Disentangling the impacts of climate and land-cover changes on distribution of common pheasant Phasianus colchicus along elevational gradients in Iran

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Research Article

Keywords: habitat suitability modeling, Maxent, land-cover change, climate change, scenarios, Iran

Posted Date: September 23rd, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1950574/v1

Version of Record: A version of this preprint was published at Environmental Science and Pollution Research on April 12th, 2023. See the published version at https://doi.org/10.1007/s11356-023-26742-7.

Abstract

Climate and land-cover change are critical drivers of avian species range shift. Thus, predicting avian species' response to the land and climate changes and identifying their future suitable habitats can help their conservation planning. The common pheasant (*Phasianus colchicus*) is a species of conservation concern in Iran and is included in the list of Iran's protected avian species. The species faces multiple threats such as habitat destruction, land-cover change, and overhunting in the country. In this study, we model the potential impacts of these two on the distribution of common pheasant (*Phasianus colchicus*) along elevational gradients in Mazandaran province in Iran. We used Shared Socioeconomic Pathways (SSP) scenarios and the 2015–2020 trend to generate possible future land-cover projections for 2050. As for climate change projections, we used Representative Concentration Pathway (RCP) scenarios. Next, we applied current and future climate and land-cover projections to investigate how common pheasant's habitat changes between 2020 and 2050 using Species Distribution Modeling (SDM). Our results show that the species has 6000 km^2 suitable habitat; however, between 900 to 1965 km^2 of its habitat may be reduced by 2050. Furthermore, we found that the severity of the effects of climate change and land-cover change varies at different altitudes. At low altitudes, the impact of changing land structure is superior. Instead, climate change has a critical role in habitat loss at higher altitudes and imposes a limiting role on the potential range shifts. Finally, this study demonstrates the vital role of land cover and climate change in better understanding the potential alterations in avian species' habitats.

Introduction

Biodiversity is declining rapidly due to extensive human activities and environmental change (Pereira et al. 2012); for instance, 26% of mammals and 13% of birds are now threatened, according to the Red List (IUCN 2022). Hence, this issue has become a global challenge (Dinerstein et al. 2020; Milner-Gulland et al. 2021). One of the critical factors for habitat loss and fragmentation is land-use change, leading to an increasing number of species with contracted distribution (Maxwell et al. 2016). Furthermore, climate change delivers a devastating impact on reducing and altering species distribution (Moritz and Agudo 2013; Willis and Bhagwat 2009). Land-cover and climate change affect each other and can have a combined effect on biodiversity. For example, climate change can lower species' resistance to land change, while climate change impedes their capacity to deal with altering land-cover (Oliver and Morecroft 2014).

Species distribution models (SDMs) that have critical applications in ecology and conservation (Guisan et al. 2013) are practical tools for deciphering the impacts of the past and future climate and land-cover changes on species distribution (Kassara et al. 2017; Porfirio et al. 2014; Sierra-Morales et al. 2021; Yousefi et al. 2019b) and identifying high priority areas for conservation of biodiversity (Buechley et al. 2022; Kafash et al. 2022; Moradi et al. 2019; Ramírez-Albores et al. 2021; Tian et al. 2021). Climate change projections have been widely used as possible scenarios because they are more readily available and straightforward (Titeux et al. 2016). However, land-cover changes often received less attention (Titeux et al. 2017) for reasons such as lack of data with appropriate spatial resolution and relevance to the characteristics of target species (De Chazal and Rounsevell 2009; Mair et al. 2018). Nevertheless, since examining the solo effects of climate or land-use change is likely to cause overestimation or underestimation, combining these two effects can provide a more significant meaning (De Chazal and Rounsevell 2009; Oliver and Morecroft 2014).

The common pheasant (*Phasianus colchicus*) is a species of conservation concern in Iran and is included in the list of Iran's protected avian species (Ashoori et al. 2018). The species faces multiple threats such as habitat destruction, land-cover change, and overhunting across its distribution range in the country (Ashoori et al. 2018). The species is particularly threatened in Mazandaran province since land-cover change is happening at an accelerated rate, and natural habitats of the species are being converted to agriculture and human settlement in the province (Dadashpoor and Salarian 2020; Jahanifar et al. 2020; Sadaty and Nazari 2021). Furthermore, a recent study has shown that climate change could be a major problem for biodiversity conservation in Iran, and avian species are under risk of climate change in the country (Sheykhi Ilanloo et al. 2020; Yousefi et al. 2019a).

Thus, in this research, we aimed to predict the habitat suitability of common pheasant under several climate and land-cover change scenarios in Mazandaran province. The results of this study can be used in the conservation of the species in its rapidly changing environment in Mazandaran province.

Methods

Study area

Mazandaran province (Fig. 1), located in the north of Iran, is surrounded by the Caspian Sea from the north and the Alborz Mountain range from the south. With an area of about $23{,}000\ km^2$ and elevations ranging from 20 meters below sea level to over 5000 meters. This region is home to numerous swamps and sea-level plains, vast rice fields, and mountains covered with dense forests and rivers. According to the national census conducted in 2016, three million people live in Mazandaran, of which three hundred thousand are engaged in agriculture, animal husbandry, and fishery (Iran 2019).

Studied species and species data

We utilized field observations of species between 2015 and 2018, conducted by the Department of Environment of Mazandaran, Iran. According to the field report, surveys were based on direct observation and sound recognition. We used grid sampling in order to resample data in a one-kilometer radius. Finally, 631 occurrence records were prepared and used in distribution modeling.

Current and future land cover and climate data

This research used nine variables to model the common pheasant geographic distribution, including four bioclimatic and land-cover parameters and a topographic parameter. We obtained land-cover data for the year 2020 from the ESA-CCI (European Space Agency - Climate Change Initiative) project and generalized that into five classes of forest, cropland, pasture, built-up areas, and others based on IPCC classes for change detection (ESA 2017). We used all but the last class ("others") in modeling, as they are more relevant to this species distribution and its nesting and breeding (Coates et al. 2017; Perkins et al. 1997; Riley et al. 1998; Smith et al. 1999). Correlation analysis of parameters is given in Supplementary Table S1.

Three scenarios of RCP2.6, RCP4.5, and RCP8.5 were incorporated to project the possible climate variations in 2040–2060. The aforementioned "Representative Concentration Pathways" (RCPs) are global radiative forcing levels of 2.6, 4.5, and 8.5 W/m^2 by the end of the century, and describe climatic scenarios leading to a very low forcing level (RCP2.6), a medium stabilization scenario (RCP4.5), and a very high baseline emission scenario (RCP8.5) (Van Vuuren et al. 2011). We used averages of multiple GCPs (Global Climate Models), namely CCSM4, CNRM-CM5, HadGEM2-ES, MIROC-ESM-CHEM, and MPI-ESM-LR as bioclimatic variables for each scenario.

We used the SSP scenarios to estimate how the land cover might change in the study area. These scenarios are based on five distinct narratives. Each scenario describes the earth's socio-economic trends and environmental changes in the twenty-first century. These scenarios aim to identify the socio-economic challenges for mitigation and adaptation purposes (Riahi et al. 2017). SSP1 and SSP3 describe scenarios, one with low and another with high challenges for both adaptation and mitigation. In addition, SSP4 is characterized to represent low adaptation and high mitigation narrative, and SSP5 vice versa. Ultimately, SSP2 is designed to portray a world with intermediary challenges for both adaptation and mitigation (Popp et al. 2017).

Six IAMs (Integrated Assessment Models) have been developed to quantify these scenarios based on different assumptions and uncertainties. Each SSP has a baseline scenario containing only current climate change policies to estimate future conditions. In addition to these baseline scenarios, other scenarios have been developed that use different climate change policies. We used baseline scenarios of the IMAGE model to project future land cover change for the Middle East and Africa (MAF) (Riahi et al. 2017; Van Vuuren et al. 2017). SSP scenario data is available at https://tntcat.iiasa.ac.at/SspDb/ (accessed on 2022/04/05). Alongside SSP scenarios, we calculated the land cover change between 2015 and 2020 and used linear regression to estimate the total change in 2050. We named this the Trend scenario.

We calculated the change ratio of the cropland, forest, pasture, and built-up land cover classes between 2020 and 2050. We then multiplied this by the area of these classes in our study area to project land cover changes for 2050. The summary of individual land cover changes is presented in Table 1.

Table 1
Land-cover changes between 2020 and 2050. Values are occupied areas for each land type (km2) and change concerning the Baseline

	Baseline	Trend	SSP1	SSP2	SSP3	SSP4	SSP5
Cropland	8230	9019 (10%)	9872 (20%)	10575 (28%)	11003 (34%)	10997 (34%)	11130 (35%)
Forest	7604	6520 (-14%)	6594 (-13%)	5310 (-30%)	4657 (-39%)	4813 (-37%)	5267 (-31%)
Pasture	4475	4351 (-3%)	4364 (-2%)	4884 (9%)	5067 (13%)	4936 (10%)	4994 (12%)
Built-up	392	1390 (255%)	766 (95%)	739 (88%)	714 (82%)	857 (119%)	744 (90%)
Other	2856	2278 (-20%)	1962 (-31%)	2050 (-28%)	2117 (-26%)	1955 (-32%)	1424 (-50%)

Following Préau et al. (2019), we used Dyna-CLUE to spatially allocate land changes in the area. This program comprises two parts: the spatial allocation section and non-spatial aggregated demand. The spatial allocation includes land conversion matrix, conversion elasticity, and location characteristics. The conversion matrix represents which lands can be converted to each other. The conversion elasticities indicate the expense and difficulty of converting one land to another. We used logistic regression to determine the potential characteristics of each land type regarding environmental variables (Verburg and Overmars 2009). Logistic regression was deployed using the Sickit-Learn library in Python programming language. Eventually, the land-cover map for 2050 was simulated by entering the spatial parameters and land-cover change scenarios into the Dyna-CLUE (For detailed information, check Supplementary Table S3-S9).

Species Distribution Modeling

We used Maxent 3.4.1 (Phillips et al. 2017), a presence-only algorithm that estimates a species' geographic distribution by determining the distribution with the highest entropy given a set of features derived from environmental conditions. Maxent implements linear (L), quadratic (Q), product (P), threshold (T), and hinge (H) of provided environmental variables as features. Linear features are equal to continuous environment variables, quadratics are their squares, and products are products of pairs of continuous variables. Threshold makes a binary feature based on an arbitrary value. The hinge feature is similar to the linear feature, but it is constant below a certain threshold (Phillips et al. 2006).

Additionally, Maxent uses the LASSO penalty to reduce model overfitting, which can be adjusted by a multiplier constant (Merow et al. 2013). Parameter optimization in Maxent involves feature selection and regularization tuning (Li et al. 2020). Maxent was executed based on a set of predetermined parameters, and the parameters that reached the best AUC were selected. This procedure was accomplished using the ENMeval library in R programming language (Kass et al. 2021).

To reduce bias in modeling, we masked one county in which there was no conducted survey and implemented a kernel-density map of all occurrences as a bias file (Fourcade et al. 2014). We ran Maxent with the maximum iteration of 500, and data partitioning was based on five-fold cross-validation. Finally, we converted continuous habitat suitability to binary outputs to compare scenarios and the amount of lost and gained areas. We used the maximum test sensitivity plus specificity threshold for this task (Liu et al. 2016).

Results

Land cover changes

All of our scenarios have a rapid expansion of cropland and built-up areas. They differ in the intensity of these radical changes. Based on scenarios, 3 to 12 percent of the study area will transition to croplands, mainly at the expense of forests. The most significant reduction in forests is in the SSP3 scenario, in which about $2900\ km^2$ will be deforested. Deforestation occurs more in the northern part of the forest margins and in the eastern parts of the province, where they are converted to croplands. Built-up areas have exponential growth and become tripled in the Trend scenario. The growth of residential areas is higher in the center of the study area and its western part. Specifically, Chalus and Kojur areas are highly potential for rapid urban expansion. Land cover maps of scenarios are shown in Fig. 2.

Species distribution

Based on grid search, product, linear, quadratic, and hinge features with a regularization multiplier of one were must optimal parameters for this case study. The maxent performance evaluations demonstrate high predictive power (AUC = 0.84, 0.82 and MSE = 0.14, 0.13 for train and test data, respectively). The most influential variables were the distance to forest and annual temperature. Furthermore, according to the jack-knife test (Supplementary Fig. S1), distance to cropland had the highest gain, indicating that they had the most relevant information by themselves. Table 2 summarizes variables and their contribution to our model.

Table 2
Model variables and their contributions

Variable	Description	Relative contribution	Permutation importance	Source
Topography	Slope	10	11	(Farr et al. 2007)
Bioclimatic	Bio01: annual mean temperature	20.9	27.6	(Fick and Hijmans 2017)
	Bio04: temperature seasonality	2.7	3.5	
	Bio12: annual precipitation	6.4	6.9	
	Bio15: precipitation seasonality	2	8.2	
Land-cover	Forest: distance to the forest areas	24.1	20.7	(ESA 2017)
	Cropland: distance to the cropland areas	18.1	8.1	
	Pasture: distance to the pasture areas	7	6.4	
	Built-up: distance to the built-up areas	8.7	7.7	

Current and future distribution

The average maximum test sensitivity plus specificity threshold for test data was 0.5. As presented in Fig. 3B, newly suitable areas are introduced in each scenario while some decline. Still, the rate of habitat loss is much greater than the gain in habitats. The species range will likely be negatively affected since our projections show a loss of between 900 to 1,965 km^2 of suitable habitats. We found that the impact of land change is more significant than climate change in our case study. Our results showed that the current land-cover trend would lead to the worst-case scenario. Moreover, suitable areas projected using RCP 8.5 are less than the RCP 2.6 scenario, demonstrating that habitat areas are further reduced as climate conditions become more severe.

According to the Baseline suitability map (Fig. 4A), this species has a wide geographical distribution in the region, primarily comprising margins of forest areas and near croplands. As for future projections, many suitable areas will be lost even in best-case scenarios. The best and worst cases (Fig. 4B and C) show that while the west coastline of the region and the Miankaleh peninsula (northern part of the region) will be completely uninhabitable, suitable areas increase in the central and eastern parts of the region, especially in Abas-Abad and southern parts of Sari County.

Ultimately, we calculated the total suitable cells in each defined altitudinal range for each scenario to analyze the potential elevation shift in the species habitat. Our result shows a distinct trend between only climate-change scenarios and climate and land change scenarios. Habitat is reducing in all altitudinal levels for only climate-change scenarios. However, there is an upward shift in habitat area for climate-land change scenarios until a certain altitude (Fig. 5).

Discussion

This study aimed to model the species distribution of common pheasant in northern Iran and then predict the possible extent of habitat changes based on climate and land-cover change. Our results show that as the forests and cropland distance increases, the likelihood of this species presence diminishes. Grain waste in agricultural lands is one of the primary food sources for this species. Also, forest edges and dense herbaceous ground are suitable for nesting and spawning (Ashoori et al. 2018; H. Giudice and T. Ratti 2020). Temperature also has a high effect on the distribution; since this species leaves the nest after a spawning period, a significant increase in temperature will reduce the fertility and biodiversity of this species (Harsh 2021).

Climate change has been noted to negatively influence species' habitats in Iran (Yousefi et al. 2019a). Nevertheless, the effects of land-cover change have been overlooked. Results indicate that an alteration in land-cover play a more vital role in shaping the projected distribution of this species in the region. Scenarios based solely on climate change have habitat loss, but habitat growth is insignificant. On the other hand, scenarios that consider land-cover change on top of climate change have an increase in habitat level almost as much as predicted by only-climate change scenarios. Still, the rate of habitat reduction in these scenarios is twice as much as in climate-only scenarios. Therefore, we conclude that scenarios considering the effects of land-cover change can better predict species range shift, which in our study has occurred due to the expansion in cultivated areas, resulting in increased food access.

Increasing the level of agriculture means that as some areas at lower altitudes will be uninhabitable for this species, this species can migrate to a higher altitude and still have access to its popular food source, as observed by Ashoori et al. (2018). Our result shows the only case where the habitat level is higher than the current time is in the combined climate change scenarios and land-cover change in middle altitude (Fig. 5). However, all projected scenarios show a downward trend, indicating climate change's negative effect at higher altitudes. Thus, the altitudinal shift is limited due to constraints imposed by climate change.

We used SSP scenarios and the Trend scenario to present land-cover change scenarios. In our study, SSP scenarios had two limitations. First, the SSP scenarios had a low spatial resolution. They were given for the Middle East and Africa, of which our study area is a small part. Second, these scenarios had mediocre land-cover classification details for the region. Better-scale land change scenarios with more detailed classes can improve the study of the effects of land-cover change.

Conclusion

In this study, we projected the impacts of land cover and climate change on the distribution of common pheasant. We showed that the severity of the effects of climate change and land-cover change varies at different altitudes. At low altitudes, the impact of changing land-cover is superior. Instead, climate change has a critical role in habitat loss at higher altitudes. As shown in this study, the use of land-cover change scenarios and climate change data can show new dimensions of how avian species distribution will change in the future. Our research has a clear message for the conservation of avian species under future climate and land-cover changes. That is, sometimes, the role of land-cover change can be greater than climate change in reshaping species distribution. We suggest that researchers consider the potential impacts of land-cover change in their studies, even in areas where data on land-cover change is still limited.

Declarations

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. The ESA CCI LC maps are available at http://maps.elie.ucl.ac.be/CCI/viewer/download.php. All climate data alongside future scenarios are available at https://worldclim.org/.

Competing Interests

The authors declare no competing interests.

Acknowledgments

We thank the personnel of the Wildlife protection branch, Department of Environment of Mazandaran, Iran, and especially Mr. Rabiyi for their cooperation in sharing the surveying data.

Author Contributions

Mojtaba Asgharzadeh performed the computations and analysis; he drafted the manuscript and designed the figures. Ali Asghar Alesheikh has contributed to interpreting results and revising the final manuscript. Masoud Yousefi conceived the presented idea and has made contributions to interpreting results and revising the final manuscripts.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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Figures

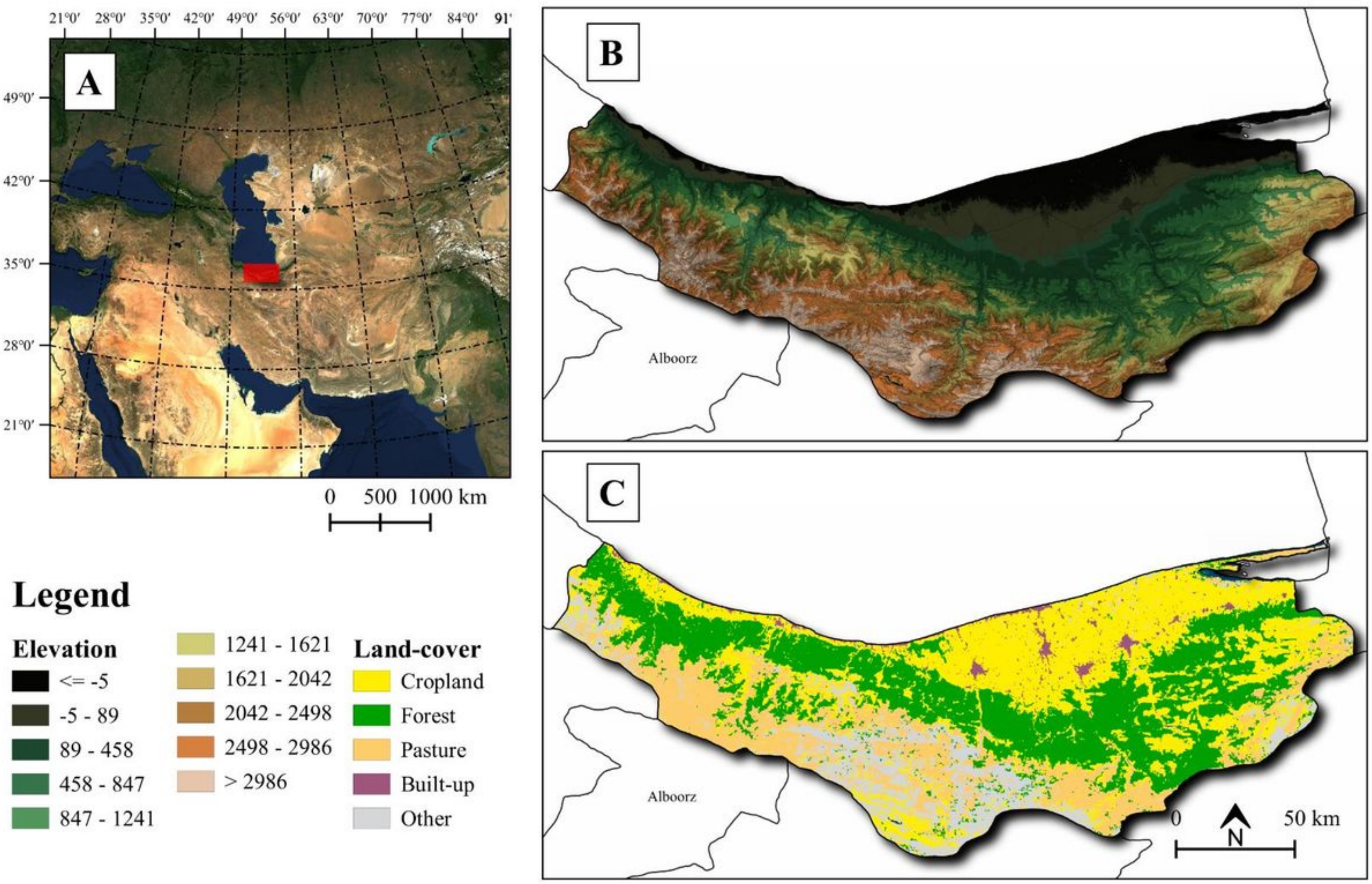

Figure 1

An overview of the study area (A), digital elevation model with quantile classification, which divides values into groups of equal sizes (B), land cover types/classes from ESA-CCI (C)

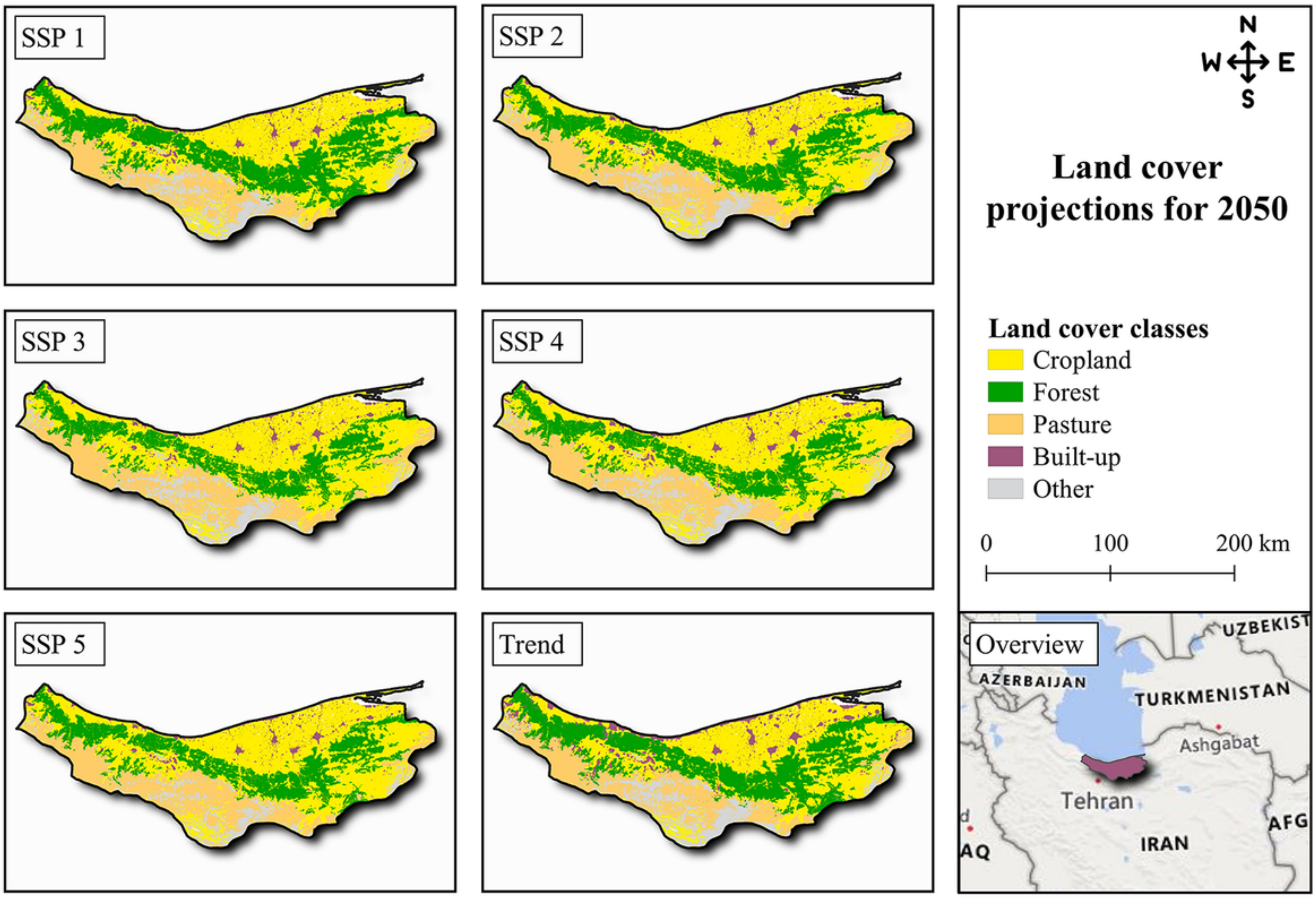

Figure 2

Map of land-cover projections for 2050 in Mazandaran province

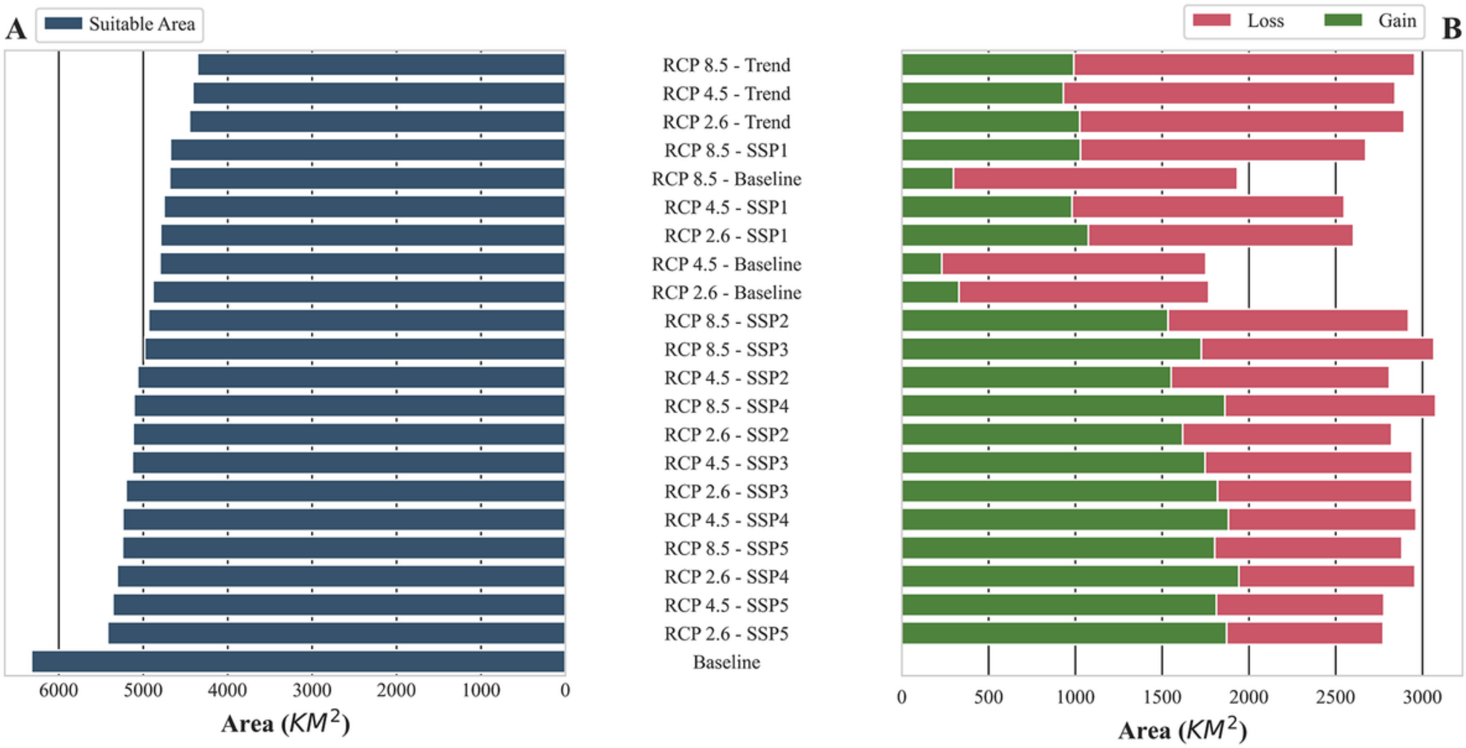

Figure 3

Changes in suitable areas based on climate and land-cover change scenarios for *Phasianus colchicus*. Cumulative suitable area for each scenario (A), Changes in suitable areas based on the current timeline (Baseline scenario) (B)

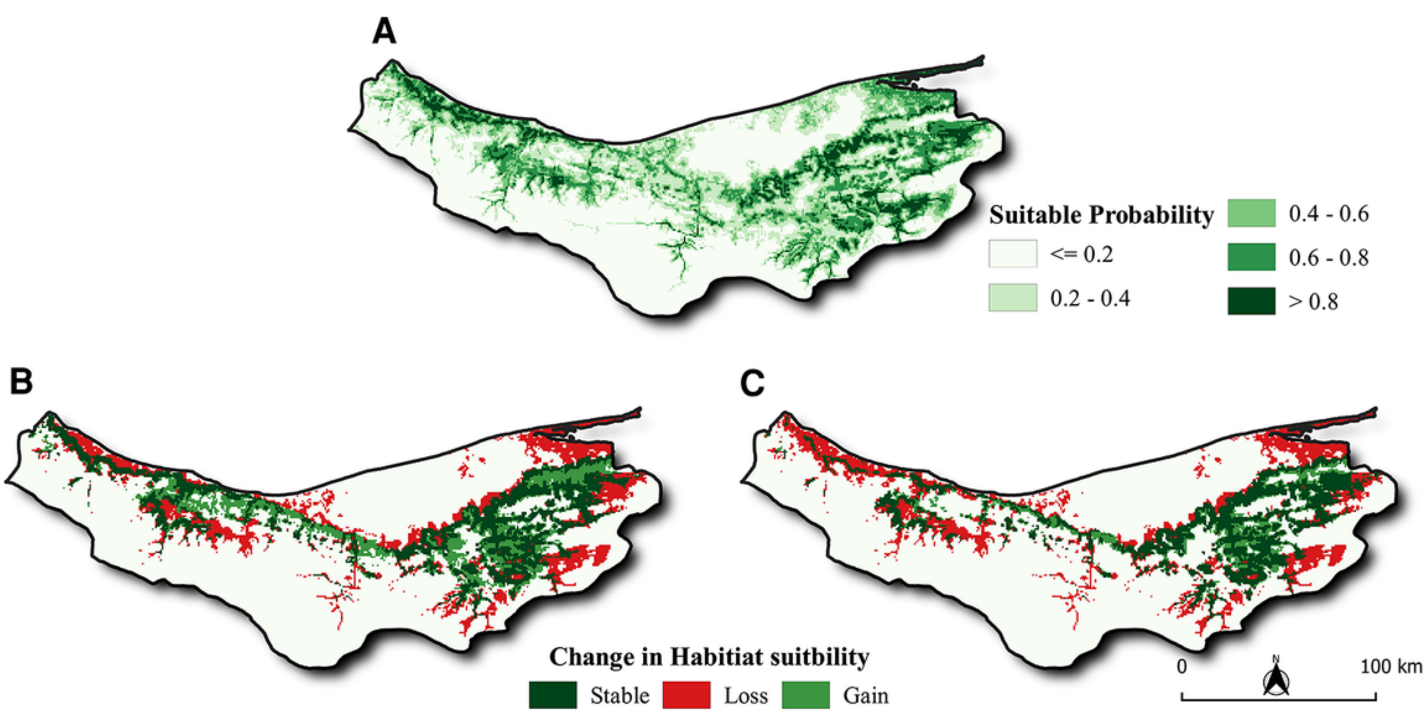

Figure 4

Habitat suitability maps: the current period (Baseline) (A); the best case scenario, based on RCP 2.6 - SSP5 (B); the worst case scenario, based on RCP 8.5 – Trend land cover (C)

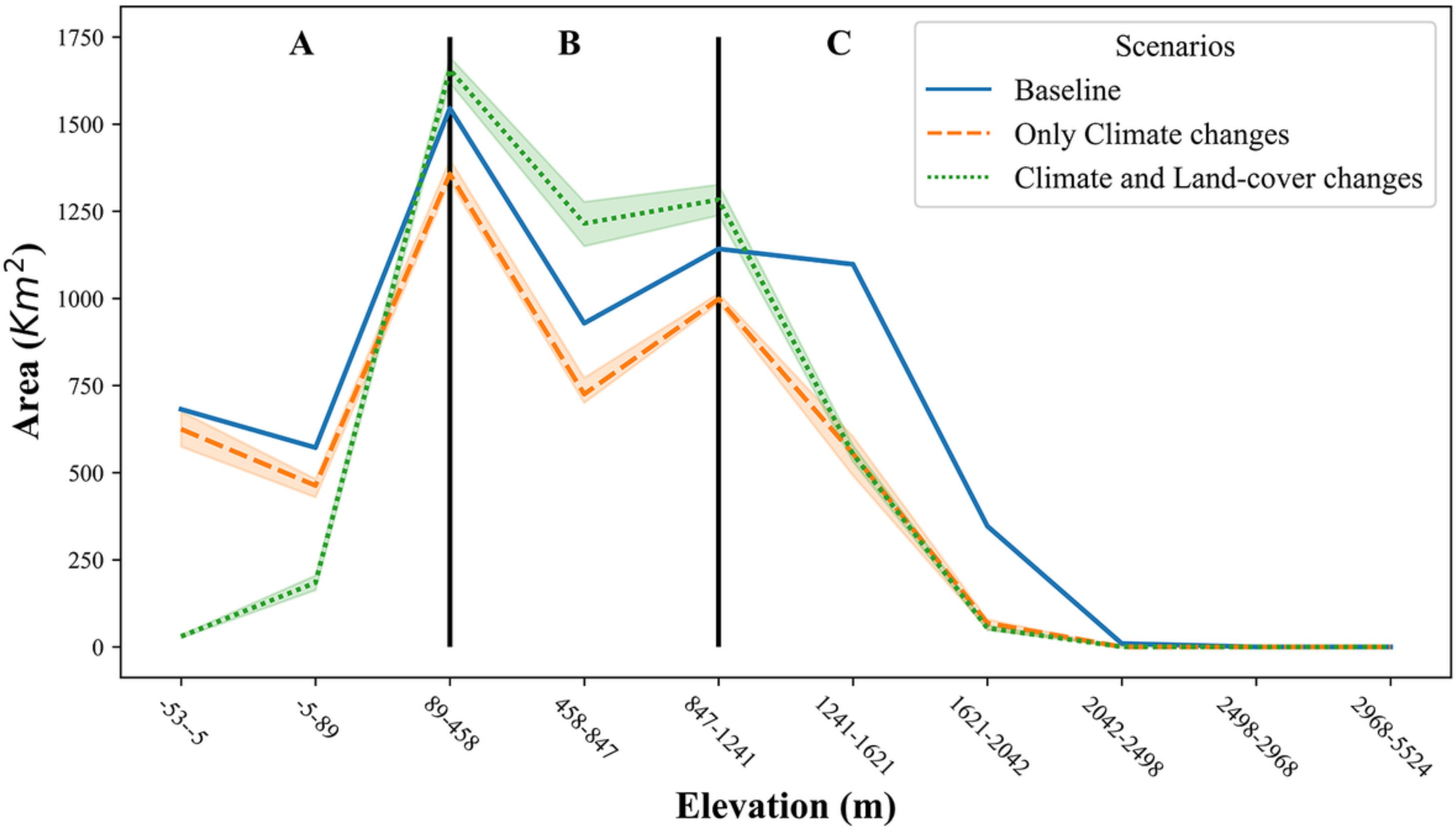

Figure 5

Altitudinal distribution of common pheasant *Phasianus colchicus* habitats based on different scenarios. We divided climate change scenarios (with baseline land-cover) and climate and land-cover change scenarios to highlight their respective effects on different elevations

Supplementary Files

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