

Article

Modeling the Suitable Habitat of Silver Pheasant (*Lophura nycthemera*) in China Under Climate and Land Cover Change

Zexu Long ¹ , Xue Sun ¹ , Yue Sun ¹, Chengjiang Tan ² and Sikan Chen ^{3,*}

¹ School of Biological Sciences, Guizhou Education University, Guiyang 550018, China; longzexu1990@gznc.edu.cn (Z.L.); sunxue0320@gznc.edu.cn (X.S.); sy1028sy@163.com (Y.S.)

² Guizhou Maolan National Nature Reserve Administration Bureau, Libo 558400, China; maolantchj@163.com

³ Guizhou Institute of Forestry Inventory and Planning, Guiyang 550003, China

* Correspondence: sikanchen@foxmail.com

Abstract

The Silver pheasant, a species in the Phasianidae family, is a widely distributed ground-dwelling bird in southern China and a national Class II protected animal. Global climate change and land use and land cover change are recognized as major drivers of wildlife habitat loss and shift, especially for species with low dispersal ability, like the Silver pheasant. However, no studies have assessed the influence of climate change and land-cover change on suitable habitat at the regional scale. In this study, we aim to assess the combined effects of climate change and land cover change on the habitat of the Silver pheasant. We used an ensemble species distribution model to predict habitat suitability for the Silver pheasant under the current scenario and three shared socioeconomic pathways (SSPs) across two time periods (2041–2070, 2071–2100). The results demonstrate that the ensemble model outperforms individual models in predicting suitable habitat for the Silver pheasant. The ensemble model achieved an area under the receiver's operating curve (AUC) of 0.90, a true skill statistic (TSS) of 0.61, and a Boyce index of 0.96, indicating excellent predictive performance. Currently, suitable habitat for the Silver pheasant in China, covering 4.33×10^5 km², primarily exists in eight provinces (Sichuan, Yunnan, Jiangxi, Fujian, Guangdong, Guangxi, Zhejiang, and Hunan). Land cover emerged as the most influential variable (43%), followed by annual precipitation amount (36%), elevation (9%), and slope (6%). Silver pheasant is projected to experience large habitat expansion (24.24% to 63.08%) depending on different scenarios and time. The centroid of suitable habitat is expected to shift northeastward, but with short distances (<39 km). Our results provide accurate predictions of the distribution patterns of the Silver pheasant habitat in China under current and future environmental change scenarios, which is the fundamental basis for scientific-based management and conservation decisions at the national level.

Keywords: ensemble modeling; biomod; Silver pheasant; climate change



Academic Editor: Yunchuan Dai

Received: 21 October 2025

Revised: 25 November 2025

Accepted: 27 November 2025

Published: 3 December 2025

Citation: Long, Z.; Sun, X.; Sun, Y.; Tan, C.; Chen, S. Modeling the Suitable Habitat of Silver Pheasant (*Lophura nycthemera*) in China Under Climate and Land Cover Change. *Diversity* **2025**, *17*, 836. <https://doi.org/10.3390/d17120836>

Copyright: © 2025 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Climate and land cover change are recognized as major drivers of biodiversity loss [1], species range contraction [2], and species range shifts [3], and are therefore changing ecosystem functions and services [4]. Species may respond to the changing environment by migrating to higher altitudes or latitudes or through physiological adaptations. Barbet-Massin et al. [5] predicted that 71% of European bird species would experience range

contraction and a 335 km median range shift by 2050. Species like Galliformes birds, with poor dispersal ability, are more likely to be affected by the rapidly changing environment. For example, 29 out of 63 Galliformes in China are predicted to shift their range over 50%, Galliformes distributed over a higher elevation face greater range shifts [6]. Significant global temperature increases, frequent extreme weather events, and altered precipitation patterns are the primary manifestations of climate change. Dramatic climate change is projected for the end of this century [7]; it is urgent and fundamentally important to evaluate how species will respond to future climate change for effective management and conservation. Land cover changes, such as deforestation, agricultural expansion, and urbanization, directly cause habitat loss and fragmentation. Under the context of climate change, these changes may hinder species (especially those with limited migration capabilities) from moving to suitable climatic zones, potentially leading to the local extinction of species. Substantial evidence emphasizes the importance of human land use changes as a cause of species declines and extinctions [8,9]. Globally, land use pressure has already slightly reduced local terrestrial biodiversity, along with average species richness (by 13.6%) and total abundance (10.7%) [10].

Species distribution models establish a functional relationship between species and environmental variables, then map this relationship to a geographic space to obtain the spatial distribution of species [11]. These models have become a commonly used tool in ecology and evolutionary biology for predicting potential changes in species distribution under different environmental change scenarios [9,12]. When using species distribution models to project species' future distribution, researchers need to make many decisions, such as statistical methods, general circulation models, and gas emission scenarios, all of which may cause uncertainty in the assessment. For example, Selvi et al. [13] obtained different prediction map patterns and model performance when modeling American beech (*Fagus grandifolia*) using various statistical methods. Among the above sources of uncertainty, statistical methods contributed to the largest variation in projections [14]. It is suggested to use ensemble approaches to forecast the impacts of climate change to improve the reliability of results [14]. Moreover, ensemble models usually demonstrate good model predictive ability [15], but sometimes do not show a particular benefit over individual tuned models [16].

Silver pheasant (*Lophura nycthemera*), a bird species in the family Phasianidae within the order Galliformes, is primarily distributed in parts of China, Southeast Asia, and South Asia, with a wide distribution in the mountainous regions of southern China [17]. Due to human disturbance, land use changes, and climate change, Silver pheasant's habitat is facing threats of fragmentation and degradation, with the IUCN observing a declining trend in the global population of the species [18]. Human disturbances in mountainous forested areas, such as gathering medicinal herbs, grazing livestock, clearing land for cultivation, and poaching, can easily lead to the destruction of Silver pheasant nests and eggs [17]. Land cover and land use changes exacerbate habitat fragmentation, leading to a decline in the Silver pheasant population [19]. Several studies have assessed climate change effects on Silver pheasant when investigating the impacts of climate change on Galliform birds, but results varied greatly [6,20]. As a Class II protected wild animal in China, the conservation of Silver pheasant's habitat is of great significance for maintaining regional biodiversity and ecological balance [21]. Silver pheasant is a sedentary species with high site fidelity and low dispersal ability [18], and might be vulnerable to a changing environment [6]. However, studies on the combined effects of climate change and land cover change on the distribution of Silver pheasant remain insufficient, particularly comprehensive analyses at regional scales [6,20]. Moreover, previous studies used an individual method (e.g., a generalized additive model), which may lead to large uncertainty in the assessment results [6]. In this

study, we aim to assess the combined effects of climate change and land-cover change on Silver pheasant in China using an ensemble modeling approach to improve the reliability of the results. In this study, we predict the suitable habitat distribution of Silver pheasant in China under the current period and two future periods (2041–2070, 2071–2100) across three different shared socioeconomic pathways (SSPs) scenarios, considering the background of climate and land cover changes. This study is crucially needed at the national level. Our results can provide a robust scientific base for management and conservation decisions regarding Silver pheasant in China under current conditions and future environmental change scenarios.

2. Materials and Methods

2.1. Study Area

Based on the range map of Silver pheasant in the IUCN Red List and information collected from the literature, we included 14 provinces in China as the study area: Sichuan, Yunnan, Guizhou, Guangxi, Guangdong, Hainan, Hunan, Jiangxi, Fujian, Anhui, Jiangsu, Hubei, Chongqing, and Zhejiang. The study area covers approximately 2.59 million km² (18.16° N–35.11° N, 97.35° E–122.12° E), with a significant elevation gradient (−4 to 6299 m). Forest is the primary land cover, accounting for approximately 51.4% of the study area, followed by farmland, at 38.5%.

2.2. Species Occurrence Data

The occurrence data of Silver pheasant used in this study were collected from four sources: (1) GBIF, where only occurrence points within China from 1980 to 2020 were selected (Available online: <https://doi.org/10.15468/dl.8evtfq> (accessed on 17 July 2025)). (2) China Bird Report Center, where we only vectorized reports between 2010 and 2024, with 91 reports being selected this way. (3) The literature, where a search for the term “Silver pheasant” was conducted on CNKI (China National Knowledge Infrastructure), limited to academic journal articles, resulting in 129 research papers. Each paper was reviewed to identify the location of the study area, and occurrence points were manually plotted in Google Earth, with one point per study, totaling 18 points. (4) Data from an infrared automatic camera monitor collected from January 2024 to January 2025. The authors deployed 42 infrared cameras in Maolan National Nature Reserve, Guizhou province; Silver pheasants were detected at 23 sites. To ensure accuracy, only human observation records from the eBird database in GBIF were used, discarding points with location accuracy estimates greater than 1000 m. A total of 1636 occurrence points met this criterion and were further overlaid with the landcover map. We removed points that were not within forests or grasslands according to the habitat type criteria of the IUCN Red List. Additionally, spatial thinning with a 2 km parameter was applied to all points to reduce sampling bias, using the R (V 4.5.1) package “spThin” [22]. After preprocessing, 434 points were retained for modeling (Figure 1).

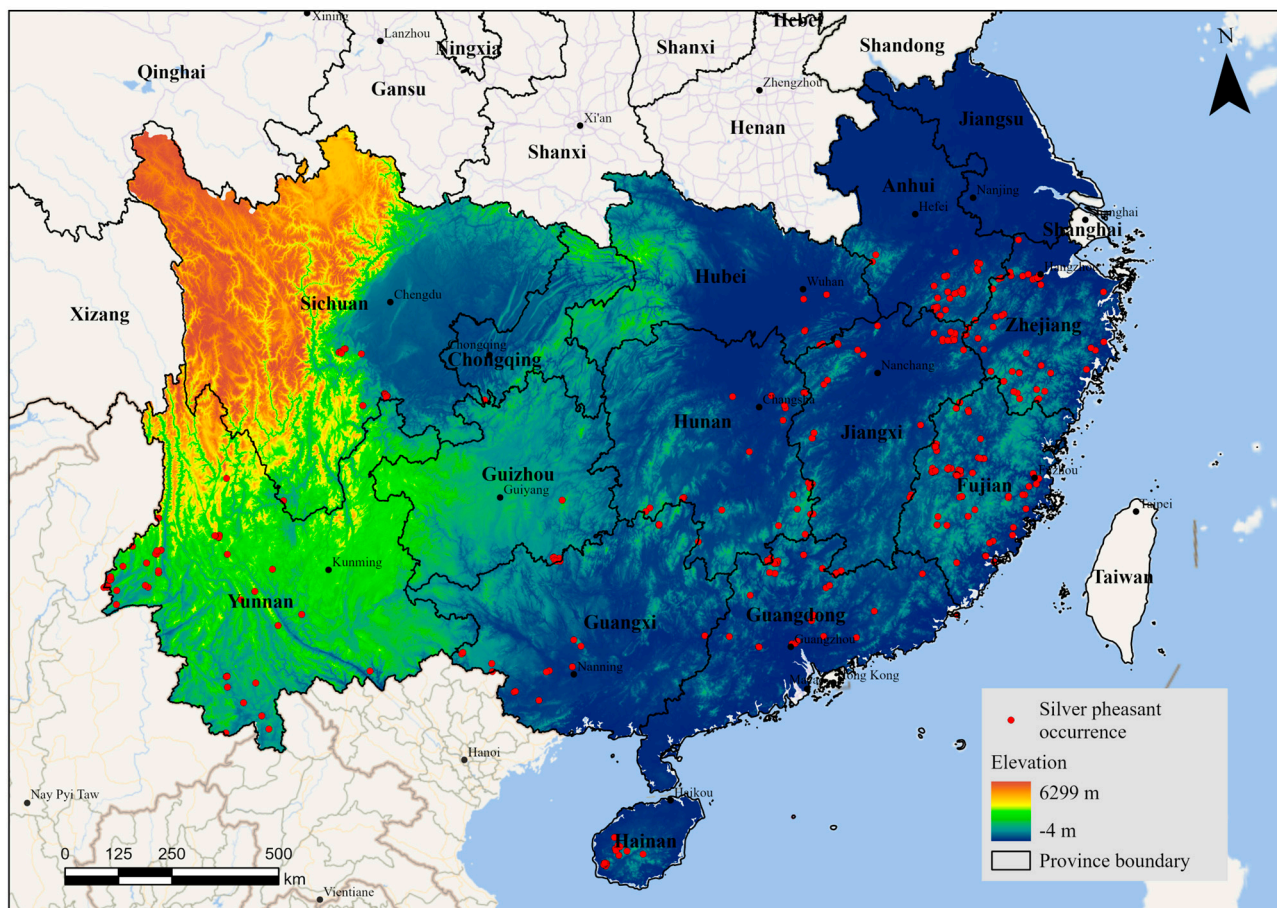


Figure 1. Schematic diagram of the study area. Red dots represent the processed occurrence points of Silver pheasant.

2.3. Environmental Predictors

Based on previous studies on Silver pheasant or Galliformes birds [6,23–25], we selected four categories of environmental predictors to characterize the habitat suitability for Silver pheasant (Table 1): climatic, topographic, and land-cover predictors. Six climatic factors, mean annual air temperature (bio1), temperature seasonality (bio4), mean daily minimum air temperature of the coldest month (bio6), annual range of air temperature (bio7), annual precipitation amount (bio12), and precipitation seasonality (bio15), were chosen from the CHELSA V2.1 dataset [26] at a horizontal resolution of 30 arc sec. Topographic factors included elevation and slope, both obtained from EarthENV [27], with a spatial resolution of 1000 m. Land cover data were obtained from a 1 km global land dataset comprising seven land types [28]: water, forest, grassland, barren, cropland, urban, permanent snow, and ice. We used this dataset as it included land cover projections from 2015 to 2100 with 5-year intervals under several SSP-RCP scenarios. We selected the 2015 prediction as the current land cover status. All variables were processed in ArcGIS Pro (V 3.4.0) through clip, resample, and projection to create raster files with a consistent resolution (1000 m) and projection coordinate system. In order to reduce the effect of multicollinearity among predictors and reduce overfitting [29], we calculated paired Pearson correlation coefficients among all environmental predictors except for land cover, which is categorical, and only retained one predictor when the absolute value of the correlation coefficients exceeded 0.7.

Table 1. Environmental predictors used to model Silver pheasant habitat suitability.

Category	Predictor Abbreviation	Description	Units	Source
Climate	bio1	mean annual air temperature	°C	CHELSA V2.1 https://chelsa-climate.org/
	bio4	temperature seasonality	°C/100	
	bio6	mean daily minimum air temperature of the coldest month	°C	
	bio7	annual range of air temperature	°C	
	bio12	annual precipitation amount	kg/m ² /year	
Topography	bio15	precipitation seasonality	kg/m ²	EarthENV https://www.earthenv.org/ https://zenodo.org/records/4584775 accessed on 10 July 2025
	elevation	elevation	m	
	slope	slope	°	
Land cover	landcover	Types of land cover	-	

For future climate data, we selected three different shared socioeconomic pathways (SSPs) scenarios: SSP126 (sustainable pathways), SSP370 (intermediate pathways), and SSP585 (traditional fossil fuel-dominated pathway). SSP126 predicts an average global temperature increase of 2.0 °C above pre-industrial levels by 2100; SSP370 predicts an average rise of 3.0 °C; and SSP585 predicts an average rise of 5.0 °C. To reduce uncertainties in future climate projections, we acquired climatic predictors from five general circulation models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL) at a spatial resolution of 1 km and calculated their averages. We selected climate data of two time periods (2041–2070, 2071–2100). Future land cover projections were derived from [28]; we used the projections of the same scenarios with climate data.

2.4. Species Distribution Model

We used the “biomod2” [30] R package to model and predict the potential ranges of Silver pheasant for both current and future scenarios. We selected five algorithms from the “biomod2” package, including the generalized linear model (GLM), generalized additive model (GAM), generalized boosting model (GBM), random forest model (RF), and maximum entropy model (MaxEnt), as they have good predictive performance [31] and are frequently used in ecological studies [32]. We only collected occurrence points of Silver pheasant, while the above algorithms require background/pseudo-absence points to construct a model. The “disk” method in “biomod2” was used to generate pseudo-absence points within a certain buffer distance around the occurrence points, which is demonstrated to decrease the effects of spatial bias in occurrence sampling and to increase model accuracy [33]. The buffer radius was set as 50 km. We randomly selected two sets of 5000 pseudo-absence points [34] to mitigate the uncertainty that one pseudo-absence set may cause. To calibrate and evaluate the models, the Silver pheasant occurrence data were randomly divided into four folds; three folds were used to train the model, and the remaining one was used as a test. This procedure was repeated four times until each fold was used as a test once. This data division was repeated three times to mitigate randomness. The area under the receiver operating curve (AUC) [35] was calculated to assess model predictive performance. We constructed an ensemble model using the AUC-weighted averaging method [36], and only included models with an AUC value higher than 0.7. We also used the true skill statistic (TSS), a threshold-dependent metric, to evaluate the model’s ability to correctly distinguish between presence and pseudo-absence locations. The Boyce index was also calculated to measure the consistency between predicted suitability and

the actual occurrence of the species. The Boyce index is especially suitable for assessing models based on presence-only data [37].

The final ensemble model was used to project onto environmental predictors representing future SSP126, SSP370, and SSP585 scenarios for two time periods: 2041–2070 and 2071–2100. Predicted habitat suitability value ranges from 0 to 1000. We converted model prediction values into binary maps, where 0 indicated absence and 1 indicated presence, using the threshold that maximizes the TSS value [38]. The same threshold was used for the current and future maps. Our model likely overestimates the current and future potential ranges of Silver pheasant because it does not account for dispersal limitations. Following previous studies [6,20], we used a 110 km buffered minimum convex polygon surrounding the current distribution range of Silver pheasant to clip distribution range predictions. This analysis used the “hull” and “buffer” functions in the R package “terra” [39]. To assess the contribution of individual environmental predictors to model performance, permutation-based variable importance was used as a stable metric [40]. We plotted the response curve between Silver pheasant habitat suitability and environmental predictors using the evaluation strip method proposed by Elith et al. [41].

Finally, we employed a MESS analysis to quantify extrapolation uncertainty by identifying areas where future environmental predictors diverge from those in the model training [42]. Positive MESS values indicate that variables fall within the calibration range, suggesting reliable projections, while negative values signal potential uncertainty due to novel conditions.

2.5. Data Analyses

We used the “BIOMOD_RangeSize” function in the “biomod2” package to compare the changes in Silver pheasant range from the current to the future scenarios. We classified range change area as either “gain” (areas predicted as habitat in the future scenario but not in the current scenario) or “loss” (areas identified as habitat in the current scenario but not in the future scenario), or “stable” (areas predicted as habitat in both the current and future scenarios) [12]. We also calculated the habitat turnover rate as follows:

$$T = \frac{G + L}{A + G}$$

where G is the gained area, L is the lost area, and A is the area under the current scenario. We calculated the centroids of Silver pheasant suitable habitat under different scenarios using the “Mean Center” tool in ArcGIS Pro [43]. These centroids were used to describe the overall trend of Silver pheasant’s future distribution [44].

3. Results

Three climatic variables, bio1, bio4, and bio6, were screened out. Seven environmental predictors were retained for the species distribution model (Figure 2). These included three climatic variables (bio7, bio12, and bio15), two topographic variables (elevation and slope), and land cover.

Figure 3 shows the boxplots of the distribution of each model evaluation metric for the five individual algorithms across two pseudo-absence datasets, four folds, and three repetitions. All individual algorithms have a mean AUC value higher than 0.76, indicating fair predictive performance; all but the random forest algorithm have a mean TSS value higher than 0.36, indicating fair classification accuracy; all individual algorithms have a mean Boyce index value higher than 0.85, indicating high consistency between predicted suitability and the occurrence of Silver pheasant (Figure 3). The ensemble model significantly improved model performance over the five individual algorithms, with an

AUC value of 0.90, a TSS value of 0.61, and a Boyce index value of 0.96. All three validation metrics demonstrated the excellent performance of the ensemble model.

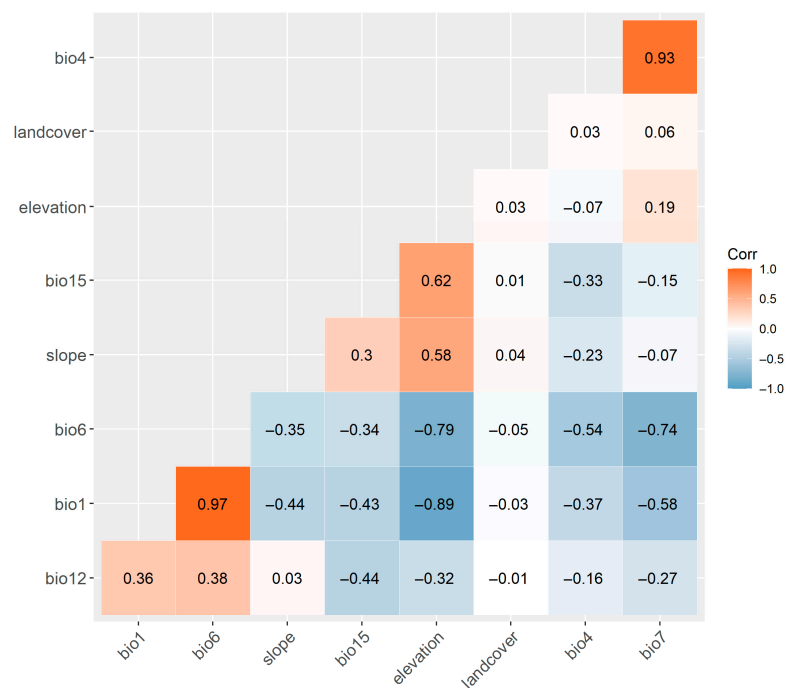


Figure 2. Correlation coefficient matrix diagram of environmental predictors.

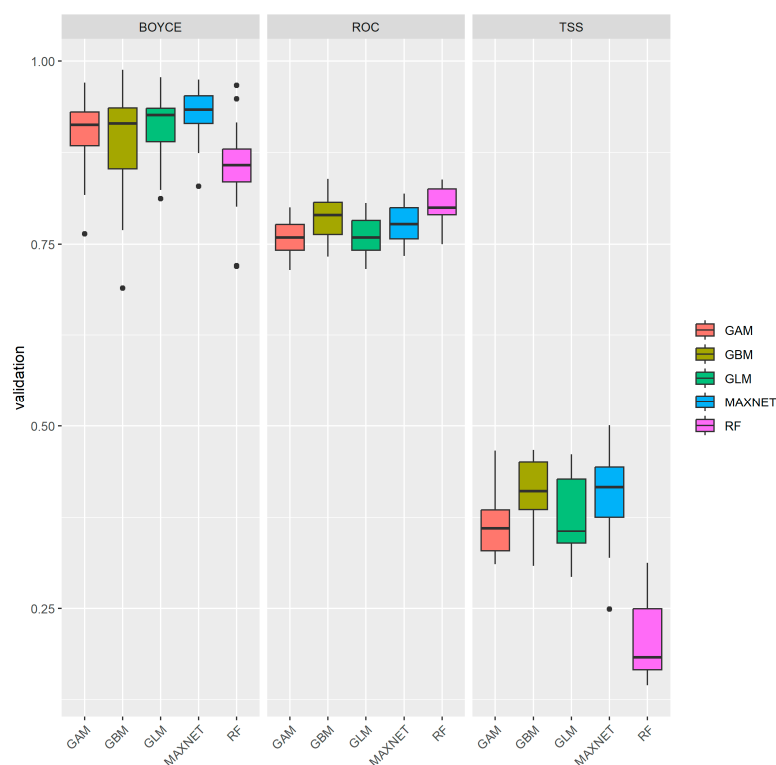


Figure 3. The validation performance of five species distribution modeling algorithms (GAM, GBM, GLM, MAXNET, and RF) using the Boyce Index (BOYCE, (left)), Area under Receiver Operating Characteristic (AUC, (middle)), and True Skill Statistic (TSS, (right)). The boxplot shows the distribution of metric values of 24 models across two pseudo-absence datasets, four folds, and three repetitions.

Variable importance showed that land cover (landcover), total precipitation amount (bio12), elevation (elevation), and slope (slope) are the four most dominant factors

(in decreasing order) that determine Silver pheasant habitat suitability (Table 2). The contribution values of land cover, total precipitation amount, elevation, and slope were estimated to be 43%, 37%, 9%, and 6%, respectively, while other variables have limited influences.

Table 2. Ranking of environmental variable importance levels of the ensemble model.

Environmental Predictor	Importance Value
landcover	0.43
bio12	0.36
elevation	0.09
slope	0.06
bio7	0.02
bio15	0.02

Figure 4 displays the response curve of Silver pheasant habitat suitability to the four most dominant variables of the ensemble model. When the land cover type is forest, the habitat suitability is the highest. The habitat suitability increases with an increase in annual precipitation amount, peaking at around 2500 kg/m²/year. Habitat suitability increases with increasing elevation but remains stable when elevation exceeds 1500 m. Slope shows a positive relationship with habitat suitability (Figure 4).

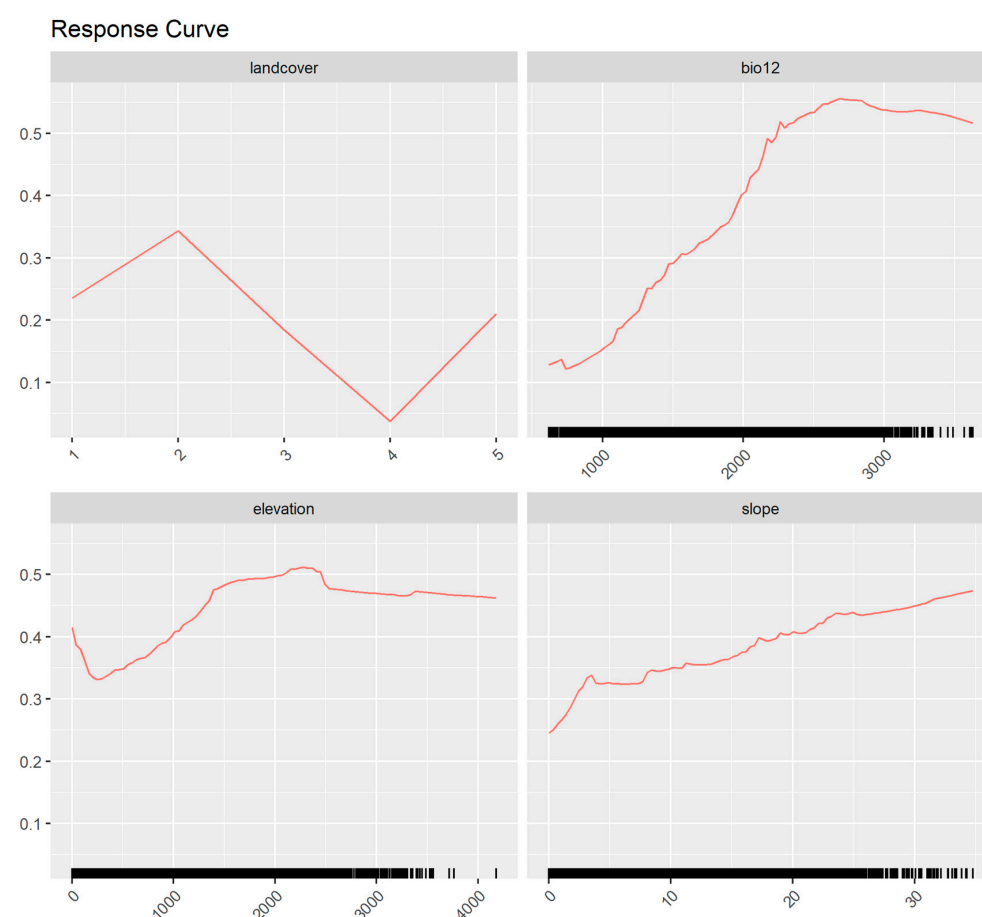


Figure 4. Response curves of major environmental predictors. Landcover: categorical land cover; bio12: annual precipitation amount in kg/m²/year; elevation: altitude in meter; slope: degree of slope. The number on the x-axis of the “landcover” plot represents different land cover categories: 1, grassland; 2, forest; 3, cropland; 4, water; 5, urban.

Figure 5 displays the current habitat suitability for Silver pheasant, as predicted using AUC-weighted mean ensemble and single algorithms and environmental predictors. De-

spite covering the same geographic extent and relying on the same environmental predictor, current predictions show that each algorithm produced different spatial suitability patterns, highlighting the variability among modeling methods.

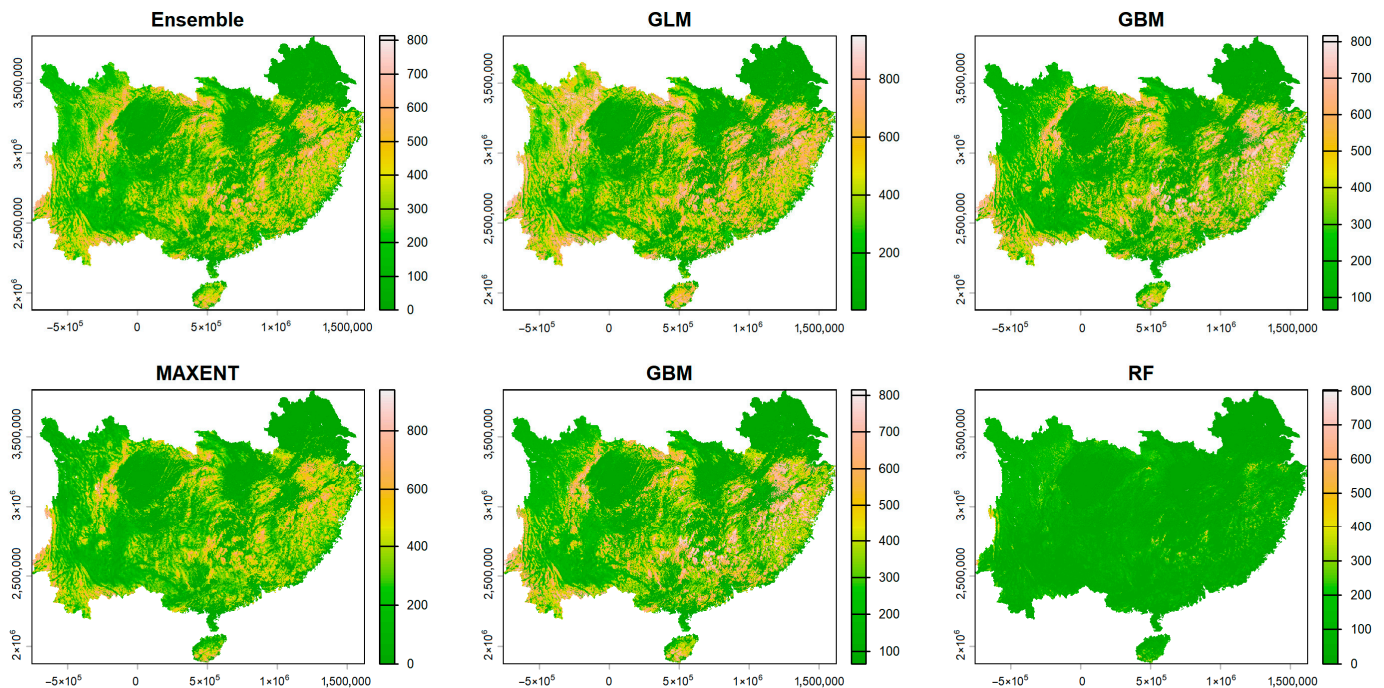


Figure 5. Prediction map of current habitat suitability for Silver pheasant as generated by the ensemble model and five species distribution modeling algorithms: Ensemble, GLM, GAM, MAXENT, GBM and RF. Colors range from green shades, indicating lower suitability, to brighter shades, indicating higher suitability.

When the threshold is 426, the TSS value of the ensemble model reaches its maximum. After binarization, there is an estimated $4.33 \times 10^5 \text{ km}^2$ suitable habitat in our study area (Figure 6). Suitable habitat is mainly distributed in the Sichuan, Yunnan, Jiangxi, Fujian, Guangdong, Guangxi, Zhejiang, and Hunan provinces, each with a suitable habitat area higher than $3 \times 10^4 \text{ km}^2$ (Table S1). The species' suitable habitat change plots (Figure 7) and table (Table 3) show that increasing habitat gains over time consistently exceeded habitat losses in future scenarios. The percentage of net suitable habitat change ranges from 24.24% (SSP370, 2070) to 63.08% (SSP126, 2100), depending on different scenarios and time periods. Gains in suitable habitat (blue area in Figure 7) are typically distributed near the current suitable habitat (yellow area in Figure 7). Currently, the centroid of Silver pheasant's suitable habitat is located in Hunan province (110.2352° E , 27.1770° N), while the centroids of future suitable habitat are also all located in Hunan province (Figure 8). The centroids of future suitable habitats are projected to shift northeastward, with movement distances range from 5 km (SSP126, 2070) to 39 km (SSP370, 2100).



Figure 6. Current suitable habitat for Silver pheasant estimated by binarizing ensemble model predictions using the threshold (4426) that maximizes TSS.

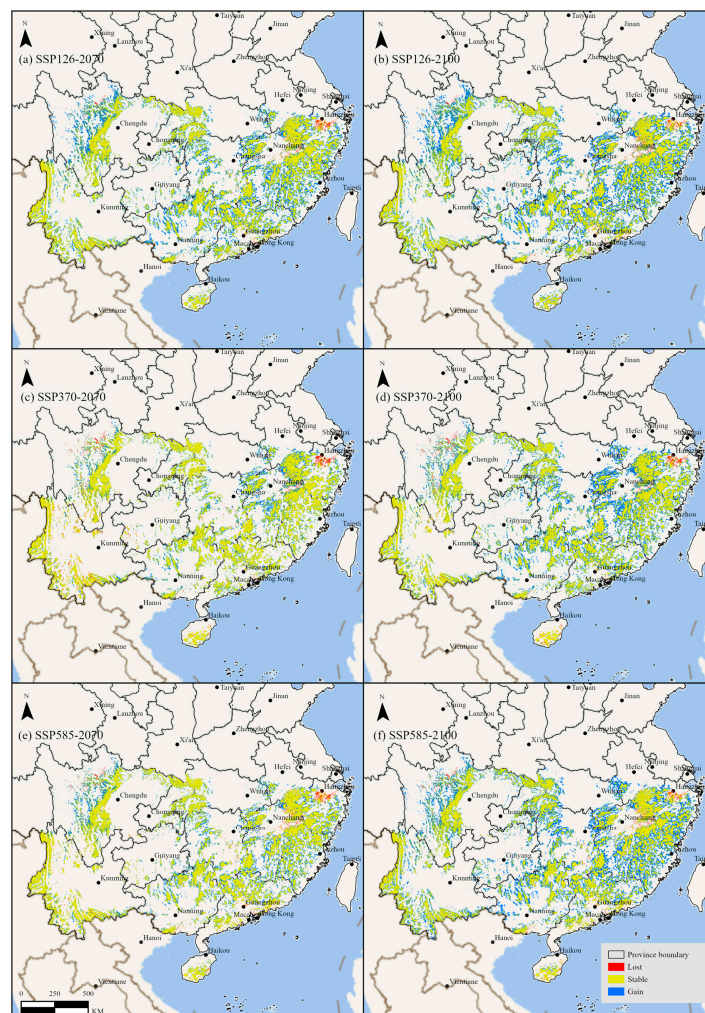


Figure 7. Projected changes in the suitable habitat of Silver pheasant under three SSP scenarios over two future time periods: (a) SSP126-2070; (b) SSP126-2100; (c) SSP370-2070; (d) SSP370-2100; (e) SSP585-2070; (f) SSP585-2100. Each row corresponds to one of the three SSP scenarios, while each column represents a different period.

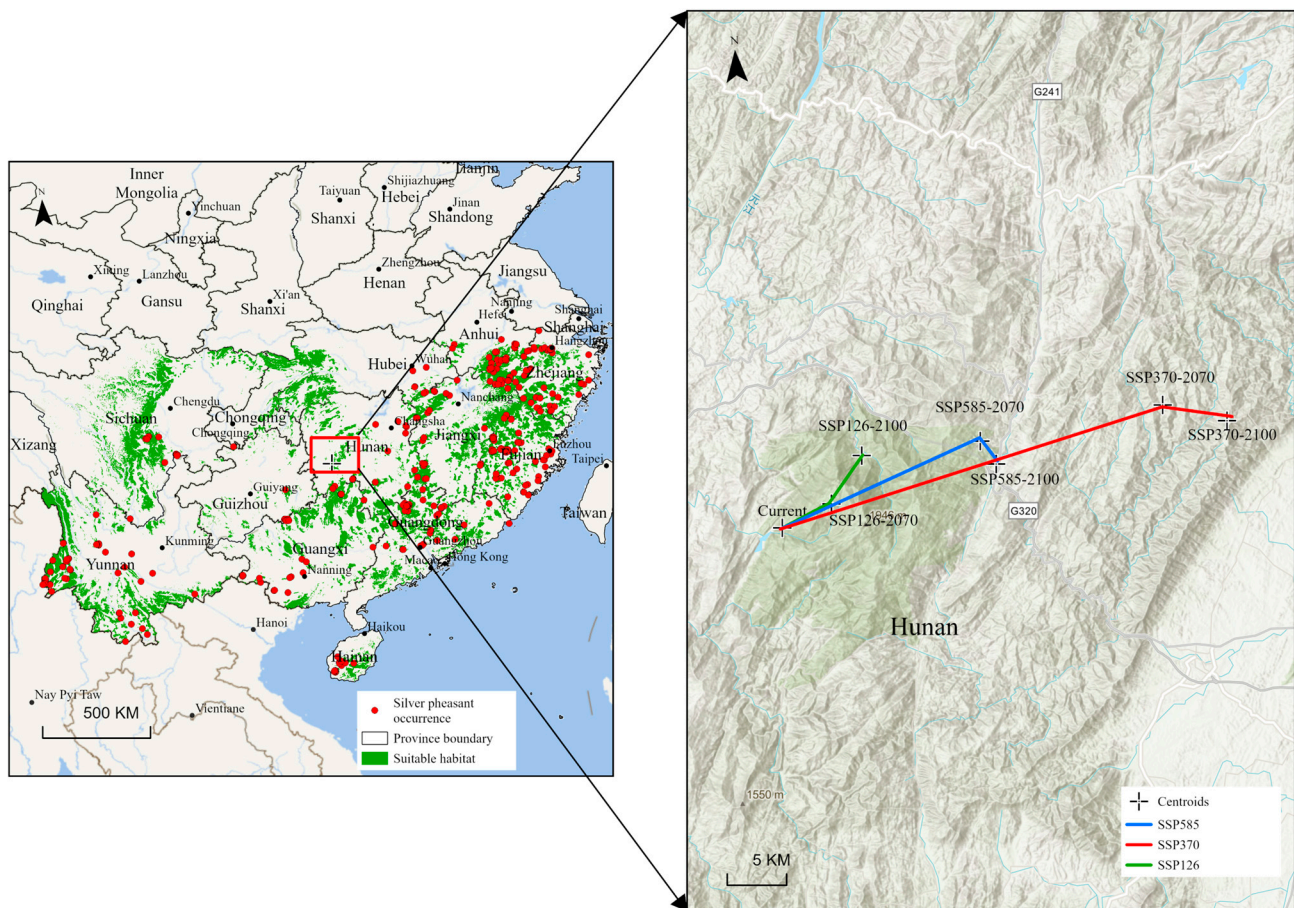


Figure 8. Centroid shifts under current and future scenarios, three different SSP scenarios (SSP126, SSP370, and SSP585) over two future time periods (2041–2070 and 2071–2100), for the Silver pheasant suitable habitat. Overview map (left) and close-up map (right) of the centroids. Color lines represent suitable habitat centroid shift path under different SSP scenarios: SSP126, green; SSP370, red; SSP585, blue.

Table 3. The table displays the calculated changes in suitable habitat area (in km²) for three different SSP scenarios (SSP126, SSP370, and SSP585) over two future time periods (2041–2070 and 2071–2100). For each scenario and period, the table presents five metrics: the “Stable” (the area of suitable habitat that remains unchanged), the “Gain” (the additional suitable habitat gained), the “Loss” (the area of suitable habitat that is lost), the “Net Change” in km² (the overall suitable habitat change accounting for loss and gain), and the “Turnover” (the percentage of suitable habitat change).

Scenario/Period	Stable (km ²)	Loss (km ²)	Gain (km ²)	Net Change (km ²)	Net Change (%)	Turnover (%)
SSP126, 2070	426,403	7087	223,096	216,009	49.83	35.06
SSP126, 2100	424,959	8531	281,967	273,436	63.078	40.60
SSP370, 2070	417,512	15,978	121,043	105,065	24.237	24.71
SSP370, 2100	423,869	9621	215,661	206,040	47.531	34.70
SSP585, 2070	421,836	11,654	146,662	135,008	31.144	27.29
SSP585, 2100	424,425	9065	274,126	265,061	61.146	40.02

4. Discussion

This study, based on multi-source occurrence data of Silver pheasant, employs an ensemble species distribution modeling approach to predict the current potential suitable habitat distribution of Silver pheasant in China and project potential suitable habitat distribution patterns under three socioeconomic development scenarios in two future time periods. To our knowledge, this is the first analysis specifically targeting the current

and future potential habitat of Silver pheasant at a regional scale. The ensemble model shows excellent predictive performance and demonstrates superiority over single-algorithm models. When using species distribution models to assess the impact of climate change on species distribution, the choice of model algorithm has the greatest impact on the uncertainty of the results [14]. Using ensemble models can reduce uncertainty, thereby increasing confidence in conservation decisions. Additionally, the choice of different general circulation models introduces uncertainty too; therefore, we selected predictions from multiple models for bioclimatic variables and used their average values instead of relying on a single model's predictions (e.g., Li et al., 2010 [6]). As shown in Figure 3, the random forest model (RF) performed unsatisfactorily on the BOYCE and TSS metrics, possibly due to a severe imbalance between pseudo-absence and species occurrence points, which can be addressed through down-sampling methods [45].

The results show that the habitat suitability for Silver pheasant increases with higher annual precipitation (bio12), indicating that Silver pheasant prefers wetter environments, as water availability is one of the key factors in its habitat selection [46,47]. Figure 4 shows that Silver pheasant habitat suitability is maximized when the land cover type is forest, consistent with previous studies. Ref. [48] concluded that the Silver pheasant prefers tree layers with high coverage; in our study, however, we did not include variables like fractional tree cover (e.g., Ding and Jiang [49]) in the model, as there is no tree cover projection for future scenarios. The positive association between habitat suitability and slope indicates that the Silver pheasant tends to select rugged terrain. This is because flatter terrain is often used by humans for activities such as farming.

This study evaluates the suitable habitat area for the Silver pheasant in China under the current conditions as 4.33×10^5 km². Compared with the distribution range in the IUCN Red List, a large area of suitable habitat exists outside the IUCN range (Figure S1). We believe the IUCN underestimates the distribution range of the Silver pheasant, as there are numerous observation records and news reports of Silver pheasants beyond the IUCN range. Wang et al. [50], in a study on the impact of climate change on the taxonomic diversity index of Galliformes in China, estimated the Silver pheasant's distribution area as 1.2×10^6 km², which is significantly larger than our estimate. The reasons for this discrepancy may include: (1) differences in study area extent, as Wang et al. (2023) [24] considered the entire country of China, while this study only included 14 provinces with Silver pheasant; and (2) differences in threshold selection, as Wang et al. (2023) [24] used a threshold corresponding to a 10% omission rate as the habitat suitability cutoff, whereas this study used the threshold that maximizing TSS as the cutoff.

Our study estimates that under future climate change and land use scenarios, suitable habitat for the Silver pheasant will expand significantly (28.15% to 67.29%). Similarly, Wang et al. [50] found that the distribution range of the Silver pheasant is expected to expand under future scenarios, although the proportion of expansion is smaller than the estimation in our study. In contrast, a study on the impact of climate change on the distribution of Phasianidae birds in Southeast Asia predicted a reduction in distribution area under different scenarios by 2100 (Namkhan et al. [20]). Silver pheasant is distributed not only in China but also in Cambodia, Myanmar, Thailand, and Vietnam. Combining our study with the study of Namkhan et al. [20], we can infer that under future scenarios, suitable habitat for Silver pheasant will decrease in the southern regions and increase in the northern regions. The centroid of habitat reflects its central position and can be used to infer the overall migration trend [50]. The spatial direction of the centroid shows a consistent northward movement under all future scenarios, while the movement distance is relatively short (within 32 km). The centroids of current and all future scenarios are situated in Hunan province. However, Li et al. [6] predicted that the centroid of Silver

pheasant's distribution range will shift from its current location in Guangxi to eastern Tibet by 2100, which we consider highly unlikely. The MESS analysis indicates that under future scenarios, the climate factors in most areas of the study region fall within the modeling range (Figure S2), with only a few areas exceeding the variable modeling range, suggesting that our model involves minimal extrapolation when predicting suitable habitat for Silver pheasant in future scenarios, indicating model robustness.

Our ensemble model provides a rigorous approach to forecasting Silver pheasant's potential suitable habitat under climate and land-cover changes, yet multiple sources of uncertainty arise from methodological decisions. Human footprint index, which is a compound metric integrating eight variables including population density, built-up area, roads, etc., was assumed to be static as there are no projections for the future. The use of a 1 km spatial scale for the environmental variables may be arbitrary. Analysis of the characteristic scale of each variable may improve model performance and the prediction map [51,52]. Ecological assumptions also introduce uncertainty. Our study was based on some assumptions: (1) Silver pheasant is currently in its preferred environmental conditions; (2) the Silver pheasant occurrence dataset represents the current distribution; (3) there is no adaptation and evolution. The extent to which these assumptions are met will affect the reliability of the assessment results.

Our results not only provide accurate predictions of the distribution patterns of Silver pheasant habitat in China under current and future environmental change scenarios, but also lay a foundational framework for subsequent assessments of landscape patterns or habitat connectivity. The modeling framework used in this study is equally applicable to evaluating the habitat distribution patterns of other terrestrial bird species at a regional scale, such as Golden pheasant (*Chrysolophus pictus*) and Lady Amherst's pheasant (*Chrysolophus amherstiae*).

5. Conclusions

In this study, we modeled current and two future time periods (2041–2070 and 2071–2100) under three shared socioeconomic pathway scenarios (SSP126, SSP370, and SSP585) for the habitat of Silver pheasant in China using an ensemble species distribution modeling approach. Our ensemble model showed excellent performance. The estimated suitable habitat under the current conditions is $4.33 \times 10^5 \text{ km}^2$, mainly distributed in the Sichuan, Yunnan, Jiangxi, Fujian, Guangdong, Guangxi, Zhejiang, and Hunan provinces. The suitable habitat is projected to expand at rates ranging from 24.24% to 63.08%. The centroids of suitable habitat under different future scenarios are generally predicted to move northeastward with relatively short move distances (<39 km). Our study was based on a correlative model, which can be integrated into a mechanistic model to improve the evaluation accuracy.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/d17120836/s1>, Figure S1: Silver pheasant range from IUCN Red List and modeled suitable habitat distribution within China. Figure S2: Multivariate environmental similarity surface (MESS) in the potential distribution area of *Lophura nycthemera* under different climate scenarios. (a) SSP126-2070, (b) SSP126-2100, (c) SSP370-2070, (d) SSP370-2100, (e) SSP585-2070, and (f) SSP585-2100. Table S1: Area of suitable habitat for Silver pheasant in each province.

Author Contributions: Z.L.: Conceptualization (lead); data curation (equal); software (equal); visualization (equal); writing—original draft (lead). X.S.: resources (equal); software (equal); writing—review and editing (equal). Y.S.: data curation (equal); visualization (equal); writing—review and editing (equal). C.T.: resources (equal), data curation (equal); S.C.: project administration (equal); resources (equal); conceptualization (equal). All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by Guizhou Provincial Key Technology R&D Program (2023-225), the Doctoral Program of the Science Research Foundation of Guizhou Education University (2021BS041, 2021BS042, 2024YB005), the Guizhou Forestry Administration Scientific Research Project (QLKH [2023] 11, QLKH [2025] 11), and the Special Survey of Phasianidae Populations in the Maolan National Nature Reserve.

Data Availability Statement: The data that support the findings of this study are openly available in Zenodo: <https://zenodo.org/uploads/17395560>, accessed on 19 October 2025.

Acknowledgments: We are grateful to the Maolan National Nature Reserve for the assistance with the field work. We also express our gratitude to the three anonymous reviewers for their valuable suggestions.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Pimm, S.L.; Raven, P. Extinction by numbers. *Nature* **2000**, *403*, 843–845. [CrossRef] [PubMed]
2. Root, T.L.; Price, J.T.; Hall, K.R.; Schneider, S.H.; Rosenzweig, C.; Pounds, J.A. Fingerprints of global warming on wild animals and plants. *Nature* **2003**, *421*, 57–60. [CrossRef]
3. Oliver, T.H.; Morecroft, M.D. Interactions between climate change and land use change on biodiversity: Attribution problems, risks, and opportunities. *Wiley Interdiscip. Rev. Clim. Change* **2014**, *5*, 317–335. [CrossRef]
4. Hooper, D.U.; Adair, E.C.; Cardinale, B.J.; Byrnes, J.E.; Hungate, B.A.; Matulich, K.L.; Gonzalez, A.; Duffy, J.E.; Gamfeldt, L.; O'Connor, M.I. A global synthesis reveals biodiversity loss as a major driver of ecosystem change. *Nature* **2012**, *486*, 105–108. [CrossRef]
5. Barbet-Massin, M.; Thuiller, W.; Jiguet, F. The fate of European breeding birds under climate, land-use and dispersal scenarios. *Glob. Change Biol.* **2012**, *18*, 881–890. [CrossRef]
6. Li, R.; Tian, H.; Li, X. Climate change induced range shifts of Galliformes in China. *Integr. Zool.* **2010**, *5*, 154–163. [CrossRef]
7. Cubasch, U.; Meehl, G.A.; Boer, G.J.; Stouffer, R.J.; Dix, M.; Noda, A.; Senior, C.A.; Raper, S.U.; Yap, K.S. Projections of future climate change. In *Climate Change 2001: The Scientific Basis*; Contribution of WG1 to the Third Assessment Report of the IPCC (TAR); Cambridge University Press: Cambridge, UK, 2001; pp. 525–582.
8. Sala, O.E.; Chapin, F.S.; Armesto, J.J.; Berlow, E.; Bloomfield, J.; Dirzo, R.; Huber-Sanwald, E.; Huenneke, L.F.; Jackson, R.B.; Kinzig, A. Global biodiversity scenarios for the year 2100. *Science* **2000**, *287*, 1770–1774. [CrossRef]
9. Jetz, W.; Wilcove, D.S.; Dobson, A.P. Projected Impacts of Climate and Land-Use Change on the Global Diversity of Birds. *PLOS Biol.* **2007**, *5*, e157. [CrossRef] [PubMed]
10. Newbold, T.; Hudson, L.N.; Hill, S.L.L.; Contu, S.; Lysenko, I.; Senior, R.A.; Börger, L.; Bennett, D.J.; Choimes, A.; Collen, B.; et al. Global effects of land use on local terrestrial biodiversity. *Nature* **2015**, *520*, 45–50. [CrossRef]
11. Elith, J.; Leathwick, J.R. Species distribution models: Ecological explanation and prediction across space and time. *Annu. Rev. Ecol. Evol. Syst.* **2009**, *40*, 677–697. [CrossRef]
12. Dar, S.A.; Singh, S.K.; Wan, H.Y.; Kumar, V.; Cushman, S.A.; Sathyakumar, S. Projected climate change threatens Himalayan brown bear habitat more than human land use. *Anim. Conserv.* **2021**, *24*, 659–676. [CrossRef]
13. Selvi, E.; Liu, D.; Bonello, P. Anticipating Shifts in American Beech Distribution in a Changing Climate. *J. Biogeogr.* **2025**, *52*, e70010. [CrossRef]
14. Buisson, L.; Thuiller, W.; Casajus, N.; Lek, S.; Grenouillet, G. Uncertainty in ensemble forecasting of species distribution. *Glob. Change Biol.* **2010**, *16*, 1145–1157. [CrossRef]
15. Hao, T.; Elith, J.; Guillera-Arroita, G.; Lahoz-Monfort, J.J. A review of evidence about use and performance of species distribution modelling ensembles like BIOMOD. *Divers. Distrib.* **2019**, *25*, 839–852. [CrossRef]
16. Hao, T.; Elith, J.; Lahoz-Monfort, J.J.; Guillera-Arroita, G. Testing whether ensemble modelling is advantageous for maximising predictive performance of species distribution models. *Ecography* **2020**, *43*, 549–558. [CrossRef]
17. Zheng, G. *Pheasants in China*; Higher Education Press: Beijing, China, 2015.
18. BirdLife International. *Lophura nycthemera*. The IUCN Red List of Threatened Species 2025; BirdLife International: Cambridge, UK, 2025; p. e.T22679220A280964662.
19. Zheng, J.; Ding, P.; Xu, X.; Xia, G. Effects of habitat patch on *Lophura nycthemera* population. *Chin. J. Appl. Ecol.* **2006**, *17*, 951–953.
20. Namkhan, M.; Sukumal, N.; Savini, T. Impact of climate change on Southeast Asian natural habitats, with focus on protected areas. *Glob. Ecol. Conserv.* **2022**, *39*, e02293. [CrossRef]
21. Xiong, X.; Tan, C.; Yu, D.; Yu, P. Population size and protection countermeasures of silver pheasant at maolan national nature reserve, Guizhou Province. *Sichuan J. Zool.* **2002**, *21*, 244–246.

22. Aiello-Lammens, M.E.; Boria, R.A.; Radosavljevic, A.; Vilela, B.; Anderson, R.P. spThin: An R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography* **2015**, *38*, 541–545. [\[CrossRef\]](#)
23. Chhetri, B.; Badola, H.K.; Barat, S. Modelling climate change impacts on distribution of Himalayan pheasants. *Ecol. Indic.* **2021**, *123*, 107368. [\[CrossRef\]](#)
24. Wang, B.; Ye, W.; Xu, Y.; Zhong, X.; Zhang, J.; Yang, N.; Yang, B.; Zhou, C. Climate change affects Galliformes taxonomic, phylogenetic and functional diversity indexes, shifting conservation priority areas in China. *Divers. Distrib.* **2023**, *29*, 409–422. [\[CrossRef\]](#)
25. Liu, Z.; Tian, S.; Lu, S.; Zhu, Z.; Peng, Y.; Li, X.; An, L.; Li, J.; Xu, J.; Wang, Y. Climate and land-use changes threaten the effectiveness of protected areas for protecting Galliformes in Southeast Asia. *Front. Ecol. Evol.* **2023**, *11*, 1216769. [\[CrossRef\]](#)
26. Karger, D.N.; Conrad, O.; Böhrer, J.; Kawohl, T.; Kreft, H.; Soria-Auza, R.W.; Zimmermann, N.E.; Linder, H.P.; Kessler, M. Climatologies at high resolution for the earth's land surface areas. *Sci. Data* **2017**, *4*, 170122. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Amatulli, G.; Domisch, S.; Tuanmu, M.-N.; Parmentier, B.; Ranipeta, A.; Malczyk, J.; Jetz, W. A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. *Sci. Data* **2018**, *5*, 180040. [\[CrossRef\]](#)
28. Chen, G.; Li, X.; Liu, X. Global land projection based on plant functional types with a 1-km resolution under socio-climatic scenarios. *Sci. Data* **2022**, *9*, 125. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Guisan, A.; Thuiller, W. Predicting species distribution: Offering more than simple habitat models. *Ecol. Lett.* **2005**, *8*, 993–1009. [\[CrossRef\]](#)
30. Thuiller, W.; Georges, D.; Engler, R.; Breiner, F. biomod2: Ensemble Platform for Species Distribution Modeling, R Package Version 3. 2016. Available online: <https://CRAN.R-project.org/package=biomod2> (accessed on 10 July 2025).
31. Valavi, R.; Guillera-Arroita, G.; Lahoz-Monfort, J.J.; Elith, J. Predictive performance of presence-only species distribution models: A benchmark study with reproducible code. *Ecol. Monogr.* **2021**, *92*, e01486. [\[CrossRef\]](#)
32. Song, H.; Ordonez, A.; Svenning, J.-C.; Qian, H.; Yin, X.; Mao, L.; Deng, T.; Zhang, J. Regional disparity in extinction risk: Comparison of disjunct plant genera between eastern Asia and eastern North America. *Glob. Change Biol.* **2021**, *27*, 1904–1914. [\[CrossRef\]](#)
33. Fourcade, Y.; Engler, J.O.; Rödder, D.; Secondi, J. Mapping species distributions with MAXENT using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. *PLoS ONE* **2014**, *9*, e97122. [\[CrossRef\]](#)
34. Barbet-Massin, M.; Jiguet, F.; Albert, C.H.; Thuiller, W. Selecting pseudo-absences for species distribution models: How, where and how many? *Methods Ecol. Evol.* **2012**, *3*, 327–338. [\[CrossRef\]](#)
35. Swets, J.A. Measuring the accuracy of diagnostic systems. *Science* **1988**, *240*, 1285–1293. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Marmion, M.; Parviainen, M.; Luoto, M.; Heikkinen, R.K.; Thuiller, W. Evaluation of consensus methods in predictive species distribution modelling. *Divers. Distrib.* **2009**, *15*, 59–69. [\[CrossRef\]](#)
37. Boyce, M.S.; Vernier, P.R.; Nielsen, S.E.; Schmiegelow, F.K.A. Evaluating resource selection functions. *Ecol. Model.* **2002**, *157*, 281–300. [\[CrossRef\]](#)
38. Liu, C.; White, M.; Newell, G. Selecting thresholds for the prediction of species occurrence with presence-only data. *J. Biogeogr.* **2013**, *40*, 778–789. [\[CrossRef\]](#)
39. Hijmans, R.J.; Barbosa, M.; Bivand, R.; Brown, A.; Chirico, M.; Cordano, E.; Dyba, K.; Pebesma, E.; Rowlingson, B.; Sumner, M.D. terra: Spatial Data Analysis. 2025. Available online: <https://CRAN.R-project.org/package=terra> (accessed on 10 July 2025).
40. Thuiller, W.; Lafourcade, B.; Engler, R.; Araújo, M.B. BIOMOD—A platform for ensemble forecasting of species distributions. *Ecography* **2009**, *32*, 369–373. [\[CrossRef\]](#)
41. Elith, J.; Ferrier, S.; Huettmann, F.; Leathwick, J. The evaluation strip: A new and robust method for plotting predicted responses from species distribution models. *Ecol. Model.* **2005**, *186*, 280–289. [\[CrossRef\]](#)
42. Elith, J.; Kearney, M.; Phillips, S. The art of modelling range-shifting species. *Methods Ecol. Evol.* **2010**, *1*, 330–342. [\[CrossRef\]](#)
43. ESRI. *ArcGIS Pro*, version 3.4.0; ESRI: Redlands, CA, USA, 2019.
44. Jia, T.; Qi, Y.; Zhao, H.; Xian, X.; Li, J.; Huang, H.; Yu, W.; Liu, W. Estimation of climate-induced increased risk of *Centaurea solstitialis* L. invasion in China: An integrated study based on biomod2. *Front. Ecol. Evol.* **2023**, *11*, 1113474. [\[CrossRef\]](#)
45. Valavi, R.; Elith, J.; Lahoz-Monfort, J.J.; Guillera-Arroita, G. Modelling species presence-only data with random forests. *Ecography* **2021**, *44*, 1731–1742. [\[CrossRef\]](#)
46. Han, W.; Wang, D. Seasonal variation in habitat selection of the silver pheasant (*Lophura nycthemera*) in Jiulongjiang National Forest Park, Hunan. *Sci. Silvae Sin.* **2017**, *53*, 71–80.
47. You, W.; Gao, X.; Mei, A.; Zhang, X.; Xu, W.; Lu, Q. Habitat Selection Research of *Lophura nycthemera* Using Infrared-Triggered Camera Technology. *Sichuan J. Zool.* **2019**, *38*, 564–570.
48. Ding, P.; Jiang, R. A Preliminary Study on the Ecology of Silver pheasants in the Western Mountains of Zhejiang Province. *Chin. J. Zool.* **1992**, *3*, 20–23. (In Chinese)

49. Liu, Y.; Liu, R.; Chen, J.; Wei, X.; Qi, L.; Zhao, L. A global annual fractional tree cover dataset during 2000–2021 generated from realigned MODIS seasonal data. *Sci. Data* **2024**, *11*, 832. [[CrossRef](#)] [[PubMed](#)]
50. Wang, Y.; Yang, Y.; Zhang, M. The influence of climate change on the potential distribution of *Ageratum conyzoides* in China. *Ecol. Evol.* **2024**, *14*, e11513. [[CrossRef](#)]
51. McGarigal, K.; Wan, H.Y.; Zeller, K.A.; Timm, B.C.; Cushman, S.A. Multi-scale habitat selection modeling: A review and outlook. *Landsc. Ecol.* **2016**, *31*, 1161–1175. [[CrossRef](#)]
52. Sun, X.; Long, Z.; Jia, J. A multi-scale Maxent approach to model habitat suitability for the giant pandas in the Qionglai mountain, China. *Glob. Ecol. Conserv.* **2021**, *30*, e01766. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.