Evaluating pollinator diversity in the Brazilian Atlantic Forest biome using geospatial and Machine Learning Tools

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Abstract

Pollinators play a central role in sustaining biodiversity and ecosystem services, consequently their response to forest regeneration in tropical landscapes needs to be quantified at large scales. Here, we assess how land cover composition and forest age influence pollinator diversity in the Brazilian Atlantic Forest — a global biodiversity hotspot undergoing extensive regeneration. We integrated land-use and forest age data from MapBiomas with 56,593 bee occurrence records from GBIF, focusing on five bee families. Using Random Forest models, we evaluated the importance of land cover types and secondary forest age intervals for predicting total occurrences and genus richness. Our results show that primary forest cover is the dominant predictor of bee genus richness, followed by late-stage secondary forests aged $>$ 26 years and riparian-associated water surfaces. In contrast, younger secondary forests ($<$ 25 years) contributed negligibly and urban dominated landscapes support less diversity overall. While total occurrence data reflected strong spatial bias towards non-vegetated and agricultural areas, genus richness emerged as a more robust parameter, avoiding bias, and mitigating over-representation from anthropic landscapes. Our findings highlight the ecological value of mature secondary forests for pollinator conservation and reinforce the need to incorporate the time dimension into restoration monitoring. Our results underscore the conservation value of mature secondary forests and the need to integrate forest age into restoration monitoring. Our approach demonstrates the utility of combining biodiversity data, geospatial data derived from remote sensing, and machine learning to produce scalable, spatially explicit insights into ecological recovery and pollination services in tropical biomes.

1. Introduction

Landscape structure, encompassing both habitat composition and spatial configuration, plays a fundamental role in sustaining biodiversity and supporting key ecosystem services such as pollination. Heterogeneous landscapes, rich in natural and semi-natural habitats, typically sustain more diverse pollinator communities and enhance pollination services (Qiu et al., 2018; Bottero et al., 2023). In contrast, simplified landscapes dominated by monocultures, pastures, or urban areas often experience pollinator declines and diminished ecosystem functioning (Kremen and Miles, 2012; Brunet and Fragoso, 2024; Hederström et al., 2024). The composition of the landscape determines the diversity and continuity of floral and nesting resources essential for pollinator survival and reproduction, while diverse vegetation types provide staggered floral resources throughout the year, reducing competition and mitigating resource scarcity (Eeraerts, 2023; Ammann et al., 2024). Moreover, heterogeneous landscapes tend to support richer and more resilient pollinator communities compared to homogeneous or highly fragmented systems (Moreira et al., 2015; Bottero et al., 2023).

Linking landscape structure to pollination services is challenging due to the complexity of ecological processes and species-specific responses, and the inherently multiscale nature of pollination systems. Different species exhibit varying sensitivities to habitat composition, configuration, and connectivity, influenced by traits such as foraging range, nesting requirements, and resilience to habitat loss (Kennedy et al., 2013). A central concern in advancing pollination research is understanding how pollinator distributions, movements, and interactions are embedded within heterogeneous landscapes. Addressing this spatial dimension is crucial for accurately predicting the occurrence and stability of pollination services.

Remote sensing and computer assisted geospatial analysis has become an essential tool for quantifying habitat composition and structural complexity across broad spatial and temporal scales, addressing key methodological challenges in landscape ecology. By linking remotely sensed data on forest composition and configuration to pollinator communities, researchers gain critical insights into the environmental factors shaping biodiversity patterns (Galbraith et al., 2015). This approach supports the identification of biodiversity hotspots, guides habitat

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restoration efforts, and enables the evaluation of conservation and restoration outcomes over time. Common applications include the use of multispectral satellite imagery (e.g., Landsat, Sentinel) and aerial photographs to classify vegetation types and calculate structural metrics, which are then integrated with biodiversity data to explore species-habitat relationships.

Several studies exemplify the effectiveness of this approach. For instance, Galbraith et al. (2019) combined Landsat-derived burn severity maps with LiDAR-based canopy metrics to show that moderately burned areas supported the highest wild bee diversity in Western North America years after fire events. Similarly, Chase et al. (2025) used airborne LiDAR to quantify fine-scale vegetation structure, finding that increased understory density predicted higher bee diversity in managed oak-hickory forests. Other studies have employed satellite-derived texture metrics as proxies for habitat heterogeneity (Hofmann et al., 2017) or mapped forest fragmentation to identify corridors that facilitate bee movement and restore pollination services (Kormann et al., 2016). Emerging technologies, such as drone-based floral mapping and spectral detection of blooms, further expand remote sensing capabilities, providing landscape-scale assessments of resource availability for pollinators (Gonzales et al., 2022). Overall, remote sensing offers scalable and repeatable methods to characterize habitat structure, facilitating biodiversity assessments and informing proactive conservation and management strategies.

Pollinators, particularly bees, are keystone components of forest and agroecosystems, supporting the reproduction of approximately 87% of flowering plant species globally (Ollerton et al., 2011) and over 50% of tree species in tropical forests such as the Brazilian Atlantic Forest (Bawa, 1990). By promoting plant genetic diversity and forest regeneration, bees underpin ecosystem functioning and sustain food webs (Ollerton, 2017). Secondary forests, which now comprise more than half of the remaining Atlantic Forest cover (Ribeiro et al., 2009; Rezende et al., 2018), play a critical role in biodiversity conservation by offering essential resources for pollinators, including floral diversity, nesting sites, and microclimatic refuges (Chazdon and Guariguata, 2016). Assessing pollinator diversity in these regenerating forests is crucial for understanding their ecological resilience and guiding conservation strategies, as forest structure and composition influence pollinator communities and the provision of pollination services (Lázaro et al., 2022; Pereira et al., 2021).

Geotechnologies enable efficient quantification of habitat structural complexity across large scales, providing proxies for biodiversity assessments and facilitating the identification of potential habitats. Integrating remotely sensed habitat metrics with species occurrence data, such as from the Global Biodiversity Information Facility (GBIF) (GBIF.org, 2025), with geopatial analysis tools and machine learning offers a robust framework for evaluating biodiversity patterns and informing conservation strategies. In this study, we apply this approach to assess how landscape composition can influence pollinator diversity in Secondary Brazilian Atlantic Forests, using existing remote sensing derived thematic maps, GBIF records, and machine learning to provide spatially explicit insights into how forest regeneration affects pollination services.

2. Methods

2.1 Study area and data sets

This study was conducted within the Brazilian Atlantic Forest (BAF) biome, a global biodiversity hotspot that originally covered over 1.5 million km². BAF area has been reduced to approximately 12% of its original extent due to centuries of deforestation and land-use and cover changes (LUCC) (Ribeiro et al., 2009; Rezende et al., 2018). Species occurrence data were obtained from GBIF (GBIF.org, 2025), through its QGIS software plugin (Noé, 2019). GBIF is an international collaborative database that provides open access to biodiversity data from different sources, such as specimen collections, field observations, and genetic data, thus supporting scientific research, policy, and conservation. All occurrence records belonging to the following five bee families (hereafter referred to as pollinators) were selected: Apidae, Halictidae, Megachilidae, Andrenidae, and Colletidae. A time frame from 1975 through 2025 (up to May 10th) was applied, resulting in 107,856 occurrence records in Brazilian territory. The official BAF biome boundaries according to the Brazilian Institute for Geography and Statistics (IBGE) (Martins and Cavararo, 2012) were used to select only those pollinator occurrence points located within the study area, yielding a total of 56,593 occurrences (Figure 1).

2.2 Forest age as a proxy of landscape structure

Forest age, or successional stage, represents the time since a disturbance and serves as an important proxy for landscape structural complexity, influencing pollinator communities as forests regrow and mature. Older, structurally complex forests generally support higher pollinator diversity compared to younger, simplified stands (Ulyshen et al., 2024), with succession-driven shifts in structure and composition enhancing resource availability. MapBiomas Silva Junior et al. (2020) is a Brazilian initiative that generates annual land use and land cover (LULC) maps from publicly available satellite images, such as Landsat and Sentinel-2, used to monitor LULC changes, deforestation, and help manage natural resources. Among Mapbiomas collections, the Deforestation and Secondary Vegetation collection, more specifically the Secondary Vegetation Age layer, enable the identification of disturbance histories, providing valuable tools for studying ecological patterns and informing conservation strategies. In this work we used the Secondary Vegetation Age layer, for the year of 2023. The methodology used to calculate the secondary vegetation age is based in Silva Junior et al. (2020), which calculated this mensuration using the annual land-use and land-cover maps from the MapBiomas Project with a spatial resolution of 30 meters using Google Earth Engine. This way, the age of each pixel represents the number of years since its transition from anthropic land use to forest cover.

2.3 Landscape structure calculation and Random Forest Regressor

For the purpose of calculating Landscape Structure metrics, MapBiomas land use and land cover classes values were reclassified into four broad categories: Forest, Agriculture, Non-Vegetated Areas, and Water Surfaces. We grouped thematically each class to facilitate the processing and analysis of the results. As a preliminary study, using such number of LULC classes could bring unnecessary complexity to the analysis, affecting the results and conclusions. Future research may expand the

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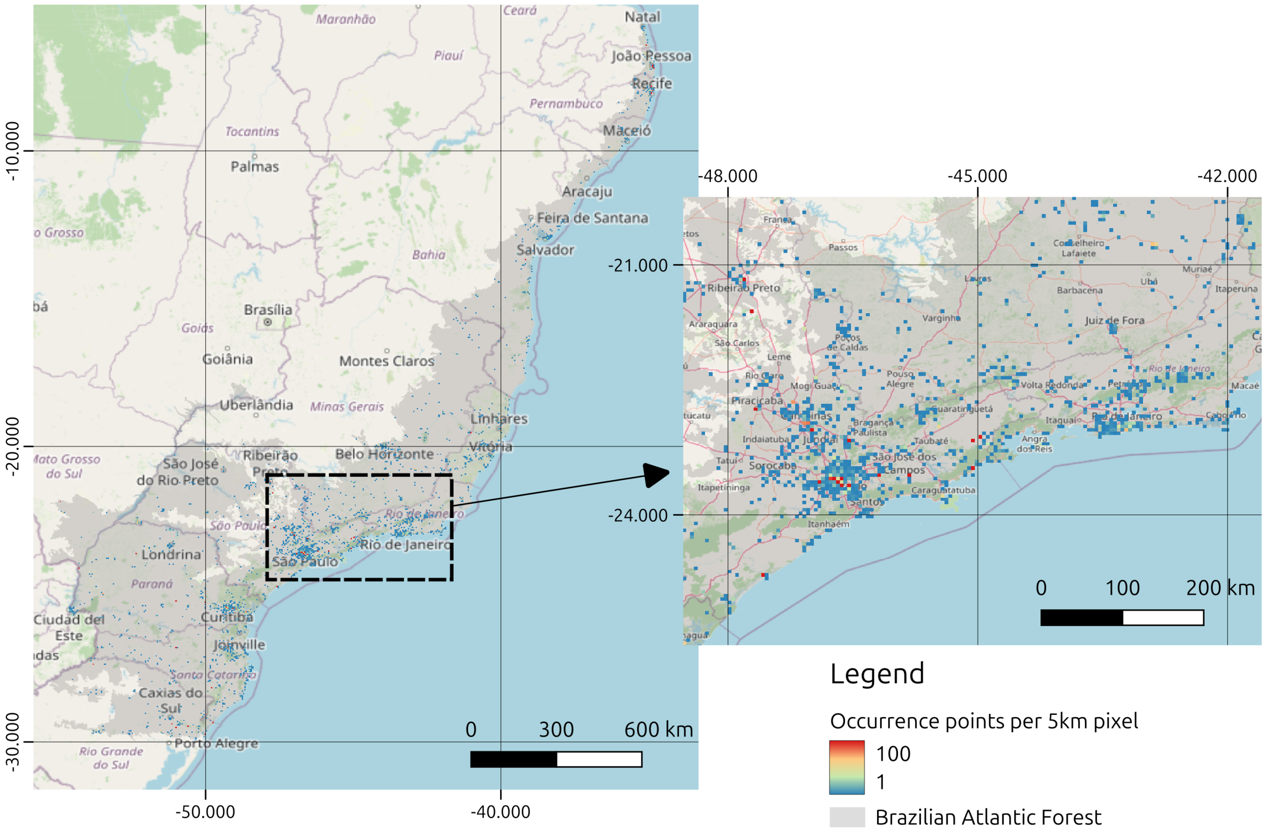

Figure 1. Spatial distribution of bee occurrence records across the Brazilian Atlantic Forest based on data retrieved from GBIF. Background source: OpenStreetMaps

analysis for one or more aggregated classes depending on their assessed importance.

The ”Forest” class (Class 1) consists of different natural vegetation formations including forests, savannas, and shrubland physiognomies. The ”Agriculture” class (Class 2) contains different types of land use for agricultural purposes, such as pastures and seasonal or perennial crops. The ”Non-Vegetated Areas” class (Class 3) includes sandbanks, bare soils and urbanized areas. Finally, the ”Water Surfaces” class (Class 4) contains water surfaces, such as rivers and oceans.

The aggregated class pixel values and their corresponding original MapBiomas values are as follows:

- Forest: Class 1, original values: 3, 4, 5, 10, 11, 12, 13, 29, 32, 49;
- Agriculture: Class 2, original values: 9, 14, 15, 18, 19, 20, 21, 36, 39, 40, 41, 46, 47, 48;
- Non-Vegetated Areas: Class 3, original values: 22, 23, 24, 25, 30;
- Water Surfaces: Class 4, original values: 26, 27, 31, 33.

The Secondary Forest Age layer was also reclassified into five-year intervals (i. e., 1–5 years, 6–10 years, 11–15 years), up to the final interval of 36–40 years.

Then, for each of the approximately 56,000 pollinator occurrence points, we generated a 5 km buffer and extracted its bounding-box. Due the large number of points, trying to optimize processing speed, we used the buffer's bounding box rather than the buffer itself, leveraging the former's simpler geometry and reduced vertex count. Finally, each bounding box was used to calculate the area proportion of each of the four aggregated land cover classes (0-1 value interval for each class, and all 4 classes adding up to 1), along with areas occupied by secondary forest pixels, where present (similarly, 0-1 interval per age interval, all intervals adding up to 1). When no secondary forest occurred within a given bounding box, all age intervals were assigned zero values. And since secondary forest pixels in the forest age product are classified under the same forest category in MapBiomas annual mappings, the ‘Forest’ land cover class (Class 1) initially includes all forest types. To create distinct predictors, we calculated the area of secondary forest for each age bracket based on the Secondary Vegetation Age layer. This area was then subtracted from the total ‘Forest’ class area to yield a variable representing ‘primary and other-aged secondary forest’ to ensure mutual exclusivity and prevent double-counting of pixels..

Regarding the GBIF data, pollinator occurrence records were tallied for each bounding box, generating two independent variables for the Random Forest Regressor: (1) the total number of occurrences, corresponding to the sum of GBIF points inside a given bounding box, and (2) the number of unique pollinator genus for each bounding box. The genus level was selected over species due to frequent missing species-level identifications in occurrence records. This approach maintained methodological simplicity by avoiding null or undefined values in species designation.

Two Random Forest Regressor models were trained using Python's Scikit-learn library and Google Colab notebooks. They were set with 500 trees and a maximum depth equal to 10 to balance accuracy and computational efficiency, maintaining reproducibility on resource-limited systems. Also, the random state was assigned to an integer (42), ensuring that the same randomness is applied every time the model was run. Both models' predictors included the Mapbiomas aggregated land cover classes and the secondary forest age intervals proportions, and one of (1) occurrence counts, and (2) genera richness as the predicted variable. Variable importance was assessed via Mean Decrease in Impurity (MDI), or Gini Importance, quantifying each predictor's total impurity reduction across the random forest.

3. Results

3.1 GBIF Data Trends

A critical aspect of the GBIF database is its inherent oversampling bias in urban/peri-urban areas and near agricultural areas, at the expense of primary or secondary forests areas. This bias arises because occurrence records can derive from human observations, resulting in higher record frequency and density in densely populated regions compared to remote or inaccessible areas (Figure 1).

To quantify this sampling bias, we summed the pixels for each of the four aggregated MapBiomas classes and secondary forest age intervals across all 56,000 sampled bounding boxes. Our analysis reveals that non-vegetated areas accounted for over the double of the pixel count of Forest areas (Figure 2); closely followed by Agriculture pixels sum as the second most prevalent class. Among secondary forest age intervals, intermediate classes (6–10 years, 11–15 years, and 21–25 years) showed the highest pixel frequency distribution among all the age intervals (Figure 3), but is fair to notice that the difference between the largest and smallest number of pixels was less pronounced than for the grouped classes.

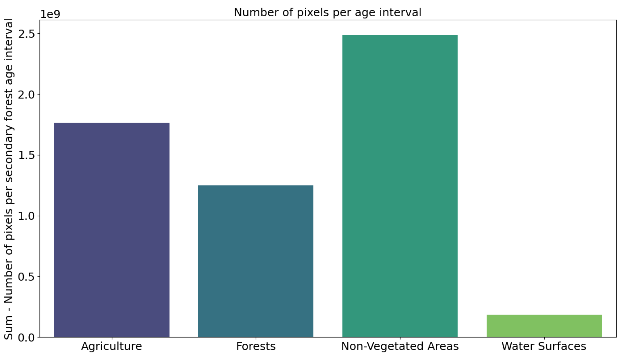

Figure 2. Total number of pixels for each of the Mapbiomas aggregated classes.

3.2 Random Forest Regressor Importance Analysis

Initially, the Random Forest model trained for the dependent variable Total occurrence count (Figure 4), which showed highest feature importance for Forest (MDI = 0.9), followed, distantly, by Non-Vegetated Areas (MDI = 0.04) and Water

Figure 3. Total number of pixels per secondary forest age interval, based on MapBiomas land cover classification. The bars represent the summed area (in pixels) occupied by each age class of secondary vegetation across the study region.

Surfaces (MDI = 0.02). Only one secondary forest interval (36–40 years) registered some importance, although minimal (MDI = 0.004). These results confirm the expected primacy of forested areas explaining for most for pollinator occurrences but simultaneously reflect GBIF's sampling bias, where Non-Vegetated Areas emerged as the second most important predictor. Notably, Water Surfaces demonstrated disproportionate influence, when taken into account its relative limited spatial coverage, suggesting a strong proportional relationship between pollinator occurrences and the presence of water bodies such as river streams, potentially mediated by enhanced tree density and biodiversity in riparian forests overall.

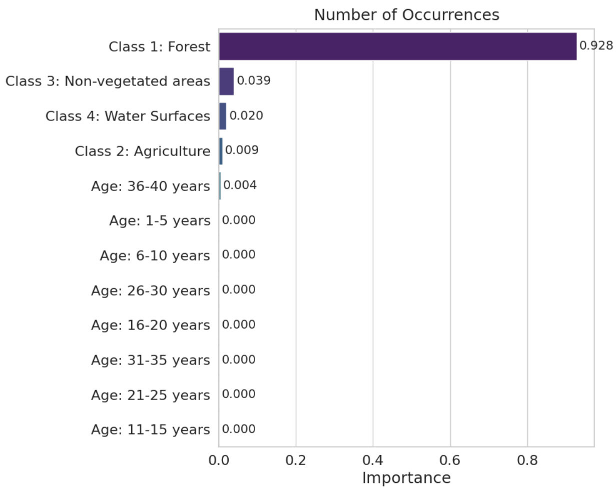

Figure 4. Relative importance of land cover classes and secondary forest age intervals in predicting the total number of bee individuals occurrences, based on a Random Forest regression model.

However, when the response variable is switched to the unique genus count, more interesting results emerge. This metric proved, overall, more robust to GBIF's sampling bias. As an aggregated measure, it inherently mitigates oversampling effects (e.g., multiple occurrences of identical genus count as only one 'occurrence'). The key findings for the Random Forest trained using unique genus count as dependent variable are: although the forest class remained dominant (MDI = 0.8), second and third most important classes were (a) 26–30 year secondary forest (MDI = 0.09) and (b) water surfaces class (MDI =

0.045). The GBIF bias is less pronounced as non-vegetated areas ranked fourth (MDI = 0.03), despite the highest spatial coverage. Regarding age intervals, no other interval, except 26-30 years exceeded the value of MDI of 0.002 and were excluded from the following interpretations (Figure 5).

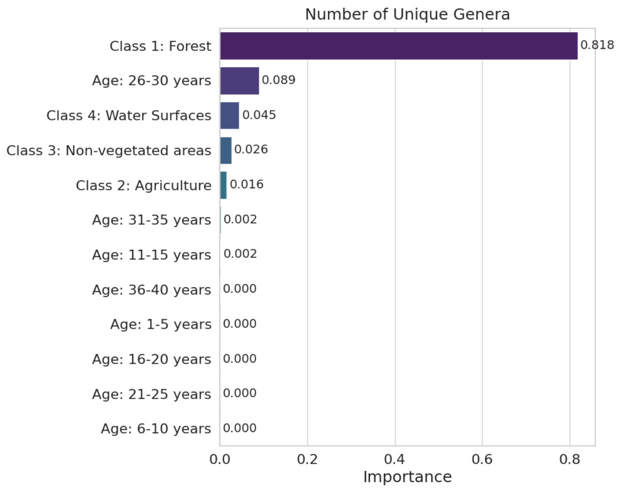

Figure 5. Relative importance of land cover classes and secondary forest age intervals in predicting bee genus richness in the Atlantic Forest biome, based on a Random Forest regression model.

4. Discussion

Our analysis reveals that forest cover is the principal determinant of bee diversity in the Atlantic Forest, with primary forests and late-stage secondary forests (specifically those in the 26–30 year age range) being the most influential predictors. This finding highlights the ecological importance of mature regenerating forests in restoring and supporting bee community composition. It also demonstrates that genus richness is a robust metric for landscape-scale diversity assessments, proving less sensitive to the inherent spatial sampling biases in the GBIF dataset, such as the raw occurrence data (Smith et al., 2021; Ulyshen et al., 2024).

Our results are consistent with established ecological theory, which posits that maturing ecosystems support higher biodiversity. As secondary forests advance in succession, they develop greater vertical stratification, microclimatic heterogeneity, and a wider array of niches that can support both generalist and forest-specialist species (Ollerton, 2017; Ammann et al., 2024). Previous studies in Neotropical regions have similarly shown that natural regeneration, particularly after the second decade, is crucial for restoring the habitat structure, resource availability, and functional stability of pollinator communities (Chazdon and Guariguata, 2016; Ramos-Fabiel et al., 2019; Ulyshen et al., 2024). The greater diversity of plants with staggered flowering times in more mature forests can also sustain bee populations throughout the year by reducing temporal gaps in resources (Ollerton, 2017; Ammann et al., 2024).

Beyond the age of individual forest patches, the broader landscape context is critical. Our findings align with evidence showing that heterogeneous mosaics of different successional stages, integrated by corridors, promote resource complementarity and facilitate pollinator movement at functional landscape scales (Kennedy et al., 2013; Moreira et al., 2015; Bottero et al., 2023).

A notable result of our study was the consistent importance of water surfaces in predicting pollinator richness. This suggests that hydrographic elements, likely associated with well-conserved riparian forests, act as local biodiversity nuclei, a pattern supported by research demonstrating the role of riparian corridors in restoring pollination services in fragmented landscapes (Kormann et al., 2016).

Despite the robustness of the methodological approach, this study has certain limitations. The spatial bias of GBIF occurrence data—favoring accessible and human-modified areas—remains a concern, potentially leading to underrepresentation of pollinator diversity in remote forest interiors (Chase et al., 2025). Although the use of genus richness helps to partially mitigate this bias, future efforts should prioritize validating large-scale models through standardized field surveys to improve the calibration and reliability of biodiversity estimates (Pereira et al., 2021; Chase et al., 2025).

The implications of our findings for conservation and ecological restoration are significant. Mature secondary forests (> 25 years old) are critical habitats for maintaining pollinator diversity and must be considered priorities in conservation planning and connectivity strategies, especially in fragmented landscapes where primary forests are scarce (Chazdon and Guariguata, 2016; Ulyshen et al., 2024). Additionally, the proximity of these mature forest patches should be strategically considered when establishing new restoration sites, as their presence may enhance species exchange and recolonization dynamics, thereby accelerating the recovery of pollinator communities and ecosystem services in regenerating areas.

In this context, adding a temporal dimension through the monitoring of restoration programs is crucial. Such monitoring is essential to understand the ecological dynamics and changes in species composition across successional stages, allowing for the evaluation of conservation and restoration outcomes over time (Lázaro et al., 2022). By tracking these changes, it becomes possible to verify the recovery of fundamental ecosystem services, such as pollination, ensuring that conservation strategies are effective and adaptive. The use of repeatable geoanalysis methods provides a scalable tool to facilitate these long-term biodiversity assessments (Galbraith et al., 2015; Gonzales et al., 2022).

Furthermore, our study offers a methodological contribution by integrating thematic maps (MapBiomas), biodiversity records (GBIF), and machine learning-based modelling (Random Forest) to assess diversity patterns at a continental scale. This approach presents itself as a replicable tool for other tropical and sub-tropical regions, allowing for standardized and cost-effective analyses to inform public policies, management plans, and biodiversity conservation initiatives (Galbraith et al., 2015; Hofmann et al., 2017; Gonzales et al., 2022).

5. Conclusions

Our analysis demonstrates that landscape structure, specifically forest cover, is the primary predictor of bee diversity in the Atlantic Forest. Crucially, the richness is most strongly associated with primary and late-stage secondary forests (>26 years old), whereas younger forests (<25 years) and landscapes dominated by anthropogenic areas support significantly lower diversity. The consistent importance of riparian areas also underscores the ecological role of hydrological corridors in supporting pollinator communities, reinforcing the value of heterogeneous landscapes for the ecosystem resilience. These findings align with ecological succession theory, demonstrating that maturing forests develop greater structural complexity and floral resources, sustaining more diverse pollinator communities, therefore reinforcing the urgent need to improve monitoring programs in mature forest remnants and incorporating long-term monitoring to track biodiversity recovery.

Methodologically, our study presents a scalable and cost-effective framework that integrates thematic maps, biodiversity records, and machine learning for large-scale landscape assessments. By using forest age as a proxy for successional dynamics, our approach offers spatially explicit insights to support conservation planning and monitor ecological restoration. Despite limitations in data coverage – especially in remote forest interiors – our results highlight the need for complementary field surveys and advocate for long-term biodiversity monitoring to guide evidence-based restoration. The approach presented here is cost-effective, replicable for other tropical biomes, and provides spatially explicit insights that are essential for monitoring restoration programs and developing more effective conservation policies, enabling a dynamic assessment of the recovery of vital ecosystem services such as pollination.

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