

UAV-Based Multi-temporal Extraction and Post-processing of *Pedicularis kansuensis* in Bayanbulak Grassland

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Abstract

Invasive plants have severely affected global ecosystem functioning and biodiversity. Existing research has primarily focused on monitoring and classification of single temporal phases, while continuous multi-temporal monitoring of key phenological stages, particularly early phenological stage monitoring, remains relatively limited. Therefore, this study utilizes UAV multispectral remote sensing data and machine learning algorithms to extract the spatial distribution of key phenological stages (seedling stage, initial flowering stage, full flowering stage, and fruiting stage) of the invasive plant *Pedicularis kansuensis* in the Bayanbulak Grassland of Xinjiang. The results demonstrate that: (1) the spatial distribution of the early growth period (seedling stage and initial flowering stage) shows high spatial coincidence with the full flowering stage, and the Random Forest algorithm can effectively achieve distribution mapping of early-stage *Pedicularis kansuensis*; (2) the spatial distribution pattern of *Pedicularis kansuensis* exhibits significant interannual variability, with an interannual spatial distribution coincidence rate of less than 15%; (3) during the growing season (excluding the fruiting stage), the Normalized Difference Vegetation Index calculated from the 555 nm and 720 nm bands is of highest importance, followed by the visible green band. These results demonstrate the feasibility of UAV multispectral remote sensing technology for monitoring early phenological stages of *Pedicularis kansuensis*, providing technical support for early warning and control.

Full Text

Multitemporal Extraction of *Pedicularis kansuensis* in the Bayinbuluk Grassland Based on UAV Images

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Abstract

Invasive plants have significantly impacted global ecosystem functions and biodiversity. Existing research has primarily focused on single-phase monitoring and classification of vegetation, with relatively few studies addressing continuous multitemporal monitoring of key phenological stages, particularly during early phenological phases. This study examined *Pedicularis kansuensis*, an invasive plant in the Bayinbuluk grassland of Xinjiang, using UAV-based multispectral remote sensing data and machine learning algorithms to extract its spatial distribution during critical phenological stages (emergence, initial flowering, peak flowering, and senescence). The results demonstrated that: (1) The Random Forest algorithm slightly outperformed Support Vector Machine, with model accuracy varying across growth stages in the following order: peak flowering stage (late July to late August) > initial flowering stage (late June to early July) > emergence stage (mid-June) > senescence stage (mid-September). Monitoring throughout the growing season revealed that spatial distributions during early growth stages (emergence and initial flowering) exhibited high spatial overlap with the peak flowering stage, and the identified key features remained consistent with those of the peak flowering stage. This indicates that the Random Forest algorithm can effectively map early-stage *P. kansuensis* distribution, providing crucial technical support for early monitoring of invasive plants; (2) The spatial distribution patterns of *P. kansuensis* showed significant inter-annual variation, with spatial overlap between years being less than 15%; (3) During the growing season (excluding the senescence stage), the most important feature for distinguishing *P. kansuensis* from other land cover types was the normalized difference vegetation index calculated from the 555 nm and 720 nm bands, followed by the visible green band. These findings demonstrate the feasibility of

using UAV multispectral remote sensing technology for monitoring early phenological stages of *P. kansuensis* and provide technical support for early warning and control measures.

Keywords: *Pedicularis kansuensis*; unmanned aerial vehicle; multispectral data; Random Forest; multitemporal imagery; key phenological stages

Invasive plants have altered plant communities and ecosystem functions worldwide, posing a severe threat to native community structure and biodiversity. Under global climate change, controlling invasive plants is crucial for maintaining grassland ecosystem stability and biodiversity. The spectral differences between invasive plants and native dominant species during phenological stages create opportunities for remote sensing monitoring of their spatiotemporal distribution. *Pedicularis kansuensis*, a semi-parasitic invasive plant, has been expanding in Xinjiang, Tibet, and Qinghai provinces of China. Its rapid spread significantly impacts grassland ecosystems and threatens local livestock development. As an annual or biennial herb with strong reproductive capacity and parasitic characteristics, this species has rapidly proliferated in the Bayinbuluk grassland of the Tianshan Mountains, posing a serious threat to native forage grasses and substantially altering the original community ecological balance.

Previous control measures for *P. kansuensis* have primarily focused on the peak flowering stage, employing manual removal, corolla removal, or mowing. However, the plant's flowering period lasts over 40 days, during which it produces numerous seeds. Mowing and manual removal often disperse these seeds, resulting in unexpected control outcomes and increased germination the following year. Existing remote sensing and UAV-based identification studies of *P. kansuensis* have concentrated on the peak flowering stage, leaving an urgent need to determine whether identification before peak flowering is feasible.

This study utilized UAV multispectral remote sensing data and machine learning algorithms to conduct multitemporal monitoring of *P. kansuensis* during key phenological stages in 2023 and 2024. By extracting and identifying *P. kansuensis* and other land cover types from multitemporal multispectral UAV data, we investigated the feasibility of extracting the species at each phenological stage and analyzed inter-annual spatial distribution changes, providing a scientific basis for developing targeted control strategies against *P. kansuensis* expansion.

1.1 Study Area Overview

The study area (Fig. 1) is located in the Bayinbuluk grassland, Hejing County, Bayingolin Mongol Autonomous Prefecture, Xinjiang (42°18'–43°34' N, 82°27'–86°17' E). Situated in a high-altitude intermountain basin with an average elevation of 2,500 m, the region has a mean annual precipitation of 265.7 mm and an average temperature of -4.8°C. The natural vegetation community is domi-

nated by perennial forage grasses, including *Stipa purpurea*, *Festuca kryloviana*, *Koeleria cristata*, *Leymus tianschanicus*, *Elymus nutans*, and *Potentilla multifida*. *P. kansuensis* is primarily distributed in the alpine grasslands around the basin periphery and sporadically in wetland areas. The growing season for *P. kansuensis* in the Bayinbuluk grassland typically spans 110 days, beginning to regreen in mid-May, entering the initial flowering stage by late June, reaching peak flowering in late July, and entering the senescence stage by late August.

This study was conducted in the Dayou' erduosi Basin of the Bayinbuluk grassland, where three sample plots were established for UAV observations and ground surveys. Each plot measured approximately 100 m \times 100 m, with three 1 m \times 1 m quadrats established in each plot. Ground surveys were conducted simultaneously after each UAV data collection to confirm plant community composition. Table 1 provides detailed information on species composition and basic characteristics of the sample plots.

1.2 Data Sources and Preprocessing

The study employed a DJI Matrice 300 RTK UAV equipped with a MS600 Pro multispectral camera system for data acquisition. The MS600 Pro camera features six spectral channels: three visible bands (blue: 450 nm, green: 555 nm, red: 660 nm), two red-edge bands (720 nm and 750 nm), and one near-infrared band (840 nm). The high-precision positioning system combined with multispectral imaging technology enabled capture of fine-scale temporal data on vegetation growth status.

UAV data collection was conducted on multiple dates in June, July, August, and September 2023, with specific sampling dates listed in Table 2. To minimize illumination effects, data acquisition was performed between 10:00-14:00 local time under clear, cloud-free conditions. Standard gray panels were photographed before and after each flight for radiometric correction, with the panel placed horizontally on open ground and the multispectral camera hovering vertically 80 cm above it to ensure shadow-free conditions.

The preprocessing workflow included: (1) Band registration and radiometric calibration using Ysense Map software, converting raw data to reflectance values using standard gray panel reflectance data; (2) Geometric correction using Pix4D software, including feature point extraction, matching, dense point cloud generation, texture mapping, and orthorectification to produce orthophotos; (3) Precise geometric registration of multi-temporal images for the same plot using ArcGIS software to ensure spatial consistency; and (4) Regional cropping.

Flight parameters were set as follows: flight altitude of 120 m, forward overlap of 80%, side overlap of 75%, and outward expansion margin of 10 m. The normalized difference vegetation index effectively eliminates reflectance effects from cloud shadows and terrain undulation. Based on this characteristic, we calculated normalized spectral indices for all possible band combinations to eliminate interference from clouds and other backgrounds, denoted as ND_{Ji},

where j and i represent specific band numbers. In the formula: $ND_{ji} = (j - i)/(j + i)$, where j and i represent reflectance values of the j -th and i -th multispectral bands, respectively.

1.3 Feature Selection and Sample Collection

The feature set comprised single-band spectral features and normalized difference vegetation indices. Single-band spectral features utilized reflectance data from the six bands of the MS600 Pro camera. Sample data were collected based on field quadrat surveys combined with visual interpretation of UAV imagery. The main land cover types in the study area included *P. kansuensis*, perennial herbaceous plants, and bare land (Plot 1 also contained river channels). Given that the study objective focused on *P. kansuensis*, samples were divided into two categories: *P. kansuensis* and other land cover types. Detailed sample information is provided in Table 3. The collected samples were split into training and validation sets at a 7:3 ratio for machine learning algorithm training and accuracy verification.

1.4 Machine Learning Methods

Support Vector Machine (SVM) is a machine learning algorithm based on statistical learning theory that finds an optimal hyperplane to separate data points of different classes by maximizing the margin between them. SVM offers advantages in handling small samples, resisting noise, and analyzing high-dimensional data, maximizing model generalization capability.

Random Forest (RF) is a machine learning algorithm that integrates multiple decision trees based on Classification and Regression Tree (CART) methodology. The algorithm resamples the training dataset into multiple subsets, trains a classification tree for each subset, and determines the final prediction through voting. RF demonstrates unique advantages in analyzing large datasets with high-dimensional features, evaluating feature importance, and resisting overfitting.

This study employed grid search to optimize key hyperparameters for both algorithms. For SVM, the penalty parameter C was tested in the range [0.1, 1, 10] with kernel functions including linear, radial basis function (RBF), and polynomial. For RF, preliminary experiments indicated that model performance stabilized with 200 trees, so this was fixed. Remaining hyperparameters were optimized via grid search: minimum leaf node samples [3, 5, 7, 10], tree depth [6, 8, 10, 15], and feature selection methods including sqrt and log2. Both algorithms used 10-fold cross-validation to determine optimal hyperparameter combinations.

Evaluation metrics included Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), F1-score, and Kappa coefficient. OA represents the proportion of correctly classified samples. PA reflects consistency between classification results and ground truth (ratio of correctly classified samples to actual

samples of that class). UA assesses classification reliability (ratio of correctly classified samples to total samples classified as that class). The F1-score is the harmonic mean of PA and UA, providing more accurate performance assessment for imbalanced datasets. The Kappa coefficient measures classification agreement, offering a more comprehensive evaluation than OA by accounting for omission and commission errors.

Feature importance was assessed using permutation importance, which evaluates each variable's contribution to model predictions. This method establishes a baseline model, then randomly shuffles values of individual features while keeping others constant, measuring performance degradation to determine importance. Unlike Gini impurity-based methods, permutation importance considers feature interactions and is unaffected by feature scale or type, providing more accurate reflection of actual contributions. Each feature was tested 10 times, with average importance scores calculated, normalized for comparability, to identify key features for *P. kansuensis* identification across different periods.

2.1 Classification Accuracy Evaluation

Comparative results of model accuracy across different monitoring periods showed that both SVM and RF performed similarly, with RF slightly outperforming SVM in most periods. Accuracy for *P. kansuensis* exhibited consistent temporal trends across all plots: lower accuracy during early growth stages in mid-June, peaking during peak flowering in late July to August, then gradually declining.

For Plot 1, the highest accuracy occurred in mid-August (peak flowering), with SVM achieving an F1-score of 99.58% and Kappa coefficient of 0.99. For Plot 2, the highest accuracy occurred in early July (initial flowering), while Plot 3 peaked in late August. Model performance in identifying *P. kansuensis* was slightly lower than for other land cover types, with Producer's Accuracy lower than User's Accuracy, indicating more *P. kansuensis* samples were misclassified as other classes than vice versa.

Detailed accuracy metrics for each plot are presented in Tables 4-6.

2.2 Spatial Distribution Changes of *P. kansuensis*

The spatial distribution of *P. kansuensis* in 2023 and 2024 revealed significant inter-annual variation (Fig. 2). Plot 1 showed relatively small inter-annual area changes, while Plot 2 exhibited obvious area variations. Plot 3 demonstrated different patterns, with smaller area changes between years but distinct spatial distribution differences. The overlapping area was only 79.10 m², representing 12.16% and 12.42% of the distribution areas in 2023 and 2024, respectively.

In Plot 1, *P. kansuensis* distribution area decreased from 777.76 m² in 2023 to 271.57 m² in 2024. Plot 2 showed large-scale distribution in 2023 (8,256.87 m²), decreasing to 7,479.11 m² in 2024. Plot 3 had the lowest overlap area among the

three plots, with distribution area increasing from 636.88 m² in 2023 to 782.20 m² in 2024, but the overlapping area accounted for only 1.98% of the total.

The spatial transition matrix for 2023-2024 (Table 7) indicates that *P. kansuensis* exhibited significant spatial distribution differences between the two years, with distribution patterns showing obvious spatial shifts, creating uncertainty for control efforts.

2.3 Feature Importance

Permutation importance analysis based on the Random Forest algorithm revealed that feature importance varied temporally. The normalized difference index calculated from the 555 nm and 720 nm bands was the most important feature in most periods (Fig. 3). Plots 1 and 2 showed similar trends, with this index being the most important feature across all periods, its relative importance increasing then decreasing, peaking in mid-August. In mid-September, feature importance patterns differed markedly from other periods, with the normalized difference index between 750 nm and 720 nm bands showing highest importance. Additionally, the near-infrared band (840 nm) demonstrated significant importance in mid-September (late growing season).

In Plot 3, the green band (555 nm) became the most important feature in late August. Its relative importance increased over time, peaking in mid- and late August, while the 720 nm band showed highest importance in mid-September.

3 Discussion

This study employed UAV multispectral data and machine learning algorithms for multitemporal monitoring and classification of *P. kansuensis* during key phenological stages. Classification accuracy during peak flowering (late July to mid-August) was significantly higher than during other stages, with Kappa coefficients \$ 0.99. This confirms that peak flowering is the most distinguishable phenological stage for differentiating *P. kansuensis* from other vegetation, consistent with numerous studies that select peak flowering or distinct phenological stages for invasive plant monitoring. The primary reason is that during this period, *P. kansuensis* reaches heights >30 cm with distinctive rose-colored corollas, facilitating identification by UAV multispectral cameras.

While classification accuracy was relatively lower during early growth stages (emergence and initial flowering), it remained above 85%, with Producer's Accuracy exceeding 80%. This lower accuracy during emergence occurs because *P. kansuensis* is relatively short (1-2 cm aboveground), creating mixed pixels that are difficult to distinguish. In contrast, accuracy was lowest during senescence (mid-September) when the plant completely withers, making its spectral characteristics extremely similar to withered grasses and reducing identification precision.

Comparison of spatial distribution areas between early stages and peak flowering

revealed high spatial overlap (Fig. 4). During the emergence stage, the maximum annual area could be monitored, indicating that early-stage distribution mapping is achievable. As plants grew, distribution areas gradually expanded from the emergence-stage baseline, reaching maximum extent during late peak flowering. This demonstrates the feasibility of early-stage monitoring for *P. kansuensis*.

Feature importance rankings showed temporal dynamics that can inform vegetation monitoring approaches across different periods. During the growing season (excluding senescence), the normalized difference vegetation index based on 555 nm and 720 nm bands was most important, followed by the green band. This differs from some studies showing red-edge bands (750 nm) as most important, primarily due to differences in classification targets, feature selection, and algorithms. Our study used a binary classification approach focusing on *P. kansuensis* identification, while others employed multi-class classification. Additionally, differences in multispectral sensor band positions (e.g., red-edge band at 735 nm vs. 720 nm) contributed to varying results.

The green band's importance increased over time, becoming most important in late August for Plot 3. Previous research has shown that *P. kansuensis* differs significantly from common forage grasses in the green band (550–680 nm) throughout the growing season, reflecting the target species' inherent spectral characteristics. However, misclassification primarily involved green grasses rather than bare land or river channels, consistent with studies showing that *P. kansuensis* is unsuitable for survival in soils with either too low or too high moisture content, requiring specific soil water conditions for seed germination.

Significant inter-annual spatial distribution differences were observed, with *P. kansuensis* following a “passenger” invasion mechanism in the Bayinbuluk grassland. The species is disadvantaged in light competition with native perennial grasses but can colonize spatial niches vacated by long-term grazing disturbances. Decomposition of litter in invaded communities may inhibit *P. kansuensis* growth the following year, causing the species to seek alternative vacant niches. This explains the observed spatial distribution shifts between years.

UAV technology offers clear advantages for small-area monitoring but has relatively high costs for large-scale data acquisition. Satellite remote sensing can quickly and economically obtain large-scale data, but identification of *P. kansuensis* is challenging due to its small size and scattered distribution, with background interference and fixed overpass times limiting high-quality imagery acquisition. Future research should: (1) Develop temporal sequence models using multitemporal remote sensing data to comprehensively consider spectral characteristics across growth stages, avoiding spectral confusion; (2) Integrate environmental factors such as soil moisture, temperature, and topography based on the species' growth habits to establish more robust monitoring models; (3) Further investigate spectral characteristics and distinguishability between *P. kansuensis* and easily confused land cover types to clarify error sources.

4 Conclusions

This study conducted UAV multispectral monitoring of the invasive plant *P. kansuensis* across different phenological stages using machine learning algorithms to obtain spatial variation during the growing season. The main conclusions are:

- 1) The Random Forest algorithm slightly outperformed Support Vector Machine, with model accuracy varying across growth stages: peak flowering stage (late July to late August) > initial flowering stage (late June to early July) > emergence stage (mid-June) > senescence stage (mid-September). Multitemporal monitoring revealed that spatial distributions during early growth stages (emergence and initial flowering) showed high spatial overlap with the peak flowering stage, with consistent key features, demonstrating the feasibility of early-stage monitoring.
- 2) All three plots exhibited significant inter-annual variation in *P. kansuensis* spatial distribution, with overlap between years <15%, indicating substantial spatial shifts that create uncertainty for control efforts.
- 3) During the growing season (excluding senescence), the most important distinguishing feature was the normalized difference index calculated from 555 nm and 720 nm bands, followed by the green band. Feature importance changed markedly during senescence, with near-infrared band importance increasing and showing significant differences across various background environments.

These results demonstrate the feasibility of UAV multispectral remote sensing technology for monitoring early phenological stages of *P. kansuensis*, providing technical support for early warning and control strategies.

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