

LANDSCAPES CHANGE DYNAMICS AND PATCH CONNECTIVITY IN THE CHITWAN–PARSA COMPLEX, NEPAL

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Received: 22nd March 2026, **Accepted:** 2nd August 2026

ABSTRACT

Land-use and land-cover (LULC) changes can lead to various environmental consequences, such as soil degradation, reduced agricultural productivity, flood risks, and the loss and fragmentation of habitats. These alterations not only modify land cover patterns but also disrupt ecological connectivity, affecting species movement, gene flow, and the overall functionality of habitats. This study combines nine spectral indices (NDVI, EVI, GCI, SAVI, BSI, NDWI, MNDWI, NDSAI, and NDBI) and topographic variables (elevation and slope) across the Chitwan–Parsa complex (CPC) for LULC mapping and enhancing accuracy. This study revealed major transitions such as increase in built-up areas from 0.88 % to 3.41 %, increase in grassland from 2.08 % to 7.36 %, decline of cropland from 16.95 % to 8.97 %, decrease in forest cover from 69.07 % to 64.09 %, increase in sand gravel from 6.28 % to 13.19 %, and declined in water bodies from 4.56 % to 2.81 %. This indicates the pressure of urbanization, hydrological stress which reshape the landscape and potentially influencing habitat quality and connectivity in CPC. Furthermore, sixteen core areas are identified across CPC by using core mapper tool. Then, least cost path analysis was done between core habitats to understand habitat dynamics, identify critical corridors, and inform conservation strategies to sustain ecological connectivity. The patches on the eastern side of the complex shows better connectivity than the ones on the western side based on cost values. Patches 5, 6, 7, 8, 9, 10, 12, 14 and 16 emerge as the most connected indicating that they are highly linked to other patches and function as key hubs in the ecological network. The study underscores the need to restore riparian zones and wetlands, protect forest–grassland–water mosaics to sustain key species such as tiger (*Panthera tigris*), one-horned rhinoceros (*Rhinoceros unicornis*), elephant (*Elephas maximus*), and gaur (*Bos gaurus*).

Keywords: Landscape Connectivity, Core Habitat Mapper, Least-Cost Path, Random Forest, Spatial Ecology, Terai Arc Landscape

INTRODUCTION

Natural and anthropogenic processes have altered the Earth's land-use and land-cover (LULC) at an exceptional rate, affecting both biodiversity and ecological systems (Murphy & Romanuk, 2014; Semenchuk *et al.*, 2022). Conversion of natural habitat to agricultural land and urban areas via human activities in over two decades (1995–2022) has caused nearly 1.4 % of global species to extinction particularly in tropical areas (Cabernard *et al.*, 2024). The global LULC change simulation results indicate that most of the developing countries particularly in Asia and Africa have experienced urbanization, cropland expansion, and deforestation (Addae *et al.*, 2025), which impacted the great loss of species from these important biodiversity hotspots. A study estimated that in Asia alone, over 26 % of cropland expansion and urbanization in the forest lands is expected to happen by 2100, where another 59.1 % comes in grassland (Addae *et al.*, 2025) resulting to habitat fragmentation, degradation, and loss (Fahrig, 2003, 2017; Liao *et al.*, 2025; Moustakas *et al.*, 2025; Sugianto *et al.*, 2022). Consequently, such fragmentation reduces overall habitat availability, alters spatial configuration and intensifies edge effects (Haddad *et al.*, 2015) that further degrades genetic diversity and animal survival (Teitelbaum *et al.*, 2020). Most of the developing countries have undergone into a major socio-economic transition (Sawada, 2023) demanding infrastructure development and industrial expansion. Additionally, climate change has exacerbated the habitat degradation and fragmentation (Parmesan *et al.*, 2022; Segan *et al.*, 2016) through accelerated natural succession, invasion, and natural calamities (Deslippe & Veenendaal, 2025; Parmesan *et al.*, 2022; Shrestha & Shrestha, 2019).

LULC change and fragmentation exert the greatest pressures in developing nations, especially those like Nepal who are in the process of a major socio-economic transition (Ning *et al.*, 2023). Southern lowland (Terai) of Nepal, particularly has experienced greater pressures of both anthropogenic activities and climate change, as they are fertile but densely populated landscape (MFSC, 2015; Thorn, 2019; Wikramanayake *et al.*, 2010). In other hand, this geographical zone is biologically rich and economically vital. The Terai Arc Landscape (TAL), a globally recognized tiger landscape connecting 16 protected areas in southern Nepal and north-eastern India is one of many important landscapes that has experienced severe anthropogenic and natural pressure in landcover conversion (MFSC, 2015; Wikramanayake *et al.*, 2010). A study on habitat fragmentation can ideally provide an insight on metapopulation dynamics, animal interaction, and ecosystem functioning. Small patches with low or no connectivity among the patches cause the risk of extinction as it increases the edge effect and reduces the dispersal for recolonization (Gillies *et al.*, 2025). In practice, understanding of these dynamics is the basis for designing and managing coupled landscapes, including wildlife corridors, which are crucial for species conservation particularly to that of larger home range and dispersal. Thus, management approaches focusing on connectivity can support the conservation of biodiversity and enhance ecosystem resilience in the anthropocentric environment (Andr n, 1994; Fletcher *et al.*, 2018; Haddad *et al.*, 2015; Hanski & Ovaskainen, 2000). LULC change and connectivity studies have been widely used in many important landscapes. However, few studies have attempted to understand the connectivity using LULC map as a conductance layer (Gelmi-Candusso *et al.*, 2025; Habib *et al.*, 2025; Lyimo *et al.*, 2024), and other use suitability as the conductance layer for identifying connectivity (Acharya *et al.*, 2023; Neupane *et al.*, 2022). However, LULC-based conductance layer would provide better accurate information (Kaszta *et al.*, 2020) as it accounts road, railways, rivers, and human settlements while considering patch connectivity.

The Chitwan–Parsa Complex (CPC) is a critical conservation zone but has experienced increasing pressure from agricultural intensification, infrastructure development, resource

extraction and linear infrastructure projects including roads, irrigation canals, and petroleum pipelines in and around protected areas (PNP, 2025; Rosales-Richard *et al.*, 2020) resulting to habitat fragmentation and broken linkages among core habitat patches. CPC includes two protected areas (Chitwan and Parsa national parks) that hold country 48 % of tiger population (DNPWC and DFSC, 2022), 93 % of one-horned rhinoceros (DNPWC, 2024), country's gaur population (DNPWC, 2020) and many threatened species (CNP, 2013; PNP, 2018). Along with the anthropogenic pressures, the natural climatic events and changes have put the existence of these threatened species at risk (MFSC, 2015; Thapa *et al.*, 2017) within the complex. Beyond its national importance, the complex forms a part of a broader ecological network extending into the Valmiki Tiger Reserve in India, and recognizing Chitwan and Parsa as a unified complex from a management perspective enables coordinated ecological management, corridor protection, and harmonized conservation policies across administrative boundaries. Its transboundary linkage can further enhance conservation outcomes through shared strategies and landscape-level planning. Thus, the recognition of Chitwan and Parsa as an integrated conservation “complex” should be both ecologically and administratively substantiated.

Understanding habitat connectivity among the important patches within the complex remains essential as protection status alone does not guarantee functional connectivity for wide-ranging species. Identifying core patches and connectivity ensures gene flow, seasonal movement, and resource access, supporting the long-term ecological stability of the protected landscape. Monitoring long-term land-use and land-cover (LULC) dynamics is therefore fundamental for assessing and understanding habitat condition patterns within the CPC. Spectral indices from Landsat imagery would be beneficial to improve the LULC classification workflow with better accuracy (Faridatul & Wu, 2018; Lee *et al.*, 2018; Zhang *et al.*, 2017). For example; vegetation related indices such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Coverage Index (GCI), Soil Adjusted Vegetation Index (SAVI) enhance vegetation classification (Gitelson *et al.*, 1996; A. Huete *et al.*, 2002; Huete, 1998; Justice *et al.*, 1998; Rouse *et al.*, 1973; Wu *et al.*, 2012). Similarly, Normalized Difference Water Index (NDWI) and Modified Normalized Difference Water Index (MNDWI) improve water body detection (Gao, 1996; McFeeters, 1996; Xu, 2006). Additionally, Bare Soil Index (BSI) improve the bare area classification (Rikimaru *et al.*, 2002) whereas Normalized Differential Sand Areas Index (NDSAI) improve sand area classification (Sahar *et al.*, 2021; Secu *et al.*, 2022), and Normalized Difference Built-up Index (NDBI) provide additional information for distinguishing built-up areas (Zha *et al.*, 2003). Therefore, this study analyses multi-decadal land-use and land-cover change (1985–2024) using Google Earth Engine and integrates these results with a connectivity analysis of the Chitwan–Parsa Complex to understand habitat dynamics, identify critical corridors, and support conservation planning. This study aims to provide a regional-level understanding of habitat change and patch connectivity to sustain long-term biodiversity conservation and formulate ecological management strategies in this ecologically significant transboundary landscape.

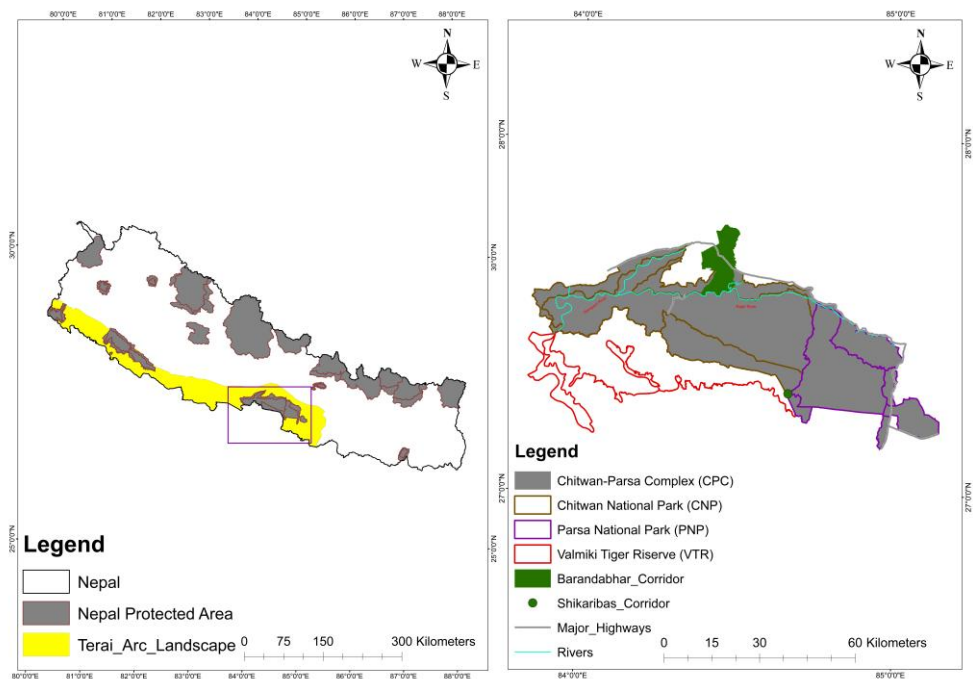
MATERIALS AND METHODS

Study Area

The Chitwan–Parsa Complex (CPC) forms the contiguous protected landscape in Nepal. The complex covers 2594.69 km² and consists of two national parks: Chitwan National Park (CNP; 952.63 km²; 27°20′–27°43′ N and 83°44′–84°45′ E) and Parsa National Park (PNP; 627.39 km²; 27°15′–27°33′ N and 84°41′–84°58′ E) & its buffer zone (CNP; 729.37 km² &

PNP; 285.3 km² (Fig. 1). This protected landscape is home for many threatened animals including over 550 bird species, 86 species of mammals, more than 50 reptile and amphibian species, and diverse aquatic fauna including fish, mugger crocodile (*Crocodylus palustris*), and gharial (*Gavialis gangeticus*) (CNP, 2013; PNP, 2018; Shah *et al.*, 2024). The surrounding buffer zones extend over 1014.67 km² where over 350,000 people resides with subsistent livelihoods primarily relying on farming, forest products, and riverbed extraction, thereby intensifying land-use pressures (CNP, 2013; PNP, 2018). People are restricted to go inside national parks for extraction however, there are a few incidents of people entering inside park for illegal activities (CNP, 2013; PNP, 2018). Park authority has been working to restore the habitat inside the park through grassland and waterhole construction and maintenance. Additionally, active intervention such as relocation of human settlements from park also helped to minimize the habitat fragmentation. This intervention involved the resettlement of Padampur village (~1,522 people) from CNP (1995-1998), and four villages (Rambhori, Bhata, Ramauli, and Pratappur; more than 473 households) from PNP (2009-2013) (Dhakal *et al.*, 2011; McLean & Stræde, 2003; Pandey *et al.*, 2025). These interventions facilitated the regeneration of sal (*Shorea robusta*) forests, grasslands, and riverine ecosystems. The landscape is characterized by subtropical climate, with average summer temperatures exceeding 35°C, mild winters near 10°C, and annual rainfall ranging from 1,500 to 2,200 mm, mostly during the monsoon season (June–September) (DNPWC and DFSC, 2022).

Fig. 1: Study Area Map Showing Chitwan-Parsa Complex (CPC) With Chitwan National Park (CNP), Parsa National Park (PNP) and Valmiki Tiger Reserve (VTR)



Sal forests dominate land cover (~70 % in CNP; ~90 % in PNP), complemented by extensive grasslands (~10 % in CNP) and riverine habitats along the East Rapti, Narayani, and Reu rivers (CNP, 2013, 2016; PNP, 2018). Connectivity between the two parks is

reinforced by two critical corridors: Barandabhar Corridor links CNP to the Mahabharat range, providing north–south movement routes for elephants, tigers, and rhinos. Similarly, the Shikaribas Corridor connects PNP with Valmiki Tiger Reserve, India, ensuring genetic exchange and ecological connectivity across trans-border landscape (Thapa & Tuladhar, 2021).

Methodology

Creating Different Spectral Indices in Google Earth Engine (GEE)

We use Landsat Level-2, Collection 2, Tier 1 Surface Reflectance (SR) images from Google Earth Engine (GEE) for three study period: 1985 (Landsat 5 TM), 2005 (Landsat 7 ETM+), and 2024 (Landsat 9 OLI) because SR data provides a more accurate representation of ground conditions avoiding atmospheric effects, thus making it highly suitable for reliable LULC mapping and change detection (Vermote *et al.*, 2016). As complete cloud-free imagery was not available for the period of 1985, a median composite was generated from the images of the year 1985–1989 to represent this baseline period. Despite the possibility of temporal smoothing, this temporal aggregation guarantees adequate cloud-free coverage throughout the study area. Images were filtered by region of interest, date range, and cloud cover percentage (<10 %). Cloud and shadow pixels were removed using the QA_PIXEL band and cloud mask function in GEE (Gorelick *et al.*, 2017), and a one-year median composite image was selected for the study area. Landsat spectral indices are crucial for increasing accuracy in LULC classification (Aryal *et al.*, 2023; Dash *et al.*, 2023; Ganjirad & Bagheri, 2024; Lee *et al.*, 2018). Thus, to improve class separability, several indices including Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Coverage Index (GCI), Soil Adjusted Vegetation Index (SAVI), Bare Soil Index (BSI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Normalized Differential Sand Areas Index (NDSAI), and Normalized Difference Built-up Index (NDBI) were calculated and added as predictor variables. These indices were computed using standard band formulas (Table 1) and merged with the cloud-free median composites of each study year in GEE for the final LULC map generation. Additionally, topographic variables (slope and elevation) were derived from the Shuttle Radar Topography Mission (SRTM) DEM and incorporated into the classification dataset. During training, the Random Forest classifier uses all input variables (spectral bands, spectral indices, slope, and elevation) together for each sample point, where each training point is converted into a feature vector that includes values from all selected bands (e.g., SR_B1–SR_B7) and derived nine indices (NDVI, NDBI, NDWI, etc.). The classifier then learns patterns by relating these combined feature values to known land cover class of each training point. Instead of using a single band or single index, the model considers multiple variables at the same time to make classification decisions. This helps model to distinguish similar classes (For example; built-up areas vs. bare soil and cropland vs. grassland) proving better accuracy of the classification.

Table 1: Spectral indices and their band formula for LANDSAT 9 and LANDSAT 7/5 images.

SN	Index	Formula	LANDSAT 9	LANDSAT 7/5	Reference
1	NDVI	$(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED})$	$(\text{B5} - \text{B4}) / (\text{B5} + \text{B4})$	$(\text{B4} - \text{B3}) / (\text{B4} + \text{B3})$	(Rouse <i>et al.</i> , 1973)
2	EVI	$2.5 * (\text{NIR} - \text{RED}) / (\text{NIR} + 6 * \text{RED} - 7.5 * \text{BLUE} + 1)$	$2.5 * (\text{B5} - \text{B4}) / (\text{B5} + 6 * \text{B4} - 7.5 * \text{B2} + 1)$	$2.5 * (\text{B4} - \text{B3}) / (\text{B4} + 6 * \text{B3} - 7.5 * \text{B1} + 1)$	(Huete <i>et al.</i> , 2002; Justice <i>et al.</i> , 1998)
3	GCI	$(\text{NIR} / \text{GREEN}) - 1$	$(\text{B5} / \text{B3}) - 1$	$(\text{B4} / \text{B2}) - 1$	(Gitelson <i>et al.</i> , 1996; Wu <i>et al.</i> , 2012)
4	SAVI	$1.5 * (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED} + 0.5)$	$1.5 * (\text{B5} - \text{B4}) / (\text{B5} + \text{B4} + 0.5)$	$1.5 * (\text{B4} - \text{B3}) / (\text{B4} + \text{B3} + 0.5)$	(Huete, 1998)
5	BSI	$((\text{RED} + \text{SWIR1}) - (\text{NIR} + \text{BLUE})) / ((\text{RED} + \text{SWIR1}) + (\text{NIR} + \text{BLUE}))$	$((\text{B4} + \text{B6}) - (\text{B5} + \text{B2})) / ((\text{B4} + \text{B6}) + (\text{B5} + \text{B2}))$	$((\text{B5} + \text{B3}) - (\text{B4} + \text{B1})) / ((\text{B3} + \text{B5}) + (\text{B4} + \text{B1}))$	(Rikimaru <i>et al.</i> , 2002)
6	NDWI	$(\text{GREEN} - \text{NIR}) / (\text{GREEN} + \text{NIR})$	$(\text{B3} - \text{B5}) / (\text{B3} + \text{B5})$	$(\text{B2} - \text{B4}) / (\text{B2} + \text{B4})$	(Gao, 1996; McFeeters, 1996)
7	MNDWI	$(\text{GREEN} - \text{SWIR1}) / (\text{GREEN} + \text{SWIR1})$	$(\text{B3} - \text{B6}) / (\text{B3} + \text{B6})$	$(\text{B2} - \text{B5}) / (\text{B2} + \text{B5})$	(Xu, 2006)
8	NDSAI	$(\text{SWIR1} - \text{RED}) / \text{SWIR1} + \text{RED}$	$(\text{B6} - \text{B4}) / (\text{B6} + \text{B4})$	$(\text{B5} - \text{B3}) / (\text{B5} + \text{B3})$	(Sahar <i>et al.</i> , 2021; Secu <i>et al.</i> , 2022)
9	NDBI	$(\text{SWIR1} - \text{NIR}) / (\text{SWIR1} + \text{NIR})$	$(\text{B6} - \text{B5}) / (\text{B6} + \text{B5})$	$(\text{B5} - \text{B4}) / (\text{B5} + \text{B4})$	(Zha <i>et al.</i> , 2003)

Note: NDVI = Normalized Difference Vegetation Index, EVI = Enhanced Vegetation Index, GCI = Green Chlorophyll Index, SAVI = Soil Adjusted Vegetation Index, BSI = Bare Soil Index, NDWI = Normalized Difference Water Index, MNDWI = Modified Normalized Difference Water Index, NDSAI = Normalized Differential Sand Areas Index, NDBI = Normalized Difference Built-up Index, NIR = Near Infrared, SWIR = Short-wave infrared, and B = Spectral Band.

Random Forest Classification

Training data were prepared by stratifying reference points into seven land use land cover (LULC) classes: built-up area, cropland, forest, grassland, other, sand and gravel, and water bodies (Table S1). To support land cover classification and analysis, sufficiently large sample points (>2500) were chosen for different years (2,610 LULC sample points for 1985, 3,011 points for 2005, and 3398 points for 2024) and visually interpreted using true-colour composites from Google Earth Engine. A Random Forest (RF) classifier was implemented in GEE due to its robustness in handling high-dimensional datasets and reducing overfitting compared to CART (Classification and Regression Tree) and SVM (Support Vector Machine) (Zafar *et al.*, 2024). The dataset was randomly split into 80 % training and 20 % testing subsets. A sensitivity analysis was conducted using different numbers of decision trees (10–300) to evaluate model stability.

Accuracy Assessment

A confusion matrix was generated to assess the performance of the RF classifier in Google Earth Engine (GEE) (Liu *et al.*, 2004). This matrix provides a detailed comparison between predicted against actual land cover classes, aiding in accuracy evaluation and identifying misclassifications (Liu *et al.*, 2004; Meyer-Baese & Schmid, 2014; Sari *et al.*, 2021). Additionally, the overall accuracy and kappa coefficient (Cohen's kappa) were computed to assess the model's performance and evaluated based in the values (Dettori & Norvell, 2020; McHugh, 2012). The kappa accuracy value ≤ 0.20 is considered poor, 0.21–0.40 is fair, 0.41–0.60 is moderate, 0.61–0.80 is good, and 0.81–1.00 is perfect (Dettori & Norvell, 2020; McHugh, 2012). The classified images were then clipped to the study area boundaries and

exported at 30 m resolution for further post-classification change detection to quantify land use land cover in the study area.

Land Use Land Cover (LULC) Change Detection Analysis

The final classified image exported from Google Earth Engine (GEE) served as the input for transition matrix analysis in ArcGIS 10.8. Land Use/Land Cover change detection for the years 1985, 2005, and 2024 was conducted using a vector-based post-classification comparison approach. Each classified LULC raster map was first converted into a polygon layer to ensure precise delineation of land-cover patches. The resulting polygon datasets were then dissolved based on their GRIDCODE attributes to merge contiguous features belonging to the same LULC class, thereby producing generalized and topologically consistent class boundaries suitable for overlay operations. Pairwise intersections were subsequently performed for the year combinations of 1985–2005, 2005–2024, and 1985–2024. This process enabled the identification of spatially overlapping areas between consecutive time periods, with each intersected feature containing both the “from” (earlier) and “to” (later) class codes. The area of each intersected polygon was calculated to quantify the magnitude of each land-cover transition. The resulting transition matrices provided a numerical representation of these changes, indicating the proportion of each class that remained stable, transitioned into another class, or emerged a new within the specified periods.

Habitat Preference and Connectivity Analysis

A species habitat matrix was developed by using a species-specific approach. We adapted a well-established habitat connectivity method, originally designed for New Jersey wildlife (the CHANJ methodology), and tailored it specifically to the mammals of our study area and the Nepalese landscape (New Jersey Division of Fish and Wildlife, 2019). A comprehensive review of ecological (habitat) requirements for 27 conservation-priority mammalian species was assigned (1 = prefer, 0 = not prefer) based on extensive literature review, including IUCN Red List assessments, whereas expert consensus was made if the information about animal preference towards habitat is not available in the literature (Table S2) (Chettri *et al.*, 2013). The scores were then aggregated and averaged to derive conservation-priority habitat values for each land cover category. In addition, major roads, such as the East-West Highway and the Bharatpur–Madi Road with buffer 20-meter distance on each side, were incorporated which pass through the core area of the parks. These roads were assigned a habitat value of zero, reflecting both non-use by focal mammals and their role as movement barriers. The resulting score was assigned to the 2024 LULC map to translate the categorical landcover data into a habitat value raster, which reflects landscape suitability, where higher values indicate higher habitat quality.

Core habitat patches were identified using the Core Mapper tool in ArcGIS 10.8 as mentioned in Gnarly Landscape Utilities: Core Mapper User Guide where parameters including minimum core area, moving window radius, minimum average habitat value, and ‘Per pixel’ minimum habitat value, were calculated (Shirk & McRae, 2013). For minimum core area, the lowest possible home range of species was cited from IUCN and existing literature (Table S2). We modified the original CHANJ methodology (New Jersey Division of Fish and Wildlife, 2019) taking 50th percentile of home-range area to accommodate multiple species that require larger home range. Raster cell meeting all threshold criteria (minimum core area, moving window radius, minimum average habitat value and per-pixel habitat value) were retained as core patches that were further used for subsequent connectivity analysis.

To model structural connectivity, the habitat value raster was reclassified into a conductance surface, where high-quality habitats (e.g., forest, grassland, and water) were assigned high conductance values, while low- or non-habitat classes (e.g., cropland, built-up, sand and gravel, and other land uses) were assigned low values based on weighted habitat values (Table S2), reflecting their relative resistance to movement. After calculating the core patches, the centroid was extracted for least cost path (LCP) analysis (Fig. S1) in R programming (R Core Team, 2025) where *gdistance* package (Etten *et al.*, 2023) was used to identify optimal routes between habitat patches based on the conductance surface. All pairwise LCPs were generated between patches, merged, and exported for further spatial interpretation. Connectivity was then quantified using a graph-theoretic framework, in which habitat patches were represented as nodes and edges were weighted by least-cost distance. A cost-distance matrix was computed among all patches and transformed into an undirected weighted graph with the *igraph* package (Csárdi *et al.*, 2025). The cost values were classified into three categories with equal percentiles: Low-cost (33rd percentile; ≤ 5150.23), Medium-cost (33rd to 67th percentiles; 5150.23–10284.58), and High-cost (67th percentile; > 10284.58). Only patch pairs with low-cost distance were considered functionally connected and included in the graph. The low-cost threshold was selected as a conservative cutoff to represent feasible dispersal and avoid overestimating functional connectivity across heterogeneous landscapes and (Adriaensen *et al.*, 2003; Avon & Berge’s, 2016). Patch-level connectivity metrics were then calculated, including degree, betweenness centrality, and closeness centrality (Estrada & Bodin, 2008; Kaur *et al.*, 2024). At the graph level, we computed overall structural properties of the network such as density, diameter, mean path length, clustering coefficient, and number of connected components. The resulting connectivity graph and metrics were exported as shapefiles and excel tables to support spatial visualization and conservation decision-making.

RESULTS

Land Use Land Cover Change (1985 – 2024)

The spectral indices used in this study in classification results achieved high reliability across all study periods with overall accuracy of (0.81, 0.82, and 0.83, and the corresponding kappa coefficients of 0.75, 0.75, and 0.78 respectively for the year 1985, 2005, and 2024 (Table 2).

Table 2: Accuracy of the Land Use Land Cover Map of each year.

Accuracy\Images	LULC 2024	LULC 2005	LULC 1985
Overall Accuracy	0.82	0.82	0.81
Kappa Accuracy	0.78	0.75	0.75
Confusion Matrix	0: [0,0,0,0,0,0,0] 1: [0,19,15,0,1,13,1] 2: [0,7,43,5,1,16,0] 3: [0,0,0,139,10,2,0] 4: [0,0,3,9,88,6,0] 5: [0,4,4,5,8,168,3] 6: [0,1,0,2,0,4,116]	0: [0,0,0,0,0,0,0] 1: [0,8,19,0,0,0,0] 2: [0,5,66,16,2,11,0] 3: [0,1,3,337,3,23,0] 4: [0,0,3,11,37,4,0] 5: [0,1,9,29,2,179,4] 6: [0,0,6,4,2,12,138]	0: [0,0,0,0,0,0,0] 1: [0,6,18,0,0,1,0] 2: [0,8,111,1,0,5,3] 3: [0,0,2,132,3,1,0] 4: [0,2,5,6,7,1,0] 5: [0,2,11,1,1,74,7] 6: [0,0,2,6,0,16,90]

The LULC analysis from 1985 to 2024 shows substantial shifts in land cover across the CPC (Table 3 and Fig. 2). Built-up areas expanded rapidly, increasing from just 0.88 % in 1985 to 3.41 % in 2024 cropland declined sharply from 16.95 % to 8.96 %. Similarly, forest cover declined gradually from 69.07 % in 1985 to 64.09 % in 2024, while grassland (2.08 % to 7.35 %) and sand and gravel (6.28 % to 13.19 %) areas showed notable increases. Importantly, water bodies decreased from 4.56 % to 2.80 % over the period.

Table 3: Land Use and Land Cover Change, where positive signs indicate an increase in area and negative signs indicate a decrease in area of LULC categories.

LULC Categories	LULC 1985		LULC 2005		Change (%)	LULC 2024		
	Area in Sq. KM	Area (%)	Area in Sq. KM	Area (%)		Area in Sq. KM	Area (%)	Change (%)
Built-Up								
Area	22.89	0.88	63.14	2.43	1.55	88.55	3.41	0.98
Cropland	439.98	16.96	306.83	11.83	-5.13	232.63	8.97	-2.86
Forest	1792.12	69.07	1773.13	68.34	-0.73	1662.94	64.09	-4.25
Grassland	53.99	2.08	95.00	3.66	1.58	190.90	7.36	3.70
Other	4.49	0.17	4.49	0.17	0.00	4.50	0.17	0.00
Sand Gravel	162.96	6.28	276.02	10.64	4.36	342.37	13.19	2.56
Water	118.26	4.56	76.07	2.93	-1.63	72.79	2.81	-0.13
		100.0		100.0			100.0	
Total	2594.69	0	2594.69	0		2594.69	0	

Land Use Land Cover Change Transition Matrix

The LULC transition matrix (Table 4 and Fig. 3) highlights the spatial dynamics and conversions between land cover classes in last four decade. The analysis reveals that forest areas were the most stable, with 1592.90 km² of forest in 1985 persisting as forest in 2024, although notable portions transitioned into grassland (101.57 km²), sand and gravel (72.35 km²), and cropland (11.26 km²). Similarly, cropland in 1985 showed high rates of conversion, with large areas shifting into sand/gravel (107.69 km²) and forest (21.05 km²), while only 184.99 km² remained cropland in 2024. Built-up areas experienced substantial growth, increasing from 22.88 km² in 1985 to 88.55 km² in 2024, largely expanding over cropland (71.29 km²) and to a lesser extent over forest and water bodies. Grasslands and sand and gravel also expanded significantly, partly at the expense of forest and cropland. Water bodies shrank overall, with portions converted to sand and gravel (51.76 km²) and cropland (8.47 km²). The intermediate decades (1985–2005; 2005–2024) exhibited similar trajectories, confirming that these changes occurred progressively rather than abruptly (Supplementary Table S3 and Fig. S2). Overall, the LULC transitions between 1985 and 2024 showed consistent patterns of forest decline, grassland and sand/gravel expansion, cropland reduction, and built-up growth (Tables 4 and Fig. 3).

Fig. 2: LULC Map of Chitwan-Parsa Complex (CPC) of the years 1985, 2005, and 2024.

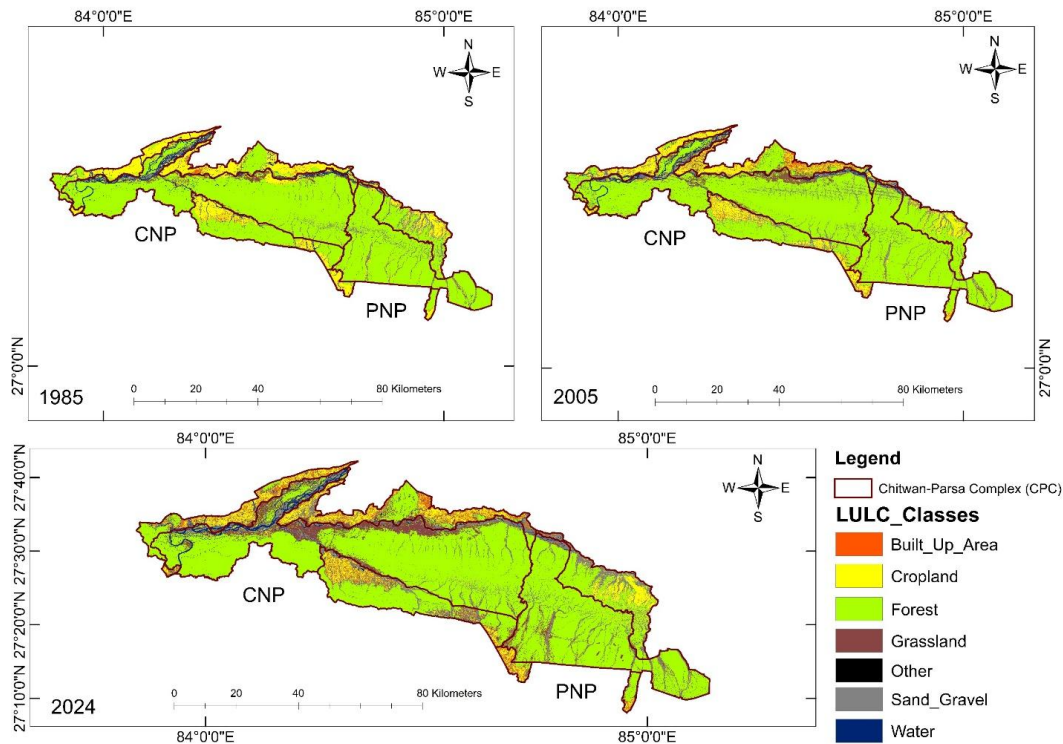
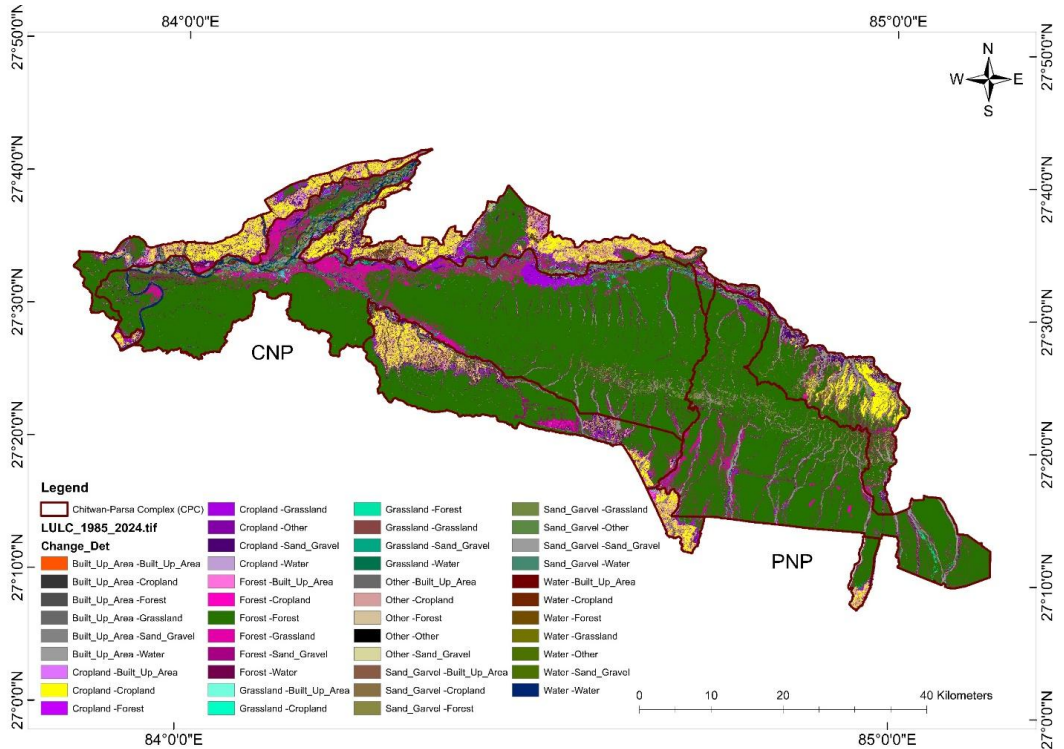


Table 4: Land Use Land Cover Change Transition Matrix of CPC (1985-2024).

		LULC 2024 Area (Sq. KM)							Total
Landcover Class		Built-Up Area	Cropland	Forest	Grassland	Other	Sand gravel	Water	
LULC 1985 Area (Sq. KM)	Built-Up Area	3.65	7.5	0.96	1.94	0	8.23	0.59	22.88
	Cropland	71.29	184.99	21.05	40.46	0.01	107.69	14.44	439.94
	Forest	3.82	11.26	1592.9	101.57	0	72.35	10.25	1792.2
	Grassland	1.17	1.69	10.36	26.07	0	11.62	3.1	54
	Other	0	0	0	0	4.49	0	0	4.49
	Sand and gravel	3.46	18.71	28.36	9.73	0	90.71	11.99	162.98
	Water	5.16	8.47	9.31	11.12	0	51.76	32.43	118.25
Total		88.55	232.63	1662.9	190.9	4.5	342.37	72.79	2594.7

Fig. 3: LULC Transition Matrix of CPC from 1985 to 2024.

Habitat Preference and Connectivity

The habitat value raster of the Chitwan-Parsa Complex (CPC) identified a strong habitat preference, with the majority of species primarily associated with natural ecosystems such as forests, grasslands, and wetlands, while showing limited or no used of human-modified landscapes. Majority of the species ($n=24$) preferred forest as a suitable habitat followed by grasslands were classified as suitable for ($n=18$). Aquatic and riparian habitats (water bodies) were found suitable for 12 species while anthropogenic land covers provided minimal theoretical habitat value, with cropland suitable for 9 species (Fig. 4).

The 50th percentile home range value for all 27 species were found to be 5.3 sq. km with moving window radius of 1.298 km. The minimum average habitat value was obtained as 0.69, where per-pixel habitat value from the two-contributing land-cover classes (forest and grassland) was found to be 0.8 (Table S2). Fulfilling these thresholds, study identified 16 final habitat patches for subsequent connectivity analysis (Table S4, Fig. S1).

Connectivity modelling in this study primarily focused on structural connectivity based on the relative importance of habitats and assessed the reachability of habitats. The cost-distance matrix represents the least-cost distances among all 16 habitat patches (Table S5), capturing how landscape resistance influences potential species movement (Fig. 5). The cost-distance matrix of habitat patches in the complex shows that the cost is higher as the patches move farther away from each other, because species are more prone to being exposed to landscape-level resistance. There were 40 connections with low-cost, 39 with medium-cost and 41 with high-cost values (Table S5). Connection between patch 8 and patch 9 and patch 16 and patch 13 had low-cost values of 648.12 and 881.85 respectively whereas

cost between patch 2 and patch 13, 14, 15 show the highest value of 22302.66, 20975.83 and 23558.61 respectively. Moreover, patch 2 has a degree of 1 and the lowest closeness value (<0.0001), appears isolated and weakly connected, lying on the periphery of the network. The connectivity analysis reveals a clear structure of core and peripheral areas within the Chitwan–Parsa landscape. The network exhibited a density of 0.33 and a clustering coefficient of 0.67. The mean shortest path length between core patches was 9,275 cost units, with a maximum path length (network diameter) of 26,083 cost units. Patches 10 and 12 have the highest degree of 7 whereas patch 2 has degree of 1 (Table S4). Patches 5, 7, 8, 9, 11, and 14 emerge as the most connected, each with a degree of 6, indicating that they are highly linked to other patches and function as key hubs in the ecological network (Table S4). Among 16 patches, patch 8 and 12 have the highest betweenness value of 0.3. Patches 3, 6 and 9 have betweenness value of 0.2 whereas remaining patches have less than 0.2. In case of closeness, only patch 8 and 9 have highest value while other patches have the same closeness value. Moreover, if the complex is divided into eastern and western at the confluence of the Riu, East Rapti, and Narayani rivers, a clear fragmentation can be observed. The patches on the eastern side showed low-cost comparing to western patches. Patches on the eastern part of the complex shows better connectivity than the one on the western side. One of the evident instances can be observed in the connectivity of Patch 2, which lies on the western end of the complex and is isolated by the Narayani River in the middle. So, the resistance factors for patch 2 can be seen to be higher, and the cost is high with 12 other patches and low with only one patch (Patch 4).

Fig. 4: Habitat Use by Mammalian Species and their weighted habitat values.

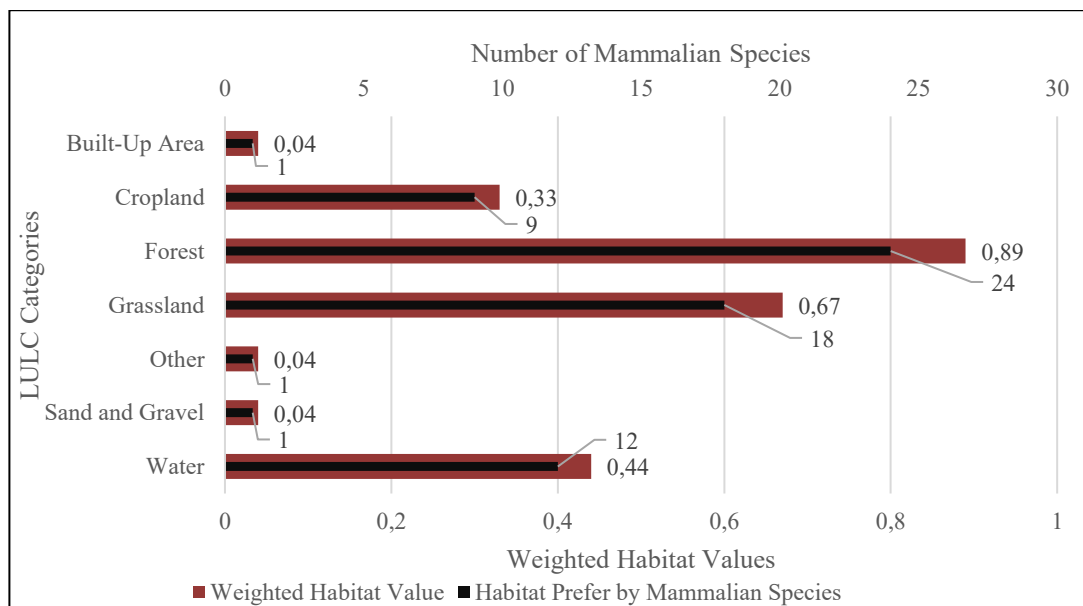
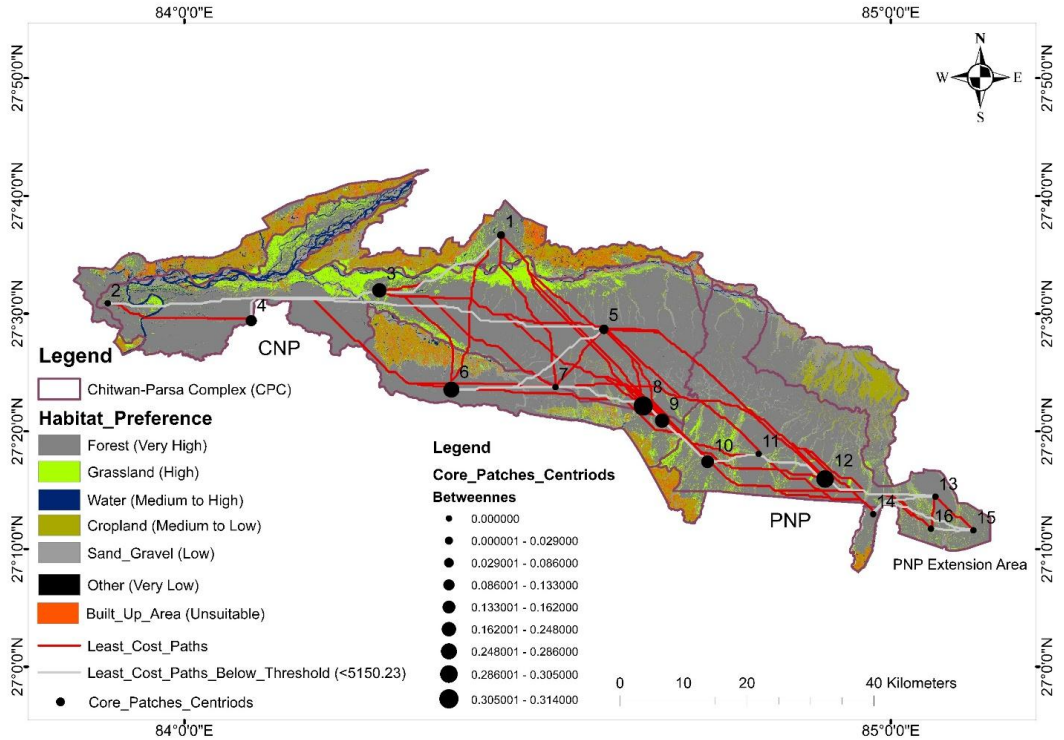


Fig. 5: Habitat preference by Mammalian Species and the Least Cost Paths in Chitwan-Parsa Complex. The black points represent centroid of habitat patches, where size corresponds to betweenness centrality value.



DISCUSSION

This study explored the land use-landcover changes over four decades in Chitwan-Parsa Complex of Terai Arc Landscape in Nepal, and attempted to identify the important habitat patches while assessing their connectivity. Model reliability with overall accuracy and kappa coefficients indicated a good level of agreement between the classified maps (Dettori & Norvell, 2020; McHugh, 2012) and reference data, confirming the robustness of the Random Forest classifier in mapping LULC across different decades. The findings of better accuracy of classification using spectral indices (overall accuracy ≥ 0.81 and kappa coefficient ≥ 0.75) aligned with the conclusion of other studies that suggest integrating spectral indices could improve the accuracy of overall mapping (Aryal *et al.*, 2023; Dash *et al.*, 2023; Faridatul & Wu, 2018; Ganjirad & Bagheri, 2024; Lee *et al.*, 2018; Zhang *et al.*, 2017). These spectral indices are essential for detecting land use feature as they treat each land use class separately according to their properties (Faridatul & Wu, 2018; Ganjirad & Bagheri, 2024).

Land Use Land Cover Change (1985 – 2024)

Over the study period, there is significant decrease in water sources (1.24 %) whereas an increase in grassland (3.3 %) and built-up area (3.54 %) annually. While water sources were observed to be converted to sand and gravel, forest to grassland, and cropland was converted to grassland and built-up area. The expansion of built-up areas reflects urban growth and

infrastructure development in Chitwan Parsa Complex (CPC). Urbanization and policy shifts in municipal level in the complex revealed an extensive cropland conversion to built-up areas in 2001-2021 (Timilsina *et al.*, 2025) resulting fragmentation in the buffer zone areas with greater edge effect (CNP, 2013; PNP, 2018) and increase in human population by ~1.5 % in buffer zone settlements and ~1.25 % beyond (Central Bureau of Statistics, 2021). Reports suggesting increase in developed areas alongside forest areas in the central Chitwan-Annapurna landscape (Adhikari *et al.*, 2022) and land encroachment in Syaulibasti in the Shikaribas corridor that connects Chitwan-Parsa Complex and Valmiki Tiger Reserve (PNP, 2018) gives instances of the pressure on wildlife habitat.

Grassland expansion is advantageous for the conservation perspectives as it provides important foraging grounds for large herbivores like rhinos (*Rhinoceros unicornis*), gaur (*Bos gaurus*), elephants (*Elephas maximus*), and ungulates (deer species) (Jnawali & Wegge, 1999; Thapa *et al.*, 2021). Such expansion of grassland could be a result of continuous investment habitat management interventions to restore and manage grasslands inside parks and the buffer zones through parks (CNP, 2013; PNP, 2018), and change in flood plain dynamics along the rivers (Bijlmakers *et al.*, 2023). Importantly, resettlement of human from old Padampur to new Padampur area in CNP has significantly increased grassland in CNP (Adhikari *et al.*, 2022). Further, study in Bardia National Park with similar terrain and landscape of Chitwan-Parsa complex suggested that tall grasslands (*Saccharum spontaneum* dominant) has been vastly expanded due to the shift of the river channel and regeneration (Bijlmakers *et al.*, 2023). Importantly, river dynamics and shifting inundation regimes shape plant communities by altering sediment deposition and disturbance regimes (Corenblit *et al.*, 2024; Jones *et al.*, 2011). However, this observed increase may not entirely represent genuine habitat gain, as satellite-based classifications often include low-stature vegetation and early successional patches within the “grassland” category. Despite these apparent gains, the proliferation of *Mikania micrantha* within these grasslands, wetlands, and riverine forests continues to degrade habitat quality (Murphy *et al.*, 2013). However, such active management interventions help to maintaining a balanced grassland–forest mosaic and controlling targeted invasive species, thus sustain the ecological integrity of the park (Williams *et al.*, 2026; Lamichhane *et al.*, 2024; Thapa *et al.*, 2021) as they are more vulnerable for invasive species (Dhakal *et al.*, 2024).

Forest loss has become serious concern since 1950s, after malaria eradication program and Terai settlement program from the government (Gautam *et al.*, 2004). Historical evidence demonstrated that the buffer zone of Chitwan National Park also depicted an earlier trend of forest loss accompanied by agricultural expansion (Baidya *et al.*, 2009). Additionally, declining water bodies in the complex is a serious concern in the context of climate change as it threatens the aquatic biodiversity and reduces main water sources for terrestrial wildlife (Acharya & Basu, 2024) impacting animal assemblage inside the park that forces animals to transverse suboptimal or human-dominated terrains resulting interaction between wildlife and human (Pant *et al.*, 2021). Human-wildlife conflict has been increasing over the period especially from animals requiring large home range including elephant, rhino, tiger and leopard (Acharya *et al.*, 2016; Baral *et al.*, 2022; Neupane *et al.*, 2017; Sharma *et al.*, 2021). Thus, promoting sustainable agroforestry practices in buffer zones, particularly in the settlements zone, and maintaining grassland can reduce the people’s dependency on natural habitat limiting human-wildlife interaction.

Habitat preference and Connectivity

The Chitwan-Parsa complex is a protected area dominated by forest and grassland with major rivers and its tributaries passing through it. As shown by the habitat matrix, most of the priority mammals have a preference towards forest, grassland, and water highlighting the importance of integrated forest–grassland–wetland mosaic for the ecological integrity of the parks, especially for gaur, rhinoceros, and elephants (Dhakal *et al.*, 2025; Neupane *et al.*, 2022; Pant *et al.*, 2021). Additionally, human-induced changes across the landscape also highly alter the habitat use pattern. One of the striking examples is the decrease in rhino population in the eastern complex of CNP and an increase in the western complex, which was caused by the construction of a dike (among other factors) that altered the habitat of the rhino (Subedi *et al.*, 2013). In an important note, road network that has been constructed for wildlife monitoring and patrolling within national park also contributed for land use changes. For example, there is over 314 km of road networks within CNP (CNP, 2013), resulting fragmentation and high-cost for wildlife movement.

The connectivity based on degree, betweenness, and closeness suggests that patches 8, 12, 6, and 9 have potential of becoming a resilient hub for the complex. Although their size is less than 100 sq. km, these complex plays a crucial role in maintaining structural connectivity in CPC. These small patches can be function as dispersal stepping stones and movement route highlighted by (Rocha *et al.*, 2021; Tiang *et al.*, 2021; Tulloch *et al.*, 2016; Wintle *et al.*, 2019). These core patches are located near settlements area in CPC. So, they could be dispersal pathways to thread species movement through human dominant matrices as a stepping stone. Studies from Nepal's Terai Arc Landscape emphasise the importance of corridor patches that lie within human dominant landscapes for maintaining wildlife dispersal and gene flow between protected areas (Bhatt *et al.*, 2023; Thapa & Tuladhar, 2021; Wegge *et al.*, 2018). Although larger habitat patches are generally considered more ecologically stable due to greater habitat availability and resource diversity (MacArthur & Wilson, 1967), smaller patches can still play disproportionately important roles in maintaining functional connectivity (Tulloch *et al.*, 2016). In this study, the largest patch exhibited high local connectivity (high degree) but relatively low betweenness, indicating limited importance for long-distance network connectivity. Three core patches (notably 13, 15, and 16) within the extended core area of Parsa National Park have high importance in regard to their strategic location and high degree of connectivity, suggesting facilitation of local dispersal for wide-ranging mammals. Notably, the habitat extension in this region has proven beneficial for threatened species such as *Bos gaurus*, *Panthera tigris*, and *Elephas maximus* (Dhakal *et al.*, 2025; PNP, 2018). In the other hand, patch 9 and 10 that lies close to Shikaribas corridor that connects transboundary protected landscape (CNP-PNP-VTR) has a high degree of connectedness exhibiting it a steppingstone and structural connectivity hub for wildlife dispersal across a heterogeneous matrix of forest, grassland, cropland, and sand–gravel landscapes. Instead of ecological importance of that corridor, Syaulibasti area of that corridor suffers from land encroachment (PNP, 2018; Thapa & Tuladhar, 2021). Additionally, its neighbouring patches (8, 9, and 12) have been established to be resilient hubs, so patch 10 can also support in maintaining permeability across increasingly modified landscapes surrounding the Shikaribas corridor.

The high-cost values between 2 and 13, 14 and 15 patches indicated that their path was separated by built-up areas, cropland and non-habitat zones such as highways. The path between patch 14 and 15 separated by East-West Highway. Overall, patches 5, 6, 7, 8, 9, 11, 12, 14, and 16 form the backbone of the connectivity network and are therefore likely to be important priorities for long-term landscape-level conservation planning.

CONCLUSION AND CONSERVATION IMPLICATION

Overall, the study emphasizes that the forest–grassland–wetland mosaic is indispensable for maintaining mammalian diversity and connectivity in the Chitwan-Parsa Complex (CPC), while anthropogenic land uses provide little habitat value for most threatened species.

Overall study provides the clear insights on landscape change dynamics of CPC with acceptable accuracy obtain with integrating nine spectral indices as band. Moreover, Fragmentation can disrupt connectivity between Chitwan and Parsa, jeopardizing long-term species movement and potentially genetic exchange. Loss of important landcovers is a serious impediment for sustainable conservation and management of ecological integrity of the CPC. The cost–distance matrix provides a quantitative foundation for identifying both well-connected habitat networks and critical barriers to movement within the park boundaries. This highlights the importance of restoring historical water sources and maintaining seasonal wetlands within forest habitats, to enhance habitat resilience and sustain species populations in the Chitwan–Parsa Complex. Conservation responses should also prioritize regulating water flow in rivers, and community engagement in habitat management. Maintaining critical habitat patches and their connectivity could ensure the long-term conservation and ecological integrity in the landscape, as they are resilient hubs for many dispersing wildlife in the complex. This information is essential for prioritizing corridors, strengthening weak links, and planning conservation interventions to maintain or enhance landscape connectivity. However, this study exclusively limited its bound to protected areas since these areas act as a source site for species. The landscape connectivity beyond protected areas is also critical, but prioritizing habitat restoration in the corridor may influence the wildlife colonization resulting greater chances of human-wildlife interface in multi-use land. Additionally, this study holds some additional limitations. For example, the least-cost path analysis represents potential structural connectivity based on landscape resistance rather than realized functional connectivity, as the model was not validated using empirical animal movement data such as GPS telemetry, camera-trap detections. The conductance surface primarily incorporated LULC classes and major roads, while other dynamic factors such as seasonal flooding, human disturbance, invasive species, and climate variability were not explicitly included. Future studies integrating higher-resolution remote sensing, species-specific dispersal data, and dynamic resistance surfaces along with genetic connectivity would further improve the reliability of habitat connectivity assessments within Chitwan-Parsa-Valmiki protected area network.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to the anonymous reviewers whose insightful and constructive feedback significantly enhanced the quality of this research.

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SUPPLEMENTARY FILES

Supplementary Tables

Table S1: LULC Categories used to study land use change in Chitwan-Parsa Complex for the period of 1985-2024.

SN	Classes	Description
1	Built-Up Area	Land covered by buildings and other man-made structures. Residential, commercial services, industrial area, mixed urban or built-up lands
2	Cropland	Lands covered with temporary crops followed by the harvest period, Crop fields, and pastures
3	Forest	Includes all land with woody vegetation in accordance with the national GHG inventory's criteria for defining forest land, subdivided into managed areas and by ecosystem type in accordance with the IPCC Guidelines.
4	Grassland	This category includes rangelands and pasture land that is not considered as cropland. It also includes systems with vegetation that fall below the threshold used in the forest land category and are not expected to exceed, Without human intervention, the threshold used in the forest land category. The category also includes all grassland from wildlands to recreational areas, as well as agricultural and silvo-pastoral systems, subdivided into Managed and unmanaged, consistent with national definitions.
5	Other	Unidentified Class
6	Sand and gravel	Sand and gravel are granular materials made of broken rock fragments and mineral particles.
7	Water	Lakes, reservoirs, streams, rivers, swamps

Table S2: Habitat Preference by Mammalian Species (Mammalian Species Matrix) in Chitwan-Parsa Complex.

The matrix was created with the help of an expert opinion, where a value of 1 was assigned to habitat preferred by mammalian species, and 0 was assigned to habitats not preferred by mammalian species. The lowest possible home range is cited from published literature. If the species does not have estimated home range on published literature, we gave N/A value for these species. Presence points were downloaded from Global Biodiversity Information Facility (GBIF) on 31 October 2025. Letters in Parentheses represent the global IUCN red list status.

SN	Scientific Name	Minimum Home Range (Km ²) and reference	LULC Categories						
			Built Up Area	Crop land	Forest	Grass land	Other	Sand Gravel	Water
1	<i>Elephas maximus</i> (EN)	150 Williams et al., 2020	0	0	1	1	0	0	1
2	<i>Aonyx cinerea</i> (VU)	1 Hussain et al., 2011	0	0	1	1	0	0	1
3	<i>Macaca assamensis</i> (NT)	0.5 Boonratana et al., 2020	0	1	1	0	0	0	0
4	<i>Panthera tigris</i> (EN)	20 Goodrich et al., 2022.	0	0	1	1	0	0	1
5	<i>Manis pentadactyla</i> (CR)	0.96 Challender et al., 2020.	0	1	1	1	0	0	0
6	<i>Neofelis nebulosa</i> (VU)	30 Gray et al., 2021.	0	0	1	0	1	0	0
7	<i>Panthera pardus</i> (VU)	8.8 Stein et al., 2025.	0	0	1	1	0	0	0
8	<i>Prionailurus viverrinus</i> (VU)	4 Mukherjee et al., 2025.	0	0	1	1	0	0	1
9	<i>Tetracerus quadricornis</i> (VU)	N/A	0	0	1	0	0	0	0
10	<i>Rousettus leschenaultii</i> (NT)	N/A	1	1	1	0	0	0	0
11	<i>Platanista gangetica</i> (EN)	N/A	0	0	0	0	0	0	1
12	<i>Bos gaurus</i> (VU)	32 Sankar et al., 2013.	0	0	1	0	0	0	0
13	<i>Rhinoceros unicornis</i> (VU)	20 DNPWC, 2024.	0	1	1	1	0	0	1
14	<i>Capricornis sumatraensis</i> (VU)	N/A	0	1	1	1	0	0	0
15	<i>Caprolagus hispidus</i> (EN)	0.001 DNPWC, 2023.	0	0	0	1	0	0	1
16	<i>Axis porcinus</i> (EN)	0.05 Timmins et al., 2015.	0	0	0	1	0	0	1
17	<i>Manis crassicaudata</i> (EN)	1.5 Gray et al., 2023.	0	1	1	1	0	0	0
18	<i>Pardofelis marmorata</i> (NT)	5.3 Ross et al., 2016.	0	0	1	0	0	0	0

19	<i>Kerivoula picta</i> (NT)	0.06	Huang et al., 2020.	0	1	1	1	0	0	0
20	<i>Rusa unicolor</i> (VU)	3	Sankar & Goyal, 2004.	0	0	1	1	0	0	1
21	<i>Melursus ursinus</i> (VU)	9	Joshi et al., 1995.	0	1	1	1	0	0	0
22	<i>Lutrogale perspicillata</i> (VU)	2.13	Hussain & Choudhury, 1997.	0	0	1	0	0	1	1
23	<i>Hyaena hyaena</i> (NT)	44	Kruuk, 1976.	0	0	1	1	0	0	0
24	<i>Rucervus duvaucelii</i> (VU)	10	Duckworth et al., 2015.	0	0	1	1	0	0	1
25	<i>Semnopithecus hector</i> (NT)	0.45	Chhangani et al., 2006.	0	1	1	0	0	0	0
26	<i>Bubalus arnee</i> (EN)	15	Kaul et al., 2019.	0	0	1	1	0	0	1
27	<i>Cuon alpinus</i> (EN)	23	Kamler et al., 2015.	0	0	1	1	0	0	0
Total Habitat Points				1	9	24	18	1	1	12
Habitat preference Status				Unsuitable	Medium to Low	Very High Use	High	Low	Very Low	Medium to High
Weighted Habitat Value				0.04	0.33	0.89	0.67	0.04	0.04	0.44

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Table S3: Land Use Land Cover Change Transition Matrix of Chitwan-Parsa Complex for the periods between 1985-2005 and 2005-2024.

	Landcover Class	LULC 2005 Area (Sq. KM)							Total
		Built Up Area	Cropland	Forest	Grassland	Other	Sand_Gravel	Water	
LULC 1985 Area (Sq. KM)	Built Up Area	1.74	12.13	1.50	1.08	0.00	5.48	0.95	22.88
	Cropland	50.07	247.83	37.70	31.36	0.00	60.53	12.46	439.95
	Forest	3.42	14.18	1663.17	29.84	0.00	74.66	6.90	1792.16
	Grassland	1.75	4.51	15.89	22.12	0.00	6.86	2.87	54.00
	Other	0.00	0.00	0.00	0.00	4.49	0.00	0.00	4.49
	Sand_Gravel	2.29	15.30	43.51	3.56	0.00	85.61	12.69	162.96
	Water	3.88	12.88	11.37	7.04	0.00	42.89	40.21	118.25
Total		63.14	306.83	1773.13	95.00	4.49	276.02	76.07	2594.69
	Landcover Class	LULC 2024 Area (Sq. KM)							Total
		Built Up Area	Cropland	Forest	Grassland	Other	Sand_Gravel	Water	
LULC 2005 Area (Sq. KM)	Built Up Area	12.84	30.00	2.35	5.00	0.00	10.65	2.30	63.14
	Cropland	56.70	149.39	7.22	17.71	0.01	69.19	6.60	306.82
	Forest	5.04	23.88	1570.52	97.51	0.00	66.49	9.72	1773.16
	Grassland	2.14	2.53	23.12	48.52	0.00	16.10	2.59	94.99
	Other	0.00	0.00	0.00	0.00	4.49	0.00	0.00	4.49
	Sand_Gravel	9.94	24.01	57.80	18.77	0.00	145.26	20.23	276.01
	Water	1.89	2.83	1.94	3.39	0.00	34.66	31.35	76.07
Total		88.55	232.63	1662.94	190.90	4.50	342.37	72.79	2594.69

Table S4: Patch area and patch-level connectivity metrics of the habitats within Chitwan-Parsa Complex based on cost-distance threshold.

Patch	Patch Area	Degree	Betweenness	Closeness
1	25.24	4	0.0286	0.0001
2	40.95	1	0.0000	0.0001
3	5.70	3	0.2476	0.0001
4	186.79	2	0.1333	0.0001
5	530.10	6	0.0857	0.0001
6	72.72	5	0.2857	0.0001
7	12.87	6	0.0000	0.0001
8	9.97	6	0.3143	0.0002
9	17.26	6	0.2476	0.0002
10	32.36	7	0.1619	0.0001
11	50.15	6	0.0000	0.0001
12	60.44	7	0.3048	0.0001
13	19.61	5	0.0000	0.0001
14	12.30	6	0.0000	0.0001
15	21.61	4	0.0000	0.0001
16	7.86	4	0.0000	0.0001

Table S5: The Cost distance matrix among the habitat patches within Chitwan-Parsa Complex. High, medium and low cost distance were represented by the red, blue, and green colors.

Patch	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0															
2	10405	0														
3	3679	6737	0													
4	7382	3575	3714	0												
5	3958	12233	5707	9209	0											
6	4971	9327	4205	6304	4303	0										
7	4649	11775	5292	8752	1958	2506	0									
8	6110	14124	7598	11101	2365	4972	2501	0								
9	6686	14757	8231	11734	2923	5614	3143	648	0							
10	8270	16369	9843	13346	4477	7235	4764	2272	1632	0						
11	9274	17549	11023	14525	5316	8472	5993	3508	2869	1389	0					
12	11054	19329	12803	16306	7096	10296	7811	5333	4693	3093	1897	0				
13	14028	22303	15776	19279	10070	13256	10785	8293	7653	6038	4896	3021	0			
14	12701	20976	14450	17952	8743	11910	9439	6946	6307	4692	3554	1683	1855	0		
15	15284	23559	17032	20535	11326	14512	12041	9549	8909	7294	6152	4277	1358	2993	0	
16	14229	22504	15978	19481	10271	13457	10986	8494	7855	6240	5098	3222	882	1931	1074	0

Supplementary Figures

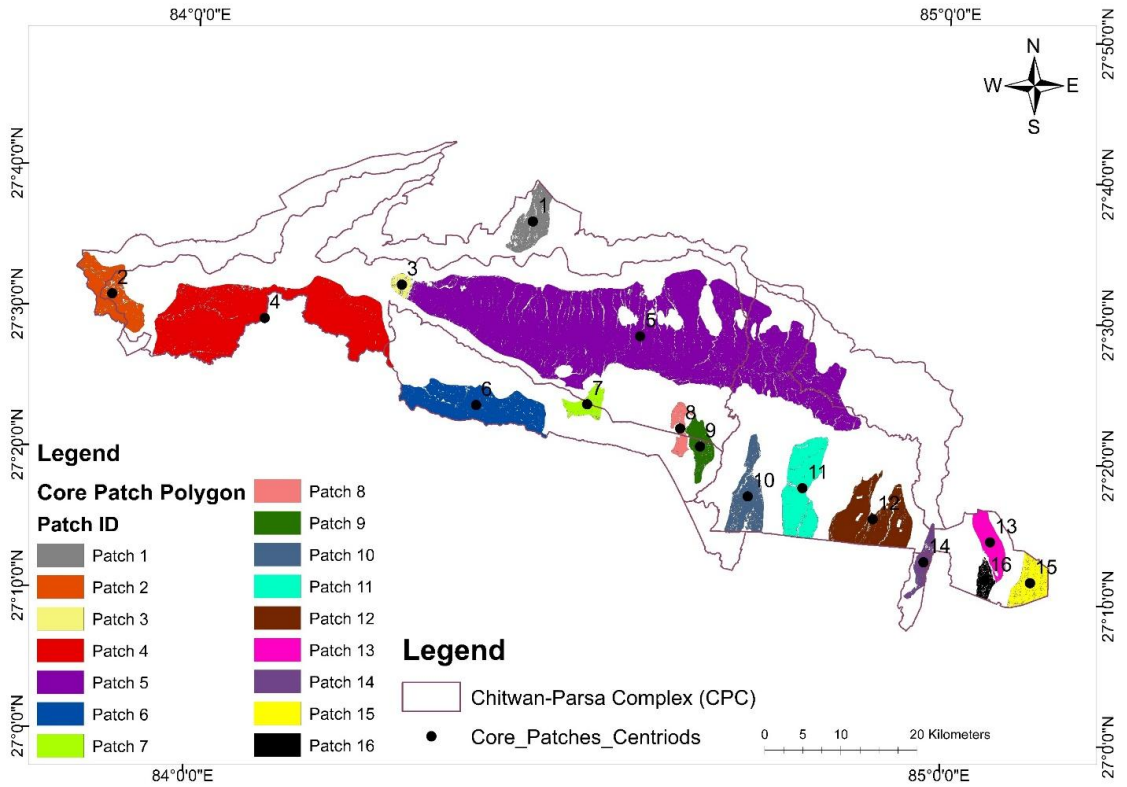
Fig. S1: Core Patches identified within Chitwan-Parsa Complex and their centroids.

Fig. S2: LULC Transition Matrix of different land use landcover categories in Chitwan-Parsa Complex for the period of 1985 to 2005 and 2005 to 2024.

