Prediction of Distribution Areas of Major Poisonous Weeds in Xinjiang Based on a Random Forest Model (Postprint)

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Abstract

As one of China' s major pastoral regions, Xinjiang faces a severe threat to animal husbandry and the ecological environment from grassland degradation, particularly degradation dominated by toxic weeds. Traditional remote sensing methods encounter considerable difficulty in identifying toxic weeds, whereas machine learning prediction models that integrate multi-source environmental factors can effectively enhance the accuracy of toxic weed identification. In this study, based on a random forest model and through analysis of ecological factors and the distribution data of toxic weeds, we assessed the main ecological factors influencing the distribution of five typical toxic weed species in Xinjiang, and predicted their potential distribution areas under current (1970–2020) and future (2021–2040) climate scenarios. The results show that: (1) All model evaluation metrics (Accuracy, Precision, Recall, and F1-score) exceed 0.90, indicating that the model has high accuracy and strong generalization capability. (2) Key factors affecting the distribution of toxic weeds include isothermality, temperature seasonality (coefficient of variation), and elevation, among others. (3) According to model predictions, under both current and future climate scenarios, the distribution areas of toxic weeds are mainly concentrated in regions such as Altay, Urumqi, Changji, Tacheng, and Ili. (4) Under the SSP126 scenario, the distribution of toxic weeds exhibits an overall northward and southward shift with relatively small fluctuations and short migration distances of the distribution centroid; under the SSP245 scenario, intensified ecological stress leads to greater distribution fluctuations, longer migration distances, and reduced ecosystem stability. By revealing the main ecological factors influencing toxic weed distribution and the trends in distributional changes, this study provides a scientific basis and data support for the management of toxic weeds in Xinjiang.

Full Text

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Abstract

As one of China' s major pastoral regions, Xinjiang faces significant threats from grassland degradation, particularly poisonous weed proliferation, which adversely affects animal husbandry and ecological stability. Traditional remote sensing techniques encounter limitations in accurately identifying poisonous weed species. Conversely, machine learning models integrating multisource environmental factors offer substantial improvements in prediction accuracy concerning the poisonous weed distribution. This study employed a Random Forest model to analyze ecological drivers and poisonous weed distribution data, aiming to identify the primary environmental variables influencing the spatial patterns of five representative poisonous weed species in Xinjiang. Furthermore, the potential distribution areas of these species were predicted under current (1970–2020) and near-future (2021–2040) climatic conditions based on different shared socioeconomic pathway scenarios. The model demonstrated high predictive performance, with evaluation metrics, including Accuracy, Precision, Recall, and F1-score, all exceeding 0.90, confirming its robustness and generalization capability. The key ecological variables influencing poisonous weed distribution include isothermality, temperature seasonality, and elevation. According to the model projections, the current and future potential distribution areas are predominantly located in northern Xinjiang, particularly in Altay, Urumqi, Changji, Tacheng, and Ili. Under the SSP126 scenario, the poisonous weed distribution exhibited relatively stable spatial shifts, with slight northward and southward movements and shorter migration distances. Contrarily, under the SSP245 scenario, increased ecological stress portended greater distributional fluctuations, longer migration distances, and a notable decline in ecosystem stability. This research highlights the importance of integrating ecological and climatic variables with machine learning approaches for effective species distribution modeling. The findings provide valuable insights into the ecological behavior of poisonous weeds and offer a scientific basis for regional grassland management strategies in Xinjiang. By forecasting the spatial responses of poisonous species under varying climate change scenarios, this study supports the development of adaptive management plans to mitigate the ecological and economic effects of poisonous weed encroachment in arid and semi-arid pastoral systems.

Keywords: Random Forest model; ecological factors; poisonous weeds; potential distribution area

1 Introduction

Xinjiang ranks as one of China' s principal pastoral regions, with its natural grassland area ranking third nationally. These grasslands constitute the material foundation for livestock development and represent a critical component of Xinjiang' s natural ecological environment. However, long-term impacts from both natural and anthropogenic factors—including climate change, overgrazing, blind reclamation, and population growth—have induced grassland degradation. This degradation manifests as the annual deterioration of high-quality forage and rapid expansion of poisonous weeds, leading to large-scale desertification and weed encroachment that severely constrain sustainable development of the grassland livestock economy. Poisonous weed-induced degradation differs from other degradation types as it does not present typical characteristics such as bare ground or reduced total vegetation cover. Consequently, traditional remote sensing indicators like Normalized Difference Vegetation Index (NDVI) encounter significant difficulties in identifying poisonous weeds across large regions, sometimes even producing false trends of "greening" in grassland remote sensing imagery. Previous studies on poisonous weed identification and distribution prediction have been limited by high model complexity, incomplete feature selection, and insufficient recognition accuracy, restricting their practical application.

The Random Forest model represents a widely used machine learning method that employs ensemble learning to combine multiple weak classifiers (individual decision trees) into a stronger classifier. Analysis of several common machine learning models reveals that Random Forest exhibits stronger anti-overfitting capabilities, broader applicability, easier parameter adjustment, and higher robustness. Due to its high accuracy in regression and classification tasks, Random Forest has been extensively applied in plant distribution prediction and poisonous weed identification. For instance, Zhang et al. successfully predicted the potential suitable areas of *Praxelis clematidea* in China using Random Forest combined with GIS technology, analyzing environmental factors and classifying suitability levels while comparing future climate scenario changes. Jiang et al. conducted national-scale potential distribution predictions and suitability evaluations for *Pinus koraiensis* using Random Forest, validating integrated application effects in Fushun City. These studies demonstrate that Random Forest' s strong anti-overfitting capability, broad applicability, parameter adjustability, and high prediction accuracy confer significant advantages in plant distribution prediction and poisonous weed identification.

However, existing research exhibits several limitations: model feature selection predominantly relies on conventional climatic factors with insufficient integration of ecological variables; limited investigation into the spatiotemporal distribution of typical poisonous weeds in Xinjiang and their potential expansion patterns under future climate scenarios; and lack of systematic analysis on centroid migration trajectories and spatial dynamics of poisonous weeds, which restricts the practical management value of these models.

Therefore, this study aims to combine Random Forest modeling with multi-source ecological factor data and distribution information for typical poisonous weeds in Xinjiang to: (1) identify key ecological factors influencing their distribution; (2) predict current and future potential distribution areas; (3) map centroid migration trajectories; and (4) analyze spatial dynamics under different climate scenarios. The research provides scientific foundations and data support for poisonous weed control and grassland degradation management in Xinjiang while offering references for similar arid pastoral regions.

1.1 Study Area Overview

Xinjiang exhibits diverse geomorphological types, including plains, mountains, and deserts. The climate is predominantly temperate continental and alpine. Due to its inland location far from oceans, precipitation is scarce while evaporation rates are high, resulting in an arid climate with annual precipitation mostly below 200 mm.

1.2 Data Sources

1.2.1 Poisonous Weed Distribution Data Poisonous weed distribution data were obtained from the Global Biodiversity Information Facility (GBIF) and the National Specimen Platform of China (NSII). The study collected 1,237 distribution records for five poisonous weed species: *Aconitum leucostomum* (white-throated monkshood), *Sophora alopecuroides* (foxtail sophora), *Ligularia narynensis* (Naryn ligularia), *Anabasis aphylla* (leafless anabasis), and *Oxytropis glabra* (small-flowered oxytropis). These species were selected due to their wide distribution, significant toxicity, and substantial threats to grassland ecosystems and livestock safety in Xinjiang.

1.2.2 Ecological Factor Data Historical data encompassed 19 global bioclimatic variables, soil information, elevation data, and grazing intensity data for Xinjiang. Future climate data were based on the CMIP6 ESM1-5 climate model, selecting four scenario combinations (SSP126 and SSP245) for two periods (2021-2040 and 2041-2060), using 19 global bioclimatic variables for analysis. SSP126 and SSP245 represent low and medium emission scenarios, corresponding to different socioeconomic development pathways and greenhouse gas emission levels. Historical climate data (1970-2020), monthly average climate data (2021-2040), and elevation data were downloaded from the WorldClim environmental database. Grazing intensity data were based on 2.5-minute livestock density distribution maps (spatial resolution 3 min) and integrated with Xinjiang county-level statistical data through spatiotemporal interpolation. Soil data were obtained from the Earth Resources Data Cloud Platform (www.gis5g.com). All data were uniformly resampled to 2.5-minute resolution and spatially processed. This study adopted major ecological factors referenced from existing research, with newly added ecological factors detailed in Table 1.

1.3 Methods

1.3.1 Data Preprocessing For the distribution data of five poisonous weed species, duplicate points and points without coordinate information were removed. To address missing values in environmental factor data, mean imputation was applied, replacing missing data with the mean of observed values for each factor. After defining target and feature variables, standardization was performed. Pseudo-negative samples were generated using ArcGIS' s random point generation tool. The Extract Values to Points tool integrated poisonous weed distribution data with historical ecological factor data into training datasets, where presence points were assigned a value of 1 and absence points a value of 0. The training dataset was split 70:30 for training and testing.

1.3.2 Random Forest Model Training Random Forest is a typical machine learning algorithm that integrates multiple decision trees for classification and regression, exhibiting strong anti-overfitting capabilities and high prediction accuracy. For poisonous weed identification, it effectively distinguishes poisonous weeds from non-poisonous vegetation using multisource environmental factors (soil, climate, and topography), improving identification efficiency and accuracy. The SMOTE method was used to balance the dataset and initialize the model. Hyperparameters were set including bootstrap sampling, maximum tree depth, maximum features, minimum sample leaf size, minimum sample split size, and number of decision trees. Bootstrap sampling determines whether samples are drawn with replacement, affecting tree diversity and robustness. Maximum tree depth and maximum features control tree complexity to prevent overfitting. Minimum sample leaf size and minimum sample split size limit node splitting and leaf generation, enhancing model generalization capability. The number of decision trees reduces variance.

1.3.3 Hyperparameter Optimization Random Forest hyperparameter settings directly influence model complexity and generalization capability. Improper parameter selection may lead to overfitting or underfitting. This study employed random search combined with 5-fold cross-validation for hyperparameter optimization to improve model performance.

1.3.5 Poisonous Weed Distribution Prediction Based on the trained Random Forest model, different probability thresholds were set to generate gradient distribution probability maps for poisonous weeds across five levels: 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9, and >0.9. Future climate scenario predictions were spatially compared with current period simulations to quantitatively analyze spatial pattern changes of poisonous weed distribution areas in Xinjiang under future climate scenarios. Additionally, to investigate spatiotemporal migration characteristics of poisonous weed centroids, ArcGIS' s centroid calculation tool was used to construct migration trajectories across different periods.

1.3.6 Model Accuracy Evaluation To assess model classification performance, 5-fold cross-validation was conducted on the test set. Based on test set predictions, Accuracy, Precision, Recall, and F1-score metrics were comprehensively used to evaluate model precision and generalization capability. This process helps reduce overfitting risk and avoids result bias from sample partition errors. Different metrics are defined in Table 3. Five-fold cross-validation was performed for each of the five poisonous weed species to determine optimal hyperparameter values.

2 Results

2.1 Model Hyperparameters

Based on determined hyperparameters, random search was applied separately for each of the five poisonous weed species after 5-fold cross-validation. Optimal hyperparameter values are shown in Table 4.

2.2 Model Accuracy Evaluation

Using the determined hyperparameters, the Random Forest model achieved all evaluation metrics >0.90 for the five poisonous weed species after 5-fold cross-validation (Table 5), reflecting high precision and generalization capability in predicting potential distributions.

2.3 Key Ecological Factors Influencing Poisonous Weed Distribution

Random Forest feature importance assessment and correlation matrix analysis identified the top three ecological factors for the five poisonous weed species as isothermality (bio03), temperature seasonality (bio04), and elevation. Species-specific responses varied: *Aconitum leucostomum* distribution was also influenced by soil silt content (T_{Silt}) and minimum temperature of the coldest month (bio06); *Ligularia narynensis* and *Sophora alopecuroides* showed high sensitivity to minimum temperature of the coldest month (bio07); *Anabasis aphylla* was primarily affected by minimum temperature of the coldest month (bio07); and *Oxytropis glabra* distribution correlated closely with mean diurnal temperature range (bio02).

2.4 Current Period Poisonous Weed Distribution Prediction

Current period (1970–2020) predictions show distribution areas for all five poisonous weed species concentrated in Altay, Urumqi, Changji, Tacheng, and Ili regions. *Sophora alopecuroides*, *Ligularia narynensis*, and *Anabasis aphylla* exhibited larger distribution ranges. Among simulated distribution areas, these three species had >24.04% of regions with invasion probability >0.8. *Sophora alopecuroides* and *Anabasis aphylla* showed substantial distribution areas in Altay, Tacheng, Changji, and Urumqi, while *Oxytropis glabra* concentrated in southern Altay, Tacheng, and northwestern Urumqi. *Aconitum leucostomum* and *Ligularia narynensis* exhibited severe invasion in Ili. Northern Bayingolin Mongol Autonomous Prefecture and southern Turpan showed relatively low invasion intensity.

2.5 Future Climate Scenario Predictions

Under the SSP126 scenario, *Sophora alopecuroides*, *Ligularia narynensis*, and *Anabasis aphylla* maintained relatively extensive distributions, with >25.49% of areas showing invasion probability >0.8. Under both future scenarios, invasion regions for the five poisonous weeds remained consistent, concentrated in Altay, Urumqi, Changji, Tacheng, and Ili. *Sophora alopecuroides*, *Anabasis aphylla*, and *Oxytropis glabra* distributions in both scenarios concentrated in Altay, Tacheng, Changji, and Urumqi. *Aconitum leucostomum* remained widely distributed in Ili, while *Ligularia narynensis* showed new suitable areas in southern Bayingolin in addition to its large distribution in Ili. Compared with the current period, Karamay and Bortala also face invasion risks. Northern Bayingolin and southern Turpan maintained relatively low invasion intensity.

2.6 Spatial Pattern Changes

Spatial change trends for poisonous weeds are illustrated in Figures 7 and 8. Under SSP126, *Aconitum leucostomum* showed the largest expansion, with invasion areas of 42,446.25 km^2 (17.84% of total area). *Sophora alopecuroides* exhibited the greatest contraction in both scenarios, with contraction areas of 69,867.00 km^2 (23.98%) under SSP126 and 68,449.50 km^2 (21.20%) under SSP245. *Anabasis aphylla* and *Ligularia narynensis* retained large stable areas under both scenarios, while *Oxytropis glabra* showed relatively high fluctuation with similar expansion and contraction areas. Overall, distribution fluctuations were greater under SSP245 than SSP126.

2.7 Prediction of Poisonous Weed Distribution Centroid Migration

Using 1970–2020 as the baseline period, centroid migration trajectories under SSP126 and SSP245 scenarios (Figures 9 and 10) show overall northward and southward migration of poisonous weed distribution areas during 2021–2040 and 2041–2060. Under SSP126, cumulative migration distances for all species were lower than under SSP245. *Sophora alopecuroides* showed the longest cumulative migration distance under both scenarios. Under SSP126, *Aconitum leucostomum* had the shortest migration distance, while under SSP245, *Ligularia narynensis* had the shortest migration distance.

3 Discussion

3.1 Model Evaluation and Analysis of Key Ecological Factors

This study employed 5-fold cross-validation for model training and validation, using Accuracy, Precision, Recall, and F1-score metrics to comprehensively evaluate model performance across different probability thresholds. All evaluation metrics exceeded 0.90, indicating high prediction accuracy and generalization capability. The variable selection process incorporated not only conventional climatic factors like precipitation and temperature but also grazing intensity and soil properties to enhance reflection of actual ecological characteristics in the study area. Further analysis revealed that isothermality, temperature seasonality, and elevation significantly influence poisonous weed distribution. For *Aconitum leucostomum*, isothermality was the key variable, consistent with Yang et al.' s findings. *Anabasis aphylla*, a drought-tolerant plant growing in arid low mountain gravel deserts, shows high survival probability under low precipitation in the driest month, demonstrating strong adaptation to arid environments. Important factors affecting its distribution were unrelated to precipitation. Peng' s research indicates that *Anabasis aphylla* seed germination is unaffected by precipitation, further confirming the dominant role of temperature factors over precipitation factors in this study. *Ligularia narynensis* is also influenced by precipitation in the warmest quarter, requiring higher moisture conditions, consistent with Hou et al.' s research. *Oxytropis glabra* and *Sophora alopecuroides* growth are affected by mean diurnal temperature range and mean temperature in the wettest quarter, respectively, aligning with Zhang et al. and Lu et al.' s findings.

3.2 Potential Distribution Patterns Under Different Climate Scenarios

The five poisonous weed species showed distinct regional concentration, primarily in Altay, Urumqi, Changji, Tacheng, and Ili. These regions are characterized by arid climate, concentrated summer precipitation, diverse topography, high habitat heterogeneity, and long-term overgrazing with frequent human disturbance, creating vegetation degradation and ecological niche vacancies that facilitate poisonous weed invasion. At the species level, *Sophora alopecuroides*, *Ligularia narynensis*, and *Anabasis aphylla* demonstrated strong ecological adaptability and dispersal capacity, with >24.04% of areas showing invasion probability >0.8, indicating stable populations across broad ecological gradients with strong stress resistance and competitive advantages. Ili represents a high-risk area for *Aconitum leucostomum* and *Ligularia narynensis*, potentially associated with humid climate and intensive grassland utilization. In contrast, *Sophora alopecuroides*, *Anabasis aphylla*, and *Oxytropis glabra* concentrated in Altay, Tacheng, and Changji, more significantly affected by human disturbance. Northern Bayingolin and southern Turpan maintained relatively low invasion intensity due to ecological stability and dry climate. Under future SSP126 and SSP245 scenarios, potential distribution areas for the five poisonous weeds will continue concentrating in these regions while expanding toward Karamay and Bortala. Notably, *Ligularia narynensis* formed new high-risk areas in the Altun Mountains of southern Bayingolin, suggesting its potential to cross arid, cold, high-altitude ecological barriers. Overall, expansion under SSP245 was more significant than under SSP126, reflecting stronger adaptability of poisonous weeds under high radiative forcing conditions. From an ecological risk perspective, the northern slope of the Tianshan Mountains economic belt, southern Altai Mountains, and Ili River Valley represent future key invasion areas, providing favorable growth conditions due to suitable climate, good water-heat conditions, and strong human interference.

3.3 Spatial Response and Migration of Poisonous Weeds Under Different Climate Scenarios

Under different climate change scenarios, various poisonous weeds exhibited significant spatial response differences. *Aconitum leucostomum* showed clear expansion trends under both SSP126 and SSP245 scenarios, reflecting strong environmental adaptability and potential invasion risk. In contrast, *Sophora alopecuroides* exhibited substantial contraction trends under both scenarios, with more significant contraction under SSP245, indicating high sensitivity to adverse climate factors such as high temperature and drought. *Anabasis aphylla* and *Ligularia narynensis*, which prefer moist or alpine environments, showed smaller distribution changes under different climate scenarios, possibly due to their strong adaptability to ecological buffer zone characteristics, thereby resisting adverse climate change impacts to some extent. *Oxytropis glabra* fluctuated frequently between expansion and contraction, showing poor niche stability. Overall, under SSP126, climate change was relatively mild with limited temperature increases and insignificant precipitation pattern changes, resulting in smaller grassland ecosystem degradation trends. Under this scenario, poisonous weed distribution changes were relatively small, with overall slow northward and southward migration, short centroid movement distances, and low spatial volatility. In contrast, under SSP245, climate variability was significantly enhanced, with regional annual mean temperature increases, uneven spatiotemporal precipitation distribution, frequent extreme weather events, and 叠加 soil quality deterioration, intensifying habitat fragmentation, increasing centroid migration distances, and raising distribution pattern instability. These results align with Dai et al.' s conclusion that species distribution volatility increases under medium-high emission scenarios. Chen et al.' s MaxEnt model studies similarly indicate that plant distribution changes become more complex under stronger climate pressures, further verifying the reliability and scientific validity of this study' s results.

4 Conclusion

This study reveals spatial distribution characteristics and key ecological drivers of major poisonous weeds in Xinjiang based on Random Forest modeling. The findings indicate that isothermality, temperature seasonality, and elevation are the primary factors affecting their distribution. Poisonous weeds mainly concentrate in Urumqi, Changji, Tacheng, and Ili, with the highest invasion risks in ecologically vulnerable areas such as the northern Tianshan slope, southern Altai Mountains, and Ili River Valley. Distribution patterns differ significantly under different climate scenarios: under the mild SSP126 scenario, migration is slower with smaller fluctuations; under the high-variability SSP245 scenario, distribution fluctuations are greater with significantly increased centroid migration distances, indicating intensified habitat fragmentation and declining ecosystem stability trends.

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Figure 1

Figure 1: Figure 1

Figure 4

Figure 2: Figure 4

Figures

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Figure 5

Figure 3: Figure 5

Figure 6

Figure 4: Figure 6

Figure 7

Figure 5: Figure 7