PhD THESIS

Research on the potential use of drones for mapping oligotrophic grasslands with *Arnica montana* in the Apuseni Mountains

(SUMMARY OF DOCTORAL THESIS)

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I. Introduction

In a globalized and interconnected world, biodiversity is seen as an indicator of biosphere health. Biodiversity is not simple about diversity of species, but also includes genetic and ecosystem diversity, along with cultural diversity.

The collection and analysis of biodiversity data as part of a management effort depends on social and political organization and depends on technology. From high-quality observations by researchers to rapid scans by sensors, technology enables the accumulation of substantial amounts of data. This data can then be used to better understand the impact of human activities on biodiversity and inform conservation policies. In natural and semi-natural surface ecosystems, the impact of human activities such as fertilization and intensive exploitation on biodiversity must be considered.

Complex management could be a solution, but to integrate biodiversity conservation into management we need quantitative and qualitative information about these ecosystems.

II. Agriculture drones

Remote Sensing, Earth Observation, and Automation.

Remote Sensing (RS) measures radiation emitted or reflected by objects to obtain information about the Earth, and the informational transition from geography to biology and ecology is revolutionary. There are two main approaches to using RS in this regard:

The direct approach involves recording data at various levels, from individual organisms to ecological communities.

The indirect approach involves modelling data together with ecological parameters and indicators, transforming the results into conventional values for the study of biodiversity.

Different technologies are used in remote sensing to automate measurements and observations: Support Vectors Machines, Object Orientated algorithms, mixed spectral analysis algorithms and more. These technologies enable data analysis and classification at distinct levels, from individual pixels to more uniform pixel segments.

Machine learning applications are increasingly part of the Agriculture 4.0 paradigm. Digitization and automation are based on the development of new methods and algorithms, such as Convolutional Neural Networks (CNN) using increasingly advanced hardware. CNN models have become the dominant method for recognizing objects in an image or video, equaling and even surpassing human performance in many areas, including RS.

Unmanned Aerial Vehicles

Unmanned/Unoccupied Aerial Vehicles (UAV) or "drones" (hereinafter used) have a military origin and continue to be important in the field of security. These vehicles come in many shapes and sizes, often designed for specialized missions.

Depending on the type of flight, drones can be fixed-wing, multi-rotor, or hybrids with wings and rotors. Depending on the landing and take-off procedure, drones may require a runway to take off/land, may land or take off from the same spot, or may be launched with a short launch pad and land using a parachute. Depending on the construction, drones can be classified by weight and size or by power supply. Depending on the load, civilian drones can be used for freight, sensor transport for ground measurements, or fly unloaded, such as for entertainment and sport competitions.

Military drones are being used in innovative ways, while having complex production chains which are under stress. In this context, drones are transformed into "smart bombs" with guided self-destruction, thanks to low-cost drone parts. Defending against drones is another aspect of the technological complexity produced by these systems. Examples of drone defense include destruction by kinetic projectile, destruction by concentrated electromagnetic rays, immobilization by net thrower, destruction by anti-drone drones, jamming communication or sensors, and infiltration of the communication system and taking control of the drone. The UN is working to form conventions to regulate and control these weapons, with the goal of internationally banning fully autonomous weapons by 2026.

Drones in Agriculture 4.0

Drones, equipped with diverse types of sensors, can collect high-resolution aerial images that help monitor soil, crop health, detect stressors and optimize farming practices through accurate data collection and analysis. CNN models are used to analyze images collected by drones and make crop predictions. For example, they can successfully detect crop height, estimate maize crop yields, measure the amount of flowers in strawberry crops, and be used to estimate yield in rapeseed and cotton crops.

Drones can be used to spray pesticides and fertilizers on farmland. They can reduce pest control costs and increase management efficiency compared to traditional methods. The images collected by drones can help identify weeds with high accuracy, allowing farmers to apply site-specific treatments. Drones can even be used to monitor rodent attacks, and can help control rodents through precision farming methods, such as adding rodenticides to specific areas.

The importance of drones in modern agriculture is becoming ever greater and presents several practical applications for good agricultural practices.

Conservation Drones

Drones are commonly used for remote sensing, providing an affordable alternative to ground-based measurement satellites. They can fill an important gap between terrestrial measurements and biodiversity assessment. Case studies in the field highlight a wide range of applications, from mapping forest areas and monitoring invasive species, to exploring relationships between vegetation and dune morphology or detecting diseased trees. In some cases, drones have been used to produce high-quality data on the vertical structure of forests, analyze sea cliff vegetation, or detect and measure whales in the ocean. In other cases, they have been used to monitor forest restoration projects or detect invasive shrubs. There are also drones used for reforestation seeding.

Drone technology is proving to be a valuable tool in biodiversity conservation efforts, allowing researchers to obtain detailed and up-to-date information about diverse ecosystems and species. There are limitations such as lower coverage compared to satellites or difficulties with automatic image classification. Despite these challenges, the potential of drones in this area is significant and continues to grow with the development of technology.

Remote sensing of grassland vegetation

Studies demonstrate the potential of drone technology and machine learning in monitoring and preserving biodiversity. Drones, through their ability to perform high-resolution remote sensing, allow researchers to obtain detailed data on various ecosystems and species. In addition, the use of machine learning algorithms such as Support Vector Machines and CNNs facilitates the processing and analysis of this data, allowing species of interest to be identified and counted. There are challenges such as the need for high resolution to detect small species and difficulties with automatic image classification. Despite these challenges, the results of studies suggest that this approach has significant potential in the field of biodiversity conservation.

Uses of *Arnica montana*

Arnica montana is a medicinal plant with various therapeutic properties: antibacterial, antitumor, antioxidant, anti-inflammatory, antifungal and immunomodulatory.

In terms of agronomic value, *A. montana* can be cultivated, but it can also be harvested sustainably, contributing to the conservation of biodiversity and High Nature Value (HNV) lands.

The oligotrophic grasslands where *A. montana* grows are complex plant and animal communities with high biodiversity. The management of these grasslands involves balancing biodiversity conservation and agricultural production. Traditional mowing or mowing twice a year is recommended for the preservation of *A. montana.* Threats to the conservation of *A. montana* in semi-natural grasslands include climate change, agricultural intensification, abandonment, and habitat loss.

A. montana is a valuable species both medicinally and agronomically. The sustainable use of this species is an exemplary case of international efforts to conserve biodiversity.

III. Objectives & methodology

The research objectives lead to a solution for monitoring oligotrophic grasslands in the Apuseni Mountains through the use of drones and by automatically counting the *Arnica montana* inflorescences in aerial images. The main objectives are:

I. Identify a methodology for studying biodiversity with the help of drones;
II. Develop software for identifying *A. montana* inflorescences in digital aerial images;
III. Explore the possibilities of using drones for mapping oligotrophic grasslands with *A. montana*, in the Apuseni Mountains.

The specific objectives are to conduct drone flights in an oligotrophic grassland in Germany to obtain drone imagery to training a CNN model, to form a robust CNN model for counting inflorescences, to conduct drone flights in several oligotrophic grasslands in Romania to obtain imagery for evaluating the performance of our model, and to build supporting software applications for using the CNN model in situ.

Methods & Technologies

Two drones were used: the "DJI S1000" model in Germany and the "DJI M300" model in Romania to obtain aerial imagery. Both drones are similar in performance. The drones carried cameras that were similar in performance, resulting in hundreds of high-resolution images from each flight. Four flights took place in the Black Forest, Todtnau, Germany (2018), producing images for the training effort of a new CNN model. Nine flights took place in the Apuseni Mountains, Ghețari, Romania (2021), producing images for the evaluation of the software system. The images were sampled randomly and blindly. For training the CNN model for counting inflorescences, images with *A. montana* were labeled using several types of labels that were defined to try to include possible cases after grouping the inflorescences and after clarity, all at low resolution. For the prototype, only clear individual inflorescences (AM1), unclear individual inflorescences (BAM1), and unclear binary inflorescences (BAM2) were included. We formed a dedicated CNN model for detecting *A. montana* inflorescences, following conventional documentation and using the following: Python programming language, specially written applications, the TensorFlow2 platform, the base CNN ResNet101 model, and manually defined labels and images (supervised learning).

The produced model, named "ArnicaAI", was evaluated on aerial images created in Ghețari. The results were collected, investigated, and statistically analyzed. Key flight factors – the GSD value and the flight time (expressed as the length of the shadow produced by sunlight) – were integrated into the statistical analysis to determine technological performance limits (best practices) regarding flight planning over grasslands. The greatest possible aerial coverage requires finding a balance between flight altitude and the quality of the visible plant details in the images produced with the drones, which is why we focused on maximizing low-resolution inflorescence detection.

IV. Results & Discussion

In this study, a software suite was assembled to manage, process, and evaluate aerial images. The software suite included support programs for organizing image collections and for composing applications. For the division of images for training, an application was created that efficiently fragments large images into small images, suitable for use with the (CNN) ResNet101 model. The model training was accomplished through the TensorFlow2 platform with a minimally customized configuration. For in situ testing, two applications were created: one that uses the model (ArnicaAI) and one that helps to report the results.

The labeling effort produced a total of 23,680 labels for machine learning (training the model). The majority were for BAM1, followed by AM1 and BAM2. Most of the labels for individual inflorescences had a low resolution, under 33 x 33 px. The model was successfully trained (**Figure 1**), reaching a learning rate of 0 and presenting internal self-evaluation indicators with satisfactory progress.

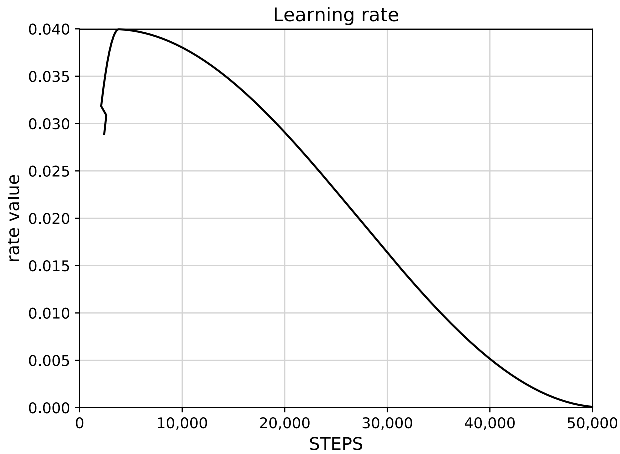

Figure 1 Model learning rate in 50000 steps (epochs).

In the results produced by ArnicaAI, several cases of overlap of the boxes marking the detected inflorescences were observed. This type of result is due to the default configuration of the model, especially the adjustment of the filters in the aspect called *"non-maximal suppression."* By adjusting the configuration, tighter and more accurate matches of the boxes on the *A. montana* inflorescences can be made. Overall, the ArnicaAI model finds AM1 inflorescences in several different situations, including where the resolution is low and where we have occlusions from other plants (Figure 2). Detections seem focused on the ligulate (ray) flowers, which is where the most detail exists at low resolution. This specialization may also be the result of overfitting as the model used

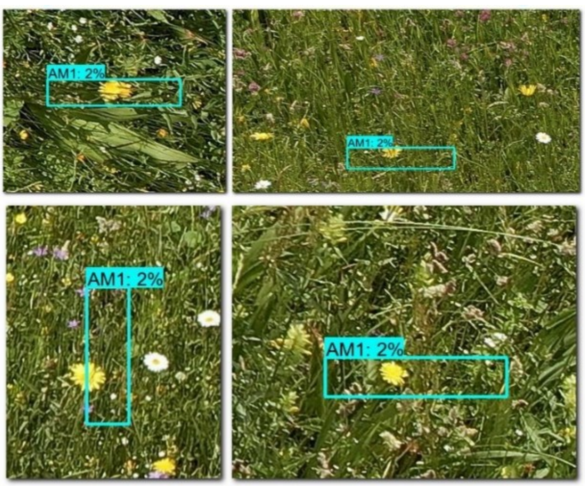

Figure 2 True positive detections.

blurry images (BAM) as negative examples to train against, leading to choosing the clearest inflorescences as AM1. The ArnicaAI model is only slightly adjusted compared to the base model's defaults, its configuration representing more of a constant in experiments, not a factor. Our model has a reduced score threshold to report as many *A. montana* detections as possible, even if many are wrong (decreases accuracy), so that we can observe the limits.

Table 1

Model evaluation for AM1 detection. MPF – mean precision per flight

Aerial Survey	Altitude (m)	Shadow size (CM)	GSD (CM)	Images	Detections	MPF (%)
JUN1	20	16	0.21	65	1570	51.23
JUN2	40	15	0.42	63	1648	49.05
JUN3	18	14	0.19	59	1450	44.92
JUN4	18	13	0.19	104	1470	51.62
JUN5	30	13	0.31	40	265	45.75
JUN6	60	30	0.65	68	911	16.03
JUL1	60	51	0.73	26	65	10.00
JUL2	40	56	0.49	37	111	10.54
JUL3	30	59	0.37	40	237	12.75

From each evaluated image, a precision value results (true positive cases of total detections, as a percentage), and for each flight, the average of these values was calculated: Flight Precision Average (Table 1, MPF). The model can be adjusted to increase precision, but this must be a decision within the management plan. The model presents a precision performance that varies between 10% and 52%, with an average success rate of 32%. Therefore, the use of the model in the field involves the use of correction coefficients to obtain a realistic estimate of *A. montana* inflorescences.

GSD (Ground Sampling Distance), as a scale of the detail in the image, is a key factor in the success of RS and of manual species identification from aerial images. For the automatic identification of inflorescences, the GSD value is as important as for manual identification. Another crucial factor is the time at which the flight was performed, the date, and the location, as these determine the shadow size produced by sunlight, and shadows add distortions to the identification process.

Table 2

Descripive statistics for the evaluation of ArnicaAI results

Variable	n	Mean	Standard Error	Min.	Max.
First analysis: between the 9 aerial surveys					
Precision (%)	9	32.43	19.27	10.00	51.61
GSD (cm)	9	0.40	0.20	0.19	0.73
Shadow size (cm)	9	29.67	20.04	13.00	59.00
Second analysis: between all the evaluated images					
Precision (%)	503	36.92	31.10	10.00	100.00
GSD (cm)	503	0.64	0.33	0.45	1.34
Shadow size (cm)	503	23.90	16.83	13.00	59.00

To determine the correction coefficients, a statistical analysis was performed on the results in two stages: first, the results were analyzed according to the flight, then the combined results were analyzed in a single set with all the evaluated images from all these flights, a set of 503 images (Table 2).

For the results between flights, a statistical analysis would have an exploratory role, having only 9 flights. For the combined set of results, several statistical tests were applied, starting with the test for the Pearson correlation coefficient (Table 3).

Table 3

Pearson's correlations.
r – correlation coefficient; p – probability; S.E. – standard error

Pair of variables	*r*	*p*	Effect	S.E. effect
Precision (%) – GSD (cm)	**−0.449** ***	<0.001	−0.483	0.045
Precision (%) – Shadow size (cm)	**−0.258** ***	<0.001	−0.263	0.045
Shadow size (cm) – GSD (cm)	**0.237** ***	<0.001	0.241	0.045

*** $p < 0.001$

The correlations between the three variables indicate statistically significant relationships, with a negative effect of GSD on precision, and a slightly negative effect of shadow size on precision. To formulate a statistical model between the three variables, a Null hypothesis (H_0) includes the two independent variables as follows:

$$\boldsymbol{Y} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{X}_1 + \boldsymbol{\beta}_2\boldsymbol{X}_2$$

The statistical model is as follows: Y - the dependent variable (Precision); β_0 - the intercept value (Precision); β_1 - GSD coefficient; X_1 - independent variable (GSD); β_2 - Shadow size coefficient; X_2 - independent variable (Shadow size).

The coefficient of determination (R^2) for this statistical model is 0.226, with a statistically significant value ($p < 0.001$). The result shows that 22.6% of the Precision variance is explained by the statistical model.

The ANOVA test confirms the Null hypothesis with GSD and Shadow size as a statistically significant model ($p < 0.001$) and 2 degrees of freedom.

The last statistical test was a linear regression that produced the following coefficients:

$$\boldsymbol{Precision}_{\%} = \mathbf{69,173 - 39,283} \times \boldsymbol{GSD_{cm}} - \mathbf{0,296} \times \boldsymbol{Shadow\_size_{cm}}$$

The linear regression model has a Precision intercept value of 69.173 with a standard error of 2.959, and it is statistically significant ($p < 0.001$). This value of approximately 70% represents the maximum precision achieved with **ArnicaAI** under optimal flight conditions according to the evaluation experiences in Ghețari. The GSD (ground sampling distance) value has a coefficient of -39.283 with a standard error of 3.874 and a standardized coefficient of -0.411, forming a negative relationship with Precision (dependent variable). The *t*-test value is -10.140 and it is statistically significant ($p < 0.001$).

The Shadow size coefficient is -0.296 with a standard error of 0.075 and a standardized coefficient of -0.160, indicating a small negative effect on Precision. The *t*-test value is -3.956 and it is statistically significant ($p < 0.001$). The correlation with the length of the shadows confirms the importance of variation in the images from the training of the ArnicaAI CNN model, so that, in addition to the transfer of learning from images with the population of *A. montana* from the Black Forest to the population from Ghețari, the timing limitation was also transferred.

The coefficients of the statistical model allow for the estimation of detections if the flight parameters – GSD and shadow size – are known, and these calculations can be improved with empirical data from the use of the system and validation through manual counting, and even including other variables such as the heterogeneity of the ground surface included in the aerial images (the larger this is, the more unclear portions there are in the images).

The result of the correlation with GSD confirms the importance of images with a small ground sampling distance and presents a limit of the GSD value: a maximum of 0.45 cm to obtain good precision with our CNN model, ArnicaAI. Given that the flights for training imagery took place in a shorter interval, between morning and lunch, with shadows of length in the range of 17-25 cm, we can observe a sharp loss of performance in the evaluation for images with shadows larger than 25 cm. This indicates the most suitable hours for aerial surveys with ArnicaAI.

The results of the study are positive, but limited, and are in line with recent similar efforts that use convolutional neural networks (CNN) to detect herbaceous species. The low resolution of the plants limits performance and overlapping vegetation increases errors. For *A. montana*, the training was focused on the flowering phenophase, which eased the overall effort. The study confirms the methodological findings of other research that used a similar technological suite to detect inflorescences from several species. These studies have found that larger inflorescences are easier to detect and that there are difficulties that arise due to overlapping group inflorescences. This challenge is what we aim to solve in the future with the group label sets (AM2-5, AMN), to avoid confusion and to count groups of "bouquets" that can later be aggregated into a more representative total for the real situation in the grassland.

V. Conclusions & Recommendations

As part of the doctoral thesis, a specialized software suite was developed for processing and analyzing aerial images from drones. The solution is adapted to oligotrophic grasslands with *Arnica montana* L. from the Apuseni Mountains and the Black Forest. By integrating advanced algorithms, the production, labeling, and evaluation of images have been simplified or automated, thus facilitating grassland mapping. Machine learning algorithms were implemented, with training on a comprehensive dataset that included small and medium resolution details. The use of the software suite significantly reduced the time needed for processing and analyzing images, providing functional, qualitative, and promising results (Main objectives: I and II.)

The flight altitude and the GSD value have a significant impact on the quality of the images obtained in biodiversity studies based on automatic remote sensing (RS). Flights at low altitudes offer better resolution but require careful planning to obtain clear images. Too low flight altitudes can lead to images with a high level of detail but can be affected by shadows and other artifacts. In contrast, too high flight altitudes can lead to images with a poorer resolution, which can make it difficult to identify plant species and other ecological characteristics (Main objectives: I and III.)

The timing of the flight also has a significant impact on the quality of the images. Flights conducted during the day, when the Sun is at its zenith, produce the best results. On the other hand, flights conducted early in the morning or late in the afternoon, when the sun is at a lower angle, can produce images with long shadows and details unfamiliar to the trained model. Careful planning of flights and a deep understanding of the factors that influence the quality of images are essential for obtaining high-quality results (Main objectives: I and III.)

The clarity of images is essential for the correct identification of plant species and characteristics of interest in biodiversity studies based on automatic RS. More clarity translates to more detail, allowing for a more detailed analysis of habitat structure and other aspects of the ecosystem. In contrast, blurry images or those affected by unfavorable weather conditions can lead to errors in species identification and biodiversity analysis, as long shadows or dim light can make it difficult to distinguish between different plant species or can hide crucial details about habitat structure.

Obtaining clear and high-quality images is essential for biodiversity conservation with this methodology. By optimizing flight conditions and image calibration, high-quality images can be obtained that allow for a detailed and accurate analysis of species of interest. This demonstrates the importance of careful planning and implementation for biodiversity studies based on RS (Main objectives: I and III.)

The main recommendation is to continue and expand the use of drones for mapping ecosystems with *A. montana*, involving the planning and systematic execution of flights, and covering relevant areas. The use of other types of drones or sensors can be explored to obtain higher-resolution images and finer details.

The ArnicaAI model should be updated with labeled images that come from flights from sunrise to sunset in the flowering season of *A. montana*.

It is important to continue improving ArnicaAI, and to validate and calibrate the data collected through drone flights, using testing plots, comparing the data with ground measurements, and adjusting the correction coefficients.