forest restoration actions.

1.2.1. LITERATURE SEARCH

We considered full articles published in Web of Science and Scopus returning by the following search terms: [forest restoration AND (multicriteria OR decision analysis OR decision support system OR MCDA OR MCDM)], along with their equivalents in Portuguese and

Spanish. These terms were applied to the topics for the Web of Science platform and the title, abstract, and keywords for the Scopus platform. We included all papers published between January 2002 and September 2024. Based on out of 521 papers returned by this search, we selected those that fit in our review objective firstly by reading the paper's abstract and title, narrowing it down to 38 papers, and then complete reading the paper, which allowed us to reach the final 24 papers evaluated. We did not consider studies reporting commercial tree plantations, studies that only partially fit our scope and research questions or studies that do not use MCDA-based approaches for site prioritization.

1.2.2. DATA ANALYSIS

Through the descriptive analysis, we collected information on (a) the number of published papers, (b) number of authors, (c) timespan, (d) sources, (e) percentage of international co-authorship, (f) average age of documents, (g) annual growth rate, (h) number of co-authors, and (i) average number of citations. This analysis was performed using the Bibliometrix package in R 4.2.1 (Aria and Cuccurullo, 2017). Additionally, we extracted information about the paper's study areas, allowing us to analyze the countries where the studies were conducted and their insertion Biome according to Olson et al. (2001).

After data collection, we tabulated and quantified all spatial criteria founded in the results. In some cases, it was necessary to standardize certain terms related to the identified spatial criteria. This step was essential because, in several instances, spatial criteria representing the same information were referred to by different names.

For example, as will be discussed, many spatial criteria derive from maps based on the Euclidean distance to features such as forest patches, drainage networks, urban areas, and roads. In this context, authors such as Uribe et al. (2014) and Orsi and Geneletti (2010) refer to a spatial criterion as "distance from forest" or "distance from existing forest", while others (Valente et al., 2017; Souza et al., 2021), use the term "proximity to forest patches" to describe the same criterion. In both cases, the purpose of including this criterion in the decision-making is identical: to prioritize areas closer to forested regions. Therefore, we standardized this criterion as "proximity to forest patches".

Similarly, interchangeable terms such as "forest fragments" and "forest patches", or “pluviosity” and “precipitation” were also standardized, in this case, to "forest patches" and “pluviosity”, respectively. Table S1.1, included in the supplementary material, presents the various spatial criteria identified in each analyzed article, both in their original and standardized form.

These steps allow us to systematically categorize the spatial criteria set based on their thematic context, resulting in nine distinct categories, which will be presented below. This categorization aims to group spatial criteria that share a common thematic focus, as well as those derived from similar data sources or methodologies. It is important to note that this is a didactic categorization, designed to facilitate a more structured and comprehensive analysis of the spatial criteria identified in the reviewed studies. By organizing the criteria in this way, we aim to provide clearer insights into their roles and relevance within the decision-making processes.

1.3. RESULTS AND DISCUSSION

1.3.1. BIBLIOMETRIC ASPECTS

We found 24 papers reporting MCDA-based approaches that aim to select or prioritize sites to implement forest restoration actions. They came from eight different countries (Figure 2), Brazil (14), Mexico (4), United States (1), Madagascar (1), China (1), Costa Rica (1), Bolivia (1), and Greece (1), comprising six biomes. The most represented is Tropical and Subtropical Moist Broadleaf Forests (13), followed by Tropical and Subtropical Grasslands, Savannas and Shrublands (4), Tropical and Subtropical Coniferous Forests (2), Tropical and Subtropical Dry Broadleaf Forests (2); Mediterranean Forests, Woodlands and Scrub (2), and Temperate Broadleaf and Mixed Forests with only one published paper (Figure 2).

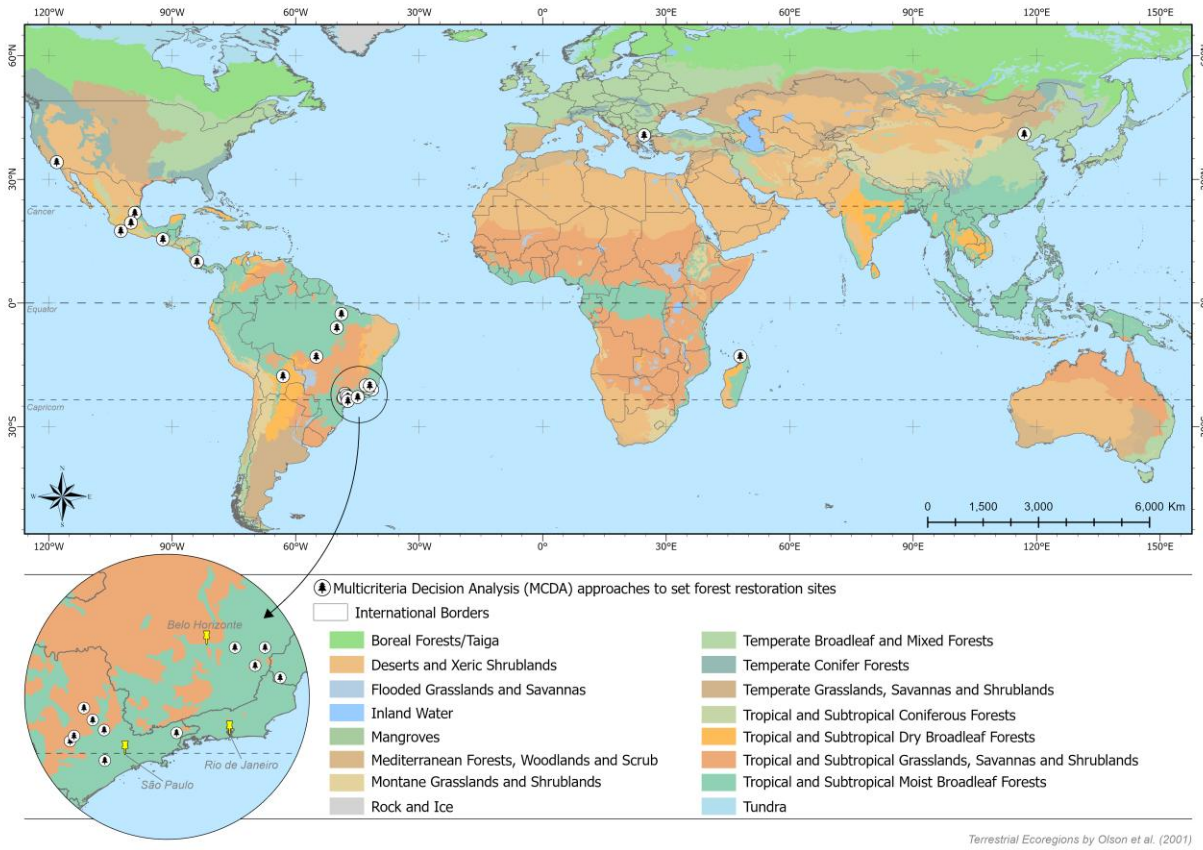


Figure 2 - World distribution of published papers (n=24) on the MCDA-based approaches to enhance forest restoration actions.

There is a clear predominance (Figure 2) of studies conducted in intertropical regions, particularly in Latin America. According to Brancalion et al. (2019), tropical forests are recognized as highly threatened biomes and hotspots for scientific advancements in the development of restoration strategies (Beltrán and Howe, 2020; Koch and Kaplan, 2022; Ruíz et al., 2023) and in the understanding of ecological succession processes (Arroyo-Rodríguez et al., 2017; Crouzeilles et al., 2017; Uriarte and Chazdon, 2016). Our results align with these findings but highlight the need for broader geographic dissemination of these methodologies worldwide.

This perspective is consistent with Borda-Niño et al. (2020), who reviewed studies on drivers of tropical forest recovery and identified a limited representation of such research in regions as Africa and Asia. Although our analysis included publications in Portuguese and Spanish, it's important to highlight that this factor did not bias the results, as only three studies

(Sartori et al., 2012a; Sartori et al., 2012b; De Almeida et al., 2020) were published in Portuguese and one (Calvo-Villalobos et al., 2018) in Spanish.

Similarly, Borda-Niño et al. (2020) identified Brazil and Mexico with the highest studies concentration. They attributed this to critical factors such as the availability of data on land use and land cover changes, deforestation patterns, and public policies that encourage restoration efforts on both public and private lands. These same factors were highlighted by Uribe et al. (2014) as essential for structuring decision-making processes in the context of MCDA approaches, especially regarding the availability of spatialized data.

In Brazil, there is a notable concentration of publications in the southeastern region (Figure 2), particularly in the states of São Paulo and Minas Gerais. This ecotone region, located in a transitional zone between the Atlantic Forest and the Brazilian savanna (Cerrado), has been the focus of numerous foundational studies for developing landscape management strategies. These studies address diverse topics such as biogeography and systematics, conservation and biodiversity, plant-animal interactions, and population and community dynamics (Marques et al., 2021). Additionally, significant contributions have been made to understanding spatial patterns of genetic diversity, the impacts of human-induced habitat loss, and climate change on these ecosystems (Colli et al., 2020).

This region also benefits from the extensive availability of free, high-resolution spatial data, including temporal land-use and land-cover series (Souza et al., 2020), rainfall regimes (de Oliveira et al., 2018), topography and soil properties (Rossi, 2017). Public institutions or non-governmental organizations (NGOs) often generate and disseminate such data, facilitating advanced spatial analyses and modeling. As highlighted by authors such as Orsi and Geneletti (2010) and Uribe et al. (2014), understanding regional dynamics and having access to spatial data at appropriate spatial and temporal scales are fundamental for implementing MCDA approaches.

However, as observed by Colli et al. (2020) and Marques et al. (2021), in the Brazilian context, the concentration of publications in the country's southeastern region is also influenced by socioeconomic factors. This region hosts the most traditional universities and national research centers (Colli et al., 2020), a reflection of the process of institutionalizing science in Brazil (Marques and Grelle, 2021), which benefit from more significant funding compared to institutions located in other parts of the country. This disparity is reflected in the regionalization of studies, highlighting the importance of adequate funding for research groups and graduate programs, particularly those in less privileged regions, such as central Brazil (Colli et al., 2020).

The literature reviewed comprised papers published between 2010 and 2023, despite the search timeframe ranging from 2002 to 2024. This finding emphasizes the pressing need to develop new methodologies that optimize resources for forest restoration, given the growing global interest in this subject and following the establishment of international agreements and commitments, such as the UN Convention on Biodiversity, the New York Declaration of Forests, and the UN Sustainable Development Goals (Lamb 2018). In this context, technological advancements are expected to play a significant role in numerous initiatives, including the transfer, compilation, and dissemination of knowledge, study cases, best practices, lessons learned, and methods for evaluating the success of restoration projects (Höhl et al. 2020).

The bibliometric database's descriptive analysis (Table 1) highlights an annual publication growth rate (9.59%), indicating recent advancements in these approaches. Moreover, the substantial number of authors (73) in the total publications is contrasted by the low rate of international co-authorship (10%), underscoring the importance of fostering greater collaboration among researchers. Such collaboration is essential to replicate successful prioritization results in diverse environments.

Table 1 - Resulting descriptive measures of the bibliometric data collection.

Descriptive Measure	Results
Articles	24
Authors	83

Timespan	2010:2023
Sources	20
International Co-Authorship *(%)*	4.16
Document Average Age *(years)*	5.38
Annual Growth Rate *(%)*	8.82
Co-Authors per Doc	3.75
Average Citations per Doc	9.60

Our research identified a progression in methodologies for prioritizing forest restoration areas using MCDA approaches shaped by foundational studies. Among the most influential works, Orsi and Geneletti (2010) presented a pioneering decision-making process that integrated ecological and socioeconomic spatial criteria to address two central questions: (1) "Where should biodiversity be protected?" and (2) "Where is reforestation likely to succeed?" This study emphasized the importance of a robust theoretical framework on forest succession and restoration ecology alongside georeferenced data at appropriate scales. Challenges such as defining criteria and their relative importance were highlighted, with the incorporation of expert and stakeholder opinions proposed as a solution to enhance accuracy.

Uribe et al. (2014) advanced the methodology by directly incorporating stakeholder preferences through interviews with academics, government officials, NGOs, and local stakeholders. While this approach provided actionable outcomes for restoration site selection, the authors acknowledged limitations, such as obtaining georeferenced data for specific spatial criteria and balancing conflicting stakeholder interests. Vettorazzi and Valente (2016) further refined the process by integrating participatory techniques (Eastman, 2003) and the Analytic Hierarchy Process (Saaty, 1990), reducing subjectivity and ensuring replicability.

For instance, their methodology was applied successfully in two distinct watersheds, demonstrating its effectiveness in prioritizing areas to improve water-related ecosystem services. Valente et al. (2017) and Aguirre-Salado et al. (2017) also showcased the flexibility of these approaches by adapting them to different contexts, such as a transition zone between the Cerrado and the Atlantic Fores, the Amazon rainforest, and later Noth and Rinner (2021) did the same to a semi-arid Mediterranean region. These adaptations demonstrated the robustness of MCDA frameworks, as criteria weights could be adjusted to reflect diverse landscape dynamics and local characteristics.

1.3.2. SPATIAL CRITERIA AND CONCEPTUAL ASPECTS

Among the 24 analyzed papers, we identified 59 distinct spatial criteria applied 138 times. As illustrated in Figure 3, these 59 spatial criteria were systematically grouped into nine thematic categories. The grouping was based on the thematic focus of each spatial criterion, the justification provided by the authors for their inclusion in decision-making processes, and their data source and methodology of acquisition. Table S1.2, included in the supplementary material provides a detailed overview of the spatial criteria within each thematic category, the frequency of their use, and the studies in which they were applied.

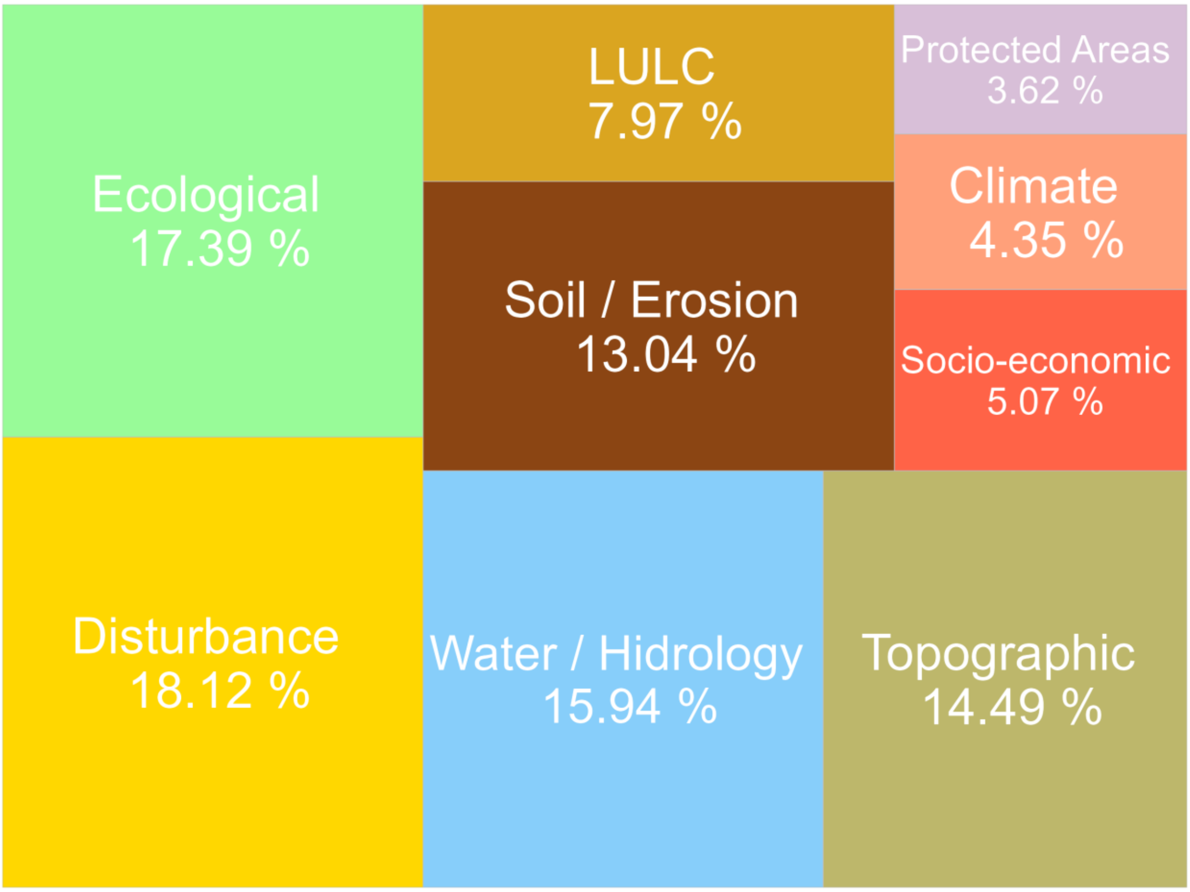


Figure 3 –Proportional contribution of spatial criterion groups to the total set of criteria employed in the evaluated decision-making processes.

Among the nine identified categories, approximately 80% of the occurrences are concentrated in those related to disturbance (25 occurrences), ecology (24), water and hydrology (22), topography (20), and soil and erosion (18). This distribution underscores two primary considerations. The first is the search for sites that will support the restoration efficiently. This is demonstrated by prioritizing restoration actions away from roads and urban infrastructure (Orsi and Geneletti, 2010; Uribe et al., 2014; Aguirre-Salado et al., 2017; Souza et al. 2021) while favoring proximity to existing forest cover (Valente et al. 2017; Li et al. 2020; Cosimo et al. 2021, Noth and Rinner, 2021) aiming to catalyze ecological succession by favoring processes as colonization and immigration (Watts and Hughes, 2024) on the restored patches.

The second consideration highlights the critical role that future forest cover will play within the landscape, particularly in managing soil and water resources. Restoration efforts aim to stabilize or prevent erosion processes (Cruz-Bello and Sotelo-Ruiz, 2013; Vettorazzi and Valente, 2016; Silva and Vieira, 2020; Rajaonarivelo and Williams, 2022), protect stream and river margins to reduce runoff velocity and sediment transport and improve water quality (Vettorazzi and Valente, 2016; Valente et al. 2021; Fernandez et al. 2023) while promoting the recovery of degraded areas (Cavalcante et al. 2022).

Spatial criteria related to disturbance sources were the most frequently employed in the analyzed decision-making processes. These criteria predominantly derive from Euclidean distance to landscape elements considered unfavorable for the success of forest restoration actions, where greater distances to these elements result in higher prioritization. The spatial criterion "Distance from Roads" is the most utilized, and it was applied in nine cases.

Roads were identified as a significant disruptive forest restoration factor for several reasons. First, their linear configuration in the landscape often splits fragments and isolates habitats, reducing habitat quality and core area size (Souza et al., 2021). Second, roads facilitate human settlement and activities (de Rezende et al., 2015), acting as conduits for deforestation, selective logging, and wildfires while hindering natural regeneration in surrounding areas (Barlow et al., 2016). Furthermore, roads increase the attractiveness of these regions for agricultural expansion due to improved transportation and production flow, posing a direct threat to nearby forest remnants and discouraging those sites allocation for restoration initiatives (Laurance et al., 2014; de Rezende et al., 2015; Souza et al., 2021).

Similarly, eight cases employed the spatial criterion "Distance from Urban Areas" to prioritize sites with greater distances from urbanized areas for restoration actions. Proximity to urban areas is widely regarded as a disturbance source, mainly due to the high concentration of human activity in cities and settlements, which are among the primary drivers of pollution, land degradation, and natural resource exploitation (Rajaonarivelo and Williams, 2022). Forest fragments and water resources near urban areas face similar adverse effects as those near roads (Karlson et al., 2014).

Other disturbance-related criteria adapted to specific local landscapes include "Distance from Roads and Infrastructure," which extends the scope of analysis to include mobility and public supply infrastructures (Fernandez et al., 2023), utilizing Euclidean distance for spatial representation. Additionally, Calvo-Villalobos (2018) employed the "Infrastructure" criterion, which considers only the presence or absence of such elements in the landscape to formulate restoration alternatives.

It is important to highlight that although large-scale restoration efforts are impractical in urban environments (Lamb, 2018), forests near cities and forest patches integrated into the urban environment are highly valued for their provision of ecosystem services and contributions to urban well-being. These include climate regulation, recreation opportunities, eco-tourism, air quality improvement, water management, and natural disaster mitigation (Adas et al., 2020; Panasolo et al., 2019). Urban forest restoration and conservation initiatives are gaining prominence as they address the challenge of balancing urban growth with ecological landscape management (Vanderley-Silva and Valente, 2023). This emerging field emphasizes green spaces, urban parks, and protected area management as critical components of sustainable urban planning (Ribeiro et al., 2022), and such initiatives should be encouraged and further developed.

In three decision-making processes, we identified spatial criteria designed to distance forest restoration actions from agricultural regions. This was achieved through the use of the spatial criterion "Distance from Agricultural Areas", in two instances, spatialized based on Euclidean distance to agricultural patches, and the criterion "Cropland Cover (%)", in one instance, applied at the watershed scale to prioritize sub-basins with a lower proportion of cropland cover (Li et al., 2020).

According to the authors, the motivation for incorporating these spatial criteria into decision-making processes stems from recognizing that areas near agriculture often face numerous human-induced pressures and are susceptible to land-use alterations (Orsi and Geneletti, 2010). Additionally, stakeholders consulted in those cases during the spatial criteria selection emphasized the importance of segregating regions designated for agricultural production from those intended for conservation (Orsi and Geneletti, 2010; Uribe et al., 2014).

This perspective touches on the ongoing debate in conservation science about "Land Sparing vs Land Sharing" (Fischer et al. 2014). The "Land Sparing" concept advocates for zoning large-scale agricultural production areas and conservation zones as separate entities. At the same time, "Land Sharing" rejects this dichotomy and promotes the integration of agricultural production and conservation (Green et al. 2005; Fischer et al. 2014).

Recent trends in conservation research suggest that both approaches offer interdependent and complementary opportunities for forest restoration, highlighting that the balance between them would depend on the landscape configuration and governance aspects (Meli et al. 2019).

Although biophysical factors less conducive to large-scale agricultural activities, such as high altitudes, steep slopes, and less fertile soils, play a significant role in promoting forest cover expansion (Borda-Niño et al. 2020), simply distancing restoration actions from agricultural fields is not an evidence-based practice for ecological landscape management (Green et al. 2005; Meli et al. 2019; Arroyo-Rodriguez et al. 2020). Also, this approach may conflict with critical command-and-control mechanisms, such as Brazil's Native Vegetation Protection Law (Guidotti et al., 2020), and similar initiatives in countries like Costa Rica (Calvo-Villa Lobos et al., 2018) and Bolivia (Fernandez et al., 2023), which mandate conservation and restoration on agricultural and private lands.

Still, regarding disturbances, recent studies (Fernandez et al., 2023; Dosis et al., 2023) have employed spatial criteria related to wildfire occurrences to guide restoration actions in affected regions. Fernandez et al. (2023) utilized the criteria "Fire Occurrence" and "Fire Intensity" based on a binary approach, assessing the presence or absence of wildfires and their intensity levels. In contrast, Dosis et al. (2023) employed the "Differenced Normalized Burn Ratio (dNBR)" as a continuous variable, where wildfire occurrences are quantified using the dNBR spectral index, and prioritization increases progressively with the burn ratio across the landscape.

The recent application of MCDA approaches to forest restoration in fire-affected regions underscores the critical role of structured decision-making processes in guiding restoration efforts. This approach is particularly essential in the current context of climate change, characterized by rising temperatures and an increasing frequency of wildfires globally (Mansoor et al. 2020; Miezite et al. 2020; Gajendiran et al. 2024).

The second group of spatial criteria with the highest presence in decision-making processes pertains to ecological criteria, mainly related to habitat patches. It accounts for 24 occurrences and 12 distinct spatial criteria (Table S1.2). Despite the relatively large number of unique criteria in this category, 50% of the occurrences correspond to the criterion "Proximity to Forest Patches."

The authors' justification for including this criterion is to promote forest connectivity and gene flow by restoring areas near existing forest cover (Almeida et al., 2019; Souza et al., 2021; Valente et al., 2017). It is also justified by the increase in the probability of seed dispersal from forest patches into restored sites (Silva and Vieira, 2020). Additionally, Lopes et al. (2020) and Noth and Rinner (2021) highlight improved soil conditions and a higher stock of water in soils near forests, factors that enhance the success of restoration actions.

Borda-Niño et al. (2020) identified proximity to forest remnants as a biophysical factor that significantly influences forest cover expansion, highlighting its role in triggering regenerative processes, a phenomenon also observed by Precinoto et al. (2022) when analyzing drivers of forest cover changes in Atlantic Forest watersheds. Studies in the Atlantic Forest demonstrate that proximity to forest patches for seed dispersal and propagule reserve purposes is significant until a threshold of approximately 600 meters, with this influence decreasing as the distance increases and with forest growth tending to occur in the first 180 meters of distance from older patches (de Rezende et al. 2015).

In practical terms, incorporating this criterion into the decision-making process prioritizes restoration close to existing forest patch edges, increasing the overall area of those patches (Stanturf et al., 2014) and also enhancing their shape, reducing the intensity of edge effects (Magnago et al., 2015), and enhancing ecological corridors (Santos et al., 2018). However, it is important to note that using "Proximity to Forest Patches" as a spatial criterion in MCDA frameworks requires careful consideration, particularly in dynamic and fragmented landscapes.

One effect of fragmentation is that the distances between patches are reduced as the number of patches increases (Fahrig, 2003; Tischendorf and Fahrig, 2000). While this can be positive for biodiversity if accompanied by adequate habitat coverage (Hanski, 2015; Watts and

Hughes, 2024), in prioritizing areas through MCDA, the reduced distances between fragments often lead to a predominance of high-priority areas throughout the study region, as all patches become closer. This outcome can undermine the effectiveness of the criterion in guiding the strategic allocation of restoration efforts.

Sartori et al. (2012b) and Souza et al. (2021), to narrow down the prioritization range based on the proximity of forest patches, considered only patches with significant core areas, thereby considerably reducing the number of high-priority areas and optimizing the performance of the spatial criterion in the MCDA context. However, conservation strategies that rank the importance of habitat patches based on their size, although widely used as management strategies, are not evidence-based (Fahrig, 2022) and overlook the critical importance of small patches for biodiversity conservation and gene flow in the landscape (Riva and Fahrig, 2022).

This point touches on another heated debate within the scientific community known as the SLOSS (Single Large or Several Small) debate, which addresses the dilemma between conserving single large (SL) or several small (SS) patches in landscapes worldwide. In delving into the SLOSS dilemma, Fahrig et al. (2022) show that while there is no evidence that protecting SL patches is better for biodiversity, this practice remains widespread among conservation agencies and programs. However, the author also acknowledges that even though there is no evidence for SL > SS as a general principle, this does not necessarily translate into a higher priority for preserving SS over SL, and that other factors, such as landscape configuration and the size of the studied ecosystem, must also be considered on decision-making.

Despite the ongoing debate, Riva et al. (2024) state that protecting as much native habitat as possible is key to safeguarding biodiversity. This requires protecting and restoring both the remaining large native ecosystems and the many small native patches in working landscapes. Above all, habitat patches must be functionally connected to ensure access to sufficient and complementary resources, reduce the risk of population extinction, and facilitate recolonization (Riva et al. 2024).

Considering this, more sophisticated strategies are emerging to incorporate spatial criteria promoting biodiversity in forest restoration decision-making processes. For instance, Cavalcante et al. (2022) utilized spatial criteria based on surfaces generated by modeling species' potential distribution and spatial connectivity derived from an approach grounded in electronic circuit theory applied to ecology.

MCDA-based approaches to forest restoration can benefit from incorporating maps generated using landscape ecology metrics informed by graph theory. These maps effectively link landscape patterns with functional ecological processes (Frazier and Kedron, 2017; Kedron et al., 2018). Although not explicitly employing an MCDA-based framework, Salazar et al. (2021) prioritized areas for forest restoration in the Brazilian Caatinga through analyses of landscape ecology metrics based on graph theory. Similarly, Tambosi et al. (2014) developed a framework to optimize biodiversity restoration efforts by employing a graph approach that integrates habitat quantity and landscape connectivity metrics. Additionally, Antongiovanni et al. (2022), using similar concepts, prioritized restoration areas also in the Brazilian Caatinga by considering landscape resilience, connectivity, and biodiversity value.

The significant prevalence of criteria categorized as ecological reflects the intention of decision-makers to prioritize sites in a manner that leverages conditions capable of catalyzing regenerative processes, capitalizing on colonization credits in regions that have experienced habitat loss, enhancing the shape and structure of existing forest patches, reducing-edge effects on forest remnants, and facilitating ecological connectivity. However, the predominance of proximity to forest fragments as a spatial criterion, even with its low efficiency in fragmented and dynamic landscapes, highlights the limited effort to optimize the selection of spatial criteria, a weakness of MCDA approaches in the context of nature conservation, as reported by Esmail and Geneletti (2018). Therefore, we advocate for greater integration of this research niche with more robust ecological analyses and modeling to provide spatial criteria to enhance the functional connectivity of habitat areas.

Regarding water criteria, 59.09% of instances involved the spatial criterion of 'proximity to drainage network.' It integrated the decision process 13 times, focusing on the protective role of riparian vegetation in preserving soil and enhancing water availability in watersheds (Mello et al. 2017; Adas et al. 2020).

From an ecological perspective, implementing forest restoration near drainage networks is advantageous due to the water flow's dispersal capacity and riparian buffers' nutrient enrichment (Borda-Niño et al. 2020, Şekercioğlu et al. 2015). However, as with most criteria based on Euclidean distance, it is essential to understand the drainage pattern within the study area clearly.

Spatializing the Euclidian distance without evaluating the drainage pattern can lead to a significant number of pixels with a high priority on the criterion map, particularly in regions with a high concentration of small streams. This makes the prioritization map biased towards such a factor, even when the criteria weights or the aggregation MCDA algorithm are changed, as reported by Valente and Vettorazzi (2008) and Vettorazzi and Valente (2016).

In this context, some strategies have been observed to avoid or reduce issues related to distance metrics. For example, some studies suggest considering only the proximity to springs (Valente et al. 2021) or prioritizing sites with less surface water presence (Li et al. 2020). Souza et al. (2021) and Li et al. (2020) considered the qualitative aspects of the drainage network, prioritizing regions based on water quality and potential aquifer contamination.

Other approaches that have the potential to represent the semantics behind spatial criteria in this category are those based on variables derived from indices used in morphometric and hydrological characterizations of the landscape, among which we can mention a high potential for drainage density maps, spatialized to from the Kernel density function of the drainage channels (Bezinska and Stoyanov, 2019). When spatialized, the raster resulting from this metric indicates in each cell the extent of the drainage channels in km² (Km/Km²) continuously, making this an easy-to-interpret and promising approach for implementation in MCDA-based analyses.

Topographic-related criteria represent another highly valued group, with 20 occurrences, dominated by the "Slope" criterion, which accounted for 70% of observations. The inclusion of slope in decision-making processes stems from two interrelated factors. First, it addresses erosion prevention, as steeper slopes are more vulnerable to erosive processes, making these areas a priority for restoration (Valente et al., 2021). Second, decision-makers often assume that flatter areas are more suitable for human activities. In contrast, steeper slopes are less favorable for such uses and more prone to erosion, thus making them better candidates for conservation and restoration efforts (Cosimo et al., 2021).

Empirical studies analyzing forest regrowth and deforestation dynamics support this rationale, identifying slope as a critical factor influencing forest cover increase, particularly following the abandonment of agriculturally marginal, steep regions (Calaboni et al., 2018; Borda-Niño et al., 2020). Similarly, Precinoto et al. (2022) observed that steep slopes are conducive to forest regrowth, whereas flat or uniformly sloped areas are more susceptible to deforestation.

Sloan et al. (2016) emphasize the socioeconomic implications of slope within landscapes, reflecting its role in shaping human occupation patterns. This perspective is corroborated by Aide et al. (2013), and Sánchez-Cuervo and Aide (2013), who observed increased rural emigration from sloped regions as agricultural activities intensified in Latin America and the Caribbean.

Thus, slope serves multiple purposes in forest restoration decision-making processes. It facilitates soil protection through forest growth while also presenting an opportunity to promote conservation and restoration initiatives. Additionally, its ease of derivation and interpretation, along with its continuous spatial representation, makes it an ideal criterion for application in MCDA-based approaches.

In addition to slope, other topographic-related criteria, such as the Topographic Wetness Index (TWI), Compound Topographic Index (CTI), aspect, and elevation, were employed in specific instances. The TWI and CTI focus on hydrologically sensitive areas by modeling surface runoff and soil moisture distribution (Cecílio et al., 2021; Bezinska and Stoyanov, 2019; Dosis et al., 2023), while elevation prioritizes headwater regions of watersheds (Fernandez et al., 2023). Aspect was used similarly to slope, addressing the impact of terrain orientation on ecological processes.

Another criterion is "Insolation," which prioritizes areas based on sunlight exposure, a factor critical for natural regeneration and secondary succession (de Rezende et al., 2015; Precinoto et al., 2022). Typically derived from DEM data, insolation is currently limited to terrain exposed to sunlight without quantifying solar radiation. However, calculating solar radiation income (Fu et al. 2002) offers great potential for more robust spatial analyses. Overall, moderate solar radiation promotes species recruitment, although areas with higher radiation may be prioritized in specific contexts, such as forest fire mitigation (Precinoto et al., 2022).

Spatial criteria related to the Soil/Erosion group were among the most frequently employed in the analyzed studies, with 18 occurrences and six distinct variations. This group addressed different pedological characteristics, with a preference for conservationist and protective aspects aimed at preventing or mitigating erosion processes through forest restoration actions.

The preference for these criteria was more evenly distributed than other categories, with the spatial criterion "Soil Erodibility" being the most widely adopted, accounting for 33.33% of occurrences in this group. Its choice is attributed to its ability to represent the inherent characteristics of different soil types and their collective influence on factors such as moisture retention, aggregation, surface crusting, and the availability of loose, erodible materials (Valente et al., 2021). This allows for the identification of areas with high erodibility values, which are directly linked to regions most sensitive to runoff within watersheds, as highlighted by Vettorazzi and Valente (2016) and Lopes et al. (2020).

The spatial criterion "Erosion Risk" was employed in 22.22% of cases, focusing on preventing and mitigating erosion in watersheds. However, the representation of this criterion varies across studies. For instance, Rajaonarivelo and Williams (2022) spatialized erosion risk using a map derived from the Revised Universal Soil Loss Equations (RUSLE). In contrast, Orsi and Geneletti (2010) calculated it based on Land Use and Land Cover (LULC) maps, incorporating slope, rainfall, and soil class. Silva and Vieira (2020) applied the "Natural Vulnerability to Erosion" criterion, which integrates multiple factors, including slope, vegetation cover, land use, pedology, geology, and geomorphology.

In addition to erosion-related criteria, researchers have also focused on soil properties conducive to establishing native vegetation. This was primarily reflected in the "Soil Class" criterion, which accounted for 22.22% of occurrences. Studies by Cruz-Bello and Sotelo-Ruiz (2013), Almeida et al. (2019), de Almeida et al. (2020), and Dosis et al. (2023) emphasized the importance of chemical properties and soil fertility in supporting restoration efforts. These concerns align with de Rezende et al. (2015) findings, which identified low soil fertility as a significant barrier to forest regeneration, presenting a practical challenge to restoration initiatives.

Criteria representing localized phenomena, such as erosion (Cruz-Bello and Sotelo-Ruiz, 2013; Souza et al., 2021) or areas with bare soil (Aguirre-Salado et al., 2017), received comparatively less attention. This is mainly due to their limited spatial coverage and applicability, as these characteristics are often binary and context-dependent.

In contrast with the previous categories, spatial criteria associated with LULC (11), socioeconomic factors (7), climatic variables (6), and protected areas (5) were utilized less frequently. Although LULC data are essential for the creation of derivative maps, such as distance maps to disturbances (e.g., urban developments, infrastructure, and agricultural activities) as well as proximity analyses concerning forest or hydrographic networks, LULC criteria were incorporated in fewer than half of the evaluated decision-making processes. This suggests that while LULC data are critical for generating secondary spatial criteria, they are often not directly integrated into decision-making.

However, there are situations where certain LULC classes are given priority, such as pastures (Valente et al. 2021) and degraded areas (Rajaonarivelo and Williams 2022). Alternatively, there are instances where preferences are assigned to all non-restrictive LULC classes, generating a criterion map with distinct priority scores for each LULC class (Cosimo et al. 2021). 'Land Use Suitability' criteria were utilized and justified by the more precise information obtained compared to traditional LULC maps. It incorporates additional factors like soil quality and slope in their development besides LULC (Vettorazzi and Valente 2016).

Turning to the other LULC-related spatial criteria, known as 'Potential Land Cover for Passive Restoration,' 'Potential for Natural Regeneration,' and 'Probability of LULC Conversion,' their names reflect concepts of significant interest among specialists and decision-makers. These concepts align with one of the primary goals of the decision-making process, which is to identify areas conducive to passive restoration or, more specifically, natural regeneration. However, these criteria are currently in a preliminary stage of spatial representation and do not fully capture the concept motivating their inclusion in decision-making. They are derived from the simple rating of different land uses (Silva and Vieira 2020), models primarily based on the distance between forest patches (Cavalcante et al. 2022), and modeling of Markov chains (Calvo-Villalobos et al. 2018).

Predicting where and how forest regeneration occurs remains a persistent issue in restoration science (Schweizer et al., 2022). Consequently, a broad spectrum of studies has been undertaken to understand the factors influencing natural regeneration. These studies are crucial for making informed choices regarding the spatial criteria evaluated in this review (Borda-Niño et al. 2020, Chazdon 2017; de Rezende et al. 2015; Piaia et al. 2020; Schweizer et al. 2022).

Although socioeconomic criteria are frequently emphasized as essential for informed decision-making (Orsi and Geneletti, 2010; Esmail and Geneletti, 2018), their integration often faces challenges due to the lack of spatially explicit and temporally consistent data, as well as practical difficulties in spatialization (Uribe et al., 2014). Notably, only a few studies, such as those by Uribe et al. (2014), Li et al. (2020), and Fernandez et al. (2023), successfully incorporated these criteria. In contrast, most other articles, lacking robust socioeconomic data, primarily considered human activities indirectly through other spatial criteria groups, particularly those related to disturbances, land use and land cover (LULC), and protected areas.

The socioeconomic dimension, however, plays a critical role in the success of forest restoration initiatives, particularly in contexts characterized by rural exodus and the abandonment of previously cultivated lands. These processes are among the primary drivers of forest regrowth or the availability of areas suitable for restoration (Borda-Niño et al., 2020; Calaboni et al., 2018; Chazdon, 2017).

Thus, one of the key challenges in MCDA approaches aimed at forest restoration and nature conservancy in general (Esmail and Geneletti, 2018) lies in effectively representing the socioeconomic component as a spatial criterion. This requires the availability of reliable socioeconomic data and the development of consistent methodologies for spatializing this kind of variable.

Climate-related criteria were considered on only six occasions (Table S2), with rainfall consistently identified as the variable of interest. While understanding rainfall patterns is essential for planning field operations and selecting appropriate species, the limited attention to these criteria in decision-making processes can be attributed to two main factors. First, spatial and temporal data availability is often insufficient, particularly in regions with sparse monitoring station coverage (Nearing et al. 2017). Second, the scale at which most MCDA analyses are conducted, typically at the watershed level, often minimizes the variability in rainfall, rendering its influence less significant in the overall assessment (Oliveira et al., 2013).

However, recent advancements in data availability, such as the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) project (Funk et al. 2015), which provides daily rainfall estimates at a spatial resolution of 500 meters, offer promising opportunities to overcome these limitations and enhance the integration of climate-related criteria into forest restoration decision-making frameworks (Katsanos et al. 2016; Rivera et al. 2018).

The authors primarily (in four instances) employed simple annual rainfall averages obtained from either rain gauge stations (Cruz-Bello et al., 2020) or meteorological satellites (De Almeida et al., 2019; 2020; Fernandez et al., 2023), spatialized using interpolation and kriging methods.

The remaining two studies incorporating climate-related criteria utilized distinct approaches; one employed "Rain Erosivity," derived from the R-factor of the USLE model, using rainfall data from meteorological stations (Vettorazzi and Valente, 2016). The other study introduced a criterion termed "Annual Average Precipitation and Potential Evapotranspiration Difference" (Cecílio et al., 2021). This criterion, in addition to rainfall data, integrated evapotranspiration estimates modeled via remote sensing. According to the authors, this approach is justified by the premise that water production is optimized in areas with higher water input (greater precipitation depth) and lower water "consumption" (reduced evapotranspiration depth) in a context where the main restoration objective would be to increase basin's streamflow.

Finally, the criteria group with the lowest representation in the evaluated decision-making processes was related to protected areas employed in only five instances. In three cases (Calvo-Villalobos et al., 2018; Cosimo et al., 2021; Fernandez et al., 2023), the boundaries of protected areas were used as prioritization criteria, assigning higher priority within their limits and lower priority outside them. In one instance (Orsi and Geneletti, 2010), proximity to protected areas was considered and spatialized using Euclidean distance. In another instance (Silva and Vieira, 2020), the selected criterion was the forest cover deficit within protected areas, prioritizing areas within their boundaries but balancing prioritization based on the level of forest deficit.

Despite the undeniable importance of protected areas for forest conservation and restoration, this group of criteria's low adherence can be attributed to their context-dependent nature. Their application requires the presence of protected areas within the study regions.

Additionally, even in regions where protected areas are prominent in the landscape, often due to legal requirements, as in Brazil (the country with the highest number of studies evaluated here), protected areas are frequently represented by other spatial criteria. Two of the most representative categories of protected areas under Brazilian legislation are associated with riparian vegetation (mandating native vegetation along riverbanks, lakes, and springs, with buffer zones varying based on factors like watercourse width) and slope (areas with slopes exceeding 45° are classified as protected, while those between 25° and 45° are considered restricted-use areas). Spatial criteria commonly used, such as proximity to watercourses and slope, already address these requirements, rendering their explicit inclusion redundant in decision-making processes and, therefore, often excluded in such cases.

1.4. CONCLUSIONS

This systematic review underscores the critical role of spatial criteria in MCDA-based approaches for prioritizing forest restoration sites. Identifying 59 spatial criteria, categorized into nine thematic groups, highlights the diversity of environmental, ecological, and socioeconomic factors shaping restoration planning. However, our findings reveal a strong geographic concentration of studies in tropical regions, particularly in Latin America, indicating the need for broader application of these methodologies across diverse biomes.

A clear pattern emerges when selecting spatial criteria, focusing on disturbances, ecological processes, hydrology, soil, and topography. In contrast, criteria related to land use and land cover (LULC), socioeconomic aspects, climate, and protected areas remain underrepresented. This suggests that while restoration planning commonly prioritizes biophysical and ecological factors, there is a gap in the explicit integration of socioeconomic and policy-driven criteria, which are fundamental for ensuring long-term restoration success.

The selection of spatial criteria should accurately represent the landscape's ecological and socioeconomic dynamics. This requires systematically evaluating habitat connectivity, forest fragmentation, hydrological processes, erosion risk, and anthropogenic pressures, among other landscape attributes. The effectiveness of MCDA-based approaches depends on the semantic precision of spatial criteria, ensuring that each criterion is conceptually relevant and methodologically robust in its representation.

Future research should focus on standardizing methods, protocols, and variables to enhance comparability across studies rather than expanding the number of criteria. Establishing standard guidelines for spatial criteria selection and weighting will strengthen the reliability of MCDA applications, enabling more consistent and scalable restoration planning across different ecological and socio-political contexts.

REFERENCES

Adas, M. A. A., Hardt, E., Miraglia, S. G. el K., and Semensatto, D. (2020). **Reforest or perish: ecosystem services provided by riparian vegetation to improve water quality in an urban reservoir (São Paulo, Brazil).** Sustentabilidade Em Debate, 11(1), 226–243. https://doi.org/10.18472/sustdeb.v11n1.2020.28152

Aguirre-Salado, C. A., Miranda-Aragón, L., Pompa-García, M., Reyes-Hernández, H., Soubervielle-Montalvo, C., Flores-Cano, J. A., and Méndez-Cortés, H. (2017). **Improving identification of areas for ecological restoration for conservation by integrating USLE and MCDA in a gis-environment: A pilot study in a priority region northern Mexico.** ISPRS International Journal of Geo-Information, 6(9). https://doi.org/10.3390/ijgi6090262

Aide, T. M., Clark, M. L., Grau, H. R., López-Carr, D., Levy, M. A., Redo, D., Bonilla-Moheno, M., Riner, G., Andrade-Núñez, M. J., and Muñiz, M. (2013). **Deforestation and Reforestation of Latin America and the Caribbean (2001-2010).** Biotropica, 45(2), 262–271. https://doi.org/10.1111/j.1744-7429.2012.00908.x

Antongiovanni, M., Venticinque, E. M., Tambosi, L. R., Matsumoto, M., Metzger, J. P., and Fonseca, C. R. (2022). **Restoration priorities for Caatinga dry forests: Landscape resilience, connectivity and biodiversity value.** Journal of Applied Ecology, 59(9), 2287–2298. https://doi.org/10.1111/1365-2664.14131

Aria, M., and Cuccurullo, C. (2017). **bibliometrix: An R-tool for comprehensive science mapping analysis.** Journal of Informetrics, 11(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Arroyo-Rodríguez, V., Fahrig, L., Tabarelli, M., Watling, J. I., Tischendorf, L., Benchimol, M., Cazetta, E., Faria, D., Leal, I. R., Melo, F. P. L., Morante-Filho, J. C., Santos, B. A., Arasa-Gisbert, R., Arce-Peña, N., Cervantes-López, M. J., Cudney-Valenzuela, S., Galán-Acedo, C., San-José, M., Vieira, I. C. G., … Tscharntke, T. (2020). **Designing optimal human-modified landscapes for forest biodiversity conservation.** Ecology Letters, 23(9), 1404–1420. https://doi.org/10.1111/ele.13535

Arroyo-Rodríguez, V., Melo, F. P. L., Martínez-Ramos, M., Bongers, F., Chazdon, R. L., Meave, J. A., Norden, N., Santos, B. A., Leal, I. R., and Tabarelli, M. (2017). **Multiple successional pathways in human-modified tropical landscapes: new insights from forest succession, forest fragmentation and landscape ecology research.** Biological Reviews, 92(1), 326–340. https://doi.org/10.1111/brv.12231

Barlow, J., Lennox, G. D., Ferreira, J., Berenguer, E., Lees, A. C., Nally, R. Mac, Thomson, J. R., Ferraz, S. F. D. B., Louzada, J., Oliveira, V. H. F., Parry, L., Ribeiro De Castro Solar, R., Vieira, I. C. G., Aragaõ, L. E. O. C., Begotti, R. A., Braga, R. F., Cardoso, T. M., Jr, R. C. D. O., Souza, C. M., … Gardner, T. A. (2016). **Anthropogenic disturbance in tropical forests can double biodiversity loss from deforestation.** Nature, 535(7610), 144–147. https://doi.org/10.1038/nature18326

Beinat, E., and Nijkamp, P. (1998). **Multicriteria Analysis for Land-Use Management** (E. Beinat and P. Nijkamp, Eds.; Vol. 9). Springer Netherlands. https://doi.org/10.1007/978-94-015-9058-7

Beltrán, L. C., and Howe, H. F. (2020). **The frailty of tropical restoration plantings.** Restoration Ecology, 28(1), 16–21. https://doi.org/10.1111/rec.13066

Bezinska, G. V, and Stoyanov, K. S. (2019). **Modelling and Hydro-Morphometric Analysis of Sub-Watershed. A Case Study of Mesta River Southwestern Bulgaria.** European Journal of Geography, 10(2), 77–88. https://land.copernicus.eu/imagery-in-situ/eu-dem

Bonn Challenge (2014). **The challenge: a global effort**. http://www.bonnchallenge.org/content/challenge (*accessed 05 Mar 2025*)

Borda-Niño, M., Meli, P., and Brancalion, P. H. S. (2020**). Drivers of tropical forest cover increase: A systematic review.** Land Degradation and Development, 31(11), 1366–1379. https://doi.org/10.1002/ldr.3534

Brancalion, P. H. S., Niamir, A., Broadbent, E., Crouzeilles, R., Barros, F. S. M., Almeyda Zambrano, A. M., Baccini, A., Aronson, J., Goetz, S., Reid, J. L., Strassburg, B. B. N., Wilson, S., and Chazdon, R. L. (2019). **Global restoration opportunities in tropical rainforest landscapes.** Science Advances, 5(7), 3223–3226. https://doi.org/10.1126/sciadv.aav3223

Brancalion, P. H. S., Schweizer, D., Gaudare, U., Mangueira, J. R., Lamonato, F., Farah, F. T., Nave, A. G., and Rodrigues, R. R. (2016). **Balancing economic costs and ecological outcomes of passive and active restoration in agricultural landscapes: the case of Brazil.** Biotropica, 48(6), 856–867. https://doi.org/10.1111/btp.12383

Calaboni, A., Tambosi, L. R., Igari, A. T., Farinaci, J. S., Metzger, J. P., and Uriarte, M. (2018). **The forest transition in São Paulo, Brazil: Historical patterns and potential drivers.** Ecology and Society, 23(4). https://doi.org/10.5751/ES-10270-230407

Calvo-Villalobos, J. E., Bermúdez-Rojas, T., and Vega-Bolaños, H. (2018). **Dinámica de uso de suelo y sitios prioritarios para la restauración forestal del Corredor Biológico Río Tibás, Costa Rica.** Revista Geográfica de América Central, 1(62), 128. https://doi.org/10.15359/rgac.62-1.6

Cavalcante, R. B. L., Nunes, S., Viademonte, S., Rodrigues, C. M. F., Gomes, W. C., Ferreira, J. da S., Pontes, P. R. M., Giannini, T. C., Awade, M., de S. Miranda, L., and Nascimento, W. R. (2022). **Multicriteria approach to prioritize forest restoration areas for biodiversity conservation in the eastern Amazon.** Journal of Environmental Management, 318, 115590. https://doi.org/10.1016/j.jenvman.2022.115590

CBD (*Convention on Biological Diversity*) (2011). **Ways and means to support ecosystem restoration**. UN Convention on Biological Diversity, Montreal, Canada.

Cecílio, R. A., Oliveira-Ravani, L. T., Zanetti, S. S., and Mendes, H. de A. (2021). **Method for classifying sites to Atlantic Rainforest restoration aiming to increase basin's streamflows.** IForest, 14(1), 89–94. https://doi.org/10.3832/IFOR3658-013

Chazdon, R. L. (2017). **Landscape restoration, natural regeneration, and the forests of the future.** Annals of the Missouri Botanical Garden, 102(2), 251–257. https://doi.org/10.3417/2016035

Colli, G. R., Vieira, C. R., and Dianese, J. C. (2020). **Biodiversity and conservation of the Cerrado: recent advances and old challenges.** In Biodiversity and Conservation (Vol. 29, Issue 5, pp. 1465–1475). Springer. https://doi.org/10.1007/s10531-020-01967-x

Cosimo, L. H. E., Martins, S. V., and Gleriani, J. M. (2021). **Suggesting priority areas in the buffer zone of Serra do Brigadeiro State Park for forest restoration compensatory to bauxite mining in Southeast Brazil.** Ecological Engineering, 170. https://doi.org/10.1016/j.ecoleng.2021.106322

Crouzeilles, R., Ferreira, M. S., Chazdon, R. L., Lindenmayer, D. B., Sansevero, J. B. B., Monteiro, L., Iribarrem, A., Latawiec, A. E., and Strassburg, B. B. N. (2017). **Ecological restoration success is higher for natural regeneration than for active restoration in tropical forests.** Science Advances, 3(11). https://doi.org/10.1126/sciadv.1701345

Cruz-Bello, G. M., and Sotelo-Ruiz, E. D. (2013). **Coupling Spatial Multiattribute Analysis and Optimization to Identify Reforestation Priority Areas.** Mountain Research and Development, 33(1), 29–39. https://doi.org/10.1659/MRD-JOURNAL-D-12-00085.1

De Almeida, F. C., Silveira, E. M. D. O., Acerbí Junior, F. W., França, L. C. D. J., Bueno, I. T., and Terra, B. J. O. (2020). **Análise Multicritério na Definição de Áreas Prioritárias para Recuperação Florestal na Bacia do Rio Doce, em Minas Gerais.** Nativa, 8(1), 81. https://doi.org/10.31413/nativa.v8i1.8130

De Almeida, F. C., Silveira, E. M. D. O., De Paiva, L. L., and Júnior, F. W. A. (2019). **Mapping Priority Areas for Forest Recovery Using Multicriteria Analysis in the Brazilian Atlantic Forest.** Raega - O Espaço Geográfico Em Análise, 46(3), 113. https://doi.org/10.5380/raega.v46i3.67075

de Oliveira, J. P. B., Cecílio, R. A., Pruski, F. F., Zanetti, S. S., and Moreira, M. C. (2018**). Assessing the use of rainfall synthetic series to estimate rainfall erosivity in Brazil**. Catena, 171, 327–336. https://doi.org/10.1016/j.catena.2018.07.031

de Rezende, C. L., Uezu, A., Scarano, F. R., and Araujo, D. S. D. (2015). **Atlantic Forest spontaneous regeneration at landscape scale.** Biodiversity and Conservation, 24(9), 2255–2272. https://doi.org/10.1007/s10531-015-0980-y

Dosis, S., Petropoulos, G. P., and Kalogeropoulos, K. (2023). **A Geospatial Approach to Identify and Evaluate Ecological Restoration Sites in Post-Fire Landscapes.** Land, 12(12). https://doi.org/10.3390/land12122183

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

Eastman, J. R. (2003). **IDRISI Kilimanjaro: Guide to GIS and Image Processing.** Clark University: Worcester, MA, USA, 1(May), 87–131. https://doi.org/10.1109/TGRS.2002.802519

Esmail, B. A., and Geneletti, D. (2018). **Multi-criteria decision analysis for nature conservation: A review of 20 years of applications.** Methods in Ecology and Evolution, 9(1), 42–53. https://doi.org/10.1111/2041-210X.12899

Fahrig, L. (2003). **Effects of Habitat Fragmentation on Biodiversity.** Annual Review of Ecology, Evolution, and Systematics, 34(1), 487–515. https://doi.org/10.1146/annurev.ecolsys.34.011802.132419

Fahrig, L., Watling, J. I., Arnillas, C. A., Arroyo-Rodríguez, V., Jörger-Hickfang, T., Müller, J., Pereira, H. M., Riva, F., Rösch, V., Seibold, S., Tscharntke, T., and May, F. (2022). **Resolving the SLOSS dilemma for biodiversity conservation: a research agenda.** Biological Reviews, 97(1), 99–114. https://doi.org/10.1111/brv.12792

Fernandez, J., Maillard, O., Uyuni, G., Guzmán-Rojo, M., and Escobar, M. (2023). **Multi-Criteria Prioritization of Watersheds for Post-Fire Restoration Using GIS Tools and Google Earth Engine: A Case Study from the Department of Santa Cruz, Bolivia.** Water (Switzerland), 15(20). https://doi.org/10.3390/w15203545

Fischer, J., Abson, D. J., Butsic, V., Chappell, M. J., Ekroos, J., Hanspach, J., Kuemmerle, T., Smith, H. G., and von Wehrden, H. (2014). **Land Sparing Versus Land Sharing: Moving Forward.** Conservation Letters, 7(3), 149–157. https://doi.org/10.1111/conl.12084

Frazier, A. E., and Kedron, P. (2017). **Landscape Metrics: Past Progress and Future Directions.** Current Landscape Ecology Reports, 2(3), 63–72. https://doi.org/10.1007/s40823-017-0026-0

Fu, P., and Rich, P. M. (2002). **A geometric solar radiation model with applications in agriculture and forestry.** Computers and Electronics in Agriculture, 37, 25–35. www.elsevier.com/locate/compag

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J. (2015). **The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes.** Scientific Data, 2. https://doi.org/10.1038/sdata.2015.66

Gajendiran, K., Kandasamy, S., and Narayanan, M. (2024). **Influences of wildfire on the forest ecosystem and climate change: A comprehensive study.** In Environmental Research (Vol. 240). Academic Press Inc. https://doi.org/10.1016/j.envres.2023.117537

Gama, V. F., Martensen, A. C., Ponzoni, F. J., Hirota, M. M., and Ribeiro, M. C. (2013). **Site Selection for Restoration Planning: A Protocol with Landscape and Legislation Based Alternatives.** Natureza and Conservação, 11(2), 158–169. https://doi.org/10.4322/natcon.2013.025

Green, R. E., Cornell, S. J., Scharlemann, J. P. W., and Balmford, A. (2005**). Farming and the fate of wild nature.** Science, 307(5709), 550–555. https://doi.org/10.1126/science.1106049

Guidotti, V., Ferraz, S. F. de B., Pinto, L. F. G., Sparovek, G., Taniwaki, R. H., Garcia, L. G., and Brancalion, P. H. S. (2020). **Changes in Brazil's Forest Code can erode the potential of riparian buffers to supply watershed services.** Land Use Policy, 94. https://doi.org/10.1016/j.landusepol.2020.104511

Hanski, I. (2015). **Habitat fragmentation and species richness.** In Journal of Biogeography (Vol. 42, Issue 5, pp. 989–993). https://doi.org/10.1111/jbi.12478

Höhl, M., Ahimbisibwe, V., Stanturf, J. A., Elsasser, P., Kleine, M., and Bolte, A. (2020). **Forest landscape restoration - What generates failure and success?** Forests, 11(9). https://doi.org/10.3390/F11090938

Karlson, M., Mörtberg, U., and Balfors, B. (2014). **Road ecology in environmental impact assessment.** Environmental Impact Assessment Review, 48, 10–19. https://doi.org/10.1016/j.eiar.2014.04.002

Katsanos, D., Retalis, A., and Michaelides, S. (2016). **Validation of a high-resolution precipitation database (CHIRPS) over Cyprus for a 30-year period.** Atmospheric Research, 169, 459–464. https://doi.org/10.1016/j.atmosres.2015.05.015

Kedron, P. J., Frazier, A. E., Ovando-Montejo, G. A., and Wang, J. (2018). **Surface metrics for landscape ecology: a comparison of landscape models across ecoregions and scales.** Landscape Ecology, 33(9), 1489–1504. https://doi.org/10.1007/s10980-018-0685-1

Koch, A., and Kaplan, J. O. (2022). **Tropical forest restoration under future climate change.** Nature Climate Change, 12(3), 279–283. https://doi.org/10.1038/s41558-022-01289-6

Lamb, D. (2018). **Undertaking large-scale forest restoration to generate ecosystem services.** In Restoration Ecology (Vol. 26, Issue 4, pp. 657–666). Blackwell Publishing Inc. https://doi.org/10.1111/rec.12706

Laurance, W. F., Clements, G. R., Sloan, S., O'Connell, C. S., Mueller, N. D., Goosem, M., Venter, O., Edwards, D. P., Phalan, B., Balmford, A., Van Der Ree, R., and Arrea, I. B. (2014). **A global strategy for road building.** Nature, 513(7517), 229–232. https://doi.org/10.1038/nature13717

Li, H., Ma, Z., Zhu, Y., Liu, Y., and Yang, X. (2020). **Planning and prioritizing forest landscape restoration within megacities using the ordered weighted averaging operator.** Ecological Indicators, 116. https://doi.org/10.1016/j.ecolind.2020.106499

Lopes, T. R., Moura, L. B., Nascimento, J. G., Fraga Junior, L. S., Zolin, C. A., Duarte, S. N., Folegatti, M. V., and Santos, O. N. A. (2020). **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, 101, 102630. https://doi.org/10.1016/j.jsames.2020.102630

Magnago, L. F. S., Rocha, M. F., Meyer, L., Martins, S. V., and Meira-Neto, J. A. A. (2015). **Microclimatic conditions at forest edges have significant impacts on vegetation structure in large Atlantic Forest fragments.** Biodiversity and Conservation, 24(9), 2305–2318. https://doi.org/10.1007/s10531-015-0961-1

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

Mansoor, S., Farooq, I., Kachroo, M. M., Mahmoud, A. E. D., Fawzy, M., Popescu, S. M., Alyemeni, M. N., Sonne, C., Rinklebe, J., and Ahmad, P. (2022). **Elevation in wildfire**

frequencies with respect to the climate change. In Journal of Environmental Management (Vol. 301). Academic Press. https://doi.org/10.1016/j.jenvman.2021.113769

Marques, M. C. M., and Grelle, C. E. V. (2021). **The Atlantic Forest: History, Biodiversity, Threats and Opportunities on the Mega-diverse Forest.** In The Atlantic Forest (Vol. 1). Springer International Publishing. https://doi.org/10.1007/978-3-030-55322-7

Marques, M. C. M., Trindade, W., Bohn, A., and Grelle, C. E. V. (2021). **The Atlantic Forest: An Introduction to the Megadiverse Forest of South America.** In C. E. V Marques Marcia C. M. and Grelle (Ed.), The Atlantic Forest: History, Biodiversity, Threats and Opportunities on the Mega-diverse Forest (1st ed., pp. 3–23). Springer International Publishing. https://doi.org/10.1007/978-3-030-55322-7_1

Meli, P., Rey-Benayas, J. M., and Brancalion, P. H. S. (2019). **Balancing land sharing and sparing approaches to promote forest and landscape restoration in agricultural landscapes: Land approaches for forest landscape restoration.** Perspectives in Ecology and Conservation, 17(4), 201–205. https://doi.org/10.1016/j.pecon.2019.09.002

Mello, K. de, Randhir, T. O., Valente, R. A., and Vettorazzi, C. A. (2017). **Riparian restoration for protecting water quality in tropical agricultural watersheds.** Ecological Engineering, 108, 514–524. https://doi.org/10.1016/j.ecoleng.2017.06.049

Mendonça, G. C. de, Costa, R. C. A., Parras, R., Oliveira, L. C. M. de, Abdo, M. T. V. N., Pacheco, F. A. L., and Pissarra, T. C. T. (2022). **Spatial indicator of priority areas for the implementation of agroforestry systems: An optimization strategy for agricultural landscapes restoration.** Science of The Total Environment, 839, 156185. https://doi.org/10.1016/j.scitotenv.2022.156185

Miezïte, L. E., Ameztegui, A., De Cáceres, M., Coll, L., Morán-Ordóñez, A., Vega-García, C., and Rodrigues, M. (2022). **Trajectories of wildfire behavior under climate change. Can forest management mitigate the increasing hazard?** Journal of Environmental Management, 322. https://doi.org/10.1016/j.jenvman.2022.116134

Nearing, M. A., Yin, S. qing, Borrelli, P., and Polyakov, V. O. (2017). **Rainfall erosivity: An historical review.** Catena, 157(May), 357–362. https://doi.org/10.1016/j.catena.2017.06.004

Noth, T., and Rinner, C. (2021**). Prioritization in wildfire restoration using GIS-based ordered weighted averaging (OWA): A case study in southern California.** AIMS Environmental Science, 8(5), 481–497. https://doi.org/10.3934/ENVIRONSCI.2021031

Oliveira, P. T. S., Wendland, E., and Nearing, M. A. (2013). **Rainfall erosivity in Brazil: A review.** Catena, 100, 139–147. https://doi.org/10.1016/j.catena.2012.08.006

Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N., Underwood, E. C., D'amico, J. A., Itoua, I., Strand, H. E., Morrison, J. C., Loucks, C. J., Allnutt, T. F., Ricketts, T. H., Kura, Y., Lamoreux, J. F., Wettengel, W. W., Hedao, P., and Kassem, K. R. (2001). **Terrestrial Ecoregions of the World: A New Map of Life on Earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity.**

BioScience, 51(11), 933–938. https://doi.org/10.1641/0006-3568(2001)051[0933:TE-OTWA]2.0.CO;2

Orsi, F., and Geneletti, D. (2010). **Identifying priority areas for Forest Landscape Restoration in Chiapas (Mexico): An operational approach combining ecological and socioeconomic criteria.** Landscape and Urban Planning, 94(1), 20–30. https://doi.org/10.1016/j.landurbplan.2009.07.014

Panasolo, A., Galvão, F., Higachi, H. Y., Oliveira, E. B. De, Campos, F., and Wroblewski, C. A. (2019). **Percepção Dos Serviços Ecossistêmicos De Áreas Verdes Urbanas De Curitiba / Perception of Ecosystem Services on Urban Green Areas in Curitiba** / Pr. Biofix, 70–80.

Piaia, B. B., Rovedder, A. P. M., Procknow, D., Camargo, B., Gazzola, M. D., Croda, J. P., and de Moraes Stefanello, M. (2020). **Natural regeneration as an indicator of ecological restoration by applied nucleation and passive restoration.** Ecological Engineering, 157. https://doi.org/10.1016/j.ecoleng.2020.105991

Precinoto, R. S., Prieto, P. V., Figueiredo, M. de S. L., and Lorini, M. L. (2022). **Edges as hotspots and drivers of forest cover change in a tropical landscape.** Perspectives in Ecology and Conservation, 20(4), 314–321. https://doi.org/10.1016/j.pecon.2022.07.001

Rajaonarivelo, F., and Williams, R. A. (2022**). Remote Sensing-Based Land Suitability Analysis for Forest Restoration in Madagascar.** Forests, 13(10). https://doi.org/10.3390/f13101727

Ribeiro, M. P., de Mello, K., and Valente, R. A. (2022). **How can forest fragments support protected areas connectivity in an urban landscape in Brazil?** Urban Forestry and Urban Greening, 74. https://doi.org/10.1016/j.ufug.2022.127683

Riva, F., and Fahrig, L. (2022). **The disproportionately high value of small patches for biodiversity conservation.** In Conservation Letters (Vol. 15, Issue 3). John Wiley and Sons Inc. https://doi.org/10.1111/conl.12881

Riva, F., Haddad, N., Fahrig, L., and Banks-Leite, C. (2024). **Principles for area-based biodiversity conservation.** Ecology Letters, 27(6). https://doi.org/10.1111/ele.14459

Rivera, J. A., Marianetti, G., and Hinrichs, S. (2018). **Validation of CHIRPS precipitation dataset along the Central Andes of Argentina.** Atmospheric Research, 213, 437–449. https://doi.org/10.1016/j.atmosres.2018.06.023

Romanelli, J. P., Meli, P., Santos, J. P. B., Jacob, I. N., Souza, L. R., Rodrigues, A. V., Trevisan, D. P., Huang, C., Almeida, D. R. A., Silva, L. G. M., Lopes Assad, M. L. R. C., Cadotte, M. W., and Rodrigues, R. R. (2022). **Biodiversity responses to restoration across the Brazilian Atlantic Forest.** In Science of the Total Environment (Vol. 821). Elsevier B.V. https://doi.org/10.1016/j.scitotenv.2022.153403

Rossi, M. 2017. **Mapa pedológico do Estado de São Paulo: revisado e ampliado**. São Paulo: Instituto Florestal, 2017. V.1. 118p. (inclui Mapas)

Ruíz, J., Vargas, O., and Rodríguez, N. (2023). **Restoration priorities: Integrating successional states and landscape resilience in tropical dry forest compensation projects in Colombia.** Applied Geography, 157, 103021. https://doi.org/10.1016/j.apgeog.2023.103021

Saaty, T. L. (1990). **How to make a decision : The Analytic Hierarchy Process.** European Journal of Operational Research, 48, 9–26.

Saaty, T. L. (2008). **Decision making with the analytic hierarchy process.** 1(1).

Salazar, A. A., Arellano, E. C., Muñoz-sáez, A., Miranda, M. D., da Silva, F. O., Zielonka, N. B., Crowther, L. P., Silva-ferreira, V., Oliveira-reboucas, P., and Dicks, L. V. (2021). **Restoration and conservation of priority areas of caatinga's semi-arid forest remnants can support connectivity within an agricultural landscape.** Land, 10(6). https://doi.org/10.3390/land10060550

Sánchez-Cuervo, A. M., and Aide, T. M. (2013). **Consequences of the Armed Conflict, Forced Human Displacement, and Land Abandonment on Forest Cover Change in Colombia: A Multi-scaled Analysis.** Ecosystems, 16(6), 1052–1070. https://doi.org/10.1007/s10021-013-9667-y

Santos, J. S., Cristina, C., Leite, C., Cristina, J., Viana, C., Rosa, A., Marques, M., Souza, V. De, Ribeiro, A., and Mendonça, D. (2018). **Delimitation of ecological corridors in the Brazilian Atlantic Forest.** Ecological Indicators, 88(January), 414–424. https://doi.org/10.1016/j.ecolind.2018.01.011

Sartori, A. A. C., Nossack, F. Á., da Silva, R. F. B., and Zimback, C. R. L. (2012a). **Forest restoration aiming at the conservation of water resources by Weighted Linear Combination.** Floresta, 42(1), 201–212. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84861567984andpartnerID=40andmd5=4b77863eb211b304ab58fd1bda86a64b

Sartori, A. A. da C., Silva, R. F. B. da, and Zimback, C. R. L. (2012b). **Combinação linear ponderada na definição de áreas prioritárias à conectividade entre fragmentos florestais em ambiente SIG.** Revista Árvore, 36(6), 1079–1090. https://doi.org/10.1590/S0100-67622012000600009

Schweizer, D., Petter, G., Gomes César, R., Ferraz, S., de Souza Moreno, V., Brancalion, P. H. S., and Bugmann, H. (2022). **Natural forest regrowth under different land use intensities and landscape configurations in the Brazilian Atlantic Forest.** Forest Ecology and Management, 508, 120012. https://doi.org/10.1016/j.foreco.2022.120012

SDG (*Sustainable Development Goals*) (2015). **Goal 15**. www.un.org/sustainabledevelopment/biodiversity/ (*accessed 05 Mar 2025*)

Şekercioğlu, Ç. H., Loarie, S. R., Oviedo-Brenes, F., Mendenhall, C. D., Daily, G. C., and Ehrlich, P. R. (2015). **Tropical countryside riparian corridors provide critical habitat and connectivity for seed-dispersing forest birds in a fragmented landscape.** In Journal of Ornithology (Vol. 156, pp. 343–353). Springer Verlag. https://doi.org/10.1007/s10336-015-1299-x

Silva, T. C. M., and Vieira, I. C. G. (2020). **Identification of priority areas for ecological restoration in Eastern Para, Brazil.** Floresta e Ambiente, 27(2), 1–9. https://doi.org/10.1590/2179-8087.014418

Souza, C. M., Shimbo, J. Z., Rosa, M. R., Parente, L. L., Alencar, A. A., Rudorff, B. F. T., Hasenack, H., Matsumoto, M., Ferreira, L. G., Souza-Filho, P. W. M., de Oliveira, S. W., Rocha, W. F., Fonseca, A. V., Marques, C. B., Diniz, C. G., Costa, D., Monteiro, D., Rosa, E. R., Vélez-Martin, E., … Azevedo, T. (2020). **Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine**. Remote Sensing, 12(17). https://doi.org/10.3390/RS12172735

Souza, A. R. de, Dupas, F. A., and Silva, I. A. da. (2021). **Spatial targeting approach for a payment for ecosystem services scheme in a peri-urban wellhead area in southeastern Brazil.** Environmental Challenges, 5, 100206. https://doi.org/10.1016/j.envc.2021.100206

Stanturf, J. A., Palik, B. J., and Dumroese, R. K. (2014). **Contemporary forest restoration: A review emphasizing function.** Forest Ecology and Management, 331, 292–323. https://doi.org/10.1016/j.foreco.2014.07.029

Tambosi, L. R., Martensen, A. C., Ribeiro, M. C., and Metzger, J. P. (2014). **A framework to optimize biodiversity restoration efforts based on habitat amount and landscape connectivity.** Restoration Ecology, 22(2), 169–177. https://doi.org/10.1111/rec.12049

Tischendorf, L., and Fahrig, L. (2000). **How should we measure landscape connectivity?** In Landscape Ecology (Vol. 15).

Tuinenburg, O. A., Bosmans, J. H. C., and Staal, A. (2022). **The global potential of forest restoration for drought mitigation.** Environmental Research Letters, 17(3). https://doi.org/10.1088/1748-9326/ac55b8

Uriarte, M., and Chazdon, R. L. (2016). **Incorporating natural regeneration in forest landscape restoration in tropical regions: synthesis and key research gaps.** Biotropica, 48(6), 915–924. https://doi.org/10.1111/btp.12411

Uribe, D., Geneletti, D., del Castillo, R. F., and Orsi, F. (2014). **Integrating stakeholder preferences and GIS-based multicriteria analysis to identify forest landscape restoration priorities.** Sustainability (Switzerland), 6(2), 935–951. https://doi.org/10.3390/su6020935

Valente, R. A., de Mello, K., Metedieri, J. F., and Américo, C. (2021). **A multicriteria evaluation approach to set forest restoration priorities based on water ecosystem services.** Journal of Environmental Management, 285. https://doi.org/10.1016/j.jenvman.2021.112049

Valente, R. A., Petean, F. C. de S., and Vettorazzi, C. A. (2017). **Multicriteria Decision Analysis for Prioritizing Areas for Forest Restoration.** Cerne, 23(1), 53–60. https://doi.org/10.1590/01047760201723012258

Valente, R. de 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(6), 1408–1417. https://doi.org/10.1016/j.foreco.2008.07.006

Vanderley-Silva, I., and Valente, R. A. (2023). **Functional connectivity supported by forest conservation in urban sprawl landscape in São Paulo, Brazil.** GeoJournal, 88(3), 3011–3028. https://doi.org/10.1007/s10708-022-10789-z

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

Voogd, J. H. (1982). **Multicriteria Evaluation for Urban and Regional planning** (Issue 1982). https://doi.org/10.6100/IR102252

Watts, K., and Hughes, S. (2024). **Fragmentation impacts may be mixed for conservation but generally bad for restoration.** Restoration Ecology. https://doi.org/10.1111/rec.14260

2. CHAPTER II

STRUCTURE, FUNCTIONALITY, AND DYNAMICS OF FOREST COVER IN A HUMAN-MODIFIED WATERSHED OF THE ATLANTIC FOREST–CERRADO TRANSITIONAL ECOTONE

Abstract

Understanding landscape dynamics is critical for effective environmental planning and conservation. Human-induced changes disrupt ecological processes, impacting biodiversity, habitat connectivity, and ecosystem services. However, spatiotemporal habitat structure and functionality analyses remain limited, particularly in dynamic human-modified watersheds. This study investigates landscape transformations in the Atlantic Forest–Cerrado transitional ecotone, utilizing high-resolution Land Use and Land Cover (LULC) maps over a 35-year period (1986–2021). We quantified forest cover dynamics (stability, loss, and gain), assessed structural metrics (patch area, shape, and isolation), and evaluated functional connectivity using the graph theory-based Probability of Connectivity (PC) index. Spatiotemporal analysis revealed a 33.79% decline in pasture areas, replaced by agriculture (doubled in extent) and silviculture (sixfold increase). Despite stable total forest cover, old-growth forests decreased by 18.7% and were replaced by secondary vegetation, reflecting basin-scale forest rejuvenation trends observed in broader regions. Deforestation peaked in 2021 (37.25 km²), underscoring policy enforcement challenges despite forest gain this year. Forest patches became more elongated and proximate by 2021, driven by riparian restoration post-2012 legal protections, which enhanced connectivity (PC) in the central basin. Spatially consistent PC maps demonstrated their utility for guiding conservation and restoration decisions. These findings highlight the need for targeted strategies to address habitat rejuvenation, prioritize old-growth forest conservation, and leverage connectivity models for resilient landscape planning in human-modified watersheds.

Keywords: Landscape ecology; landscape management; habitat connectivity; spatio-temporal analysis; forest rejuvenation.

2.1. INTRODUCTION

Anthropogenic alterations in landscape configuration are the primary drivers of habitat loss and biodiversity erosion worldwide (Barlow et al., 2016). Agricultural expansion, population growth, and infrastructure development, are among the main contributors to global forest cover degradation (Watson and Venter, 2016; Altman et al., 2024).

Latin America has experienced a 60% increase in human impact on natural environments over recent decades, reaching 61% in tropical dry forests such as the Cerrado Biome and up to 134% in tropical rainforests like the Amazon and the Atlantic Forest (Zalles et al., 2021). These landscape modifications disrupt key ecological processes and compromise essential ecosystem services, including water cycle regulation, carbon storage, pollination, biodiversity maintenance, and climate regulation (Duffy et al., 2020; Decocq et al., 2016; Flach et al., 2021; Baldí et al., 2022).

Beyond habitat loss, human interventions alter forest cover through fragmentation, increased edge effects, microclimatic changes, biodiversity reduction (Dias et al., 2023), and decreased functional connectivity between habitat patches (Martinez Pardo et al., 2023). Additionally, as land use intensifies, matrix permeability declines, further restricting gene flow and species movement (Prevedello and Vieira, 2010; Ruffell et al., 2017).

Despite these significant impacts, few studies provide long-term spatiotemporal analyses capable of describing landscape structure changes and their implications for ecological connectivity (Vancine et al., 2024). Conventional land cover assessments often capture general patterns but may obscure underlying processes, such as the replacement of older forests by younger secondary vegetation, creating a misleading perception of stability (Bürgi et al., 2005; Dias et al., 2023; Vancine et al., 2024).

Recent studies in the Atlantic Forest (Rosa et al., 2021; Zalles et al., 2021; Vancine et al., 2024; Dias et al., 2023; Martinez Pardo et al., 2023) have shown that, despite the apparent maintenance of forest cover, the replacement of older forests with early-successional vegetation has led to a rejuvenation of forest cover. This phenomenon may reduce habitat quality and compromise the long-term ecological resilience of the landscape. Additionally, Rosa et al. (2021) highlight that forest patch isolation has increased by 36.4% across the Atlantic Forest, emphasizing the need to consider not only the quantity but also the spatial distribution and ecological integrity of forest remnants in conservation and restoration strategies.

Most of these analyses have been conducted at broad spatial scales (Rosa et al., 2021; Vancine et al., 2024; Dias et al., 2023), providing a comprehensive view of large-scale patterns but potentially failing to capture local-scale dynamics that are critical for ecological restoration planning and landscape management.

There is a growing demand from land managers and decision-makers for information on the temporal legacy of landscapes, particularly regarding the long-term dynamics of habitat patches and matrix permeability. Such information is crucial for integrating strategies that enhance both the structural and functional aspects of habitat areas into decision-making processes for conservation and forest restoration (Gama et al., 2013; Dalloz et al., 2017; Volk et al., 2018; César et al., 2021).

This study aims to fill this gap by analyzing the temporal legacy of the landscape, evaluating Land Use and Land Cover (LULC) changes between 1986 and 2021, and assessing the spatiotemporal structural and functional dynamics of habitat areas in a human-modified watershed. We examine structural parameters such as patch size, shape, and degree of isolation over time, along with functional connectivity metrics, quantified through the graph-based approach Probability of Connectivity (PC) (Saura and Pascual-Hortal, 2007). Furthermore, we propose a spatial representation of PC across the landscape, offering a valuable tool for its incorporation into conservation and restoration decision-making processes.

2.2. MATERIAL AND METHODS

2.2.1. STUDY AREA

The study area encompasses the Sarapuí River basin (1549.75 km²), which spans nine municipalities in São Paulo state, Brazil, and is positioned near major urban centers such as Sorocaba and the metropolitan region of São Paulo (Figure 1). Originally dominated by the Atlantic Forest Biome, the basin's primary phytophysiognomy was classified as a Dense Ombrophilous Forest (DOF) (IBGE, 2012, 2019), situated in a transitional ecotone with the Brazilian Cerrado, which contributes to its ecological heterogeneity (Mello et al., 2017).

The landscape is marked by a fragmented mosaic of forest patches embedded in an agricultural-pastoral matrix (Soares et al., 2022) with a dense drainage network (Mello et al., 2017; Morales and Valente, 2023). These patches are unevenly distributed, with the southern portion of the basin characterized by higher elevations and steeper slopes (Morales and Valente, 2023). These regions are close to the Serra do Mar Environmental Protection Area (APA), a critical Atlantic Forest corridor, and are adjacent to legally protected zones such as the Jurupará State Park and Itupararanga Reservoir APA (Figure 1).

Most of the basin falls within a humid subtropical zone with an oceanic climate (Cfa) characterized by the absence of a dry season and hot summers. However, the southernmost third, where the basin's headwaters are located, exhibits a cooler climate due to its higher altitude and proximity to the Serra do Mar geological formation. This region experiences temperate summers and is classified as Cfb according to the Köppen scale (Alvares et al., 2014).

Soil composition varies across the basin, with red and yellow Latosols predominating in forested uplands, while Gleysols occur in low-lying central and western areas (Mello et al., 2017), influencing vegetation structure. Historical deforestation, driven by agricultural expansion (Calaboni et al., 2018), has left forest remnants predominantly in less accessible topographic regions. Despite anthropogenic pressures from urban and agricultural sprawl, the basin retains ecological significance due to its proximity to protected areas and transitional biome characteristics, offering a dynamic context for studying forest habitat dynamics.

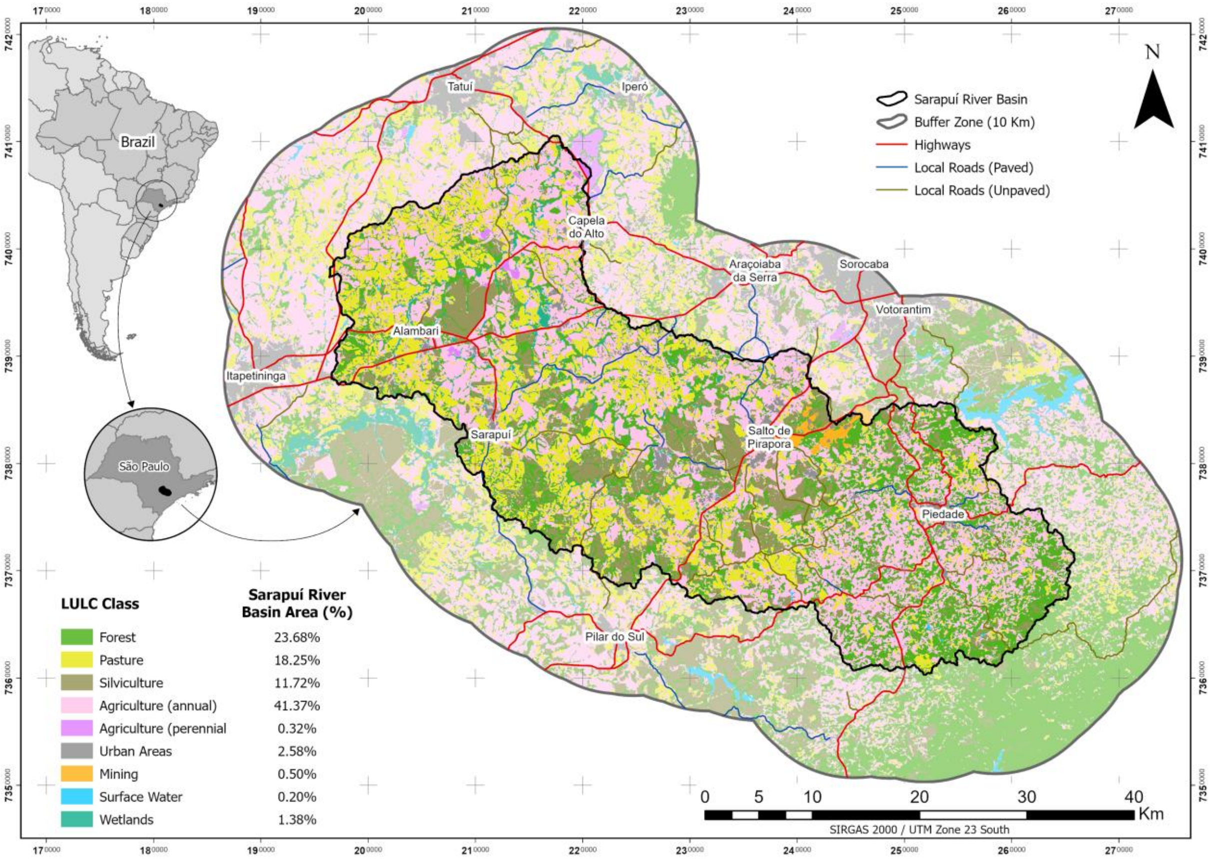


Figure 1 – Location map and Land Use and Land Cover (2021) in the Sarapuí river Basin, Brazil.

2.2.2. LANDSCAPE SPATIOTEMPORAL ANALYSIS

The dataset comes from collection seven of the *MapBiomas* project (Souza et al. 2020). This collaborative and open-source platform reconstructs annual land use and land cover data with a spatial resolution of 30 m based on the supervised classification of Landsat satellite images (Souza et al. 2020). We used data for every fifth year between 1986 and 2021, which were clipped to the limits of the basin and projected to the Universal Transverse Mercator (UTM) Coordinate System, 23-South, using the SIRGAS 2000 Datum as the geodetic reference.

Subsequently, the LULC data were reclassified into nine classes, as shown in Figure 1, where the classes related to sugarcane, agriculture and pasture, soybeans, and other temporary crops were reclassified to annual agriculture; the classes related to coffee and *citrus* were re-classified to perennial agriculture; forest formation and savanna formation (which represented less than 3% in the years analyzed) were classified as forest and considered as habitat areas.

This reclassification was necessary to simplify the analysis and form more representative classes that made sense for the space-time analysis. For the LULC dynamics, we calculated the proportion of each land use class in the Sarapuí River basin each year, analyzed and comparatively evaluated the changes in the percentages of landscape coverage.

2.2.3. FOREST COVER DINAMICS

To analyze the temporal dynamics of forest cover, in addition to quantifying the total area per year, and considering that forest cover is not homogeneous, but rather composed of forests in different successional stages, we paid special attention to identifying the events that occurred in a given habitat patch in each year, with the following possible events, given the year in question (t_n) and the year immediately preceding it (t_{n-1}):

a. *Stable Forest*: an event where there is the presence of forest in t_{n-1} and in t_n.
b. *Forest Gain*: an event where there is absence of forest in t_{n-1} and presence of forest in t_n.
c. *Forest Loss*: an event where there is forest presence in t_{n-1} and absence in t_n.

Therefore, we first produced binary rasters of forest cover (*1 = forest, 0 = no forest*) based on the LULC maps of each year. Subsequently, equations 1, 2, and 3 were used in the raster calculator tool of the *ArcGIS-Pro v.3.4.2* software to obtain the patches belonging to each event (stable, gain, and loss) in each year.

$$Stable_n = Stable_{n-1} \times Forest_n \quad \textit{Equation 1.}$$

$$Gain_n = Forest_n - Forest_{n-1} \quad \textit{Equation 2.}$$

$$Loss_n = Forest_{n-1} - Forest_n \quad \textit{Equation 3.}$$

We assumed 1986 to have 100% stable forest cover given the impossibility of verifying the remaining, gained, and lost patches, as it was the first year of the historical series. In this context, the remaining forest cover of 1986 in each subsequent year is referred to as *Old-growth*

Forest, while the forest patches resulting from forest gain each year are referred to as *Regenerating Forest*.

Although a large part of the remaining vegetation from 1986 is composed of primary forests, our data do not allow us to assume that 100% of these patches are primary forests, so we opted for the nomenclature *Old-growth Forest*. Likewise, it is possible that forests considered regenerating in 1991, for example, have reached higher successional stages and can be considered primary forests. However, our data also do not allow for such an assumption; therefore, to those patches, we adopted the nomenclature *Regenerating Forest*.

Furthermore, to assess the pattern of deforestation in the basin, we identified whether forest loss occurred in *old-growth* or *regenerating* forests each year, which allowed us to identify the proportion of these two classes of forest cover annually. For this, also in the raster calculator, the following equations were used:

$$Old\ gowth\ loss_n = \ Loss_n \times Stable_{n-1} \qquad \textit{Equation 4.}$$

$$Regenerating\ loss_n = Loss_n \times Gain_{n-1} \qquad \textit{Equation 5.}$$

We then analyzed the annual results regarding the proportion of the loss, gain, and stable forest, the proportion of deforestation in old-growth and regenerating forests, and the proportion of old-growth and regenerating forests in the total forest cover per year.

2.2.4. HABITAT PATCHES STRUCTURAL DYNAMICS

The structure of the habitat patches was assessed by the total number of patches (*np*), their size in hectares (*Area*), the complexity of their shape (shape index – *Shape*), and their proximity, by the Euclidean distance to the nearest neighbor (*ENN*). These metrics were calculated in batches in the Fragstats v4.2.681 (McGarigal et al., 2023) software, as described in Kupfer (2012).

For *Area*, *Shape*, and *ENN*, the habitat patches were grouped by year and divided into five classes, defined by the natural breaks' method, considering the record of all the years analyzed. Then, for each year, we calculated simple estimators for each class. Namely, the total number of patches (*np*), total, minimum, maximum, average, median, and standard deviation values, and then the years were analyzed comparatively.

The indexes selected for evaluating the structure of habitat areas in the spatiotemporal context constitute simple and consolidated descriptors for evaluating the structural configuration of patches in the context of landscape ecology (Lang and Blaschke, 2009; Frazier and Kedron, 2017; Lausch et al., 2015).

With them, we seek to analyze fundamental components for the understanding of the dynamics of forest areas in the basin, the size and quantity of patches, and their dynamics over the years that can indicate structural richness, fragmentation, and capacity to shelter species (Lang and Blaschke, 2009; Lausch et al., 2015), the complexity of the shapes, indicative of elongated patches with greater density of edges, making it more subject to their effects (Lang and Blaschke, 2009; Lausch et al., 2015) and the closest distance to the neighboring patch (*ENN*), indicative of the degree of isolation or proximity between habitat patches, also indicative of fragmentation and with effects on forest connectivity (Frazier and Kedron, 2017).

2.2.5. HABITAT PATCHES FUNCTIONAL DYNAMICS

The functional dynamics of habitat patches were analyzed using the Probability of Connectivity (*PC*) metric, a graph-theory-based landscape ecology approach developed by Saura and Pascual-Hortal (2007). This metric integrates habitat availability, interpatch dispersal probabilities, and graph structures (Martensen et al., 2017), providing a robust framework to assess the functional connectivity of habitat patches in fragmented landscapes.

The PC metric is defined as the probability that two animals, randomly placed within the landscape, fall into habitat areas that are reachable from each other (*interconnected*), given a set of n habitat patches and the connections (Pij) among them (Saura and Pascual-Hortal, 2007).

The choice of the PC metric was motivated by its ability to link landscape patterns to their functional significance (Frazier and Kedron, 2017) and its relatively modest data requirements, as most of the graph-based landscape metrics (Calabrese and Fagan, 2004). Additionally, the PC metric has proven effective in tracking connectivity in human-modified landscapes across various contexts (Gurrutxaga et al. 2010; Tambosi et al. 2014; Martensen et al., 2017; Huang et al. 2020; Ribeiro et al. 2022; Antongiovanni et al. 2022).

The PC index is calculated using the following expression:

$$PC = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j P_{ij}^{*}}{A_L^2} \qquad \textit{Equation 6.}$$

where a_i and a_j are the areas of the habitat patches *i* and *j*, and A_L is the total landscape area. The dispersal probability (*Pij*) characterizes the feasibility of direct movement between patches i and j, without passing through intermediate habitat patches (Saura and Pascual-Hortal, 2007).

To simplify the model, we considered the Euclidean distance between patches and assigned a movement probability (*Pij*) of 0.5 for a maximum dispersal distance of 200 meters. This conservative approach was based on few evidence suggesting that many Atlantic Forest species have dispersal capabilities below 200 meters across gaps (Crouzeilles et al., 2010).

The analysis was implemented using the software Graphab 2.8.1 (Foltête et al., 2021), which integrates all graph construction and spatial analysis steps. Based on the total forest raster for each year, connectivity networks were constructed for the Sarapuí River Basin, defining *nodes* and *links*. The PC was then calculated for each node and link, and the node results were interpolated to produce continuous maps representing the spatial distribution of the index across the landscape.

The results of the PC analysis were log-transformed to address the skewed distribution of data, with very high PC values concentrated in a few patches. Descriptive statistics (minimum, maximum, mean, median, and standard deviation) were calculated for the PC values of nodes and links each year. The analysis focused on nodes and links with at least 1% PC, significantly reducing the sample size, and also considered all log-transformed values for a clearer comparison of their distributions.

The interpolated PC surface was also log-transformed and compared year by year. Finally, for each year, we plotted the basin map with the log-transformed PC surface as the background, overlaying the forest patches, nodes, and links with PC values greater than 0.10%.

2.3. RESULTS AND DISCUSSION

Between 1986 and 2021, the land use and land cover configuration in the Sarapuí River basin changed substantially (Figure 2). We observed a significant decline in pasture areas, which decreased by 33.79% in 2021 compared to the beginning of the historical series. At the same time, there was a substantial increase in agricultural areas, which nearly doubled in proportion compared to 1986, and in forestry plantations, which also experienced a substantial increase, reaching 11.72% of the basin area in 2021, more than six times the 1986 proportion.

During the period, native vegetation remained relatively stable, particularly between 1986 and 2011, with only a 0.72% variation in landscape proportion. In the following years, there was a more substantial increase, with 1.55% in 2016 and 1.54% in 2021, although still modest compared to the growth of agricultural and forestry areas.

Rosa et al. (2021), analyzing the Brazilian Atlantic Forest, found similar trends in land use and land cover dynamics between 1986 and 2018. They reported a substantial reduction in pasture areas (-20%), a twofold increase in agricultural areas, and a fourfold increase in forestry plantations, while native vegetation remained relatively stable. The authors attribute these results to agro-silvopastoral land use dynamics, where agriculture and forestry almost entirely replaced pasture areas.

Calaboni et al. (2018), focusing on the state of São Paulo, also highlighted the replacement of pastures by agriculture and forestry, attributing this trend to technological advancements in production systems, such as the intensification of agricultural machinery and chemical fertilizers, particularly after the 1980s.

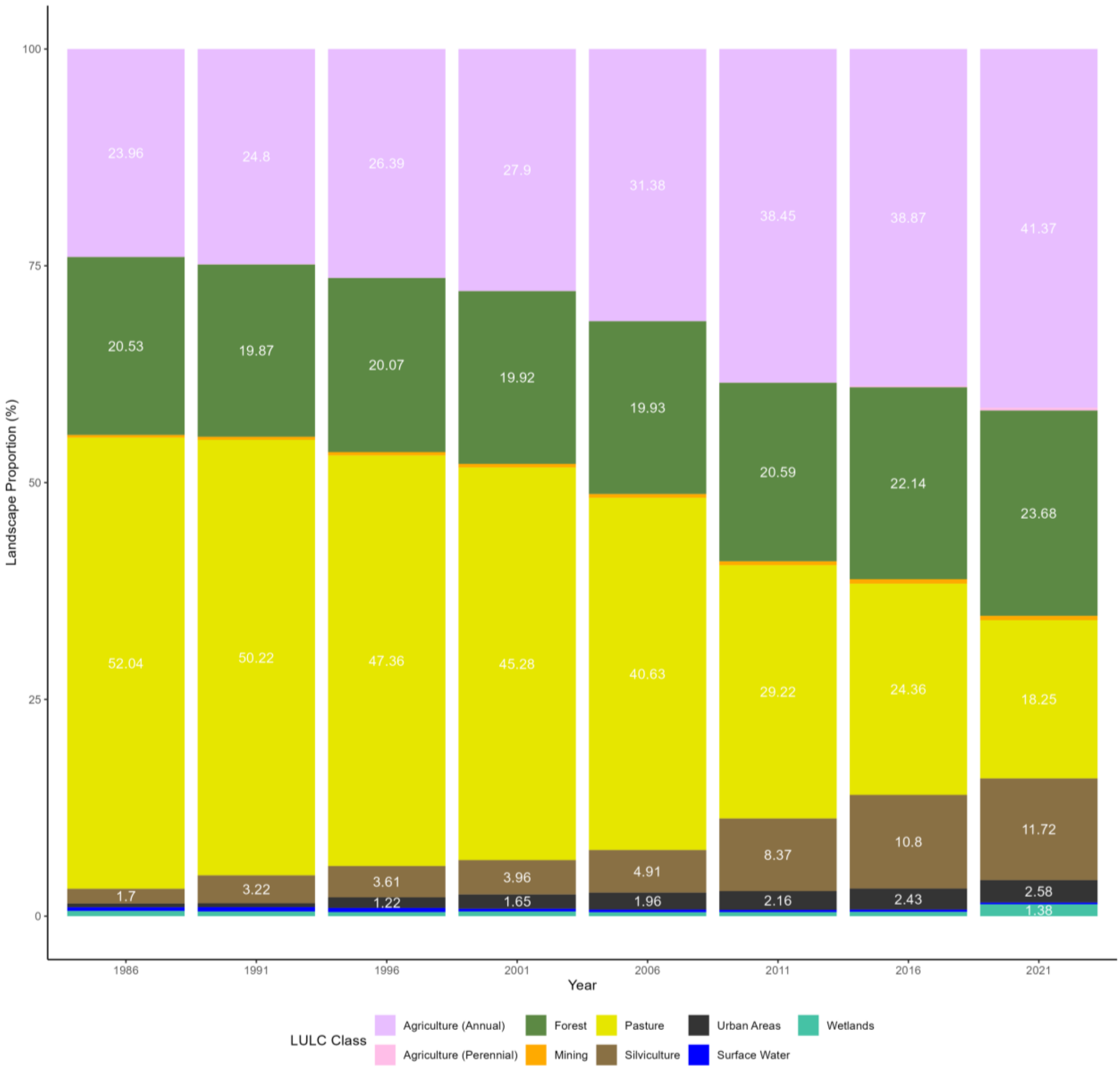


Figure 2 – Annual Land Use and Land Cover classes proportion for the Sarapuí River Basin, Brazil (1986-2021).

However, the relative stability of native forest areas regarding overall proportion hides forest loss and gain dynamics over the years. Figure 3 provides a more detailed perspective on this aspect. A downward trend in deforestation was observed between 1991 and 2016, reaching its lowest point in 2016 with 10.96 km² of forest loss. However, in 2021, deforestation increased significantly, reaching 37.25 km², surpassing the highest recorded loss in 1991. This peak in 2021’s deforestation is not evident when analyzing only the total forest area, as 2021 also recorded the highest forest gain, with 61 km², almost twice the previous period and nearly three times that of other analyzed years, allowing for an overall increase in forest proportion despite the high deforestation rates.

Since 2006, there has been a trend of increasing forest gain, which can be partly attributed to important legal mechanisms, such as the enactment of the Atlantic Forest Law (Federal Law n° 11.428) in 2006 and the Native Vegetation Protection Law (also known as the New Forest Code - Federal Law n° 12.651) in 2012. These regulations are recognized as significant public policies for combating deforestation and promoting forest restoration in Brazil (Brancalion et al., 2019; Crouzeilles et al., 2019; Zalles et al., 2021).

Although Brazilian environmental legislation has become more robust since 2006, the high deforestation rate observed between 2016 and 2021 can be partially attributed to the Brazilian government's policies and rhetorics (2016–2022), marked by scientific and climate denialism and the systematic dismantling of public agencies responsible for combating deforestation and environmental crimes. Researchers and environmentalists widely denounced these setbacks at the time (Guidotti et al., 2020; Levis et al., 2020; Rajão et al., 2022; Sparovek et al., 2019; Tavares et al., 2019), recognizing them as a turning point in the previously achieved environmental progress.

When we look at the deforestation dynamics, another aspect of great relevance for biodiversity conservation and strategic restoration planning can be analyzed: the type of forest that has been lost and its impact on the composition of forest vegetation in the landscape, where secondary forests have replaced old-growth forests. Except for 2016, for all years analyzed, the loss of old-growth forest exceeds the loss of regenerating forest, resulting in a gradual replacement of forest vegetation in the basin, with a gradual increase in regenerating native vegetation to the detriment of already established forests.

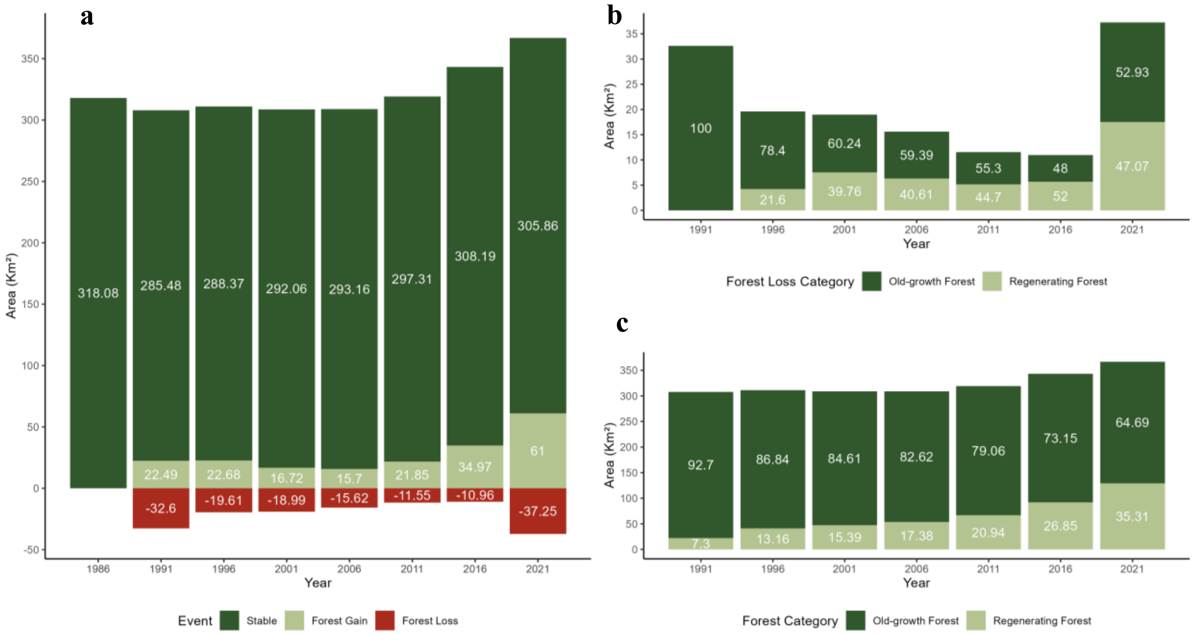


Figure 3 – Forest Cover Dynamics (a), Deforestation Dynamics (b), and Forest Type Proportion (c) in the Sarapuí River Basin, Brazil (1986-2021).

This same pattern has recently been recognized through spatiotemporal approaches. Dias et al. (2023), working on a larger scale in the northeastern Brazil region (Atlantic Forest), found similar results revealing rejuvenation, fragmentation, and increased edge effects in forest patches. Vancine et al. (2024), working with the entire Atlantic Forest biome, which exceeds Brazilian territorial limits, also found the same pattern of rejuvenation in native vegetation.

Similarly, Rosa et al. (2021) found an ongoing reduction of older native forest cover and a continuous increase of younger native forest cover in the Brazilian Atlantic Forest. They draw attention to the consequences of this dynamic for biodiversity and for forest conservation and restoration planning. Thus, our results demonstrate that the vegetation rejuvenation reported by previous studies on larger scales also occurs at the river basin level.

Despite the importance of secondary forests (Martin et al., 2013; Poorter et al., 2016), the fundamental role of primary forests in maintaining biodiversity and ecosystem services is known (Gibson et al. 2011; Rosa et al. 2021), especially in landscapes where habitat loss is not recent, and fragmentation processes have already been established (Watts and Hughes, 2024). In these scenarios, regenerative processes no longer count on the colonization credits in landscapes under the post-habitat loss relaxation period, requiring immigration to recolonize restored habitats (Watts and Hughes, 2024).

However, as mentioned by Martin et al. (2013), the complete recovery of species composition in degraded environments may take centuries or may not even occur. Old-growth forests are also essential to combat species extinction since a wide range of plants, animals, and microorganisms unable to recolonize secondary forests rely on older, less altered, and biodiverse habitats to persist in human-modified landscapes (Rosa et al. 2021).

In addition to this dynamic, our results also show that, on average, 98% of forest patches are composed of fragments smaller than 75 hectares (Figure 4), highlighting the high degree of fragmentation in the basin (Soares et al., 2022). This scenario, although slowly changing, shows a trend of increasing the number of patches with an area greater than 75 ha and a concomitant reduction in the total proportion of area occupied by small fragments. In 2021, these smaller patches represented 43.95% of the total forest area, the lowest proportion in the historical series, marking a reduction of 6.97% compared to 1991, when this group of fragments still covered more than 50% of the basin's forest area.

Table S2.1, in the supplementary material, presents the annual values and divides them into classes for the number of patches, percentage of the number of patches in total, and area, percentage of area in total. It also includes the minimum, average, maximum, median, and standard deviation values for the area parameter.

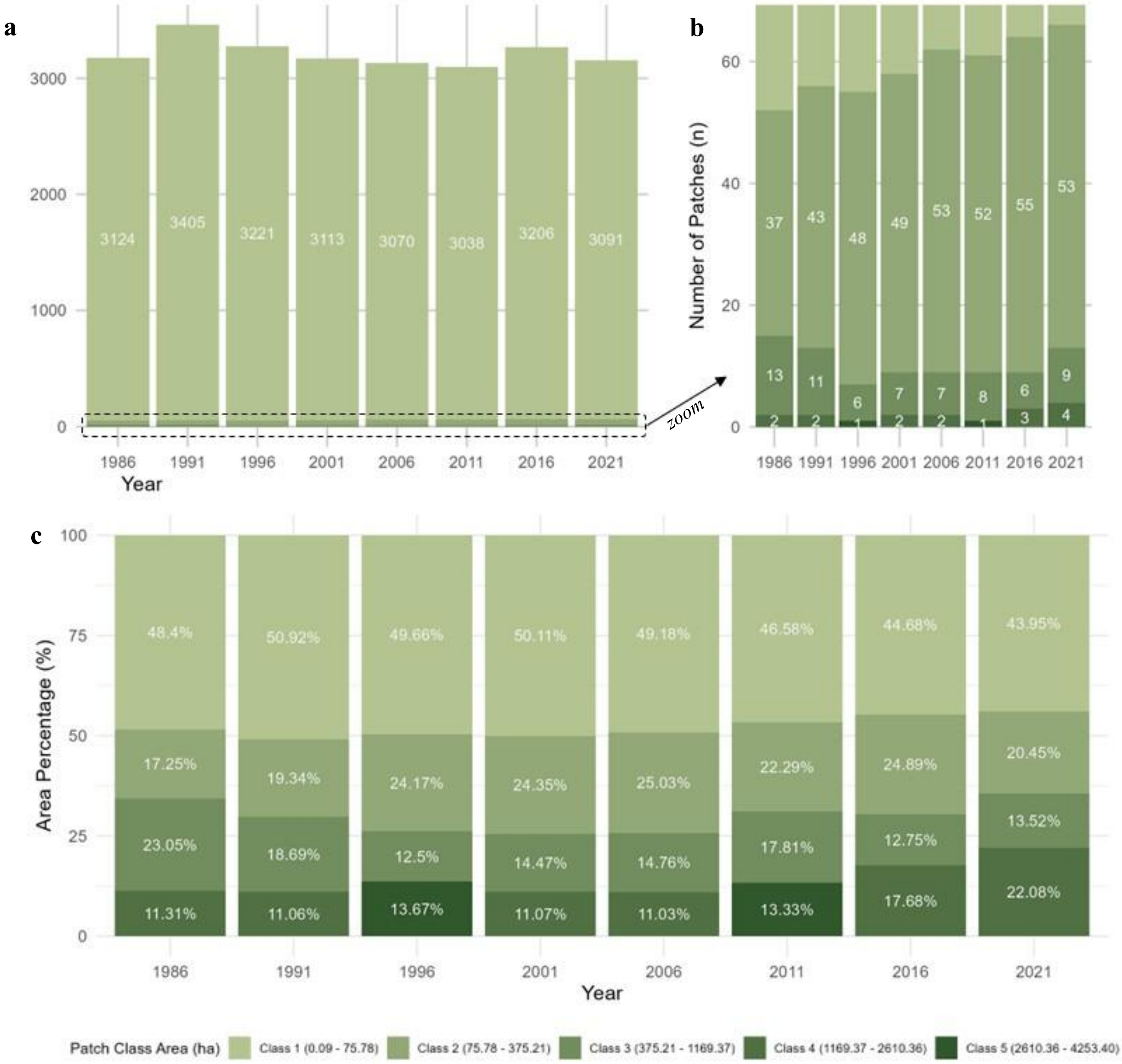


Figure 4 – Patch Count by Area Class (a and b) and Habitat Proportion Across Area Classes (c) in the Sarapuí River Basin, Brazil (1986-2021).

However, the effects of historical fragmentation in the region are still evident. In 1986 and 1991, forest patches with areas between 375 and 2,610 hectares totaled 15 and 13 patches, respectively, representing 34.36% and 29.75% of the forested area. This number decreased in quantity and percentage until 2006, when it began to grow again, reaching 35.6% of the forested area of the basin in 2021, distributed across 13 patches. Notably, in more recent years, fragments between 1,169 and 2,610 ha began to represent a more significant portion of the total area, reversing the trend observed at the beginning of the historical series, when patches between 375 and 1,169 ha were more representative.

In addition, a dynamic process of fusion and fragmentation of forest areas is observed. In 1996 and 2011, for example, a single forest patch represented 13.67% and 13.33% of the native vegetation area, resulting from the union of two large patches at the basin's headwaters. This dynamic illustrates the variation in the extent of forest cover and its impacts on the structural and functional configuration of habitat patches.

Over the years, the total number of fragments suggests a dynamic balance between fragmentation and patch aggregation. Although the total number of fragments fluctuates between ~3100 and 3400, an increase in larger fragments is observed, indicating forest aggregation and expansion processes.

At the same time, as seen in Figure 5, the distance to the nearest neighbor (*ENN*) suggests a slight reduction over time. The year 2021 presented the smallest variation and the lowest maximum value of the distance between fragments, less than 800 meters, possibly reflecting the formation of larger fragments and the regeneration of areas that act as ecological corridors.

The habitat patch's structure has also become more complex, as indicated by the increase in the shape index. This change may be associated with the fragmentation of previously continuous areas and the irregular expansion of some fragments.

This characteristic is also associated with the environmental policies implemented by the Native Vegetation Protection Law (2012), where one of the bases for defining Permanent Preservation Areas (PPAs) is linked to the hydrographic network and the mandatory conservation and restoration of forests along their banks, consequently increasing the shape index of the patches where the restoration was carried out, by following the hydrography, or creating more elongated patches, also due to the hydrographic network.

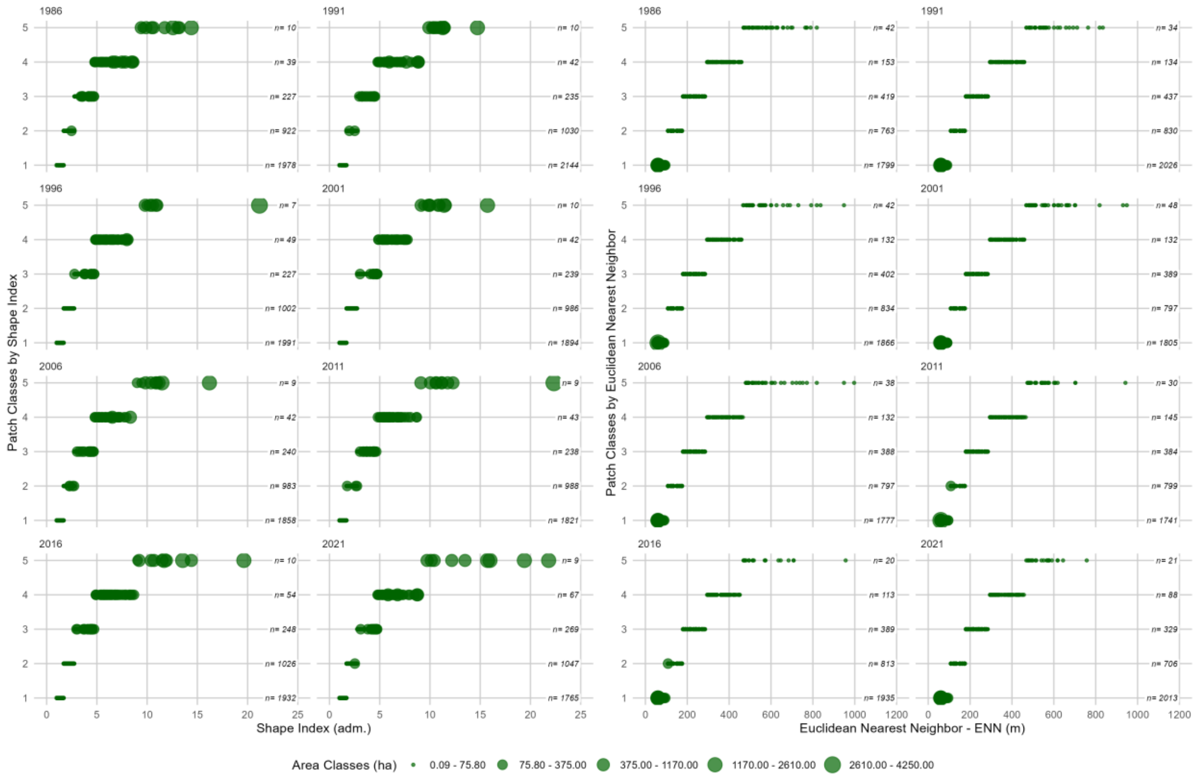


Figure 5 – Patch Classes by Shape Index and by Euclidean Nearest Neighbor (*ENN*) in the Sarapuí River Basin, Brazil (1986-2021).

Thus, the results point to a mixed process of degradation and regeneration, reinforcing the need for forest restoration strategies focused on connectivity, especially to connect small and medium-sized fragments, ensuring the maintenance of ecological flows in the basin.

Probability of Connectivity results demonstrate that few habitat patches are responsible for the basin's functional connectivity. The smaller patches showed relative stability over time, while the larger area fragments showed more expressive variations (Figure 6).

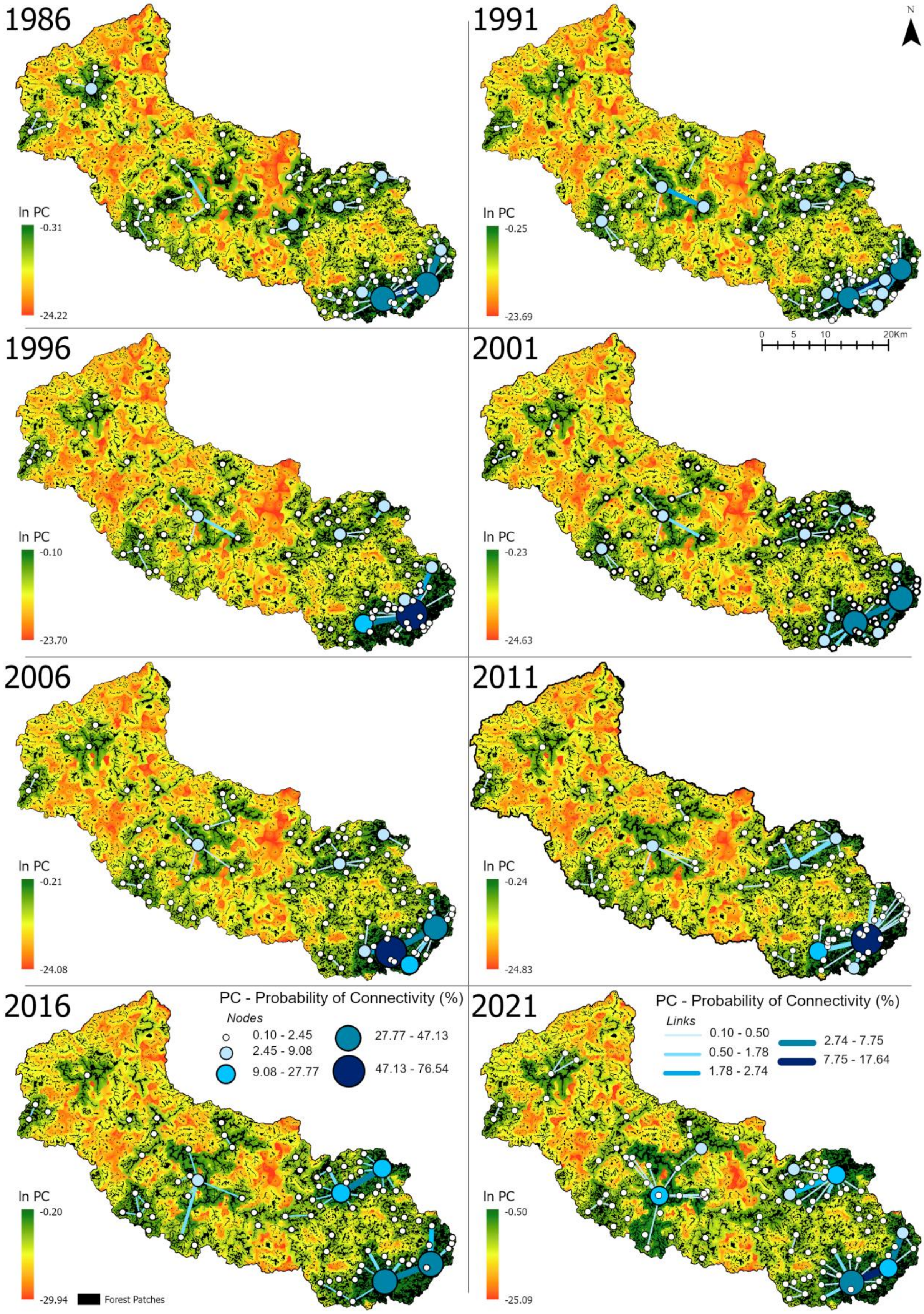


Figure 6 – Probability of Connectivity (PC) to Nodes and Links, and Log-Transformed PC Surface in the Sarapuí River Basin, Brazil (1986-2021).

Due to the significant asymmetry in PC values, Figure 7 presents the annual distribution of PC on a logarithmic scale and a cutout only for patches that presented more than 1% probability of connectivity. It is noted that despite the relative stability among the historical series, 2021 presented a higher mean and median (PC Total), indicating an increase in the functional connectivity of the basin (Figure 7a).

When we observe the patches with PC greater than 1% (Figure 7b), we see that despite lower PC values for the prominent patches individually, more patches participate with a probability greater than 10%, indicating that for 2021, connectivity is better distributed spatially, potentially extending the possibility of gene flow, immigration, and colonization in more regions of the basin, not just focused on the headwaters, where the most extensive patches are located.

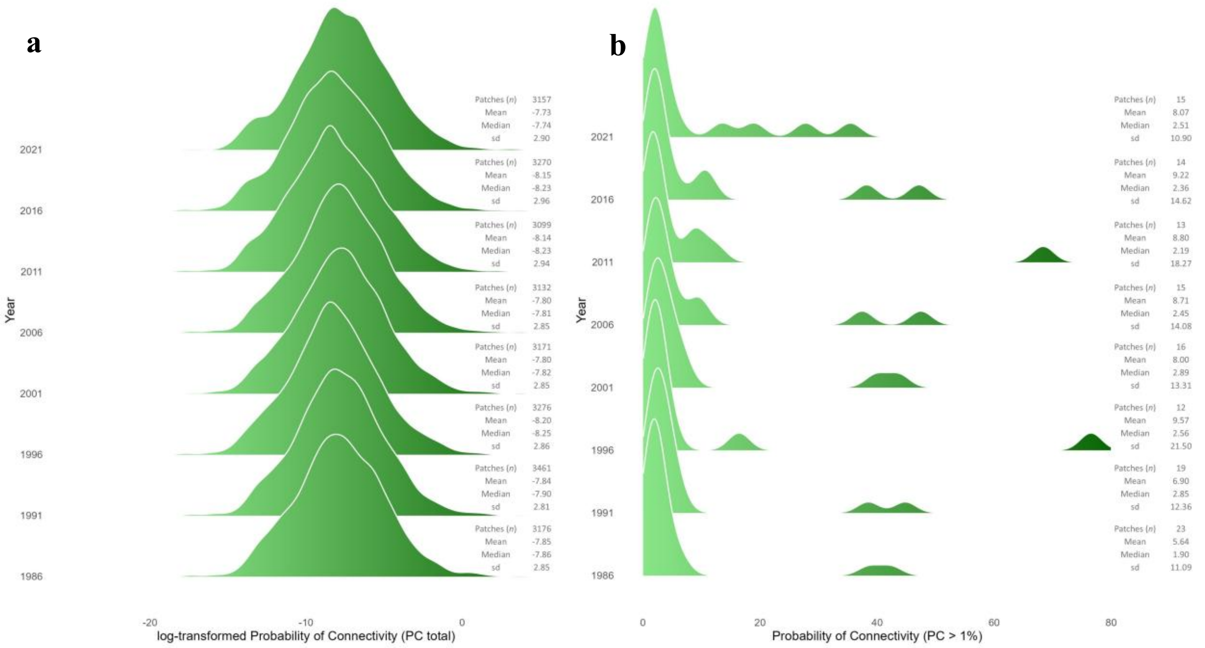


Figure 7 – Nodes Probability of Connectivity (PC) Log-Transformed (a), and Nodes With > 1% PC (b). Sarapuí River Basin, Brazil (1986-2021).

The interpolated surface of the PC presents negative values due to the logarithmic transformation, but this does not interfere with the interpretation of the connectivity patterns. The surface (Figure 6) clearly illustrates the area of influence of the patches, highlighting the basin's headwaters, which presented the highest PC values in all years; the Piedade's town north region, also an important connectivity hotspot throughout the historical series; and the region of confluence between the Pirapora and Sarapuí rivers, in the central portion of the basin, where we can observe the increase in the connected area that follows the distribution pattern of the drainage network.

The PC's surface presents a spatialization consistent with the results obtained at the patch level, demonstrating great potential for use in programs aimed at the conservation and restoration of biodiversity and for the integrated management of river basins. Its gradient spatialization provides greater detail on PC behavior in the landscape. It represents very well the connective potentials of the connectivity patches and subnetworks. Also, it represents patches and subnetworks with lower connective potentials that are not represented by the nodes and links with percentage values (i.e., circles and proportional lines, Figure 6).

Figure 8 focuses on the behavior of the PC values in the pixels of the surfaces generated for each year. In it, we can also observe the relative stability in their values but with an apparent lack of pixels before the final peaks of connectivity in all years except 2021. This presents a connection between the final peaks of connectivity with the rest of the landscape, which demonstrates a more distributed dispersion of connectivity in the landscape.

In Figure 8, we also observe a lower concentration of pixels exhibiting very low connectivity (below -15), with such areas being more prevalent in the northern section of the basin. This region is characterized by smaller and more dispersed forest patches in addition to the urban areas associated with the municipalities of Alambari, Capela do Alto, Sarapuí, Salto de Pirapora, and Piedade (see Figure 6). This illustrates the significant disruptive impact urban areas can have on landscape connectivity.

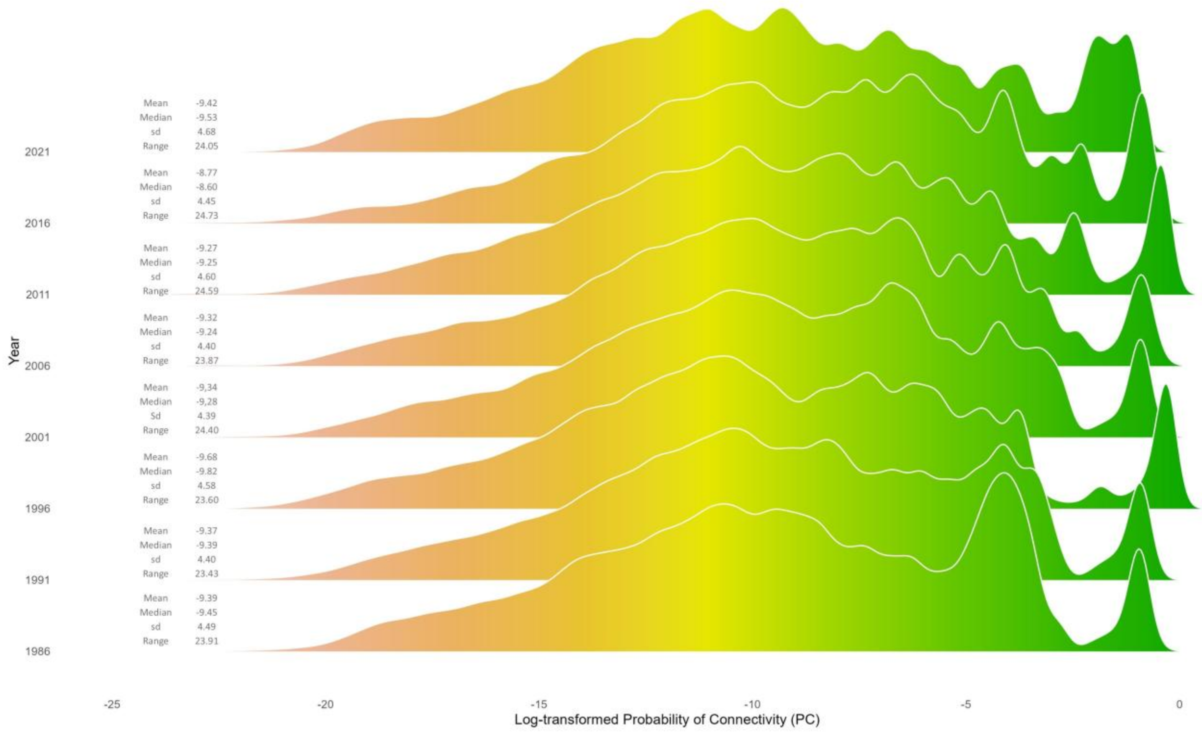


Figure 8 – Log-Transformed PC Surfaces Frequency Densities. Sarapuí River Basin, Brazil (1986-2021).

Average values ranging from -8.77 to -9.82 further align with the maps presented (Figure 6), where this range corresponds to medium and small forest patches. To our knowledge, there are no other studies that spatially represent PC in this manner. We recognize substantial potential in this approach, especially for informing decision-making processes aimed at conserving and restoring biodiversity. It offers an easily interpretable surface and continuously distributed values across the landscape, consistent with results at both the node and link levels.

Taking the most recent year analyzed, 2021, as a basis, Figure 9 presents connectivity hotspots, where the functionality of habitat patches shows more remarkable development, and potential connectivity hotspots, where the functionality of patches has increased concerning previous years but still timidly.

We can highlight hotspot a (Figure 9) as a region where the recomposition of riparian vegetation, driven by the PPAs defined by the Native Vegetation Protection Law, played a fundamental role in reconnecting previously isolated patches. This location configures a critical region of the basin, where the Pirapora and Sarapuí rivers confluence, which is essential for the basin's water security (Soares et al., 2023; Morales and Valente, 2023). Due to the width of these watercourses, the PPAs defined by the Forest Code are more extensive, ranging from 50 to 100 m from the watercourse banks, which has benefited this region in terms of increasing its functionality.

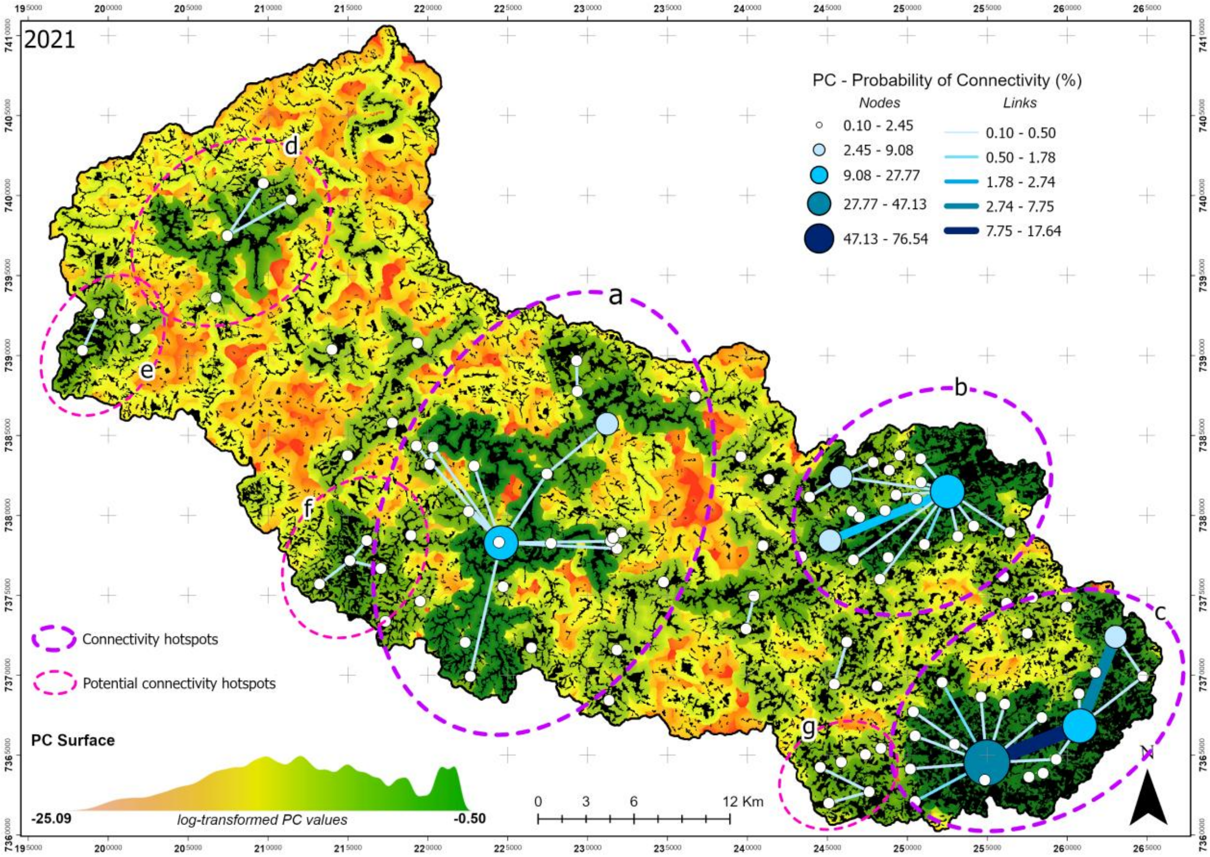


Figure 9 – Probability of Connectivity (PC) to Nodes and Links, Log-Transformed PC Surface, PC Hotspots and Potential Hotspots in the Sarapuí River Basin, Brazil (2021).

Hotspot b (Figure 9) has had potential for connectivity since the beginning of the historical series, but its importance has increased significantly since 2011. The region close to the municipality of Piedade benefits from the buffer area of the Itupararanga Hydroelectric Reservoir (whose water surface limits are outside the basin limits) and also from preservation areas maintained by a large mining company in the region, whose exploration areas are close to the municipality of Salto de Pirapora.

Hotspot c is the most consolidated in terms of connectivity, the gateway to the large Atlantic Forest massif of Serra do Mar and located in the buffer area of Jurupará State Park.

Hotspots b and c have the municipality of Piedade as a significant obstacle to their connection. Management in urban habitat areas is essential to promote such connection, which can use both the hydrographic network that crosses the municipality and urban green areas to promote such connection.

Potential hotspots, such as d, were more important in the past (1986, see Figure 6) and suffered greatly from fragmentation and habitat loss. Fortunately, in 2021, there appears to be a beginning of recovery in this area, requiring both monitoring to avoid new habitat loss events and the increase in forest patches in the region, aiming to increase its connectivity capacity and ideally promoting connection with hotspot e, a nearby region that has also shown greater participation in connectivity in the past (Figure 6).

Hotspot g represents a region that was more connected at the beginning of the historical series (1986 - 1991, Figure 6), went through periods of erosion of connective capacity, and in 2016 appeared functionally connected to hotspot c (Figure 6), however, in 2021 this connection was lost again, influenced by the duplication of the Padre Guilherme Howel Highway (BR-478), which in this section connects the municipalities of Piedade and Tapiraí, demonstrating that the dynamism between habitat gain and loss and linear structures such as roads and highways make it challenging to consolidate the connective potential of habitat areas.

2.4. CONCLUSIONS

The spatiotemporal analysis revealed critical aspects of the landscape dynamics over the 35-year study period. The Sarapuí River Basin underwent significant land-use intensification, marked by a transition from pasturelands to intensive agriculture and silviculture, which expanded by approximately ~100% and ~600%, respectively. Although total forest cover remained relatively stable, with a slight increase by the end of the series, the spatiotemporal approach revealed underlying dynamics as forest rejuvenation. Old-growth forests declined by 18.7%, replaced by regenerating vegetation, while deforestation peaked in 2021 (37.25 km²), partially masked by simultaneous forest gains. These findings highlight the risks of misinterpreting forest dynamics and habitat quality when relying solely on deforestation and reforestation rates, underscoring the need to integrate temporal legacies and structural metrics into conservation planning.

Forest patch dynamics indicated persistent fragmentation, with ~98% of patches measuring less than 75 ha. However, post-2012 legal protections for riparian zones contributed to the formation of elongated and proximate patches, enhancing connectivity in the central basin and headwaters. The spatially explicit Probability of Connectivity (PC) model demonstrated consistency between patch-level metrics and landscape-scale patterns, confirming its utility in guiding restoration and conservation strategies.

Despite these contributions, some limitations must be acknowledged. The reliance on 30 m resolution LULC data may underestimate the extent of small forest fragments. Additionally, the connectivity model, based on Euclidean distance, may not fully capture species-specific dispersal behaviors. However, its parameterization allows flexibility in incorporating different dispersal distances or resistance surfaces tailored to focal species or functional groups. Future research should integrate biodiversity surveys to assess the ecological impacts of forest regeneration and validate connectivity models with empirical data on species movement.

To address these challenges, conservation strategies should prioritize the protection of old-growth forests, expand forest restoration to consolidate connectivity gains, and adopt spatially explicit models to balance ecological and anthropogenic demands. This framework provides a replicable approach for managing transitional ecotones, where habitat quality and connectivity are essential for long-term resilience.

REFERENCES

Altman, J., Fibich, P., Trotsiuk, V., and Altmanova, N. (2024). **Global pattern of forest disturbances and its shift under climate change**. Science of the Total Environment, 915. https://doi.org/10.1016/j.scitotenv.2024.170117

Alvares, C. A., Stape, J. L., Sentelhas, P. C., Gonçalves, J. L. de M., and Sparovek, G. (2014). **Köppen's climate classification map for Brazil**. Meteorologische Zeitschrift, 22(6), 711–728. https://doi.org/10.1127/0941-2948/2013/0507

Antongiovanni, M., Venticinque, E. M., Tambosi, L. R., Matsumoto, M., Metzger, J. P., and Fonseca, C. R. (2022). **Restoration priorities for Caatinga dry forests: Landscape resilience, connectivity and biodiversity value**. Journal of Applied Ecology, 59(9), 2287–2298. https://doi.org/10.1111/1365-2664.14131

Báldi, A., Pellaton, R., Bihaly, Á. D., Szigeti, V., Lellei-Kovács, E., Máté, A., Sárospataki, M., Soltész, Z., Somay, L., and Kovács-Hostyánszki, A. (2022). **Improving ecosystem services in farmlands: beginning of a long-term ecological study with restored flower-rich grasslands.** Ecosystem Health and Sustainability, 8(1). https://doi.org/10.1080/20964129.2022.2090449

Barlow, J., Lennox, G. D., Ferreira, J., Berenguer, E., Lees, A. C., Nally, R. Mac, Thomson, J. R., Ferraz, S. F. D. B., Louzada, J., Oliveira, V. H. F., Parry, L., Ribeiro De Castro Solar, R., Vieira, I. C. G., Aragaõ, L. E. O. C., Begotti, R. A., Braga, R. F., Cardoso, T. M., Jr, R. C. D. O., Souza, C. M., … Gardner, T. A. (2016). **Anthropogenic disturbance in tropical forests can double biodiversity loss from deforestation**. Nature, 535(7610), 144–147. https://doi.org/10.1038/nature18326

Brancalion, P. H. S., Niamir, A., Broadbent, E., Crouzeilles, R., Barros, F. S. M., Almeyda Zambrano, A. M., Baccini, A., Aronson, J., Goetz, S., Reid, J. L., Strassburg, B. B. N., Wilson, S., and Chazdon, R. L. (2019). **Global restoration opportunities in tropical rainforest landscapes**. Science Advances, 5(7), 3223–3226. https://doi.org/10.1126/sciadv.aav3223

Bürgi, M., Hersperger, A. M., and Schneeberger, N. (2004). **Driving forces of landscape change-current and new directions**.

Calaboni, A., Tambosi, L. R., Igari, A. T., Farinaci, J. S., Metzger, J. P., and Uriarte, M. (2018). **The forest transition in São Paulo, Brazil: Historical patterns and potential drivers**. Ecology and Society, 23(4). https://doi.org/10.5751/ES-10270-230407

Calabrese, J. M., and Fagan, W. F. (2004). **A comparison-shopper's guide to connectivity metrics**. Frontiers in Ecology and the Environment, 10(2), 529–536. https://doi.org/https://doi.org/10.1890/1540-9295(2004)002[0529:ACGTCM]2.0.CO;2

Crouzeilles, R., Lorini, M. L., and Grelle, C. E. V. (2010). **Deslocamento na matriz para espécies da mata atlântica e a dificuldade da construção de perfis ecológicos**. Oecologia Australis, 14(4), 875–903. https://doi.org/10.4257/oeco.2010.1404.06

Crouzeilles, R., Santiami, E., Rosa, M., Pugliese, L., Brancalion, P. H. S., Rodrigues, R. R., Metzger, J. P., Calmon, M., Scaramuzza, C. A. de M., Matsumoto, M. H., Padovezi, A., Benini, R. de M., Chaves, R. B., Metzker, T., Fernandes, R. B., Scarano, F. R., Schmitt, J., Lui, G., Christ, P., … Pinto, S. (2019). **There is hope for achieving ambitious Atlantic Forest restoration commitments.** Perspectives in Ecology and Conservation, 17(2), 80–83. https://doi.org/10.1016/j.pecon.2019.04.003

Decocq, G., Andrieu, E., Brunet, J., Chabrerie, O., De Frenne, P., De Smedt, P., Deconchat, M., Diekmann, M., Ehrmann, S., Giffard, B., Mifsud, E. G., Hansen, K., Hermy, M., Kolb, A., Lenoir, J., Liira, J., Moldan, F., Prokofieva, I., Rosenqvist, L., … Wulf, M. (2016). **Ecosystem Services from Small Forest Patches in Agricultural Landscapes**. Current Forestry Reports, 2(1), 30–44. https://doi.org/10.1007/s40725-016-0028-x

Dias, T. da C., Silveira, L. F., and Francisco, M. R. (2023). **Spatiotemporal dynamics reveals forest rejuvenation, fragmentation, and edge effects in an Atlantic Forest hotspot, the Pernambuco Endemism Center, northeastern Brazil**. PLOS ONE, 18(9), e0291234. https://doi.org/10.1371/journal.pone.0291234

Duffy, C., O'Donoghue, C., Ryan, M., Kilcline, K., Upton, V., and Spillane, C. (2020). **The impact of forestry as a land use on water quality outcomes: An integrated analysis**. Forest Policy and Economics, 116. https://doi.org/10.1016/j.forpol.2020.102185

Flach, R., Abrahão, G., Bryant, B., Scarabello, M., Soterroni, A. C., Ramos, F. M., Valin, H., Obersteiner, M., and Cohn, A. S. (2021). **Conserving the Cerrado and Amazon biomes of Brazil protects the soy economy from damaging warming**. World Development, 146. https://doi.org/10.1016/j.worlddev.2021.105582

Foltête, J. C., Vuidel, G., Savary, P., Clauzel, C., Sahraoui, Y., Girardet, X., and Bourgeois, M. (2021). **Graphab: An application for modeling and managing ecological habitat networks[Formula presented]**. Software Impacts, 8. https://doi.org/10.1016/j.simpa.2021.100065

Frazier, A. E., and Kedron, P. (2017). **Landscape Metrics: Past Progress and Future Directions**. Current Landscape Ecology Reports, 2(3), 63–72. https://doi.org/10.1007/s40823-017-0026-0

Gibson, L., Lee, T. M., Koh, L. P., Brook, B. W., Gardner, T. A., Barlow, J., Peres, C. A., Bradshaw, C. J. A., Laurance, W. F., Lovejoy, T. E., and Sodhi, N. S. (2011). **Primary forests are irreplaceable for sustaining tropical biodiversity**. Nature, 478(7369), 378–381. https://doi.org/10.1038/nature10425

Guidotti, V., Ferraz, S. F. de B., Pinto, L. F. G., Sparovek, G., Taniwaki, R. H., Garcia, L. G., and Brancalion, P. H. S. (2020). **Changes in Brazil's Forest Code can erode the potential of riparian buffers to supply watershed services**. Land Use Policy, 94. https://doi.org/10.1016/j.landusepol.2020.104511

Gurrutxaga, M., Lozano, P. J., and del Barrio, G. (2010). **GIS-based approach for incorporating the connectivity of ecological networks into regional planning**. Journal for Nature Conservation, 18(4), 318–326. https://doi.org/10.1016/j.jnc.2010.01.005

Huang, J. L., Andrello, M., Martensen, A. C., Saura, S., Liu, D. F., He, J. H., and Fortin, M. J. (2020). **Importance of spatio–temporal connectivity to maintain species experiencing range shifts.** Ecography, 43(4), 591–603. https://doi.org/10.1111/ecog.04716

IBGE. (2012). **Manual Técnico da Vegetação Brasileira** (IBGE, Ed.; 2nd ed., Vol. 1, Issue 1). https://doi.org/ISSN 0101-4234

IBGE. (2019). **Biomas e Sistema Costeiro-Marinho do Brasil: compatível com a escala 1:250.000**. In Instituto Brasileiro de Geografia e Estatística (Vol. 45, Issue 1).

Kupfer, J. A. (2012). **Landscape ecology and biogeography: Rethinking landscape metrics in a post-FRAGSTATS landscape**. Progress in Physical Geography: Earth and Environment, 36(3), 400–420. https://doi.org/10.1177/0309133312439594

Lang, S., and Blaschke, T. (2009). **Análise da Paisagem com SIG** [Brazil version]. Oficina de Textos.

Lausch, A., Blaschke, T., Haase, D., Herzog, F., Syrbe, R. U., Tischendorf, L., and Walz, U. (2015). **Understanding and quantifying landscape structure - A review on relevant process characteristics, data models and landscape metrics**. Ecological Modelling, 295, 31–41. https://doi.org/10.1016/j.ecolmodel.2014.08.018

Levis, C., Flores, B. M., Mazzochini, G. G., Manhães, A. P., Campos-Silva, J. V., Borges de Amorim, P., Peroni, N., Hirota, M., and Clement, C. R. (2020). **Help restore Brazil's governance of globally important ecosystem services**. In Nature Ecology and Evolution (Vol. 4, Issue 2, pp. 172–173). Nature Research. https://doi.org/10.1038/s41559-019-1093-x

Martensen, A. C., Saura, S., and Fortin, M. J. (2017). **Spatio-temporal connectivity: assessing the amount of reachable habitat in dynamic landscapes**. Methods in Ecology and Evolution, 8(10), 1253–1264. https://doi.org/10.1111/2041-210X.12799

Martin, P. A., Newton, A. C., and Bullock, J. M. (2013). **Carbon pools recover more quickly than plant biodiversity in tropical secondary forests**. Proceedings of the Royal Society B: Biological Sciences, 280(1773). https://doi.org/10.1098/rspb.2013.2236

Martinez Pardo, J., Saura, S., Insaurralde, A., Di Bitetti, M. S., Paviolo, A., and De Angelo, C. (2023). **Much more than forest loss: four decades of habitat connectivity decline for Atlantic Forest jaguars**. Landscape Ecology, 38(1), 41–57. https://doi.org/10.1007/s10980-022-01557-y

McGarigal K., SA Cushman, and E Ene. 2023. **FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical Maps**. Computer software program produced by the authors; available at the following web site: https://www.fragstats.org

Mello, K. de, Randhir, T. O., Valente, R. A., and Vettorazzi, C. A. (2017). **Riparian restoration for protecting water quality in tropical agricultural watersheds**. Ecological Engineering, 108, 514–524. https://doi.org/10.1016/j.ecoleng.2017.06.049

Morales, M. V., and Valente, R. A. (2023). **Hydrological Inferences from Morphometric Analysis of the Sarapuí River Watershed**. In INPE (Ed.), XX Simpósio Brasileiro de Sensoriamento Remoto (Vol. 12, Issue 10, pp. 292–295). INPE. https://proceedings.science/p/164147?lang=pt-br

Poorter, L., Bongers, F., Aide, T. M., Almeyda Zambrano, A. M., Balvanera, P., Becknell, J. M., Boukili, V., Brancalion, P. H. S., Broadbent, E. N., Chazdon, R. L., Craven, D., De Almeida-Cortez, J. S., Cabral, G. A. L., De Jong, B. H. J., Denslow, J. S., Dent, D. H., DeWalt,

S. J., Dupuy, J. M., Durán, S. M., … Rozendaal, D. M. A. (2016). **Biomass resilience of Neotropical secondary forests**. Nature, 530(7589), 211–214. https://doi.org/10.1038/nature16512

Prevedello, J. A., and Vieira, M. V. (2010). **Does the type of matrix matter? A quantitative review of the evidence**. In Biodiversity and Conservation (Vol. 19, Issue 5, pp. 1205–1223). https://doi.org/10.1007/s10531-009-9750-z

Rajão, R., Nobre, A. D., Cunha, E. L. T. P., Duarte, T. R., Marcolino, C., Soares-Filho, B., Sparovek, G., Rodrigues, R. R., Valera, C., Bustamante, M., Nobre, C., and Santos de Lima, L. (2022). **The risk of fake controversies for Brazilian environmental policies**. Biological Conservation, 266. https://doi.org/10.1016/j.biocon.2021.109447

Ribeiro, M. P., de Mello, K., and Valente, R. A. (2022). **How can forest fragments support protected areas connectivity in an urban landscape in Brazil?** Urban Forestry and Urban Greening, 74. https://doi.org/10.1016/j.ufug.2022.127683

Rosa, M. R., Brancalion, P. H. S., Crouzeilles, R., Tambosi, L. R., Piffer, P. R., Lenti, F. E. B., Hirota, M., Santiami, E., and Metzger, J. P. (2021). **Hidden destruction of older forests threatens Brazil's Atlantic Forest and challenges restoration programs**. Science Advances, 7(4). https://doi.org/10.1126/sciadv.abc4547

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

Saura, S., and Pascual-Hortal, L. (2007). **A new habitat availability index to integrate connectivity in landscape conservation planning: Comparison with existing indices and application to a case study**. Landscape and Urban Planning, 83(2–3), 91–103. https://doi.org/10.1016/j.landurbplan.2007.03.005

Soares, D. R., Nahssen, M. H. C., Soares, F. da S., Morales, M. V., Rigonato, M. B., Germano, A. D., and Valente, R. A. (2022). **Conectividade estrutural da vegetação nativa para o planejamento da conservação florestal.** Research, Society and Development, 11(4), e39811427492. https://doi.org/10.33448/rsd-v11i4.27492

Souza, C. M., Shimbo, J. Z., Rosa, M. R., Parente, L. L., Alencar, A. A., Rudorff, B. F. T., Hasenack, H., Matsumoto, M., Ferreira, L. G., Souza-Filho, P. W. M., de Oliveira, S. W., Rocha, W. F., Fonseca, A. V., Marques, C. B., Diniz, C. G., Costa, D., Monteiro, D., Rosa, E. R., Vélez-Martin, E., … Azevedo, T. (2020). **Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine**. Remote Sensing, 12(17). https://doi.org/10.3390/RS12172735

Sparovek, G., Reydon, B. P., Guedes Pinto, L. F., Faria, V., de Freitas, F. L. M., Azevedo-Ramos, C., Gardner, T., Hamamura, C., Rajão, R., Cerignoni, F., Siqueira, G. P., Carvalho, T., Alencar, A., and Ribeiro, V. (2019). **Who owns Brazilian lands?** Land Use Policy, 87. https://doi.org/10.1016/j.landusepol.2019.104062

Tambosi, L. R., Martensen, A. C., Ribeiro, M. C., and Metzger, J. P. (2014). **A framework to optimize biodiversity restoration efforts based on habitat amount and landscape connectivity**. Restoration Ecology, 22(2), 169–177. https://doi.org/10.1111/rec.12049

Tavares, P. A., Brites, A. D., Sparovek, G., Guidotti, V., Cerignoni, F., Aguiar, D., Metzger, J. P., Rodrigues, R. R., Pinto, L. F. G., de Mello, K., and Molin, P. G. (2019). **Unfolding additional massive cutback effects of the native vegetation protection law on legal reserves, Brazil**. Biota Neotropica, 19(4). https://doi.org/10.1590/1676-0611-bn-2018-0658

Vancine, M. H., Muylaert, R. L., Niebuhr, B. B., Oshima, J. E. de F., Tonetti, V., Bernardo, R., De Angelo, C., Rosa, M. R., Grohmann, C. H., and Ribeiro, M. C. (2024). **The Atlantic Forest of South America: Spatiotemporal dynamics of the vegetation and implications for conservation**. Biological Conservation, 291, 110499. https://doi.org/10.1016/j.biocon.2024.110499

Watson, J. E. M., and Venter, O. (2019). **Mapping the Continuum of Humanity's Footprint on Land**. In One Earth (Vol. 1, Issue 2, pp. 175–180). Cell Press. https://doi.org/10.1016/j.oneear.2019.09.004

Watts, K., and Hughes, S. (2024). **Fragmentation impacts may be mixed for conservation but generally bad for restoration**. Restoration Ecology. https://doi.org/10.1111/rec.14260

Zalles, V., Hansen, M. C., Potapov, P. V, Parker, D., Stehman, S. V, Pickens, A. H., Parente, L. L., Ferreira, L. G., Song, X.-P., Hernandez-Serna, A., and Kommareddy, I. (2021). **Rapid expansion of human impact on natural land in South America since 1985**. In Sci. Adv (Vol. 7). https://www.science.org

3. CHAPTER III

MAPPING THE HUMAN FOOTPRINT AT RIVER BASIN SCALE: POTENTIAL FOR CONSERVATION AND INTEGRATED MANAGEMENT

Abstract

Mapping the human footprint at the watershed scale is essential for informed conservation and integrated management. This study adapts a well-established framework to produce a high-resolution (30 m/pixel) Human Footprint (HF) map of the Sarapuí River basin in São Paulo, Brazil. Four key proxies representing human pressures (i.e., human settlements, land use changes, human access, and electrical infrastructure) were quantified using diverse, high-resolution spatial datasets from governmental and research sources. Each dataset was standardized to a standard scale and aggregated to generate a composite HF map. The results reveal that areas proximate to urban centers and major road networks exhibit elevated HF scores. At the same time, predominantly agricultural and fragmented forest regions display lower scores, suggesting significant potential for conservation and restoration initiatives. Statistical analyses indicate moderate to strong correlations between individual pressure proxies and the overall HF, underscoring the dominant influence of settlement and access pressures. This detailed, high-resolution approach not only enhances the detection of localized human activity hotspots compared to traditional coarse-resolution assessments but also provides a replicable framework for other watersheds. The HF map developed herein is valuable for guiding evidence-based decision-making and public policy to mitigate human impacts while promoting sustainable land use and biodiversity conservation.

Keywords: Human Footprint; Human Pressures; Landscape Management; Environmental Planning.

3.1. INTRODUCTION

Historically, human expansion has significantly changed natural ecosystems, resulting in a large-scale transformation of natural environments driven primarily by the increasing demand for natural resources, food, housing, infrastructure, and electric power generation (Watson and Venter, 2019).

This dynamic results in a wide range of Human Pressures (HP) that manifest in terrestrial and marine ecosystems worldwide (Venter et al., 2016a). The expression and intensity of these pressures underscore the need for interdisciplinary collaboration, as they result from a synergistic interaction between demographic, political, environmental, and socioeconomic factors (Tapia-Armijos et al., 2017).

Human pressures manifest across landscapes in diverse ways, with their effects varying in intensity and scale over time and space (Gassert et al., 2023; Watson and Venter, 2019). These pressures are often associated with the built environments at local and regional levels, leading to increased pollution, soil degradation, and habitat loss (Barlow et al., 2016; Rajaonarivelo and Williams, 2022).

Roads and human access further amplify these impacts by facilitating human activities such as, selective logging, wildfires (Barlow et al., 2016; de Rezende et al., 2015), deforestation (Karlson et al., 2014), and animal roadkill (Teixeira et al., 2020).

Patterns of natural resources exploitation, different production systems, and the presence and extent of infrastructure also exert different pressures on natural ecosystems. Electrical power infrastructures, for example, are a reliable indicator of a region's technological advancement and intensity of use. Artificial night lights can serve as a proxy for human activity, and their effects can be noted not only in disrupting wildlife behavior but also in contributing to significant power consumption and CO_2 emissions (Linares Arroyo et al., 2024).

In the last decades, the ability to map diverse aspects of human influence across the Earth's surface has substantially improved, thanks to increasing developments in platforms and sensors for obtaining spatial data, as well as advances in computational capacity to process an ever-increasing data amount (Allan et al., 2023; Gassert et al., 2023; Watson and Venter, 2019). Such advances allow identifying and quantifying environmental pressures previously over-looked, such as sparse human settlements, low-intensity agricultural farming, and infrastructure systems as unpaved roads and small water reservoirs (Gassert et al., 2023; Watson and Venter, 2019).

Considering the possibilities promoted by scientific advances and the need to develop methodologies that assist in landscape management, Sanderson et al., (2002) proposed a frame-work to map human influence on landscapes, consisting of: (1) identify different human pres-sures sources; (2) acquire or develop data on different human pressures; (3) assign relative scores to different pressures; and (4) overlay the different human pressures to create the Human Footprint (HF) map (Watson and Venter, 2019).

Since then, the methodology has been implemented in different contexts, such as global (Gassert et al., 2023; Venter et al., 2016b) and regional scales (Li et al., 2018; Pertierra et al., 2017; Tapia-Armijos et al., 2017; Woolmer et al., 2008; Yang et al., 2014), coastal regions (Allan et al., 2023), and studies focusing on spatial-temporal trends of human occupation (Mu et al., 2022; Shen et al., 2020; Williams et al., 2020; Venter et al., 2016a).

However, despite the efforts and availability of global datasets, HF mapping still needs to be expanded to watershed and landscape-scale analysis, which is often unattainable due to low spatial resolution and a lack of updated data. Spatial analyses of this nature are strategically important and aligned with global goals and agreements to combat climate change and coun-teract human-induced disturbances that lead to ecosystem services degradation (Kaval, 2019; Lamb, 2018; Low et al., 2023).

. Therefore, the present study uses high-resolution and temporally updated data to adapt the framework for obtaining the Human Footprint map to the river basin scale. We also explore the potential of this product to aid decision-making and develop public policies that assist in landscape management and biodiversity conservation efforts.

3.2. MATERIAL AND METHODS

3.2.1. STUDY AREA

The study area comprises the Sarapuí River basin, which spans 1549.75 sq km, includes parts of nine municipalities in São Paulo state, Brazil (see Figure 1), and is home to approximately 120,228 inhabitants (IBGE, 2022). Located close to large urban centers such as Sorocaba city and the metropolitan region of São Paulo, the Sarapuí river basin faces constant anthropogenic pressures for agricultural and urban sprawl due to the demands from these large cities (Mello et al., 2017).

The area in question is situated in a transitional ecotone region between the Atlantic Forest and the Brazilian Cerrado, with its predominant original phytophysiognomy classified as a Dense Ombrophylous Forest (IBGE, 2012) that is currently highly fragmented (Soares et al., 2022). The occupation pattern of the basin follows that observed in São Paulo state by Calaboni et al. (2018), where historically, deforestation occurred on a large scale to expand pastures and agricultural areas in a context where the region was seen as an agricultural frontier to be explored.

The studied landscape is currently characterized by a predominantly agricultural matrix (41.37%) permeated by forest patches (23.68%), silviculture (11.72%), and pastures (18.25%), along with other less common land uses. Urban areas represent 2.59 % of the basin area. This includes Sarapuí, Alambarí, Piedade, and Salto de Pirapora, in addition to low-density urban areas in these and other municipalities, as well as important highways such as SP-270 that connects the interior of the state to the capital, São Paulo. (Figure 1).

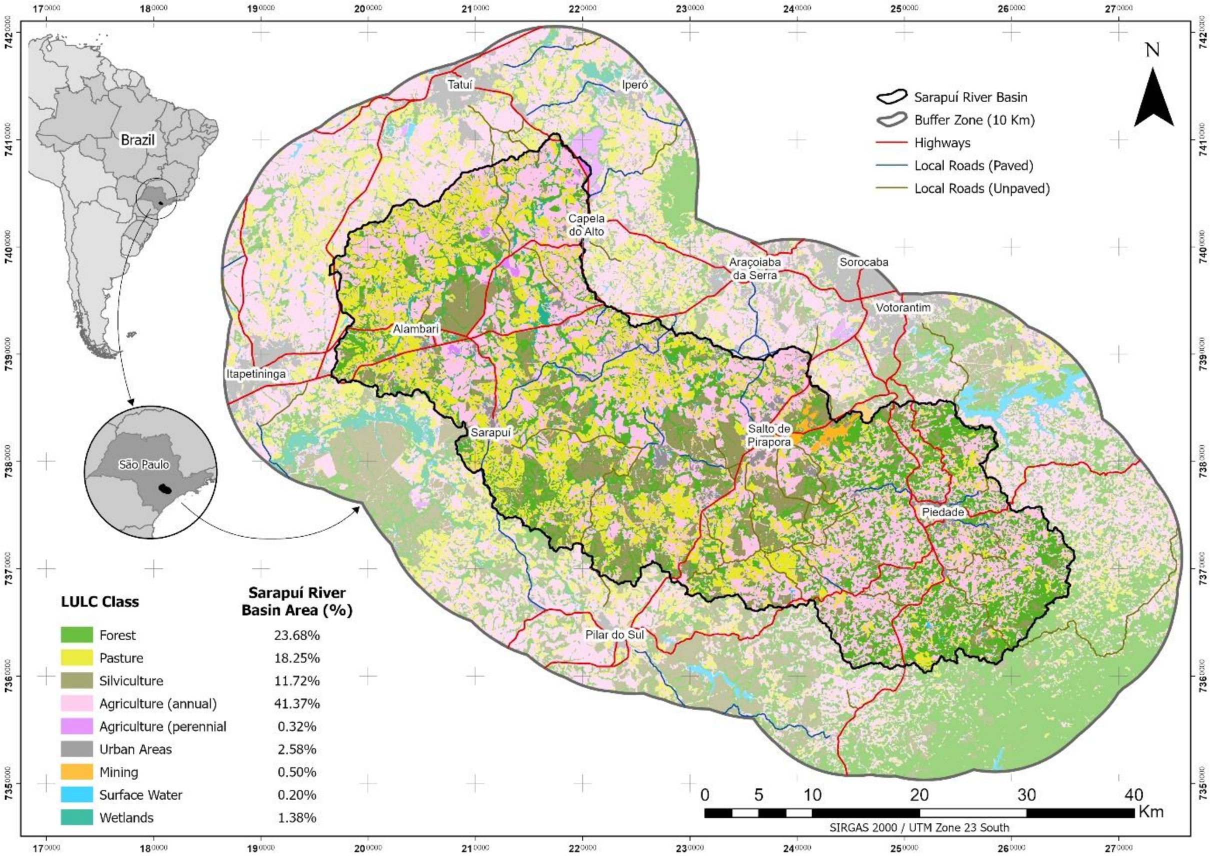


Figure 1 - Location map and land use/land cover of Sarapuí River basin, São Paulo state, Brazil.
Source: LULC adapted from MapBiomas (2021), collection 8.

Most of the basin is characterized as a humid subtropical zone with an oceanic climate, without a dry season and a with hot summers (Cfa), except for its southernmost third, where the headwaters of the basin are located, which, due to its higher altitude and proximity to the Serra do Mar geological formation, has temperate summers and is classified according to the Köppen scale as Cfb (Alvares et al., 2014). In this region, we also find the highest, steepest (Morales and Valente, 2023) and most forested areas (Soares et al., 2022), connected to the large remnant of the Atlantic Forest in the Serra do Mar Environmental Protection Area (APA).

In addition, in the regions neighboring the basin, there are important legally protected areas, such as the Jurupará State Park in the south, inside of the Serra do Mar APA's, the Ipanema National Forest in the north-east, close to Sorocaba and Iperó municipalities, and the

Itupararanga APA's, the buffer zone of the Itupararanga reservoir located to the east of the basin near the urban centers of Votorantim and Piedade (Figure 1).

3.2.2. HUMAN FOOTPRINT ASSESSMENT

To map the Human Footprint in the Sarapuí river basin, we adopted the framework first proposed by Sanderson et al. (2002) with adaptations made by Woolmer et al. (2008) and Tapia-Armijo et al. (2017) working on regional scales. However, our approach goes further, incorporating datasets of high spatial resolution, resulting in a scale of 30m/pixel, and also incorporating an approach to model the influence of the human pressure score continuously according to the variation in the dataset, instead of the traditional rigid human pressure score classes.

We also evaluated the different human pressures by their descriptive statistics and by a pixel-to-pixel correlation analysis among them and with the final Human Footprint map.

Assessing the Human Footprint involves geographic proxies of human influences (Sanderson et al., 2002), namely: (1) Human Settlement, (2) Human Land Use Changes, (3) Human Access, and (4) Electrical Infrastructure pressures, which in the present study were obtained from eight different datasets. To reflect the relative contribution of each dataset to human impact, it is necessary to standardize their measurement scales to a common scale, where 0 represents low human impact, and 10 high human impact on the landscape.

Table 1 summarizes the process of obtaining the human pressure rasters and briefly describes the datasets, the data origin, the scoring logic, and the maximum scores assigned. In the subsequent sub-sections, this procedure is detailed for each dataset. We rely on high-resolution data freely available by government institutions, research agencies, and non-governmental organizations to apply the methodology to the river basin scale. Much of the dataset used comes from mappings derived from globally available remote sensing images, making the methodology replicable worldwide. However, some datasets are local, and regional data and infrastructure information can be challenging to obtain for some regions and situations.

Table 1 - Human Pressure Proxies, Datasets, Sources, and Scoring Logic used to obtain the Human Footprint map in the Sarapuí River basin, Brazil.

Human Pressure Proxies	Datasets	Source	Scoring Logic	Máx. Score
Human Settlements	Urban Areas	MapBiomas 2021 LULC map (See Souza et al., 2020 for MapBiomas data)	Score 10 for urban areas and 0 for all others LULC classes.	20
	Population Density	IBGE 2022 Brazilian Demographic Census	Scores increase linearly, starting with 0 for 0 hab/km² and reaching 10 for 1000 hab/km² or more.	
Human Land Use Changes	LULC degree and permanence of human land transformation	MapBiomas 2021 LULC map	Different scores for each LULC class, ranging from 0 to 10.	10
	Land alterations from damming	MapBiomas 2021 LULC map	Scores decrease as the distance to dams increases. (Scores vary based on distance intervals and dam size classes).	
	Mining land alterations	MapBiomas 2021 LULC map	Scores decrease as distances to mining areas increase (Scores vary based on distance intervals).	
Human Access	Highways and Local Roads	MapBiomas 2023 Infrastructure Module	Scores decrease as distances to roads increase (Scores vary based on distance intervals and types of roads).	10
Electric Infrastructure	Nighttime Light	VIIRS Day/Night Band (Elvidge et al., 2017), and Landsat's 8 red, green and NIR bands (USGS, 2021)	Scores increase linearly as nighttime light values increase.	10
	Transmission Lines	MapBiomas 2023 Infrastructure Module	Scores decrease as distance to transmission lines increases (Scores vary based on distance intervals).	

To fully capture the human influences on the periphery of the studied basin, we buffered its boundary to 10 km. All spatial data considered in this analysis were projected to the Universal Transverse Mercator (UTM) system, with the SIRGAS 2000 Datum, zone 23 South, as the geodetic reference. Spatial and statistical analyses were performed using the ArcGIS Pro and QGIS 3.28.4 Geographic Information Systems (GIS), Google Earth Engine (GEE) and R version 4.1.0 (R Core Team, 2025).

The following items describe the procedures for obtaining the rasters, including obtaining and processing the datasets and subsequent assignment of scores, followed by the overlay procedures and statistical analyses.

3.2.3. DATASETS, SCORES AND HUMAN PRESSURE RASTERS

3.2.3.1. Human Settlements

To map the influence of urban settlements, we used two datasets: the urbanized areas, extracted from the 2021 Land Use and Land Cover (LULC) map, and population density, obtained from the results of the 2022 Brazilian Demographic Census conducted by the Brazilian Institute of Geography and Statistics (IBGE, 2022).

The LULC map, also used to produce different datasets (see below), is produced from the supervised classification of Landsat satellite images conducted by the MapBiomas project, that has been working and expanding since 2015 (Souza et al., 2020) with numerous applications in conservation and territorial planning projects (Dias et al., 2023; Mas et al., 2019; Rosa et al., 2021).

We used the LULC data collection 8, which is composed of 16 different land use classes (MapBiomas, 2021). To adapt it to our case study, we reclassified the original map into nine LULC classes as shown in Figure 1.

Thus, for the dataset referring to urbanized areas, the procedure adopted was a simple reclassification of the LULC map, assigning a score of 10 to urban areas and 0 to other land use classes.

Data from the Brazilian 2022 Demographic Census by the IBGE was used for population density. The Census results are made available in tabular format, requiring integration with the shapefile of census sectors also made available by the IBGE. 1652 census sector polygons covered the entire study area including its 10 km buffer. The population density was determined by dividing the number of inhabitants per sector by the sector area in sq km.

This map of inhabitants per sq km was then converted to a scale ranging from 0 to 10. These scores increase linearly, starting at 0 for areas with 0 inhabitants per sq km and reaching 10 for areas with 1000 inhabitants per sq km and greater (Venter et al., 2016a). The raster for human settlement pressures was then obtained by simply summing both datasets using the raster calculator. Pixels with summed values exceeding 10 were then assigned the maximum score of 10.

3.2.3.2. Human Land Use Changes

To map overall land use change, we follow the procedure introduced by Woolmer et al. (2008) when adapting the HF mapping at a regional scale in North America. We used derived from the 2021 LULC map (Figure 1): (1) the degree and permanence of human transformation for each LULC class, (2) alterations to hydrology resulting from dams and water reservoirs, and (3) alterations on the landscape caused by mining activity.

The first dataset was obtained from assigning human influence scores to each LULC class based on their degree of transformation and persistence (Woolmer et al., 2008). Thus, we assigned a score of 10 to urban and mining classes, 7 to annual agriculture, 6 to perennial agriculture, 4 to pasture, 3 to forestry and surface water, 1 to wetlands, and 0 to native forest. These scores were adjusted to better reflect the landscape characteristics of the Sarapuí River basin while maintaining the methodological basis proposed by Woolmer et al. (2008).

Hydrological changes resulting from dams and water reservoirs represent significant human-induced land modifications (Siegmund-Schultze et al., 2018). These changes affect not only the immediate flooded area but also a zone that expands with the size of the reservoir (Havlíček et al., 2022; Woolmer et al., 2008). We mapped a dam’s influence on human footprint according to its Euclidian distance to the dam and the size of its flooded area, as shown in Table 2.

The dams considered in the study were extracted from the surface water class in the LULC map and includes small dams for agricultural and animal watering to large reservoirs for multiple purposes, such as the Itupararanga reservoir, which was built for public water supply (~2.15 $m^3\ s^{-1}$ between 2005 and 2018) for about 1 million of people, and power generation distributed by a private company (~11$m^3\ s^{-1}$) (Barbosa et al., 2021).

Table 2 - Human Pressure scores used for standardizing the dataset related to dams for the Sarapuí River basin Human Footprint assessment.

Reservoir Size (ha)	Euclidean Distance (m)				
	0 – 500	500 – 1500	1500 – 2500	2500 – 5000	5000 – 10000
+ 70ha	8	8 – 4	4 – 2	2 – 1	1 – 0
30 – 70ha	6	6 – 3	3 – 1.5	1.5 – 0.75	0.75 – 0
10 – 30ha	4	4 – 2	2 – 1	1 – 0	0
- 10ha	1	0	0	0	0

To implement the scoring system outlined in Table 1, we initially created four Euclidean distance maps, each corresponding to a specific size class. We then generated 15 maps, one for each of the score ranges with values greater than zero in Table 2, assuming linear relationships between the score value and distance to the dam. These 15 maps were then aggregated by raster sum using raster calculator, with the maximum score limited to 10 and cells with no data assigned a value of 0.

Finally, the last dataset in Human Land Use Change refers to mining, which changes topography, watercourses and topsoil, and may serve as a source of water and air pollution (Cocheci et al., 2019; Woolmer et al., 2008).

This dataset is also derived from the 2021 Land Use and Land Cover (LULC) map. We extracted the mining areas, calculated the Euclidean distance to their boundaries, and assigned scores based on Table 2. Similar to the previous dataset, we used linear functions to match the distance range values with the corresponding human pressure score range (Table 3).

Table 3 - Human Pressure scores used for standardizing the dataset related to mining for the Sarapuí River basin Human Footprint assessment.

Euclidean Distance (m)	0 - 500	500 - 1500	1500 - 2500	2500 - 5000	5000 - 10000
Score	8	8 - 4	4 - 2	2 - 1	1 - 0

Once the datasets related to human land use changes were obtained, the final representative raster was generated by simply summing the three datasets in the raster calculator and setting the resulting raster's overall human pressure to a maximum score of 20.

3.2.3.3. Human Access

Human footprint mapping on broader scales considers highways, railways, and waterways as human access (Mu et al., 2022; Sanderson et al., 2002; Venter et al., 2016b). However, our study area only has highways and local roads, including state highways with the highest traffic flow and local paved or unpaved roads with the lowest traffic. The latter are generally managed by municipalities (Figure 1).

The human access data, available in vector format (*shapefile*), were sourced from the infrastructure module of the MapBiomas platform (2023), aggregating spatial data from various Brazilian government agencies, including the IBGE and the National Department of Transportation Infrastructure (DNIT). We applied minor corrections through on-screen scanning of updated high-resolution images from Google Earth .

Subsequently, three maps were generated based on Euclidean distances to each highway category, with human pressure scores assigned as per Table 4. Like other distance maps, we assumed a linear relationship between the score value and the distance range.

Table 4 - Human Pressure scores used for standardizing the dataset related to human access for the Sarapuí River basin Human Footprint assessment.

Human Access	Euclidean Distance (m)				
	0 - 90	90 - 500	500 - 1000	1000 - 3000	3000 - 5000
State Highway	10	8 – 6	6 – 4	4 – 1	1 – 0
Local Road (Paved)	8	6 – 4	4 – 2	2 – 0	0
Local Road (Unpaved)	6 – 4	4 – 2	2 – 0	0	0

Finally, the raster for human access was obtained by combining the three standardized distance rasters using the raster calculator, and setting the maximum score for the final raster to 10

3.2.3.4. Electrical Infrastructure

Mapping electrical infrastructure provides a proxy for population distribution and is correlated with human settlement and resource exploitation patterns (Watson and Venter, 2019a). To capture the influence of electrical infrastructure as a source of human pressure, we used two datasets: (1) remote sensing data of nighttime lights and (2) power transmission lines.

To generate the Nighttime Lights Raster (*NLR*) on a scale consistent with our approach, we adopted the methodology proposed by Román et al. (2019) to increase the resolution of the Day/Night Band (*DNB*) image obtained by the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor.

To do this we used two data sources: DNB images, which provide nighttime reflectance information at a coarse spatial resolution (500 meters); and a 30-meter spatial resolution optical imagery obtained from the Landsat 8 satellite, offering detailed observations of the built environment layout (Román et al., 2019). We used the annual average of monthly cloud-free DNB composite images from 2021 made available by the Earth Observation Group of the Payne Institute for Public Policy by Colorado School of Mines (Elvidge et al., 2017), and the annual median for 2021 of the red, green, and near-infrared bands of the Landsat 8 satellite duly processed and made available in reflectance values by the U.S. Geological Survey (USGS, 2021)

In this context, the methodology to increase the resolution of the DNB image is simple and requires images from the Normalized Difference Vegetation Index (*NDVI*) and Normalized Difference Water Index (*NDWI*), both generated from Landsat 8 imagery, in addition to the DNB band imagery from VIIRS (Román et al., 2019).

The two sets of images were obtained from cloud processing using the Google Earth Engine (GEE) platform. Equations 1, 2, and 3 represent the methods for obtaining NDVI, NDWI, and the normalized nighttime reflectance raster (NNRn). Equation 4 represents the method for obtaining the nighttime lights raster (NLR), which is a function of the normalized nighttime reflectance raster and NDVI.

$$NDVI = \frac{\rho NIR - \rho Red}{\rho NIR + \rho Red} \qquad Equation\ 1.$$

Where, ρNIR and ρRed are the surface reflectance of near-infrared and red bands respectively.

$$NDWI = \frac{\rho Green - \rho NIR}{\rho Green + \rho NIR} \qquad Equation\ 2.$$

Where, $\rho Green$ and ρNIR are the surface reflectance of green and near-infrared bands respectively.

$$NNR_n = \frac{DNB}{DNB_{max}} \qquad Equation\ 3.$$

Where, *DNB* and DNB_{max} are, respectively, the surface reflectance of VIIRS Day/Night Band and the maximum value for the VIIRS Day/Night Band reflectance in the study area (in this case 84.8503 $nW.cm^{-2}.sr^{-1}$).

$$NLR = \frac{NNR_n - NDVI}{NNR_n + NDVI} \qquad Equation\ 4.$$

As a last step for this dataset, we removed the influence of pixels related to surface water that can be confused with nighttime reflectance; these were identified based on the NDWI results, where pixels above 0.2 were identified as water bodies and assigned the value of 0 in the nighttime lights dataset (Román et al., 2019). The resulting raster was then standardized to the human pressure scale with values ranging from zero to ten using a linear function.

In addition to NLR, we used data from the MapBiomas infrastructure module to account for the human pressure caused by transmission lines in the raster representing Electrical Infrastructure impacts. Using shapefiles of transmission lines crossing our study area, we computed the Euclidean distance to these lines and applied a linear decay function, assigning a score of 3 at 0 meters from the lines, decreasing to 0 at 3000 meters.

Finally, the electrical infrastructure raster was obtained by summing the NLR and the transmission lines raster, with a maximum score capped at 10.

3.2.4. Human Footprint Map

The Human Footprint map was obtained by overlaying the four human pressure rasters (Human Settlements, Human Land Use Changes, Human Access, and Electrical Infrastructure), where the resulting pixel score refers to the sum of the human pressure rasters, with a theoretical maximum score of 50.

To understand the behavior of each human pressure raster, we calculated simple statistics such as the maximum, minimum, mean, median, and standard deviation of the scores and visually analyzed the distribution of score frequencies using density graphs. The same descriptive analysis was also conducted on the final Human Footprint raster.

To determine which human pressure rasters have the greatest influence on the human footprint in the basin, we performed a pixel-by-pixel correlation analysis between all input and output rasters. This analysis also allowed us to assess whether the proxies correlate, indicating overlapping pressures from different sources.

3.2.5. Implications for Landscape Management

To evaluate the potential application of the Human Footprint map in environmental management strategies, we first categorized the HF raster into five classes (i.e. very low, low, medium, high, and very high) using the natural breaks method.

Next, utilizing very high-resolution imagery (2m) from the China-Brazil Earth Resources Satellite (CBERS-04A), we analyzed the results at the river basin scale by visually examining different regions of the watershed, identifying HF patterns, and assessing their implications for integrated watershed management.

The imagery used in this study was acquired on June 30, 2021, aligning with the other input datasets, and was freely provided by the National Institute for Space Research (INPE, 2021). We used Level-4 processed images with radiometric and geometric corrections already applied, obtained from the *Wide Scan Multispectral and Panchromatic Camera* (WPM) sensor onboard the CBERS-04A satellite. This sensor provides 8-meter resolution images for the visible spectrum (Red, Green, and Blue) and the Near-Infrared (NIR) bands, as well as 2-meter resolution images for the panchromatic band. To generate the 2-meter resolution color composite, we applied the pan-sharpening technique following the methodology described by Silva and Costa (2023).

This analysis allowed us to explore how the HF map can support evidence-based decision-making, guide conservation and restoration efforts, and inform public policies to balance environmental sustainability with socioeconomic demands.

Additionally, we discussed how this approach can enhance land-use planning by identifying key areas under human pressure, thereby enabling targeted interventions to mitigate negative impacts and promote ecosystem resilience.

3.3. RESULTS AND DISCUSSION

Our results represent the first Human Footprint (HF) mapping at the watershed level in Brazilian terrestrial environments. In this context, we emphasize that the availability of high-resolution spatial data is a fundamental factor for developing baseline territorial studies and supporting decision-making processes. Our study's use of high-resolution (30 m) data enables a more detailed detection of human pressures than global assessments that typically employ coarser resolutions (Sanderson et al., 2002; Watson and Venter, 2019). This enhanced spatial resolution is particularly advantageous for identifying localized human activity hotspots, thereby informing more targeted conservation and management strategies at the watershed level.

Figure 2 demonstrates the level of detail obtained in each human pressure raster. As expected, the raster for human settlements exhibits more pixels with higher scores in regions close to urban centers (Figure 2a). Most pixels in the basin have low human settlement scores (Figure 2a1), with a mean of 0.66, a median of 0.14, and a coefficient of variation (CV) of 1.89.

This is due to the predominantly agricultural character of the basin, where only 2.58% of the landscape is classified as human settlements (Figures 1, 2a, and 2a1).

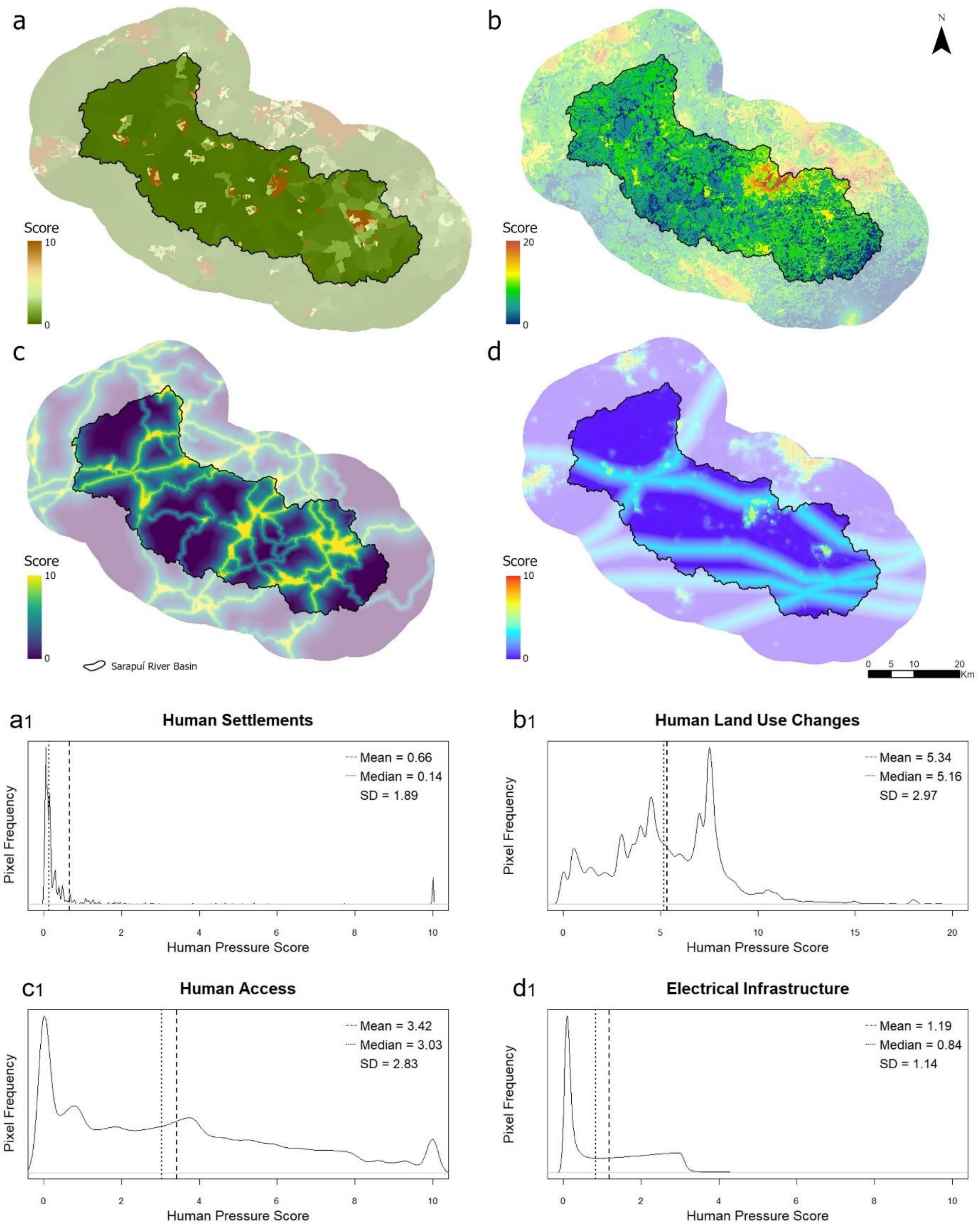


Figure 2 -Human pressure rasters (a - d) and their respective density plots (a_1 – d_1) in the Sarapuí River basin, São Paulo state, Brazil. a and a_1: human settlements. b and b_1: human land use changes. c and c_1: human access. d and d_1: electrical infrastructure.

It is also evident in Figure 2a that, in the basin headwaters, particularly in the municipality of Piedade, there is a more evenly distributed human presence between rural and urban environments. This pattern is primarily attributable to the characteristics of local agricultural activity, which is marked by small, family-owned farms (approximately 77% in 2017, see Palmeira et al., 2020) primarily cultivating onions, potatoes, artichokes, pumpkins, khaki, sweet potatoes, strawberries, and other horticultural crops (Mello et al., 2017).

Palmeira et al. (2020) state that 56% of the municipality's population resides in rural areas, distributed across approximately 84 rural neighborhoods. As visually confirmed in Figure 2a, this spatial configuration culminates in increased human pressure resulting from these settlements.

Schneider and Costa (2013), in their socio-environmental and productive diagnosis of the region's agroecosystems, found that the production system for these crops follows a conventional agricultural model, characterized by intensive use of synthetic fertilizers and pesticides, a heavy reliance on fossil fuels, and significant pressures on natural resources. Similarly, Américo et al. (2017), while evaluating land-use conflicts in permanently preserved areas under the Native Vegetation Protection Law (*Federal Law n° 12.651/2012*), identified that although the municipality maintains a significant portion of its preserved area covered by native forest, improper land use persists, with pastures and agriculture exerting considerable pressure on the landscape.

However, the socio-environmental scenario described by Schneider and Costa (2013) has likely evolved over the past decade, driven partly by public policies aimed at forest restoration and conservation following the implementation of Law n° 12.651 in 2012, as demonstrated by Américo et al. (2017). Furthermore, there is significant potential for adopting improved agricultural practices and transitioning from conventional production to agroecological models. Given the high prevalence of family-run farms, smaller property sizes, and diversified regional production, local managers have a unique opportunity to develop public policies promoting nature conservation and food security.

Regarding the raster of human land use changes, this layer exhibits a broader range of scores (0–20) than the other human pressure rasters; however, most pixels attain HF scores below 10. This raster also presents the highest mean (5.34), median (5.16), and variability (SD = 2.97). A distinct cluster of human pressure is evident in the eastern region of the basin, near the urban centers of Salto de Pirapora (within the basin) and Votorantim (adjacent to the basin).

This region is additionally impacted by extensive mining activity, which is primarily focused on cement production and concentrated near the urban perimeter of Salto de Pirapora. Furthermore, the area is influenced by the Itupararanga reservoir, which, although located outside the basin, lies within 10 km and significantly influences the region. Woolmer et al. (2008), in a regional analysis of the Human Footprint along the eastern border between Canada and the United States, similarly noted that mining and hydrological alterations due to damming substantially increase the human footprint in their areas of influence, even in regions with moderate or low population density.

The raster corresponding to human access had the highest mean, median, and standard deviation (3.42, 3.03, and 2.83, respectively; see Figure 2c1). Clusters with the highest scores are located at road intersections, especially in urban and peri-urban areas (Figure 2c). This observation reinforces the importance of high-resolution data, particularly for capturing the presence of unpaved rural roads and differentiating between highways and local roads. A higher density of roads is also observable in the basin headwaters, notably at the intersection of two high-traffic highways in Piedade, intermingled with several paved and unpaved local roads connecting the multiple rural neighborhoods.

We found slightly higher mean and median values for the raster representing electrical infrastructure (Figure 2d) than those in the human settlement raster (1.19 and 0.84, respectively, as shown in Figure 2d1). However, this layer predominantly comprises pixels with low human pressure scores (below 4) and lacks clusters of high human pressure, even in urbanized areas. High-score pixels are so infrequent that they are not discernible in the density graph (Figure 2d1).

The Human Footprint (HF) map obtained for the Sarapuí River basin (Figure 3a) reveals human pressure scores ranging from 0 to 47, with an average score of 10.61, a median of 9.68, and a standard deviation of 6.06. The distribution of scores is right-skewed, with a concentration of values between 0 and 20 (Figure 3b). Studies such as those by Sanderson et al. (2002), Woolmer et al. (2008), Venter et al. (2016), and Tapia-Armijos et al. (2017) suggest that this score range encompasses areas with varying degrees of human influence, from those with minimal human impact, considered "wilder" (<4), to areas categorized as experiencing less (<10) or moderate (<20) human impact.

Given the significant portion of the basin with HF scores below 20, we emphasize the Sarapuí River basin's considerable potential for conservation. This also presents opportunities for forest restoration actions, as many regions classified as experiencing lower human impact are not currently forested. However, these areas' relatively lower disturbance levels provide favorable conditions for ecological processes essential to successful forest regeneration. As highlighted in previous studies, human-induced disturbances remain one of the primary threats to ecosystems in the early stages of recovery (Borda-Niño et al., 2020).

The urban centers of Piedade and Salto de Pirapora exhibit the highest concentrations of Human Footprint, corresponding to the largest populations in the basin, 59,970 and 43,748 inhabitants, respectively (IBGE, 2022). Moreover, the municipality of Salto de Pirapora is notably impacted by high-intensity mining operations located near its urban perimeter (Figures 1, 2a, 2b, and 4). In contrast, the human impact in Piedade is more spatially distributed, driven by a combination of high rural population density and an extensive network of roads. This pattern results in more diffuse and widespread human-induced pressures across the region (Figures 1, 2a, 2c, and 4).

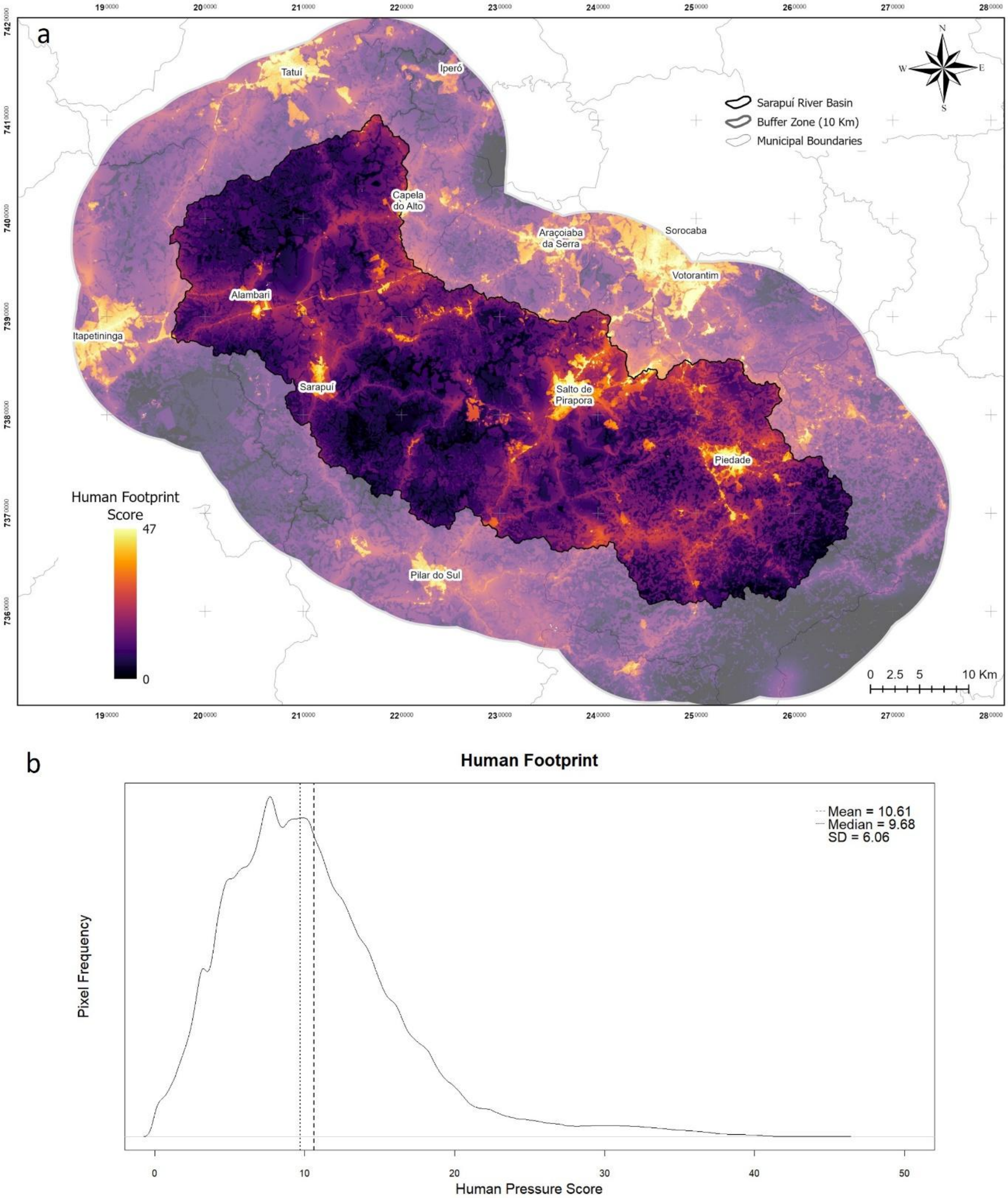


Figure 3 – a: Human Footprint map. b: Human Footprint density plot. Sarapuí River basin, São Paulo state, Brazil.

Correlation analysis revealed weak correlations between the human pressure rasters, with correlation coefficients ranging from 0.18 to 0.31, and moderate to strong correlations between the human pressure rasters and the human footprint map, with coefficients ranging from 0.46 to 0.75 (Table 5).

Table 5 – Correlation matrix among the human pressure rasters and the human footprint map. Sarapuí River basin, São Paulo state, Brazil.

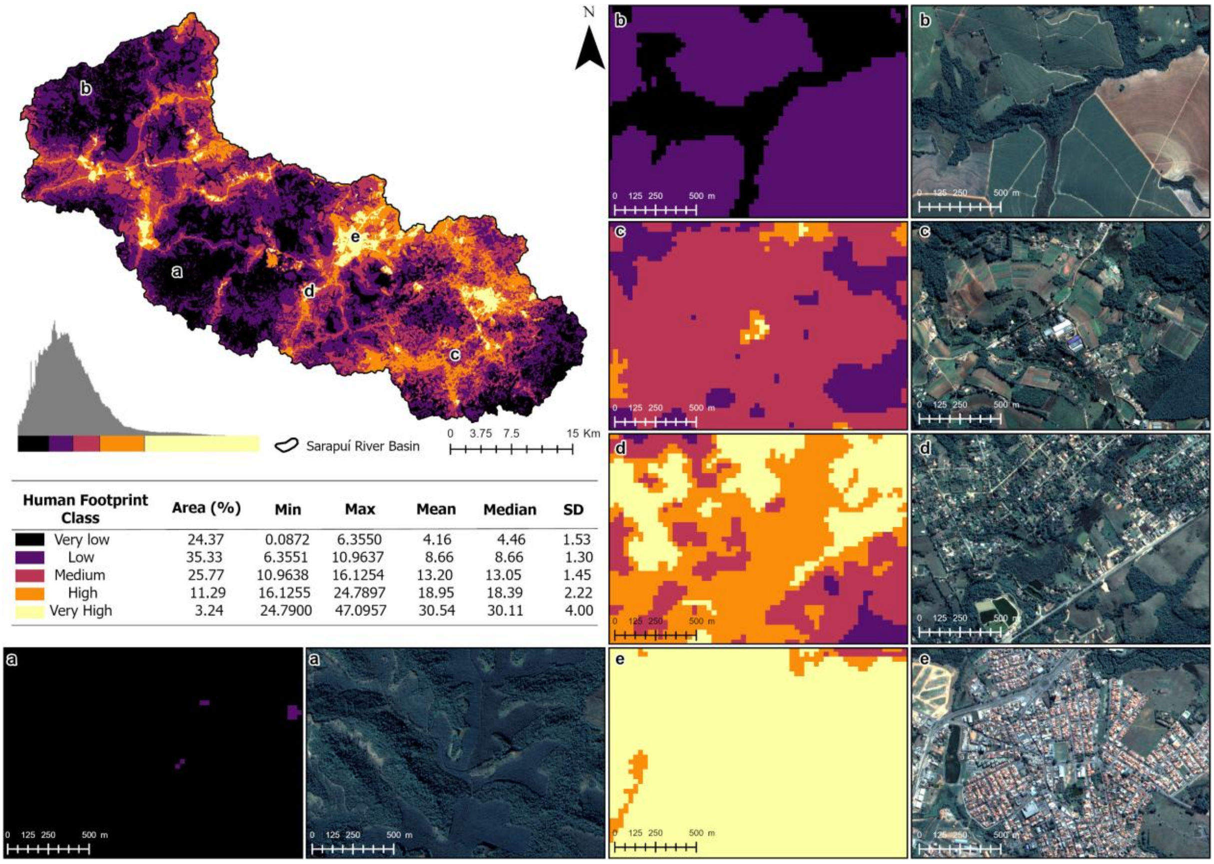
Rasters	Human Settlements	Human LULC Changes	Human Access	Electrical Infraestructure	Human Footprint Map
Human Settlements	1				
Human LULC Changes	0.31	1			
Human Access	0.31	0.27	1		
Electrical Infraestructure	0.26	0.18	0.21	1	
Human Footprint	0.65	0.75	0.74	0.46	1

Table 2 clearly illustrates the patterns observed in the human pressure rasters (Figure 2) and the HF map (Figure 3). The most significant contributions to the overall Human Footprint arise from LULC changes and human access pressures. These factors exhibit a widespread spatial influence across the basin, particularly in areas associated with agricultural activities and road networks.

In contrast, pressures related to human settlements are more concentrated in urban areas and regions with higher population density, which limits their overall contribution to the HF values. Finally, the influence of electrical infrastructure pressures remains the least prominent, reflecting the predominantly agricultural character of the Sarapuí River basin and the lower density of electrical infrastructure across the landscape.

To better understand the extent of the Human Footprint (HF) across the landscape and to facilitate comparisons with the very high-resolution imagery used for evaluating the results, the HF map was categorized into five classes based on natural breaks in pixel values (see Figure 4). The landscape is predominantly characterized by medium to very low HF values, with less than 15% of the area exhibiting high or very high HF scores. This pattern again highlights the Sarapuí River basin’s considerable potential for nature conservation and forest restoration initiatives.

Notably, the class with the highest proportion in the landscape (low HF, 35.33%) also demonstrates the lowest variability (SD = 1.30). In contrast, the class with the smallest proportion (very high HF, 3.24%) presents the highest variability (SD = 4.00). This variation arises from the mix of land use and land cover (LULC) classes that compose areas with very low HF values. The lowest scores are typically associated with forested regions, while slightly higher values are observed in silviculture, pastures, and agriculture areas. However, these areas maintain an overall low HF due to their distance from the road network and low population density.



Human Footprint Class	Area (%)	Min	Max	Mean	Median	SD
Very low	24.37	0.0872	6.3550	4.16	4.46	1.53
Low	35.33	6.3551	10.9637	8.66	8.66	1.30
Medium	25.77	10.9638	16.1254	13.20	13.05	1.45
High	11.29	16.1255	24.7897	18.95	18.39	2.22
Very High	3.24	24.7900	47.0957	30.54	30.11	4.00

Figure 4 – Human Footprint map categorized by the HF values natural breaks. Sarapuí River basin, São Paulo state, Brazil.

Figure 4a provides a detailed depiction of areas with very low Human Footprint (HF), characterized by the predominance of native forest vegetation, but also includes the potential for less impactful land uses such as silviculture, primarily with Eucalyptus spp. and Pinus spp. In the area shown in Figure 4b, the role of native vegetation in maintaining the very low HF class is evident; however, adjacent agricultural lands are classified as having low HF. This landscape typifies a basin region where the agricultural matrix predominates, and forest habitats are highly fragmented (see Chapter II).

Public policies promoting forest conservation and restoration are highly recommended for these regions. Payment for Ecosystem Services (*PES*) programs have proven effective in achieving additional ecosystem service provision and delivering socio-economic benefits (Börner et al., 2017). Such programs are considered strategic for watershed management, particularly in balancing environmental conservation with human development goals (Rigonato et al., 2023).

Figure 4c illustrates a common scenario in the basin's headwaters, where there is a combination of high rural population density, extensive road networks, and intensive agricultural activity. This combination results in a significant concentration of medium and high HF class pixels, with lower HF values associated with native forest cover and higher HF values corresponding to urbanized areas, often located in rural neighborhoods that have developed along major highways.

There is a clear opportunity to develop public policies to reduce human pressures on the landscape in these contexts. Incentivizing biodiversity-friendly land cover, such as agroforestry systems, presents a promising strategy. These systems not only enhance biodiversity and ecosystem service provision but also improve the income of smallholder farmers, offering a sustainable alternative to conventional agriculture (Arroyo-Rodríguez et al., 2020). Agroforestry aligns well with the agricultural practices predominant in the headwaters of the basin, which are primarily focused on horticultural crops (Gori Maia et al., 2021; Gonçalves et al., 2021; Padovan et al., 2022).

The scenario illustrated in Figure 4d exemplifies a recurring phenomenon in the basin, where clusters of high and very high HF emerge in planned neighborhoods along high-traffic highways but at a considerable distance from municipal urban centers. The combination of built environments, population density, electrical infrastructure, and proximity to major roads generates significant human pressures in these areas. Nevertheless, these regions are often characterized by high-end residential developments, where environmental best practices, such as maintaining green areas and protecting riparian vegetation are mandatory following current environmental legislation.

Finally, Figure 4e highlights the regions classified as having very high HF, primarily concentrated in the urban centers of the basin's municipalities. Given the convergence of high scores for all human pressure proxies analyzed in these areas, this distribution aligns with expectations. In addition to the urbanized zones, clusters of very high HF were also observed in mining areas, particularly those adjacent to Salto de Pirapora, further amplifying the HF in the municipality's urban area due to the mining operations' sphere of influence.

Tapia-Armijos et al. (2017) highlight that the interactions between humans and the landscape are complex, but understanding these dynamics through spatial tools like Human Footprint (HF) analysis is a powerful approach to improving land management. Our high-resolution mapping enabled a level of detail far superior to that found in global datasets (Venter et al., 2016a; Mu et al., 2022), demonstrating significant potential for its incorporation into environmental planning at the watershed scale. This is particularly important given the current lack of spatial analyses that effectively quantify and map areas under the influence of human-induced disturbances. This remains a critical gap in watershed-level management and conservation efforts but has been overcome thanks to the development of spatial analyses such as the HF assessment.

3.4. CONCLUSIONS

Adapting the Human Footprint assessment framework to the watershed scale yielded highly satisfactory results. The availability of spatial data with high resolution, spatially and temporally, was a key factor contributing to its strong performance, highlighting the importance of high-quality spatial data across various aspects of our territory to develop comprehensive and informative analyses.

At our scale of analysis, we found that the human-induced pressures driving the Human Footprint are primarily related to settlement and access, which correspond to areas with the highest concentration of people and where human movement is most prevalent. Furthermore, the study area demonstrates significant potential for forest conservation and restoration, alongside the need for public policies that promote sustainable agricultural practices in regions with high rural populations. Such policies can help mitigate human impacts while promoting food security, diversifying production, combating rural depopulation, and providing ecosystem services such as water, biodiversity, and pollination.

For future steps in mapping the Human Footprint in watersheds, we see the need to incorporate more significant levels of detail, such as distinguishing between pressures exerted by different agricultural production systems and integrating temporal aspects to assess the dynamics of the Human Footprint within the landscape. This approach may provide valuable insights to validate actions aimed at reducing human pressure and identify emerging pressure hotspots, their causes, and potential mitigation measures. We hope this framework will contribute to environmental and territorial planning and be adapted and applied to other watersheds.

REFERENCES

Allan, H., Levin, N., and Kark, S. (2023). **Quantifying and mapping the human footprint across Earth's coastal areas**. Ocean and Coastal Management, 236. https://doi.org/10.1016/j.ocecoaman.2023.106476

Alvares, C. A., Stape, J. L., Sentelhas, P. C., Gonçalves, J. L. de M., and Sparovek, G. (2014). **Köppen's climate classification map for Brazil**. Meteorologische Zeitschrift, 22(6), 711–728. https://doi.org/10.1127/0941-2948/2013/0507

Américo, C., Marin, R. N. A., and Valente, R. A. (2017). **Identificação de conflito de uso da terra em áreas de preservação permanente no munícipio de Piedade - SP**. In INPE (Ed.), XVIII Simpósio Brasileiro de Sensoriamento Remoto - SBSR (pp. 3385–3392). INPE.

Arroyo-Rodríguez, V., Fahrig, L., Tabarelli, M., Watling, J. I., Tischendorf, L., Benchimol, M., Cazetta, E., Faria, D., Leal, I. R., Melo, F. P. L., Morante-Filho, J. C., Santos, B. A., Arasa-Gisbert, R., Arce-Peña, N., Cervantes-López, M. J., Cudney-Valenzuela, S., Galán-Acedo, C., San-José, M., Vieira, I. C. G., … Tscharntke, T. (2020). **Designing optimal human-modified landscapes for forest biodiversity conservation.** Ecology Letters, 23(9), 1404–1420. https://doi.org/10.1111/ele.13535

Barbosa, C. C., Calijuri, M. do C., dos Santos, A. C. A., Ladwig, R., de Oliveira, L. F. A., and Buarque, A. C. S. (2021). **Future projections of water level and thermal regime changes of a multipurpose subtropical reservoir (Sao Paulo, Brazil)**. Science of the Total Environment, 770. https://doi.org/10.1016/j.scitotenv.2020.144741

Barlow, J., Lennox, G. D., Ferreira, J., Berenguer, E., Lees, A. C., Nally, R. Mac, Thomson, J. R., Ferraz, S. F. D. B., Louzada, J., Oliveira, V. H. F., Parry, L., Ribeiro De Castro Solar, R., Vieira, I. C. G., Aragaõ, L. E. O. C., Begotti, R. A., Braga, R. F., Cardoso, T. M., Jr, R. C. D. O., Souza, C. M., … Gardner, T. A. (2016). **Anthropogenic disturbance in tropical forests can double biodiversity loss from deforestation**. Nature, 535(7610), 144–147. https://doi.org/10.1038/nature18326

Börner, J., Baylis, K., Corbera, E., Ezzine-de-Blas, D., Honey-Rosés, J., Persson, U. M., and Wunder, S. (2017). **The Effectiveness of Payments for Environmental Services**. World Development, 96, 359–374. https://doi.org/10.1016/j.worlddev.2017.03.020

Calaboni, A., Tambosi, L. R., Igari, A. T., Farinaci, J. S., Metzger, J. P., and Uriarte, M. (2018). **The forest transition in São Paulo, Brazil: Historical patterns and potential drivers**. Ecology and Society, 23(4). https://doi.org/10.5751/ES-10270-230407

Cocheci, R. M., Ianoş, I., Sârbu, C. N., Sorensen, A., Saghin, I., and Secăreanu, G. (2019). **Assessing environmental fragility in a mining area for specific spatial planning purposes**. Moravian Geographical Reports, 27(3), 169–182. https://doi.org/10.2478/mgr-2019-0013

de Rezende, C. L., Uezu, A., Scarano, F. R., and Araujo, D. S. D. (2015). **Atlantic Forest spontaneous regeneration at landscape scale**. Biodiversity and Conservation, 24(9), 2255–2272. https://doi.org/10.1007/s10531-015-0980-y

Dias, T. da C., Silveira, L. F., and Francisco, M. R. (2023**). Spatiotemporal dynamics reveals forest rejuvenation, fragmentation, and edge effects in an Atlantic Forest hotspot, the Pernambuco Endemism Center, northeastern Brazil**. PLOS ONE, 18(9), e0291234. https://doi.org/10.1371/journal.pone.0291234

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F. C., and Ghosh, T. (2017). **VIIRS night-time lights**. International Journal of Remote Sensing, 38(21), 5860–5879. https://doi.org/10.1080/01431161.2017.1342050

Gassert, F., Venter, O., Watson, J. E. M., Brumby, S. P., Mazzariello, J. C., Atkinson, S. C., and Hyde, S. (2023). **An operational approach to near real time global high-resolution mapping of the terrestrial Human Footprint**. Frontiers in Remote Sensing, 4. https://doi.org/10.3389/frsen.2023.1130896

Goncalves, N., Andrade, D., Batista, A., Cullen, L., Souza, A., Gomes, H., and Uezu, A. (2021). **Potential economic impact of carbon sequestration in coffee agroforestry systems**. Agroforestry Systems, 95(2), 419–430. https://doi.org/10.1007/s10457-020-00569-4

Gori Maia, A., Eusebio, G. dos S., Fasiaben, M. do C. R., Moraes, A. S., Assad, E. D., and Pugliero, V. S. (2021). **The economic impacts of the diffusion of agroforestry in Brazil**. Land Use Policy, 108, 105489. https://doi.org/10.1016/j.landusepol.2021.105489

Havlíček, M., Dostál, I., and Pavelková, R. (2022). **Water Reservoirs as a Driver of Anthropogenic Changes in Landscape and Transport Networks: The Czech Republic Experience**. Water (Switzerland), 14(12). https://doi.org/10.3390/w14121870

Instituto Brasileiro de Geografia e Estatística IBGE. (2012). **Manual Técnico da Vegetação Brasileira** (IBGE, Ed.; 2nd ed., Vol. 1, Issue 1). https://doi.org/ISSN 0101-4234

Instituto Brasileiro de Geografia e Estatística (IBGE). **Censo Demográfico 2022**. Rio de Janeiro: IBGE, 2022.

Karlson, M., Mörtberg, U., and Balfors, B. (2014). **Road ecology in environmental impact assessment**. Environmental Impact Assessment Review, 48, 10–19. https://doi.org/10.1016/j.eiar.2014.04.002

Kaval, P. (2019). **Integrated catchment management and ecosystem services: A twenty-five year overview**. Ecosystem Services, 37. https://doi.org/10.1016/j.ecoser.2019.100912

Lamb, D. (2018). **Undertaking large-scale forest restoration to generate ecosystem services**. In Restoration Ecology (Vol. 26, Issue 4, pp. 657–666). Blackwell Publishing Inc. https://doi.org/10.1111/rec.12706

Li, S., Wu, J., Gong, J., and Li, S. (2018). **Human footprint in Tibet: Assessing the spatial layout and effectiveness of nature reserves**. Science of the Total Environment, 621, 18–29. https://doi.org/10.1016/j.scitotenv.2017.11.216

Linares Arroyo, H., Abascal, A., Degen, T., Aubé, M., Espey, B. R., Gyuk, G., Hölker, F., Jechow, A., Kuffer, M., Sánchez de Miguel, A., Simoneau, A., Walczak, K., and Kyba, C. C. M. (2024). **Monitoring, trends and impacts of light pollution. In Nature Reviews Earth and Environment** (Vol. 5, Issue 6, pp. 417–430). Springer Nature. https://doi.org/10.1038/s43017-024-00555-9

Low, J. M. L., Gladstone-Gallagher, R. V., Hewitt, J. E., Pilditch, C. A., Ellis, J. I., and Thrush, S. F. (2023). **Using Ecosystem Response Footprints to Guide Environmental Management Priorities**. In Ecosystem Health and Sustainability (Vol. 9). American Association for the Advancement of Science. https://doi.org/10.34133/ehs.0115

Mas, J. F., Vasconcelos, R. N. de, and Franca-Rocha, W. (2019). **Analysis of high temporal resolution land use/land cover trajectories**. Land, 8(2). https://doi.org/10.3390/LAND8020030

Mello, K. de, Randhir, T. O., Valente, R. A., and Vettorazzi, C. A. (2017). **Riparian restoration for protecting water quality in tropical agricultural watersheds**. Ecological Engineering, 108, 514–524. https://doi.org/10.1016/j.ecoleng.2017.06.049

Morales, M. V., and Valente, R. A. (2023). **Hydrological Inferences from Morphometric Analysis of the Sarapuí River Watershed**. In INPE (Ed.), XX Simpósio Brasileiro de Sensoriamento Remoto (Vol. 12, Issue 10, pp. 292–295). INPE. https://proceedings.science/p/164147?lang=pt-br

Mu, H., Li, X., Wen, Y., Huang, J., Du, P., Su, W., Miao, S., and Geng, M. (2022). **A global record of annual terrestrial Human Footprint dataset from 2000 to 2018**. Scientific Data, 9(1). https://doi.org/10.1038/s41597-022-01284-8

Padovan, M. P., Nogueira, F. F., Ruas, F. G., Rodrigues, A. C. C., and Arco-Verde, M. F. (2022). **Financial analysis of a complex agroforestry system for environmental restoration purpose in the Brazilian Rainforest**. Agroforestry Systems, 96(2), 235–248. https://doi.org/10.1007/s10457-021-00655-1

Palmeira Júnior, R. C. (2020**)**. **A Crise Hídrica na Agricultura Familiar em Piedade/SP** [Master's degree, Campinas State University - Unicamp]. http://lattes.cnpq.br/3096572653548171

Pertierra, L. R., Hughes, K. A., Vega, G. C., and Olalla-Tárraga, M. A. (2017). **High resolution spatial mapping of human footprint across antarctica and its implications for the strategic conservation of avifauna**. PLoS ONE, 12(1). https://doi.org/10.1371/journal.pone.0168280

R Core Team (2025). **R: A Language and Environment for Statistical Computing**. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Rajaonarivelo, F., and Williams, R. A. (2022). **Remote Sensing-Based Land Suitability Analysis for Forest Restoration in Madagascar**. Forests, 13(10). https://doi.org/10.3390/f13101727

Rigonato, M. B., Mello, K. de, Valente, R. A., and Faria, L. C. (2023). **Payment for Water-Related Ecosystem Services as a Strategic Watershed Management Approach**. Journal of Environmental Protection, 14(08), 660–684. https://doi.org/10.4236/jep.2023.148038

Román, M. O., Stokes, E. C., Shrestha, R., Wang, Z., Schultz, L., Sepúlveda Carlo, E. A., Sun, Q., Bell, J., Molthan, A., Kalb, V., Ji, C., Seto, K. C., McClain, S. N., and Enenkel, M. (2019). **Satellite-based assessment of electricity restoration efforts in Puerto Rico after Hurricane Maria**. PLoS ONE, 14(6). https://doi.org/10.1371/journal.pone.0218883

Rosa, M. R., Brancalion, P. H. S., Crouzeilles, R., Tambosi, L. R., Piffer, P. R., Lenti, F. E. B., Hirota, M., Santiami, E., and Metzger, J. P. (2021). **Hidden destruction of older**

forests threatens Brazil's Atlantic Forest and challenges restoration programs. Science Advances, 7(4). https://doi.org/10.1126/sciadv.abc4547

Sanderson, E. W., Jaiteh, M., Levy, M. A., Redford, K. H., Wannebo, A. V, and Woolmer, G. (2002). **The Human Footprint and the Last of the Wilderness**. BioScience, 52(10), 891–904.

Schneider, F., and Costa, M. B. B. da. (2013). **Diagnóstico Socioeconômico, Produtivo e Ambiental dos Agroecossistemas na Microbacia Hidrográfica do rio Pirapora -Município de Piedade/SP**. Revista Brasileira de Agroecologia, 1(8), 217–231.

Shen, F., Yang, L., He, X., Zhou, C., and Adams, J. M. (2020). **Understanding the spatial–temporal variation of human footprint in Jiangsu Province, China, its anthropogenic and natural drivers and potential implications**. Scientific Reports, 10(1). https://doi.org/10.1038/s41598-020-70088-w

Siegmund-Schultze, M., do Carmo Sobral, M., Alcoforado de Moraes, M. M. G., Almeida-Cortez, J. S., Azevedo, J. R. G., Candeias, A. L., Cierjacks, A., Gomes, E. T. A., Gunkel, G., Hartje, V., Hattermann, F. F., Kaupenjohann, M., Koch, H., and Köppel, J. (2018). **The legacy of large dams and their effects on the water-land nexus**. In Regional Environmental Change (Vol. 18, Issue 7, pp. 1883–1888). Springer Verlag. https://doi.org/10.1007/s10113-018-1414-7

Silva, A. G. P., and Costa, J. P. D. S. (2023). **Pan-sharpening by PCA on WPM/CBERS-04A Images Using a Single Matrix on Different Images: A Case Study**. In INPE (Ed.), XX Simpósio Brasileiro de Sensoriamento Remoto (pp. 1969–1972). INPE. https://proceedings.science/p/164569?lang=pt-br

Soares, D. R., Nahssen, M. H. C., Soares, F. da S., Morales, M. V., Rigonato, M. B., Germano, A. D., and Valente, R. A. (2022). **Conectividade estrutural da vegetação nativa para o planejamento da conservação florestal**. Research, Society and Development, 11(4), e39811427492. https://doi.org/10.33448/rsd-v11i4.27492

Souza, C. M., Shimbo, J. Z., Rosa, M. R., Parente, L. L., Alencar, A. A., Rudorff, B. F. T., Hasenack, H., Matsumoto, M., Ferreira, L. G., Souza-Filho, P. W. M., de Oliveira, S. W., Rocha, W. F., Fonseca, A. V., Marques, C. B., Diniz, C. G., Costa, D., Monteiro, D., Rosa, E. R., Vélez-Martin, E., … Azevedo, T. (2020). **Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine**. Remote Sensing, 12(17). https://doi.org/10.3390/RS12172735

Tapia-Armijos, M. F., Homeier, J., and Draper Munt, D. (2017). **Spatio-temporal analysis of the human footprint in South Ecuador: Influence of human pressure on ecosystems and effectiveness of protected areas**. Applied Geography, 78, 22–32. https://doi.org/10.1016/j.apgeog.2016.10.007

Teixeira, F. Z., Rytwinski, T., and Fahrig, L. (2020). **Inference in road ecology research: what we know versus what we think we know**. In Biology Letters (Vol. 16, Issue 7). Royal Society Publishing. https://doi.org/10.1098/rsbl.2020.0140

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., and Watson, J. E. M. (2016a). **Global terrestrial Human Footprint maps for 1993 and 2009**. Scientific Data, 3. https://doi.org/10.1038/sdata.2016.67

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., and Watson, J. E. M. (2016b). **Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation**. Nature Communications, 7. https://doi.org/10.1038/ncomms12558

Watson, J. E. M., and Venter, O. (2019). **Mapping the Continuum of Humanity's Footprint on Land**. In One Earth (Vol. 1, Issue 2, pp. 175–180). Cell Press. https://doi.org/10.1016/j.oneear.2019.09.004

Williams, B. A., Venter, O., Allan, J. R., Atkinson, S. C., Rehbein, J. A., Ward, M., Di Marco, M., Grantham, H. S., Ervin, J., Goetz, S. J., Hansen, A. J., Jantz, P., Pillay, R., Rodríguez-Buriticá, S., Supples, C., Virnig, A. L. S., and Watson, J. E. M. (2020). **Change in Terrestrial Human Footprint Drives Continued Loss of Intact Ecosystems**. One Earth, 3(3), 371–382. https://doi.org/10.1016/j.oneear.2020.08.009

Woolmer, G., Trombulak, S. C., Ray, J. C., Doran, P. J., Anderson, M. G., Baldwin, R. F., Morgan, A., and Sanderson, E. W. (2008). **Rescaling the Human Footprint: A tool for conservation planning at an ecoregional scale**. Landscape and Urban Planning, 87(1), 42–53. https://doi.org/10.1016/j.landurbplan.2008.04.005

Yang, F., Matsushita, B., Yang, W., and Fukushima, T. (2014). **Mapping the human footprint from satellite measurements in Japan**. ISPRS Journal of Photogrammetry and Remote Sensing, 88, 80–90. https://doi.org/10.1016/j.isprsjprs.2013.11.020

4. CHAPTER IV

A MULTICRITERIA APPROACH TO PRIORITIZE FOREST RESTORATION AREAS AIMING AT THE STRUCTURAL AND FUNCTIONAL ENHANCEMENT IN HUMAN-MODIFIED LANDSCAPES

Abstract

Forest restoration in human-modified landscapes requires strategic prioritization to balance ecological recovery with socioeconomic constraints while optimizing resources and outcomes, being a key strategy for reversing biodiversity loss, mitigating climate change, and enhancing ecosystem services. However, its success is constrained by many of biophysical, ecological, climatic, and anthropogenic factors that interact across spatial and temporal scales. The complexity of these variables presents significant challenges for restoration planning, demanding structured approaches that can integrate diverse sources of spatial information. In this context, this study proposes a spatially explicit decision-making framework based on Multicriteria Decision Analysis (MCDA) to prioritize areas for forest restoration in a transitional watershed of the Atlantic Forest–Cerrado ecotone, Brazil. The proposed framework integrates six spatial criteria (i.e. Human Footprint, Connectivity Probability, Drainage Density, Slope, Soil Erodibility, and Mean Annual Precipitation), selected based on a meta-analysis of works that aim to prioritize areas for forest restoration within the scope of MCDA approaches. The resulting prioritization map reveals spatial heterogeneity in restoration suitability, with high-priority areas predominantly located in regions of low anthropogenic pressure and high ecological potential. The methodological approach presented here demonstrates the potential of MCA to support transparent and replicable decision-making processes in forest restoration planning. Furthermore, the results offer valuable inputs for territorial management, public policy design, and implementing Payment for Ecosystem Services (PES) programs, contributing to more strategic and effective ecological restoration actions.

Keywords: Forest restoration; Multicriteria Decision Analysis (MCDA); Human-modified landscapes; Spatial optimization; Restoration Planning.

4.1. INTRODUCTION

Forest restoration efforts play a fundamental role in landscape regeneration processes and the maintenance of Ecosystem Services (E.S.). They are widely recognized as one of the most promising and powerful strategies to address global challenges such as climate change and biodiversity loss (Brancalion et al., 2025). This recognition has grown significantly over the past decades, bringing forest restoration to the forefront of global discussions (Lamb, 2018). As a result, it has become a key component of various international commitments, including the Bonn Challenge, which aims to restore 350 million hectares by 2030 (Bonn Challenge, 2014), and the U.N. Sustainable Development Goals (SDG, 2015), where Goal 15 emphasizes restoring degraded landscapes to achieve a "land-degradation neutral world" by 2030 (Lamb, 2018).

Coordinating forest restoration initiatives to fulfill structural and functional roles within the landscape is essential (Vettorazzi and Valente, 2016). This includes enhancing connectivity and genetic flow and providing soil and water protection within the landscape However, achieving successful outcomes remains a significant methodological challenge, largely due to the complexity of the landscape characteristics that must be taken into account (Höhl et al., 2020).

Given the substantial human and financial resources required for large-scale forest restoration projects (Lamb, 2018), it is evident that approaches must be developed to select restoration areas in an integrated manner, considering the landscape's biophysical, ecological, climatic, and anthropogenic characteristics. Furthermore, structuring a decision-making process that enhances efficiency and accuracy in planning and implementing these actions is crucial.

In this context, structured decision-making processes within Multi-Criteria Decision Analysis (MCDA) have demonstrated significant potential (Cavalcante et al., 2022; Cecílio et al., 2021; Valente et al., 2021). This spatial analysis approach prioritizes areas based on biophysical, ecological, climatic, and anthropogenic aspects of the landscape, spatially represented to form a set of maps that integrate the decision-making process as decision factors (*criteria* and *constraints*) (Drobne and Lisec, 2009; Esmail and Geneletti, 2018). According to Vettorazzi and Valente (2016), its key advantage lies in aggregating spatial criteria while considering their relative importance to the study objective.

According to Esmail and Geneletti (2018), a successful MCDA application should begin with a clearly defined decision-making context, including an explicit objective and identifying key stakeholders involved in the process. The next step involves identifying landscape characteristics influencing the dynamics of the process under study and their representation through spatial criteria, which serve as indicators of the suitability level of each criterion for achieving the desired objective.

However, as these authors note, MCDA applications in environmental contexts are often subject to setbacks from inadequate structuring. This may arise due to an unrepresentative set of criteria, an excessive or unbalanced number of spatial criteria, or insufficient attention given to critical steps such as criteria normalization, which is essential to ensure that each criterion is represented on a standard scale for analysis (Malczewski and Rinner, 2015).

Therefore, for an accurate prioritization of areas within the MCDA framework, methodological rigor must be complemented by a solid conceptual understanding of the proposed objective. In other words, a deep knowledge of the landscape characteristics influencing the achievement of the objective is necessary to ensure the decision-making process's assertiveness and efficiency.

Thus, in prioritizing areas for forest restoration, criteria selection requires a comprehensive understanding of the ecological factors that drive successful restoration and the anthropogenic factors that significantly influence its outcomes.

Nonetheless, determining which locations can be restored most effectively remains a significant gap in restoration science (Brancalion et al., 2016; Höhl et al., 2020; Lamb, 2018).

However, it is known that the solution involves catalyzing the ecological succession process (Borda-Niño et al., 2020), thereby promoting the reestablishment of ecological functions while simultaneously reducing implementation costs.

In the context of MCDA-based approaches aimed at forest restoration, the selection of spatial criteria should accurately represent the landscape's ecological, biophysical, and socio-economic dynamics. A systematic evaluation of habitat connectivity, forest fragmentation, hydrological processes, erosion risk, and anthropogenic pressures, among other landscape attributes, is necessary. The effectiveness of the prioritization depends on the semantic precision of spatial criteria, ensuring that each criterion is conceptually relevant and methodologically robust in its representation to achieve the objective.

Recent results (see Chapter I) indicate that spatial criteria focusing on human disturbances, ecological processes, hydrology, soil and erosion, and topography predominate in prioritizing areas for forest restoration, in contrast there is a gap in the explicit integration of socio-economic and policy-driven criteria, which are fundamental for ensuring long-term restoration success.

Additionally, there is a lack of ecological criteria that effectively perform their spatial representation in MCDA-based approaches, particularly in dynamic and fragmented landscapes. Criteria such as Euclidean distance to habitat patches are commonly used; however, in these environments, where smaller distances between patches prevail, such spatial criteria tend to be overly broad, reducing prioritization efficiency.

In this context, this study aimed to structure a decision-making process for forest restoration that promotes structural and functional transformations in the landscape, enhancing the success of restored areas. Based on a critical meta-analysis of structured decision-making processes within MCDA reported in the literature (Chapter I), we structured our decision-making process by identifying best practices and proposing two new approaches for spatializing spatial criteria: one for ecological criteria, considering habitat connectivity (Chapter II) instead of simple Euclidean distance, and another incorporating the socioeconomic characteristics of the intervention area through human footprint mapping (Chapter III), which also integrates aspects related to human-induced disturbances.

In this context, this study proposes an integrated MCDA-GIS approach to prioritize areas for forest restoration. The proposed framework aims to bridge methodological gaps by considering the relative influence of multiple criteria and evaluating their sensitivity and impact on the results. Thus, this research contributes to the technical enhancement of prioritization analysis and its practical application in public policies and local restoration strategies.

4.2. MATERIAL AND METHODS

4.2.1. CONCEPTUAL MODEL

The forest restoration prioritization framework presented in this study was structured within the context of MCDA analysis, with particular attention to the spatial criteria that compose the criteria set. The objective was to guarantee that the spatial representation of each criterion reflected its ecological relevance and potential contribution to the effectiveness of restoration initiatives. The framework also ensured that the influence of each criterion on the delineation of priority areas was weighted according to its relative importance.

To achieve this, we based our approach on a meta-analysis (Chapter I) that reviewed 24 scientific papers reporting similar decision-making processes with the same objective. Thus, this analysis indirectly incorporated the contributions of 83 authors and an even more significant number of experts and practitioners consulted in these decision-making processes.

The following sections detail the study area and the steps and procedures for structuring our framework. Finally, we present a scenario analysis based on the identified priority areas to provide a broader understanding of the opportunities for restoration within the studied basin.

4.2.2. STUDY AREA

The Sarapuí River basin (Figure 1), spanning nine municipalities in São Paulo state, Brazil, lies in a transitional ecotone between the Atlantic Forest and Cerrado biomes, offering a heterogeneous landscape critical for ecological restoration. Originally dominated by Dense Ombrophilous Forest (IBGE, 2012), the basin now exhibits a fragmented mosaic of forest remnants (23.68% coverage) embedded in an agricultural-pastoral matrix (41.37% agriculture, 18.25% pasture), with urban areas occupying 2.59% of the territory (MapBiomas, 2021). These remnants are concentrated in the southern uplands, characterized by steep slopes, higher elevations, and cooler Cfb-climate zones (Alvares et al., 2014), adjacent to the Serra do Mar Environmental Protection Area.

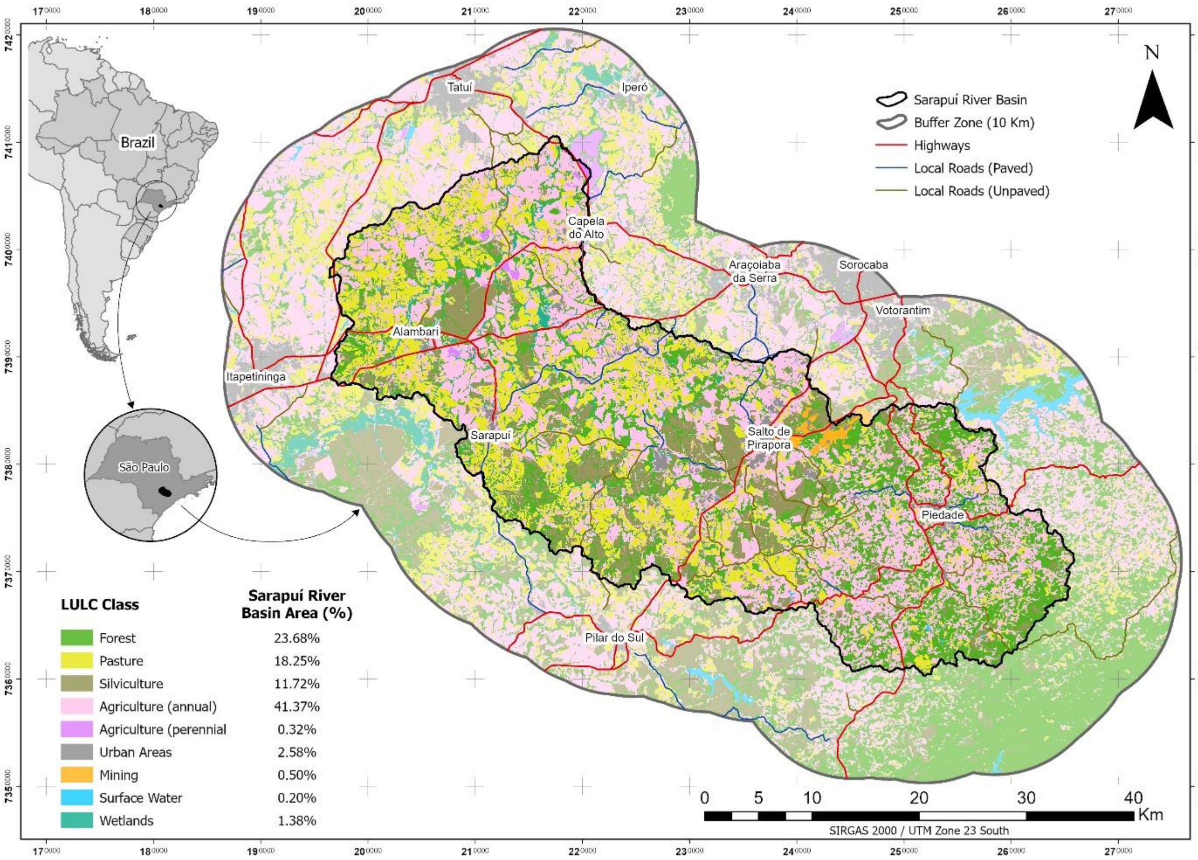


Figure 2 - Location map and land use/land cover of Sarapuí River basin, São Paulo state, Brazil.
Source: LULC adapted from MapBiomas (2021), collection 8.

Anthropogenic pressures, driven by proximity to urban centers like Sorocaba and São Paulo's metropolitan region, have historically fueled deforestation for agriculture and pasture

(Calaboni et al., 2018), leaving forest patches restricted mainly to less accessible terrain. Key infrastructure, such as the SP-270 highway, exacerbates fragmentation, while soil variability, Latosols in forested uplands, and Gleysols in low-lying areas (Mello et al., 2017) influence restoration potential. The basin's humid subtropical climate (Cfa/Cfb) further supports diverse revegetation strategies.

Proximity to legally protected areas, including Jurupará State Park and Itupararanga Reservoir APA (*Environmental Protection Area*), underscores opportunities to enhance connectivity through restoration. This dynamic interplay of biophysical gradients, land-use legacies, and socio-economic drivers positions the Sarapuí basin as a strategic model for prioritizing restoration in transitional biomes under anthropogenic stress.

4.2.3. CRITERIA SET

4.2.3.1. SELECTION AND SPATIALIZATION

To address the complex task of prioritizing areas for forest restoration, the set of criteria was identified to fulfil two fundamental objectives: (i) selecting criteria that support regenerative processes in the target environments, and (ii) incorporating those through which future forest cover can perform mitigating or protective functions within the post-intervention landscape (see Chapter I). Furthermore, care was taken to ensure that the spatial criteria were conceptually consistent with their intended role in the decision-making process, accurately reflecting the semantic rationale underlying their selection.

Accordingly, we ensured that our criteria adhere to six fundamental premises for the effective functioning of GIS-MCDA approaches, which are often overlooked in environmental and conservation decision-making contexts (Esmail and Geneletti, 2018). As outlined by Malczewski (2000), these premises are: (*1*) spatial criteria must be *understandable* and *measurable*, meaning that their level in a given decision problem indicates the degree to which the associated objective is achieved; (*2*) the criteria set must be *complete*, covering all relevant aspects of the problem and adequately indicating the extent to which the overall objective is fulfilled; (*3*) the criteria set must be *operational* (i.e., they can be meaningfully used in the analysis); (*4*) the criteria set must be *decomposable* (i.e., the performance of an alternative on one attribute can be evaluated independently of its performance on other attributes); (*5*) the criteria set must be *non-redundant* (to avoid issues of double counting); and finally, (*6*) the criteria set must be *minimal* (the number of attributes should be kept as small as possible).

Furthermore, our criteria set aimed to address common issues related to spatial representation to optimize their representativeness and efficiency within the decision-making process. As demonstrated in Chapter I, spatial criteria associated with human-induced disturbances, ecological factors, hydrology, and pedology, although widely acknowledged as fundamental for restoration prioritization, often suffer from inefficient spatialization. One of the main reasons for this inefficiency is the reliance on simple Euclidean distance metrics for representation (e.g., distance to roads or proximity to forest patches) or the use of spatial data generated within the framework of Boolean logic applied to thematic maps, where values are represented discretely rather than continuously (e.g., soil types). This approach can significantly affect prioritization outcomes, as reported by several authors (Malczewski, 2000; Eastman et al., 2020).

Finally, the criteria set also sought to incorporate socio-economic landscape characteristics, a factor widely recognized as crucial for the planning of forest restoration efforts (Höhl et al., 2020; Lamb, 2018), yet rarely integrated into decision-making processes for restoration prioritization (see Chapter I).

As a result, we defined six spatial criteria to guide the decision-making process. The selection was based on criteria representing ecological, anthropogenic, hydrological, pedological, rainfall regime, and socio-economic aspects of the resident population.

We propose two alternative criteria spatialization approaches to address common issues reported regarding spatial criteria that are often spatialized based on Euclidean distances (e.g., proximity to habitat areas or watercourses). First, to represent the ecological criterion, we propose using the landscape ecology index Probability of Connectivity (PC), as defined by Saura and Pascual-Hortal (2007). This index is based on the habitat availability concept, interpatch dispersal probabilities, and graph structures and will be detailed in the following sections.

We also propose using drainage density instead of proximity to watercourses for the hydrological criterion. This choice is particularly relevant given the dendritic nature of the drainage network in our study area (Morales and Valente, 2023), which would result in an overly extensive spatial criterion if proximity to the drainage network were considered, an issue already reported by authors such as Valente and Vettorazzi (2009) and Vettorazzi and Valente (2016) in similar situations.

Additionally, considering the importance of two fundamental aspects often overlooked or superficially addressed in decision-making processes, human-induced disturbances and socio-economic factors, we propose using the Human Footprint map adapted to the watershed scale developed in Chapter III. The Human Footprint mapping efficiently integrates landscape features associated with human-induced disturbances, such as proximity to roads and highways, infrastructure developments, and high human mobility areas, as well as aspects like population density and economic activities (Woolmer et al., 2008; Venter et al., 2016; Watson and Venter, 2019). This approach incorporates the concept of distancing from human disturbances while also considering the spatial distribution of human settlements and their impacts, two critical factors for the success of forest restoration efforts.

The selected environmental criteria and their data sources are presented in Table 1, followed by a description of the procedure used to obtain each spatial criterion and the justification for their inclusion in the decision-making processes.

All spatial data considered in this analysis were projected to the Universal Transverse Mercator (*UTM*) system, with the SIRGAS 2000 Datum, zone 23 South, as the geodetic reference. Spatial and statistical analyses were performed using ArcGIS Pro, QGIS 3.28.4, Google Earth Engine (*GEE*), TerrSet liberaGIS Geospatial Monitoring and Modeling System, and *R* version 4.1.0 (R Core Team, 2025).

Table 1 – Criteria Set and Data Sources used to prioritize areas for forest restoration in the Sarapuí River basin, São Paulo state, Brazil.

Spatial Criteria	Data Sources
Human Footprint	Land Use and Land Cover Map (MapBiomas, 2021); Brazilian Demographic Census (IBGE, 2022); MapBiomas (2023) Infrastructure Module; VIIRS Day/Night Band (Elvidge et al., 2017); and Landsat's 8 red, green and NIR bands (USGS, 2021). See Chapter III and Souza et al., (2020) for MapBiomas data.
Probability of Connectivity	Land Use and Land Cover Map (MapBiomas, 2021). See Chapter II.
Drainage Density	Digital Elevation Model (*DEM*) from the ALOS (*Advanced Land Observing Satellite*) PALSAR (*Phased Array L-Band Synthetic Aperture Radar*) sensor, obtained by the Alaska Satellite Facility (ASF, 2021). See Morales and Valente (2023).
Slope	Digital Elevation Model (*DEM*) from the ALOS (*Advanced Land Observing Satellite*) PALSAR (*Phased Array L-Band Synthetic Aperture Radar*) sensor, obtained by the Alaska Satellite Facility (ASF, 2021). See Morales and Valente (2023).
Soil Erodibility	High-resolution soil erodibility map of Brazil (Godoi et al., 2021).
Average Annual Precipitation	CHIRPS (*Climate Hazards Group InfraRed Precipitation with Stations*) precipitation time series from 1991 to 2021. (See Funk et al., 2015)

a) Human Footprint

The Human Footprint (HF) criterion was incorporated to address anthropogenic pressures critical for ensuring restoration resilience and mitigating human-induced disturbances. Adapted from Sanderson et al. (2002), this criterion integrates four proxies (i.e., *Human Settlements*, *Land Use Changes*, *Human Access*, and *Electrical Infrastructure*) standardized to 0–10 scales (see Chapter III). High-resolution data (30 m/pixel), including MapBiomas LULC (2021), IBGE population density (2022), road networks, and VIIRS nighttime lights (2021), were overlaid to generate a composite HF map (max score = 50).

The HF map identifies gradients of human pressure, prioritizing areas distant from roads, urban centers, and intensive agriculture while integrating socio-economic factors (e.g., population density and mining impacts). This approach avoids oversimplified Euclidean distance metrics by holistically capturing disturbance drivers (e.g., proximity to infrastructure, land use legacies) that threaten restoration success (Venter et al., 2016; Tapia-Armijos et al., 2017). Low HF zones (35.3% of the basin) align with restoration opportunities in fragmented agricultural or silviculture areas, whereas high HF regions (e.g., urban areas and mining zones) require targeted mitigation. By embedding HF into the criteria set, we address both Human-induced disturbances and socio-economic barriers, ensuring restored forests persist under anthropogenic stress.

b) Probability of Connectivity

The spatial criterion for representing the ecological aspect, which aimed to enhance species dispersal, gene flow, and ecological resilience, was operationalized using the Probability of Connectivity (PC) index (Saura and Pascual-Hortal, 2007). This graph theory-based metric evaluates the likelihood of two randomly placed individuals inhabiting interconnected habitat patches, incorporating patch areas, interpatch dispersal probabilities, and total landscape area.

As detailed in Chapter II, the spatialization of this criterion employed a conservative approach: Euclidean distances between patches and a dispersal probability (P_{ij}) of 0.5 for maximum 200-meter gaps. Graph theory principles underpinned the analysis, where habitat patches (*nodes*) and potential connections (*links*) were modeled to align landscape structure with ecological functionality (Frazier and Kedron, 2017; Martensen et al., 2017).

The workflow was implemented in Graphab 2.8.1 (Foltête et al., 2021), generating connectivity networks for the Sarapuí River Basin. PC values were interpolated into continuous surfaces, log-transformed to deal with the skewed distribution, and mapped to visualize spatial connectivity patterns.

c) Drainage Density

This spatial criterion is intended to bring the concept of prioritizing regions with more natural drainage channels to the decision-making process. This approach aligns with what is observed in the literature and aims to promote the establishment of riparian vegetation in the watershed, which is beneficial for soil protection, reduced runoff, water infiltration, improved water quality, and ecological enrichment.

Additionally, utilizing this metric in prioritization decision-making processes aims to improve the method's accuracy, considering the shortcomings of spatialization alternatives like Euclidean distance to the drainage network, which can result in a map with a predominance of fragile pixels, particularly in naturally well-drained areas. The hydrographic network generated for the basin was produced by Morales and Valente (2023) and rectified based on topographic maps from the Geographical and Cartographic Institute of the State of São Paulo (IGC) and current images from the Sentinel 2A and CBERS 04A satellites.

The spatial criterion was then spatialized by implementing the Kernel density function of the drainage channels, resulting in a continuous surface where each cell represents the density of drainage channels in Km/Km^2.

d) Slope

The inclusion of slope in the criteria set is because this landscape feature carries important aspects when aiming for forest restoration. One crucial benefit of forest cover is its protective role in steep regions, which can help prevent landslides, erosion, and soil loss (Valente et al. 2021; Cosimo et al. 2021). Moreover, prioritizing these areas for forest restoration can also have a positive social impact, as they are often considered marginal for practical activities.

As economic sectors, including agriculture (Calaboni et al. 2018; Borda-Niño et al. 2020), gradually abandon these regions (Aide et al. 2013; Sánchez-Cuervo and Aide 2013;

Sloan et al. 2016), there is an opportunity to leverage them for forest restoration initiatives. The criterion was spatialized using the DEM Digital Elevation Model produced by Morales and Valente (2023) for the Sarapuí River basin, which was generated from high-resolution images captured by the ALLOS Satellite and its PALSAR sensor. In a GIS environment, slope values (%) were obtained from interpolation as a function of altitude values.

e) Soil Erodibility

The inclusion of this spatial criterion in the set is driven by conservation and protective intentions, aiming to prevent or mitigate erosion processes in the basin by increasing forest cover on more erodible soils. The USLE`s (Universal Soil Loss Equation) K factor is a consolidated variable in soil management and conservation science, which is being developed to represent the intrinsic propensity of that soil to erosion.

Its spatialization was carried out using the High-Resolution Soil Erodibility Map of Brazil produced by Godoi et al. (2021). It is available in raster format with 250 meters per pixel spatial resolution. This raster was converted into a regular point grid, with each point representing the centroid of a cell and retaining its corresponding soil erodibility value. This grid was then used to spatialize the criterion through Empirical Bayesian Kriging (Gribov and Krivoruchko, 2020), resulting in a continuous K factor raster expressed in $t.ha.h.ha^{-1}.M.J.^{-1}.mm^{-1}$, with a spatial resolution of 30 meters per pixel.

f) Average Annual Precipitation

The insertion of spatial criteria related to rainfall in processes of prioritizing areas for forest restoration is observed on several occasions, especially in tropical regions where rain-fall is a critical factor in watershed management (Oliveira et al. 2013). This criterion is intended to prioritize areas of intense rainfall, aiming to protect the soil, reduce runoff, and increase water infiltration into the soil profile, besides favoring the establishment of regions restored by providing more excellent water supplies.

Spatial criteria regarding rainfall can be challenging to obtain, and the lack or scarcity of data is a constant problem for their inclusion in decision-making processes (Oliveira et al. 2013). In this context, data from the CHIRPS (*Climate Hazards Group InfraRed Precipitation with Stations*) precipitation time series were used, which has been available for a large part of the planet since 2014 (Funk et al. 2015) and has been widely tested and evaluated worldwide (Rivera et al. 2018; Cavalcante et al. 2020; Shen et al. 2020), demonstrating whether a viable source of data to spatialize precipitation data.

The CHIRPS dataset was produced by blending precipitation estimates based on infra-red cold cloud duration (*CCD*) observations calibrated using Tropical Rainfall Measuring Mission (*TRMM*) Multi-Satellite Precipitation Analysis (*MSPA*) with *in situ* station data from a variety of sources, including national and regional meteorological services (Rivera et al. 2018). Offering a spatial resolution of 0.05° (approximately 5 Km) and several temporal scales (monthly, decadal, pentanal, or daily time steps) makes CHIRPS favorable for analyzing precipitation variations at small basin scales (Rivera et al. 2018).

Thus, the average annual rainfall for the watershed was obtained from a 30-year time series (1991 - 2021) of daily observations of CHIRPS rainfall data. Using the Google Earth Engine (*GEE*) platform, the CHIRPS database was accessed, the rainfall data was grouped by year and added together, and the simple average of annual rainfall was later calculated. All calculations are done at the pixel level, and subsequently, the image is exported to be analyzed locally.

Finally, the resulting image was transformed into a regular grid point, represented by the centroid of each cell with its appropriate rainfall value. Such a grid was used to spatialize the criterion based on Ordinary Kriging (Oliveira et al. 2013), resulting in a continuous rainfall raster expressed in mm/year.

g) Restrictions

The restrictions imposed on our land-use class analysis are not included in forest restoration actions within this project's scope. These classes are: (1) forests, since restoration actions are not implemented in areas already covered by native forest; (2) urban areas, because forest restoration under this project's scope does not include urban interventions; (3) mining areas, as these regions represent large-scale, long-term mining operations that are not expected to cease their activities; and (4) surface waters. The four mentioned land-use classes were extracted from the LULC map and were used to create Boolean masks in all processes, thereby excluding the pixels corresponding to these areas from all analyses.

4.2.3.2. EVALUATION AND FUZZY MEMBERSHIP

One of the key features of MCDA-based analyses is the use of normalization techniques to standardize criteria to a standard scale. This process ensures the equitable consideration of different criteria values in decision-making, assuming spatial homogeneity of preferences (Malczewski and Rinner, 2015). Fuzzy membership functions are commonly employed to transform the range of original criteria values into a priority scale from zero to one. The selection of an appropriate fuzzy membership function depends on the spatial distribution characteristics of the criteria in conjunction with the decision-making context.

However, this critical step is often overlooked in MCDA analyses, as Malczewski (2000) and Esmail and Geneletti (2018) mentioned. Among the key shortcomings reported by these authors, which critically affect the prioritization, are the lack of a prior assessment of the original spatial criteria values (Esmail and Geneletti, 2018) and the frequent practice of evaluating all cells within the study area without excluding areas restricted from prioritization (Malczewski, 2000).

According to Malczewski (2000), conducting a descriptive analysis of each spatial criterion, while excluding restricted cells, is an essential step before selecting fuzzy membership functions and defining the corresponding crisp values. Such an approach helps ensure the normalized criteria map accurately represents the ideal range of values for prioritization.

Therefore, an individual analysis was conducted to standardize each spatial criterion, focusing on its distribution and relevance to the study objective. Subsequently, the appropriate fuzzy membership functions were applied using the '*Fuzzy Set Membership Function*' tool from the Decision Support Module of TerrSet Libera GIS Geospatial Monitoring and Modeling System. After completing this process, the normalized criteria underwent a descriptive statistical analysis, including minimum, maximum, mean, median, and standard deviation values and an assessment of their distribution. An integrated pixel-to-pixel correlation analysis was performed among all spatial criteria using the '*r.covar*' algorithm available in GRASS within QGIS 3.28.

These procedures enabled a comprehensive evaluation of the characteristics and functionality of each spatial criterion, leading to the definition of the membership functions and crisp values of each criterion as well It also allowed the evaluation of correlations between spatial criteria, which is essential to prevent the use of redundant criteria in the decision-making process.

4.2.3.3. INFLUENCE ANALYSIS AND WEIGHT DEFINITION

After applying the fuzzy membership functions, obtaining the standardized spatial criteria, and conducting a joint evaluation of the criteria set via correlation analysis, we assigned weights to each spatial criterion for prioritization.

In this context, the weight assignment was also informed by the meta-analysis results presented in Chapter I. We adopted the ranking of criteria importance identified by quantifying each criterion group's contribution to the total number of spatial criteria in the analyzed decision-making processes (see Chapter I, Figure 3).

The initial approximation of weights was based on the relative contributions of each criteria group. However, as recommended by authors such as Malczewski (2000), Malczewski and Rinner (2015), and Esmail and Geneletti (2018), MCDA-based analyses for area prioritization perform best when using the smallest number of criteria necessary to achieve the objective, thereby avoiding redundancies and the inclusion of non-representative criteria. Our framework adheres to this principle by reducing the number of selected spatial criteria compared to the broader categories identified in the literature while ensuring their representation in decision-making.

To achieve this, we proposed representative spatial criteria that, in some cases, integrate multiple previously identified categories. The Human Footprint criterion incorporates contributions from categories related to human-induced disturbances, socio-economic aspects, and land use and land cover (LULC). The Probability of Connectivity integrates contributions from ecological criteria, protected areas, and LULC. Meanwhile, Drainage Density and Slope account for contributions related to hydrological and topographic categories, respectively, as well as areas of environmental protection (due to Brazilian legislation that safeguards steep terrains and areas near watercourses; see Brazilian Federal Law No. 12,651/2012).

Thus, the first approximation of weights was defined, as shown in Table 2. The relative contribution of socio-economic and disturbance-related criteria was assigned to the Human Footprint, which also received half of the contribution from the LULC category. The contribution of ecological criteria was allocated to the Probability of Connectivity, which also received the other half of the LULC contribution and one-third of the contribution from the protected areas category. Drainage Density and Slope were assigned the contributions of the hydrological and topographic criteria, respectively, along with one-third of the contribution from the protected areas category. Finally, Soil Erodibility received the contribution from the soil/erosion category, and the Average Annual Precipitation criterion was assigned the contribution from the climatic criteria category.

Table 2 First approximation of the weight for the spatial criteria considered in the decision-making process of forest restoration in the Sarapuí River basin, São Paulo state, Brazil.

Spatial Criteria	Weight
Human Footprint	0.2718
Probability of Connectivity	0.2259
Drainage Density	0.1715
Slope	0.1570
Soil Erodibility	0.1304
Average Annual Precipitation	0.0435

Following this initial approximation, we evaluated the influence of each spatial criterion on our prioritization map. This step allows us to identify spatial criteria that are either overestimated (i.e., exerting more significant influence than their assigned importance) or underestimated (exerting less influence than their assigned importance), enabling appropriate compensation when necessary.

Thus, to analyze the influence of spatial criteria, we used a *one-at-a-time* approach that explores the influence of the criteria by evaluating the impact of their removal on the final prioritization map (Malczewski and Rinner, 2015), aiding in verifying and calibrating criteria weight (Vanderley-Silva and Valente, 2023).

The implementation followed a structured process. First, the spatial criteria were aggregated using their initially assigned weights. Then, a correlation analysis was conducted between the spatial criteria and the first prioritization map obtained. The criterion with the highest correlation (i.e., the most influential) was identified and removed from the next aggregation round, with its weight redistributed equally among the remaining criteria. This process was iteratively repeated until only the last pair of spatial criteria remained, ultimately revealing the criterion with the lowest correlation with the prioritization map (i.e., the least influential).

This analysis aimed to verify whether the assigned weight-based ranking of importance was reflected in the final results, ensuring consistency with the influence ranking obtained through the one-at-a-time analysis. After completing this analysis, the weights were adjusted accordingly, allowing the aggregation process to proceed.

To perform the adjustment, we conducted a series of simulations in which varying percentages (5%, 10%, 15%, and 20%) were subtracted from the weights of spatial criteria whose influence was found to exceed their relative importance in the decision-making process, as identified through correlation analysis. The subtracted weights were then redistributed to the least correlated criteria with the one from which the weight was removed. At the end of each simulation, a new correlation analysis was performed between the resulting prioritization map and the spatial criteria, and the adjustment outcomes were subsequently evaluated.

4.2.4. PRIORITIZATION

4.2.4.1. WEIGHTED LINEAR COMBINATION (WLC)

After obtaining the compensated weights for each spatial criterion, we proceeded with their aggregation and the subsequent evaluation of the prioritization map. For aggregation, we applied the Weighted Linear Combination (WLC) method, the most commonly used approach in MCDA-based spatial analyses (Malczewski and Rinner, 2015).

According to these authors, the WLC model consists of a map combination procedure that assigns a set of criterion weights, W_1, W_2, … , W_n to the i-th decision alternative (*location*) and combines these weights with the corresponding criterion (*attribute*) values, C_1, C_2, …, C_n, (i = 1, 2, …, n), as follows:

$$S = \sum W_i \, x \, C_i \qquad \text{Equation 4.}$$

Where, S = Adequacy / W_i= Final weight compensated for criterion i / C_i = criterion score in factor i.

After aggregation, we conducted a Sensitivity Analysis (SA) to assess the robustness of the final prioritization map. For this purpose, we once again employed *one-at-a-time* approach, this time varying the weights of the criteria individually by 10% (with two increments, one above and one below the original weight) while keeping the others constant. The sensitivity measure for a factor (S_i) is defined as the proportion of its variance (i.e., the variance of the pixel values for each criterion) relative to the total variance of the prioritization map ($S_i = V_i/V_t$), as described by Eastman (2015) and Peñacoba-Antona et al., (2021).

According to Chen et al. (2009), the procedure enables multiple simulations to quantify how weight changes systematically affect the final results. Through this process, it was possible to identify which criteria have the greatest influence on the variability of the outcome, as well as to visualize the spatial dynamics of these changes and assess the robustness of the model. The simulations used the MCE (Multi-Criteria Evaluation) decision support module within the TerrSet IDRISI Geospatial Monitoring and Modeling System.

4.2.4.2. PRIORITY CLASSES

After obtaining the prioritization map and assessing its robustness, we evaluated the output by calculating its descriptive statistics and subsequently conducted the zoning of prioritization classes. To this end, the classes were defined based on the natural breaks' method, considering the frequency distribution of pixel values. Five priority classes were established: very low, low, medium, high, and very high priority for forest restoration.

4.2.5. RESTORATION SCENARIOS

4.2.5.1. INTERSECTIONS AND OPPORTUNITIES WITH LAND USE

To evaluate restoration scenarios and opportunities across the landscape, we calculated the proportion of each land use and land cover class not subject to the restrictions with-in each prioritization class. This allowed us to identify each class's most abundant land use and land cover categories. Furthermore, we performed a top-rank analysis based on the cells with the highest prioritization values, overlaying these scenarios on the LULC map to pin-point conflicting land uses and identify opportunities for the most suitable cells in our prioritization map. Accordingly, we analyzed these three scenarios by ranking cells corresponding to the top 1%, 5%, and 10% of prioritization values.

4.3. RESULTS AND DISCUSSION

The initial results in structuring the decision-making process for forest restoration in the Sarapuí River basin consist of the spatial criteria selected to integrate the MCDA. Figure 2 presents the spatial criteria for the basin in their original scales. Based on these rasters, we conducted a descriptive analysis of each criterion, along with an interpretation of their relevance to the objective of the analysis. These evaluations were particularly important for the subsequent step, which involved applying fuzzy membership functions to standardize the spatial criteria on a standard priority scale (0-1).

The Human Footprint map (Figure 2a) shows the predominance of regions experiencing low to moderate human influence (HF score < 20), with areas considered to have high and very high influence representing only 11.29% and 3.24% of the landscape, respectively. This pattern reinforces the high potential of the basin for forest restoration initiatives, as lower levels of human-induced disturbances are favorable for the success and development of restored areas (Tapia-Armijos et al., 2017; Borda-Niño et al., 2020).

The map excerpt presented in Figure 2a highlights distinct clusters of high human influence in the northern portion of the basin, particularly along major roads such as the SP-250, which connects the cities of Itapetininga and Sorocaba the two major urban centers in the region. Elevated levels of human pressure are also evident near urban centers within the basin, especially in the Salto de Pirapora and Piedade municipalities. Notably, Piedade exhibits more broadly distributed human impacts across urban and rural areas, reflecting its significant population in these zones (see Chapter III and Palmeira et al., 2020). Within the decision-making framework, areas experiencing intense human pressure are considered unsuitable for restoration and should therefore be avoided from prioritization.

The Probability of Connectivity (PC) map (Figure 2b) was derived from the log-transformed PC surface obtained in Chapter II. This spatialization proved consistent with the patch-level results and demonstrates high potential for use in biodiversity conservation, forest restoration and integrated watershed management programs. Especially in MCDA-based approaches, the continuous spatial representation and linearity of the PC metric are valuable characteristics that enhance the efficiency of prioritization in this kind of analysis (Malczewski, 2000; Malczewski and Rinner, 2015; Esmail and Geneletti, 2018).

The Drainage Density (Figure 2c) is consistent with the spatial distribution of the drainage network described by Morales and Valente (2023), showing a greater abundance of drainage channels in regions where first to third-order streams are more prevalent, typically located in the upper slopes of the basin. Jones et al. (2022) state that upper slope areas are critical in water infiltration and contribute to water flow towards lower slopes and valley floors. These landscape positions warrant special attention in forest restoration planning, as reforestation efforts in such areas can significantly enhance infiltration, percolation, and moisture retention, ultimately contributing to improved watershed hydrology and the functioning of the water cycle.

The Slope (Figure 2d) is characterized by predominantly flat to gently undulating terrain, with a mean and median of 11.94% and 10.97%, respectively. Although escarpments are present, they are minimally representative of the landscape, occurring only in isolated locations at the southern headwaters of the basin. With a predominance of pixels exhibiting slopes below 45%, its spatial distribution also indicates a limited extent of Permanent Preservation Areas (PPAs) due to the Slope, as defined by current Brazilian legislation (see Federal Law No. 12.651/2012).

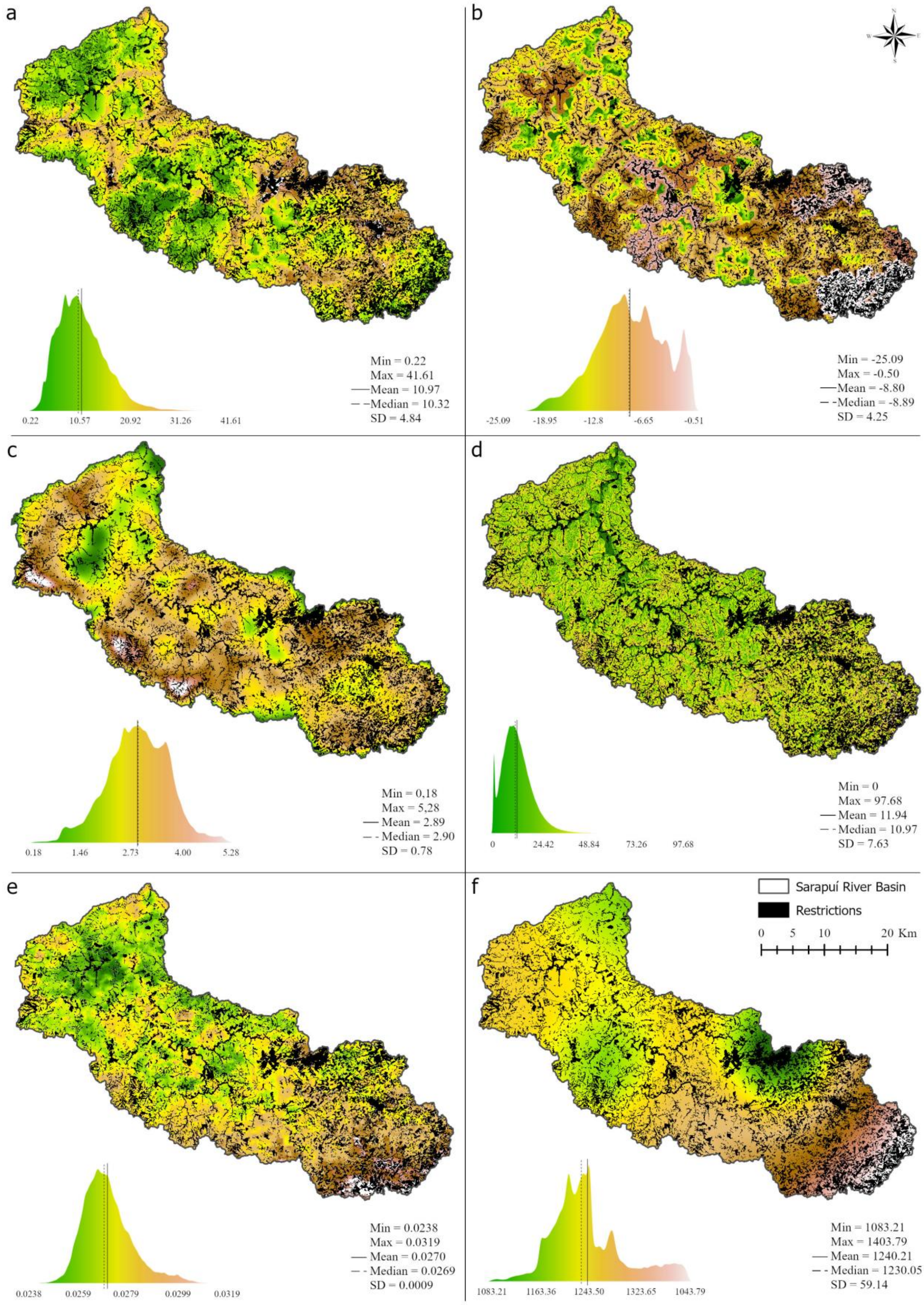


Figure 2 – Spatial Criteria Set (*original scale*) and restrictions. a: Human Footprint (*HF Scores*); b: Probability of Connectivity (*Log-Transformed PC values*); c: Drainage Density

(*Km/Km²*); d: Slope (*%*); e: Soil Erodibility (*Mg.ha.h.ha*$^{-}$*1.MJ*$^{-1}$*.mm*$^{-1}$); and f: Annual Average Precipitation (*mm/m²*). Sarapuí River basin, São Paulo state, Brazil.

The predominance of gently undulating to flat terrain within the basin suggests a potential for land-use conflicts when allocating areas for restoration, as flatter regions are generally more conducive to large-scale agricultural activities (Borda-Niño et al., 2020).

Soil erodibility (Figure 2e) ranged from 0.0238 to 0.0319 Mg.ha.h.ha^{-}1.MJ^{-1}.mm^{-1}, with a mean value of 0.0270, indicates a predominance of medium erodibility soils in the basin, according to the classification proposed by Mannigel et al. (2002) for soils in the State of São Paulo. Soils with high erodibility (between 0.030 and 0.0450 Mg.ha.h.ha^{-}1.MJ^{-1}.mm^{-1}, as per Mannigel et al. (2002) were found only in the headwaters in the extreme south of the basin.

Although medium erodibility predominates in the basin, as highlighted by Coelho et al. (2024), proper land management practices, that combine mechanical and vegetative erosion control techniques and a usage aligned with its suitability, are essential to prevent soil and environmental degradation. The authors also emphasize the importance of evaluating erodibility in conjunction with other environmental factors, such as rainfall regime and topography, since even soils with medium or low erodibility may be prone to erosion depending on these factors and land use and management characteristics.

Regarding spatial representation, average annual precipitation (Figure 2f) ranges from 1,083.21 to 1,403.79 mm/year, with a mean of 1,240.21 mm/year and a median of 1,230.05 mm/year. The low standard deviation (59.14 mm/year) and the narrow rainfall range of just 320.58 mm/year between the wettest and driest areas suggest limited spatial variability in precipitation across the basin.

Nearing et al. (2013) point out that significant changes in rainfall regimes are generally not observed at the spatial scales commonly used in MCDA-based prioritization methodologies, such as the watershed level. However, incorporating rainfall as a criterion in the decision-making process remains essential, given its interaction with physical landscape characteristics like soil erodibility and slope. This consideration is particularly important in restoration prioritization, where future forest cover is expected to contribute to the ecological and conservation-oriented management of soil and water resources.

The correlation matrix among spatial criteria (Table 3) generally indicates low-magnitude correlations, suggesting that the criteria are mainly independent. The Human Footprint presented weak negative correlations with most other criteria, particularly with Drainage Density and Probability of Connectivity. These results suggest that areas with higher human presence exhibit lower landscape connectivity and drainage density levels. Meanwhile, Slope showed weak correlations with all other criteria, reinforcing its relative independence within the dataset.

Table 3 – Correlation matrix among all the spatial criteria (*original scale*). Sarapuí River basin, São Paulo state, Brazil.

Spatial Criteria	Human Footprint	Probability of Connectivity	Drainage Density	Slope	Soil Erodibility	Average Annual Precipitation
Human Footprint	1					
Probability of Connectivity	-0.1722	1				
Drainage Density	-0.2380	0.3229	1			
Slope	-0.0353	0.1542	0.1672	1		
Soil Erodibility	0.1656	0.2459	0.0486	0.1726	1	
Average Annual Precipitation	0.0526	0.2880	0.0375	0.2268	0.6214	1

The highest positive correlation observed was between Average Annual Precipitation and Soil Erodibility, suggesting that areas with higher rainfall tend to have soils more susceptible to erosion, possibly due to increased surface runoff. The Probability of Connectivity showed moderate positive correlations with both Soil Erodibility and Precipitation, reflecting the influence of environmental factors on landscape structure and connectivity. All remaining correlations were below 0.3, indicating a lack of strong redundancy among the selected criteria, supporting their integration in a multi-criteria evaluation approach.

Following the spatial representation and evaluation of the spatial criteria and the correlation analysis, we proceeded to standardize the criteria onto a standard suitability scale ranging from zero to one. To achieve this, we applied linear fuzzy membership functions, adjusting the crisp values of each criterion to ensure their representativeness and relevance in the decision-making process.

We used a decreasing linear function for the Human Footprint criterion, as we aimed to prioritize areas under lower human pressure for forest restoration. Accordingly, the crisp value corresponding to the highest priority was set at 0.22 (i.e., the lowest pixel value), while the crisp value of 24.79 was assigned the lowest priority.

Although the maximum Human Footprint value reaches 41.61 (Figure 4a), values above 20 are relatively infrequent. Thus, including the entire range in the fuzzy function would result in an excessively broad standardized criterion, reducing its efficiency in prioritization. Therefore, we selected 24.79 as the upper crisp value, as it marks the threshold for the class defined as "very high human influence," according to the findings presented in Chapter III. This approach ensures that the spatial criterion adequately reflects its intended concept (i.e., prioritizing areas under lower human influence) within the decision-making process.

We applied an increasing linear fuzzy membership function for the Probability of Connectivity. In this case, we aimed to prioritize areas with higher connectivity within the landscape, favoring immigration and colonization processes that are fundamental for restoring biodiversity in degraded environments (Watts and Hughes, 2024). As highlighted by the authors, habitat restoration efforts should be aimed at extending and linking source populations to increase population sizes, reduce the risk of local extinctions, maximize colonization benefits, and accelerate the realization of biodiversity restoration outcomes.

It is important to recognize that alternative standardization strategies may be more appropriate in landscapes undergoing recent fragmentation, where the surrounding matrix remains largely forested and retains a relatively high degree of connectivity. In such contexts, prioritizing areas with intermediate connectivity potential may yield more ecologically meaningful results. A suitable methodological approach involves using a Gaussian fuzzy membership function, wherein the inflection point representing the highest priority is determined using a centrality metric, such as the mean or median, depending on the underlying data distribution. The lower and upper bounds, corresponding to the lowest priority values, are defined based on the minimum and maximum values of Probability of Connectivity (PC). This approach allows for a more nuanced prioritization that reflects the transitional nature of the recently fragmented landscape.

In our case, we applied an increasing linear membership function using the minimum and maximum values from the original distribution of the criterion. The lowest priority (value of zero) was assigned to the minimum PC value (-25.09), while the highest priority (value of one) was assigned to the maximum value (-0.50).

For the Drainage Density criterion, we defined the minimum (0.18) and maximum (5.28) observed values as the crisp limits of an increasing linear fuzzy membership function. This standardization emphasized selecting areas with higher drainage density, thereby prioritizing portions of the landscape characterized by a greater concentration of watercourses over those with sparser hydrographic networks.

For the slope criterion, due to the predominance of flat terrain across the basin and a skewed distribution concentrated below 25%, it was necessary to define a threshold for identifying higher-priority areas during the standardization process. An increasing linear fuzzy membership function was applied to standardize this spatial criterion, with limits set at 0% and 30% slope, where priority increases proportionally with slope.

The 30% threshold was selected based on the distribution of pixel values in the slope raster (Figure 2d) and considering factors such as the unsuitability of areas with this level of steepness and above for extensive agricultural activities (IBGE, 2013), as well as the tendency for such areas to be abandoned, as reported by Barlow et al. (2016). It is also important to highlight those prioritizing areas above 30% slope represents a significantly more restrictive condition than that established by Federal Law No. 12.651/2012, which designates slopes greater than 45° (100%) as Permanent Preservation Areas (PPAs) and classifies areas between 25° (46.63%) and 45° (100%) as restricted-use zones.

Finally, an increasing linear fuzzy membership function was applied to both Soil Erodibility and Average Annual Precipitation, using their minimum and maximum values as crisp thresholds. For Soil Erodibility, the lower and upper bounds were set at 0.0238 and 0.0319 $Mg.ha.h.ha^{-1}.MJ^{-1}.mm^{-1}$, respectively. For Average Annual Precipitation, the minimum and maximum values were defined as 1,083.21 mm/year and 1,403.79 mm/year. This standardization approach emphasizes selecting areas exhibiting higher soil erodibility and greater rainfall intensity, which are more susceptible to erosive processes.

Figure 3 presents the spatial criteria after applying fuzzy membership functions, thereby standardized to a common prioritization scale ranging from zero (*lowest priority*) to one (*highest priority*).

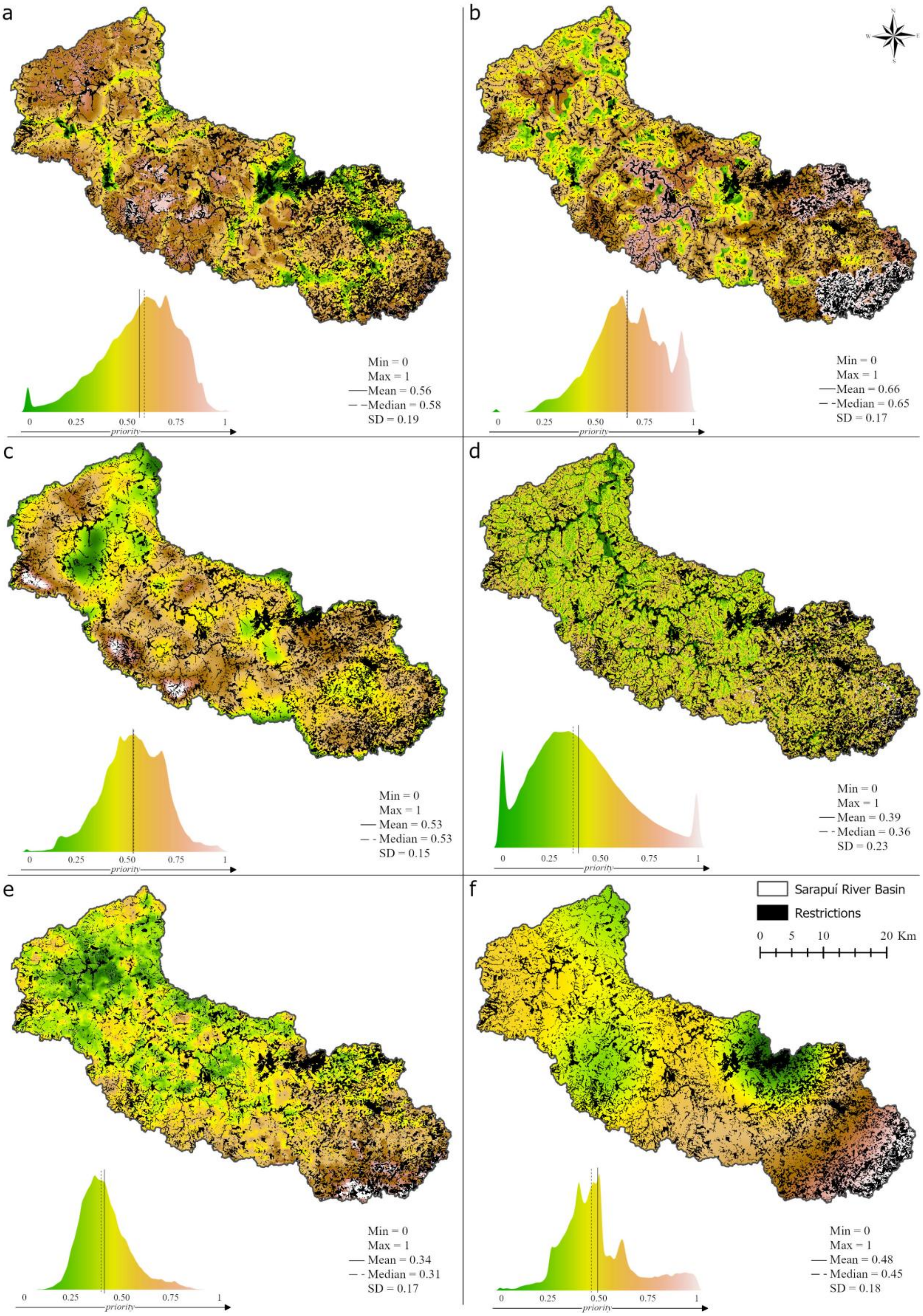


Figure 3 – Spatial Criteria Set (*standardized scale*) and restrictions. a: Human Footprint; b: Probability of Connectivity; c: Drainage Density; d: Slope; e: Soil Erodibility; and f: Annual Average Precipitation. Sarapuí River basin, São Paulo state, Brazil.

This standardization process led to significant shifts in the spatial representation and interpretability of the original data. In their raw form (Figure 2), the spatial criteria exhibited diverse value ranges and distribution patterns, often limiting direct comparison due to differences in units and scales. By transforming these criteria using fuzzy membership functions (Figure 3), each dataset was normalized according to its conceptual relevance to forest restoration, enabling consistent integration within the multicriteria framework. The transformation also allowed the prioritization logic to be more explicitly reflected in the spatial distribution of values, enhancing the decision-making potential of each criterion.

Notably, areas under lower human pressure were clearly emphasized in the standardized Human Footprint map through a decreasing linear function, which effectively inverted the prioritization logic by assigning higher suitability values to areas with lower anthropogenic disturbance. In contrast, regions exhibiting higher ecological connectivity were reinforced through an increasing linear function applied to the Probability of Connectivity criterion. Similarly, increasing fuzzy functions for Drainage Density, Soil Erodibility, and Average Annual Precipitation highlighted areas of greater ecological sensitivity and relevance.

A particularly notable transformation was observed in the Slope criterion. While the original slope map was predominantly characterized by flat to gently undulating terrain, applying a fuzzy membership function with an upper threshold of 30% substantially redefined the spatial pattern by assigning higher priority values to steeper areas. This adjustment reflects the increased ecological and hydrological relevance of such zones in restoration planning. Overall, the fuzzy standardization process ensured conceptual consistency across the various criteria and enhanced their discriminatory power to identify priority areas for effective forest resto-ration.

The application of fuzzy membership functions also influenced the statistical relationships among the spatial criteria, as evidenced by the comparison between the pre- and post-standardization correlation matrices (Tables 3 and 4). In the original scale, most correlations were weak or moderate, with the highest positive correlation observed between Average Annual Precipitation and Soil Erodibility (*r* = 0.6214), suggesting a tendency for more erodible soils to occur in areas with higher rainfall.

Additionally, the Human Footprint criterion showed weak to moderate negative correlations with ecological and hydrological variables such as Drainage Density and Probability of Connectivity, indicating that areas with intense human influence tend to be less connected and less hydrologically structured.

Table 4 – Correlation matrix among all the spatial criteria (*standardized scale: 0-1*). Sarapuí River basin, São Paulo state, Brazil.

Spatial Criteria	Human Footprint	Probability of Connectivity	Drainage Density	Slope	Soil Erodibility	Average Annual Precipitation
Human Footprint	1					
Probability of Connectivity	0.1599	1				
Drainage Density	0.2301	0.3336	1			
Slope	0.0274	0.1571	0.1784	1		
Soil Erodibility	-0.1719	0.2542	0.0440	0.1764	1	
Average Annual Precipitation	-0.0621	0.2961	0.0475	0.2276	0.6369	1

After the fuzzy transformation, although the general structure of relationships among criteria was preserved, important correlation magnitude and direction shifts were observed. The most prominent change occurred in the Human Footprint criterion, which presented positive correlations with all other criteria in the standardized scale, a direct result of applying a decreasing fuzzy function that inverted the direction of the original values.

Consequently, what was previously interpreted as a negative association with ecological and environmental factors became a positive alignment in the prioritization context.

Additionally, the correlation between Precipitation and Soil Erodibility remained strong (r = 0.6369), reinforcing the intrinsic environmental relationship between these variables, while correlations among the other criteria generally remained weak to moderate.

This preservation of low redundancy among criteria in the fuzzy scale supports their continued suitability for integrated analysis. At the same time, the observed shifts highlight how standardization not only enables comparison but also realigns the data to reflect decision-making priorities more effectively.

After standardizing the criteria set, we conducted an influence analysis to determine the ranking of spatial criteria based on their impact on the prioritization map. The results of this analysis are presented in Table 5, which shows the correlation coefficients between each spatial criterion and the aggregated output at the end of each iteration. It is important to note that the previously most correlated criterion was removed from the analysis in each iteration, and its weight was evenly redistributed among the remaining criteria.

Table 5 – Influence analysis results for spatial criteria on the aggregation results. Correlation coefficients obtained in each round (1 to 5) and the average correlation for each criterion ($\overline{x}$). Sarapuí River basin, São Paulo state, Brazil.

Spatial Criteria	WLC_1	WLC_2	WLC_3	WLC_4	WLC_5	$WLC_{\overline{x}}$
Human Footprint	0.59	0.61	0.70	-	-	0.63
Probability of Connectivity	0.67	-	-	-	-	0.67
Drainage Density	0.57	0.55	0.58	0.52	0.74	0.59
Slope	0.53	0.62	-	-	-	0.57
Soil Erodibility	0.34	0.38	0.44	0.81	-	0.49
Average Annual Precipitation	0.38	0.42	0.46	0.75	0.69	0.54

From the influence analysis, we derived a ranking that allowed us to compare the order of importance with the order of influence, as presented in Table 6. This comparison reveals an inversion in the influence ranking relative to the importance ranking between the Human Footprint and the Probability of Connectivity, as well as between Soil Erodibility and Average Annual Precipitation.

Table 6 –Criteria set ranking in order of importance for the decision-making process and their influence on the output. Sarapuí River basin, São Paulo state, Brazil.

Rank	Importance	Influence
1	Human Footprint	Probability of Connectivity
2	Probability of Connectivity	Human Footprint
3	Drainage Density	Drainage Density
4	Slope	Slope
5	Soil Erodibility	Average Annual Precipitation
6	Average Annual Precipitation	Soil Erodibility

Notably, the spatial criteria that exhibited an inversion between importance and influence occupy the first and last positions in the ranking and are also those with the smallest initial weight differences (Table 2). Additionally, the central tendency measures of their distributions (means and medians) are higher for the most influential criteria in both cases (Figure 4), indicating a considerable frequency of high-priority pixels for these criteria (Probability of Connectivity and Average Annual Precipitation) compared to those deemed more important (Human Footprint and Soil Erodibility).

Moreover, it is important to consider that Average Annual Precipitation is moderately correlated with Soil Erodibility ($r = 0.6369$), a value significantly higher than the other correlations within the criteria set. This relation likely increased the influence of Average Annual Precipitation in the final aggregation map.

Once the influence ranking was established, we ran simulations in which weights were progressively reduced from the most influential criteria (Probability of Connectivity and Average Annual Precipitation) and redistributed to the criteria least correlated with them, namely Human Footprint and Slope. The results of this analysis for the four scenarios (with weight reductions of 5%, 10%, 15%, and 20%) are presented in Table 7.

Table 7 – Adjusted criterion weights and correlation coefficients (r) between environmental criteria and the prioritization map for the four evaluated scenarios. Sarapuí River basin, São Paulo state, Brazil.

Spatial Criteria	$WLC_{5\%}$		$WLC_{10\%}$		$WLC_{15\%}$		$WLC_{20\%}$	
	Weight	r	Weight	r	Weight	r	Weight	r

Human Footprint	0.2785	0.60	0.2853	0.61	0.2920	0.61	0.3033	0.63
Probability of Connectivity	0.2146	0.65	0.2033	0.64	0.1920	0.65	0.1715	0.59
Drainage Density	0.1715	0.56	0.1715	0.56	0.1715	0.56	0.1715	0.55
Slope	0.1637	0.54	0.1705	0.55	0.1772	0.56	0.1885	0.58
Soil Erodibility	0.1304	0.34	0.1304	0.33	0.1304	0.32	0.1304	0.31
Average Annual Precipitation	0.0413	0.37	0.0392	0.37	0.0370	0.36	0.0348	0.35

As the adjustments became more intense (15% and 20%), distortions emerged in the expected order of criterion influence, particularly concerning the Slope criterion, which began to exhibit an influence more significant than or equivalent to that of Drainage Density. This fact contradicts the initial hierarchical logic of importance. Such an inversion is undesirable, especially considering that drainage density represents a fundamental hydrological factor for guiding restoration efforts in critical areas such as riparian zones. In contrast, although relevant, the slope has less spatial representativeness within the basin.

Additionally, scenarios involving more significant weight reduction for the Probability of Connectivity criterion (as in the 15% and 20% adjustments) tended to weaken its ability to adequately represent the ecological functionality of the landscape, particularly by reducing its contrast with the Human Footprint criterion. This contrast is desirable, given that both criteria occupy the upper extremes of the importance hierarchy.

Even after the applied adjustments, this high influence exerted by the Probability of Connectivity can be partially explained by its moderate correlations with the other components of the criteria set (ranging from r = 0.15 to r = 0.33). Although these correlations are not particularly strong, their recurring presence reinforces the central role of ecological connectivity as an integrative criterion capable of broadly reflecting landscape structure and functionality. This behavior aligns with the nature of the index used, which incorporates both habitat availability and potential movement between patches (Saura and Pascual-Hortal, 2007), attributes influenced by the landscape matrix's biophysical and spatial characteristics.

In the case of the Average Annual Precipitation criterion, its higher-than-expected influence primarily results from its strong correlation with Soil Erodibility (r = 0.6369), suggesting an association between areas with higher precipitation and soils more susceptible to particle loss. This association underscores the need to consider the combined effects of climate and soil in restoration planning, particularly in tropical regions where intense rainfall accelerates erosive processes (Coelho et al., 2024). Thus, the increased influence of this criterion, though not intended initially, represents a response of the model to the basin's specific environmental conditions, which impart greater practical relevance to the interactions between variables.

These observations do not indicate flaws in the model; instead, they reveal inherent characteristics of the landscape and the selected criteria. The existence of associations between correlated criteria, such as Precipitation and Erodibility, or between Connectivity and the biophysical attributes of the matrix tends to reinforce specific prioritization patterns. In contexts like the Sarapuí River basin, characterized by high environmental heterogeneity and intense anthropogenic pressure, such patterns should be interpreted as legitimate manifestations of ongoing ecological dynamics, which multi-criteria analysis seeks to capture and incorporate into the decision-making process.

Using the weights obtained from the 10% adjustment presented in Table 7, we produced a forest restoration prioritization map for the Sarapuí River Basin (Figure 4). The application of our prioritization model resulted in a continuous gradient of suitability values for forest restoration. The spatial distribution of these values reveals a marked heterogeneity across the basin, with high and very-high priority areas predominantly concentrated in the southern and southwestern regions. In contrast, lower-priority areas are mainly associated with the central-northern zones.

The prioritization values range from 0.12 to 0.88, and the distribution exhibits a near-normal pattern with closely aligned central tendency measures (mean = 0.51 and median =

0.52). This behavior indicates that the final aggregation is not biased toward any specific spatial criterion.

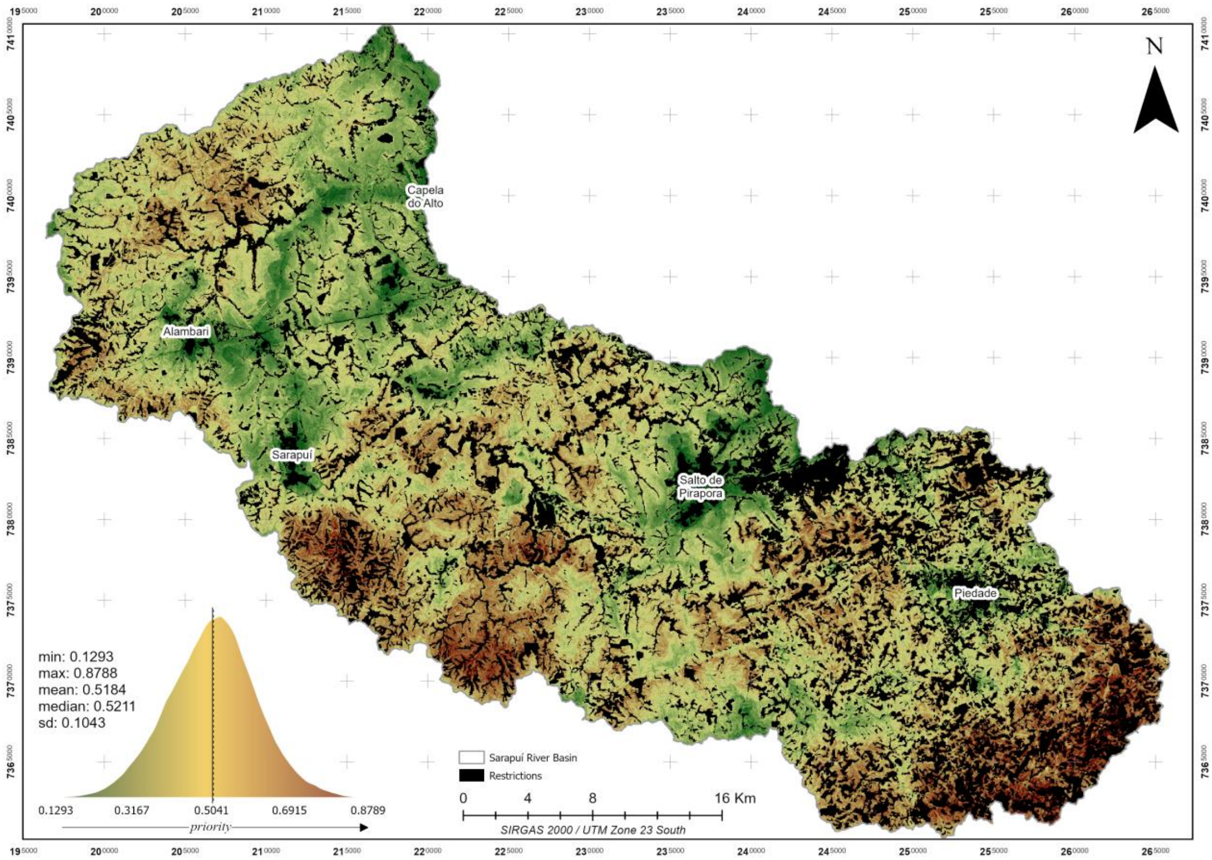


Figure 4 – Forest Restoration Priority Map for the Sarapuí River Basin (Continuous Scale). São Paulo state, Brazil.

The continuous prioritization map offers not only a reliable spatial representation of areas with restoration potential but also highlights the value of integrating multiple environmental and anthropogenic criteria to capture the complex dynamics of the landscape. Notably, the smooth gradient produced by this approach delineates transitional zones that may benefit from tailored intervention strategies.

This level of spatial nuance is critical for informing targeted restoration efforts that aim to enhance ecological connectivity, mitigate anthropogenic pressures, and account for socioeconomic constraints. These findings align with the recommendations of Malczewski and Rinner (2015) and are further supported by the contributions of Tapia-Armijos et al. (2017) and Borda-

Niño et al. (2020), who emphasize the importance of integrative, context-sensitive approaches in spatial decision-making for ecosystem restoration.

To further evaluate the robustness of the decision-making process, a sensitivity analysis was performed to assess the influence of individual criteria on the final prioritization outcome. This analysis quantified both the absolute and proportional variations in the output resulting from incremental adjustments (±10%) in the weights assigned to each criterion. The results, summarized in Table 8, reveal the relative sensitivity of each criterion, providing insights into their respective contributions to the overall prioritization. Criteria with higher sensitivity values exert greater influence on the spatial distribution of priority areas, underscoring their critical role in shaping restoration decisions.

Table 8 – Sensitivity Analysis Results for the Forest Restoration Prioritization Map of the Sarapuí River Basin, São Paulo State, Brazil.

Spatial Criteria	Variance	Sensitivity	Sensitivity (%)
Human Footprint	1020.82	0.175	17.5
Probability of Connectivity	974.96	0.167	16.7
Drainage Density	976.75	0.168	16.8
Slope	1001.79	0.172	17.2
Soil Erodibility	999.85	0.172	17.2
Average Annual Precipitation	850.54	0.146	14.6
Total	5824.72	1	100

The analysis revealed that pixel value variation in the final aggregation map, indicative of the model's sensitivity to changes in criterion weights, ranged from 14.6% to 17.5%. This relatively narrow range confirms the overall stability and robustness of the aggregated prioritization output. It suggests that the final map does not disproportionately reflect any single criterion, despite variations in their initial relative weights, thereby supporting the methodological soundness of the multi-criteria integration.

The consistent sensitivity values reinforce the reliability of our MCDA-GIS framework in heterogeneous landscapes such as the Sarapuí River Basin. By ensuring that no single criterion disproportionately influences the outcome, our approach provides a balanced assessment that captures the intrinsic ecological processes (e.g., connectivity as reflected by the Probability of Connectivity) and anthropogenic pressures (as represented by the Human Footprint). Moreover, the sensitivity analysis contributes to validating our method's robustness, enhancing confidence in its applicability for strategic decision-making in restoration planning.

Building on these results, we divided the basin into five distinct priority classes based on natural breaks in the distribution of the continuous prioritization values. This zonation enabled us to evaluate forest restoration scenarios by comparing the established priority classes with the current land-use and land-cover patterns. In doing so, our approach not only identifies areas with high ecological restoration potential but also explores potential land-use conflicts across the various priority classes.

Figure 5 presents the categorized prioritization map, which segments the basin into five classes ranging from very low to very high restoration potential, alongside three restoration scenarios that consider the top 1%, 5%, and 10% of pixels with the highest suitability values. The figure further illustrates the spatial intersection between these high-priority zones and the existing land uses, providing a detailed view of land-use conflict dynamics among the five priority zones.

Annual agriculture is the primary category across all priority zones due to its predominance in the landscape matrix. Nonetheless, it is noteworthy that the proportion of silviculture increases as the restoration priority escalates, whereas pasture areas are more prevalent in the intermediate priority classes. In silviculture's case, 45.8% of the top 1% of prioritized pixels and 32.9% of the pixels within the very high-priority class are under forestry management.

The observed conflict in these high-priority regions poses a more significant threat since forestry cultivation generally requires less stringent biophysical conditions than annual agriculture (i.e. slope, soil fertility, and proximity to roads and infrastructure). These characteristics have contributed to the widespread recommendation of silviculture as a viable land-use alternative for reforestation in areas unsuitable for annual cropping (EMBRAPA, 2012).

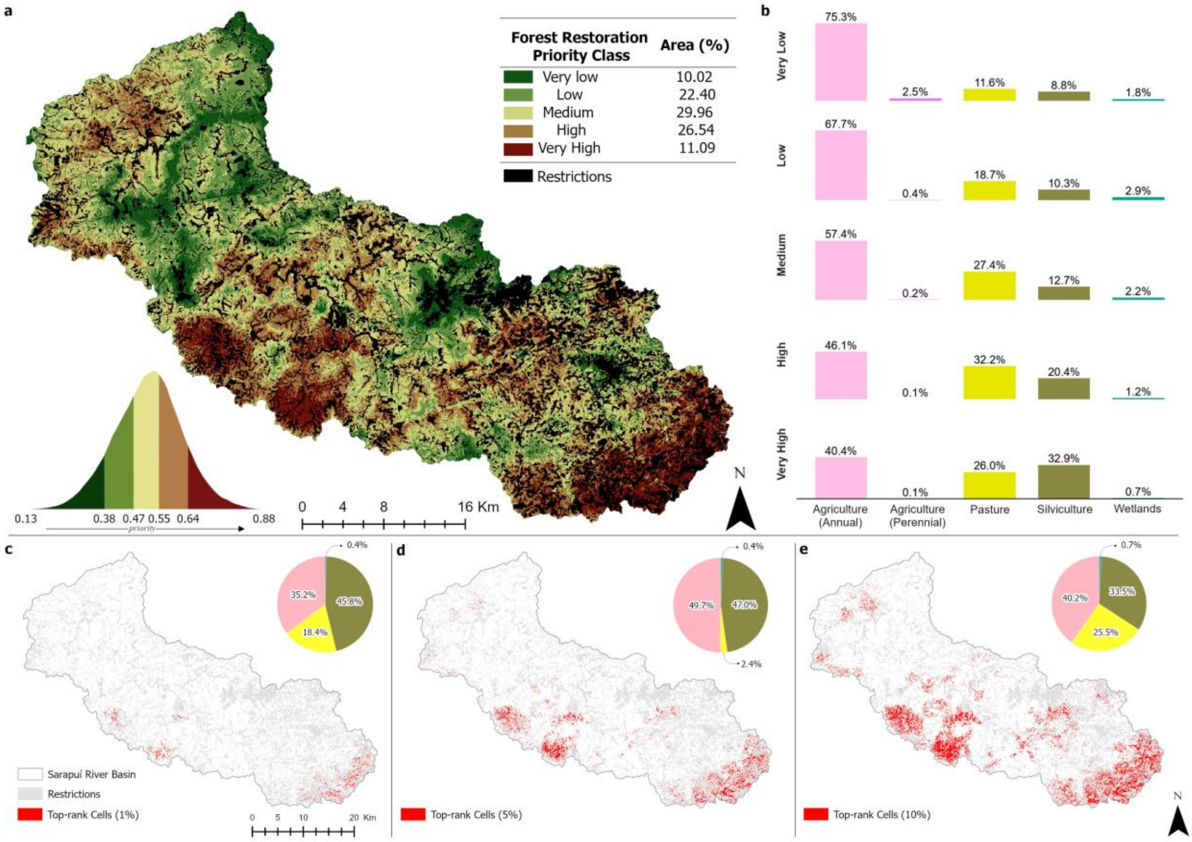


Figure 5 – Forest Restoration Priority Classes (a), land use conflict in the different priority classes (b), and prioritization scenarios (c, d, and e) for the Sarapuí River Basin. São Paulo state, Brazil.

Although pasture lands are more dominant in the medium and high-priority classes, these regions also display significant potential for forest restoration. This scenario is particularly relevant because the majority of these pasture areas are unproductive and degraded; when restoration initiatives are promoted in these areas, they not only have the potential to improve ecological functionality but may also generate income for rural producers through mechanisms such as payments for ecosystem services and carbon credit negotiations.

4.4. CONCLUSIONS

The site prioritization for forest restoration in this study represents a comprehensive and methodologically sound solution, both conceptually and technically. This framework addresses critical gaps in restoration planning by successfully integrating spatial criteria that promote ecological processes, avoid human-induced disturbances, and account for socio-economic aspects in target areas while enhancing the capacity of restored forest cover to fulfill mitigation and protective functions in the post-intervention landscape.

Incorporating Probability of Connectivity, Human Footprint mapping and Drainage Density effectively filled methodological gaps previously identified in similar decision-making processes. These criteria captured ecological relevance, human-induced disturbances, socio-economic dimensions, and hydrological processes, contributing to a more holistic spatial representation. Their conceptual suitability and technical robustness support their continued use in Multicriteria Decision Analysis (MCDA) conservation and restoration planning frameworks in human-modified landscapes.

Despite the predominance of agriculture in the matrix, the prioritization scenarios revealed that silviculture represents a conflicting land use in high-priority areas. In contrast, pasturelands emerge as promising opportunities for restoration, particularly in regions classified as medium to high priority. Often degraded and unproductive, these areas also offer potential for socio-economic gains through mechanisms such as Payment for Ecosystem Services (PES) and carbon credit initiatives.

Overall, the proposed framework demonstrated replicability and robustness, offering a practical and scalable approach for spatial decision-making. The set of criteria and their hierarchical structure are recommended for application in similar contexts, particularly in tropical forest landscapes undergoing intense anthropogenic pressures. This work contributes to the broader goal of aligning forest restoration initiatives with ecological functionality, social relevance, and territorial resilience principles.

REFERENCES

Aide, T. M., Clark, M. L., Grau, H. R., López-Carr, D., Levy, M. A., Redo, D., Bonilla-Moheno, M., Riner, G., Andrade-Núñez, M. J., and Muñiz, M. (2013). **Deforestation and Reforestation of Latin America and the Caribbean (2001-2010)**. Biotropica, 45(2), 262–271. https://doi.org/10.1111/j.1744-7429.2012.00908.x

Alvares, C. A., Stape, J. L., Sentelhas, P. C., Gonçalves, J. L. de M., and Sparovek, G. (2014). **Köppen's climate classification map for Brazil**. Meteorologische Zeitschrift, 22(6), 711–728. https://doi.org/10.1127/0941-2948/2013/0507

Bonn Challenge (2014). **The challenge: a global effort**. http://www.bonnchallenge.org/content/challenge (accessed 05 Mar 2025)

Borda-Niño, M., Meli, P., and Brancalion, P. H. S. (2020). **Drivers of tropical forest cover increase: A systematic review**. Land Degradation and Development, 31(11), 1366–1379. https://doi.org/10.1002/ldr.3534

Brancalion, P. H. S., Hua, F., Joyce, F. H., Antonelli, A., and Holl, K. D. (2025). **Moving biodiversity from an afterthought to a key outcome of forest restoration**. Nature Reviews Biodiversity. https://doi.org/10.1038/s44358-025-00032-1

Brancalion, P. H. S., Schweizer, D., Gaudare, U., Mangueira, J. R., Lamonato, F., Farah, F. T., Nave, A. G., and Rodrigues, R. R. (2016). **Balancing economic costs and ecological outcomes of passive and active restoration in agricultural landscapes: the case of Brazil**. Biotropica, 48(6), 856–867. https://doi.org/10.1111/btp.12383

Calaboni, A., Tambosi, L. R., Igari, A. T., Farinaci, J. S., Metzger, J. P., and Uriarte, M. (2018). **The forest transition in São Paulo, Brazil: Historical patterns and potential drivers**. Ecology and Society, 23(4). https://doi.org/10.5751/ES-10270-230407

Cavalcante, R. B. L., Ferreira, D. B. da S., Pontes, P. R. M., Tedeschi, R. G., da Costa, C. P. W., and de Souza, E. B. (2020). **Evaluation of extreme rainfall indices from CHIRPS precipitation estimates over the Brazilian Amazonia**. Atmospheric Research, 238. https://doi.org/10.1016/j.atmosres.2020.104879

Cavalcante, R. B. L., Nunes, S., Viademonte, S., Rodrigues, C. M. F., Gomes, W. C., Ferreira, J. da S., Pontes, P. R. M., Giannini, T. C., Awade, M., de S. Miranda, L., and Nascimento, W. R. (2022). **Multicriteria approach to prioritize forest restoration areas for biodiversity conservation in the eastern Amazo**n. Journal of Environmental Management, 318, 115590. https://doi.org/10.1016/j.jenvman.2022.115590

Cecílio, R. A., Oliveira-Ravani, L. T., Zanetti, S. S., and Mendes, H. de A. (2021). **Method for classifying sites to atlantic rainforest restoration aiming to increase basin's streamflows**. IForest, 14(1), 89–94. https://doi.org/10.3832/IFOR3658-013

Chen, Y., J. Yu, K. Shahbaz and E. Xevi. 2009. **A GIS-Based Sensitivity Analysis of Multi-Criteria Weights**. 18th World IMACS / MODSIM Congress, Cairns, Australia 13-17 July 2009.

Cosimo, L. H. E., Martins, S. V., and Gleriani, J. M. (2021). **Suggesting priority areas in the buffer zone of Serra do Brigadeiro State Park for forest restoration compensatory to bauxite mining in Southeast Brazil**. Ecological Engineering, 170. https://doi.org/10.1016/j.ecoleng.2021.106322

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

Eastman, R. J. (2015). **Terrset Manual**.

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F. C., and Ghosh, T. (2017). **VIIRS night-time lights**. International Journal of Remote Sensing, 38(21), 5860–5879. https://doi.org/10.1080/01431161.2017.1342050

Esmail, B. A., and Geneletti, D. (2018). **Multi-criteria decision analysis for nature conservation: A review of 20 years of applications**. Methods in Ecology and Evolution, 9(1), 42–53. https://doi.org/10.1111/2041-210X.12899

Foltête, J. C., Vuidel, G., Savary, P., Clauzel, C., Sahraoui, Y., Girardet, X., and Bourgeois, M. (2021). **Graphab: An application for modeling and managing ecological habitat networks[Formula presented]**. Software Impacts, 8. https://doi.org/10.1016/j.simpa.2021.100065

Frazier, A. E., and Kedron, P. (2017). **Landscape Metrics: Past Progress and Future Directions**. Current Landscape Ecology Reports, 2(3), 63–72. https://doi.org/10.1007/s40823-017-0026-0

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J. (2015). **The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes**. Scientific Data, 2. https://doi.org/10.1038/sdata.2015.66

Godoi, R. de F., Rodrigues, D. B. B., Borrelli, P., and Oliveira, P. T. S. (2021**). High-resolution soil erodibility map of Brazil**. Science of The Total Environment, 781, 146673. https://doi.org/10.1016/j.scitotenv.2021.146673

Gribov, A., and Krivoruchko, K. (2020). **Empirical Bayesian kriging implementation and usage**. Science of the Total Environment, 722, 137290. https://doi.org/10.1016/j.scitotenv.2020.137290

Höhl, M., Ahimbisibwe, V., Stanturf, J. A., Elsasser, P., Kleine, M., and Bolte, A. (2020). **Forest landscape restoration - What generates failure and success?** Forests, 11(9). https://doi.org/10.3390/F11090938

IBGE. (2012). **Manual Técnico da Vegetação Brasileira** (IBGE, Ed.; 2nd ed., Vol. 1, Issue 1).

IBGE. (2013). **Manual Técnico de Uso da Terra** (3rd ed., Vol. 7).

Jiang, H., and Eastman, J. R. (2000). **Application of fuzzy measures in multi-criteria evaluation in GIS**. International Journal of Geographical Information Science, 14(2), 173–184. https://doi.org/10.1080/136588100240903

Jones, J., Ellison, D., Ferraz, S., Lara, A., Wei, X., and Zhang, Z. (2022). **Forest restoration and hydrology**. In Forest Ecology and Management (Vol. 520). Elsevier B.V. https://doi.org/10.1016/j.foreco.2022.120342

Lamb, D. (2018**). Undertaking large-scale forest restoration to generate ecosystem services**. In Restoration Ecology (Vol. 26, Issue 4, pp. 657–666). Blackwell Publishing Inc. https://doi.org/10.1111/rec.12706

Malczewski, J. (2000). **On the use of weighted linear combination method in GIS: Common and best practice approaches**. Transactions in GIS, 4(1), 5–22. https://doi.org/10.1111/1467-9671.00035

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

Mannigel, A. R., Carvalho, M. D. P. e, Moreti, D., and Medeiros, L. D. R. (2002). **Fator erodibilidade e tolerância de perda dos solos do Estado de São Paulo**. Acta Scientiarum, 24(5), 1335–1340. https://doi.org/10.4025/actasciagron.v24i0.2374

Martensen, A. C., Saura, S., and Fortin, M. J. (2017). **Spatio-temporal connectivity: assessing the amount of reachable habitat in dynamic landscapes**. Methods in Ecology and Evolution, 8(10), 1253–1264. https://doi.org/10.1111/2041-210X.12799

Mello, K. de, Randhir, T. O., Valente, R. A., and Vettorazzi, C. A. (2017). **Riparian restoration for protecting water quality in tropical agricultural watersheds**. Ecological Engineering, 108, 514–524. https://doi.org/10.1016/j.ecoleng.2017.06.049

Morales, M. V., and Valente, R. A. (2023). **Hydrological Inferences from Morphometric Analysis of the Sarapuí river Watershed**. In INPE (Ed.), XX Simpósio Brasileiro de Sensoriamento Remoto (Vol. 12, Issue 10, pp. 292–295). INPE. https://proceedings.science/p/164147?lang=pt-br

Oliveira, P. T. S., Wendland, E., and Nearing, M. A. (2013). **Rainfall erosivity in Brazil: A review**. Catena, 100, 139–147. https://doi.org/10.1016/j.catena.2012.08.006

Palmeira Júnior, R. C. (2020). **A Crise Hídrica na Agricultura Familiar em Piedade/SP** [Master's, Campinas State University - Unicamp]. http://lattes.cnpq.br/3096572653548171

Peñacoba-Antona, L., Gómez-Delgado, M., and Esteve-Núñez, A. (2021). **Multi-criteria evaluation and sensitivity analysis for the optimal location of constructed wetlands (METland) at oceanic and mediterranean areas**. International Journal of Environmental Research and Public Health, 18(10). https://doi.org/10.3390/ijerph18105415

R Core Team (2025). **R: A Language and Environment for Statistical Computing**. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Rivera, J. A., Marianetti, G., and Hinrichs, S. (2018). **Validation of CHIRPS precipitation dataset along the Central Andes of Argentina**. Atmospheric Research, 213, 437–449. https://doi.org/10.1016/j.atmosres.2018.06.023

Sánchez-Cuervo, A. M., and Aide, T. M. (2013). **Consequences of the Armed Conflict, Forced Human Displacement, and Land Abandonment on Forest Cover Change in Colombia: A Multi-scaled Analysis**. Ecosystems, 16(6), 1052–1070. https://doi.org/10.1007/s10021-013-9667-y

Sanderson, E. W., Jaiteh, M., Levy, M. A., Redford, K. H., Wannebo, A. V, and Woolmer, G. (2002). **The Human Footprint and the Last of the Wilderness**. BioScience, 52(10), 891–904.

Saura, S., and Pascual-Hortal, L. (2007). **A new habitat availability index to integrate connectivity in landscape conservation planning: Comparison with existing indices and application to a case study**. Landscape and Urban Planning, 83(2–3), 91–103. https://doi.org/10.1016/j.landurbplan.2007.03.005

SDG (Sustainable Development Goals) (2015). **Goal 15**. www.un.org/sustainabledevelopment/biodiversity/ (accessed 05 Mar 2025)

Shen, Z., Yong, B., Gourley, J. J., Qi, W., Lu, D., Liu, J., Ren, L., Hong, Y., and Zhang, J. (2020). **Recent global performance of the Climate Hazards group Infrared Precipitation with Stations (CHIRPS)**. Journal of Hydrology, 591. https://doi.org/10.1016/j.jhydrol.2020.125284

Sloan, S., Goosem, M., and Laurance, S. G. (2016). **Tropical forest regeneration following land abandonment is driven by primary rainforest distribution in an old pastoral region**. Landscape Ecology, 31(3), 601–618. https://doi.org/10.1007/s10980-015-0267-4

Souza, C. M., Shimbo, J. Z., Rosa, M. R., Parente, L. L., Alencar, A. A., Rudorff, B. F. T., Hasenack, H., Matsumoto, M., Ferreira, L. G., Souza-Filho, P. W. M., de Oliveira, S. W., Rocha, W. F., Fonseca, A. V., Marques, C. B., Diniz, C. G., Costa, D., Monteiro, D., Rosa, E. R., Vélez-Martin, E., … Azevedo, T. (2020). **Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine**. Remote Sensing, 12(17). https://doi.org/10.3390/RS12172735

Tapia-Armijos, M. F., Homeier, J., and Draper Munt, D. (2017). **Spatio-temporal analysis of the human footprint in South Ecuador: Influence of human pressure on ecosystems and effectiveness of protected areas**. Applied Geography, 78, 22–32. https://doi.org/10.1016/j.apgeog.2016.10.007

Valente, R. A., de Mello, K., Metedieri, J. F., and Américo, C. (2021). **A multicriteria evaluation approach to set forest restoration priorities based on water ecosystem services**. Journal of Environmental Management, 285. https://doi.org/10.1016/j.jenvman.2021.112049

Valente, R. de O. A., and Vettorazzi, C. A. (2009). **Comparação entre métodos de análise de sensibilidade empregados na tomada de decisão com a avaliação multicriterial**. Scientia Forestalis, 37(82), 197–211.

Vanderley-Silva, I., and Valente, R. A. (2023). **Functional connectivity supported by forest conservation in urban sprawl landscape in São Paulo, Brazil**. GeoJournal, 88(3), 3011–3028. https://doi.org/10.1007/s10708-022-10789-z

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., and Watson, J. E. M. (2016). **Global terrestrial Human Footprint maps for 1993 and 2009**. Scientific Data, 3. https://doi.org/10.1038/sdata.2016.67

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

Watson, J. E. M., and Venter, O. (2019). **Mapping the Continuum of Humanity's Footprint on Land**. In One Earth (Vol. 1, Issue 2, pp. 175–180). Cell Press. https://doi.org/10.1016/j.oneear.2019.09.004

Watts, K., and Hughes, S. (2024). **Fragmentation impacts may be mixed for conservation but generally bad for restoration**. Restoration Ecology. https://doi.org/10.1111/rec.14260

Woolmer, G., Trombulak, S. C., Ray, J. C., Doran, P. J., Anderson, M. G., Baldwin, R. F., Morgan, A., and Sanderson, E. W. (2008). **Rescaling the Human Footprint: A tool for conservation planning at an ecoregional scale**. Landscape and Urban Planning, 87(1), 42–53. https://doi.org/10.1016/j.landurbplan.2008.04.005

CONCLUDING REMARKS

The present Thesis proposed an integrated approach to support spatial decision-making in human-modified landscapes, prioritizing forest restoration areas. Throughout this research, it became clear that effective restoration planning cannot be limited to the simple reforestation of degraded areas. Instead, it must incorporate a deeper understanding of landscape functionality, land use legacy, ecological processes, and human pressures. This study demonstrates that a robust decision-making process for restoration must be conceptually sound and methodologically rigorous, integrating ecological, biophysical, and socioeconomic criteria within a spatially explicit framework.

Chapter I revealed a fragmented and often inconsistent application of spatial criteria in restoration prioritization studies. While disturbance-related and ecological criteria were frequently employed, there was a notable lack of consensus regarding the selection and standardization of these criteria. Standard metrics, such as simple Euclidean distances to forest fragments, were shown to be inadequate for representing landscape processes in dynamic and fragmented landscapes. Moreover, the limited incorporation of social and economic dimensions into decision frameworks highlighted a critical gap in the literature. In response to these issues, this study proposed using the Probability of Connectivity (PC) as a more robust ecological criterion and adapting the Human Footprint metric to capture anthropogenic pressures and socioeconomic dynamics at the river basin scale. These elements offer a more comprehensive basis for spatial decision-making in restoration efforts.

Building upon these insights, Chapter II applied the concepts to the Sarapuí River Basin, where a spatiotemporal analysis over 35 years revealed complex patterns of land use and forest cover change. Such dynamics were only observable through the explicit combination of spatial and temporal scales, enabling the differentiation of gain, loss, and stability events at the patch level. These findings go beyond simple comparisons of two static maps, offering a more nuanced understanding of the temporal legacy of habitat patches. Notable phenomena identified using the proposed methodology include the simultaneous occurrence of patch aggregation and fragmentation and the rejuvenation of forest cover. The spatialization of the Probability of Connectivity further enabled the identification of functional connectivity hotspots, highlighting the metric's potential for incorporation into conservation and restoration decision-making processes at the watershed scale. This approach addresses the methodological weaknesses identified in Chapter I, particularly the limitations of Euclidean distance-based metrics for representing ecological aspects of landscapes. These findings underscore the need for restoration strategies responsive to landscape dynamics and prioritizing connectivity as a pathway for ecological recovery.

Moving forward, Chapter III advanced the methodological contributions of this research by adapting the Human Footprint methodology, initially developed for global assessments, to a watershed-scale application suitable for local decision-making. This adaptation provided a detailed spatial diagnosis of human pressures, integrating land use, access, infrastructure, and socioeconomic variables. The resulting maps highlighted areas of high anthropogenic impact, serving as critical tools for identifying constraints and opportunities for restoration. By demonstrating the feasibility of incorporating socioecological complexity into spatial decision frameworks, this chapter addresses a significant limitation in the literature regarding structured decision-making processes in environmental contexts.

Finally, Chapter IV synthesized these findings into a robust and replicable Multicriteria Decision Analysis (MCDA) framework for restoration prioritization. The proposed model integrates ecological (e.g., PC), biophysical (e.g., slope, erodibility, precipitation), and anthropogenic (e.g., Human Footprint) criteria while also addressing methodological challenges such as the over-reliance on Euclidean distance metrics in fragmented and hydrologically complex landscapes. The inclusion of drainage density as a criterion exemplifies the model's attention to landscape-specific processes, particularly in overcoming the limitations of simple distance-based metrics in well-drained areas.

A critical component of the framework was evaluating spatial criteria prior to normalization, including analyses of distributions, ranges, and the ecological meaning of each variable. This careful pre-processing step ensured that the normalization process preserved the integrity and comparability of the data, directly contributing to the efficiency and reliability of the decision-making process. Additionally, the model incorporated correlation analyses to identify and address potential redundancies among criteria, refining the variable set and enhancing the framework's robustness. The weights assigned to each criterion were informed by an extensive review of the scientific literature, ensuring a theoretically grounded and contextually relevant prioritization framework. This rigorous weighting approach further reinforces the model's transparency and replicability.

The resulting prioritization maps offer a practical and scientifically sound tool to guide restoration efforts, supporting allocating limited resources to areas with the highest potential for ecological recovery. This framework has clear applications in public policy, conservation programs, watershed management, and Payment for Environmental Services (PES) initiatives, demonstrating its value as a decision-support instrument for integrated and effective landscape management.

In summary, this Thesis demonstrates that effective restoration planning requires more than a collection of spatial datasets. It demands a careful conceptualization of what each criterion represents, a critical reflection on its ecological and social relevance, and a methodological framework that is transparent, adaptable, and grounded in the dynamics of the landscape. Integrating ecological connectivity, anthropogenic pressures, and landscape-specific characteristics into a single decision framework represents a significant contribution to landscape restoration, addressing longstanding gaps in the literature and offering a replicable model for diverse environmental contexts.

This work reaffirms that forest landscape restoration is a key strategy for achieving the 2030 Agenda for Sustainable Development Goals, promoting biodiversity conservation, climate change mitigation, and the resilience of social-ecological systems. It is hoped that the methods, reflections, and insights presented here will inspire future research, guide practical applications, and inform the development of more effective, context-sensitive restoration policies.