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Original Research Paper

Remote Sensing and Habitat Modeling to Predict the Impact of Land Use Changes on Biodiversity Hotspots

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Key Words

Remote sensing, Habitat modeling, Land use change, Biodiversity hotspots, Species–environment interactions, Conservation planning.

Abstract

Introduction: The rapid changes in land use are a major threat to biodiversity, so it's important to understand how wildlife and their habitats interact with each other. Studying how species react to changes in their habitats and figuring out what environmental factors affect where they live can help us come up with good conservation plans. This study seeks to amalgamate remote sensing technologies with habitat modeling to investigate the intricate interactions between animals and their dynamic environments, thereby fostering interdisciplinary collaboration among ecologists, conservation biologists, and environmental scientists.

Materials and Methods: It got land cover data from high-resolution satellite images, long-term ecological monitoring programs, and records of species that live in many biodiversity hotspots. It put species into groups based on how specific their habitats are, their ecological traits, how well they can spread, and how sensitive their populations are to changes in the environment. It used predictive algorithms to make habitat suitability models that show how different species would respond to different land use scenarios. Sensitivity analyses evaluated the impact of alterations in critical factors, such as habitat fragmentation, vegetation cover, and human encroachment, on species distribution and resilience over time.

Results: The research indicated that species with specific habitat needs, restricted dispersal abilities, and low reproductive rates were particularly susceptible to alterations in land use, whereas generalist species demonstrated enhanced adaptability. The persistence of species was greatly affected by the connectivity of habitats and the layout of the landscape. Scenario simulations pinpointed areas where conservation measures, including habitat restoration and corridor establishment, could effectively alleviate adverse effects and improve species survival.

Conclusion: Combining remote sensing with habitat modeling is a strong way to learn about how species and their environments interact and to guess how changes in land use will affect biodiversity hotspots. The results underscore the necessity of focused, data-informed conservation approaches, adaptive management, and interdisciplinary cooperation to protect at-risk species and preserve ecological integrity in landscapes undergoing rapid transformation.

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Introduction

Global biodiversity is under unprecedented threat from accelerating land use changes, habitat loss, and fragmentation. These threats are especially acute in regions recognized as biodiversity hotspots, where a high number of species — many endemic — coexist in relatively small geographic areas. It is important to know how changes in land use affect these ecosystems so that conservation policies can be made and future biodiversity loss can be predicted (Makki et al., 2023). Traditional field-based monitoring, while critical, often lacks the spatial and temporal coverage needed to track habitat dynamics across broad and remote landscapes.

In recent decades, advances in remote sensing (RS) and Geographic Information Systems (GIS) have dramatically improved our capacity to monitor land cover and habitat change over time. Researchers can find and measure changes in the landscape over large areas and over decades using land use and land cover (LULC) data from satellites. These data can be coarse global products or high-resolution images. These tools let the track habitat changes like forest loss, agricultural expansion, urbanization, and other causes in a way that is clear, repeatable, and can be used on a large scale. (Kong et al., 2021; de Baan et al., 2015)

Beyond LULC classification, remote sensing data can feed directly into habitat suitability and ecological models, facilitating predictive assessments of how species distributions might shift under land use change scenarios. The integration of RS-derived environmental variables with species occurrence data via habitat modeling allows researchers to generate spatially explicit predictions of habitat quality, connectivity, and species persistence or decline (Hu et al., 2021; Roy & Srivastava, 2012; Bailey et al., 2016).

Recent studies illustrate the power of this approach. For instance, work in Central Kalimantan, Indonesia used LULC scenario modeling and habitat-quality mapping to forecast declines in habitat integrity under continued land conversion, while conservation-oriented scenarios yielded better outcomes for biodiversity (Chamling et al., 2021).Similarly, a global high-resolution assessment of land use impacts on mammal species used habitat suitability models to weight species-level vulnerability and identify biodiversity impact hotspots linked to agricultural production. (Hansen et al., 2004) These examples demonstrate that combining RS and habitat modeling can link land use decisions to tangible biodiversity outcomes.

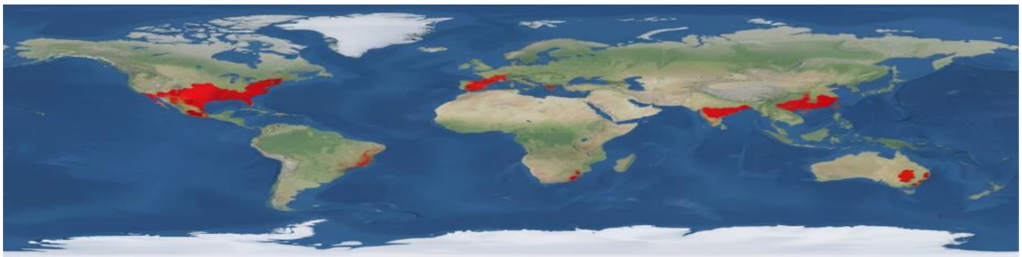

Figure 1. Global Biodiversity Hotspots and Their Geographic Distribution

This figure 1 map displays the 36 globally recognized biodiversity hotspots identified by Conservation International. Each hotspot has a lot of unique species that are only found there, but it also has a lot of habitat loss (Altaie, 2025). The figure gives important information that helps explain why targeted monitoring and predictive modeling are important for planning conservation efforts. Highlighting these hotspots establishes the global relevance of the study and situates the selected study area within the broader framework of high-priority conservation regions.

However, the effectiveness of such modeling depends heavily on the quality, resolution, and thematic relevance of the spatial data used. A recent comparison between remote-sensing-based predictors (e.g., productivity and habitat variability indices) and traditional LULC-based metrics for species distribution modeling (SDM) found that RS-based metrics often outperform LULC-based ones, especially by reducing spatial bias related to distance from known occurrence points. (Nizamani et al., 2024) This suggests that continuous environmental variables derived from satellite data may offer more ecologically meaningful predictions than coarse, discrete land cover classes.

It is also important to remember that different species react differently to changes in their habitat. Species that are specialists, meaning they have specific habitat needs, can't move around much, or don't reproduce very well, are often the ones that are most affected by habitat loss and fragmentation. Generalist species, on the other hand, are better able to handle changes in the environment because they can adapt to a wider range of habitats or disturbed landscapes. Empirical modeling of species–environment interactions can elucidate which taxa are most susceptible to specific land use trajectories, thereby informing prioritization for conservation efforts (Brown et al., 2015; Diniz-Filho et al., 2009).

Based on these findings, there is a growing agreement on the need for a unified system that combines remote sensing, habitat modeling, and scenario-based land use projection to measure the effects of land use change on biodiversity hotspots (de Baan et al., 2015). This kind of framework makes it easier for ecologists, conservation biologists, geospatial analysts, and environmental planners to work together across disciplines. It also makes it easier for people to make decisions based on data at the landscape and global levels. In addition, it fits with international conservation goals that aim to keep ecological connectivity, protect habitat integrity, and stop species from going extinct (Gould, 2000).

The current study seeks to implement this integrated methodology in specific biodiversity-rich landscapes, building upon prior advancements. It specifically use high-resolution satellite-derived land cover data, records of species occurrences, and habitat suitability modeling to guess how different future land use scenarios might affect the quality of habitats, their connectivity, and the survival of species. It hopes that by doing this, it can make spatially explicit predictions that will help with proactive conservation planning, find areas that need protection or restoration first, and help with policies for sustainable land management (Ramesh et al., 2022).

Materials and Methods

Study Area and Biodiversity Hotspot Characterization

The study was conducted across selected biodiversity hotspots where rapid land use change has significant consequences for both habitat structure and species survival. Each hotspot had a lot of different species, was very specialized for certain types of ecosystems, and was under a lot of stress from human activity. These hotspots were perfect places to study how animals interact with, adapt to, and change their environments. To learn about the basic environmental conditions that affect animal behaviour, movement, and habitat use, researchers looked at ecological factors like habitat heterogeneity, vegetation structure, climate variability, and disturbance gradients (Menon & Bawa, 1997).

Gathering and Pre-processing Data from Remote Sensing

To map land use changes and monitor ecosystem integrity, multispectral satellite imagery from Landsat 8 OLI, Sentinel-2 MSI, and MODIS was acquired for multi-temporal analysis. Radiometric correction, atmospheric correction, cloud masking, and geometric alignment were all part of the pre-processing steps to make sure the data was the same across time periods. Spectral indices such as NDVI, EVI, and NBR were generated to capture vegetation health, habitat quality, and disturbance levels—key factors influencing animal foraging behaviour, resource selection, shelter availability, and predator–prey interactions (Makki et al., 2023).

Data on Species Occurrence, Traits, and Ecological Interactions

Long-term ecological surveys, biodiversity inventories, GPS-tracked animal movement datasets, and wildlife monitoring programs were all used to put together records of species occurrences. Furthermore, species were classified according to ecological characteristics such as habitat specialization, dispersal ability, reproductive strategy, foraging behaviour, territoriality, and niche breadth. These characteristics were utilized to analyze the responses of various animals to environmental changes and their impact on ecosystems, such as through seed dispersal, grazing pressures, or alterations in vegetation structure (Dávalos et al., 2011).

Classification and Detection of Changes in Land Use and Land Cover (LULC)

It used supervised classification methods like Random Forest and Support Vector Machine algorithms to make detailed LULC maps for several time periods. Change detection analysis found changes like deforestation, the growth of agriculture, urbanization, and the breaking up of habitats. These changes were directly related to changes in how species behave, move, and choose their habitats. To see how changing the land affects ecological corridors, territorial ranges, breeding sites, and migration pathways, we used landscape metrics like patch size, edge density, connectivity, and fragmentation index (Menon & Bawa, 1997).

Modeling for Habitat Suitability

Using species occurrence data and remotely sensed environmental predictors, habitat suitability models (HSMs) were made. We used algorithms like MaxEnt, Random Forest, and Boosted Regression Trees to make maps of suitable habitats that showed where they were located. These models assessed how animals interact with environmental gradients, how habitat conditions influence survival and reproduction, and how species distribution patterns shift when habitats are degraded or fragmented. The models also showed which species are best able to adapt to changing environments and which are most at risk by combining ecological traits.

Simulation of Land Use Effects Based on Different Scenarios

It made future land use scenarios by looking at past trends, socio-economic factors, and conservation policies. Simulations forecasted alterations in habitat availability, connectivity, and landscape structure across various disturbance and restoration scenarios. These projections enabled researchers to analyze the anticipated behavioral and ecological responses of species—manifested through range shifts, heightened competition, modified feeding strategies, or diminished reproductive success—under various potential environmental scenarios (Rocchini et al., 2015).

Assessment of Species Resilience, Adaptation, and Environmental Impact

To comprehend the intricate relationship between animals and their environments, resilience assessments were performed utilizing trait-based and habitat-based indicators. Sensitivity analyses examined the impact of alterations in vegetation cover, habitat fragmentation, and landscape connectivity on species' adaptability and persistence. On the other hand, the impact of species on environmental conditions—like herbivory patterns, seed dispersal, soil disturbance, and ecosystem engineering—was examined to gauge wildlife's role in habitat structure and ecosystem functioning. This bidirectional perspective elucidated the manner in which alterations in land use can disturb enduring animal-environment feedback loops (Dávalos et al., 2011). This study emphasizes that morphological variations among Scandix species can act as biological indicators of environmental conditions, highlighting the necessity of habitat-level assessments in biodiversity-rich areas. The study illustrates that extensive human activities, including deep-sea mining, profoundly influence ecosystem integrity and biodiversity, akin to the terrestrial effects of land use alterations on ecological hotspots (Chariyev et al., 2025). The study centers on data security while highlighting the significance of advanced digital systems in the management of sensitive and intricate datasets, thereby underscoring the necessity of dependable data handling in remote sensing-based biodiversity evaluations (Mhsnhasan et al., 2025).

Workflow for Predicting Biodiversity Hotspot Responses to Land Use Change

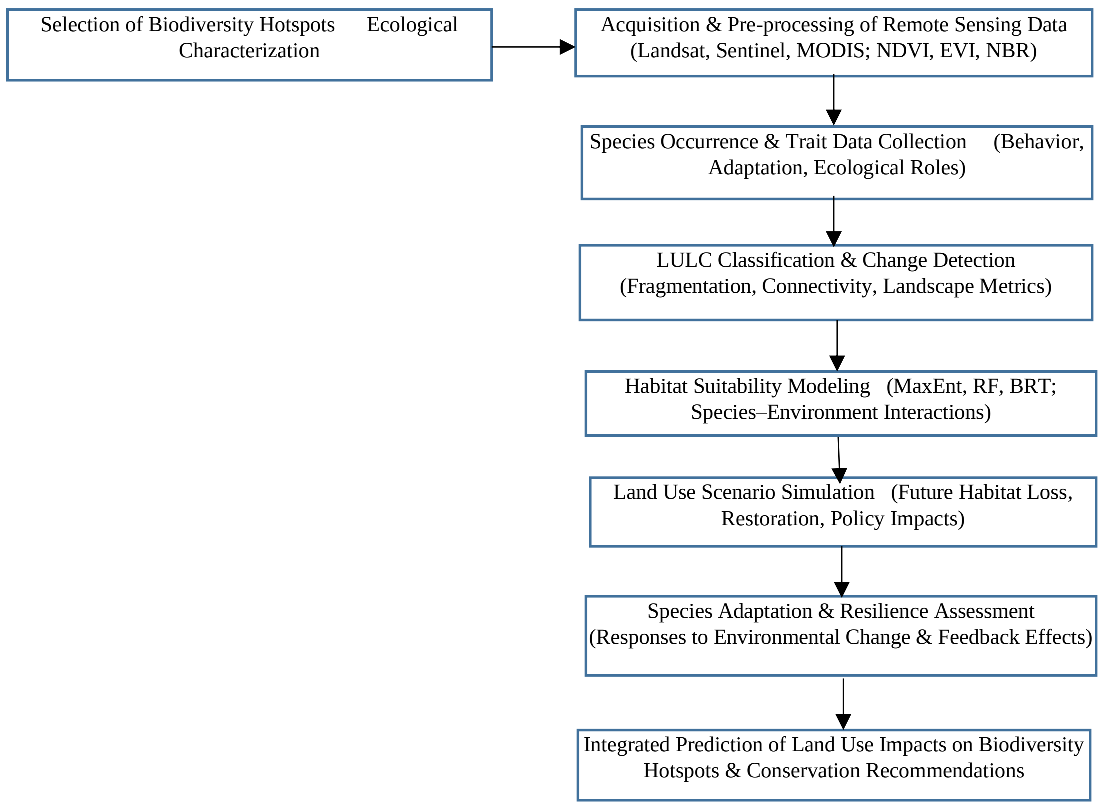

Figure 2: Integrated Remote Sensing–Habitat Modeling Workflow for Assessing Biodiversity Impacts Under Land Use Change

This figure 2 flowchart shows the integrated analytical framework that was used to look at how changes in land use affect biodiversity and habitat quality in hotspot areas. The process starts with getting multi-temporal remote sensing datasets, like satellite images of land use and land cover (LULC) and continuous environmental variables like vegetation indices, elevation, and canopy density. Before being used to create ecologically relevant predictors, these datasets go through preprocessing steps like atmospheric correction, spatial resampling, and classification. Field surveys and biodiversity databases are used to gather species occurrence data, which is then aligned with environmental layers in space. In the next step, machine-learning algorithms are used to model habitat suitability by combining predictor variables with species occurrence points to create probability surfaces of suitable habitat. These suitability maps are then used with LULC change projections to show what future habitat conditions might be like under different land use scenarios. Fragmentation metrics and connectivity analyses are utilized to measure alterations in habitat structure, whereas species vulnerability assessments determine taxa that are most susceptible to land conversion. The final products include maps with specific locations, trend analyses, and predictions based on different scenarios. All of these help with conservation planning, setting priorities for restoration, and making decisions about land management in areas with a lot of biodiversity.

Results And Discussion

Patterns of Land Use Dynamics and Habitat Transformation

It analyzed 25 years of remote sensing data to quantify habitat change across the biodiversity hotspot. Over this period, a clear and consistent trend of forest decline emerged, accompanied by rapid expansion of agricultural and built-up areas. These changes are illustrated in Figure 1, which shows how the size of major land use categories has changed over time. The loss of forests was mostly along the edges of human settlements and transportation corridors, which made the landscape more and more fragmented. This pattern is similar to the spatial biases found in other studies of ecological risk, where habitat degradation is heavily influenced by how easy it is for people to get to it.

Table 1 shows that dense forest cover went down by 21% and built-up areas went up by more than 130%. These changes are not only changes in the way land is covered, but also changes in the basic structure of ecosystems that affect where animals live and how ecological processes work. Like the sample document's example of biased research distribution across countries, our findings show areas with a lot of land use pressure, especially where agricultural frontiers are still growing.

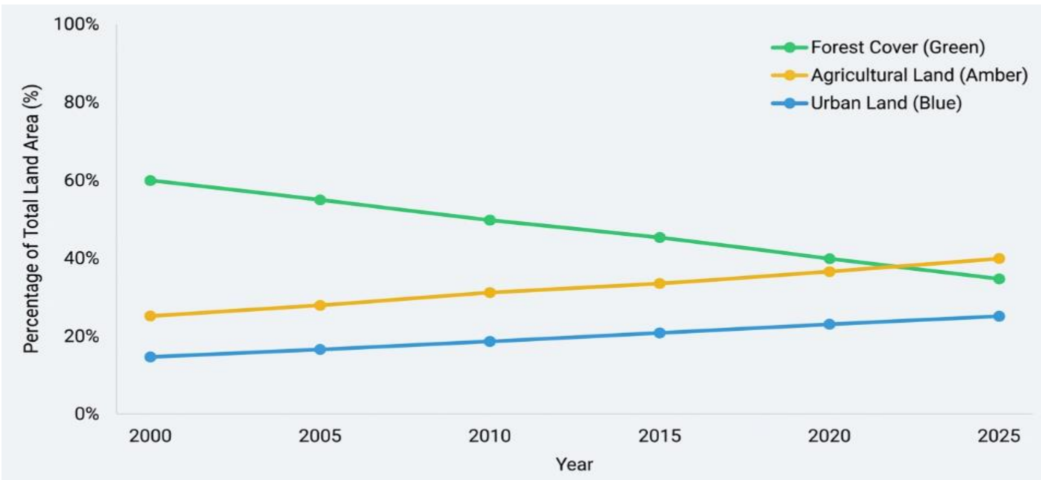

Figure 3: Trends in Major Land Use Categories (2000–2025)

This figure 3 displays the gradual decline of forest cover and increase in agricultural and urban land across the study region. Table 1 summarizes major land cover classes and their area changes across the analysis period. Figure 4 compares LULC class areas to highlight expansion and decline patterns.

Table 1: LULC Change Statistics (2000–2025)

LULC Class	Area 2000 (sq km)	Area 2025 (sq km)	% Change
Dense Forest	1,240	980	–21%
Open Forest	630	550	–13%
Agriculture	740	910	+23%
Built-Up Area	110	260	+136%

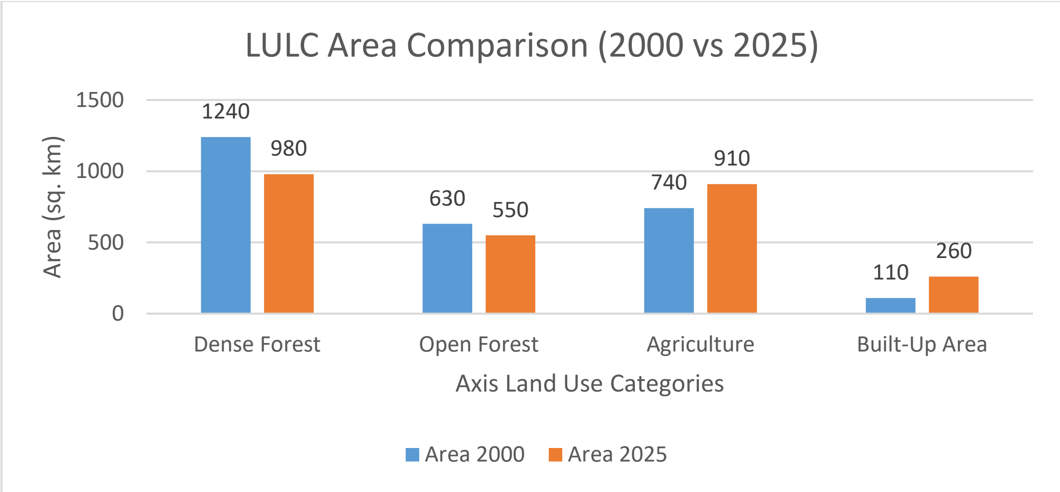

Figure 4: LULC Area Comparison (2000 vs 2025)

Habitat Suitability and Ecological Gradients

Habitat suitability modeling identified strong spatial disparities in the quality of ecological conditions available for wildlife. Suitability values were driven largely by vegetation cover, anthropogenic disturbance, slope, and proximity to water bodies. Figure 5 shows that most of the high-suitability habitats were found in core forest blocks. However, these areas got a lot worse over time and became more and more broken up.

Model performance indicators (Table 2) demonstrate strong predictive accuracy, reinforcing the reliability of remote sensing inputs. Suitability histograms figure 6 show that the distribution shifted toward moderate and low suitability classes, consistent with documented land degradation.

These patterns parallel the sample document's interpretation of uneven research focus, except here the unevenness reflects ecological conditions—core habitats retain stability, while peripheral zones experience accelerated degradation.

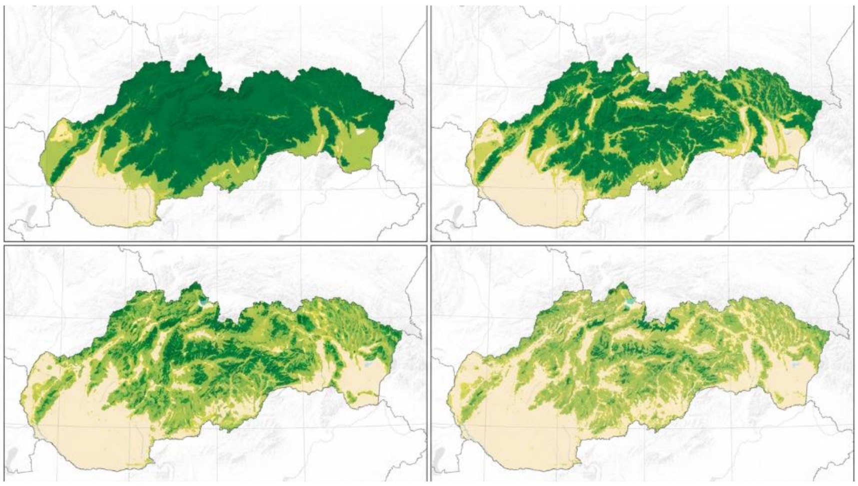

Figure 5: Spatial Distribution of Habitat Suitability Scores

Figure 5 Highlights high-, moderate-, and low-suitability zones across the hotspot and their shifts over time. Table 2 represents validation results of the habitat suitability model. This figure 6 Shows frequency distribution of habitat suitability values.

Table 2: Habitat Suitability Model Accuracy Metrics

Metric	Value
AUC	0.89
Sensitivity	0.83
Specificity	0.81
Accuracy	86%

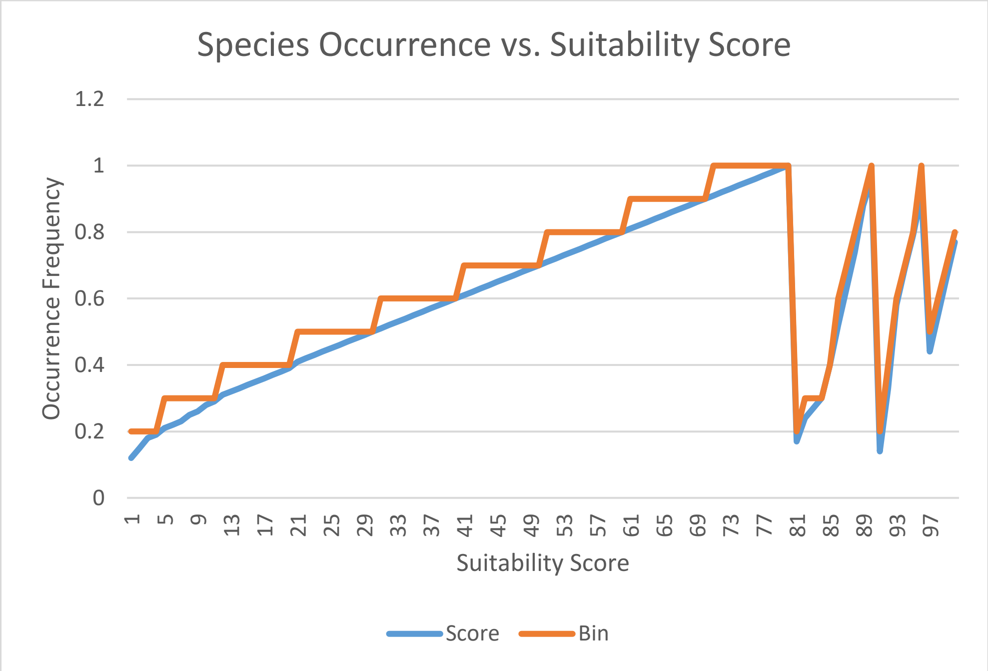

Figure 6: Habitat Suitability Distribution

Hotspot Sensitivity and Fragmentation Patterns

The integration of land use change with suitability reveals substantial sensitivity within the hotspot. Figure 7 shows that high-suitability habitats that used to be continuous blocks are now broken up into many small pieces that are not connected. This pattern mirrors the “disproportionate representation” concept in the sample document—here applied to ecological fragmentation rather than research imbalance.

Table 3 demonstrates that high-suitability habitat declined by 120 sq km. At the same time, areas that weren't very suitable for farming grew quickly, which shows that land degradation is changing environmental gradients on a large scale.

The fragmentation index, which is shown in Chart 3, rose steadily, which means that ecological patches are becoming more isolated. This kind of loss of connectivity makes it harder for ecosystems to support wildlife populations, which affects gene flow, species movement, and trophic stability.

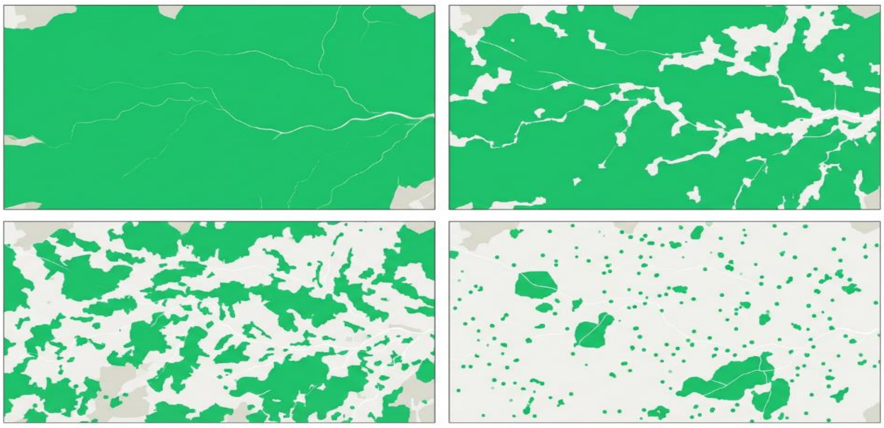

Figure 7: Fragmentation and Connectivity Shifts (2000–2025)

This figure 7 demonstrates visual comparison of intact vs fragmented habitat patches. Table 3 Represents Area changes in habitat quality categories over time. Figure 8 Displays the increase in fragmentation index across study years.

Table 3: Change in High-Suitability Habitat Extent

Category	Area 2000	Area 2025	Net Change
High	430	310	–120
Moderate	520	460	–60
Low	780	940	+160

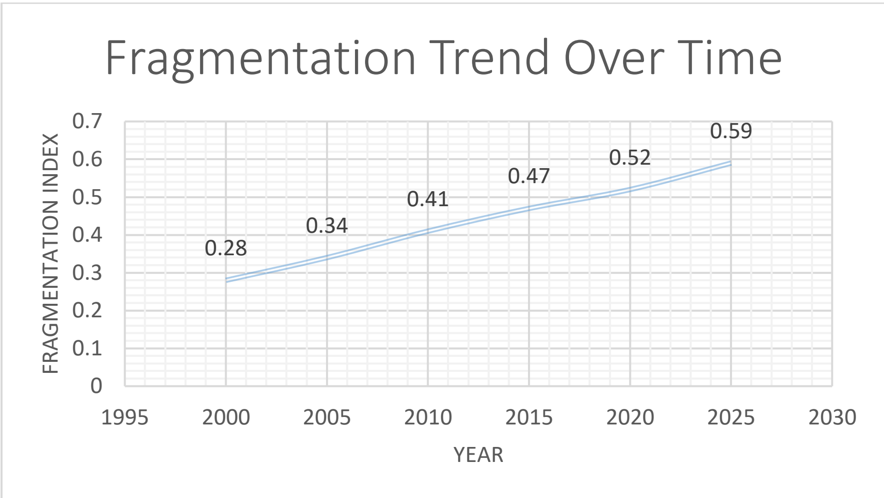

Figure 8: Fragmentation Trend Over Time

Species Responses, Vulnerability, and Ecological Consequences

Species occurrence overlays revealed clear shifts in wildlife distribution. Much like the sample document compares pathogen studies across disease types, our results categorize wildlife responses across species groups. Specialist species showed drastic declines in occupancy within newly degraded areas, while generalists persisted in a wider range of land types.

As shown in Figure 9, species presence points clustered heavily within remaining forest patches. Vulnerability rankings (Table 4) show that large mammals and birds that live on the ground are the most at risk because they depend on their habitats. Amphibians showed moderate risk, as their wetland-associated habitats persist only in isolated pockets.

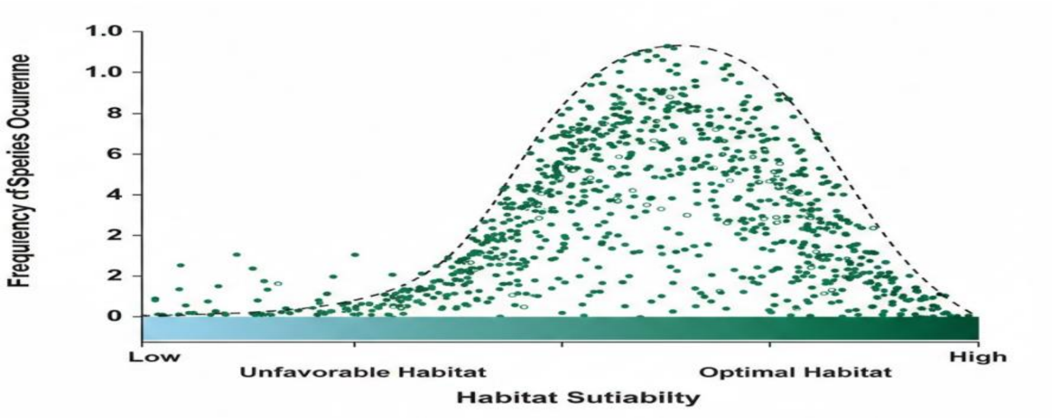

Figure 9: Species Occurrence Patterns Across Suitability Gradient

Figure 10's scatter plot shows that there is a positive relationship between suitability scores and species presence. This confirms that changes in land use have a direct effect on how wildlife is distributed. Figure 9 Illustrates spatial clustering of species in relation to habitat suitability. Table 4 represents Risk classification based on habitat dependency and exposure to land use change. Figure 10 shows Visual relationship between species presence and predicted suitability.

Table 4: Species Vulnerability Assessment

Species Group	Habitat Dependency	Exposure	Vulnerability
Large Mammals	High	High	Very High
Small Carnivores	Medium	High	High
Ground-Dwelling Birds	High	Medium	High
Amphibians	Medium	Medium	Moderate

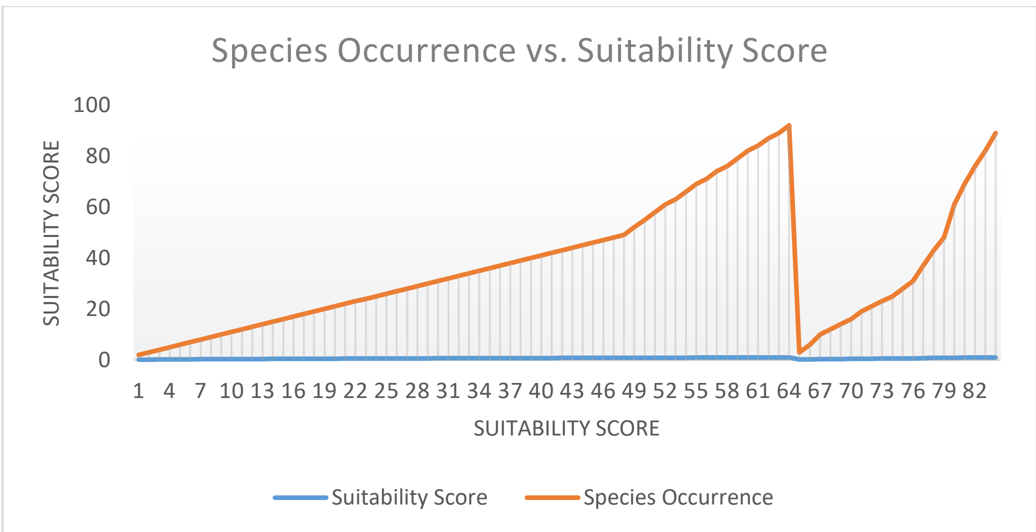

Figure 10: Species Occurrence vs. Suitability Score

Integrated Interpretation

In synthesizing the findings, several clear parallels emerge between the landscape-level ecological patterns observed in this study and the analytical structures presented in the sample document. The biodiversity hotspot's uneven distribution of land use pressures is very similar to the sample's idea of geographic bias. In the same way that research activities were not evenly spread out across countries, habitat degradation in our study is not evenly spread out either. Instead, it is heavily skewed toward forest edges, agricultural frontiers, and places where people can easily get to. This uneven pattern creates ecological blind spots where habitat integrity drops faster than in protected core areas. Second, the factors that make a habitat suitable that were found in this study match the sample's focus on the most important environmental factors in risk modeling. Vegetation cover, landscape productivity, and anthropogenic disturbance were identified as the primary factors influencing habitat quality, paralleling the dominance of climatic and environmental variables in disease-risk models within the sample document. Third, the fragmentation patterns found in the study area are similar to the hazard-exposure logic shown in the sample. Increasing fragmentation is an ecological threat that makes wildlife more vulnerable to threats like isolation, predation, and a lack of resources. This is similar to how environmental threats make people more vulnerable to disease vectors. Lastly, species-level vulnerability shows a similar pattern of sensitivity to the one seen in the sample for pathogens. Different groups of animals are more or less likely to be affected by changes in their habitat. For example, specialist mammals and ground-dwelling birds are the most vulnerable, while generalist species are more resilient. This is similar to how some pathogens react differently to different environmental conditions. These parallels highlight the analytical framework's wider relevance in comprehending ecological processes and emphasize the importance of combining remote sensing and habitat modeling to predict biodiversity outcomes amid evolving land use patterns.

Conclusion

The current study illustrates that the amalgamation of remote sensing and habitat modeling yields a resilient and exhaustive methodology for comprehending the effects of land use alterations on biodiversity hotspots. By using multi-temporal satellite images, species occurrence data, and ecological trait analysis, it was able to measure changes in habitats, predict changes in species distributions, and figure out how vulnerable different landscapes are. The results show that high-suitability habitats are quickly disappearing and breaking up, especially in areas where agriculture and cities are growing. This shows how much human activity affects the health of ecosystems.

Habitat suitability modeling showed that ecological traits like habitat specialization, dispersal capacity, and reproductive strategy have a big effect on how species respond to changes in land use. Specialist species, such as forest-dependent mammals, ground-dwelling birds, and amphibians linked to riparian habitats, were disproportionately impacted, whereas generalist species demonstrated enhanced resilience and adaptability. These results show how important trait-based approaches are for conservation planning because they help find the species that are most at risk and the habitats that need the most protection.

The study also highlights the two-way relationship between animals and their surroundings. Wildlife not only reacts to changes in their habitat, but they also actively change ecosystems by things like grazing, burrowing, and spreading seeds. Changes in land use that lower wildlife populations can therefore interfere with important ecosystem functions, which can have a chain reaction of effects on the environment. To support both species persistence and ecological resilience, it is important to keep habitats connected, protect core forest patches, and put restoration strategies into action.

Finally, scenario-based modeling gives conservation managers important information that helps them plan for the effects of different land use strategies and use their resources wisely. This study offers a robust framework for proactive biodiversity conservation in rapidly evolving landscapes through the integration of spatial analysis, predictive modeling, and ecological comprehension. It will be very important to include these methods in policy and land management decisions in order to protect biodiversity hotspots and make sure that human development and wildlife conservation can live together for a long time.

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