Monitoring invasive and expansive species in the Krkonoše Mts using UAV multitemporal data and botanical research

Lucie Kupková[1], Lucie Červená [1], Jakub Lysák [1], Záboj Hrázský [1], Markéta Potůčková [1], Alex Šrollerů[1], Barbora Novotná [1], Michaela Vítková [2], Jan Pergl [2], Jan Čuda [2], Natálie Kolombová [2,3], Klára Kušková [2,3], Josef Kutlvašr [2,3], Irena Perglová [2], Jiří Sádlo[2], Vojtěch Vítek [2], Petr Pyšek [2,4]

[1] Department of Applied Geoinformatics and Cartography, Faculty of Science, Charles University, Prague, Czech Republic - (lucie.kupkova, lucie.cervena, jakub.lysak, zaboj.hrazsky, marketa.potuckova, alex.srolleru novotnabarbora10)@natur.cuni.cz

[2] Department of Invasion Ecology, Institute of Botany, Czech Academy of Sciences, Průhonice, Czech Republic - (michaela.vitkova, jan.pergl, jan.cuda, natalie.kolombova, klara.kuskova, josef.kutlvasr, irena.perglova, jiri.sadlo, petr.pysek)@ibot.cas.cz, vojtech.vitek94@gmail.com

[3] Faculty of Environmental Sciences, Czech University of Life Sciences, Prague, Czech Republic

[4] Department of Ecology, Faculty of Science, Charles University, Prague, Czech Republic

Keywords: UAV data, expansive species, invasive species, *Lupinus polyphyllus*, detection, deep learning, Krkonoše Mountains

Abstract

The Krkonoše Mountains are a unique ecological region facing increasing pressure from alien invasive and native expansive plant species, which threaten biodiversity and ecosystem stability. This study investigates the potential of UAV-based remote sensing for detecting and monitoring selected invasive species with focus on *Lupinus polyphyllus*. The primary objectives were (1) to acquire UAV multispectral data for several plots at multiple time points during the growing season in order to identify the best dates for the species detection, (2) to collect reference botanical data, (3) to test the suitability and reliability of mapping invasive/expansive species from UAV imagery using deep learning methods, and (4) to evaluate the effectiveness of various management interventions. High-resolution UAV imagery was processed using the SegUNet deep learning model, achieving classification accuracies up to 95.7%. The results indicated that species detection was most effective during flowering but also viable in spring due to distinct leaf morphology. One of the key findings of the analysis is that centimeter-range spatial resolution enables the detection and monitoring of *Lupinus* and other species during their growth and flowering stages, to a significant degree without requiring botanical input data. Our study confirms the applicability of UAV remote sensing for invasive species detection, offering a cost-effective and scalable solution for landscape-level monitoring in the future. Long-term monitoring will be essential for refining detection strategies, improving classification models, and testing the reliability, especially for detection after management interventions.

1. Introduction

The Krkonoše National Park (KRNAP) is one of the most significant centres of geobiodiversity in Europe composed by a mosaic of several unique ecosystems. Meadows belong to the most valuable habitats but they are threatened by the expansions and invasions of various species. Biological invasions are globally considered one of the main threats to the biodiversity of natural ecosystems (Pyšek et al., 2020). In mountain regions, yet, environmental stress (short growing season, nutrient availability, frost, wind, increased levels of ultraviolet radiation) poses a significant barrier to the spread of alien species into mountainous regions. However, global warming, changes in nitrogen availability, and local anthropogenic disturbances are causing ecosystem changes that for sensitive mountain communities are difficult, or even impossible, to adapt to (Alexander et al., 2018).

As a result, native species diversity is decreasing and rare species, including endemics and glacial relicts, are facing decline or even local extinction. At the same time, the spread of alien species leads to taxonomic and functional homogenization of communities (Haider et al., 2018; Yang et al., 2021) and impacts ecosystem services and functions (Pecl et al., 2017). This includes not only spreading alien species to the Czech Republic (invasive), but also the spread of native species from habitats naturally richer in nutrients and/or in the foothills (expansive). Uncontrolled expansive species can cause damage comparable to that of alien invasive species (Hejda et al. 2021).

The early detection of new outbreaks of expansive/invasive species significantly increases the chances of their complete eradication, thereby substantially reducing the economic costs of such interventions. This makes the use of advanced remote sensing methods very promising.

Remote sensing plays an increasingly significant role in detecting and mapping invasive plant species (Singh et al., 2024; Rakgoale et al., 2024). This technology enables efficient and cost-effective monitoring of invasions across large areas, which would be challenging using standard vegetation mapping. Satellite data (Sentinel-2, PlanetScope, WorldView-3) are used for tracking changes in invasive species distribution, providing repeated measurements over time that facilitate the monitoring of species spread and their response to management interventions (Zagajewski et al., 2024; Schulze-Brüninghoff et al. 2021). Aerial data, which often have a higher spatial resolution than satellite imagery, have been successfully employed for detailed mapping of smaller areas (Sabat-Tomala et al. 2024). Various machine approaches (machine learning, OBIA, CNNs) are applied in data analysis (Valente et al. 2022; Wijesingha et al. 2020; Sabat-Tomala et al. 2022).

Currently, the use of drones/UAVs is gaining importance in the field of environmental monitoring (Kupková et al., 2023) and in the detection of invasive plants (Weisberg et al., 2021). Sensors mounted on drones enable collection of high-resolution data on vegetation condition and, above all, offer high operational

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-821-2025

flexibility in imaging. This proves to be a key feature in monitoring invasive plants, as acquiring images during the appropriate phenological stages, or during multiple stages (active growth, flowering, seed production, senescence), facilitates accurate species identification even based solely on RGB or multispectral images (Weisberg et al., 2021). The high spatial resolution of UAV imagery also enables the detection of less extensive areas of invasive plants.

The aim of our study is to develop a methodology for monitoring selected invasive/expansive plant species from UAV multispectral multitemporal imagery in combination with botanical ground truth data. To achieve this, we set up the following goals:

1. To acquire multispectral UAV data for plots with selected native expansive (*Veratrum album* subsp. *lobelianum*, *Senecio nemorensis* agg.) and alien invasive (*Rumex alpinus* and *Lupinus polyphyllus*) species in the KRNAP in various dates during the season in order to identify the best dates for the species detection with respect to phenology and different management practices.

2. To collect botanical reference data along with the UAV data acquisition.

3. To test the suitability and reliability of mapping invasive/expansive species from collected high spatial resolution UAV imagery using selected classification/detection methods, mainly deep learning.

4. To evaluate the effectiveness of various management interventions (mowing, grazing, mulching, chemical treatment, manual removal, and no management) and the potential for detecting management efficiency using drones.

In this paper we focus particularly on the detection and management issues of North American species *Lupinus polyphyllus* (hereafter referred to as *Lupinus*) which is an abundant invasive neophyte with a long tradition of cultivation (Pyšek et al., 2022). In addition to ornamental purposes, it has been planted by hunters as a game food. It reproduces mainly by seeds, but is also able to spread vegetatively by rhizomes. It poses a serious threat to the acidophilic mountain flora especially due to the symbiosis with the N-fixing bacteria *Bradyrhizobium* in *Lupinus* root nodules increasing level of available forms of nitrogen in environment where nitrogen is often limiting factor (Pergl et al. 2023). Therefore, the change in the availability of this essential element causes a vegetation shift accompanied by the decline of rare montane species.

2. Area of interest

KRNAP is situated in the northern part of the Czech Republic (see Figure 1), along the border with Poland. Covering an area of approximately 370 km², it protects the highest mountain range in the country, the Krkonoše Mountains, which includes the peak of Sněžka (1,603 m), the highest point in the Czech Republic. KRNAP is characterized by rugged terrain, glacial cirques, alpine meadows, and extensive spruce forests.

Due to its diverse landscapes and significant elevation differences, KRNAP hosts a unique mix of Central European and Arctic-Alpine flora and fauna. Established in 1963, KRNAP is part of a transboundary biosphere reserve shared with Poland, emphasizing the region’s ecological importance. KRNAP is home to a variety of valuable ecosystems, including subalpine tundra, peat bogs, and ancient spruce and beech forests. These habitats support rare and endemic species such as the Alpine shrew (*Sorex alpinus*) and the Krkonoše bellflower (*Campanula bohemica*). However, invasive/expansive plant species pose a growing threat to these fragile ecosystems. Alien species like *Lupinus* (large-leaved lupine) spread aggressively, outcompeting native flora and altering soil composition.

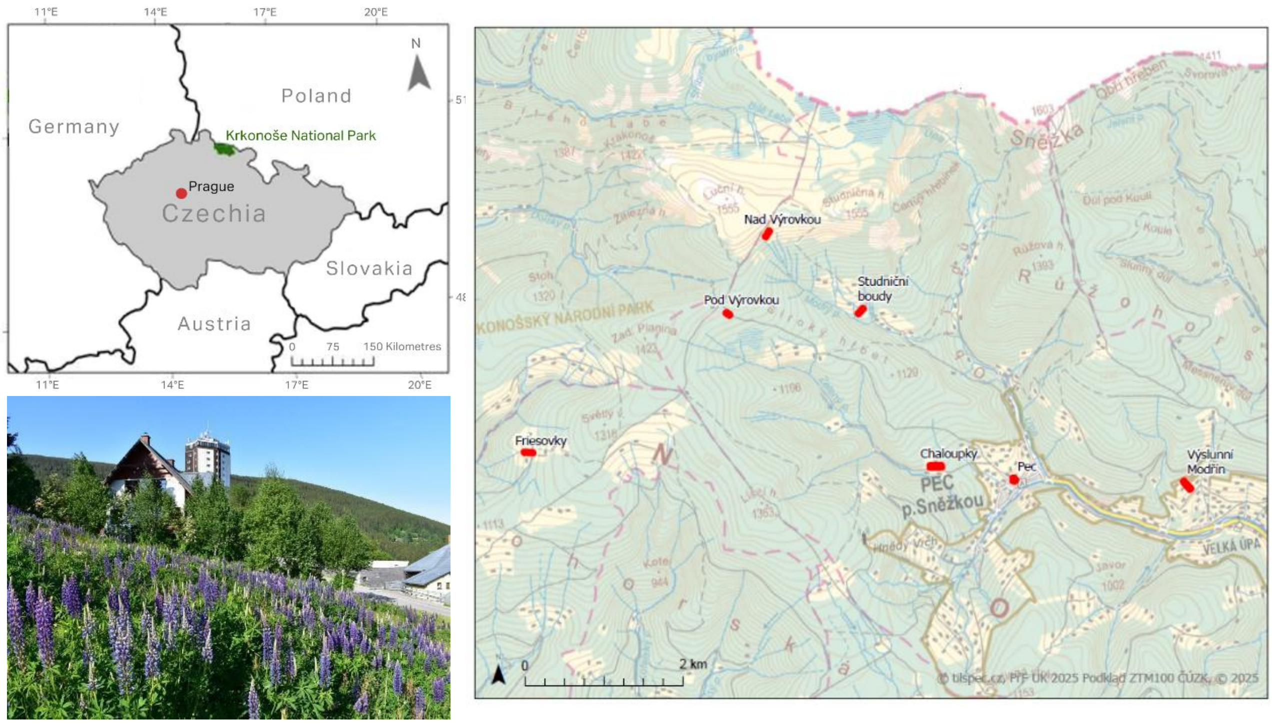

Figure 1. Location of the KRNAP within Czechia, plots for invasive/expansive species in the area of the KRNAP and picture of *Lupinus* in the central part of Pec pod Sněžkou municipality.

Their proliferation disrupts ecological balance, reducing biodiversity and impacting species that rely on native plant communities.

For study of invasive/expansive species detection and management we selected eight plots within the cadastral areas of Pec pod Sněžkou, Strážné, and Velká Úpa (ranging in size from 0.45 to 1.1 ha). *Lupinus* dominates on the plots Chaloupky, Pec, and Výsluní Modřín (see Figure 1).

3. Methods

3.1 UAV data acquisition

UAV imagery was collected four times in 2024 (May, June, July, August). The data were captured using a DJI Mavic 3M equipped with an RGB camera featuring a 4/3 CMOS 20 MP image sensor and four cameras for acquiring multispectral imagery: NIR 860 nm ± 26 nm, RedEdge 730 nm ± 16 nm, Red 650 nm ± 16 nm, Green 560 nm ± 16 nm. The data were captured mostly under stable conditions (clear sky or consistently overcast). The captured data have a spatial resolution of 1 cm. The acquired images, before processing, represent a data volume of around 500GB.

3.2 Botanical data acquisition

Botanical data were collected shortly after UAV image acquisition (several days to one week). We mapped the occurrence of target invasive/expansive species, other significant dominant species forming stands (e.g., native *Vaccinium myrtillus*, alien *Imperatoria ostruthium*), conspicuously flowering species (e.g., *Taraxacum officinale*), physiognomically similar species (e.g., *Petasites hybridus* and *Telekia speciosa*), and distinctive objects (e.g., a pile of stones). The target species were mapped in various phenological stages and levels of vitality (e.g., browsed individuals, frost-damaged plants, etc.). We consistently aimed to capture the variability of phenophases and vitality across the entire site.

We used GPS Trimble devices (models Geo 7X and 6000, as well as Trimble Juno and Trimble R8) with sub-decimeter accuracy, further refined by ground-based corrections to an accuracy of a few centimeters (see Figure 2). At each site, we surveyed several dozen points, focusing on both alien and native dominant vegetation. Specifically, 218 points were recorded at the Chaloupky site, 129 points at the Pec site, and 203 points at the Výsluní Modřín site. The measurements were not always optimal. The accuracy was negatively affected primarily by terrain topography. We obtained less precise results in valleys with limited GPS satellite visibility and in locations with poor internet connectivity, which is necessary for ground-based GPS corrections.

For each recorded plant occurrence, the following attributes were documented: plant height, cover within a circle of a specified radius, vitality, and phenological stage. The radius of the circle around each point was defined in such a way that the mapped plant covered as much of the circle as possible. These data served as reference points/polygons for training and validating UAV image classification for the target sites with vegetation stands of the studied invasive and expansive plant species, as well as for control vegetation plots. For each record, photograph was taken to allow for the later verification.

3.3 Management interventions

Since one of the project objectives is to monitor the effectiveness of management interventions, permanent plots for long-term monitoring of various control strategies were established in agreement with landowners and tenants. The permanent plots for management practice and its efficiency monitoring are square-shaped, measuring 25 m² (5×5 m), with an embedded subplot of 10 m² (3.16×3.16 m). The larger plot is oriented so that its opposite sides align with the N–S and W–E directions (applicable for both flat and sloped terrain), and the embedded subplot is always placed in the SW corner of the larger plot. A phytosociological relevé was recorded for each plot, documenting the cover of all species using a percentage scale between May and July. The earlier sampling period in May proved particularly suitable for species such as *Lupinus* and *Telekia*, as invasive dominants had not yet grown too tall, allowing for better visibility of their understory. Additional species appearing later in the season, such as *Agrostis capillaris*, were subsequently recorded. Conversely, in the subalpine zone of the KRNAP, sampling had to be postponed by a month to ensure that the vegetation was at a comparable growth stage.

Figure 2. Field collection of botanical data (upper photo) and UAV data acquisition (lower photo).

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-821-2025 |

The original plan to include all types of management within a single site or in closely situated locations proved impractical due to technical constraints and, in some cases, conditions related to agricultural subsidies. The variability of management interventions was best captured for *Lupinus*, which was thus chosen as the model species. Through collaboration with the working group of the KRNAP Administration, we were also able to incorporate manual removal and chemical treatment. As a result, we covered the full range of management methods proposed in the project for the KRNAP, including mowing, grazing, mulching, chemical treatment, manual removal, and no management. The cover of the target species ranged from 1% to 90%. At each site and for each management type, a control was selected either in an unaffected stand or, if no such area was available at the same site, in a stand with the lowest possible cover of the target species.

At several time points—spring aspect, vegetation peak, immediately after management intervention, and after a longer post-treatment period—we assessed the following attributes for target species in the permanent plots: plant height, vitality, phenology, and cover. The same attributes were measured across the entire flight area after each drone survey for every mapped individual/population of the invasive/expansive species and other physiognomically similar dominants, as done in the previous research activity. This detailed mapping of species responses to different management types directly in field conditions allows for a more precise comparison of the effectiveness of interventions with results obtained from drone imagery.

3.4 Data pre-processing

The images were processed using the Pix4D software suite. Within the KRNAP area, 31 RGB datasets were successfully generated (8 locations, 4 time points, with one dataset missing for the Pec location), along with the same number of multispectral (MS) datasets with a spatial resolution of 1 cm and an equal number of digital surface models (DSM). The image positions, initially determined in-flight using RTK GNSS technology, were refined during processing using ground control points and validated with check points. The average root mean square error (RMSE) of image orientation at the ground control points ranged from 0.8 to 1.7 cm. The total surveyed area covers 5.8 hectares.

The training and validation polygons obtained from field measurements with centimeter-level accuracy, combined with recorded characteristics of homogeneous vegetation stands (radius, species, coverage, etc.), include 1,250 polygons, covering approximately 0.2% of the surveyed area, specifically 0.95 million image pixels. Of these, approximately 41% of the polygons were manually corrected based on a comparison of polygon positions and the actual location of the target species in the GIS environment. The adjusted portion of the training and validation dataset represents 37% of its total area.

3.5 Detection of *Lupinus* on orthorectified UAV multispectral imagery

The aim of the pilot testing, conducted after data acquisition in the first season, was to:

- Identify a suitable algorithm to ensure a detection success rate of at least 90%
- Design the entire processing workflow to enable maximum automation (particularly concerning the definition of training data)
- Define the most suitable timeframes and phenological stages for detecting selected species based on the results
- Refine the requirements for data collection (imaging conditions, flight parameters, image resolution, number of botanical data).

Based on a literature review (e.g., Valente et al., 2022; Qian et al., 2020; Massetti et al., 2023), testing of vegetation species detection methods using deep learning (DL) approaches was carried out. Due to the relatively small amount of in-situ data, the heterogeneity of the study sites, and previous experience of the research team, statistical approaches (such as maximum likelihood) were deemed unsuitable. In the following year, after additional data acquisition, the random forest algorithm will be tested as an alternative (Bergamo et al., 2023; Sabat Tomala et al., 2022; Kattenborn et al., 2019).

In this pilot phase, deep learning implementations available in ArcGIS Pro and ENVI software were evaluated. Both platforms offer solutions utilizing several pre-trained convolutional networks, which help address the challenge of limited training data and significantly reduce the time required for preprocessing inputs for the convolutional network. Testing was performed on four species in selected areas. In all cases, the training and validation datasets contained only two classes: the target invasive/expansive species and the “other” (background) class.

The detection of *Lupinus* was conducted at the Výsluní Modřín site based on UAV data acquired on June 12, 2024. After evaluating various software solutions and convolutional network implementations, the SegUNet neural network in ENVI was selected for this task. Built on the U-Net architecture (Ronneberger et al., 2015), it performs pixel-wise classification.

For training, only a portion of the study area was utilized, where 66 *Lupinus* polygons (circles) were delineated in the field (see Figure 3 for a detailed example). The trained model was then applied to the entire dataset, and accuracy was assessed using 133 polygons, of which 66 had been included in the learning process.

Additionally, the use of a Class Activation Raster was explored. This visualization highlights the regions of the input image that contribute most to the model’s classification decisions. Different threshold values were applied to refine the detection of the target category. The tests indicated that the maximum entropy parameter provided the best results, with thresholds of 0.3, 0.4, and 0.5 being examined. Figure 4 illustrates the detected extent of *Lupinus*, color-coded according to the applied thresholding.

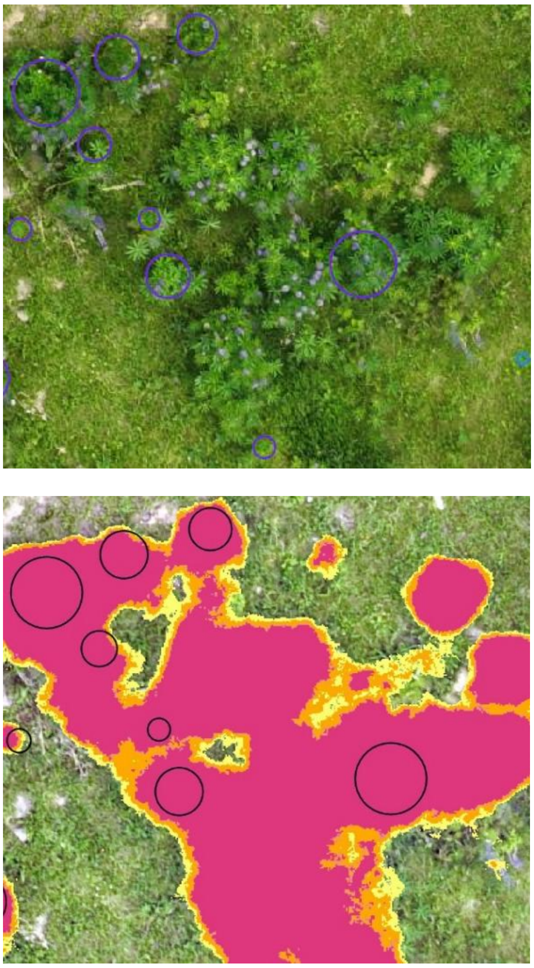

Figure 3. *Lupinus* overlayed with training polygons (upper image) and output of detected *Lupinus* using SegUNet neural network in ENVI (lower image).

4. Results and Discussion

The result of *Lupinus* detection is shown in Figure 4. The final processing accuracy value indicates the percentage of pixels identified by botanists where *Lupinus* was detected by the trained model. Using a threshold value of 0.5 for maximum entropy from the activation raster, a processing accuracy of 88.6% was achieved. At a threshold of 0.4, the accuracy increased to 92.8%, and at 0.3, it reached 95,7%. However, this accuracy assessment does not provide information on where *Lupinus* was incorrectly classified in areas where it was not actually present.

These results place our method among the most accurate approaches when compared with previous studies that have applied remote sensing and machine learning techniques for detecting *Lupinus* or similar invasive species (refer to table 1). Wijesingha et al. (2024) utilized UAV-RGB imagery with a deep learning semantic segmentation model, achieving an accuracy of 91.6%. Wijesingha et al. (2020), who employed Object-Based Image Analysis (OBIA) with Random Forest classification using UAV-borne RGB, thermal, and surface model data, our approach provided comparable results. They reported an average prediction accuracy of 89%, with 88% of classified pixels matching digitized pixels. The study by Schulze-Brüninghoff et al. (2021), which used WorldView-3 satellite imagery and a combination of deep learning, gradient boosting, generalized linear models, and ensemble methods, achieved a median area under the receiver operating characteristic curve of 77%. This performance is lower than our results, suggesting that UAV-based approaches, coupled with deep learning models such as SegUNet, can provide superior detection performance compared to high-resolution satellite imagery when identifying *Lupinus*. Sabat-Tomala et al. (2024) utilized airborne HySpex hyperspectral images and a combination of support vector machine (SVM) and random forest (RF) classifiers. Their results showed an F1-score range of 0.78–0.85, with a user accuracy of 88% for RF and 92% for SVM, and an overall accuracy (OA) of 89–94%. Their highest accuracy values are comparable to our highest reported accuracy of 95.7%.

In most cases, management interventions were carried out by landowners or tenants, while the removal and chemical treatment of *Lupinus* were implemented by the KRNAP working group. Five permanent plots were designated for manual removal. One of these represented the early stage of *Lupinus* invasion into an acidophilous grassland dominated by *Nardus stricta*, where the invasive species covered only 2%, whereas in the other plots selected for uprooting, its coverage ranged between 25% and 40%.

The areas designated for chemical treatment with 8% Roundup were treated at the end of the season, considering organic farming requirements, and the effectiveness of the intervention is not yet known. Manual removal was conducted twice a year—at the end of June and then monitored again at the turn of October and November. Although by autumn of the first season, *Lupinus* appeared weaker than in the surrounding stands and had a coverage of only a few percent, this method proved to be very labour-intensive (requiring 4 hours to remove *Lupinus* from a 25 m² plot in dry, rocky soil). Moreover, the low regeneration rate might have also been influenced by prolonged dry weather. In one plot, however, the vitality of *Lupinus* was significantly reduced even before spraying (greyed-out leaves), despite normally being at full strength at that time of year. Similarly, its response to mowing was weaker, with fewer and shorter new inflorescences developing. Some interventions were implemented too late to prevent further spread of the invasive species, in some cases due to conflicts with other conservation priorities—such as mowing or mulching during the seed production phase of *Lupinus*. A primary management method is often supplemented with additional practices, adjusted according to local conditions. As a result, while we do not obtain a pure effect of a single method as in controlled garden experiments, the outcomes more accurately reflect real-world conditions in the study areas. Interestingly, *Lupinus* was completely eradicated from an enclosure grazed by sheep but not by cattle.

Regarding the timing of invasive species detection, some species are best identified in UAV imagery during flowering, while others can be effectively detected in early spring due to their distinct leaf morphology and faster growth compared to native plants. *Lupinus* can be successfully detected in both cases and also in June, as it is a significantly dominant species with a robust growth habit.

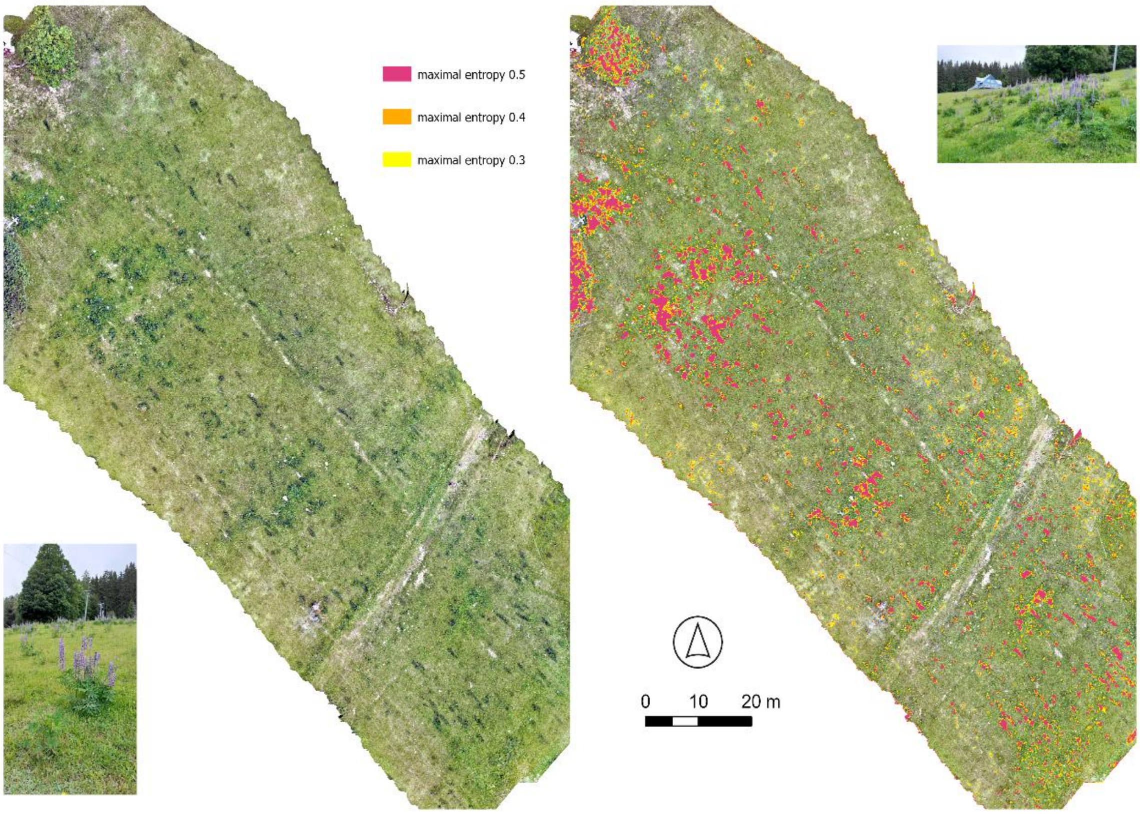

Figure 4. Detection of *Lupinus* at the site Výsluní Modřín (left) and original orthoimage before depicting *Lupinus* before the detection (right).

Study	RS data source	Botanical data	Spatial resolution	Method used for detection	Accuracy
Wijesingha et al., 2024	UAV-RGB	Manual digitization of RGB images.	0.01	Deep Learning semantic segmentation model.	91.60%
Wijesingha et al., 2020	UAV-borne RGB, thermal, and surface model data	Manual digitization of aerial images with field comparison.	0.009	Object-Based Image Analysis (OBIA) with Random Forest classification.	Average prediction accuracy of 89%. The largest difference between classified and digitized lupine area was 5%. 88% of all classified pixels matched digitized pixels.
Schulze-Brüninghoff et al., 2021	WorldView-3	Random squares, expert evaluation of lupine share.	0.3; 1.24	DL: Deep Learning, GBM: Gradient Boosting Machine, GLM: Generalised Linear Model, XRT: Extremely Randomized Trees, DRF: Distributed Random Forest, SE: Stacken Ensembles.	Area under the receiver operating characteristic curve - median 77%
Sabat-Tomala et al., 2024	Airborne HySpex HS images	Field measurements of lupine and co-occurring plants in dense patches.	0.5	SVM, RF	F1: 0.78-0.85; UA RF 88% SVM 92%; (OA: 89–94%)

Table 1: Selected publications dealing with *Lupinus* detection/classification.

The most recent UAV data were collected in August 2024, but the full effects of management interventions were not yet evident. Therefore, additional UAV data will be acquired in 2025 at three different time points to further test the detection of both species' occurrence and the success of eradication efforts.

One of the key findings of the analysis is that centimeter-range spatial resolution enables the detection and monitoring of *Lupinus* and other species during their growth and flowering stages, to a significant degree without requiring botanical input data. However, this approach will be further tested, particularly to assess how it affects detection accuracy. We will also continue to verify this approach, with a particular focus on determining the extent to which various management interventions, leading to plant damage and mortality, may limit this capability.

To confirm the feasibility of monitoring the effectiveness of management interventions using remote sensing, long-term observation is required. Although some studies mention this possibility (Sabat-Tomala et al., 2024; Wijesingha et al., 2020´; Rajdus et al., 2020) in general terms, an extended monitoring effort that provides clear findings has not yet been conducted. The plots established for long-term monitoring should provide a definitive answer to this question in the future.

5. Conclusions

The primary objectives of our study were to acquire multispectral UAV data for selected expansive/invasive species in the KRNAP across different seasonal time points, determine the optimal timing for detection in relation to phenology and management practices, collect botanical reference data, and evaluate the reliability of high-resolution UAV imagery for species classification using deep learning. Additionally, the study aimed to assess the effectiveness of various management interventions, including mowing, grazing, mulching, chemical treatment, manual removal, and no management, and explore the potential of UAVs for monitoring management success.

Through our analysis, we confirmed that UAV-based remote sensing is highly effective in detecting invasive and expansive species, particularly *Lupinus*, with high precision. By using SegUNet for semantic segmentation, we achieved a processing accuracy 95.7%, surpassing or matching previous studies. This highlights the advantage of advanced deep learning methods in invasive species mapping, particularly when applied to UAV-derived high-resolution imagery. However, further validation is necessary to assess false positives and improve generalizability across different environments and datasets.

The collection of botanical reference data alongside UAV imagery allowed us to validate and improve the classification accuracy of deep learning models. The ability to capture species at different phenological stages enhances its applicability, providing critical insights into their seasonal variability and spread dynamics. The results indicate that detection accuracy is highest during flowering, but early spring observations also proved valuable due to distinct leaf morphology and growth characteristics. In case of *Lupinus* we proved that its robust growth habit allows for very successful detection also during early summer. Detectability also depends on the matrix, when under height grass canopy it is impossible to recognize small *Lupinus* seedlings. Such detectability is even worse, when windy weather blurred the photos and then only large flowering plants are visible.

The evaluation of management interventions revealed varying degrees of effectiveness in controlling *Lupinus*. While uprooting significantly reduced plant coverage, it proved labour-intensive and was likely influenced by environmental conditions, such as prolonged drought. Other interventions, such as mowing and chemical treatment, showed mixed results depending on timing and intensity. Grazing by sheep led to complete eradication in some areas, whereas cattle grazing was not effective at all. These findings emphasize the need to tailor management strategies to specific site conditions and invasive species growth dynamics.

To further validate the use of UAVs in monitoring management success, long-term observation is necessary. While previous studies have suggested the feasibility of remote sensing for this purpose, extended monitoring efforts with definitive conclusions remain scarce. The permanent plots established in this study provide a valuable foundation for continuous assessment of species persistence and eradication success. Future UAV campaigns at multiple time points will enhance detection methodologies, ensuring the integration of remote sensing into effective and adaptive invasive species management strategies.

Acknowledgement: The research was supported by the Technology Agency of the Czech Republic – project SS07020317: "Monitoring the spread and management of invasive and expansive species using advanced earth observation methods", project SS07010417 "Earth observation technologies for the surveillance activities of the Czech Environmental Inspectorate", and to the European Commission, CINEA Horizon Europe project no. 101081307 "Towards Sustainable Land-Use in the Context of Climate Change and Biodiversity in Europe (Europe-LAND)". Team from Institute of Botany was also supported by long-term research development project (RVO 67985939) from the Czech Academy of Sciences.

6. References

Alexander, J.M., Chalmandrier, L., Lenoir, J., Burgess, T.I., Essl, F., Haider, S., Kueffer, C., McDougall, K., Milbau, A., Nuñez, M.A., Pauchard, A., Rabitsch, W., Rew, L.J., Sanders, N. J., Pellissier L., 2018. Lags in the response of mountain plant communities to climate change. *Global Change Biology* 24: 563–579. https://doi.org/10.1111/ gcb.13976

Bergamo, T.F., de Lima, R.S., Kull, T., Ward, R.D., Sepp, K., Villoslada, M. (2023). From UAV to PlanetScope: Upscaling fractional cover of an invasive species Rosa rugosa. *Journal of Environmental Management*, 336, 117693.

Haider, S., Kueffer, C., Bruelheide, H., Seipel, T., Alexander, J.M., Rew, L.J., Arévalo, J.R., Cavieres, L.A., McDougall, K.L., Milbau, A., Naylor, B.J., Speziale, K., Pauchard, A., 2018. Mountain roads and nonnative species modify elevational patterns of plant diversity. *Global Ecology and Biogeography* 27: 667–678. https://doi.org/10.1111/ geb.12727

Hejda, M., Sádlo, J., Kutlvašr, J., Petřík, P., Vítková, M., Vojík, M., Pyšek, P., Pergl, J., 2021. Impact of invasive and native dominants on species richness and diversity of plant communities. *Preslia*, 93, 181–201. doi: 10.23855/preslia.2021.181

Kattenborn, T., Lopatin, J., Förster, M., Braun, A.C., Fassnacht, F.E., 2019: UAV data as alternative to field sampling to map woody invasive species based on combined Sentinel-1 and Sentinel-2 data. *Remote Sensing of Environment*, 227, 61–73.

Kupková, L., Červená, L., Potůčková, M., Lysák, J., Roubalová, M., Hrázský, Z., Březina, S., Epstein, H.E., Müllerová, J., 2023. Towards Reliable Monitoring of Grass Species in Nature Conservation: Evaluation of the Potential of UAV and PlanetScope Multi-Temporal Data in the Central European Tundra. *Remote Sensing of Environment* 294: 113645. https://doi.org/10.1016/j.rse.2023.113645.

Massetti, L., Mo, A., Cini, E., Paterni, M., Merlino, S., Ciccarelli, D., 2023. Detection of Yucca gloriosa in Mediterranean coastal dunes: A comparative analysis of field-based sampling, human interpretation of UAV imagery and deep learning to develop an effective tool for controlling invasive plants. *Regional Studies in Marine Science*, 68, 103265.

Pecl, G.T., Araújo, M.B., Bell, J.D., Blanchard, J., Bonebrake, T.C., Chen, I.-C., Clark, T.D., Colwell, R.K., Danielsen, F., Evengård, B., Falconi, L., Ferrier, S., Frusher, S., Garcia, R.A., Griffis, R.B., Hobday, A.J., Janion-Scheepers, C., Jarzyna, M.A., Jennings, S., Williams, S.E., 2017. Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science* 355, Iss. 6332, eaai9214. https://doi.org/10.1126/science.aai9214

Pergl, J., Vítková, M., Hejda, M., Kutlvašr, J., Petřík, P., Sádlo, J., Vojík, M., Dvořáčková, Š., Fleischhans, R., Lučanová, A., Pyšek, P., 2023. Plant-soil interactions in the communities dominated by alien and native plants. *Perspectives in Plant Ecology, Evolution and Systematics*, 59, 125721.

Pyšek, P., Hulme, P.E., Simberloff, D., Bacher, S., Blackburn, T.M., Carlton, J.T., Dawson, W., Essl, F., Foxcroft, L.C., Genovesi, P., Jeschke, J.M., Kühn, I., Liebhold, A.M., Mandrak, N.E., Meyerson, L.A., Pauchard, A., Pergl, J., Roy, H.E., Seebens, H., van Kleunen, M., Vilà, M., Wingfield, M.J., Richardson, D.M., 2020. Scientists' warning on invasive alien species. *Biological Reviews*, 95, 1511–1534. doi: 10.1111/brv.12627

Pyšek, P., Sádlo, J., Chrtek jr., J., Chytrý, M., Kaplan, Z., Pergl, J., Pokorná, A., Axmanová, I., Čuda, J., Doležal, J., Dřevojan, P., Hejda, M., Kočár, P., Kortz, A., Lososová, Z., Lustyk, P., Skálová, H., Štajerová, K., Večeřa, M., Vítková, M., Wild, J., Danihelka, J., 2022. Catalogue of alien plants of the Czech Republic (3rd edition): species richness, status, distributions, habitats, regional invasion levels, introduction pathways and impacts. *Preslia* 94, 4, 447–577. https://doi.org/10.23855/preslia.2022.447

Qian, W., Huang, Y., Liu, Q., Fan, W., Sun, Z., Dong, H., Wan, F., Qiao, X., 2020. UAV and a deep convolutional neural network for monitoring invasive alien plants in the wild. Computers and Electronics in Agriculture 174, 105519.

Rajdus, T., Svehlakova, H., Plohak, P., Stalmachova, B. 2020. Management of invasive species Solidago canadensis in Ostrava region (Czech Republic). *IOP Conf. Ser.: Earth Environ.* Sci. 444 012046. DOI 10.1088/1755-1315/444/1/012046

Rakgoale, P.B., Ngetar, S.N., 2024: Detecting Invasive Alien Plant Species Using Remote Sensing, Machine Learning and Deep Learning: A Systematic Review. *Journal of Sensors*, 2024, 8854675. doi.org/10.1155/2024/8854675

Ronneberger, O., Fischer, P., Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In Medical image computing and computer-assisted intervention – MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18 (pp. 234–241). Springer International Publishing.

Sabat-Tomala, A., Raczko, E., Zagajewski, B., 2022. Mapping Invasive Plant Species with Hyperspectral Data Based on Iterative Accuracy Assessment Techniques. *Remote Sens.*, 14, 64. doi.org/10.3390/rs14010064

Sabat-Tomala, A., Raczko, E., Zagajewski, B., 2024. Airborne Hyperspectral Images and Machine Learning Algorithms for the Identification of Lupine Invasive Species in Natura 2000 Meadows. *Remote Sens.*, 16, 580. doi.org/10.3390/rs16030580

Schulze-Brüninghoff, D., Wachendorf, M., Astor, T., 2021. Potentials and Limitations of WorldView-3 Data for the Detection of Invasive Lupinus polyphyllus Lindl. in Semi-Natural Grasslands. Remote Sens., 13, 4333. doi.org/10.3390/rs13214333

Singh, K.K., Surasinghe, T.D., Frazier, A.E., 2024. Systematic review and best practices for drone remote sensing of invasive plants. *Methods in Ecology and Evolution*, 15, 998–1015. doi.org/10.1111/2041-210X.14330

Valente, J., Doldersum, M., Roers, C., Kooistra, L., 2022. Deep learning for Rumex obtusifolius detection in grasslands using off-the-shelf models. International *Journal of Applied Earth Observation and Geoinformation*, 112, 102864. doi.org/10.1016/j.jag.2022.102864

Weisberg, P.J., Dilts, T.E., Greenberg, J.A., Johnson, K.N., Pai, H., Sladek, C., Kratt, C., Tyler, S.W., Ready, A., 2021. Phenology-Based Classification of Invasive Annual Grasses to the Species Level. *Remote Sensing of Environment*, 263, 112568. https://doi.org/10.1016/j.rse.2021.112568.

Wijesingha, J., Astor, T., Schulze-Brüninghoff, D., Wachendorf, M., 2020. Mapping Invasive Lupinus polyphyllus Lindl. in Semi-natural Grasslands Using Object-Based Image Analysis of UAV-borne Images. *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science*. https://doi.org/10.1007/s41064-020-00121-0

Wijesingha, J.S.J., Schulze-Brüninghoff, D., Wachendorf, M., 2024. Mapping invasive Lupine on grasslands using UAV images and deep learning. Conference Paper. https://www.researchgate.net/publication/378590186

Yang, Q., Weigelt, P., Fristoe, T.S., Zhang, Z., Kreft, H., Stein, A., Seebens, H., Dawson, W., Essl, F., König, C., Lenzner, B., Pergl, J., Pouteau, R., Pyšek, P., Winter, M., Ebel, A.L., Fuentes, N., Giehl E.L.H., Kartesz, J., Krestov, P., Kukk, T., Nishino, M., Kupriyanov, A., Villasenor, J.L., Wieringa, J.J., Zeddam, A., Zykova, E., van Kleunen, M., 2021. The global loss of floristic uniqueness. *Nature Communications*, 12, 7290. doi: 10.1038/s41467-021-27603-y

Zagajewski, B., Kluczek, M., Zdunek, K.B., Holland, D., 2024: Sentinel-2 versus PlanetScope Images for Goldenrod Invasive Plant Species Mapping. *Remote Sens.*, 16, 636. doi.org/10.3390/rs16040636