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Examining the rationality of Giant Panda National Park's zoning designations and management measures for habitat conservation: Insights from interpretable machine learning methods

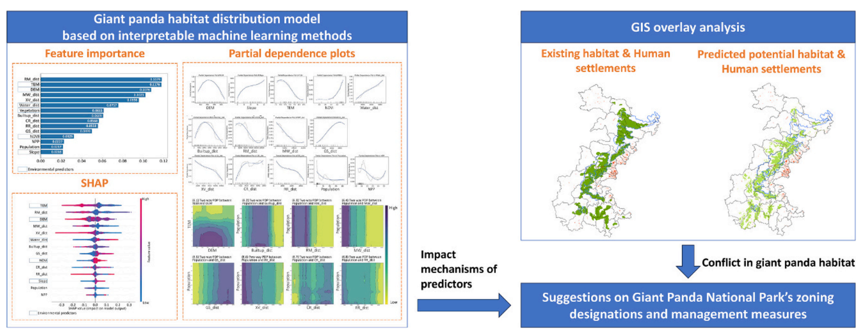
Yuhan Xu, Jun Tang *

Department of Landscape Architecture, School of Architecture, Southeast University, Nanjing 210096, China

HIGHLIGHTS

- A species distribution model was constructed based on the Random Forest algorithm.
- Interpretable machine learning revealed the impact mechanisms of variables.
- Areas where conflicts exist were identified through overlay analysis.
- Our methods can be used for other data-poor national parks or protected areas.

GRAPHICAL ABSTRACT



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ABSTRACT

Examining the rationality of zoning designations and management measures in the initial establishment of national parks in China is of great significance for supporting decision-making regarding habitat conservation. There exists a research gap in exploring the threshold effects of both environmental and human-related factors on habitat distribution in the context of national parks. However, it may be a challenge because of the limited species distribution data. Our study aims to put forward an analytical framework that integrates species distribution models (SDMs) with interpretable machine learning methods. A case study was performed in the Sichuan region of the Giant Panda National Park (GPNP). We constructed a SDM based on the Random Forest algorithm and made use of accessible remote sensing and big data to predict the distribution of giant panda habitat (GPH) in 2020. Interpretable machine learning methods, namely Partial dependence plots (PDPs) and SHapley Additive exPlanations (SHAP), were utilized to uncover the underlying mechanisms of environmental and anthropogenic variables influencing the GPH distribution. Through GIS overlay analysis, areas where conflicts between human settlements, transportation infrastructure, and GPH exist were identified. Our findings indicated a potential 28.44 % decrease in GPH from 2014 to 2020. Environmental factors such as temperature, topography, and vegetation type, as well as anthropogenic factors including distance to built-up areas and transportation infrastructure, notably distance to national roads, provincial roads and city arterial roads, influenced the GPH

Abbreviations: GPNP, Giant Panda National Park; GPH, giant panda habitat; FGPS, fourth giant panda survey; SDM, species distribution model; RF, Random Forest; PDPs, partial dependence plots.

* Corresponding author.
E-mail addresses: xuyh_seu@163.com (Y. Xu), juntseu@163.com (J. Tang).

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distribution with threshold effects significantly. The overlay analysis revealed escalated conflicts between human settlements, transportation infrastructure, and GPH in 2020 compared to 2014. Currently, the Sichuan region of the GPNP implements two zones: a core protection zone and a general control zone, covering 63.71 % of the GPH, while 36.29 % remains outside the management scope. Drawing from the analysis above, this study provided suggestions for the adjustment of zoning designations and management measures in the GPNP.

1. Introduction

The significance of biodiversity conservation has achieved a global consensus (Whitehorn et al., 2019). Human activities pose a primary threat to the survival of species (Baur and Erhardt, 1995; Kong et al., 2022). The establishment of various natural protected areas, including national parks, wildlife sanctuaries, heritage sites, and nature reserves, is an essential strategy for safeguarding species habitats (Barredo et al., 2016; Friedlander et al., 2017; Margules et al., 1982). China has made efforts to set up national parks to enhance the protection of prominent natural ecosystems (Huang et al., 2020; Tang, 2020). In 2022, the National Forestry and Grassland Administration of China, in collaboration with other relevant administrations, released the "Construction Plan for National Parks and Major Projects for Wildlife and Plant Conservation (2021-2035)" (National Forestry and Grassland Administration of China et al., 2022), which emphasizes the high fragmentation of wildlife habitats as one of the main challenges. This plan aims to address the critical issue of habitat fragmentation, highlighting the need to designate important wildlife habitats, improve habitat quality, expand habitat coverage, and implement conservation and restoration measures for key species.

The establishment of national parks in China is relatively recent, and the land use patterns, as well as transportation networks, within the national parks boundaries exhibit a high level of complexity (Chen et al., 2023; X. Zhang et al., 2022). While the initial outcomes of the official establishment of China's first group of national parks have shown promising results in improving habitat quality (Chen et al., 2023), the protection system is still in need of further development (Huang et al., 2020; Zhang et al., 2022). The conflict between biodiversity conservation and socio-economic development remains a pressing issue, as human activities and the ongoing exploitation of natural resources continue to pose disruptions to wildlife habitats (Feng et al., 2022; Wang et al., 2012; Zhao et al., 2020). Consequently, a comprehensive assessment of changes in wildlife habitat suitability, coupled with overlay analysis, is crucial to identify areas where conflicts between habitats and human settlements exist. This will enable targeted adjustments to the designations of zoning boundaries and the implementation of effective management measures within the national parks in order to mitigate and avoid conflicts between habitats and human activities (Ma et al., 2022).

Most researches regarding habitat conservation relied on collecting foundational data through various methods, including questionnaires, in-depth or focus group interviews, biological sample collection, and repeated visual count surveys (Barocas et al., 2023; Sharma et al., 2021). However, conducting comprehensive large-scale surveys is time-consuming and resource-intensive in Chinese large-scale national parks, with key species surveys often taking place only once every 5–10 years. Utilizing accessible key species distribution data and species distribution models (SDMs) can be an alternative way to ensure the conservation of biodiversity at the initial stage (Politi et al., 2021). SDMs are powerful tools to identify the potential habitats and help decision-makers to designate zoning of national parks (Banerjee et al., 2022). The utilization of remote sensing data, including climate, elevation, and land-cover maps, along with multi-temporal open-source maps and machine learning algorithms, has made it possible to predict habitat distribution accurately with the equipment of SDMs (Cooper et al., 2023; Diao et al., 2022). Therefore, considering the limited species distribution data in Chinese national parks or other data-poor regions, it is necessary to develop SDMs based on open-source remote sensing and big data to predict habitat distribution accurately, providing scientific insights for effective conservation management (Elith and Leathwick, 2009).

In terms of specific research methods, commonly used SDMs include the Maximum Entropy Models (Khosravi et al., 2022; Peng et al., 2020; Xi et al., 2020) and Biomod2 models (Thuiller et al., 2016), which encompass various machine learning algorithms, significantly enhancing the precision of species distribution prediction. It is noteworthy that in recent years, the interpretability tools have opened the "black box" model for machine learning algorithms, making them applicable in species distribution or habitat assessment models (He et al., 2022; Z. Zhang et al., 2022). Explainable artificial intelligence provides a means to gain a deeper understanding of the nonlinear relationships between different variables and species habitat distribution. Understanding the mechanisms of how various factors influence habitat can assist decision-makers in formulating relevant strategies. However, few studies considered both environmental and human-related variables, and there exists a research gap in applying these methods to guide the planning and management of national parks.

Geographic Information System (GIS) overlay analysis is a commonly used spatial analysis method that involves overlaying different geographic datasets to identify and analyze spatial relationships and interactions between various variables (Lokhande et al., 2017; Yalew et al., 2016). By overlaying the distribution of suitable habitats and human settlements, areas where conflicts exist can be identified (Dai, 2022; Khosravi et al., 2022; Xi et al., 2020). However, existing studies often simplified the identification by overlaying habitats and human settlements, providing management recommendations only for the conflict zones. There remains a research gap in understanding the radiating effects of areas where conflicts exist on the surrounding environment, as well as in uncovering the mechanisms and threshold effects of human settlements and transportation infrastructure on habitat distribution.

We aim to put forward a useful approach based on accessible GIS-based remote sensing and big data to examine the rationality of zoning designations and management measures for habitat conservation within data-poor Chinese national parks. This study introduced an analytical framework that integrates ecological SDMs with state-of-the-art interpretable machine learning algorithms, providing new insight into the application of common data types and machine learning methods. Using the giant panda habitat (GPH) in Sichuan Province as a case study, we unveiled the impact mechanisms of environmental and anthropogenic variables on GPH distribution. The research objectives are threefold: (1) Construct a predictive model for GPH using the Random Forest algorithm, and employ one-way partial dependence plots (PDPs), two-way PDPs and the Shapley Additive exPlanations (SHAP) to elucidate the levels of influence and threshold effects of environmental and human-related variables on habitat distribution. (2) Assess the rationality of current national park boundaries in protecting GPH based on the existing habitats from the fourth giant panda survey (FGPS) and predicted potential habitats, providing valuable insights for the designations of zoning boundaries. (3) Utilize overlay analysis to identify regions where human-wildlife conflicts exist or may exist in Sichuan Province. Drawing upon the understanding of the impact mechanisms of anthropogenic factors on GPH distribution, recommendations can be proposed for zoning designations and management measures of the Giant Panda National Park (GPNP).

2. Materials and methods

2.1. Study area

The giant panda (*Ailuropoda melanoleuca*) is listed as one of the 12 keystone, flagship and umbrella species requiring urgent conservation efforts during the "14th Five-Year Plan" period, as outlined in the "Construction Plan for National Parks and Major Projects for Wildlife and Plant Conservation (2021-2035)" (National Forestry and Grassland Administration of China et al., 2022). The giant panda demonstrates a notable umbrella species effect (Barua, 2011; Li and Pimm, 2016), whereby the conservation effectiveness of the GPH is positively associated with biodiversity within protected areas (Wang et al., 2023). Hence, the establishment of national parks to efficiently safeguard and rehabilitate GPH emerges as a pivotal approach to bolstering biodiversity across the region. The GPNP spans across three provinces, namely Sichuan, Shaanxi, and Gansu, with Sichuan Province accounting for 20,177 km^2, representing 74.36 % of the total area. The boundaries of the GPNP within Sichuan Province were delineated based on the vectorization of the "Giant Panda National Park General Master Plan (Draft for Public Consultation)" (National Forestry and Grassland Administration of China, 2019), as illustrated in Fig. 1(B). Since the GPNP does not contain all GPH, a total of 41 administrative divisions, which were identified as having existing or potential habitats for giant pandas in the most recent "Fourth Giant Panda Survey (FGPS)" (Forestry Administration of Sichuan Province, 2015), were selected as the study area (Fig. 1).

According to the "Land Spatial Ecological Restoration Plan of Sichuan Province (2021-2035)" (Sichuan Provincial Department of Natural Resources, 2022a), the gradual encroachment of residential land into ecological spaces in Sichuan Province has been posing a significant threat to biodiversity. As shown in Fig. 1(C), some parts of human settlements and cropland are very close to forest and grassland in the eastern part of the study area, demonstrating the evident conflicts between cropland, human settlements, and ecological spaces. The "Land Spatial Planning of Sichuan Province (2021-2035)" (Sichuan Provincial Department of Natural Resources, 2022b) outlines the future development of one megacity, eleven large cities, seven medium-sized cities, and 127 small cities, with an anticipated urbanization rate of 70 %. There is no doubt that the further expansion of human settlements will intensify human-wildlife conflicts without effective and meticulous control measures. Although the establishment of the GPNP aims to enhance habitat protection, the mechanisms and threshold effects of human activities on GPH remain inadequately understood, making it difficult to formulate effective management strategies. Additionally, due to the ongoing construction phase of national parks in China, spatial divergence exists between the designated national park boundaries and the habitat distribution, resulting in the incomplete inclusion of all habitats within the protected areas (Feng et al., 2022; Wang et al., 2023). GPH continues to face disturbances from timber extraction, road construction, and economic development, resulting in issues of habitat loss, fragmentation, and degradation (Hong et al., 2016; Wang et al., 2022; Wei and Wei, 2022), with certain regions experiencing a downward trend in pandas presence density (Yang et al., 2020).

Hence, it is imperative to utilize historical survey data of Sichuan Province to forecast the shifting distribution of GPH and unravel the intricate mechanisms behind the influence of various factors, particularly the threshold effects of anthropogenic factors. This approach served a dual purpose: first, it facilitated the adaptive adjustment of zoning boundaries, ensuring the inclusion of a broader coverage of GPH within the GPNP. Second, considering the varying threshold effects of different anthropogenic factors allowed for the optimization of adaptive

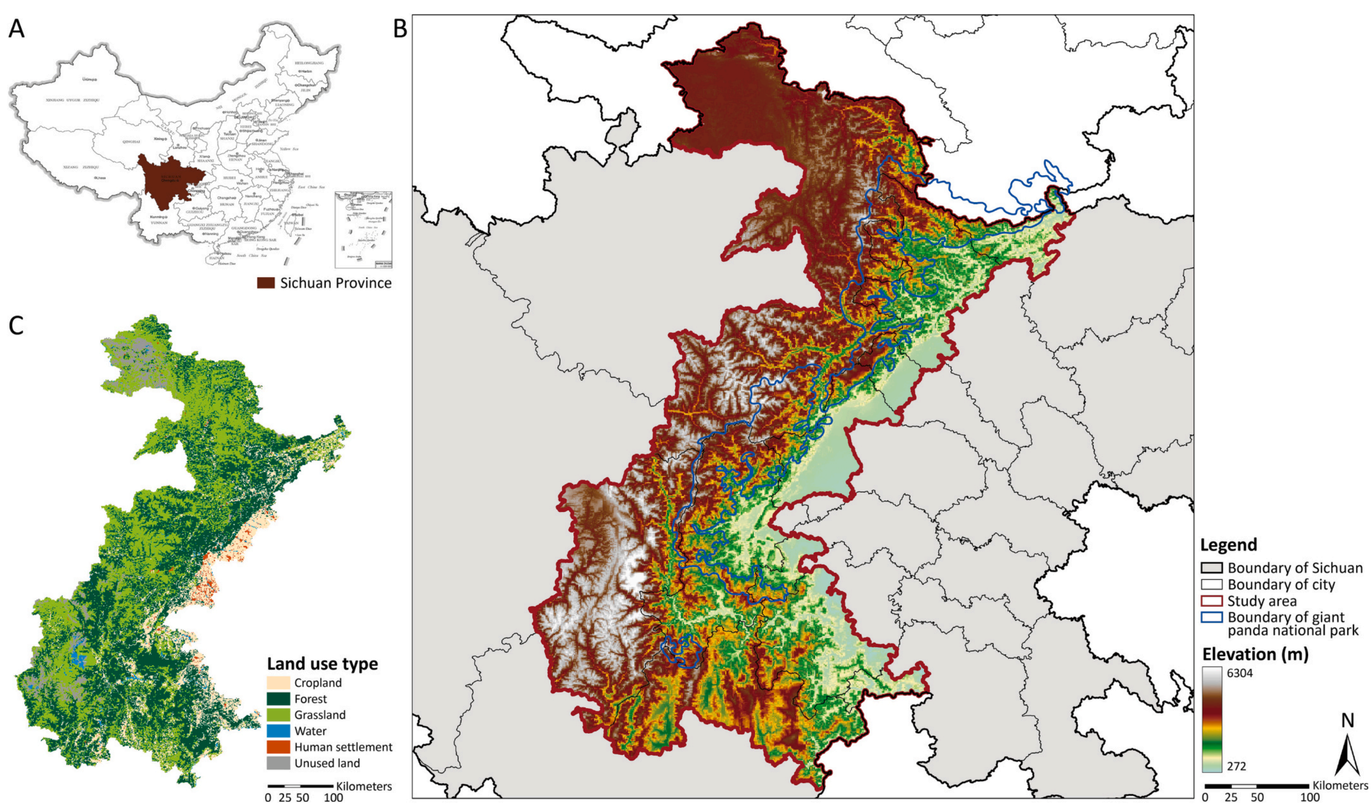

Fig. 1. Study area. (A) Sichuan Province's position in China, (B) elevation of study area and boundary of giant panda national park, (C) land use map of the study area in 2020.
Note: Land use types were divided into cropland, forest, grassland, water, human settlement and unused land. Human settlement refers to urban and rural residential areas, as well as other industrial, mining, and transportation areas. Unused land refers to land that is not currently utilized, including hard-to-use land.

management measures.

2.2. Data source

Considering the scale of the study area and the availability of data, this study adopted a 1 km grid as the analytical unit. The data used in this study included environmental and anthropogenic data for the years 2014 and 2020. The environmental data comprised variables such as elevation, slope, temperature, vegetation type, water, and the distribution of GPH. Meanwhile, the anthropogenic data included land use, transportation infrastructure, nighttime light intensity and population density. The land use data employed in this study was classified into six primary categories: cropland, forest, grassland, water, human settlement, and unused land. Following data preprocessing, all variables were standardized and visualized as raster points or raster polygons with a resolution of 1 km using ArcGIS Pro 2.5. Detailed information regarding the data name, period, resolution, preprocessing procedures, and sources can be found in Table 1.

2.3. Methods and analytical framework

2.3.1. Species distribution model construction

SDMs are widely utilized by researchers and conservationists. The remarkable progress in computer science has propelled the development of species distribution modeling algorithms, with machine learning techniques such as Random Forest (RF) being extensively employed for predicting species habitat distribution. The RF algorithm comprises multiple independent decision trees, and the collective output of the model is determined by the combined decisions of each tree in the forest (Breiman, 2001). One notable advantage of RF is its capability to directly analyze high-dimensional data without the need for dimensionality reduction techniques, while also providing predictor importance values. Previous studies have demonstrated that RF achieves higher accuracy in predicting species habitat distribution compared to other algorithms (Rather et al., 2020a; See et al., 2021; Williams et al., 2009).

Before formally constructing the SDM, we also employed the Autogluon framework, which can carry out automatic hyperparameter tuning and model selection, to compare different algorithms, including common machine learning algorithms like K-Nearest Neighbors Uniform, Light Gradient Boosting Machine, RF, and eXtreme Gradient Boosting (for detailed information, please see Table A.1 in Appendix A Supplementary material). Despite the fact that certain algorithms demonstrated superior accuracy and computational speed compared to RF, we opted for RF due to its extensive application in studies of fauna habitat distribution (Liu et al., 2013; Marston et al., 2023; Rather et al., 2020b; Shanley et al., 2021; Vezza et al., 2015).

As shown in Fig. 2, the prediction of species habitat distribution using the RF algorithm relies on two essential types of data: species distribution data obtained from previous surveys and predictors (also known as independent variables) from two different time periods. Predictors can encompass both environmental and anthropogenic variables. In this study, a SDM was trained using data from 2014. By incorporating predictors from 2020, it becomes feasible to evaluate the suitability of each sample in 2020 as GPH.

According to the FGPS (Forestry Administration of Sichuan Province, 2015) and relevant studies (Feng et al., 2022; Kong et al., 2022; Wang et al., 2023; Wei and Wei, 2022), the selected predictors for GPH prediction included six environmental variables: elevation, slope, temperature, vegetation type, Normalized Difference Vegetation Index, and distance to water. Additionally, nine anthropogenic predictors related to human activities were considered, including distance to railways and metros, distance to five types of roads, distance to built-up areas, nighttime light intensity and population density.

We chose five road-related predictors for two main reasons. First, according to the FGPS (Forestry Administration of Sichuan Province, 2015), road traffic had risen from the third to the second position in the ranking of disturbance intensity compared to the Third Giant Panda Survey. This indicates that road traffic continues to have a sustained impact on GPH, and the degree of impact is continuously rising. Roads are widely distributed within GPH, with a total road length exceeding 1000 km. Among different road types, motorways are the most obstructive, causing the most severe fragmentation of habitats (Bruschi

Table 1
Datasets used in this study.

Name	Period	Raw data resolution	Data processing procedures	Data source
Environmental variables				
Giant panda habitat	2014	/	Obtained through Image Vectorization	Giant Pandas in Sichuan: The Fourth Survey Report on Giant Pandas in Sichuan Province (Forestry Administration of Sichuan Province, 2015)
DEM Elevation	2015[a]	30 m	Resampled from 30 m resolution to 1 km resolution	NASA SRTM3 (https://www.earthdata.nasa.gov/sensors/srtm)
Slope	2015[a]	/	Derived from elevation analysis	
Temperature	2014, 2020	1 km	/	https://www.resdc.cn/DOI/DOI.aspx?DOIID=96 (Xu, 2022a)
Normalized Difference Vegetation Index	2014, 2019[b]	1 km	/	https://www.resdc.cn/data.aspx?DATAID=257 (Xu, 2018)
Vegetation type	2000[a]	1 km	/	http://data.tpdc.ac.cn/zh-hans/data/ab193a70-63a5-4df6-9bc1-d9b5ac5fb044/ (Li Xin, 2019)
Water	2014, 2020	Vector	/	Open Street Map (https://www.openstreetmap.org/)
Anthropogenic variables				
Land use	2015[c], 2020	1 km	Reclassified into 6 categories	https://www.resdc.cn/DOI/DOI.aspx?DOIID=54 (Xu et al., 2018)
Transportation infrastructure	2014, 2020	Vector	Vector data, Reclassified into 5 categories	Open Street Map (https://www.openstreetmap.org/)
NPP-VIIRS Nighttime light intensity	2014, 2020	1 km	/	https://www.resdc.cn/DOI/DOI.aspx?DOIID=105 (Xu, 2022b)
Population density	2014, 2020	1 km	/	https://landscan.ornl.gov/ (Dobson et al., 2000)

[a] Typically, DEM elevation, slope, and vegetation type exhibit minimal variations over the years, and owing to the protracted data update cycle, we utilized identical datasets for both the 2014 and 2020 periods.
[b] Due to the fact that only data from January to June is available for the year 2020 at the time of data release, the annual data for 2020 was unavailable. Consequently, the NDVI data from 2019 was used as a substitute for 2020.
[c] We utilized a multi-temporal land-use dataset comprising a total of 11 periods, including the years 1980, 1990, 1995, 2000, 2005, 2008, 2010, 2013, 2015, 2018, and 2020. Unfortunately, we can only substitute the data from 2015 for the absent 2014 dataset.

et al., 2015) ...

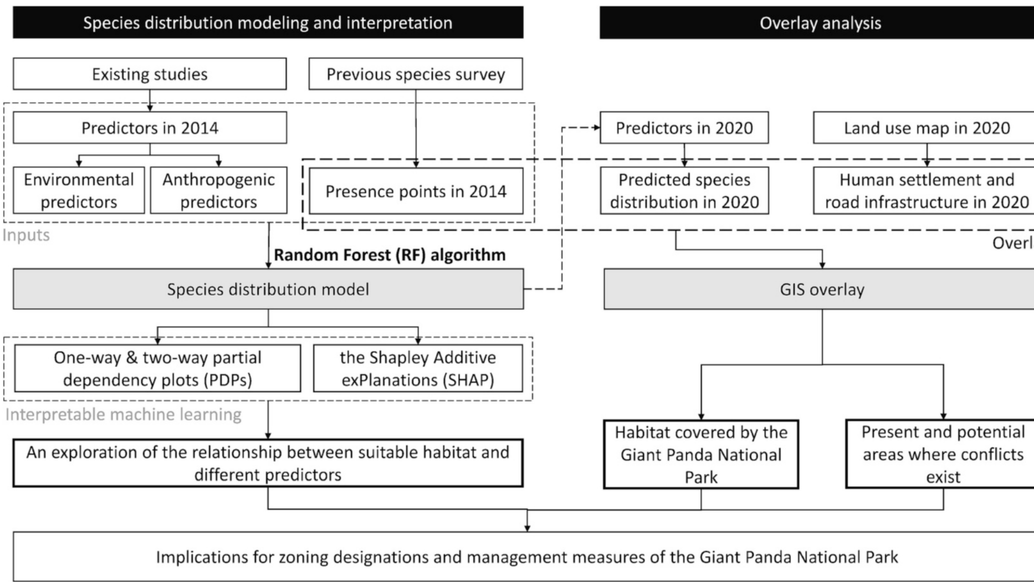

Fig. 2. Methods and analytical framework.

et al., 2015; Forman, 2005). While national and provincial roads have reduced levels of closure, they carry relatively heavy traffic flow, presenting challenges for giant pandas to traverse (He et al., 2019; Xu et al., 2006). County and township roads exhibit weaker fragmentation effects on habitats. In addition, our study area encompasses multiple cities, counties, and districts, so roads within urban built-up areas also need consideration. The fragmentation effects of city arterial and residential roads on space may differ.

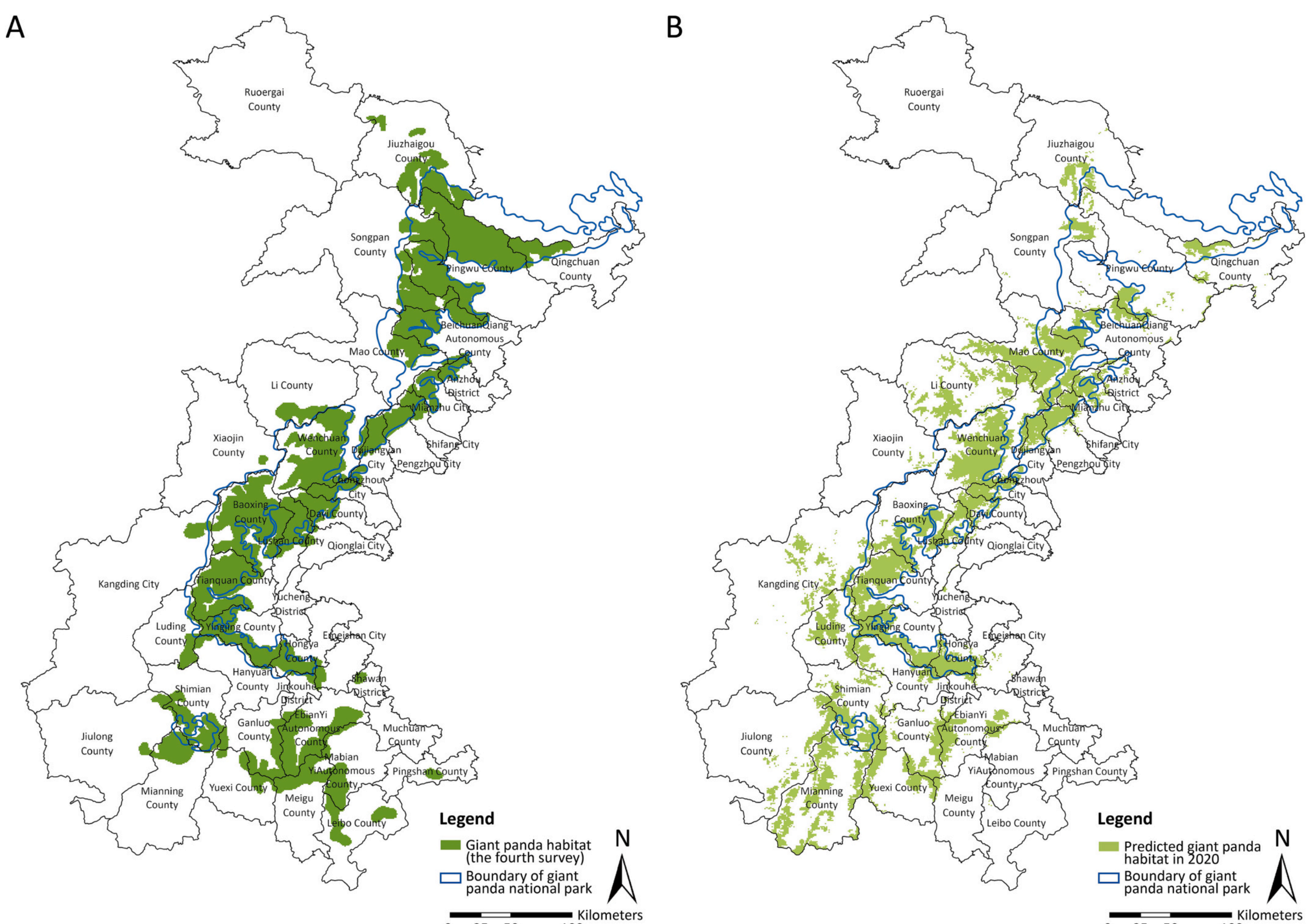

Fig. 3. (A) Giant panda habitat distribution map (the fourth giant panda survey), (B) predicted giant panda habitat distribution map in 2020.

Second, according to the "Giant Panda National Park General Master Plan (Draft for Public Consultation)" (hereinafter referred to as "the Plan") (National Forestry and Grassland Administration of China, 2019), other human disturbances, such as industrial enterprises, mining enterprises, and hydropower stations (Luo et al., 2022), have been explicitly required to relocate from the GPNP. Therefore, we did not consider such human-related predictors in our study. Furthermore, factors such as grazing, logging, tourism activities, distribution of staple bamboo, and geological disasters are also associated with GPH (Hong et al., 2016; Wei and Wei, 2022). However, owing to the unavailability of statistical results pertaining to these factors in two consecutive years at a broader research scale, they were excluded from consideration as predictor variables.

Utilizing the data from the FGPS in Sichuan Province (Fig. 3(A)), all data points within the study area were annotated. Data points indicating the presence of GPH were labeled as 1, while those without were labeled as 0. These annotations served as the dependent variable. Among the annotated data points, there were 35,469 labeled as 1 and 134,357 labeled as 0. Based on the 2014 data, a training dataset was constructed comprising the aforementioned 15 predictor variables and 1 dependent variable. Subsequently, using the widely adopted machine learning library Scikit-learn in Arcpy, a RF classification model was trained. The dataset was split into 70 % training set and 30 % testing set.

The data attributes used in the study and detailed data descriptions were provided in Table 2 and Table A.2 in Appendix A Supplementary material. We also carried out pearson correlation analysis and the univariate correlations of all variables were presented in Fig. A.1 in Appendix A Supplementary material.

Table 2
Data attributes used in the study.

Predictor type	Predictor name	Abbreviation	Unit	Range (SD)
Environmental predictors	DEM Elevation	DEM	m	267–7443 (1223.32)
	Slope	Slope	°	0.00–75.63 (12.67)
	Temperature	TEM	°C	−9.14-29.05 (4.59)
	Vegetation type	Vegetation	/	/
	Normalized Difference Vegetation Index	NDVI	/	0.01–0.92 (0.15)
	Distance to water	Water_dist	m	0.28–95,045.81 (19,087.34)
Anthropogenic predictors	Distance to railways and metros	RM_dist	m	0.65–342,918.91 (73,526.15)
	Distance to motorways	MW_dist	m	0.05–404,663.13 (85,396.14)
	Distance to national roads and provincial roads	GS_dist	m	0.05–58,777.24 (10,988.11)
	Distance to county roads and township roads	XV_dist	m	3.27–176,179.90 (35,997.43)
	Distance to city arterial roads	CR_dist	m	0.41–70,992.61 (14,535.85)
	Distance to city residential roads	RR_dist	m	0.01–96,438.78 (18,515.09)
	Distance to built-up areas	Builtup_dist	m	0.00–113,742.82 (17,584.65)
	NPP-VIIRS Nighttime light intensity	NPP	/	0.00–66.80 (0.90)
	Population density	Population	Person/km^2	0.00–30,341 (398.22)

2.3.2. *Interpretable machine learning methods*

Explaining the machine learning models allows us to understand the model's reliance and weighting on predictors, as well as the extent to which different predictors influence the outcomes. This is crucial in deciphering the underlying mechanism behind the model's predictions or decisions, thereby providing decision-makers with more precise and dependable support (Murdoch et al., 2019). To enhance the interpretability of machine learning models, researchers have developed various explanatory techniques and methods, among which partial dependence plots and the Shapley Additive exPlanations are commonly used.

Partial dependence plots (PDPs) are valuable tools for visualizing the relationship between predictors and dependent variables. They allow researchers to control the values of other predictors and examine the impact of a target predictor on the predicted outcomes. In the field of ecology, PDPs provide insights into the influence of each predictor on prediction results and their interactions with one another (Alnahit et al., 2022; Cutler et al., 2007). One-way PDPs enable the examination of model sensitivity to individual predictors, while two-way PDPs illustrate the independent effects of two predictors on results, revealing their respective contributions. Moreover, two-way PDPs capture interaction effects, showcasing the combined influence of two predictors when they vary simultaneously. This facilitates the exploration of complex non-linear relationships among predictors.

The Shapley Additive exPlanations (SHAP) is a Python package used for explaining the predictions of machine learning models. It offers a methodology based on the Shapley value theory from cooperative game theory to quantify the contribution of each predictor to the model's predictions (Lundberg et al., 2018; Lundberg and Lee, 2017). By computing the Shapley value of each predictor value with respect to the prediction outcome, SHAP provides a quantitative measure of the contribution of each predictor to the prediction.

By combining one-way PDPs, two-way PDPs and SHAP to interpret a well-trained RF model, we can gain insights into the influence of various predictors on habitat distribution and their marginal effects. In this study, we employed the PartialDependenceDisplay function from the scikit-learn library and the SHAP package to analyze the influence of environmental and anthropogenic predictors. This integrated approach allowed us to explore and uncover the intricate relationship between GPH and different predictors.

2.3.3. *Overlay analysis*

Map overlay, facilitated by the advancements in GIS, has been extensively applied in environmental planning and landscape architecture. As shown in Fig. 2, the overlay analysis in this study consisted of two main components. First, by overlaying the current GPNP boundaries with the GPH in 2014 and the predicted habitat distribution in 2020, the extent of habitat coverage within the existing national park can be determined, thereby providing a reference for adjusting the national park's boundaries. Second, by overlaying the habitat distribution obtained from the 2014 survey, the predicted habitat distribution for 2020, and the various anthropogenic variables such as human settlements and transportation infrastructure within the study area in 2020, two objectives can be achieved. On one hand, it helped identify spatial conflicts within the study area. On the other hand, according to the current situation in Sichuan Province and revealed impact mechanisms and the threshold effects of human settlements and transportation infrastructure on GPH, the suggestions on the adjustment of zoning designations and management measures from a spatial control perspective can be proposed.

3. Results

3.1. Potential habitat prediction and model evaluation

Our RF classification model exhibited an accuracy of 0.9815, precision of 0.9780, recall of 0.9909, and an F1-score of 0.9862. The kappa coefficient, calculated based on the confusion matrix, was 0.93. It indicated a good fit of the model. Using the predictors from 2020, the model was applied to predict suitable regions for giant panda survival in 2020. The results were presented in Fig. 3(B).

3.2. Species distribution model interpretation

The importance of predictors was ranked through the trained model, as shown in Fig. 4(A). Among the environmental predictors, temperature was found to be the most important, followed by elevation. These findings aligned with the habitat preferences of giant pandas. Regarding predictors related to human activities, the distance to railways and metros was identified as the most important factors, followed by the distance to motorways. This could be attributed to the fact that such major transportation infrastructure not only leads to habitat loss but also results in population isolation of giant pandas (He et al., 2019; Qiu et al., 2019). According to the FGPS (Forestry Administration of Sichuan Province, 2015), the impact of motorways on the GPH distribution was reported to be the greatest among various road types, which aligned with the findings of this study.

One-way and two-way PDPs, as well as SHAP, were employed to explore the non-linear correlations and the marginal effects of predictors on GPH distribution. One-way PDPs may exhibit minor fluctuations or significant variations, but in explanatory research, more attention should be paid on the overall trends rather than local changes. To address this, we utilized spline curves to capture the overall trend. As depicted in Fig. 4(C) and (D), the gray line represented the original curve, while the blue line represented the fitted spline curve. Notably, the variable "Vegetation type" held no numerical significance and thus was excluded from the PDP analysis. To investigate the natural environmental requirements for GPH, a two-way PDP analysis was conducted between temperature and elevation. In addition, two-way PDPs between distance to built-up areas, distance to six types of transportation infrastructure and population density were drawn in order to explore the impact of human disturbance and their joint effects on GPH (Fig. 4(E)).

The SHAP interpreter was used to analyze the RF model, and a summary plot (Fig. 4(B)) was generated. The summary plot combines predictor importance and predictor effects. Each point on the plot represents a predictor and an instance's Shapley value. The position on the y-axis is determined by the predictor type, while the position on the x-axis is determined by the Shapley value. The color represents the magnitude of the predictor value, ranging from small to large. The points are jittered in the y-axis direction, allowing us to understand the distribution of Shapley values for each predictor. As shown in Fig. 4(B), a higher value for "TEM" (indicated by a redder color) corresponded to a

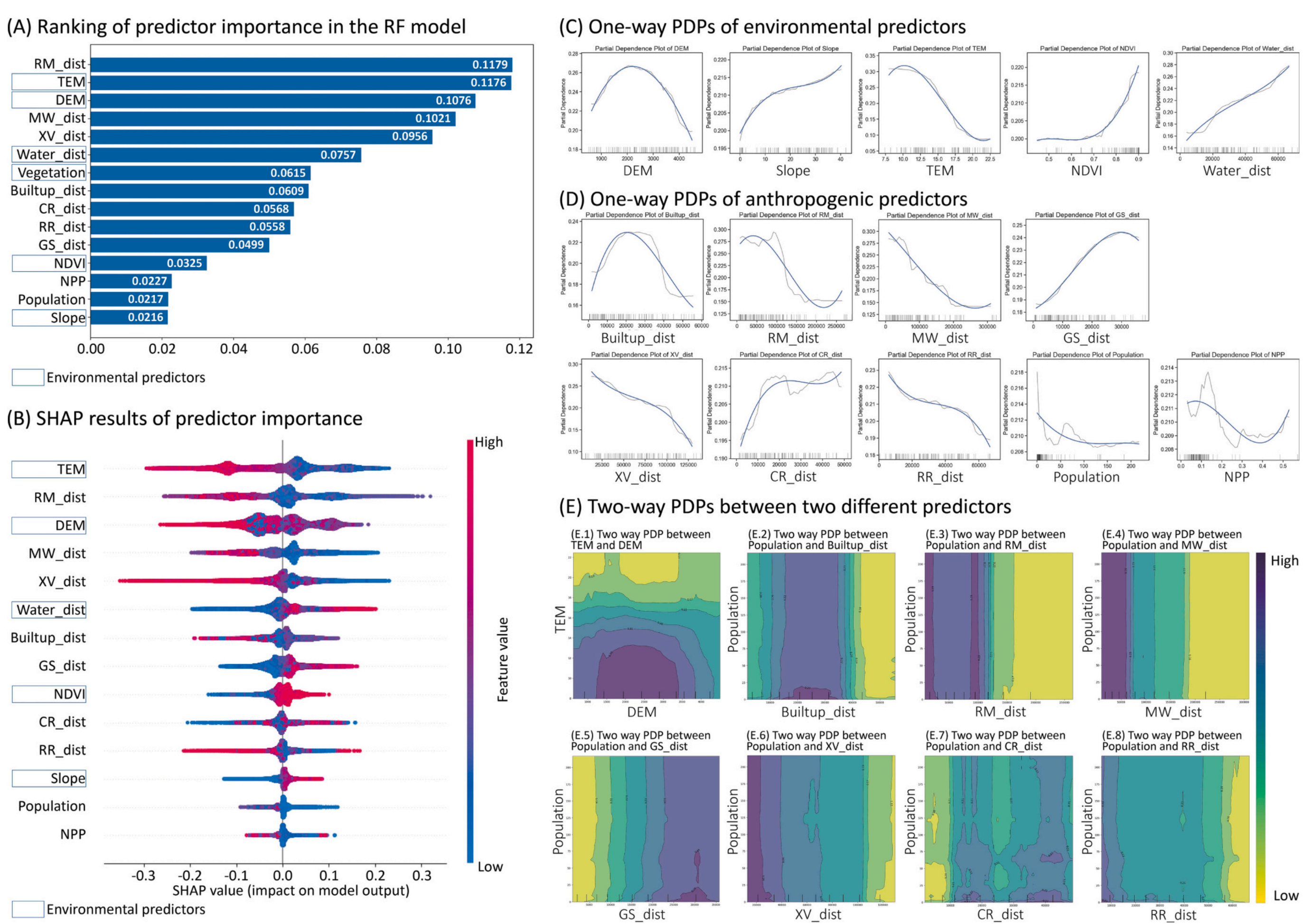

Fig. 4. Species distribution model interpretation. (A) ranking of predictor importance in the Random Forest model for giant panda habitat prediction ("*" represents environmental predictors.), (B) SHAP results of predictor importance based on the RF models (Note: the relative importance of predictors was ranked from up to down.), (C) one-way PDPs of environmental predictors, (D) one-way PDPs of anthropogenic predictors, (E) two-way PDPs between two different predictors.

smaller Shapley value. This indicated that as the temperature increased, the model assigned a lower likelihood of the point being suitable habitat. Conversely, a higher value for "GS_dist" (also indicated by a redder color) corresponded to a larger Shapley value. This suggested that as the distance to the national roads and provincial roads increased, the model assigned a higher likelihood of the point being suitable habitat.

Regarding environmental predictors, the rankings in Fig. 4(A) clearly demonstrated the crucial role of natural environment in GPH suitability. Fig. 4(C) one-way PDPs and Fig. 4(E.1) a two-way PDP between elevation and temperature provided compelling evidence regarding the specific requirements of suitable GPH. It is evident that the optimal habitat for giant pandas is predominantly located in mountainous regions characterized by temperatures ranging from 7.5 to 15 °C, elevations between 1500 and 3500 m, and NDVI of 0.75 or higher. Importantly, the near-negligible impact of NDVI values below 0.75 on the model's predictions underscored the significant role of vegetation coverage in GPH suitability. These findings aligned seamlessly with the outcomes obtained from the SHAP summary plot (Fig. 4(B)). The interpretation of our predictive model was in accordance with previous studies that have evaluated the environmental requirements for giant pandas (Ruan et al., 2021; Zhen et al., 2018).

In relation to anthropogenic predictors, the analysis of one-way PDPs revealed two primary mechanisms for the impact of six types of transportation infrastructure. As the predictor values increased, there was a corresponding increase in the likelihood of suitable habitat, as observed for "GS_dist" and "CR_dist". Conversely, "RM_dist", "MW_dist", "XV_dist", and "RR_dist" exhibited a contrasting effect, indicating a decrease in the probability of suitable habitats with increasing predictor values. These identified mechanisms aligned with the impact patterns observed in SHAP results (Fig. 4(B)). To gain insights into the influence of different levels of transportation infrastructure on habitat distribution, we superimposed the distribution maps of the habitats from the FGPS, predicted habitats for the year 2020, and the spatial distribution of various transportation infrastructure, as shown in Fig. A.2 in Appendix A Supplementary material.

In 2014, railways, metros, motorways, county roads, township roads, and city residential roads were predominantly concentrated within the primary urban areas situated on the eastern side of the GPH, resulting in a higher likelihood of suitable habitats as the distance to these roads decreased. The influence of national and provincial roads on habitats was particularly noteworthy. Fig. A.2(c) and (e) in Appendix A Supplementary material illustrated that the national and provincial road networks in Sichuan Province were well-established in 2014, evidently fragmenting the GPH into multiple patches. Subsequent to 2014, the network structure of national and provincial roads continued to densify, further exacerbating their impact on the GPH. Moreover, in 2014, city arterial roads were primarily concentrated within the urban area of Chengdu city, with scattered distribution across other regions. However, by 2020, the coverage and quantity of city arterial roads had significantly increased. The one-way PDP of national and provincial roads demonstrated a positive linear relationship between the distance to these roads and the probability of suitable habitats within the range of 0–30 km. Beyond this threshold, the influence gradually diminished. Similarly, the one-way PDP analysis of city arterial roads also exhibited a positive linear relationship between the distance to these roads and the probability of suitable habitat within the range of 0–10 km, followed by a diminishing effect. Previous studies by He et al. (2019) suggested that the influence of national roads extended beyond a radius of 5 km, while provincial roads had an impact beyond 1.5 km. However, our findings indicated that transportation infrastructure such as national and provincial roads, as well as city arterial roads, may possess a broader scope of influence on GPH.

Regarding the distance to built-up areas, the one-way PDP analysis indicated that within a 5-km radius of human settlements, the likelihood of suitable habitats for giant pandas was relatively low. As the distance to human settlements increased, the probability of suitable habitats progressively rose. Nevertheless, beyond a distance of 20 km, there was no substantial impact on habitat suitability. The observed decline in probability after a distance of 35 km may be attributed to the limited presence of human settlements and habitat distribution on the western side of the study area. With respect to the "Population" predictor, the one-way PDP analysis revealed that the majority of data points are concentrated within the range of 0–50 individuals per square kilometer. Within this range, an increase in population density substantially diminished the probability of suitable habitats for giant pandas.

According to the results obtained from the one-way PDP analysis, it was evident that population distribution, human settlements, and transportation infrastructure all exerted an influence on GPH, and these effects exhibited marginal effects. Thus, in order to delve deeper into the potential synergistic effects between population density and human settlements, as well as six types of transportation infrastructure, on the prediction of suitable GPH, we conducted a two-way PDP analysis. Fig. 4 (E) provided insights into the joint influence of population density with distance to built-up areas and distance to transportation infrastructure on habitat suitability. Notably, the analysis revealed that the impact of population density on habitat suitability became negligible when considering its interaction with human settlements and transportation infrastructure. This finding reaffirmed the previously documented severe negative impact of transportation infrastructure development and human settlements on suitable GPH (Forestry Administration of Sichuan Province, 2015).

3.3. Overlay analysis results

According to the overlay analysis of the GPH from the most recent FGPS and GPNP boundaries (Fig. 3(A)), the Sichuan region of the GPNP covers 63.71 % of the GPH within the province, while 36.29 % remains outside the protected area of the national park. In contrast, Fig. 3(B) displayed the predicted habitat distribution in 2020, indicating that only 47.67 % of the GPH falls within the Sichuan region of the GPNP. The FGPS (Forestry Administration of Sichuan Province, 2015) emphasized the GPH in China has been fragmented into 33 patches due to topography such as mountains and rivers, as well as the distribution of vegetation and bamboo, human settlements, cropland, and transportation network. This fragmentation has led to the formation of 33 localized populations of giant pandas, exacerbating issues related to their population segregation. Moreover, the existence of geological hazards and the significant impacts of human activities continue to intensify the challenges faced by giant pandas in their survival. It is noteworthy that the current GPNP encompasses a limited number of habitat patches, specifically 18, highlighting the incomplete incorporation of all habitats within the protected boundaries of the GPNP. This necessitates additional efforts to guarantee the comprehensive protection and conservation of GPH within the boundaries of the national park.

Overlay analysis revealed that in the year 2020, the conflicts between human settlements and GPH, as well as transportation infrastructure and GPH, intensified compared to the year 2014. Consequently, the predicted habitats for 2020 exhibited a significant reduction of 28.44 % in comparison to the findings from the FGPS (Forestry Administration of Sichuan Province, 2015). Referring to Table 3, which provided the zoning framework for the management of the GPNP, it is notable that the current core protection zones of the GPNP still accommodate a population of 5553 individuals. Among these, the Sichuan region harbors 4009 residents, indicating the most prominent conflict among the three provinces encompassing the GPNP. Analysis of Fig. 5 revealed that the conflict between a large human settlement patch and the GPH is primarily concentrated in Chongzhou City. Additionally, smaller human settlement patches can be observed in multiple counties (cities, districts), including Dujiangyan City, Shawan District, Dayi County, Pingshan County, and Wenchuan County, within the GPH identified in the FGPS (Forestry Administration of Sichuan Province, 2015), each measuring less than 1 km^2.

Table 3
The Zoning framework for the management of the Giant Panda National Park. Unit: square kilometers, individuals.

Management zone		Area	Cropland	Collective land	Population
Giant Panda National Park	Core protection zone	20,140	20	3724	5553
	General control zone	6994	194	4035	115,285
	Subtotal	27,134	214	7758	120,838
Sichuan region	Core protection zone	15,519	13	2974	4009
	General control zone	4659	109	2532	85,924
	Subtotal	20,177	122	5506	89,933

Source: Giant Panda National Park General Master Plan (Draft for Public Consultation) (National Forestry and Grassland Administration of China, 2019).

Significantly, Fig. 5(C) and (D) highlighted the close proximity of Dujiangyan City's central urban area to the GPH, with certain rural settlements already encroaching upon the habitat range. Dujiangyan City is one of the cities (counties, districts) with the most prominent ecological issues within the study area. Encompassing a total area of 1206.84 km^2, the city exhibits conducive conditions for urban development. By the end of 2020, the city's population had reached 710,000, with an urbanization rate of 61.49 % and a population density of 588 individuals per square kilometer. Comparative analysis between the habitat from the FGPS in 2014 and the predicted habitat in 2020 revealed indications of habitat degradation and loss in Dujiangyan City. As documented in the "Spatial Planning of Dujiangyan City (2021-2035)" (Dujiangyan City Planning and Natural Resources Bureau, 2023), the GPH has been significantly influenced by human activities, notably agricultural development and tourism. Specifically, the mid-low mountain areas of Longmen Mountain face challenges arising from the expansion of industries such as kiwi fruit and Magnolia, leading to the simplification of local commercial forest communities. Furthermore, the Qingcheng Mountain Scenic Area necessitates effective coordination between tourist development and ecological environmental preservation.

4. Discussion

4.1. *Conflicts in giant panda habitat*

The GPH presents a complex human-wildlife relationship, where planners have selectively excluded certain conflicting human settlements, such as Emeishan City, Shawan District, and Kangding City, from the designated boundaries due to their overlap with the habitat identified in the FGPS. Although these regions demonstrate human-wildlife conflicts, the establishment of the GPNP needs to strike a balance between national park zoning and the future economic development

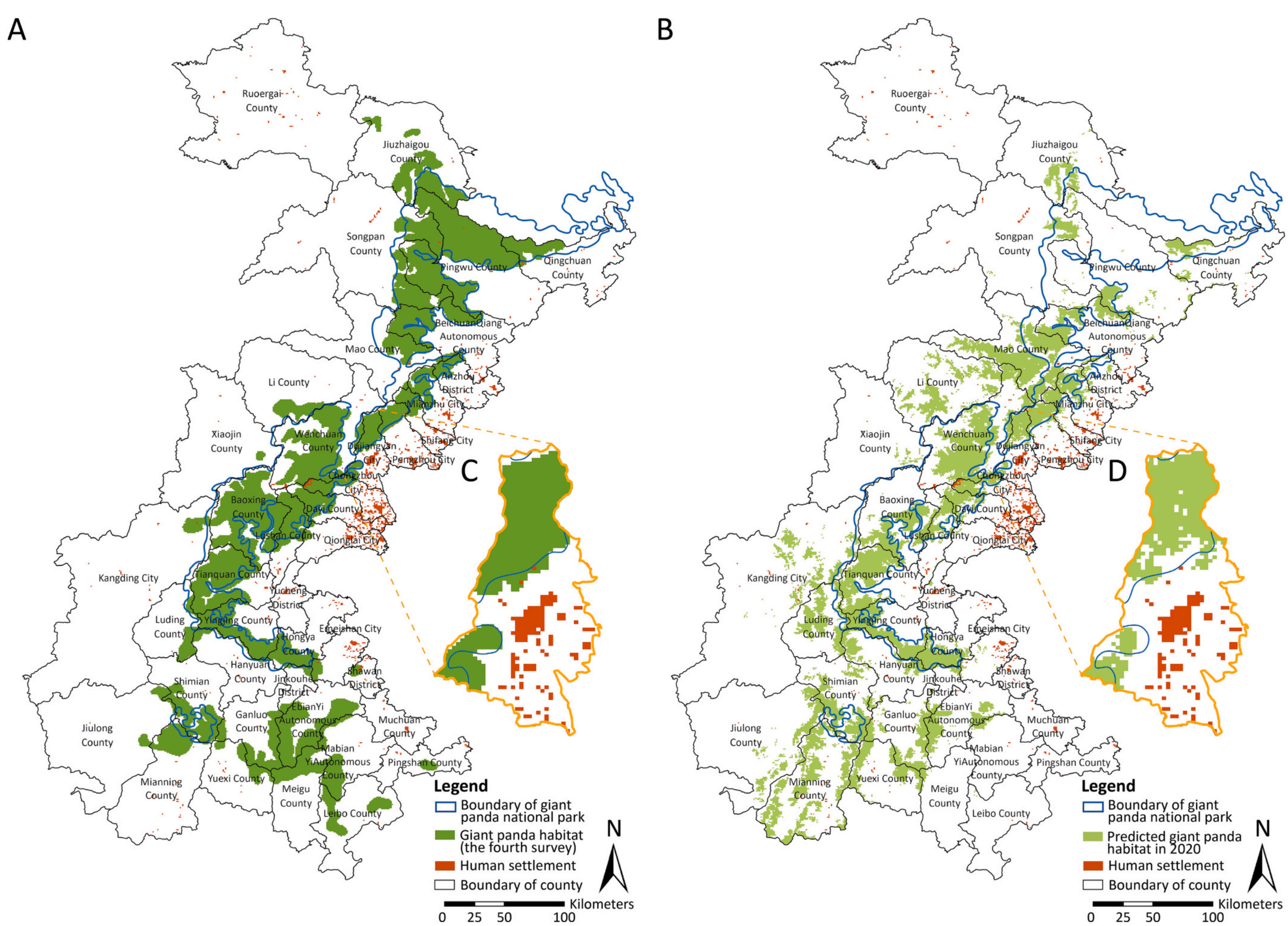

Fig. 5. (A) Map overlay of habitat (the fourth survey) and human settlements in 2020, (B) map overlay of predicted habitat in 2020 and human settlements in 2020, (C) map overlay of habitat (the fourth survey) and human settlements in 2020 in Dujiangyan, (D) map overlay of predicted habitat in 2020 and human settlements in 2020 in Dujiangyan.

demands of Sichuan Province. Consequently, these areas and their surrounding regions have not been incorporated into the GPNP. The primary function of national park establishment is the protection of important natural ecosystems, emphasizing the preservation of their authenticity and integrity by mitigating human disturbances. However, Sichuan Province faces unique challenges characterized by a monolithic local industrial structure, low household income levels, and incomplete infrastructure. In order to stimulate economic development, there is a pressing demand to exploit natural resources and develop infrastructure, creating a prominent contradiction with ecological conservation objectives. Addressing this issue demands diligent cooperation between the national park management institution and local governments, with a focus on aligning all levels of spatial and land-use planning. Concrete measures must be formulated to effectively balance economic development aspirations with the imperative of safeguarding ecological integrity.

As human settlements connect to the surrounding areas via various types of transportation infrastructure, they generate population and material flows that have negative impacts on the natural environment. For instance, the continuous noise and pollution generated by vehicular traffic on high-level motorized roads can disrupt surrounding vegetation communities and cut off ecological connections between different habitats. According to the “the Plan” document (National Forestry and Grassland Administration of China, 2019), the major railways traversing the current GPNP include the Xicheng High-Speed Railway, the Chengdu-Lanzhou High-Speed Railway, the Lanzhou-Chongqing Railway, and the Wuhan-Guangzhou High-Speed Railway. Existing motorways encompass the Ya'an-Xichang and Dujiangyan-Wenchuan routes, while ongoing construction projects include the Mianyang-Jiuzhaigou, Ya'an-Kangding, Deyang-Dujiangyan, and Pujiang-Dujiangyan motorways. Additionally, several routes, such as the G213, G350, G543, G544, S208, S308, S410, S421, and S433, constitute the national and provincial roads network. Observing the transportation infrastructure depicted in Fig. A.2 in Appendix A Supplementary material for the years 2014 and 2020, it becomes evident that the rapid development of Sichuan Province's economy has facilitated the substantial expansion of its transportation network. Numerous railway lines, motorways, and national and provincial roads have led to the fragmentation of GPH. Consequently, the conflict between transportation infrastructure and GPH is particularly escalated.

4.2. Suggestions on zoning designations and management measures

When the GPNP was established, the Chinese central government put forward requirements for the designations of zoning boundaries. It was stipulated that the GPNP should respectively cover 80 % of the giant panda population and 70 % of their habitat. These two indicators were determined as the core technical standards for the zoning of the GPNP. However, at present, the Sichuan region of the GPNP only covers 63.71 % of the GPH within Sichuan Province, which is lower than the average of all three regions. As shown in Fig. 3(A), the current GPNP failed to include the FGPS's complete coverage of GPH in counties (cities, districts) such as Jiuzhaigou County, Shawan District, Ebian Yi Autonomous County, and Ganluo County within the protected area of the national park. Therefore, boundary adjustments should be made promptly during the next planning phase. According to the predicted results in Fig. 3(B), there is a possibility of significant potential habitat distribution in Mao County, Mianning County, Luding County, and Li County. These areas should be given special attention during next on-site investigations. The previous survey of GPH was completed in 2014. In the recent ten years, the advancement of technologies, such as remote sensing and artificial intelligence, have held great potential for significantly enhancing the efficiency of monitoring and conservation tasks for national park managers. Therefore, we recommend that the species distribution survey of giant pandas be conducted every five years, enabling better adjustment of national park planning in response to changes in species requirements.

Currently, the GPNP employs a two-tier zoning management system. Approximately 74.22 % of the park's area is designated as the core protection zone, wherein all human activities are strictly prohibited. This region serves as a critical area for the maintenance of the existing giant panda population's normal reproduction and migration. The remaining 25.78 % of the park's area is designated as the general control zone, with specific limitations and prohibitions clearly defined. In order to enhance the density of the giant panda population and facilitate connectivity between habitat patches, priority should be given to the inclusion of significant panda activity areas within the core protection zone of the GPNP, while potential habitats should be encompassed within the general control zone. However, due to the vast expanse of GPH and the intricate human-wildlife relationship, practical implementation poses challenges. Therefore, during the initial phases of national park establishment, the authorities can collaborate with local governments and other nature reserve management institutions to conduct real-time monitoring and periodic assessments of panda activity ranges. The protection boundary and zoning management of the GPNP, along with other nature reserves, should undergo dynamic adjustments. In this process, gradual integration of surrounding nature reserves into the national park can be pursued. The boundaries of the national park can be dynamically modified via implementing an adaptive zoning framework, which takes into account the changing conservation demands of giant pandas and other wildlife species.

Regarding human settlement control, according to “the Plan” document (National Forestry and Grassland Administration of China, 2019), human activities are generally prohibited in the core protection zone, and the control measures require the completion of ecological relocation for all indigenous inhabitants by the end of the pilot period in 2025. Based on the findings of this study, we further recommend that, if settlements are located within the important living areas for giant pandas (i.e., adjusted core protection zone of the national park), these residents should be gradually relocated in accordance with the requirements of the “the Plan” document (National Forestry and Grassland Administration of China, 2019). In the analysis presented in Section 3.2, it was observed that there was a minimal possibility of suitable habitats within a range of 0–5 km from the human settlements, and the possibility gradually increased within a range of 5–20 km. Therefore, we suggest that a 5-km buffer zone around the important activity areas of giant pandas should also be gradually included in the core protection zone. Existing human settlements should be relocated in a phased manner, and following relocation, the ecological environment of the converted and cultivated land should be restored before it is integrated into the core protection zone of the national park.

In terms of transportation control, “the Plan” document specifies requirements for speed limits, restricted navigation, and low-noise management for waterway vessels, while control lines along existing roads and major facilities are subject to management within the general control zone (National Forestry and Grassland Administration of China, 2019). Within the general control zone, human activities are regulated in accordance with the law, allowing for the construction of linear infrastructure that is deemed necessary, unavoidable, and compliant with county-level or higher-level spatial planning, and facilities for flood control and water supply. At present, the core protection zone of the Sichuan region in the GPNP continues to be impacted by the presence of major high-level motorized roads, such as national and provincial roads. However, implementing strict enforcement of the prohibition of human activities within this zone presents practical challenges. In recognition of this issue, “the Plan” document includes provisions for managing control lines along roadsides and major facilities within the general control zone (National Forestry and Grassland Administration of China, 2019). Nonetheless, ensuring effective protection of the critical GPH within the general control zone may be a challenging task. Through our analysis in Section 3.2, it became apparent that the disturbance radius of national roads, provincial roads and city arterial roads on GPHs can extend beyond 10 km. In consequence, it is recommended that the national park adheres to consistent regulations as waterway vessels concerning significant railways, motorways, and other transportation infrastructures traversing the core protection zone. Such regulations should encompass requirements for speed limits, traffic control, and low-noise management. Furthermore, for future transportation infrastructure planning, it is advisable to allocate a buffer zone of at least 10 km to facilitate the establishment of ecological corridors and the restoration of potential habitats.

5. Conclusions

This study attempted to put forward an analytical framework, utilizing interpretable machine learning methods, to explore the rationality of the zoning boundaries and management measures for protecting wildlife habitats in data-poor Chinese national parks. By performing a case study in the Sichuan region of the GPNP, our research revealed the mechanisms through which environmental and anthropogenic factors influenced the distribution of GPH, identified the threshold of influence, and employed overlay analysis to pinpoint existing conflicts within the study area. According to our findings, recommendations were proposed for zoning designations and management measures. The methods and analytical framework proposed in our study can also be implemented in other national parks or protected areas with limited species distribution data.

By constructing a SDM based on the RF algorithm, we discovered that the GPH in Sichuan Province may have decreased by 28.44 % in 2020 compared to 2014. Further analysis using PDPs and SHAP values revealed that environmental factors such as temperature, topography, and vegetation type significantly influenced the distribution of GPH. Regarding human-related factors, according to the one-way PDP analysis, population density, human settlements, and transportation infrastructure represented by national roads, provincial roads and city arterial roads all had an impact on the GPH. Furthermore, these impacts exhibited marginal effects. For instance, the probability of existing GPH was lowest within a 5-km radius of human settlements, gradually increasing within the range of 5–20 km. Different levels of transportation infrastructure, especially national roads, provincial roads and city arterial roads, had negative effects on GPH, with the influence range potentially exceeding 10 km. The swift expansion of the transportation system in Sichuan Province from 2014 to 2020 may have been a substantial factor contributing to habitat degradation.

The Sichuan region of the GPNP covers 63.71 % of the GPH within Sichuan Province, indicating that 36.29 % is presently not encompassed within the boundary of the national park. We recommend conducting species distribution surveys for giant pandas and planning adjustments for national parks every five years during the early stages of national park development. For optimal protection, the national park should incorporate the important activity areas of giant pandas into the core protection zone and designate potential habitats as the general control zone. However, in practical implementation, the overall planning of the national park needs to consider the distribution of existing residents, their livelihoods, ecological tourisms, and the status of infrastructure. Therefore, collaboration between the national park management authorities, local governments, and other nature reserve management institutions is essential. This collaboration would involve the establishment of dynamic zoning, gradual integration of surrounding nature reserves into the national park, and relocation of human settlements. In terms of specific control measures, we suggest that human settlements within the important activity areas of giant pandas and their 5-km buffer zone should be gradually relocated and incorporated into the core protection zone after ecological restoration. For existing important transportation infrastructure that crosses the habitats, speed limits, traffic control, and low-noise management measures should be implemented. For planned transportation facilities that have not yet been constructed, it is recommended to reserve a buffer space of at least 10 km between them and the core protection zone.

Our study has several limitations. First, the data accuracy for constructing the SDM was at a resolution of 1 km, and it lacks data related to different human activity types. Future improvements can be made with higher-resolution, real-time, and more comprehensive data. Second, the study was constrained by the defined research scope, and the marginal areas may be influenced by factors outside the scope of the study. This limitation can result in less accurate prediction models and weaker interpretability for certain factors. Expanding the study area and considering a wider range of factors would enhance our understanding of ecological dynamics and SDM interpretability.

CRediT authorship contribution statement

Yuhan Xu: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. **Jun Tang:** Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to polish and improve the writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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