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Modeling Potential Impacts of Climate Change on the Distribution of Wooly Wolf (*Canis lupus chanco*)

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The Central Asian wolves form a cohort within the wolf-dog clade known as the wooly wolf (*Canis lupus chanco*). These wolves are poorly studied and their current extent and distribution remain unknown. Apex predators already existing at higher elevations like wooly wolves can be severely affected by climate change because of the absence of suitable refuge. Concomitantly, in the era of Anthropocene, the change in land use land cover (LULC) is rapidly increasing. Even the most adaptable species occurring in human-dominated landscapes may fail to survive under the combined impact of both climate change and human pressure. We collected 3,776 presence locations of the wooly wolf across its range from published literature and compiled 39 predictor variables for species distribution modeling, which included anthropogenic factors, climatic, vegetation, and topographic features. We predicted the change in their distribution under different anthropogenic factors, climate change, and land-use land-cover change scenarios. Wolf showed affinity toward areas with low to moderately warm temperatures and higher precipitations. It showed negative relationships with forests and farmlands. Our future projections showed an expansion of wolf distribution and habitat suitability under the combined effects of future climate and LULC change. Myanmar and Russia had the introduction of high and medium suitability areas for the wooly wolf in future scenarios. Uzbekistan and Kazakhstan showed the consistent loss in high suitability areas while Mongolia and Bhutan had the largest gain in high suitability areas. The study holds great significance for the protection and management of this species and also provides opportunities to explore the impact on associated species.

Keywords: Central Asia, future prediction, habitat suitability, predator, species distribution model, global warming

INTRODUCTION

Climate change triggers stark effects on species geographic ranges, leading to range shifts and disruptions in the functioning of ecosystems (Colwell et al., 2008; Lenoir and Svenning, 2015; Lenoir et al., 2017; Pecl et al., 2017). Climate change also causes regional weather fluctuations with respect to precipitation, affecting resource distribution and availability and consequently impacting habitat and ecological processes of faunal species (Parmesan, 2006; Chen et al., 2011;

Schewe and Levermann, 2012; Jayasankar et al., 2015). Although species are known to adapt both genetically and behaviorally to circumstances, their adaptive responses are often insufficient due to rapid changes in anthropogenic land-use patterns and their synergistic effects with climate change (Brodie, 2016) thus, threatening them to the verge of extinction (Jump and Penuelas, 2005; Bradshaw and Holzapfel, 2006; Radchuk et al., 2019).

The extinction of large carnivores may have cascading effects on the functioning of an ecosystem in multiple ways (Terborgh et al., 2010). However, when conserved, large carnivores can recover and colonize even in human-dominated landscapes (Chapron et al., 2014). Anthropogenic activities leading to change in land use may also promote large carnivore populations in the future (Milanesi et al., 2017). Studies from the Scandinavian countries and the United States reported that wolves have not only recovered but have also started exploring new habitats in human-dominated landscapes (Mladenoff et al., 1995; Wabakken et al., 2001; Gurarie et al., 2011; Carricondo-Sanchez et al., 2020).

Wolves are known as charismatic as well as umbrella species that have been extensively studied in America and Europe (Mech and Boitani, 2003) with only a few studies from Asia (Khan et al., 2022). The Holarctic gray wolf is also known as Himalayan or Tibetan wolf in the central and south-east Asian countries continues to be an enigma concerning its nomenclature due to the novel genetic insights from across its range (Sharma et al., 2004; Aggarwal et al., 2007; Shrotriya et al., 2012; Fan et al., 2016). Since different terms were used for these wolves according to the different regions where they were found, the term wooly wolf (Arnold, 2016; Joshi et al., 2020; Lyngdoh et al., 2020) was first used by Pocock (1941) to address these wolves. They are known for their hypoxic adaptations for surviving at extremely high altitudes of the Tibetan Plateau, Himalaya, Mongolia, China, and Manchuria (Zhang et al., 2014; Werhahn et al., 2018). Recent genomic studies have suggested that the south Asian region is an important center for the evolution of the gray wolf and the Tibetan wolf is an ecologically significant unit (ESU) (Hennelly et al., 2021).

Existing literature on the wooly wolf focuses majorly on its genetics (Aggarwal et al., 2007; Werhahn et al., 2017), diet (Chetri et al., 2017; Werhahn et al., 2019; Lyngdoh et al., 2020; Reshamwala et al., 2021), public perception (Bhatia et al., 2017; Kusi et al., 2020) and conflict with humans, habitat suitability, and distribution in localized regions (Kabir et al., 2017; Subba et al., 2017; Rana et al., 2018). However, its global geographical extent and potential habitat remain unknown. In this study, we explore two aspects of the wooly wolf distribution. First, we evaluate the current available wooly wolf habitat across its entire distribution. Further, we predict the changes in their suitable habitat under future climatic and land-use change scenarios. A protected area (PA) network plays an important role in the conservation of species regionally. Therefore, we also evaluated the extent and importance of the current PA network for wolf conservation in the range countries. To the best of our knowledge, this is the first study that shows the global extent of wooly wolves and helps in finding key priority areas that may be of management importance in the face of climate change and other anthropogenic factors. Thus, this study holds great conservation and management significance for this species.

MATERIALS AND METHODS

Study Area

We considered all wolf-ranging regions from Central Asia, Mongolia, Chinese Turkestan, and Tian Shan mountains to the high-altitude plateaus of Tibet, Qinghai, Shensi, Szechwan, Yunnan, and the Himalaya in this study. The topographical features of these regions mainly consist of deserts, grasslands, glaciers, mountains, and river basins. We delineated the study area boundary by creating a polygon surrounding the extreme extents of the above-mentioned regions in Google Earth (**Figure 1**). Parts of the following countries were included in the intensive study area—Afghanistan, Pakistan, Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan, India, Nepal, Bhutan, Myanmar, China, Mongolia, and Russia. The study area comprised about 18.63 million km^2. The broad habitat types of the study area include alpine tundra, alpine steppe, wetlands, open grasslands, sparse shrubs, and coniferous forests (Werhahn et al., 2020). In addition to wooly wolves, other predator species in the study area include snow leopard (*Panthera uncia*), red fox (*Vulpes vulpes*), Tibetan fox (*Vulpes ferrilata*), Pallas's cat (*Otocolobus manul*), Eurasian lynx (*Lynx lynx*), and brown bear (*Ursus arctos*). The major prey species of the study area are urial (*Ovis vignei*), ibex (*Capra ibex*), kiang (*Equus kiang*), blue sheep (*Pseudois nayaur*), Tibetan gazelle, Tibetan argali (*Ovis ammon hodgsoni*), white-lipped deer (*Cervus albirostris*), Himalayan marmot, wooly hare, several species of pika (*Ochotona* spp.), and rodents. Livestock also adds a considerable amount to the diet of predators in the study area (Lyngdoh et al., 2020; Khan et al., 2022).

Wooly Wolf Location Data

Presence locations of wooly wolves (both direct and indirect evidence) were obtained from published literature and publicly available dissertations. We collected 3,776 presence locations of woolly wolves (**Figure 1** and **Supplementary Table 1**) for Afghanistan, Pakistan, Kyrgyzstan, India, Nepal, Bhutan, China, and Mongolia which included data from our telemetry study and sightings on wooly wolves.

Preparation of Geospatial Layers

We gathered a total of 39 predictor variables from various sources to develop species distribution model for wooly wolves for current and future prediction (**Supplementary Table 2**). We selected topographic, vegetation, and anthropogenic variables that may govern the distribution of the wooly wolf. These factors included climatic variables, aridity Index (AI), potential evapotranspiration (PET), cloud cover, normalized difference vegetation index (NDVI), digital elevation model (DEM), land use land cover (LULC), slope, aspect, topographic position index, terrain ruggedness, vector ruggedness, hill shade, distance to the nearest water source, distance to nearest glaciers, distance to nearest roads, human footprint, and population density. We did a

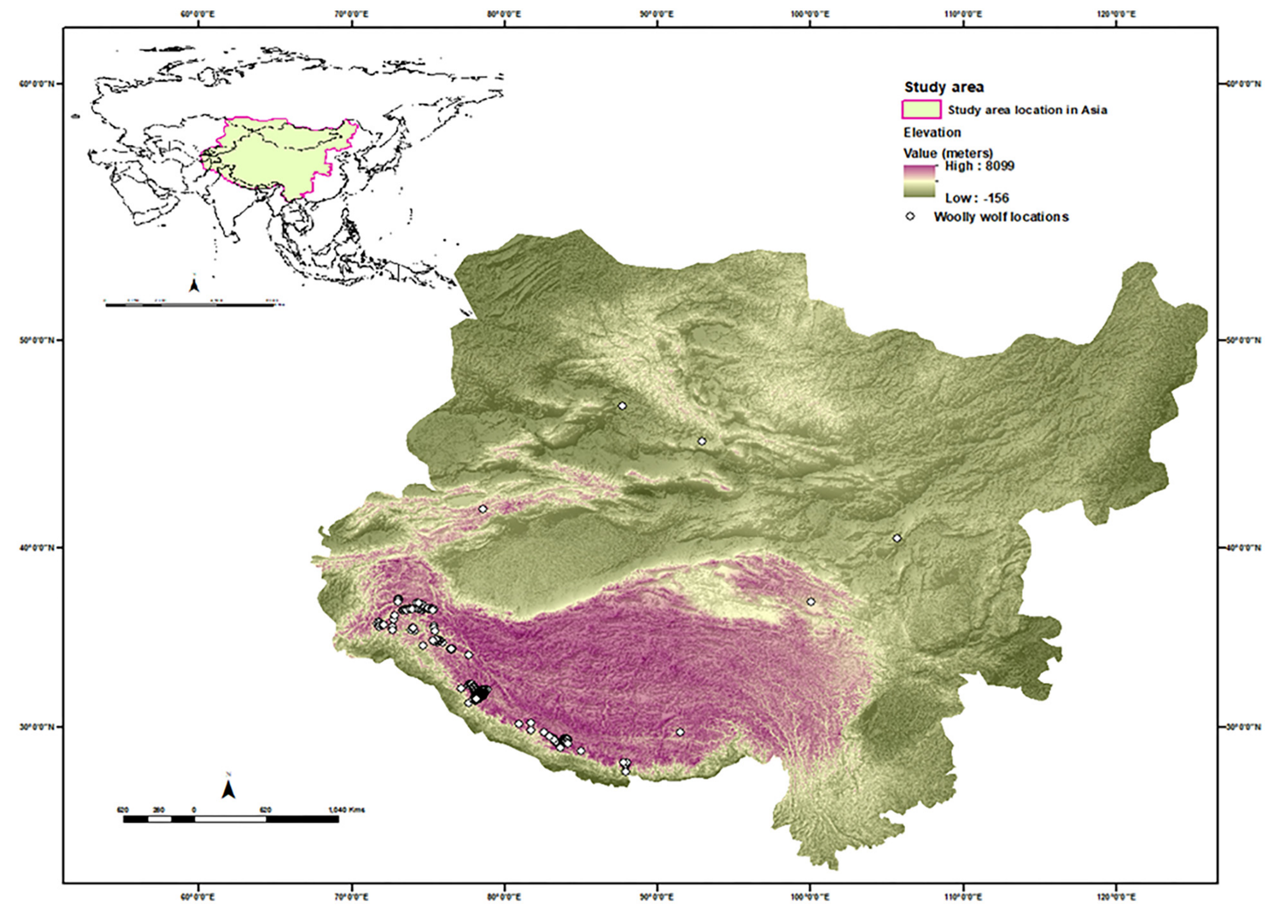

FIGURE 1 | Map of the study area along with collated presence locations used for distribution modeling of the wooly wolf.

Pearson's correlation test between the 39 variables prior to species distribution modeling and eliminated highly correlated variables (>0.6). Thus, we finalized 18 variables for final analyses in the current and future scenarios (**Supplementary Table 2**). We then extracted the values of all the variables according to the intensive study area boundary. We overlaid boundaries of PAs pertaining to the intensive study area which was available from https://www.protectedplanet.net/en/thematic-areas/wdpa to understand the suitable habitat of the wooly wolf inside and outside PAs. Though this is the only database available of comprehensive information for PAs across the globe, we want to point out that the above data have certain discrepancies regarding the coverage of all PAs of the countries included in the study. We acquired an updated PA layer for India from https://indiabiodiversity.org/map and merged it with the existing information. However, for other countries, such updated information was not available.

Analysis

Modeling Current Distribution

We used MaxEnt (version 3.4.1k) for developing species distribution models for the wooly wolf. MaxEnt is based on occurrence/presence records (locations where the species has been found) together with environmental variables or constraints for the surrounding study area (Phillips et al., 2006; Phillips and Dudík, 2008) and is one of the recent approaches which can be used (Hernandez et al., 2006; Wisz et al., 2008). We developed six MaxEnt models using the default settings, except for the feature classes, to check for initial model fitting using all locations for different grid divisions within the study area. We used linear, quadratic, and hinge feature classes, best suited for small sample sizes (Morales et al., 2017) for our models to help smooth the variable responses and reduce the noise (Elith et al., 2011; Merow et al., 2013; Morales et al., 2017). Hinge features provide at least as much flexibility in the fitted response to predictor variables as threshold features, while tending to reduce overfitting to the training data. To account for sampling bias, we applied the bias correction method by creating bias grid files that can be fed into the MaxEnt software (Dudík et al., 2005; Phillips et al., 2009). In a biased file, the cell values reflect the sampling effort and give a weight to random background data used for modeling (Fourcade et al., 2014). We produced these sampling probability surfaces by deriving the Gaussian Kernel Density of sampling localities (Elith et al., 2010). Previous studies have shown that correcting sampling bias has yielded improved model fitting especially with smaller sample sizes (Fourcade et al., 2014). The spatial distance used to quantify the region of spatial bias was kept at 50 and 100 km, respectively.

To avoid clustering of presence locations, we divided the entire study area into grids of 1 × 1 km, 2 × 2 km, 3 × 3 km, 5 × 5 km, 7 × 7 km, and 10 × 10 km and selected one random point location falling in each grid using R software (R Core Team). For each grid size, separate analyses were performed. Such divisions were selected to incorporate all possible scales and values of variable contributions for analysis. Accordingly, we finalized 774, 486, 357, 254, 206, and 162 presence locations, respectively, for further analysis. We conducted the analyses with all the divisions using both 50 and 100 km bias files (12 models). Concurrence between model accuracy and output decreased with an increased grid size (Seo et al., 2009). The models with increased grid sizes selected more area as potential distribution range. We assume that the small grid size combination incorporated all possible fine-scale values of variables used and provide a significant spatial distribution output. Otherwise, an overestimated predicted range might lead to inappropriate selection of conservation priority areas (Seo et al., 2009). Moreover, the analysis was conducted with a small sample size over a large study area, it was important to include all possible fine-scale information available for a robust output. Hence, we used results for only 1 × 1 km grid size with 100 km bias.

We then developed five different models with combinations of regularization multipliers (0.25, 0.5, 1, 1.5, and 2) and selected the most significant combination based on the area under the receiver operating characteristic curve (AUC) value. Regularization multiplier is a modifiable parameter that adds new constraints to the model and is thus used to evaluate the best potential combination of parameters teaming up with the feature classes (Morales et al., 2017). This is used to prevent the over-fitting of the model by controlling the intensity of the chosen feature classes (Elith et al., 2010). Previous studies have shown that for small sample sizes it is best to use intermediate regularization multipliers for better model fitting (Radosavljevic and Anderson, 2014; Morales et al., 2017). We assessed the model performance by the mean AUC value (Hosmer et al., 2000) and visual inspection of the identified suitable area of the output maps for each model. We finalized regularization multiplier 2 to be the most significant for further analysis as the AUC graph and the output map coincided in showing meaningful representations in concurrence to the species' ecology (Radosavljevic and Anderson, 2014). We then partitioned our presence locations randomly into 5 sets of training and testing samples. All the training sets included rare locations from the far-off regions such as Mongolia. We opted for this approach to train the models with a wider set of information. We developed models with the above sets of training and testing samples (5 models) and the model performance was assessed by the AUC values. We calculated mean variable response curves and Jackknife of regularized training gain test to evaluate the importance of each predictor and percent contribution and permutation importance (**Supplementary Figure 1**). We applied a 10-percentile training presence logistic threshold to generate the species distribution maps. We calculated the average of the 5 distribution models to predict the current distribution of wooly wolves. The final layer was classified into equal intervals (0–33%, 33–66%, 66–100% suitability) of three suitability areas—low, medium, and high and tabulated the area for each class.

Projecting Future Distributions

We used two future scenario settings to assess the likely changes in suitable habitats for wooly wolves for climatic variables and LULC for RCP4.5 and RCP8.5. We used the A1B scenario of the future LULC layer as this scenario had data balanced across all resources (Li et al., 2017). We used the same environmental layers for both the current and future distribution models. We used the MICROC 5 model of the Global Climatic Model (GCM) for the future climate scenarios as the warmest future change is obtained through this model (Wazneh et al., 2020). We used 29 models of various combinations to generate the future projections (**Supplementary Table 3**). Similar to the analysis for current distribution (see section "Modeling Current Distribution"), we generated the average model for each scenario, classified them into suitability areas, and tabulated the areas for each class. We projected the future distributions for two timelines—2050 and 2070. We developed a total of 63 MaxEnt models (**Supplementary Table 3**) using 774 locations and 18 environmental variables to predict the potentially suitable habitat for wooly wolves.

RESULTS

The MaxEnt model used for wooly wolf distribution was reliable as statistical estimation of averaged accuracy for five models was 94.8% ± 0.54 *SD* and 94.5% ± 0.50 *SD* for training and test AUC, respectively. Regularization multiplier 2 was the most suitable for the wooly wolf to avoid overfitting of the models. Of the total study area, 5.31% was inside PA and 94.69% was outside PA.

Current Distribution

Among the variables used to predict the current distribution – DEM, vector ruggedness measure (VRM), mean diurnal temperature (Bio2), precipitation of coldest quarter (Bio19), precipitation of driest month (Bio14), and LULC were the most important factors driving the habitat suitability in the study area (**Figure 2**). Wolf showed a positive relation toward higher elevation, but the peak dropped after 5,000 m which is consistent with wolf ecology. However, the distribution did not show any variation with ruggedness indicating wolves' preferences toward all kinds of terrain. Wolf showed affinity toward areas with lower to moderately warm temperatures and higher precipitations. It showed negative relations with forests and farmlands, reflecting its affinity more toward open barren areas. Only ∼12% of the study area corresponded to suitable area (Medium + High) for wooly wolf (**Figure 3**) of which only ∼1% is under PA and the rest outside PA. Among the countries, the most suitable habitat for wooly wolves was in China followed by Kyrgyzstan, India, Tajikistan, Pakistan, and Afghanistan.

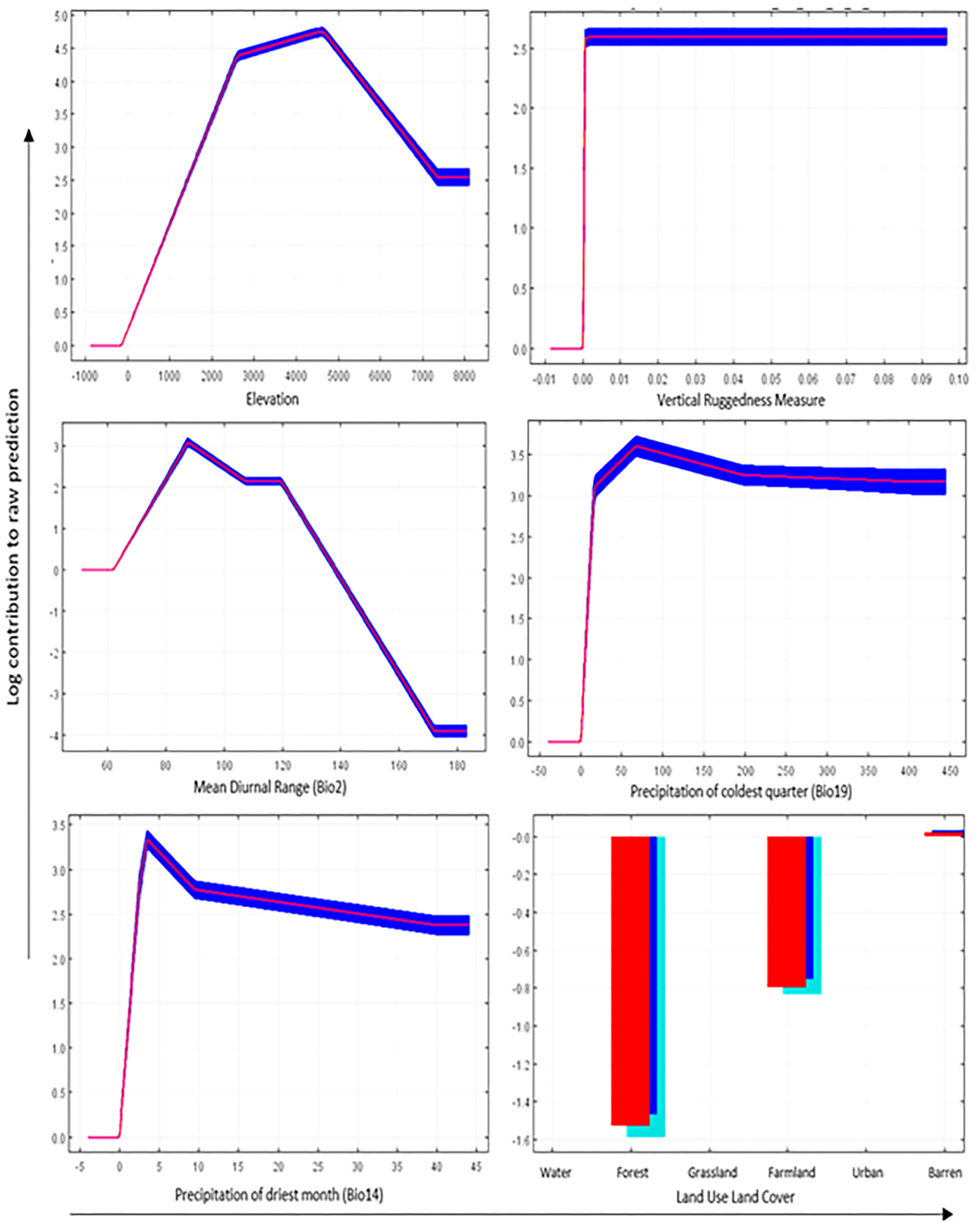

FIGURE 2 | MaxEnt model response area curves of the predictor variables influencing wooly wolf distribution: elevation; vertical ruggedness; mean diurnal range (Bio2); precipitation of coldest quarter (Bio19); precipitation of driest month (Bio 14) and land use land cover.

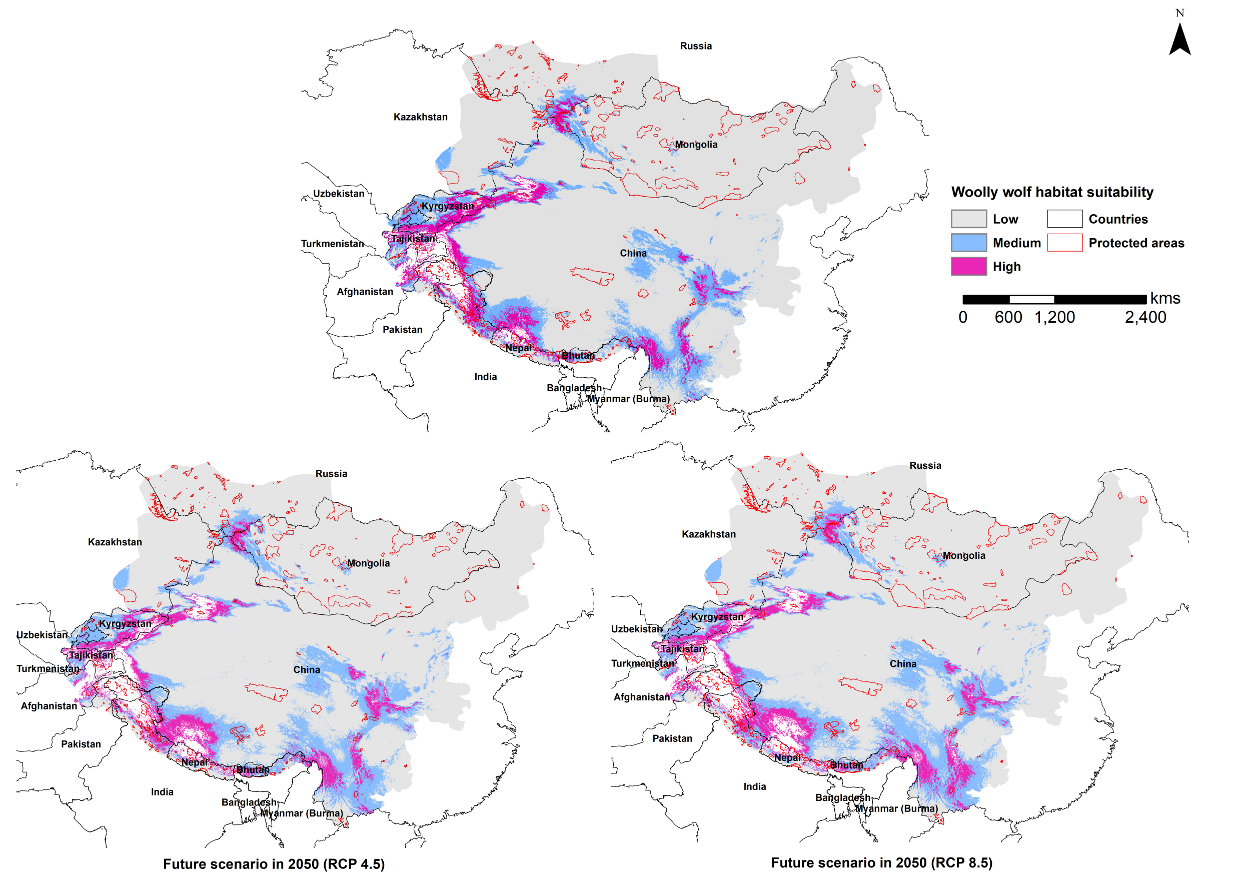

FIGURE 3 | Wooly wolf distribution model showing current and future trends of suitable habitat for the species for two future climate scenarios (RCP 4.5 and 8.5) for the year 2050 with the countries and protected areas boundary within the intensive study area.

Future Projections

The future climate scenarios RCP 4.5 and 8.5 both predict an increase in global temperature for the years 2050 and 2070. Our future projections showed an expansion of wolf distribution and habitat suitability under the combined effects of future climate and LULC (**Figure 3**). The results for both the scenarios for both timelines showed expansion of range in medium and high suitability classes (**Table 1**). Most expansions occurred in the southern and south western parts of the study area. This indicates that wooly wolf distribution was mainly affected by the change in future climatic conditions which in turn governed the changes in future land-use scenario. It was interesting to find that Myanmar and Russia had the introduction of high and medium suitable areas for wooly wolves in the future scenarios (**Figure 4**). Uzbekistan and Kazakhstan showed consistent loss in high suitable area while Mongolia and Bhutan had the highest gain in suitable area (**Figure 4**). Kyrgyzstan and Tajikistan had increase of suitable areas inside PA and decrease outside PA (**Supplementary Table 4**).

For the current scenario, we calculated the low, medium, and high habitat suitability of wooly wolves. The result showed that the maximum areas of PA in Nepal, India, China, and Mongolia were highly suitable for wooly wolves. Moreover, the highly suitable areas for wooly wolves were found more outside PAs in Uzbekistan, Afghanistan, Pakistan, Kazakhstan, Tajikistan, and Bhutan (**Table 2**).

DISCUSSION

This study provided a probabilistic current distribution and predicted the likely changes in the suitable habitats for wooly wolves across 15 countries in Central Asia under climate change. The study shows an increase in habitat suitability of wooly wolves within its probable distribution range under the combined effects of climate and land-use changes in the future. The primary reason behind this could be the increase in the availability of barren areas and agricultural lands due to the melting of glaciers under rising temperatures. Both RCP 4.5 and RCP 8.5 emissions scenarios predict a rise in temperature in the years 2050 and 2070. The future land-use change for the year 2050 predicts increase in agricultural land use, high pressure on forest resources, and expansion of plantation forestry (Sleeter et al., 2012). Studies have shown that climate change due to rising temperature and expansion of agriculture along altitudinal gradient synergistically affect the niches of mammals (Brodie, 2016). Wolves could be

TABLE 1 | Results showing patterns of current and future suitability areas for wooly wolves under different suitability classes.

Suitability classes	Current in km^2 (% of suitable area)	RCP 4.5_2050 in km^2 (%of suitable area)	RCP 8.5_2050 in km^2 (%of suitable area)	RCP 4.5_2070 in km^2 (%of suitable area)	RCP 8.5_2070 in km^2 (%of suitable area)
Low	16,433,200 (88.18%)	15,904,179 (85.34%)	15,749,894 (84.52%)	15,886,401 (85.25%)	15,618,637 (83.81%)
Medium	1,716,970 (9.21%)	2,006,435 (10.77%)	2,133,739 (11.45%)	2,031,728 (10.90%)	2,178,296 (11.69%)
High	485,389 (2.60%)	725,001 (3.89%)	751,979 (4.04%)	717,487 (3.85%)	838,640 (4.5%)

affected by these factors and lead to changes in the distribution and behavioral patterns of the species. Our distribution model shows a strong negative relationship with forests than with agriculture and a positive relation with barren areas (**Figure 2**). This was further supported by the distribution of wooly wolf suitable habitats outside PAs in future scenarios (**Table 1**) and the introduction of suitable habitats in Myanmar and Russia. Our results show wooly wolves prefer moderately warmer and contiguous wet areas. It is known that warmer and wetter conditions may favor certain species expansion (Hof et al., 2012). We believe that such conditions could lead to land-use changes, especially the expansion of agriculture. It has been found that land-use changes (agriculture, plantations, etc.) can increase the structural, functional, and temporal connectivity to generalist species by providing refugia during less favorable climatic conditions facilitating range expansions (Auffret et al., 2015; Elmhagen et al., 2015).

We found that protected areas hardly provide suitable areas for wooly wolves throughout their distribution range. The future scenario is also similar except that the suitable area increased more inside the PAs in Kyrgyzstan and Tajikistan. Although our calculations of the PA network could be an underestimation due to the unavailability of recently updated datasets for all countries, the overall trend is unlikely to be affected by such errors. Therefore, the wolf conservation should be pivoted to community conservation areas outside the PA network. Large-ranging species require landscape-level planning and management, which are difficult to achieve through the existing PA network system. Our distribution modeling for wooly wolf further has potential drawbacks due to the lack of presence data from North and Eastern parts of its range. Almost no literature is available from the central Asia countries and much of the Chinese part. To avoid overprediction or underestimation of its habitat, we ensured to use all locations from these understudied regions for training in all our model datasets. However, more presence locations from these regions would aid in robust modeling and predictions.

Species that are generalist in nature with the ability to move far can colonize new areas and track their shifting areas according to climatic suitability (Colwell et al., 2008). Arctic and sub-arctic generalist mammal species have been known to expand their ranges due to the impact of climate change (Hof et al., 2012). It has been suggested in previous studies that species can make large elevational shifts over short linear distances in areas with steep topography. This is because contiguous habitats are found along elevational gradients (Colwell et al., 2008; Brodie, 2016). There are evidence of upslope range shifts due to climate change by snow leopards and Ethiopian wolves (Trouwborst and Blackmore, 2020). Our results showed major habitat suitability changes in the south and south-western parts of the study area that had the most variations in altitudes due to the presence of several mountain ranges.

Gray wolves are known to act as buffers in climate change by mediating and facilitating other animal species (Wilmers and Getz, 2005). Range expansion may lead to intra-guild as well as interspecific competition and predation as suggested by Pamperin et al. (2006) in their study on red foxes (*Vulpes vulpes*), which underwent range expansion in the higher altitudes leading to incidences of killing of arctic foxes (*Alopex lagopus*). The

TABLE 2 | Country-wise suitable habitat of wooly wolf suitable within (PA) and outside protected areas (OPA) in current scenarios.

Countries	System	Low	Medium	High
Uzbekistan	PA	0.34	0.43	0.00
	OPA	99.66	99.57	100.00
Mongolia	PA	14.04	33.23	87.04
	OPA	85.96	66.77	12.96
Myanmar	PA	0.00	1.59	NA
	OPA	100.00	98.41	NA
Afghanistan	PA	2.78	15.23	4.70
	OPA	97.22	84.77	95.30
Pakistan	PA	1.46	1.07	0.59
	OPA	98.54	98.93	99.41
Russia	PA	3.70	10.84	0.00
	OPA	96.30	89.16	100.00
Kazakhstan	PA	28.42	6.59	0.00
	OPA	71.58	93.41	100.00
China	PA	72.08	46.85	78.07
	OPA	27.92	53.15	21.93
Kyrgystan	PA	0.03	0.38	0.45
	OPA	99.97	99.62	99.55
Tajikistan	PA	10.48	25.14	19.26
	OPA	89.52	74.86	80.74
Bhutan	PA	3.91	1.05	0.00
	OPA	96.09	98.95	100.00
Nepal	PA	0.80	16.50	100.00
	OPA	99.20	83.50	0.00
India	PA	50.49	80.49	99.72
	OPA	49.51	19.51	0.28

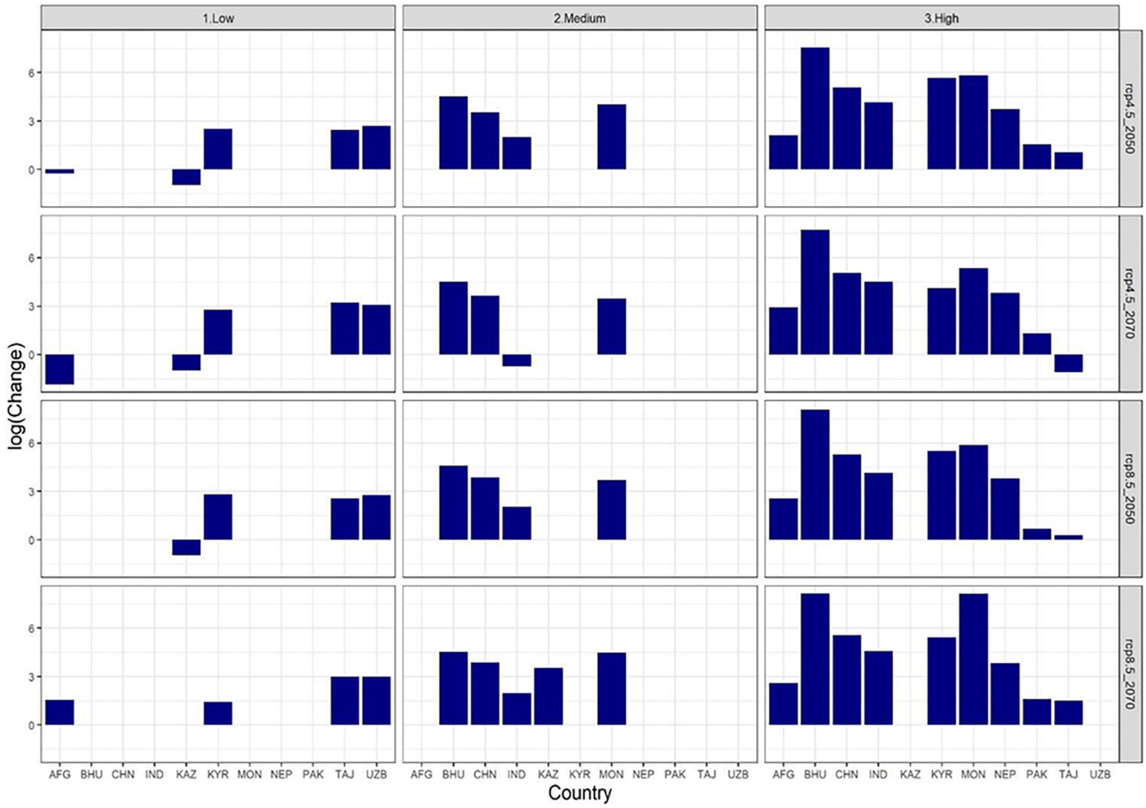

FIGURE 4 | Country-wise gain/loss of wooly wolf suitable habitat in four future scenarios with respect to current suitable habitat in three suitability classes.

increase in habitat suitability of wooly wolves in the future can lead to habitat sharing or usurping of species of more or less similar guilds or niches such as snow leopards, brown bears, red foxes, and lynx. Both gray wolves and brown bears are reported to expand their ranges under the influence of climate change (Hof et al., 2012; Falcucci et al., 2013). Such range changes of top predators like wolves may affect prey populations due to limiting effects on other predator species.

Unfavorable weather conditions may affect ranges of certain animals in a positive or negative interaction with wolves affecting their distribution and range expansion. Again, land use changes might indirectly favor predator species such as wolves, and increase predation pressure and conflict (Festa-Bianchet et al., 2011; Elmhagen et al., 2015). Thus, the response of prey in range expansion of wolf would be an important aspect to be focused on in future because if prey does not respond in the same manner, it can lead to enhanced conflict or even mass extinction. Studies have shown that wild ungulates would become more susceptible to disease in the future due to climate change, habitat shrinking, increased concentration and movement of human, livestock within shared habitats of wild animals introducing various pathogens and vectors (Hu and Jiang, 2011). Prey species in Central Asia such as Przewalski's gazelle *(Procapra przewalskii)*, Mongolian gazelle *(Procapra gutturosa)*, Siberian ibex *(Capra sibirica)* and goitered gazelle *(Gazella subgutturosa),* and saiga antelopes (*Saiga tatarica*) are prone to disease outbreaks due to the increasing temperature as well as shared rangelands with livestock (Pruvot et al., 2020; Khanyari et al., 2021). Due to climate change, such responses of prey species might lead to a decline in their population and the spread of disease amongst predators like wolves.

This study across different countries showed that Bhutan, Mongolia, Kyrgyzstan, Nepal, China, and India had increased suitable habitat, mostly outside PAs. These countries already have existing conflict issues with wolves (Watanabe et al., 2010; Alexander et al., 2015; Karimov et al., 2018; Din et al., 2019). Synergistic positive effects of climate and land-use change can favor invasive species and expansion of temperate species to higher altitudes (Bellard et al., 2013; Elmhagen et al., 2015). Our results suggested that the elevation plays an important role in wooly wolf distribution in current and future scenarios without change in the preferred range of 2,500–5,000 m, which aligns with a similar previous study (Habib et al., 2013). We also predict the range expansion of wolves in Myanmar and Russia where there was low habitat suitability for wolf distribution before. This might lead to the colonization of a new predator species, disrupting the current prey-predator guild and the sudden rise of conflict with humans. Thus, this study shows the importance of predictive modeling, which could help in management planning for such scenarios priorly.

Our results indicate Kazakhstan to have decreased wooly wolf habitat suitability area in the future. Earlier studies have shown that the wolf population in this country has been declining due to a reduction in saiga population and hunting (Leontiev, 2018). Gray wolves, which were once the most widespread land carnivore (Paquet and Carbyn, 2003), have now vanished from 26% of their geographical extent (Wolf and Ripple, 2017). Similarly, the wooly wolf is subjected to human persecution and conflict for centuries, a consequence of thriving in a resource-scarce habitat (Lyngdoh et al., 2020). The main reasons for conflict with humans across their distribution range are due to livestock depredation and retaliation by humans (Mishra, 1997; Namgail et al., 2007; Jamtsho and Katel, 2019). We propose that changes in wolf distribution may aggravate the conflict situation across various wolf-ranging countries in the future, mainly because of their increasing presence in human-dominated landscapes. This study paves the way for future administrative mechanisms for wolf management in these countries.

CONCLUSION

Studies have shown that climate change has affected mammal species in the northern hemisphere more due to the combined effect of different drivers such as land-use change, anthropogenic food subsidies, and hunting. This study provides baseline information on how the distribution of a generalist top predator species would alter under the combined effects of climate and land-use change. Holistic spatial information about local populations of predators is important because of the knowledge gaps from lesser-known areas. While this study does not support the complete range shift for wooly wolves, we predict an increase in suitability area across their distribution range. This study provides insights regarding the gain or loss of suitable habitat in wolf range countries within and outside PAs. Based on such projections, conscious management decisions need to be taken regarding the conservation of this species in a country-specific manner. Hotspot areas where future conflict with humans could arise due to increased livestock numbers resulting in depredation should be considered priority areas for management. Understanding the spatial distribution of wooly wolves across its range is necessary to plan monitoring and management strategies. Lack of this understanding may also hinder our conservation efforts and mitigation strategies under climate change scenarios. Similar information on future trends of prey species and co-predators should be at hand to have overall information of the landscape ecosystem. Transboundary protocols based on such future trends are the need of the hour for the conservation of the wooly wolf.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The animal study was reviewed and approved by the Wildlife Institute of India.

AUTHOR CONTRIBUTIONS

SK, HR, and AB collected the data and wrote the manuscript. SS and SL helped in analysis and discussion. BH conceptualized, supervised, and edited the manuscript. SG and RK helped in discussion, analysis, and editing. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2022.815621/full#supplementary-material

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