HABITAT SUITABILITY FOR ENDEMIC AND VULNERABLE WHITE-NAPED TIT (*MACHLOLOPHUS NUCHALIS*) IN ARID AND SEMI-ARID LANDSCAPES OF INDIA

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ABSTRACT

The White-naped Tit (*Machlolophus nuchalis*) is a vulnerable bird endemic to India that faces serious threats due to habitat loss, degradation, and fragmentation of habitat. Using MaxEnt niche modelling and compiled species occurrence data, we predicted White-naped Tit's habitat suitability in India's arid and semi-arid biogeographic zones. Our analysis suggests that 6.74 % (~50,612 km²) of the total area is suitable for White-naped Tit. Land cover change detection reveals that rangelands that contain suitable habitat types, support the preferred flora of *Acacia spp.* and have the high frequency of sightings for the target species, are the most declining form of land cover in the study area. Our findings help to provide a baseline understanding of the White-naped Tit's range and its association with land cover and other physical factors, which may be taken in consideration for short- and long-term conservation management approaches for this threatened species

Keywords: White-naped Tit, Ecological Niche, Habitat Assessment, MaxEnt, Habitat Suitability Mapping

INTRODUCTION

Passerines are valuable indicators of landscape and biodiversity changes due to environmental modifications (Civantos *et al*., 2018). They, however, suffer from a series of human practices, including development, deforestation, conversion of habitats to agricultural land, over-grazing and tourism (McNeely, 2003; Inskipp & Baral, 2010; Lobo- Araújo *et al*., 2024). Rare and Endemic species can be especially vulnerable to extinctions due to their low density and greater vulnerability to changes in the environment (Işik, 2011). Endemic species have limited geographic distributions and require specific habitats, making them especially sensitive to habitat change (Işik, 2011). Slight shifts in land cover caused by deforestation, urbanization, or agricultural development can dramatically limit accessible habitat, putting its existence at risk (Meyer & Turner, 1992). These changes can cause habitat fragmentation, isolating populations and reducing genetic diversity, making the species more vulnerable to extinction (Templeton, 1990). The habitat degradation and loss has led to almost 9 % of the estimated terrestrial species towards extinction, due to inadequate habitat for long-term survival (IPBES, 2019). Knowledge of the distribution of species is essential for understanding their ecology, management and conservation planning, considering the worldwide decline in biodiversity (Bani *et al*., 2002; Pereira *et al*., 2012). The first step of establishing a conservation strategy for any threatened, endangered, or endemic species is to identify areas that are suitable and inhabited. Programs developed for protecting such species also need to incorporate the conservation of suitable habitats. Landscape-scale data on species distribution and the environmental conditions that support them are necessary for such efforts to be successful (Guisan *et al*., 2013). Habitat suitability modeling (HSM), also referred to as "species distribution modeling" (SDM) or "ecological niche modelling" (ENM) is a statistical model that produces a correlative model of the environmental conditions that comply with a species' ecological needs and can identify potential habitat based on species occurrence data and environmental data (Guisan & Zimmermann, 2000; Hirzel & Le Lay, 2008; Elith & Leathwick, 2009; Barve *et al*., 2011; Uusitalo *et al*., 2019; Zhang *et al*., 2019).

This study focuses on White-naped Tit (*Machlolophus nuchalis,* formerly: *Parus nuchalis*) an endemic passerine species in India that is classified as Vulnerable (VU) by IUCN red list. This species has two distinct populations in India that inhabits parts of north-western drylands and the southern deccan region (Potter & Dhondt, 2019).

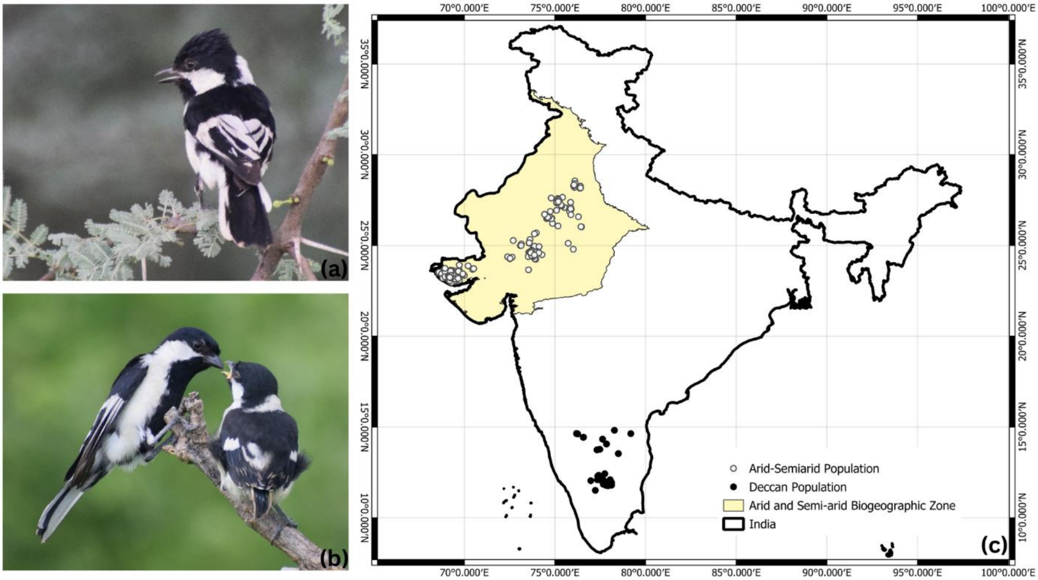
Despite its conservation value, the White-naped Tit is poorly studied in a number of ecological and conservation aspects. The important gaps include lack of comprehensive population estimates across its range, insufficient data on its population trends, evaluation of potential habitats and influence of habitat fragmentation on its distribution and survival. To cover this gap, we aim to evaluate the existing spatial pattern and optimal suitability of the White-naped Tit (*Machlolophus nuchalis*) in the arid and semi-arid zones using the MaxEnt model to determine high priority areas for conservation and state of land cover classes that holds the suitable habitats essential for survival for our target species.

MATERIALS AND METHODS

Study Area

The study was conducted in India's Arid and Semi-Arid biogeographic region, which spans approximately 7,50,000 km^2 and is located between 68°E and 80°E and 30°N and 20°N (Fig. 1c.). The present study is carried out on one of the two distinct population of *Machlolophus nuchalis* existing in India. The arid biogeographic zone occurs mainly in the western parts of Rajasthan and Gujarat including the Thar and Kuchh Deserts (Sharma *et al*., 2013). Due to excessive amounts of evaporation and low humidity, along with annual precipitation averaged at less than 250 mm, this zone is characterized by hyper-arid conditions with summers reaching above 50°C and winters sometimes falling below freezing. India's semi-arid biogeographic zone includes portions of Haryana, Gujrat, and Rajasthan. This zone experiences hot summers, mild winters, and moderate humidity levels. It also receives between 250 and 750 mm of rainfall annually (Jain *et al*., 2007). The Aravalli Ranges create a unique ecotone, a region that lies between semi-arid and arid zones. These ranges greatly influence the biogeography of both zones. Dominant flora in these zones includes *Prosopis cineraria, Acacia Senegal, Acacia nilotica, Ziziphus nummularia, Ziziphus mauritiana, Capparis decidua, Grewia tenax, Grewia villosa, Grewia flavescens, Prosopis juliflora, Azadirachta indica* and *Cenchrus ciliaris, Cenchrus peniseliformes, Aristida hystrix, Eleusine compressa* etc.

Fig. 1: (a&b) White-naped tit clicked at rangelands and agroecosystems in study area. (c) Distribution of White-naped tit in India.



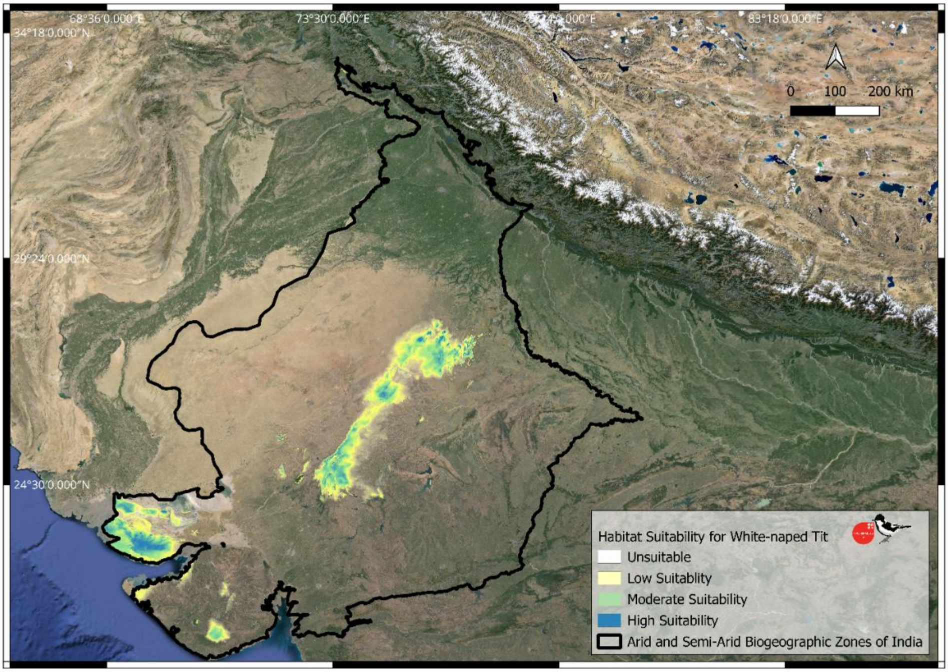
Data Collection and Analysis: We incorporated our field-collected data with *M. nuchalis* records that were submitted to eBird (eBird, 2024) between 2017 and 2024 in order to obtain appropriately large sample sizes throughout a wide geographic area. The presence of White-naped Tit was recorded in both breeding and non-breeding seasons in its preferred habitats using point count and line transects. White-Naped Tits shows increased vocalization activity during breeding, which allows for its detection by acoustic surveys. The amplified vocal effort, especially territorial and contact calls, greatly increases detectability, and as a result, more sightings are recorded at this time. This trend agrees with observations from other observers and citizen science records, which also record more frequently during the breeding season. After extracting all of the sightings (n=2014) from ebird, the data was further filtered to only include sightings that occurs in India's arid and semi-arid regions (n=1447). The environmental data used in the habitat suitability analysis were derived from remote sensing data, including land cover (Karra *et al*., 2021), elevation, and bioclimatic variables (Fick & Hijmans, 2017), and were standardized and processed for modeling with Q-GIS (QGIS, 2024). Habitat suitability models were created using machine learning algorithms such as Maximum Entropy Modeling (MaxEnt) (Phillips *et al*., 2024) to predict habitat suitability based on environmental data. Model performance was assessed using indices such as AUC-ROC and True Skill Statistic (TSS). Habitat suitability is represented as a continuous probability value (ranging from 0 to 1). To categorize this into levels of suitability, we used threshold-based classification: 0= Unsuitable; 0.01-0.4= Low Suitability; 0.41-0.70= Moderate Suitability and >0.7= High Suitability. The land cover change detection and visualization of were performed with R (R Core Team, 2024). In this approach, the model was tested using 20-fold cross-validation, which means it was ran with 20 replicates to obtain its optimal results. 70 % of the location point data was used to train the Maxent model, with the remaining 30 % having been used to validate it. The output was in logistic format. This study conducted an in-depth examination of how land cover changed from 2017 to 2023 in suitable area (received as output of MaxEnt SDM) of *M. nuchalis*. Sentinel-2 high-resolution satellite data was collected and processed using QGIS 3.20 and R for atmospheric correction and calibration. The study area was classified into land cover classes using classes defined by ESRI (Karra *et al.*, 2021), the predominant classes in suitable habitat are: 1) Farmlands- Human plotted grasses, crops, and cereals that are not at tree height; 2) Rangelands- Open spaces with uniform vegetation cover, wild cereals and grasses without evident human plotting (not a plotted field) examples include open savanna with few to no trees, pastures, and natural meadows. Moderate to sparse cover of bushes, shrubs, and tufts of grass; savannas with very sparse grasses, trees, or other plants; mixture of small clusters of plants or single plants scattered on a landscape that reveals exposed soil or rock; 3) Built area- Large homogenous impermeable surfaces, examples include homes, densely populated villages, towns, and cities, man-made structures, major road and rail networks; and asphalt; 4) Bare grounds- exposed rock or soil, deserts and sand dunes, dry salt flats and pans, dried lake beds, and regions with very little to no vegetation throughout the year; 5) Trees- Any noticeable clustering of tall (~15 m) dense vegetation, usually with a closed or dense canopy; examples include wooded areas; and 6) Water- Ponds, lakes, and flooded salt plains with little to no sparse vegetation that were primarily immersed in water for the whole year. The difference in land cover classes between the two time periods was computed using the change detection method.

RESULTS

The MaxEnt model performed well in predicting the appropriate habitat for *M. nuchalis*. The AUC score was 0.944, showing high prediction accuracy. The model's True Skill Statistic (TSS) was 0.791, indicating its reliability. The predicted suitable habitat for *M. nuchalis* (Fig. 2) covers approximately 50,612 km² which represents 6.74 % of the total extent of the study area, divided into ~8169 km² area of high suitability, ~18,255 km² area of moderate suitability and ~24,188 km² area of low suitability.

The environmental variables that contributed the most significantly to the model were Maximum Temperature of Warmest Month, Elevation, Precipitation Seasonality (Coefficient of Variation), Min Temperature of Coldest Month, and Annual Precipitation, contributing 31.2 %, 9.7 %, 7.8 %, 6.2 % and 5.8 % respectively. Eelevation does not have a strong impact on the abundance of *M. nuchalis* (slope of the regression line for elevation = -0.0007160), the counts remain relatively constant across different elevations, with higher abundance at elevation between 100 to 300 m. In the suitable areas, dynamic habitats like farmlands and rangelands dominates at 100 to 400 meters and 100 to 500 meters respectively which can influence the types of vegetation and microenvironment that *M. nuchalis* prefers.

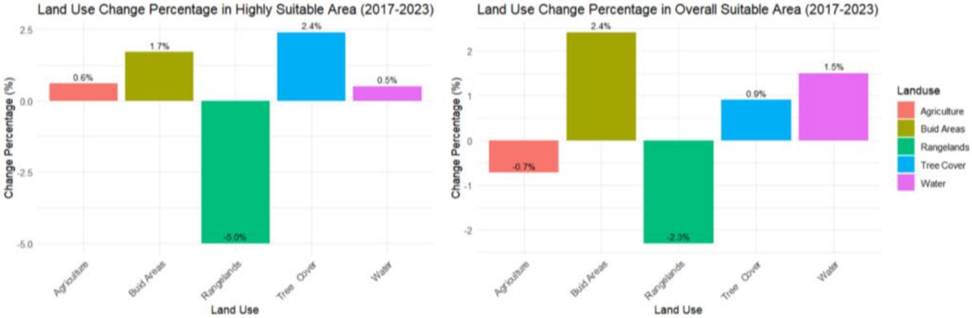
Fig. 2: The spatial distribution of predicted suitable habitat for *M. nuchalis*



Land Cover Analysis within Suitable Habitat

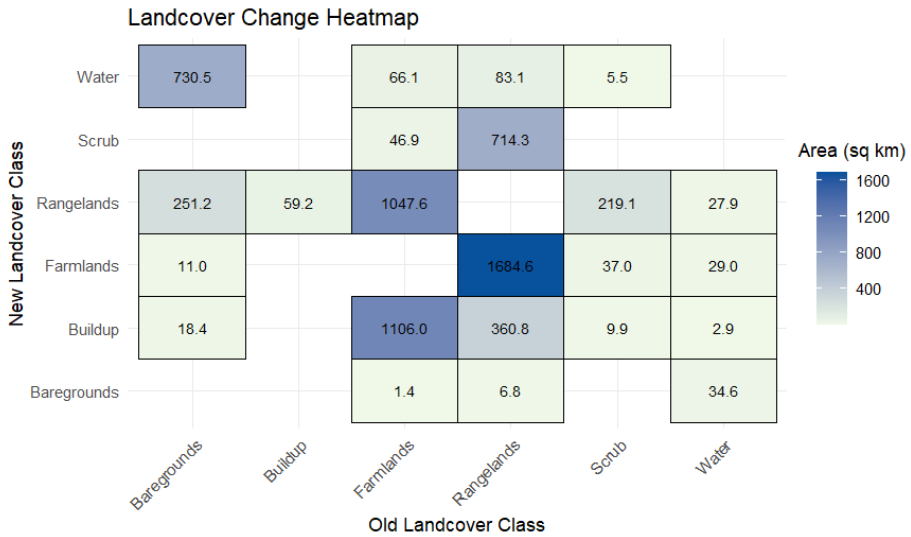
The current land cover within the predicted overall suitable area comprises 45.6 % agricultural lands, 37.6 % rangelands, and 7.4 % build areas. While 52.2 % rangelands, 27.9 % agricultural lands and 6.2 % build areas. Land change detection has shown considerable changes in land cover within suitable habitats over the past few years, spanning 2017-2023. Rangeland area has declined by 5 % in highly suitable areas and by 2.3 % in overall suitable areas, but agricultural land cover has increased by 0.6 % in highly suitable areas and reduced by 0.7 % in overall suitable areas. Other landcover has risen significantly in highly suitable areas and overall suitable areas with build areas, increasing 1.7 % and 2.4 %, respectively (Fig. 3).

Fig. 3: Land Cover Changes within highly suitable and overall predicted habitat (2017-2023)



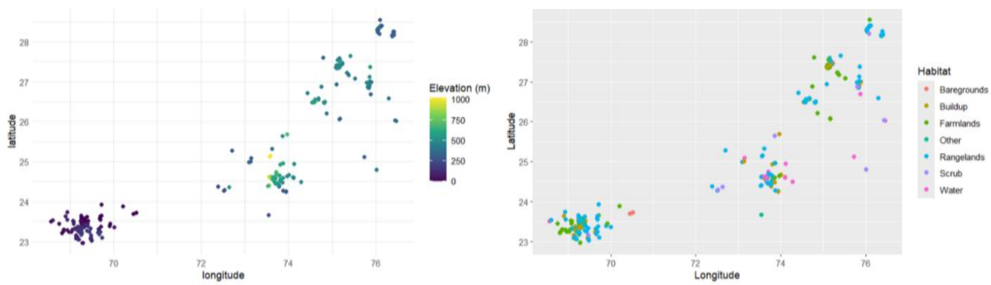
The analysis of land cover changes (Fig. 4) within the predicted suitable area for *M. nuchalis* reveals a change from rangelands to farmlands, which covers 1684.6 km². These transitions show the dynamic character of land cover in the appropriate area. Approximately 1498 km² of different habitat was converted to buildup indicating increase in urbanization in predicted suitable areas.

Fig. 4: Conversion of land covers within suitable area



Observations from rangelands are widely distributed across the geographical area (Fig. 5), indicating that rangelands are a common and widespread land cover in this region. Observations from farmlands and built-up areas are similarly distributed across the landscape, though their distribution is more constrained than rangelands. Scrublands are scattered out in certain areas, indicating their more localized presence. Observations from bareground and other land cover types are infrequent, indicating that certain land cover types are less common in preference of *M. nuchalis*.

Fig. 5: The spatial and geographical distribution of occurrence points, (Left) highlighting elevation and (Right) different land covers in Arid and Semi-arid landscapes.



DISCUSSION

The MaxEnt model has performed well in predicting suitable habitat for numerous species (Dai *et al*., 2011; Björklund *et al*., 2020). Temperature extremes are a key factor in determining the suitable habitat for tits (Van Noordwijk *et al*., 1995; Leech & Crick, 2007; Glądalski *et al*., 2016). The maximum temperature of the warmest month is a critical determinant for distribution of *M. nuchalis*, many bird species are sensitive to high temperatures (Jiguet *et al*., 2006), which can directly affect their habitat suitability (Brambilla, 2018). Additionally, precipitation seasonality, which measures the variation in precipitation throughout the year (Pascale *et al*., 2015), is crucial for species that depend on regular water availability and for ecosystems where water stress can have profound effects (McCluney *et al*., 2012).

Rangelands provide essential habitat for endangered species (Chaudhry *et al*., 2011; Barry & Huntsinger, 2021). The shift in land cover in *M. nuchalis* appropriate habitat from 2017 to 2023 reveals considerable changes, with a 5 % decrease in rangeland areas within highly suitable zones and a 2.3 % decrease in overall suitable areas. The conversion of rangelands to farmlands indicates the habitat's dynamic nature (Mazloum *et al*., 2021). These areas are distinguished by sparse and drought-resistant vegetation, which includes thorny shrubs, sparse grasses, and adapted tree species (Mathur & Pandey, 2016). The vegetation is adapted to low and unpredictable rainfall, with species of Acacia, Prosopis, Cenchrus, and Aerva being prominent (Dagar & Gupta, 2020; Chaudhari *et al*., 2024). Climate change, Agriculture, Urbanization, and Industrial expansion encroach on rangeland is threatening their integrity (Toutain *et al.*, 2010; Joyce & Marshall, 2017; Mosisa & Asefa, 2022).

The published observations from scrublands and bare ground further suggest that these habitats, while present, are preferred by the species (Ahlawat *et al*. 2018). Various studies and reports suggest that the White-naped Tit demonstrates a distinct preference for thorny forest habitats. Trivedi (2009) identified thorny forests as the typical habitat for this species. Acacia spp are most favored tree species within observed habitats. Potter & Dhondt (2019) observed that these birds frequently hunt for arthropods within the canopies of A. senegal and prefers them for nesting. This preference is consistent with observations in different regions, such as the scrub forests of Kutch, where Tiwari & Rahmani (1996) documented the species' affinity for *A. leucophloea*, *A. nilotica*, and other similar species. Joshua *et al*. (2007) also reported sightings primarily in large patches of Acacia, Prosopis, and Salvadora trees along dry riverbeds in the same district. Additionally, Dookia (2007) reported the presence of the White-naped Tit in the Thar Desert, where the species favors trees such as *A. tortillis* and *A. nilotica*. Intensive surveys by Tiwari (2001) in arid and semi arid environments suggest that the preferred habitats of *M. nuchalis* include not only thorn dry deciduous forests but also crop fields and fellowlands having preferred tree species. In terms of territory size, the White-naped Tit maintains larger territories compared to other members of the Paridae family (Potter & Dhondt, 2019; Perrins, 1979). Kala & Joshua (2011) reported finding 16 pairs of White-naped Tits within a 2 km² study area in the thorn forests of the Aravalli hills, Rajasthan, estimating each territory to be slightly more than 12 hectares. The consistent preference for Acacia species across various studies underscores the critical role these trees play in the ecology of the White-naped Tit.

When reviewing the distribution map of *M. nuchalis* across several platforms, it appears that this species is more usually found in the Aravalli hills or at higher elevations in the study area. Our linear regression model shows that, while elevation is a statistically significant predictor, it is not the most important factor influencing *M. nuchalis* habitat preference. Other environmental factors, including vegetation type (Tiwari, 2001; Dookia, 2007; Jones, 2007; Sharma & Koli, 2014), water availability (Sharma & Koli, 2014), and anthropogenic disturbances (Kala & Joshua, 2011; Schorn, 2024), are likely to have a greater impact on the distribution of this and other tit species.

The integration of eBird data in this study has proven to be a valuable approach for understanding the distribution and habitat preferences of the White-naped Tit. Our approach aligns with numerous studies worldwide that have successfully applied eBird data to enhance avian research (Sullivan *et al*., 2017; Roy *et al*., 2019; Stuber *et al*., 2022). Incorporating eBird data enables researchers to validate findings from field observations and expand the geographical scope (Zhang, 2020). Integrating citizen science data with standard research methods is a significant tool for improving our understanding of avian ecology and directing conservation initiatives (Sullivan *et al*., 2014).

Our habitat suitability model makes spatially explicit predictions that are critical for conservation planning. The habitat suitability map can inform the creation of new protected areas such that the most suitable habitats for the target species are legally defended (Garrote *et al*., 2020). Areas once favorable but have been degraded should be given top priority for rehabilitation (Asadalla *et al.*, 2021), such as reforesting indigenous trees like Acacia and Prosopis for the White-naped Tit. Suitability predictions can also be incorporated in land-use plans to reduce issues between agriculture, urbanization, and conservation (Li *et al*., 2022). Through projection of future climate conditions, MaxEnt can forecast how habitats of species will evolve in response to temperature and precipitation changes (Bora & Saikia, 2024). Regions modeled as suitable but without existing records can be targeted by field surveys to enhance species distribution information. Habitat Suitability results be applied by governments and conservation agencies in EIAs to evaluate the effect of development projects and implement protection of habitats (Gontier *et al*., 2010).

CONCLUSIONS

This study highlights the current and estimated distribution of suitable habitats for the White-naped Tit (*Machlolophus nuchalis*) and the significant land cover changes affecting these areas. Given the limited distribution of white-naped tit in arid and semi-arid regions, protection measures should be implemented, particularly in areas with moderate to high predicted suitability. The integration of MaxEnt modelling with land cover analysis provides a comprehensive understanding of habitat suitability and the land use dynamics. Such information is critical for developing conservation programs and management plans for all species, but notably for those that are more severely impacted by anthropogenic activities, such as rare, endemic, and threatened.

Some key conservation recommendations include strengthening enforcement & policies, Expanding totally protected areas in arid and semi-arid zones, Minimizing habitat destruction & mitigating anthropogenic disturbances, Education & public awareness including sensitization of indigenous and local communities for community-based conservation model. The White-naped Tit prefers habitats dominated by Acacia, Prosopis, and Salvadora species, showing a strong association with sparse, drought-adapted vegetation in arid and semi-arid landscapes. MaxEnt model outputs indicate that extreme temperatures limit habitat suitability, while moderate precipitation seasonality plays a crucial role in ensuring water availability. Climate change and increasing aridity pose significant threats, along with habitat loss due to rangeland conversion into agricultural fields and urban areas. Although the species can utilize fallow lands and agricultural landscapes, key tree species must be retained for habitat suitability. While often recorded at higher elevations, vegetation structure and water availability are more critical factors than elevation alone.

Accounting for the limitation, present model relies on presence-only data from citizen science platform, which does not account for false absences, and its accuracy is influenced by sampling biases, particularly data concentration in easily accessible locations. Seasonal bias in occurrence data arises from the species' higher detectability during the breeding season due to vocalization. Observer skill variability further introduces potential species misidentifications. While SDMs predict suitable habitat, they do not confirm actual occupancy due to factors like dispersal limitations and competition. Additionally, microhabitat preferences, such as nesting sites and specific tree associations, are not fully captured in broad-scale models, and fine-scale features like tree height, canopy cover, and insect abundance remain difficult to integrate.

Future research should focus on improving habitat characterization through field-measured vegetation and prey availability data, validating model predictions with independent surveys, assessing the long-term impacts of land-use changes, and incorporating movement ecology data (e.g., radio telemetry, GPS tracking), studying breeding biology, nesting success, and interactions with other species within its habitat that could provide valuable insights into its ecological role and conservation needs and enhance understanding of habitat connectivity and species dispersal patterns.

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CONFLICT OF INTEREST

The authors state that they have no conflicts of interest.

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