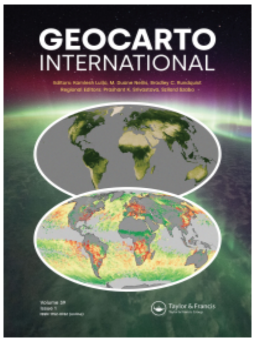

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RESEARCH ARTICLE

Wildlife persists in the Midlands Black Rhino Conservancy, Zimbabwe, but requires an emergency conservation plan

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ABSTRACT

The persistence of wildlife in the Midlands Black Rhino Conservancy (MBRC), Zimbabwe, highlights both species resilience and landscape value, yet escalating anthropogenic pressures demand urgent conservation action. This study aimed to: (i) model land use/land cover (LULC) changes from 1985–2055 using multi-decadal Landsat imagery; (ii) assess the frequency, distribution and impact of fires between 2010–2025; (iii) evaluate vegetation disturbance from mining through a Bayesian framework; and (iv) determine the status and abundance of key wildlife via systematic transect surveys. Future scenarios were predicted using cellular automata–artificial neural networks (CA-ANN). Fire regimes were analysed using Landsat, FIRMS and dNBR indices, while Bayesian regression models quantified mining impacts. Species distribution was modelled with MaxEnt. Results show shrinking suitable habitats, with many species increasingly confined to fragmented populations. Despite these challenges, the findings underscore opportunities for proactive biodiversity management through robust local and international conservation policies.

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Land use and land cover change; habitat fragmentation; remote sensing and GIS; fire regime dynamics; mining-induced disturbance; species distribution modelling

1. Introduction

Wildlife populations in African savannah ecosystems are increasingly threatened by a combination of anthropogenic and natural pressures, including habitat loss, land-use change, resource extraction and fire disturbances (Luiselli et al. 2025). The processes of habitat loss and fragmentation represent some of the most pervasive global drivers of biodiversity decline, posing severe challenges to species persistence, ecosystem functioning and ecological resilience (Mutanga and Gandiwa 2023). These phenomena have consequently emerged as central themes of investigation within the disciplines of ecology and conservation biology (Wiens et al. 2010), where researchers seek to understand their mechanisms, quantify their impacts

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and develop strategies for biodiversity conservation and sustainable ecosystem management (Macdonald and Willis 2013).

The persistence of wildlife populations in the Midlands Black Rhino Conservancy (MBRC) landscape demonstrates remarkable ecological resilience; however, their survival remains precarious in the absence of deliberate and urgent conservation interventions. Human-induced processes such as habitat loss and fragmentation, environmental contamination, climate change, overexploitation and the introduction of invasive species are exerting increasing pressures on the persistence of wild populations (Chase et al. 2016; Palma et al. 2024; Henrich et al. 2025). Mining activities within and around the conservancy have led to extensive vegetation clearance, soil degradation and habitat fragmentation, directly reducing the carrying capacity of the ecosystem (Antwi et al. 2008; Schueler et al. 2011). Concurrently, the expansion of agriculture and associated settlement encroachment has further restricted available habitats, heightening competition for resources between wildlife and human activities (Chanyandura et al. 2021; Mugaviri et al. 2022). These pressures have not only eroded habitat quality but have also increased the susceptibility of the area to secondary disturbances such as recurrent fires and illegal resource extraction (Mugaviri et al. 2022). While populations of sable antelope (*Hippotragus niger*), African buffalo (*Syncerus caffer*), black rhinoceros (*Diceros bicornis*), plains zebra (*Equus quagga*), impala (*Aepyceros melampus*) and blue wildebeest (*Connochaetes taurinus*) continue to exist in the MBRC, they are increasingly confined to fragmented patches of suitable habitat (Mugaviri et al. 2022). The ecological importance of the MBRC is underscored by its capacity to harbour flagship species such as the black rhinoceros, which is globally listed as Critically Endangered on the IUCN Red List, making its survival in the MBRC of both national and international conservation concern. The black rhinoceros, in particular, faces a heightened risk of local extinction without targeted management, given its slow reproductive rate and susceptibility to habitat loss and poaching threats (Chanyandura et al. 2021). Since the conservancy's formation, changing land use on and around member properties, notably expansion of mining activities and conversion to crop farming has fragmented the once-continuous rhino habitat. This fragmentation has produced a highly clumped (aggregated) population structure in which rhino occur in isolated pockets rather than a well-connected metapopulation. The resulting spatial configuration increases vulnerability to localized population crashes and undermines the original objectives of the consortium. These ecological realities necessitate a re-evaluation of conservation priorities in the MBRC. The interplay of land use change, fire disturbance and mining-induced habitat degradation calls for an evidence-based emergency conservation plan. Such a plan should not only aim to secure the persistence of existing wildlife populations but also enhance habitat connectivity, mitigate human–wildlife conflicts and strengthen community participation in conservation governance. In this context, an integrated approach combining remote sensing, ecological modelling and field-based wildlife assessments provides an essential scientific foundation for guiding effective conservation strategies in the MBRC.

The black rhinoceros (Diceros bicornis) is a focal conservation species within the Midlands Black Rhino Conservancy (MBRC), and its long-term persistence is strongly dependent on landscape structure, vegetation composition and disturbance regimes. In this study, black rhino conservation is explicitly embedded within the integrative modelling framework, with land use and land cover dynamics, fire frequency and severity, mining disturbance and habitat suitability treated as interacting drivers shaping species-specific habitat conditions rather than generic biodiversity outcomes. By explicitly centreing the black rhinoceros in the analysis, the study moves beyond landscape-level change assessment to evaluate how past and projected environmental transformations influence the spatial configuration, quality and connectivity of habitats critical for black rhino movement, foraging and refuge within MBRC. The conservation status of wildlife species within the MBRC has remained uncertain since the most recent formal assessment conducted in 2020. To address this knowledge gap, field surveys were undertaken in 2023, 2024 and 2025 to generate updated information on species status. While some species may continue to persist within the MBRC and adjoining landscapes, their precise conservation status has previously lacked clarity. Nevertheless, opportunities still exist to mitigate biodiversity decline through the implementation of robust conservation policies at both local and international scales, as highlighted by the Kunming-montreal global biodiversity framework (Framework 2022; Henrich et al. 2025). Such policy frameworks require accurate and timely wildlife population data to inform evidence-based decision-making (Framework 2022). Given that population trajectories are highly dynamic and often subject to abrupt changes under escalating human disturbances, wildlife monitoring systems should be designed to rapidly generate reliable information on species status (Gaynor et al. 2018). This, in turn, would facilitate adaptive management interventions and improve conservation outcomes. Advances in remote sensing technology have enabled the large-scale and efficient acquisition of land use land cover (LULC), and wildlife monitoring data (Luiselli & Pacini, 2025). However, the subsequent data processing and classification stages present significant analytical bottlenecks (Camps-Valls 2009). Recent developments in machine learning and deep learning methodologies have attracted substantial attention due to their potential to significantly reduce the time and computational effort required for image processing. Landsat data has often been used in detecting the dynamics of land cover such as assessment of surface mining extent and reclamation as well as tracking land area change in places with underground mining.

Globally, human-induced activities constitute the dominant drivers of environmental transformation (Coetzee and Chown 2016). Alarmingly, the contemporary pace of vertebrate extinction is reaching magnitudes comparable to those recorded during the most catastrophic mass extinction events in geological history (Henrich et al. 2025). While mining promises significant economic advancement in West Africa, it simultaneously poses profound threats to biodiversity and the integrity of natural ecosystems (Rehman et al. 2021). In Ghana, for instance, gold mining contributes approximately 5.7% to the national GDP; however, the proliferation of illegal mining activities has generated notable adverse consequences (Schueler et al. 2011; Gbedzi et al. 2022). These include forest degradation, depletion of soil nutrients, destruction of wildlife habitats, contamination of water bodies and overall threats to human health through diminished environmental quality (Schueler et al. 2011; Gbedzi et al. 2022). The principal pathways driving forest loss encompass agricultural expansion, mining and the development of mining-related infrastructure, as well as urban growth (Gbedzi et al. 2022). There is unequivocal evidence that mining is globally responsible for extensive deforestation (Antwi et al. 2008). Terrestrial biodiversity is projected to be primarily impacted by land use changes within the next century (Antwi et al. 2008).

At the landscape scale, spatial variation in fire regimes contributes significantly to heterogeneity (Zwolak 2009). Large-scale fires exhibit spatial variation in intensity, creating post-fire mosaics of vegetation patches with differing severities (Chia et al. 2016). Such fire-induced heterogeneity can strongly influence animal populations by determining the ecological context of habitats within affected sites (Kalies et al. 2010). For example, mosaics of burnt and unburnt vegetation may benefit species capable of moving between fire-age classes to exploit diverse resources, such as shelter and food (Santos et al. 2014). Within these heterogeneous landscapes, unburnt refuges often serve as critical sanctuaries for species that would otherwise be extirpated or rendered scarce in severely burned areas (Rey et al. 2019). The spatial extent and proximity of these refuges play a decisive role in shaping the pace and success of population recovery in fire-impacted regions (Rey et al. 2019). Large-scale environmental disturbances are known to exert profound ecological impacts, yet such effects often deviate from initial expectations (Banks et al. 2011). Thus, understanding the immediate ecological consequences of major disturbances, such as wildfires, on individuals, populations and habitats is vital to anticipating the impacts of predicted increases in disturbance frequency under future climate scenarios (Banks et al. 2011).

Although the Midlands Black Rhino Conservancy (MBRC) continues to support remnant populations of ecologically significant wildlife species, these populations are increasingly confined to fragmented and vulnerable habitats. This situation raises profound concerns regarding their long-term viability and underscores the urgent need for evidence-based conservation interventions. Recent ecological assessments and field-based surveys indicate that wildlife within the MBRC persists under precarious conditions. Without the implementation of a comprehensive emergency conservation framework, these populations face a heightened risk of decline and potential local extirpation. The Conservancy has however faced a number of challenges (i) management and enforcement complications: fragmented ownership and land-use mosaics make coordinated anti-poaching patrols, monitoring and response more difficult and expensive (ii) heightened human–wildlife conflict: expansion of farming and mining brings people and livestock closer to rhino habitat, increasing negative interactions and pressures on the species (iii) loss of landscape connectivity: blocked or degraded movement corridors limit dispersal and recolonization between subpopulations (iv) Genetic risks: isolation can reduce gene flow, increasing inbreeding and reducing adaptive potential (v) Increased risk of localized extirpation: small, clumped groups are more likely to decline to unsustainable levels following disease outbreaks, poaching incidents, or habitat disturbance. While the MBRC was created to centralize protection and reduce poaching risk, contemporary land-use change (mining and agriculture) has fragmented habitat and produced a clumped population structure that threatens connectivity, genetic health and population resilience—compromising the consortium's founding conservation goals.

The study aims to state potential proactive biodiversity management. To achieve this aim, we (i) modelled land use/land cover (LULC) changes from 1985–2055 using multi-decadal Landsat imagery; (ii) assessed the frequency, distribution and impact of fires between 2010–2025; (iii) evaluated vegetation disturbance from mining through a Bayesian framework; and (iv) determine the status and abundance of key wildlife via systematic transect surveys. We hypothesize that: anthropogenic land-use change, recurrent fires and mining-related vegetation disturbance in the MBRC between 1985 and 2025 have caused significant degradation and fragmentation of wildlife habitat, producing measurable declines and range contractions in key wildlife populations; moreover, the combined (cumulative or interactive) effects of these stressors are larger than the effect of any single stressor alone. The novelty of this study lies in its integrated, multi-scalar approach to assessing the persistence of wildlife in the MBRC under intensifying anthropogenic threats.

2. Materials and methods

2.1. Ethics statement

All research activities were conducted in accordance with ethical standards for ecological and conservation research. Field surveys, vegetation plots and road transects were strictly non-invasive and designed to minimize disturbance to wildlife and habitats. No animals were captured, handled, or harmed during the study. Research access and permits were formally granted by the MBRC Board, and all procedures respected the rights of landholders and stakeholders. The study complied with international ethical frameworks, including the International Union for Conservation of Nature (IUCN) guidelines for research involving threatened species, the Convention on Biological Diversity (CBD) and the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES). Given that the black rhinoceros (*Diceros bicornis*) is a CITES Appendix I species, all research activities adhered to the highest protection standards. Data collected were used exclusively for scientific and conservation purposes to support evidence-based wildlife management.

2.2. Study area

The MBRC is a consortium of 14 privately and communally owned properties situated in central Zimbabwe between the Munyati River to the north and the Sebakwe River to the south (Figure 1). The partnership was established in 1986 at the height of an intense poaching wave that was driving white and black rhino losses across Zimbabwe's peripheral regions (Mugaviri et al. 2022). The consortium's founding rationale was strategic: moving and concentrating rhino into a central, coordinated landscape would reduce opportunities for horn smuggling along international corridors and improve collective anti-poaching protection through shared law enforcement, monitoring and management. Over the decades, the conservancy has provided a managed landscape for rhino protection, pooled resources for security and veterinary response and created a framework for cooperative land use planning among member properties (Du Toit 1994). By sitting in the geographic heart of the country, the conservancy aimed to close off easy transit routes used by poachers operating between neighbouring states.

The MBRC is situated in the Midlands Province of Zimbabwe, lying within the central plateau of the country (Figure 1). Geographically, the conservancy extends between latitudes approximately 18°48′S to 19°00′S and longitudes 30°00′E to 30°24′E. It is strategically located close to major urban centres such as Gweru and Kwekwe, making it accessible while still retaining ecological integrity. The area is bounded by Sebakwe Dam to the south, which serves as a significant hydrological feature that supports both biodiversity and local communities through water provision (Mugaviri et al. 2022). Vegetation within the MBRC is primarily dominated by grasslands and patches of woodland, with significant representation of miombo woodland species such as *Brachystegia spiciformis* and *Julbernardia globiflora*. Grasslands

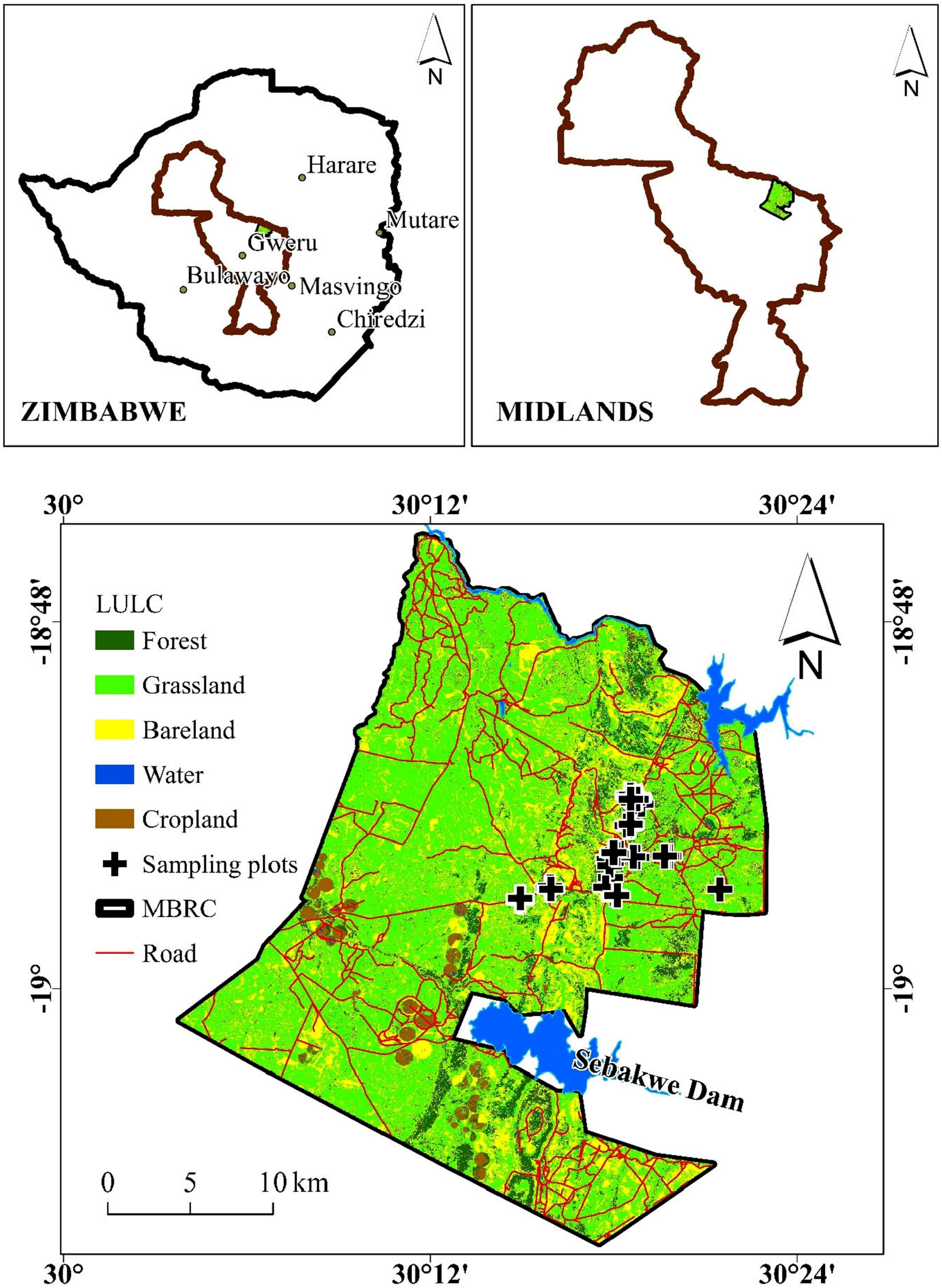

Figure 1. Location of the Midlands Black Rhino Conservancy (MBRC) in the Midlands Province of Zimbabwe, showing the conservancy boundary, major hydrological features, land cover types and surrounding landscape context. The map provides an overview of the study area used for ecological and conservation analyzes.

provide key forage resources for herbivores, while riparian vegetation along river systems enhances ecological diversity. Land use and land cover within the conservancy are varied, with dominant classes including grassland, forest patches, cropland, bareland and water bodies. Croplands are primarily located in the southern and peripheral zones, while extensive grassland and woodland areas form the core conservation habitats. Soils in the region are typically derived from granitic and gneissic parent material, with sandy loams and clay loams prevailing. These soils support both agricultural activities and natural vegetation growth but are highly susceptible to erosion, especially in overgrazed or disturbed areas. The MBRC lies within the agro-ecological region III of Zimbabwe, characterized by a semi-arid to sub-humid climate. Rainfall is seasonal, with an average annual precipitation ranging between 650 and 800 mm, received mainly during the summer months from November to March. Mean annual temperatures range between 18 and 24 °C, with cooler conditions during winter (May to August) and higher temperatures exceeding 30 °C in peak summer. Topographically, the conservancy lies on the central watershed of Zimbabwe, with elevations ranging between 1200 and 1500 m above sea level. The terrain is generally gently undulating, with slopes varying from flat low-lying areas around Sebakwe Dam to moderately steep gradients in upland zones. These variations in slope and elevation contribute to habitat heterogeneity and biodiversity richness. The MBRC is home to a diversity of wildlife species, with the flagship species being the critically endangered black rhinoceros (*Diceros bicornis*). Other notable species include sable antelope (*Hippotragus niger*), African buffalo (*Syncerus caffer*), zebra (*Equus quagga*), impala (*Aepyceros melampus*), wildebeest (*Connochaetes taurinus*) and a range of smaller herbivores. The area also supports a variety of carnivores and bird species, making it ecologically significant for conservation and biodiversity research. This combination of diverse vegetation, varied land use, moderate climate and rich wildlife assemblages underscores the ecological importance of the MBRC as a critical biodiversity refuge in Zimbabwe's central savannah landscapes.

2.3. Land use land cover (LULC) classification

For the purposes of LULC classification and change detection, a range of spatial datasets from multiple sources were utilized. Medium-High resolution satellite imagery, specifically Landsat images for the years 1985, 1995, 2005, 2015 and 2025, served as the primary sources of remotely sensed data. These datasets encompass various timeframes and sensor types to capture LULC transitions over time. To mitigate the influence of seasonal variability on classification outcomes, only images acquired during the same season were selected. To ensure phenological consistency, all images used were captured during the dry season (August)—a period characterized by minimal vegetation growth variability (Corner et al. 2013). This timeframe is considered optimal for distinguishing between different LULC classes. The study employed reflective bands from Landsat imagery with a spatial resolution of 30 metres to extract multi-temporal LULC change data. Raw satellite imagery was pre-processed before it can be effectively used for mapping purposes (Coppin and Bauer 1996). Essential corrections include radiometric and geometric adjustments. Geometric distortions in raw data may arise from systematic errors, such as the relative motion between the Earth's rotation and the satellite's orbit, and from random anomalies. These distortions typically result in spatial displacement along the north–south and east-west axes. Rectification was achieved through the use of ground control points (GCPs), aligned with georeferenced topographic maps of the area (Aubrecht et al. 2010). To construct false-colour composite images, the visible, near-infrared (NIR) and shortwave infrared (SWIR) bands from Landsat images were layered using QGIS 3.40.10). The raw digital number (DN) values were then converted to spectral radiance, as recommended by Aubrecht et al. (2010). Atmospheric corrections were applied to eliminate the influence of atmospheric interference, following. Thematic mapping involves categorizing spatial information to represent the geographic distribution of specific land cover types imagery can be systematically analyzed to derive meaningful environmental information across temporal and spatial scales. The fundamental goal of classification is to assign each image pixel to a specific land cover category (Singh and Talwar 2015). Several parameters influenced the selection of the classification method, including map accuracy, landscape dynamics, training data requirements and algorithmic complexity (Dewan and Yamaguchi 2009a, Dewan and Yamaguchi 2009b).

2.4. Ground truth data collection

Ground truthing involves validating satellite-derived classifications by correlating pixel information with actual land surface conditions (Al-doski et al. 2013). This validation is critical for the accuracy of supervised classification procedures performed using remote sensing software (Lu et al. 2004). In this study, local knowledge was incorporated through interviews with long-time residents to identify key land cover sites. Ground reference data were acquired through two primary methods. First, field surveys conducted in September 2025 yielded 300 reference points across distinct LULC classes, recorded using high-precision GPS units. Secondly, an additional 150 validation points were extracted via manual interpretation of high-resolution imagery from Google Earth and aerial photographs. This resulted in a total of 450 ground truth points. In accordance with Al-doski et al. (2013) and Lu et al. (2004), each land cover class was represented by at least 12 reference points, each corresponding to a minimum of 50 pixels. Seventy-five percent of the reference dataset was used for image classification, with the remaining portion reserved for accuracy validation. Historical reference data for the years 1985, 1995, 2005, 2015 and 2025 were derived from archived high-resolution imagery and photographs.

2.5. Change detection and identification

Examining land use and land cover (LULC) changes is essential for implementing effective land management interventions. In remote sensing, change detection is employed to analyze variations in the condition of objects over time using multi-temporal spatial datasets. The fundamental concept of utilizing satellite imagery for change detection lies in the principle that alterations in land use and cover are expressed as changes in spectral brightness (Singh 1989; Singh et al. 1989). There are three primary methods of change detection in remote sensing: image subtraction, image ratio approach and change detection after categorization (Collins and Woodcock 1996). Image subtraction detects changes in pixels based on their grey values. As the name suggests, the image ratio method is used to determine the ratios of pixels in each band of an image (Xu et al. 2017). Furthermore, it is the most apparent method after independent image processing and classification for different periods (Singh et al. 1989); hence, post-classification change detection was selected for this work. To calculate the area change, these maps were converted from raster to polygon due to the high accuracy of polygons in determining areas. The geometry tool in ArcMap 3.0 was used to determine the area coverage of each class. Accuracy evaluation involved both overall classification accuracy and the Kappa statistic, with the latter providing a more robust measure of agreement between classified results and reference data. In this study, Kappa values ranged between 84.35% and 87.78%, underscoring the algorithm's reliability in detecting LULC transitions.

Projection of future LULC changes in the MPNP for the year 2055 was undertaken using Cellular Automata integrated with an artificial neural network (CA-ANN). To generate future simulation maps, classified maps from 1985, 2005 and 2025 were utilized as inputs and combined with spatial variables including slope, aspect and elevation. The Global Multi-resolution Terrain Elevation Data 2010 was employed to provide topographic information in raster format (Figure 2). Digital Elevation Models (DEM) generally remain static over time, though alterations may occur due to geomorphic processes such as erosion and sedimentation. Slope, aspect and elevation represent critical inputs for LULC simulation as they provide essential information about landscape topography and influence the spatial distribution of woodlands, grasslands and hydrological resources. The ANN component was trained using a multilayer perceptron with one hidden layer comprising ten neurons and a learning rate of 0.01. Model training was performed over 1,000 iterations using a sigmoid activation function and backpropagation algorithm, with convergence achieved when the change in error fell below 0.001. The CA component incorporated a Moore neighbourhood with a 5 × 5 window to capture spatial dependency and neighbourhood influence on land cover transitions. Transition probabilities were derived from observed LULC changes between historical time steps and constrained by suitability layers. The calibrated CA–ANN model was then used to simulate future LULC patterns for the year 2055, assuming persistence of observed transition dynamics and spatial interactions. Model validation procedures were conducted to assess whether the framework could accurately predict established outcomes and thereby confirm its reliability for forecasting future patterns (e.g. for the year 2055). Indicators such as overall accuracy, the Kappa coefficient and spatial similarity indices are typically applied to quantify the extent of predictive agreement. In this study, the predicted LULC map changes were validated using Kappa statistics. The neural network learning curve illustrated the progressive training process of the model, with convergence toward zero signifying enhanced model reliability. Within a cellular automata (CA) framework, the neural network learning curve graphically depicts neural network (NN) performance, reflecting its ability to approximate CA dynamics (Figure 4). It demonstrates how effectively the NN learns underlying relationships and transition rules within the dataset. A decreasing training loss indicated the NN's improved capacity to predict cell state changes. Correspondingly, if the validation loss declined and stabilized near the training loss, the NN exhibited strong generalization. Low training and validation errors reflect a robustly trained network, whereas persistently high errors suggest limitations in data quality (e.g. noise, insufficient

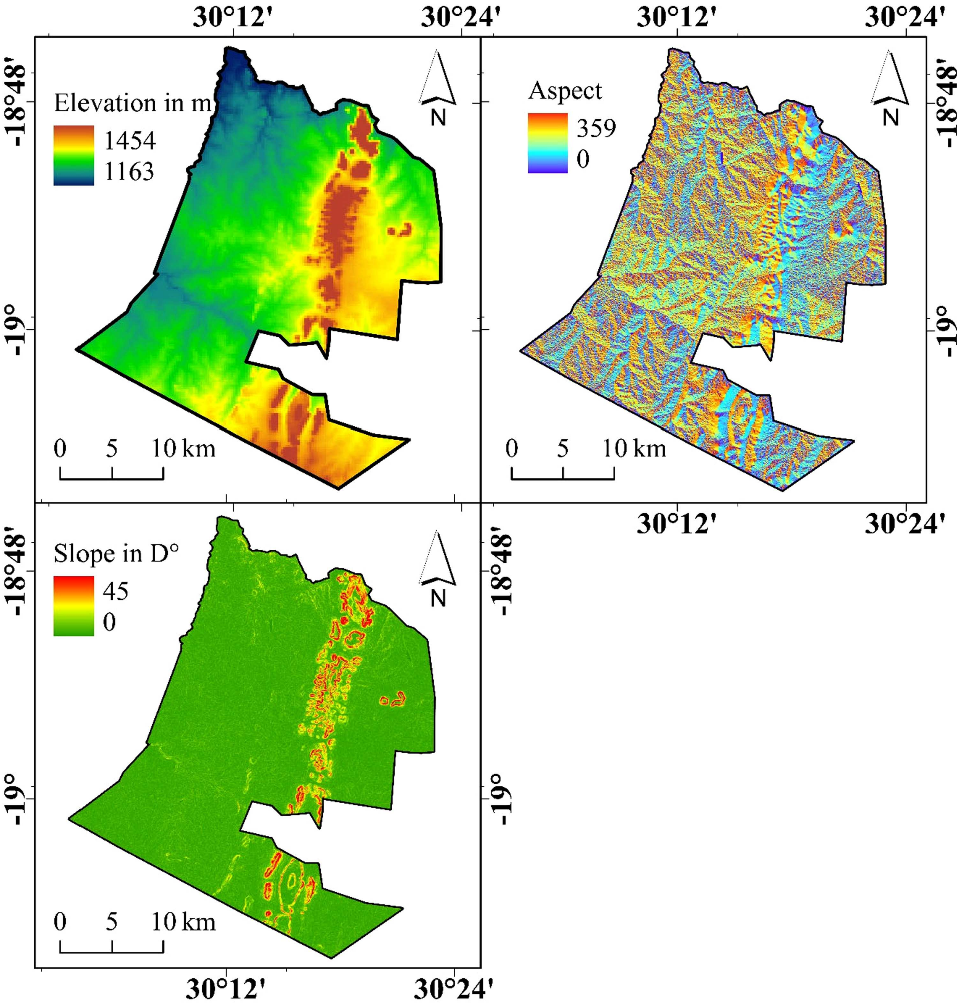

Figure 2. Spatial variables, slope, aspect and elevation were used as inputs in modelling LULC using CA-ANN.

sampling) or deficiencies in the NN architecture. The final output is a predicted landscape for the year 2055.

2.6. Accuracy assessment

The operational land imager (OLI) multispectral images, with a spatial resolution of 30 m, were sourced from the United States Geological Survey (USGS). An accurate thematic map provides an unbiased depiction of land cover across a study area. From a statistical perspective, accuracy encompasses both bias and precision, and distinguishing between these components is important, as one may be substituted or misinterpreted for the other (Swain 1982; Sonawane and Patil 2025). In the context of thematic mapping derived from remotely sensed data, accuracy generally refers to the degree of agreement between the classified map outputs and the actual land cover conditions on the ground. Thus, accuracy reflects how closely the classification corresponds to observed reality, or the 'truth'. In this study, classification accuracy ranged between 84.35% and 87.78%, with corresponding Kappa coefficients from 0.82 to 0.86 (Appendix 1). These metrics fall within acceptable thresholds and align with international standards for classification accuracy. The analysis also incorporated user accuracy (UA) and producer accuracy (PA) values for individual land cover categories, thereby ensuring a comprehensive evaluation of classification performance. The user guide of Climate Change Initiatives (CCI Land Cover (LC) team, n.d.) product gives accuracy ratings of the CCI-LC map year 2018 using GlobCover 2009 validation dataset (ESA Climate Change Initiative - Land Cover project, 2017). Classification accuracy was evaluated using an independent validation dataset generated through stratified random sampling across all land use and land cover classes. A total of validation points was allocated proportionally to class area and compared against reference information derived from high-resolution satellite imagery and field observations where available. Accuracy assessment was performed using confusion matrices from which overall accuracy, producer's accuracy and user's accuracy were calculated for each class, allowing quantification of omission and commission errors. In addition to Cohen's Kappa coefficient, these metrics were used to assess both map reliability and class-specific performance. This multi-metric approach ensured a comprehensive evaluation of classification robustness and minimized potential bias associated with reliance on a single accuracy indicator.

2.7. Methodology flowchart

The methodological flowchart (Figure 3) illustrates an integrated approach for analyzing land use/land cover (LULC) change and predicting future landscape dynamics in the Midlands Black Rhino Conservancy. Multi-temporal Landsat (5, 7 and 8) imagery and SRTM-derived topographic variables (elevation, slope and aspect) are first collected and pre-processed. Supervised classification using a random forest algorithm is applied to generate LULC maps, which are assessed using a confusion matrix to ensure acceptable classification accuracy. Validated LULC and spatial driver layers are then used as inputs for change modelling. Cellular automata, artificial neural networks and transition probability components are combined to capture both spatial neighbourhood effects and temporal transition dynamics. The calibrated model simulates LULC for 2025, which is validated using Kappa statistics. Once satisfactory performance is achieved, the model is applied to generate a predicted LULC map for 2055, representing future land cover scenarios.

2.8. Fire regime mapping and burn severity assessment

Fire (hotspot) data for this study were obtained from NASA's Fire Information for Resource Management System (FIRMS) archive as time-stamped point detections (CSV and shapefile formats) for the study bounding box and the target years (2015, 2020, 2025). FIRMS provide near-real-time and historical active-fire detections from MODIS and VIIRS and allows filtered archival downloads by date, geography, sensor and confidence level (Boroujeni et al. 2025). Downloads used the archive service (Earthdata authentication) and comprised detections flagged by sensor, acquisition time (UTC), confidence and radiative power. Initial pre-processing converted downloaded CSVs to geospatial point layers and reprojected them to the project coordinate system (WGS84/UTM zone 36S for MBRC). Records were filtered to remove duplicate detections and to retain only medium-to-high confidence observations; sensor attribute fields were preserved for downstream spatial uncertainty handling (MODIS ≈ 1 km; VIIRS I-band ≈ 375 m). Sensor spatial characteristics and product descriptions guided subsequent buffering and validation steps (Boroujeni et al. 2025). Landsat imagery for the same temporal windows was sourced as atmospherically corrected Level-2 surface reflectance (Collection 2) from USGS/Earth Explorer (or accessed via Google Earth Engine for bulk processing). Scenes were selected to bracket known fire events (one pre-fire and one post-fire scene per event), prioritizing the least-cloudy dates; surface reflectance products were used to avoid additional atmospheric correction. Cloud and shadow pixels were masked using the QA_PIXEL/Fmask attributes. Burn mapping used the Landsat normalized burn ratio (NBR) and differenced NBR (dNBR) approach: $NBR = (NIR - SWIR2)/(NIR + SWIR2)$ (Landsat 8: Band 5 and Band 7; Landsat 4–7: Band 4 and Band 7). dNBR was computed as pre-fire NBR minus post-fire NBR on a per-pixel basis; standard dNBR thresholds (after Key and Benson/USGS guidance) were applied to classify unburned, low, moderate and high severity burn classes. Small isolated speckles were removed with a minimum mapping unit (e.g. 0.5–1 ha) and polygons were smoothed/dissolved to create coherent fire-scar polygons. dNBR calculations and thresholding followed established burn-severity best practices. To integrate satellite detections and Landsat-derived scars, FIRMS points were overlaid on dNBR polygons: sensor-specific uncertainty buffers (≈375 m for VIIRS, ≈ 1 km for MODIS) allowed validation and correction of polygon extents where a strong spatial correspondence existed. Where FIRMS points existed without corresponding dNBR scars (or vice versa), manual inspection of false-colour composites (SWIR, NIR, Red) and multi-

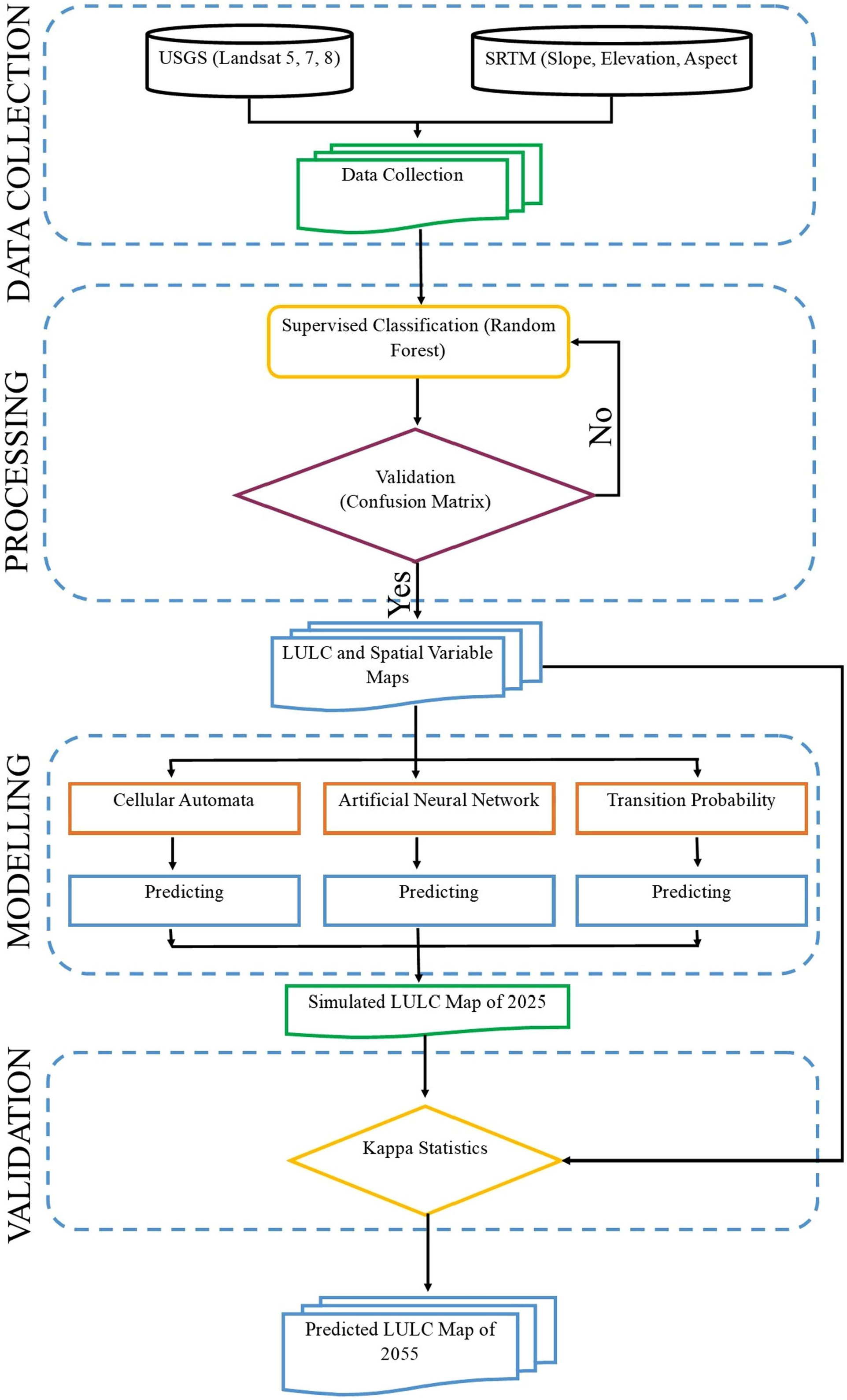

Figure 3. Methodological workflow for land use/land cover (LULC) change analysis and future scenario prediction in the Midlands Black Rhino Conservancy, integrating multi-temporal Landsat and SRTM data, random forest classification and validation and hybrid CA–ANN transition modelling to simulate LULC dynamics and predict future landscapes.

date imagery was performed to confirm burning, smoke, or agricultural burning. Final cartographic layers (false-colour Landsat base, hatched red fire-scar polygons, FIRMS point overlays, MBRC boundary, roads and sampling plots) were composed in ArcGIS Pro 3.0 with consistent symbology, scale bars, north arrows and panel layouts for 2015, 2020 and 2025 before exporting high-resolution map figures.

2.9. Mining-induced vegetation disturbance and structural change

We established 65 plots of 50 m × 50 m to assess the extent and severity of vegetation disturbance associated with mining activities. The plots were selected randomly using a stratified random sampling technique but with the limitation that they have to encompass a vast range of tree diversity as required for comparative research in contrast to sample surveys. Statistical analyzes examining the effects of mining on vegetation dynamics were conducted using a Bayesian framework (Kuyah et al. 2016). This required the application of Bayesian Piecewise Regression (BPR) alongside Bayesian Regression Modelling (BRM). The Bayesian regression models were fitted using Markov Chain Monte Carlo (MCMC) techniques to quantify the effects of distance from mining sites on vegetation attributes. Priors for model parameters—including intercepts, slope coefficients and variance components—were specified as weakly informative normal distributions to allow the data to primarily inform posterior estimates while preventing implausible parameter values. Each model was run with four independent MCMC chains for 10,000 iterations, including 2500 burn-in iterations. Convergence was assessed through visual inspection of trace plots, calculation of effective sample sizes (n_eff) and the Gelman–Rubin diagnostic ($\hat{R}$) to ensure stability and consistency across chains. Model fit and predictive performance were further evaluated using posterior predictive checks, comparing the observed vegetation attributes against the predicted distributions from the model. This approach ensures reliable parameter estimation and robust inference on the influence of mining activities on vegetation structure. Multiple tree species were recorded across sampled plots, all of which had experienced varying levels of disturbance from open-cast mining activities. These species included *Boscia mossambicensis*, *Terminalia elliptica*, *Colophospermum mopane*, *Combretum apiculatum* and *Croton megalobotrys*. Woody vegetation species were selected using a systematic, ecologically informed approach rather than random selection. The focal species (*Boscia mossambicensis, Terminalia elliptica, Colophospermum mopane, Combretum apiculatum* and *Croton megalobotrys*) were chosen because they are dominant and widely distributed across the Midlands Black Rhino Conservancy, occur across gradients of mining disturbance and represent contrasting functional traits and growth strategies relevant to disturbance response. By focusing on these ecologically representative and disturbance-responsive species, the analysis enables robust detection of mining-induced thresholds and structural shifts in vegetation, thereby providing meaningful insights into ecosystem degradation and recovery processes within the conservancy. Shifts in growth conditions following disturbance represent critical breakpoints within natural systems, which should manifest in height–diameter allometric relationships. Piecewise regression models were employed to detect such breakpoints in the allometry dataset (Moncrieff et al. 2011). Both single- and double-breakpoint models were tested, with the optimal model identified using the deviance information criterion (Moncrieff et al. 2011). Model fitting was carried out using Markov Chain Monte Carlo methods implemented in R version 4.4.0. BPR is a powerful statistical approach designed to estimate regression relationships where associations between variables (e.g. tree size and mining intensity) shift at defined thresholds or breakpoints. It accommodates nonlinear relationships and partitions datasets into distinct segments with different regression slopes. BPR enables predictions of tree dimensions (e.g. diameter at breast height) over time or relative to other parameters, such as age or environmental conditions (Wang et al. 2018). By integrating data on vegetation disturbance with growth metrics, BPR can pinpoint thresholds beyond which mining significantly alters tree growth trajectories or survival.

2.10. Spatial occurrence and habitat associations of wildlife species in MBRC

Presence-only occurrence data for multiple wildlife species were collected within the Midlands Black Rhino Conservancy (MBRC) during the summer seasons of 2023, 2024 and 2025 using structured field surveys and standardized road transect monitoring. This timeframe was designed to provide a robust contemporary baseline of species presence and spatial distribution rather than to infer long-term population trends. Surveys followed a systematic, spatially stratified design covering major habitat types, including forested areas, open grasslands and mining-disturbed landscapes along established transects. All confirmed species occurrences were georeferenced using high-precision global positioning system (GPS) units to minimize positional error and ensure spatial accuracy. A total of 450 GPS-referenced presence records were compiled across the three sampling periods, providing a robust empirical basis for spatial modelling. At each occurrence location, environmental and habitat attributes were recorded to enhance ecological interpretation. These included vegetation type and structure, soil properties (texture and compaction) and microhabitat moisture conditions, all of which influence species habitat occupancy and distribution. To improve spatial coverage and representativeness, validated citizen science records were integrated with field-collected data following quality checks to ensure consistency and reduce observational bias. The combined dataset thus provided a spatially explicit and ecologically representative depiction of wildlife occurrence patterns across the MBRC.

Species distribution and habitat suitability were modelled using the maximum entropy (MaxEnt) algorithm, incorporating land use/land cover, slope, aspect and elevation as predictor variables. Occurrence data were randomly partitioned into training (70%) and testing (30%) subsets. Model performance was evaluated using threshold-dependent omission tests (threshold = 0.1; $p < 0.05$) and threshold-independent receiver operating characteristic (ROC) analysis. These complementary evaluation metrics ensured rigorous validation of model predictive performance and supported reliable inference of current wildlife distribution and habitat suitability within the conservancy.

3. Results

3.1. Modelling land use land cover (LULC) future scenarios

The LULC time series for the Midlands Black Rhino Conservancy (MBRC) shows pronounced spatio-temporal change between 1985 and 2055 (Figure 4, Table 1). Forest area rises to a short-term peak in 1995 (2829.74 ha) but then declines to 180.07 ha by 2055, a net loss of 809.04 ha (−81.8% relative to 1985). Grassland increases to a maximum in 2015 (6567.87 ha) before declining to a predicted 3791.40 ha in 2055 (net −552.14 ha, −12.7% from 1985). Bareland demonstrates high variability but expands substantially by 2055 to 4,310.60 ha, a net gain of 1340.10 ha (+45.1%). Water extent fluctuates at low absolute values but is predicted to increase to 79.35 ha by 2055 (+69.6% relative to 1985). Farmlands increase mid-series and then contract, with a projected decline to 45 ha in 2055 (net −33 ha, −42.3% from 1985). Overall, the projection indicates a shift away from woody cover and towards greater bare ground and an unstable grassland–farmland mosaic by mid-century (Table 1). Predictive outputs from the CA-ANN model are reported with 95% confidence intervals derived from multiple simulation runs, reflecting variability in predicted land cover proportions.

The neural network learning curve shows fluctuating but generally convergent loss values between 0.06 and 0.14 across 1000 iterations (Figure 5). The curve depicts the model's error (likely the mean square error or a similar loss metric) decreasing over approximately 1000 training epochs. The convergence of the error to a low, stable value indicates successful training and that the model learned effectively from the historical land use/land cover data to project the 2055 landscape scenario for the Midlands Black Rhino Conservancy (MBRC). Despite high variance, the overall trend stabilizes at lower loss values, indicating that the model is learning meaningful patterns. This suggests reasonable predictive capacity for simulating future landscape scenarios in the Midlands Black Rhino Conservancy by 2055 (Figure 6).

3.2. Fire regime mapping and burn severity assessment

The map (Figure 7) shows three snapshot years (2015, 2020, 2025) of fire scars inside the Midlands Black Rhino Conservancy (MBRC). Measured burned area was 10,422.9 ha in 2015, 2048.6 ha in 2020 and 2632.6 ha in 2025. That represents an 80.3% decline from 2015→2020, a 28.5% increase from 2020→2025 and an overall 74.7% reduction in burned area between 2015 and 2025. Spatially, the 2015 scars are large and contiguous (notably in the northern and southern quadrants), 2020 scars are fewer and more clustered

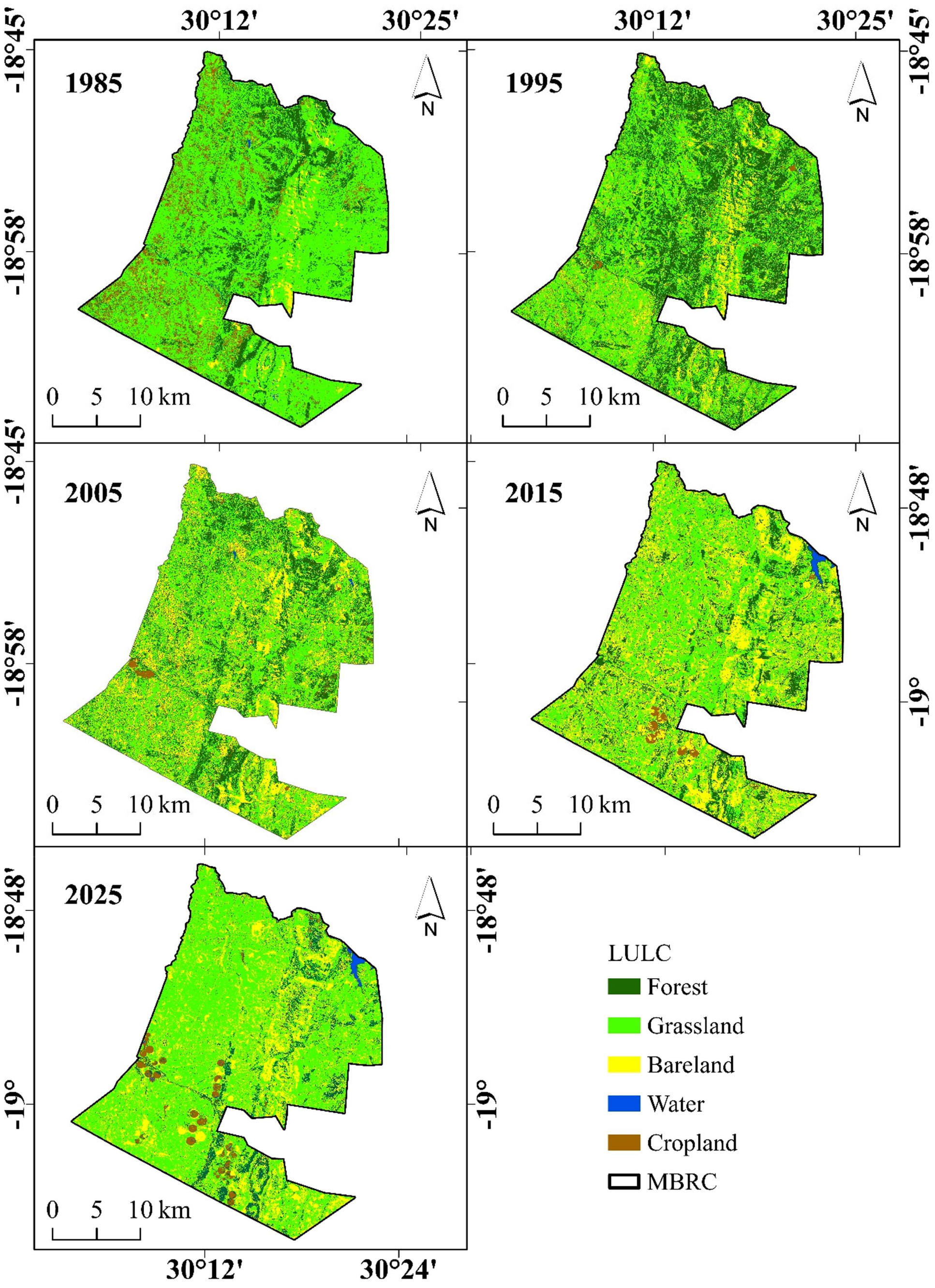

Figure 4. Land Use and Land Cover (LULC) Classification for the years 1985, 1995, 2005, 2015 and 2025 for the Midlands Black Rhino Conservancy, Zimbabwe.

Table 1. Changes in land use and land cover (LULC) classes within the Midlands Black Rhino Conservancy (MBRC) from 1985 to 2025, including projections for 2055, were generated using the CA-ANN model. The values represent the areal extent (in hectares) of each LULC category (forest, grassland, bareland, water and farmland) across the respective time periods.

classes	1985	1995	2005	2015	2025	Predicted_2055
forest	989.11	2829.74	1589.59	744.63	437.68	180.07
grassland	4343.54	4704.42	4554.18	6567.87	6005.39	3791.4
bareland	2970.50	661.81	2104.85	976.08	1741.91	4310.6
water	46.780	41	8.27058	4.88	28.4117	79.34
farmlands	78	190.95	171.03	134.4706	214.53	45

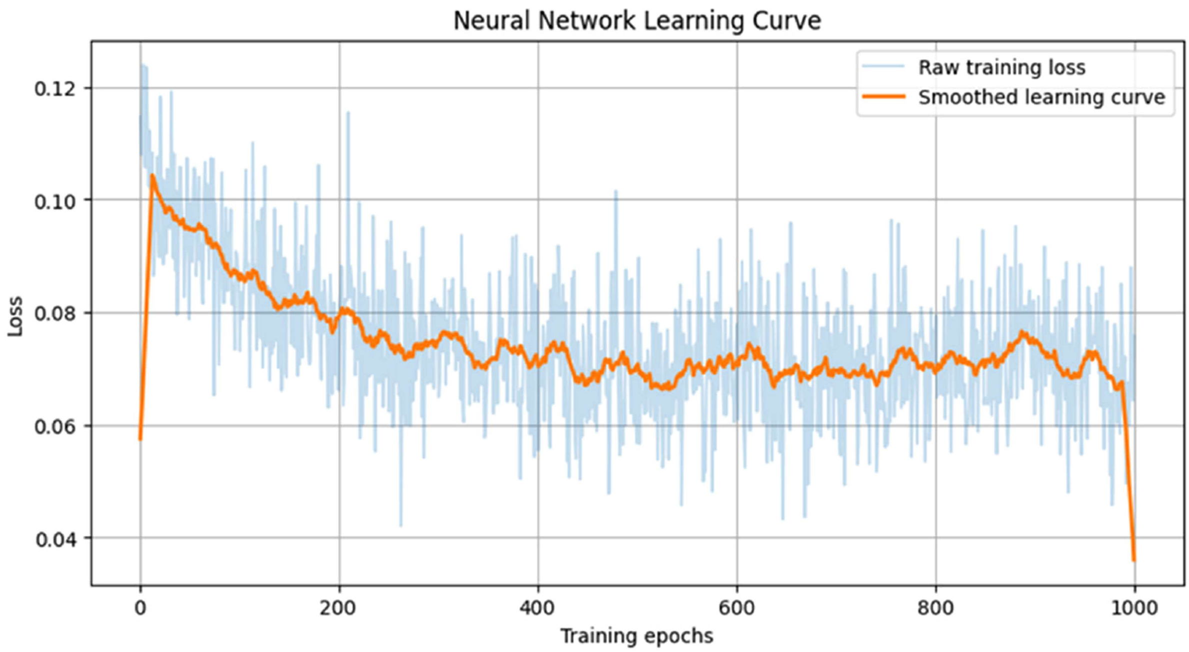

Figure 5. Learning curve for the artificial neural network (ANN) component of the Cellular Automata-Artificial Neural Network (CA-ANN) model.

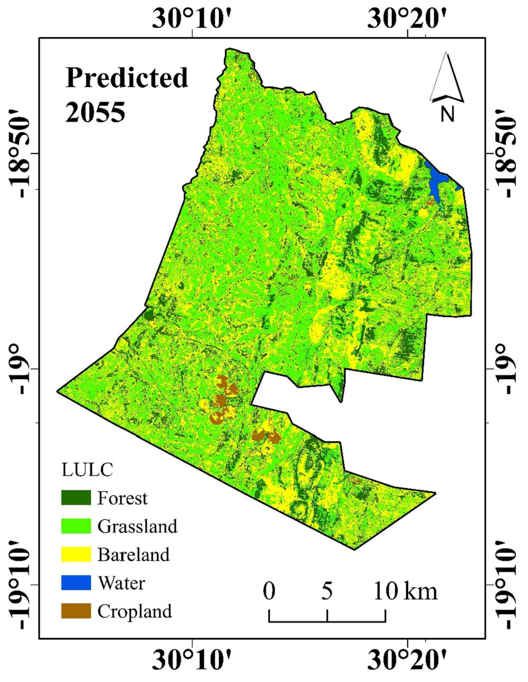

Figure 6. Predicted Land Use and Land Cover (LULC) of the Midlands Black Rhino Conservancy (MBRC) for the year 2055. The projection was simulated using a Cellular Automata-Artificial Neural Network (CA-ANN) model, based on historical LULC change trends. The map shows a potential future distribution of key classes including forest, grassland and cropland, which is critical for assessing long-term habitat suitability and informing proactive conservation management strategies for black rhino and other wildlife.

along a central–eastern corridor and 2025 shows smaller, more fragmented patches concentrated in the southwest with scattered northern patches. In short, fire incidence was episodic with a very large pulse in 2015 followed by lower, but not negligible, burning in 2020 and 2025; the location of hotspots shifted over time and fires became more fragmented by 2025.

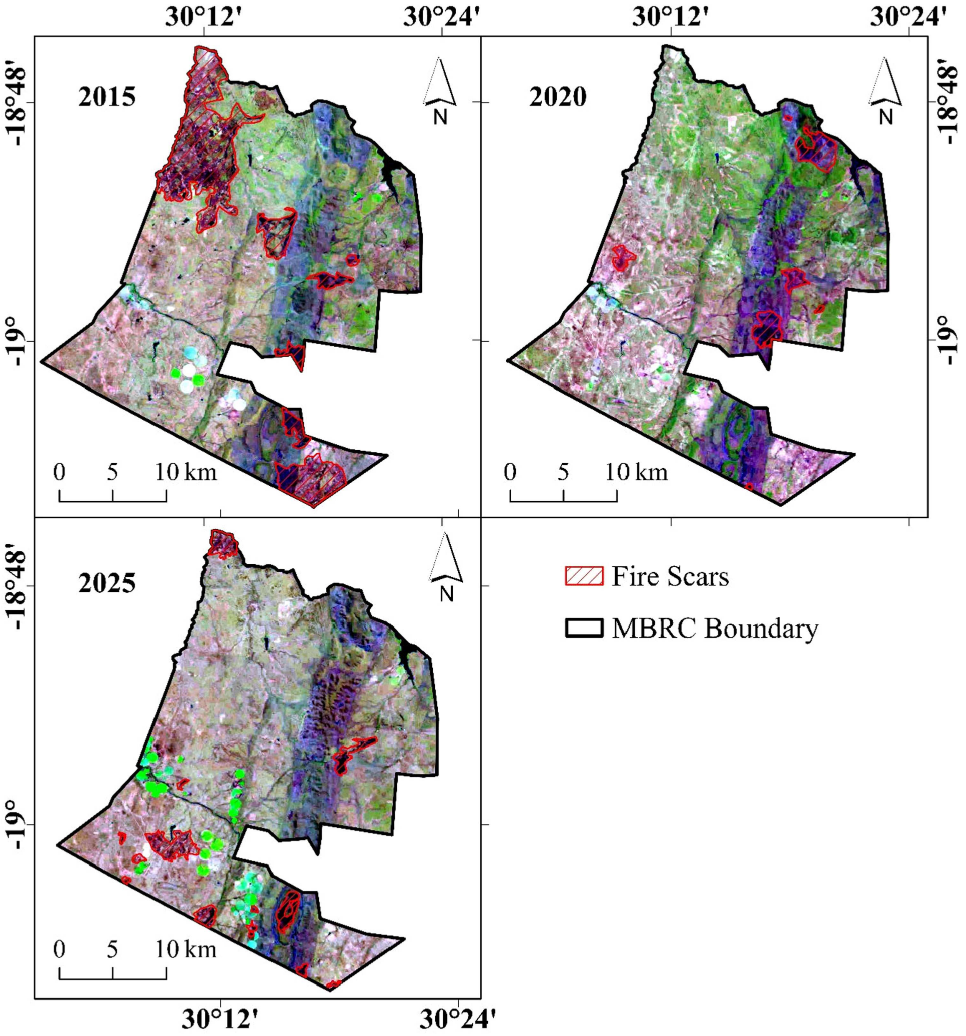

Figure 7. Spatiotemporal distribution of fire scars within the Midlands Black Rhino Conservancy (MBRC) for the years 2015, 2020 and 2025, derived from Landsat imagery and FIRMS active fire data. The map illustrates the extent and location of burned areas, highlighting temporal variations in fire occurrence across the conservancy landscape.

Normalized burn ratio (NBR) maps for 2015, 2020 and 2025 show spatial and temporal variation in fire incidences within the MBRC (Figure 8). In 2015, NBR values ranged from 0.460 to −0.146, indicating widespread fire-affected areas. By 2020, values ranged from 0.506 to −0.252, showing broader fire scars with more negative NBR pixels. In 2025, values ranged from 0.493 to −0.404, indicating a persistence of fire activity, with more intense localized impacts. Overall, fire scars declined in extent compared to 2015 but became more spatially heterogeneous and severe in certain hotspots.

3.3. Mining-induced vegetation disturbance and structural change

The Bayesian regression analysis revealed clear distance-dependent patterns in vegetation structure associated with mining activities within the MBRC (Figure 9). Basal circumference was highest at far sites (estimate = 2.41), moderate near mines (0.93) and markedly reduced at intermediate distances (−3.19), indicating pronounced suppression of stem development in zones surrounding mining operations. Tree height showed a similar trend, with elevated values near mines (1.25), followed by a decline at medium distances (−0.11) and stabilization at far sites (0.02). Long canopy length mirrored height responses, being greatest near mining areas (1.25) and reduced at intermediate distances. Diameter at breast height increased progressively with distance from mines, from 0.49 at medium sites to 0.72 at far

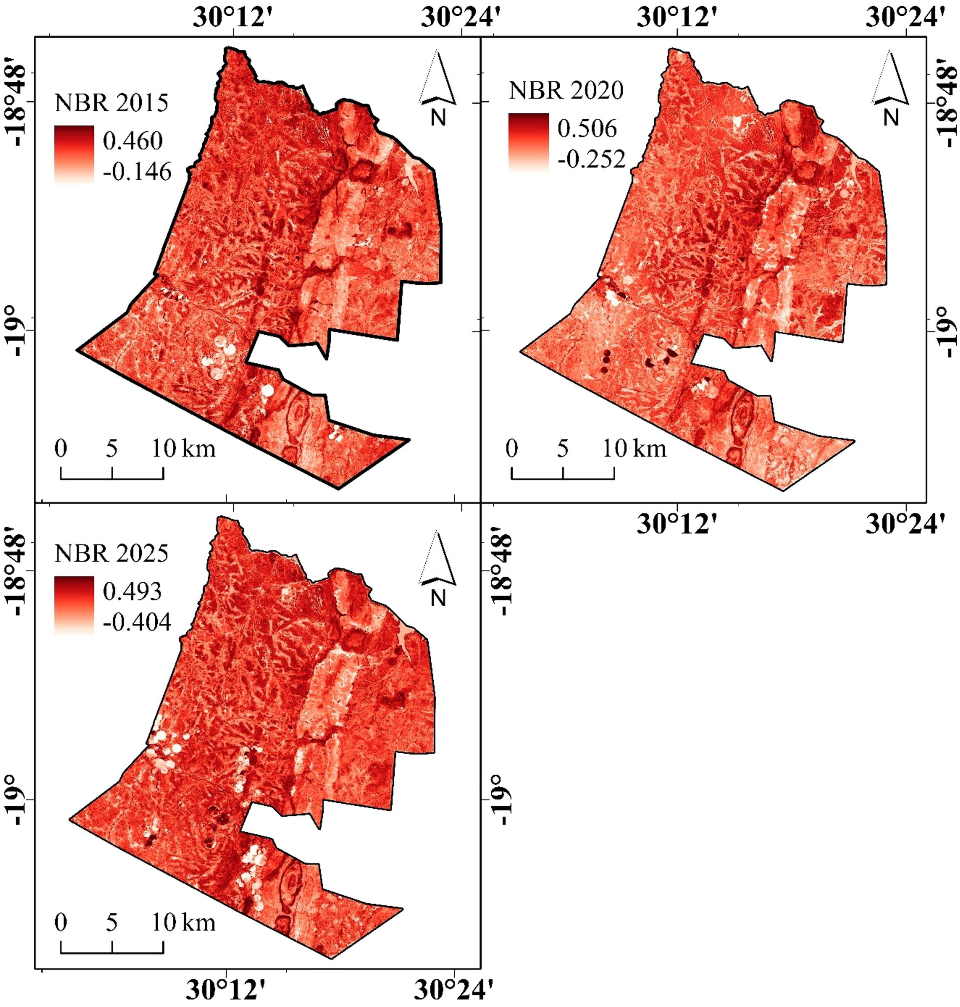

Figure 8. Spatial distribution of the normalized burn ratio (NBR) in the Midlands Black Rhino Conservancy (MBRC), illustrating vegetation condition and burn severity patterns across the landscape.

sites, suggesting gradual recovery of tree growth away from disturbance sources. Basal area followed the same gradient, with minimal values near mines (0.07) and maximum values at far sites (1.04). Overall, these results indicate localized structural alteration of vegetation associated with mining, characterized by growth suppression at intermediate distances and clear recovery in areas farther from mining influence.

3.4. Spatial occurrence and habitat associations of wildlife species in MBRC

Model performance for Wildlife Species was evaluated using the area under the receiver operating characteristic curve (AUC) and omission rates. The AUC for the training data was 0.894, and for the independent test data, it was 0.871 (Appendix 2a. Both values are well above the random prediction threshold (AUC = 0.5), indicating good model discriminatory ability. The omission rate plot (Appendix 2b shows that the model's predicted omission closely aligns with the omission observed on both training and test samples across various cumulative thresholds, suggesting the model is well-calibrated and not overfit. Specifically, at the default 10% cumulative threshold, the omission rates for training and test samples are approximately 0.1, matching the predicted omission and confirming reliable model performance. MaxEnt habitat suitability predictions include 95% confidence intervals calculated from bootstrapped replicate runs, providing an explicit measure of uncertainty around species distribution estimates. The jackknife analysis (Figure 10) indicates that land use/land cover (LULC) is the most influential variable for predicting habitat suitability, yielding the highest AUC (Area Under the Curve) value when used in

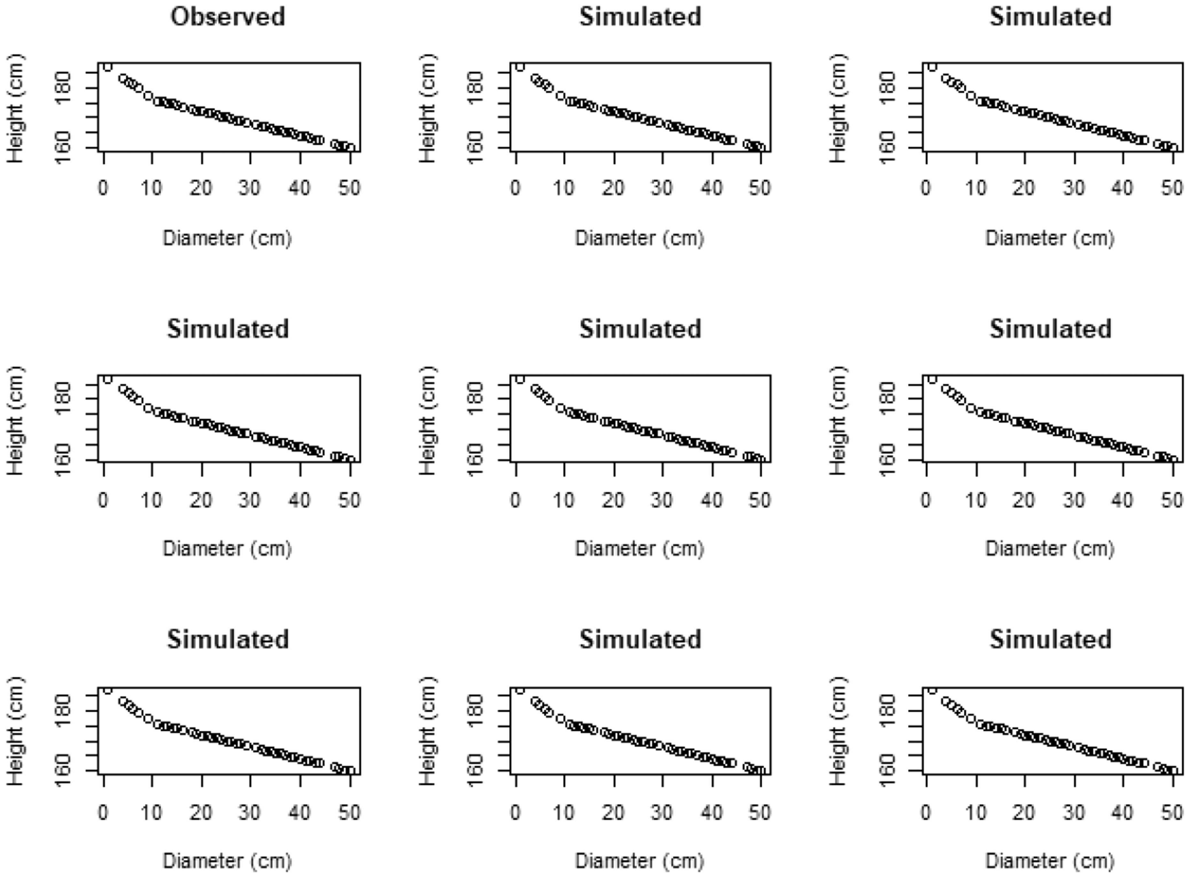

Figure 9. Simulated and observed height for the fitted models.

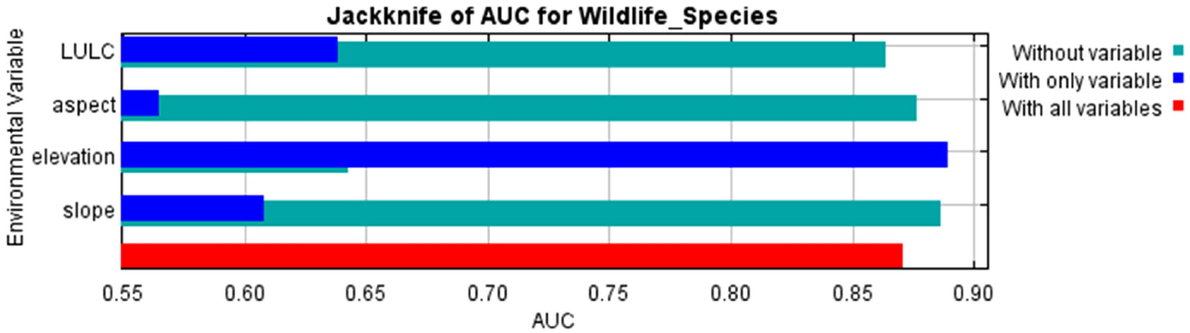

Figure 10. Jackknife test of the area under the curve for the habitat suitability models of a wildlife species in the Midlands Black Rhino Conservancy (MBRC).

isolation. Topographic variables (aspect, elevation, slope) contributed less to model performance. The model including all variables achieved the highest predictive accuracy (AUC ~0.9), demonstrating that the combination of LULC and topography provides a robust prediction. The subsequent habitat suitability map (Figure 11) identifies a mosaic of suitability categories across the conservancy. Large, contiguous patches of ‘highly suitable’ and ‘suitable’ habitat are present, interspersed with areas of ‘moderately suitable’, ‘unsuitable’ and ‘extremely unsuitable’ land, the latter likely corresponding to human-modified areas.

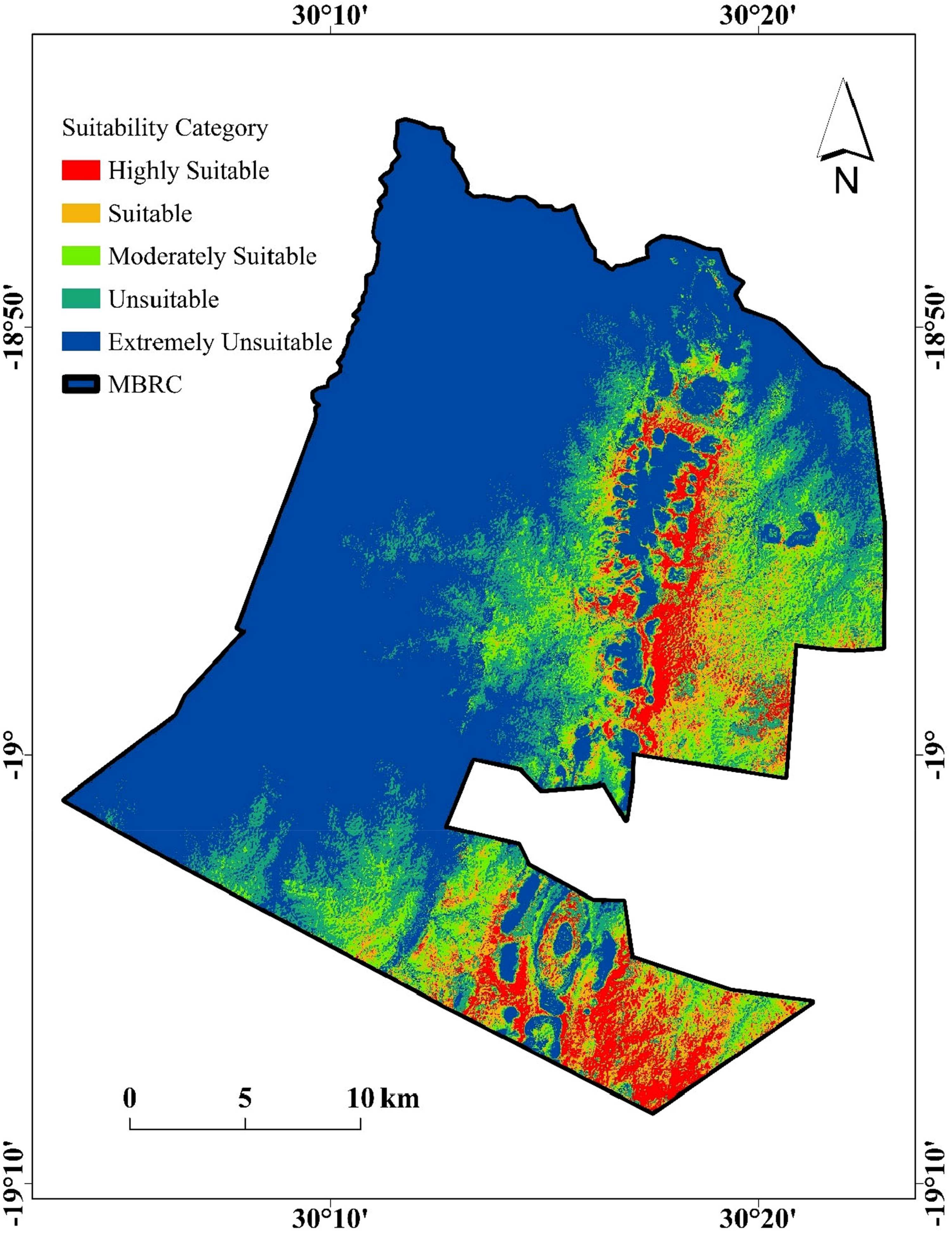

Figure 11. Habitat suitability analysis for wildlife species within the Midlands Black Rhino Conservancy (MBRC), Zimbabwe. The map classifies the landscape into five suitability categories based on key environmental variables.

4. Discussion

4.1. Modelling land use land cover (LULC) future scenarios

Between 1985 and 2055 the MBRC underwent substantial spatiotemporal reorganization of land cover: large-scale loss and fragmentation of forested areas, temporal fluctuation and an overall decline in grassland, pronounced expansion of Bareland and variable changes in farmland and water. These trends reflect a transition from a landscape containing significant woody elements toward one dominated by exposed ground and a more dynamic grassland–agriculture matrix.

The projected changes have multiple, interacting ecological consequences. Loss and fragmentation of forest and woody patches reduce habitat heterogeneity and microclimatic buffering, removing essential refugia, nesting sites and thermal shelters for many taxa (Henrich et al. 2025). Specialist forest-edge and understorey species are likely to decline first, followed by broader community impacts as trophic networks reorganize (Kalies et al. 2010). For large herbivores—particularly species that require mosaics of browse and grass (e.g. mixed browsers and grazers)—loss of woody cover and reduction in patch size lower carrying capacity, compress seasonal movement ranges and increase competition for limited resources (Mutanga and Gandiwa 2023). Reduced habitat area and connectivity elevate extinction risk from demographic and genetic stochasticity through population isolation.

Expansion of bareland has direct soil and hydrological consequences: increased surface exposure accelerates erosion, reduces soil organic matter and infiltration capacity and impedes vegetation regeneration. Those processes further entrench land degradation in a positive feedback loop (Muleta Gurmessa et al. 2024). Changes in grassland extent and composition can alter fire regimes: more continuous or more flammable grass fuels may increase fire frequency and intensity, which in turn suppresses woody recovery and favours grasses, reinforcing the trajectory toward degraded, open states (Serneels et al. 2001). Fluctuations in water extent—although small in absolute terms—can have outsized ecological effects in savannah systems by altering seasonal water availability for wildlife, affecting breeding sites for aquatic and semi-aquatic taxa and changing local plant community composition.

Collectively, these dynamics reduce ecosystem services (carbon sequestration, soil stabilization, water regulation) and increase the likelihood of human–wildlife conflict as wildlife compresses into smaller, edge-proximate habitat patches adjacent to agricultural land. Reduced landscape resilience will make MBRC populations more vulnerable to droughts, disease outbreaks and stochastic events.

The spatially explicit projections point to immediate conservation priorities. First, legal protection and strict enforcement for remaining forest fragments and riparian strips are essential to preserve refugia and maintain hydrological functions. Second, restoration should be spatially targeted: establish corridors to reconnect isolated habitat patches, prioritize erosion control and soil rehabilitation in expanding bareland zones and implement assisted natural regeneration and native species planting in degraded but restorable areas. Third, land-use planning must reconcile conservation goals with regulated agricultural and extractive (e.g. mining) activities—zoning, environmental impact assessment and restrictions on clearance in high-conservation areas are required. Fourth, integrate community-based conservation and livelihood alternatives (sustainable agroforestry, payment for ecosystem services, controlled grazing regimes) to reduce pressure on park resources and build local stewardship. Finally, adopt iterative monitoring—use remote sensing (Landsat time series) and periodic ground truthing to track change, evaluate interventions and adapt management.

The approach used here—multi-decadal Landsat analysis combined with CA-ANN spatial projection—is readily transferable across Africa because Landsat provides a consistent archive and CA-ANN explicitly models neighbourhood and non-linear transitions typical of fragmented landscapes. When applied elsewhere, the pipeline supports scenario generation, prioritization of restoration/protection areas and examination of policy alternatives. Successful transfer requires local calibration: incorporate region-specific drivers (local road and settlement growth, grazing intensity, mining concession maps, fire history, land tenure) and validate classifications and projections with local field data and stakeholder knowledge. Embedding socio-economic data and governance variables increases realism and uptake by managers. Where applied correctly, this methodology can inform spatially targeted interventions, cross-site comparisons and regional conservation planning.

The limitations of this study are that: projections are scenario-based extrapolations of historical patterns; they do not capture unforeseeable policy changes, major restoration investments or extreme climatic shocks. Model and classification uncertainty should be quantified (ensemble runs, sensitivity analysis) and reduced through iterative field validation. Future work should couple LULC projections with species-specific habitat and connectivity models, integrate climate projections and socio-economic scenarios and co-produce management pathways with local stakeholders.

Classified LULC maps from 1985, 2005 and 2025 were used to train and validate the CA-ANN model. These years were chosen to represent consistent 20-year intervals and capture long-term trends in land cover change within MBRC. While additional intermediate-year maps could potentially improve model performance by capturing finer temporal dynamics, data availability constrained the analysis to these key temporal snapshots. Future studies may incorporate more frequent time points to enhance temporal resolution and allow the CA-ANN model to better capture short-term LULC fluctuations.

The MBRC is projected to experience significant woody loss and bareland expansion by 2055 with serious implications for biodiversity, ecosystem services and park resilience. The spatially explicit results provide a robust evidence base for urgent, targeted conservation actions and offer a transferable framework for other African landscapes confronting similar anthropogenic pressures.

4.2. Fire regime mapping and burn severity assessment

Between 2010 and 2025 the MBRC experienced episodic fire events with a major large-scale burn in 2015 and substantially smaller, more spatially fragmented events in 2020 and 2025. The frequency inferred from these snapshots suggests a high-impact pulse (2015) followed by reduced burned area but recurring fires—i.e. lower area per event but persistent occurrence.

The exceptionally large burned area in 2015 (≈10,423 ha) indicates an extreme burn year. Such pulses are commonly associated with synoptic climate anomalies (drought/El Niño), elevated fuel dryness, or coincident multiple ignitions. The marked reduction by 2020 suggests either (a) changing climate conditions (wetter seasons after 2015), (b) altered ignition patterns (fewer anthropogenic ignitions), or (c) improved fire management (early-season burns, firebreaks, patrols). The modest rebound in 2025 (≈2633 ha) indicates that although the very large 2015 event was not repeated, the system remains susceptible to medium-scale burns. The spatial shift from broad contiguous scars (2015) to more clustered/fragmented scars (2020–2025) suggests either changing ignition locations (edge vs interior), landscape fuel heterogeneity, or targeted management (mosaic burning or containment).

Fires exert both immediate and lagged ecological effects (Banks et al. 2011). Immediate effects include biomass loss, mortality of smaller plants and juveniles, temporary reduction of woody browse and loss of litter and ground cover that increases erosion risk (Chia et al. 2016). For a reserve managed for black rhino (a primarily browsing species), large, high-severity fires that remove shrubs and small trees reduce food availability and shelter; this can lower body condition, increase range shifting and concentrate rhinos in unburned refugia—raising intraspecific competition and potentially exposure to poaching. Repeated or high-severity burning can shift woody–grass balances (promoting grass dominance), reduce structural complexity and reduce niche availability for species dependent on dense woody cover or tall grasses for nesting and hiding. Conversely, low- to moderate-severity fires produce flushes of nutritious regrowth and can maintain an open savanna structure beneficial to some herbivores—so the ecological outcome depends heavily on fire extent, intensity and seasonality.

Secondary effects include altered nutrient cycling (volatile N losses), increased surface runoff and sediment delivery to riparian zones and facilitation of invasive grasses that increase future fire risk (a positive feedback). Changes in vegetation structure also affect predator–prey dynamics and the availability of microhabitats for small mammals, insects and birds—affecting overall biodiversity.

Patterns and lessons from MBRC are broadly applicable to savanna/woodland protected areas experiencing mixed human and climatic pressures. Many reserves in southern Africa (and globally in Mediterranean-climate or tropical savannas) show episodic large fires linked to drought, interspersed with smaller burns. The management responses that reduce burned area (early-dry-season controlled burns, community-based ignition control, fuel breaks, rapid response) are transferable—however, adaptation is required for local rainfall patterns, fuel types and socio-economic settings. For example, in landscapes with heavy smallholder agriculture or charcoal production, ignition controls must be paired with livelihood alternatives.

From the findings the study recommends (i) Monitor annually (or seasonally) with remote sensing to detect trends in burned area, fire return intervals and severity—not just snapshots (ii) Characterize burn severity and post-fire vegetation recovery on the ground to link burned area to rhino habitat quality (iii) Implement mosaic early-season burns and fuel-break networks to reduce large contiguous high-intensity fires (iii) Engage local communities in controlled-burn planning and ignition reduction (education, alternatives to slash-and-burn) (iv) Combine fire management with anti-poaching and habitat restoration (re-sowing browse species where necessary).

The limitation of this study is that: these conclusions are based on three dates; robust frequency analysis needs continuous annual time-series and severity metrics. Future work should correlate fire events with climate records, ignition-source mapping and rhino movement/health data to quantify ecological impacts precisely.

In summary, MBRC shows an episodic, spatially shifting fire regime with one major 2015 event and smaller but recurring burns thereafter—pattern consistent with climate and human drivers and carrying substantial implications for rhino habitat, reserve management and biodiversity that are relevant to other savanna reserves.

4.3. Mining-induced vegetation disturbance and structural change

The results provide strong evidence that mining activities significantly alter vegetation structure in the MBRC. Attributes such as basal circumference, DBH and basal area indicate that vegetation closer to mines is more disturbed and fragmented, reflecting reduced growth and regeneration potential. While some vegetation attributes (height, canopy length) appear elevated immediately adjacent to mining areas, this pattern may reflect the dominance of early successional or disturbance-tolerant species rather than mature woodland growth. At medium distances from mines, structural attributes are most suppressed, suggesting a disturbance halo effect where dust deposition, soil compaction, noise and edge effects inhibit growth. At farther distances, vegetation shows signs of recovery, but the overall structural integrity remains compromised.

These vegetation disturbances have direct consequences for wildlife habitat integrity. Reduced basal circumference, DBH and basal area limit the availability of mature trees, which provide shade, forage, nesting and roosting opportunities for a wide range of species. Lower canopy cover reduces microclimatic stability, exposing understory and soil to higher temperatures and evapotranspiration rates, which further degrade habitat quality (Moncrieff et al. 2011). Such alterations diminish habitat heterogeneity, a key determinant of savannah biodiversity. For megaherbivores like black rhino and elephants, reduced tree density and patch size limit browse availability, while ungulates relying on shade during hot periods face physiological stress. Fragmented vegetation also disrupts predator–prey dynamics by altering visibility and cover, potentially reshaping the ecological community structure.

The findings underscore the far-reaching ecological footprint of mining beyond immediate excavation sites. Medium-distance suppression effects point to secondary impacts such as dust fallout, heavy-metal contamination and hydrological disruption. These anthropogenic stressors accelerate soil degradation, reduce seed viability and alter fire regimes, all of which exacerbate vegetation loss. The disturbance pattern aligns with global studies showing that mining landscapes exhibit long recovery times, even when extractive activities cease, because of persistent soil and hydrological alterations.

The modelling approach and findings are broadly transferable to other African conservancies experiencing similar pressures. Across the continent, mining, agriculture and infrastructure expansion drive habitat fragmentation and vegetation degradation. The use of Bayesian modelling with MCMC provides a robust framework to quantify vegetation responses to spatial gradients of disturbance, allowing for site-specific adaptation of management strategies. For instance, in protected areas of West Africa where bauxite mining has reduced forest cover, or in East Africa where gold mining intersects elephant corridors, this approach can quantify vegetation stress, inform buffer zone design and guide rehabilitation planning.

The results highlight the urgent need to incorporate mining-induced vegetation disturbance into conservation planning for MBRC and comparable conservancies. Priority actions should include establishing exclusion zones and ecological buffers around mining sites to minimize halo effects. Implementing vegetation rehabilitation programs in medium-distance zones where suppression is most acute. Monitoring soil quality and contamination to address secondary degradation factors such as heavy-metal accumulation. Integrating remote sensing with ground-based Bayesian modelling to continuously assess vegetation recovery trajectories.

Community involvement is equally critical. Since mining provides economic benefits, management strategies must balance local livelihoods with long-term ecological integrity. Engaging communities in restoration activities, developing alternative livelihoods and ensuring compliance with environmental regulations will enhance the effectiveness of conservation interventions.

The study reveals that mining in the MBRC has a significant negative impact on vegetation attributes, with structural degradation extending beyond immediate mining sites and altering the integrity of wildlife habitats. These spatiotemporal disturbances compromise biodiversity resilience and ecosystem functionality. By applying advanced modelling approaches, this research provides not only a site-specific diagnosis but also a transferable framework for other African protected areas under similar anthropogenic pressures. Effective mitigation requires proactive restoration, strict regulation and landscape-level planning that incorporates both ecological and socio-economic dimensions.

4.4. Spatial occurrence and habitat associations of wildlife species in MBRC

The jackknife results robustly demonstrate that habitat structure, defined by LULC, is the primary determinant of wildlife distribution in the Midlands Black Rhino Conservancy (MBRC). This is ecologically coherent as LULC directly represents the availability of critical resources like forage, cover and water. The strong performance of the ‘all variables’ model confirms that while LULC is paramount, topography (slope, elevation, aspect) fine-tunes these predictions by influencing microclimates, drainage, visibility and accessibility for different species. For instance, steep slopes may be less suitable for bulk grazers like buffalo (Matawa et al. 2012) but could provide refuge for species like kudu.

The resulting map validates the model's output, showing that wildlife persistence is not uniform. The presence of contiguous suitable habitat blocks is encouraging and likely explains the continued presence of key species. However, the interspersion of unsuitable areas, presumably from agriculture, settlements, or degraded land, creates a fragmented landscape (Zvidzai et al. 2023). This fragmentation poses significant ecological consequences: it impedes animal movement, disrupts migratory corridors, increases human–wildlife conflict along interfaces and reduces genetic exchange between sub-populations, elevating their long-term extinction risk. The persistence of species like the black rhino, which is in the conservancy's name, is particularly threatened by fragmentation as it requires large home ranges.

The core finding—that LULC is the dominant predictor of habitat suitability—is highly transferable to other savanna ecosystems in Africa and beyond. Conservation planning in similar regions can prioritize the acquisition and interpretation of high-resolution LULC data as a first step in identifying critical habitats and corridors. The methodology of combining jackknife analysis with MaxEnt (or similar) modelling provides a powerful, transferable framework for assessing wildlife distribution where direct census data is difficult to obtain. However, regional transferability requires calibrating the model with local species-specific data. For example, the importance of a specific LULC class (e.g. dense woodland) for sable antelope may be different in another region with alternative forage options. Thus, the approach is transferable, but the specific model parameters and resultant map must be region-specific.

Although longer-term datasets are desirable for detecting interannual variability and population trends, the three-year sampling window employed in this study is sufficient for presence-only species distribution modelling, where spatial representativeness and sampling consistency are critical. The dataset captures current wildlife–habitat relationships across heterogeneous land cover types and disturbance gradients within the conservancy. The resulting distribution and habitat suitability outputs should therefore be interpreted as a snapshot of present-day conditions, providing a reference framework for future long-term monitoring and adaptive conservation management in the Midlands Black Rhino Conservancy.

The objective to 'determine the current status, distribution and relative abundance of key wildlife species' is addressed synthetically. The current status is that wildlife persists, as confirmed by their predicted presence in suitable habitats. The distribution is explicitly shown by the habitat suitability map, which is a proxy for where species are most likely to be found. Relative abundance is inferred rather than measured; larger patches of highly suitable habitat are predicted to support higher densities and more viable populations than smaller, isolated patches. The title, 'Wildlife persists… but require an emergency conservation plan', is strongly supported by these results. Persistence is evident, but the fragmentation shown on the map necessitates an emergency plan focused on: (1) securing and protecting wildlife corridors between suitable habitat blocks, (2) mitigating human–wildlife conflict and (3) potentially restoring degraded areas to improve habitat connectivity and overall carrying capacity.

4.5. Implications of the disturbances on the black rhino

Land cover dynamics identified in this study have direct implications for black rhinoceros ecology, particularly through changes in woody vegetation structure that underpin forage availability, thermal cover and movement corridors. Projected declines in forest and woodland cover are likely to reduce habitat continuity, increasing fragmentation and potentially constraining black rhino ranging behaviour across the MBRC landscape. Fire regimes further interact with land cover change by modifying vegetation regeneration patterns and browse composition, which are key determinants of black rhino habitat suitability. Areas experiencing recurrent high-severity fires may exhibit reduced woody biomass and altered species composition, thereby diminishing habitat quality for browsing megaherbivores such as the black rhinoceros. Fire regimes and mining activities were assessed not only as individual disturbances but also in terms of their ecological interactions, which can modify vegetation structure, forage availability and habitat connectivity critical to black rhinoceros. Areas affected by repeated fires or mining-related vegetation loss may reduce the availability of high-quality forage, fragment movement corridors and constrain refuge areas, potentially affecting black rhino spatial ecology and habitat use. By integrating these disturbance interactions into habitat suitability assessments, the study provides a more realistic and species-centred understanding of how anthropogenic and natural disturbances shape black rhino habitat within MBRC. These insights support proactive conservation planning, highlighting zones where fire and mining mitigation could enhance habitat quality and connectivity for black rhinoceros. Mining-related disturbance introduces localized but persistent habitat degradation and barriers to movement, which may disrupt connectivity between core black rhino habitat patches. When combined with projected land cover transitions, these disturbances pose cumulative risks to spatial accessibility and functional habitat availability for black rhinoceros populations. By explicitly linking land cover evolution, fire dynamics, mining impacts and habitat suitability modelling to black rhinoceros ecological requirements, this study provides a species-centred basis for proactive conservation planning within MBRC, supporting targeted interventions aimed at maintaining habitat connectivity, forage resources and long-term population viability.

Our analysis highlights the cumulative impacts of mining, fire and land use/land cover (LULC) change on vegetation structure and wildlife habitat in the MBRC. By integrating spatial layers representing mining disturbance, fire frequency and severity and historical LULC transitions within a GIS framework, we were able to identify areas where multiple stressors overlap. Mining effects were quantified using Bayesian regression models, while fire regimes and LULC dynamics were interpreted as additional pressures influencing habitat quality and connectivity. This integrative approach revealed that regions experiencing simultaneous mining, frequent fires and intensive land cover change exhibited the greatest structural vegetation degradation and habitat fragmentation, thereby restricting the distribution and abundance of key wildlife species. Considering these cumulative pressures is critical for designing effective, evidence-based conservation interventions aimed at sustaining both habitat integrity and wildlife persistence in the MBRC.

Forest loss within MBRC is likely to reduce habitat connectivity and constrain black rhinoceros movement, limiting access to critical forage and refuge areas. Changes in forest cover and structure can indirectly influence species interactions by modifying the distribution of sympatric herbivores, predator–prey dynamics and resource availability within the landscape. By explicitly linking forest loss, disturbance regimes (fire and mining) and land cover change to black rhinoceros spatial ecology, the study provides a species-centred assessment of habitat quality, connectivity and conservation priority areas.

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Author contributions

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

References

Al-doski J, Mansor SB, Shafri HZM. 2013. Change detection process and techniques. Civil and Environmental Research. 3(10):37–45.

Antwi EK, Krawczynski R, Wiegleb G. 2008. Detecting the effect of disturbance on habitat diversity and land cover change in a post-mining area using GIS. Landsc Urban Plan. 87(1):22–32. https://doi.org/10.1016/j.landurbplan.2008.03.009

Aubrecht C, Elvidge C, Ziskin D, Rodrigues P, Gil A. 2010. Observing stress of artificial night lighting on marine ecosystems-a remote sensing application study. na. 2(1):1–10.

Banks SC, Knight EJ, McBurney L, Blair D, Lindenmayer DB. 2011. The effects of wildfire on mortality and resources for an arboreal marsupial: resilience to fire events but susceptibility to fire regime change. PLoS One. 6(8):e22952. https://doi.org/10.1371/journal.pone.0022952

Boroujeni SPH et al. 2025. Toward AI-driven fire imagery: attributes, challenges, comparisons, and the promise of VLMs and LLMs. Machine Learning with Applications. 22:100763. https://doi.org/10.1016/j.mlwa.2025.100763

Camps-Valls G. 2009. Machine learning in remote sensing data processing. 2009 IEEE international workshop on machine learning for signal processing. 1–6. https://doi.org/10.1109/MLSP.2009.5306233

Chanyandura A, Muposhi VK, Gandiwa E, Muboko N. 2021. An analysis of threats, strategies, and opportunities for African rhinoceros conservation. Ecol Evol. 11(11):5892–5910. https://doi.org/10.1002/ece3.7536

Chase MJ et al. 2016. Continent-wide survey reveals massive decline in African savannah elephants. PeerJ. 4:e2354. https://doi.org/10.7717/peerj.2354

Chia EK et al. 2016. Effects of the fire regime on mammal occurrence after wildfire: site effects vs landscape context in fire-prone forests. Forest Ecol Manage. 363:130–139. https://doi.org/10.1016/j.foreco.2015.12.008

Coetzee BW, Chown SL. 2016. A meta-analysis of human disturbance impacts on antarctic wildlife. Biological Reviews. 91(3):578–596. https://doi.org/10.1111/brv.12184

Collins JB, Woodcock CE. 1996. An assessment of several linear change detection techniques for mapping forest mortality using multitemporal landsat TM data. Remote Sens Environ. 56(1):66–77. https://doi.org/10.1016/0034-4257(95)00233-2

Coppin PR, Bauer ME. 1996. Digital change detection in forest ecosystems with remote sensing imagery. Remote Sens Rev. 13(3-4):207–234. https://doi.org/10.1080/02757259609532305

Corner RJ, Dewan AM, Chakma S. 2013. Monitoring and prediction of land-use and land-cover (LULC) change. Dhaka megacity: geospatial perspectives on urbanisation, environment and health. Springer; p. 75–97.

Dewan AM, Yamaguchi Y. 2009a. Land use and land cover change in greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization. Appl Geogr. 29(3):390–401. https://doi.org/10.1016/j.apgeog.2008.12.005

Dewan AM, Yamaguchi Y. 2009b. Using remote sensing and GIS to detect and monitor land use and land cover change in Dhaka metropolitan of Bangladesh during 1960–2005. Environ Monit Assess. 150(1249237. https://doi.org/10.1007/s10661-008-0226-5

Du Toit R. 1994. MANAGEMENT OF BLACK RH| NQ IN Z| MBABWEAN CONSERVANCIES. p. 1–9.

Framework KMGB. 2022. Kunming-montreal global biodiversity framework. Convention Biol. Divers. Kunming-Montreal Glob. Biodivers. Framew.(cbd. int).

Gaynor KM, Hojnowski CE, Carter NH, Brashares JS. 2018. The influence of human disturbance on wildlife nocturnality. Sci. 360(6394):1232–1235. https://doi.org/10.1126/science.aar7121

Gbedzi DD et al. 2022. Impact of mining on land use land cover change and water quality in the asutifi north district of Ghana, West Africa. Environmental Challenges. 6:100441. https://doi.org/10.1016/j.envc.2022.100441

Henrich M et al. 2025. Camera traps and deep learning enable efficient large-scale density estimation of wildlife in temperate forest ecosystems. Remote Sensing in Ecology and Conservation. 12(1):148–163.

Kalies E, Chambers C, Covington W. 2010. Wildlife responses to thinning and burning treatments in southwestern conifer forests: a meta-analysis. Forest Ecol Manage. 259(3):333–342. https://doi.org/10.1016/j.foreco.2009.10.024

Kuyah S et al. 2016. Trees in agricultural landscapes enhance provision of ecosystem services in sub-saharan Africa. International Journal of Biodiversity Science, Ecosystem Services & Management. 12(4):255–273.

Lu D, Mausel P, Brondizio E, Moran E. 2004. Change detection techniques. Int J Remote Sens. 25(12):2365–2401. https://doi.org/10.1080/0143116031000139863

Luiselli L et al. 2025. Red listing African goliath beetles: assessing threats and conservation needs. Afr J Ecol. 63(1):e70018. https://doi.org/10.1111/aje.70018

Macdonald DW, Willis KJ. 2013. Key topics in conservation biology 2. John Wiley & Sons.

Matawa F, Murwira A, Schmidt KS. 2012. Explaining elephant (Loxodonta africana) and buffalo (Syncerus caffer) spatial distribution in the Zambezi valley using maximum entropy modelling. Ecol Model. 242:189–197. https://doi.org/10.1016/j.ecolmodel.2012.05.010

Moncrieff GR, Chamaillé-Jammes S, Higgins SI, O'Hara RB, Bond WJ. 2011. Tree allometries reflect a lifetime of herbivory in an African savanna. Ecology. 92(12):2310–2315. https://doi.org/10.1890/11-0230.1

Mugaviri BM, Moyo GH, Pedzisai E, Maravanyika C. 2022. Spatio-temporal distribution of the black rhino (Diceros bicornis L.) in the midlands black rhino conservancy, Zimbabwe. In: Sustainable Wildlife Management. IntechOpen.

Muleta Gurmessa M, Badasa Moisa M, Jira Tesso G, Geleta Erena M. 2024. Impacts of land use land cover change on leopard (Panthera pardus) habitat suitability and its effects on human wildlife conflict in hirkiso forest, sibu sire district, Western Ethiopia. All Earth. 36(1):1–24. https://doi.org/10.1080/27669645.2024.2433798

Mutanga CN, Gandiwa E. 2023. Natural heritage: wildlife and nature preserves in the African tourism landscape. Cultural heritage and tourism in Africa. Routledge; p. 269–283. https://doi.org/10.4324/9781003153955-16

Palma L et al. 2024. African forest elephants persist in Guinea-Bissau but require an emergency conservation plan. Oryx. 58(1):125–128. https://doi.org/10.1017/S0030605323000674

Rehman G et al. 2021. Impacts of mining on local fauna of wildlife in district mardan & district mohmand khyber pakhtunkhwa Pakistan. Braz J Biol. 84:e251733. https://doi.org/10.1590/1519-6984.251733

Rey L, Kery M, Sierro A, Posse B, Arlettaz R, Jacot A. 2019. Effects of forest wildfire on inner-alpine bird community dynamics. PLoS One. 14(4):e0214644. https://doi.org/10.1371/journal.pone.0214644

Santos X et al. 2014. Is response to fire influenced by dietary specialization and mobility? A comparative study with multiple animal assemblages. PLoS One. 9(2):e88224. https://doi.org/10.1371/journal.pone.0088224

Schueler V, Kuemmerle T, Schröder H. 2011. Impacts of surface gold mining on land use systems in Western Ghana. Ambio. 40(5):528–539. https://doi.org/10.1007/s13280-011-0141-9

Serneels S, Said MY, Lambin EF. 2001. Land cover changes around a major east African wildlife reserve: the mara ecosystem (Kenya). Int J Remote Sens. 22(17):3397–3420. https://doi.org/10.1080/01431160152609236

Singh A. 1989. Review article digital change detection techniques using remotely-sensed data. Int J Remote Sens. 10(6):989–1003. https://doi.org/10.1080/01431168908903939

Singh S, Talwar R. 2015. Impact of topographic correction on high spectral resolution MODIS sensor satellite imagery of himalayan region. 2015 International Conference on Signal Processing and Communication (ICSC).

Singh J, Raghubanshi A, Singh R, Srivastava S. 1989. Microbial biomass acts as a source of plant nutrients in dry tropical forest and savanna. Nature. 338(6215):499–500. https://doi.org/10.1038/338499a0

Sonawane S, Patil NN. 2025. Performance evaluation of modified YOLOv5 object detectors for crop-weed classification and detection in agriculture images. SN Computer Science. 6(2):126. https://doi.org/10.1007/s42979-024-03520-x

Swain PH. 1982. 28 pattern recognition techniques for remote sensing applications. Handbook of statistics. Vol. 2; p. 609–620. https://doi.org/10.1016/S0169-7161(82)02031-8

Wang H et al. 2018. Graphgan: graph representation learning with generative adversarial nets. Proceedings of the AAAI conference on artificial intelligence. 32:2508–2515. https://doi.org/10.1609/aaai.v32i1.11872

Wiens JJ et al. 2010. Niche conservatism as an emerging principle in ecology and conservation biology. Ecol Lett. 13(10):1310–1324. https://doi.org/10.1111/j.1461-0248.2010.01515.x

Xu X, Zhao Y, Sima J, Zhao L, Mašek O, Cao X. 2017. Indispensable role of biochar-inherent mineral constituents in its environmental applications: a review. Bioresour Technol. 241:887–899. https://doi.org/10.1016/j.biortech.2017.06.023

Zvidzai M, Mawere KK, N'andu RJ, Ndaimani H, Zanamwe C, Zengeya FM. 2023. Application of maximum entropy (MaxEnt) to understand the spatial dimension of human–wildlife conflict (HWC) risk in areas adjacent to gonarezhou national park of Zimbabwe. Ecology and Society. 28(3):e018. https://doi.org/10.5751/ES-14420-280318

Zwolak R. 2009. A meta-analysis of the effects of wildfire, clearcutting, and partial harvest on the abundance of north American small mammals. Forest Ecol Manage. 258(5):539–545. https://doi.org/10.1016/j.foreco.2009.05.033

Appendices

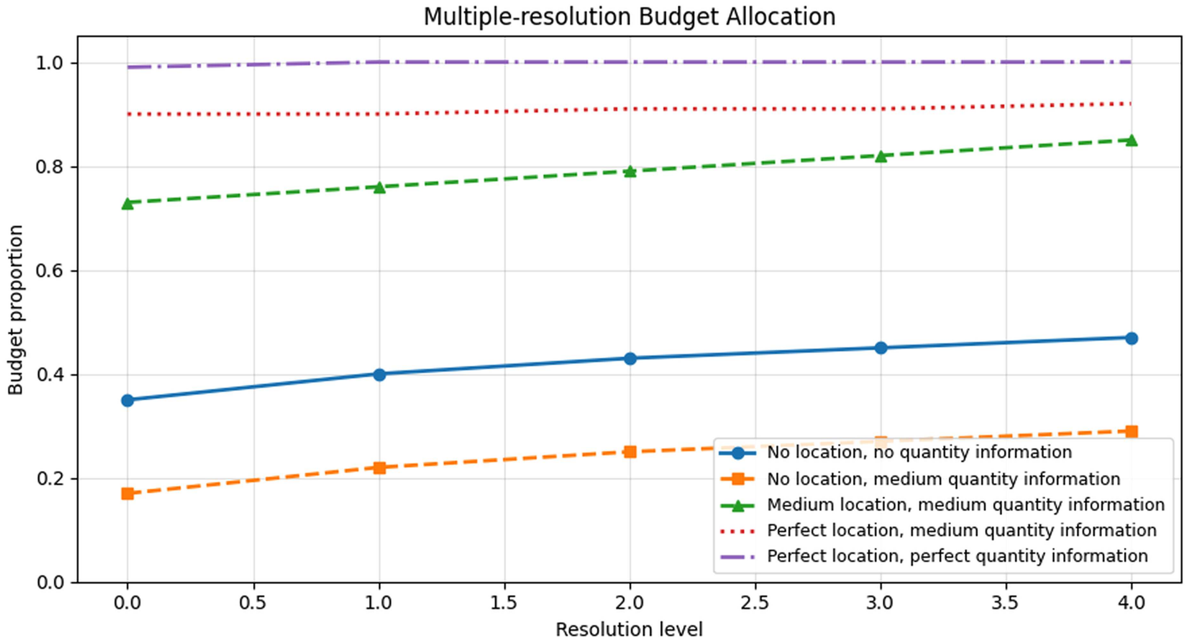

Figure A1. Multiple-resolution budget allocation showing the effects of spatial resolution and information quality on budget efficiency, comparing scenarios with varying levels of location accuracy and quantity information across resolution levels. Model performance improves with increasing locational and quantitative information, peaking under perfect conditions.

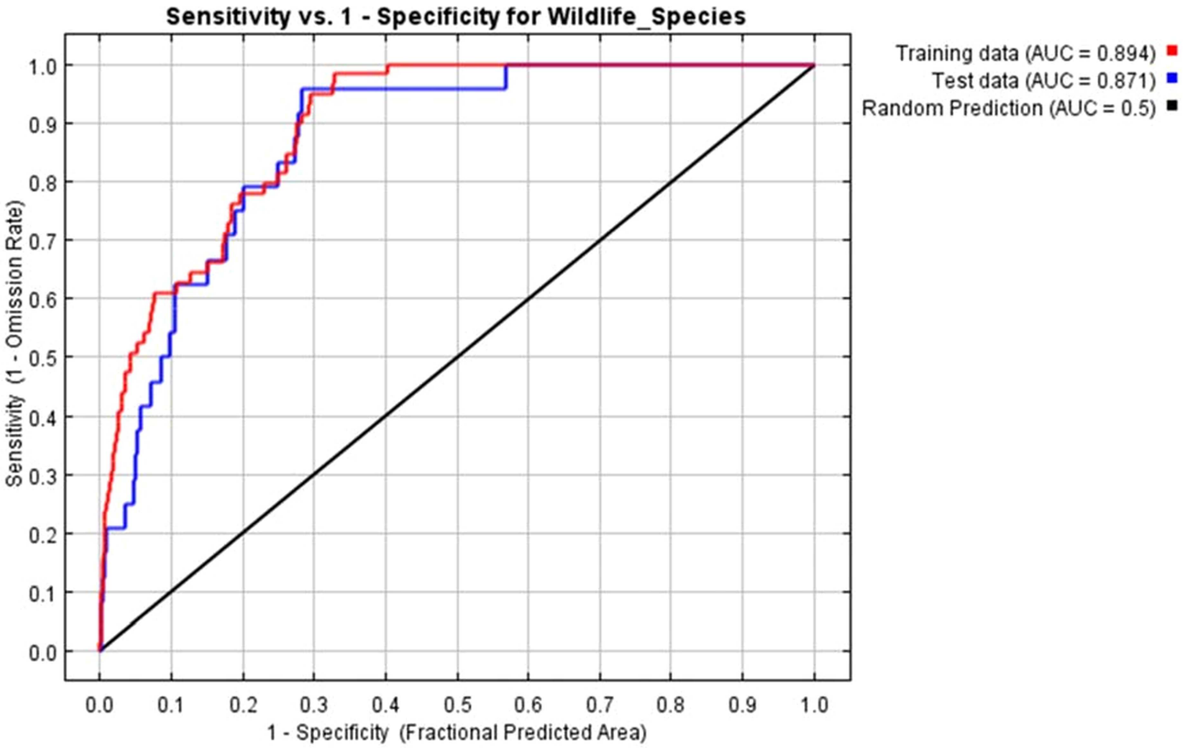

Figure A2. (a): Receiver operating characteristic (ROC) curve for the Maxent species distribution model developed for the MBRC, illustrating model discrimination performance. The plot shows sensitivity (1 − omission rate) against 1 − specificity (fractional predicted area) for training (red; AUC = 0.894) and test data (blue; AUC = 0.871). The black diagonal line represents random prediction (AUC = 0.5), indicating that the Maxent model performs substantially better than random in predicting species presence within the MBRC. (b): Omission rates and predicted area as functions of the cumulative threshold for the Maxent species distribution model developed for the MBRC. The figure illustrates omission on training samples (blue) and test samples (cyan) relative to the predicted omission (black line), alongside the fraction of background area predicted as suitable habitat (red). Agreement between observed and predicted omission indicates good model calibration, while the decline in predicted background area with increasing threshold reflects increasing model restrictiveness in delineating suitable habitat within the MBRC.