Mapping invasive Lupine on grasslands using UAV images and deep learning

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Abstract: Semi-natural grasslands are threatened by invasive species. This study employs high-resolution images captured by an unmanned aerial vehicle (UAV) and deep learning techniques to map Lupine (*Lupinus polyphyllus* Lindl.) in grasslands, which is one of the most common invasive species in European grasslands. The methodology involves RGB image acquisition, structure from motion processing, canopy height modelling, and deep learning semantic segmentation model development. The resulting models were trained on RGB data, canopy surface height data, and their combination. The models demonstrate high accuracy and efficacy in identifying Lupine distribution. These models offer a valuable tool for continuously monitoring and managing invasive Lupine, with potential applications in similar environments without retraining. The method is beneficial for early-stage invasion detection, facilitating more targeted management efforts for ecologists.

Keywords: invasive species, grassland, deep learning, segmentation, UAV images

1 Introduction

Semi-natural grasslands are complex, heterogeneous ecosystems comprising a rich mosaic of native plant species. They play a vital role in maintaining ecological stability and sustaining many ecosystem services [Gi09]. Moreover, these grasslands serve as biodiversity hotspots, contributing to soil fertility, carbon sequestration, and nutrient cycling, and they offer a valuable reservoir of genetic resources for native flora and fauna. Nevertheless, semi-natural grasslands are at risk due to various naturogenic and anthropogenic factors. Among the challenges confronting semi-natural grasslands, invasive species pose a widespread threat. Invasive species are non-native organisms that, when introduced to a new ecosystem, often outcompete native species and disrupt the ecological balance [PR11]. One such invader that has gained considerable attention in European grasslands and other herbaceous vegetation is *Lupinus polyphyllus* Lindl., commonly known as Lupine [La08]. Native to North America, Lupine has become an exemplary invasive, taking its roots far from its natural habitat and causing substantial ecological and economic consequences. Lupine's ability to flourish in non-native environments and its rapid growth and abundant seed production have made it a challenging threat in many European grasslands. Lupine is known for its ornamental

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purple or blue-violet flowers, which are appreciated in the landscape in contrast to its ecological disturbance.

During the last few decades, Lupine has invaded substantial areas of low-mountain semi-natural grasslands in the Rhön biosphere in Germany [OM05]. Like common invasive species, Lupine competes with native plant species for essential resources such as water, nutrients, and sunlight. Its rapid growth can influence the native herbaceous vegetation, which causes the loss of species diversity. On the other hand, it can disturb the foraging and nesting habits of animal species native to the local ecosystem, leading to food web imbalances. Furthermore, the presence of Lupine in grasslands could reduce their usability for forage production and livestock grazing, triggering economic losses to local farmers.

Understanding the spatial distribution of Lupine within grassland ecosystems is vital to effectively manage and monitor its expansion. Mapping the distribution of Lupine in grasslands was usually conducted by digitising high-resolution aerial images. However, due to the time- and labour-intensive workflow, the time gap between the two Lupine distribution maps was 18 years [Kl19]. Since time is crucial for limiting the expansion of rapidly growing invasive species like Lupine, a simple and repeatable workflow is required to map Lupine on grasslands. In response to this need, [Wi20] developed a workflow using unmanned aerial vehicle (UAV) borne imaging and object-based image analysis (OBIA) techniques for Lupine mapping. That developed workflow resulted in a mean overall accuracy of 89 % for estimating Lupine on grasslands. Moreover, the results indicated that the developed models can appropriately be applied to any spatial location or time.

Nevertheless, the developed workflow presented some technical difficulties related to the application of OBIA. For example, problems were encountered in determining threshold values, labelling the segments and accepting the resulting segments [Wi20]. Recent studies showed that deep learning (DL) models, such as convolutional neural network (CNN) semantic segmentation models, could be more effective than OBIA for mapping invasive species [KEF19]. Considering these findings, this study hypothesised that DL models could effectively map Lupine on grasslands. Therefore, this study employed high-resolution UAV images and DL techniques to map invasive Lupine on grasslands to prove that hypothesis.

2 Materials and Methods

Two sites in the Rhön biosphere reserve were selected as study plots for this study. One site is a former mountain hay meadow (G1), and the other one an old *Nardus stricta* grassland (G2). In both plots, a 50 m by 30 m area was selected as an experimental site. UAV-borne images were collected over both sites on three dates during the summer of 2019 (12 June – D1, 26 June – D2, 09 July – D3). In total, six datasets were collected, and they were named using the site name and the sampling date (i.e., G1-D1, G1-D2, G1-D3, G2-D1, G2-D2, and G2-D3).

UAV-borne images were acquired using a DJI Phantom IV quadcopter (DJI, China) with an off-the-shelf camera (FC330). The camera was capable of capturing high-resolution 12-megapixel images in the red (R), green (G), and blue (B) spectral bands. The UAV was operated at a flying altitude of 20 meters, which provided a 1 cm ground sampling distance. The UAV was flown on a double-grid mission containing two perpendicular flight paths. The camera operated in automatic mode, capturing nadir-looking images according to a predetermined image overlap configuration, with an 80 % overlap in both forward and side directions. All six flight sessions were conducted between 12:00 and 14:00 to avoid the shadow effects. In addition, another UAV-borne image dataset was collected on 19 August when fields were completely mowed.

The collected UAV-borne images were processed using Agisoft Photoscan software to obtain ortho-mosaic and digital surface models (DSM). The software employed structure from motion technology to stitch single images and derive a three-dimensional model. The DSM derived from the 19 August image dataset was considered as the digital terrain model (DTM), and all six DSM were subtracted from the DTM and canopy surface height (CSH) for each date and site were generated. The CSH contained the relative sward heights of the grass canopies. A reference Lupine coverage map for each dataset was created by manually digitising each RGB ortho-mosaic.

To feed into DL models, the RGB ortho-mosaic images, the CSH, and the labels (manually digitised Lupine map images) were divided into 6.55 m^2 area image chips (256 by 256 pixels). As this was a semantic segmentation problem, the famous “UNET” architecture DL models were employed to develop DL models for this study. Instead of training images from scratch with random weight initialisation, a UNET model with a “Restnet50” backbone pre-trained with “Imagenet” data was employed in this study. The pre-trained UNET model was taken from the “segmentation_model” Python library, which was compatible with Keras and TensorFlow environments [Ia19].

Three distinct models were developed based on different input datasets. The first model was only developed using RGB images (3 bands), and the second model was built with CSH data (1 band). The third model was developed using RGB and CSH data (4 bands). The model development and evaluation process employed the spatial-temporal cross-validation (SPCV) methodology, which helped to understand the robustness of the developed model for various spatial and temporal conditions. Within each cross-validation fold, a distinct spatial-temporal category dataset was reserved for testing, while the remaining data served as the basis for model training. For example, in one instance, the model was trained using all data except the G1-D1 data, and the unused data for training was employed to validate the model. The model evaluation used the accuracy and intersection over union (IoU) metrics [Ev15]. The accuracy explained how many pixels were correctly segmented over the total number of pixels, which provides an overview of the model performance. The IoU calculates the overlap between the predicted segmented region and the actual annotated region from the data. It provides a measure of how well predicted segmented regions align with actual annotated regions, which range between zero and one.

3 Results

Two example predictions from the model with RGB and CSH data are shown in Figure 1. The models trained only with RGB images showed an average accuracy of 91.6 % and an average IoU of 0.69. From each SPCV fold, the highest accuracy was obtained by the D3 datasets from both sites (G1-D3, G2-D3), and the accuracy was 95 % (IoU = 0.76). The D1 datasets from both sites (G1-D1, G2-D1) showed the lowest validation accuracy (88 % and 86 %) and IoU (0.66 and 0.61).

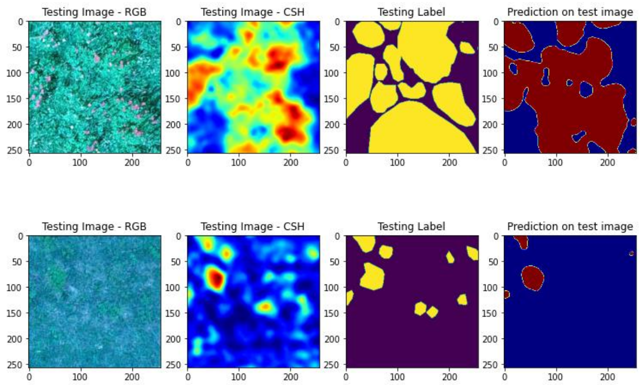

Fig. 1: An example RGB images (1st column), canopy surface height (CSH) data (2nd column), actual annotation Lupine areas as yellow colour (3rd column), and deep learning model predicted Lupine areas as red colour (4th column). The first row shows an image chip from G1-D1 dataset and the second row is a chip from G2-D3 dataset

The models developed only with the sward heights (CSH) resulted in 89.7 % of average accuracy and 0.64 of average IoU. These mean performance metrics were slightly lower than the metrics obtained by the models with the RGB data. Similar to the pattern of the results from RGB image models, the highest accuracy and IoU values were obtained by the two datasets from D3. The validation of G1-D3 resulted in 94.2 % accuracy (IoU = 0.70), while the G2-D3 achieved 93.3 % accuracy (IoU = 0.71). The D1 datasets had the lowest performance, achieving the accuracy values of 85.6 % and 82.2 % (IoU = 0.62 and 0.52), respectively, for the G1-D1 and G2-D1 datasets.

The models combining RGB images and CSH data showed no improvement compared to the RGB-only models. According to model performances, the mean accuracy of the combined data models was 91.4 % (IoU = 0.69), which was similar to the model performance from the RGB data models. Further, the relative Lupine area and the model accuracy were significantly negatively correlated (-0.90).

4 Discussion

The outcomes of this study showed that the developed methodology combining UAV images and DL can be successfully applied for mapping Lupine in semi-natural grasslands. As reported, the models with RGB images could segment Lupine with an average accuracy of 91.6 %, higher than the reported average accuracy from OBIA workflow (89.2 %) with the same dataset [Wi20]. The developed DL model provided better outcomes, avoiding complex steps such as segmentation, attribute computation, and index calculations which were done in OBIA. Further, these results confirmed that invasive species in grasslands can be successfully mapped based solely on very high resolution RGB image data without the need for additional spectral information (e.g., near-infrared).

Similarly, the model with exclusive use of CSH data could segment Lupine with 89.7 % average accuracy, which is better than reported accuracy with OBIA but slightly lower accuracy than using only RGB data models. Moreover, no other studies were found in literature reporting on the application of exclusively CSH data for the mapping of non-woody invasive species, making this study the first one to demonstrate the potential application of solely CSH data in grasslands. Nevertheless, combining RGB and CSH data did not improve model prediction capabilities compared to their single use. One possible reason could be the model architecture, which allowed only a three-band image input. To overcome that, an additional pre-step was introduced to convert a four-band image into a three-band image. This step could limit the advantage of using four bands as it is, which may lead to no improvement of the model performance even with the combination of two different data.

Similar to the results reported by [Wi20], the model outputs from this study also showed an inversely proportional relationship between segmentation accuracy and the relative Lupine share. As the Lupine area expands, the segmentation procedure tends to overestimate Lupine coverage because it becomes challenging to distinguish between Lupine and grass vegetation. Accordingly, the developed models showed higher segmentation accuracy when the relative Lupine area was lower or none (e.g., after regular mowing events). This is an important outcome that helps to identify newly invaded grasslands where the invasion is still easy to manage and control.

5 Conclusions

This study successfully demonstrated application of very high-resolution UAV-borne RGB images and DL methods for mapping invasive Lupine on semi-natural grasslands. The application of exclusively RGB images or CSH data showed that there is a possibility of mapping Lupine on grasslands in different locations and time instances. Furthermore, the developed models exhibited the potential for transferability to diverse geographic regions, thus effectively addressing the constraints inherent in the conventional approach to Lupine mapping.

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