EXAMINATION OF RED CLOVER OPTIMUM HARVESTING STATUS IN SEED PRODUCTION WITH UNMANNED AERIAL SYSTEMS (UAS)

A VETŐMAGTERMESZTÉSŰ VÖRÖSHERE OPTIMÁLIS BETAKARÍTÁSI ÁLLAPOTÁNAK VIZSGÁLATA PILÓTA NÉLKÜLI LÉGIJÁRMŰ RENDSZEREKKEL (UAS)

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Abstract

Red clover is the second most valuable and intensively produced leguminous fodder crop in Hungary. Optimum harvesting should start when 75-80 per cent of seed-heads are brown and 90 per cent or more of the seeds are past the hard-dough stage of maturity. Harvesting must be done before an appreciable amount of seed-head deterioration begins. On fall plantings the first-year crop normally matures during the months of August and September. Seed from second-year stands, if not cut back, will mature somewhat earlier. The harvesting of red clover is divided into two distinct operations: (1) the curing or preparation and (2) the hulling and separation of the seed. The curing is by windrowing or contact desiccant spraying. It is the timing of each step that can make all the difference between a good yield and a mediocre one. The agronomists decide those actions with personal on-site inspections of the heads. Their decisions rely on random point sampling. A trend has developed with the recent interest in the harvesting time estimation of red clover in seed production to meet the demands of sustainable and precise agriculture. Unmanned aerial systems (UAS) are one of the current state-of-the-art tools when it comes to supporting farm-scale phenotyping trials. In this examination, we explored the red clover seed heads classification using deep learning on a UAS RGB aerial image. We assessed different ripening status of the flower heads with a single-shot detector (SSD) deep learning model. It is proposed that drone data collection was suggested to be optimum in this study, closer to the harvest date, but not later than the ageing stage. With SSD model we can calculate the number of heads on the vegetation surface but to differentiate them (e.g., purple-, light-brown-, dark-brown flower heads) with high confidence, we need more examinations, spectral bands or fine adjustments of the model with additional data.
Keywords: *red clover, harvesting status, seed production, deep learning, single-shot detector*
JEL: *Q15, Q1, Q55*

Összefoglalás

A vöröshere a második legértékesebb és legintenzívebben termesztett pillangós takarmánynövény Magyarországon. Az optimális betakarítást akkor kell megkezdeni, amikor a gubók 75-80 százaléka barna, és a magok 90 százaléka vagy annál nagyobb arányban elérte a teljes érési stádiumot. A betakarítást még azelőtt szükséges elvégezni, hogy a magfejek jelentős mértékű károsodása megkezdődne. Az ősszel elvetett elsőéves növények általában augusztus-szeptember hónapokban érnek be. A másodéves állomány magjai, amennyiben nem kerültek visszavágásra, valamivel korábban érnek be. A vöröshere betakarítása két különálló műveletre oszlik: (1) a szárítási vagy előkészítési folyamatra, és (2) a magok kicsépelésére és *szétválasztására. A szárítás történhet rendrakással vagy kontakt szárítószer permetezéssel. Az egyes lépések időzítése döntő jelentőségű lehet a jó és közepes terméshozam közötti különbség szempontjából. Az agronómusok személyes helyszíni vizsgálatokkal, a fejeken végzett random pontmintavétellel döntenek a szükséges lépésekről. Az utóbbi időben egyre nagyobb érdeklődés mutatkozik a vöröshere vetőmagtermesztésében az érési idő előrejelzése iránt, hogy kielégítse a fenntartható és precíziós mezőgazdaság követelményeit. A pilóta nélküli légijármű rendszerek (UAS, unmanned aerial systems) jelenleg az egyik legkorszerűbb eszközök közé tartoznak a gazdasági szintű fenotípus-vizsgálatok támogatásában. E vizsgálat során mélytanulási módszerekkel vizsgáltuk a vöröshere magfejek osztályozását UAS által készített RGB légifelvételeken. Különböző virágfej érési állapotokat értékeltünk egy SSD (Single-Shot Detector) mélytanulási modell segítségével. A vizsgálatban javasoltuk, hogy a drónadatok gyűjtésére az optimális időpont a betakarításhoz közelebbi időszak, de még az öregedési stádium előtt legyen. Az SSD modellel számíthatjuk a vegetáció felszínén található virágfejek számát, azonban a fejlett osztályozáshoz (pl. lila, világosbarna, sötétbarna virágfejek) nagyobb megbízhatósággal további vizsgálatokra, spektrális sávokra vagy a modell finomhangolására és kiegészítő adatokra van még szükség.*

Kulcsszavak: *vöröshere, betakarítási állapot, magtermesztés, mélytanulás, single-shot detector*

Introduction

Machine Learning Techniques

Machine learning is a data analytics technique that teaches computers to do what comes naturally to humans and animals: learn from experience. Machine learning algorithms use computational methods to directly "learn" from data without relying on a predetermined equation as a model (JUNG et al., 2021). As the number of samples available for learning increases, the algorithm adapts to improve performance. Deep learning is a special form of machine learning (Figure 1.).

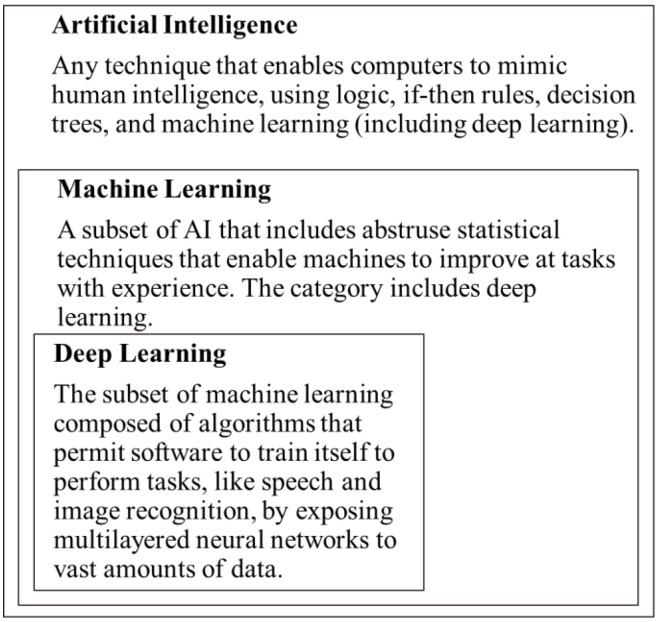


Figure 1. The set of AI (Artificial Intelligence)

Source: Own construction based on JEONG (2020)

Deep learning

Deep learning is a neural network with multiple hidden layers. Deep learning techniques require a lot of data and computation power for best performance as this method is self-tuning many parameters within vast architectures. The deep learning users need powerful computers with GPUs (Graphical Processing Units). Deep learning techniques have been extremely successful in vision (image classification), text, audio, and video. The most common software packages for deep learning are Tensorflow and PyTorch.

About the Single-Shot Detector (SSD) model

SSD has two components: a backbone model and SSD head . Backbone model usually is a pre-trained image classification network as a feature extractor (LIU et al.. 2016). This is typically a network like ResNet trained on ImageNet from which the final fully connected classification layer has been removed. It is thus left with a deep neural network that is able to extract semantic meaning from the input image while preserving the spatial structure of the image albeit at a lower resolution. For ResNet34, the backbone results in a 256 7x7 feature maps for an input image. The SSD head is just one or more convolutional layers added to this backbone and the outputs are interpreted as the bounding boxes and classes of objects in the spatial location of the final layer's activations.

Classification vs. Object Detection vs. Image Segmentation

"Image Classification" helps us to classify what is contained in an image (Figura 2.). "Image Localization" will specify the location of single object in an image whereas "Object Detection" specifies the location of multiple objects in the image. Finally, "Image Segmentation" will create a pixel wise mask of each object in the images. We can identify the shapes of different objects in the image using "Image Segmentation". But for this examination we made only object detection.

Figure 2. Classification vs. Object Detection vs. Image Segmentation

Source: Own construction based on SHARMA (2022)

The general characteristics of Red clover (Trifolium pratense L.)
Red clover is perennial which is grown for forage and is used in rotations for soil improvement. It is adapted to areas with moderate summer temperatures and adequate moisture throughout the growing season (Table 1). Unlike alfalfa, red clover will grow moderately well in slightly acid soils (JING – BOELT, 2021). However, maximum yields are obtained when soil pH is 6.0 or higher.

Table 1. Sowing data of red clover

Sowing data of red clover:	
Sowing date:	- spring 01.03-15.04 – summer 08.01-20
Row distance:	12 cm;
Sowing depth:	1-2 cm;
Seed rate:	8-9 million/ha-20-25 kg/ha;
1000 seed weight:	1.4-1.9 g diploid 2.5-2.8 g tetraploid

Source: SMITH, 1965.

Red clover usually produces two or three hay crops per year. It is characterized by rapid spring growth and low winter hardiness, which contributes to its short-lived nature (Smith, 1965).

Table 2. Yield and quality comparison of red clover with alfalfa

Yield and quality of alfalfa and red clover under a two and three-harvest schedule				
Species	**No. of cuts**	**Yield t/ha**	**Crude protein %**	**Digestable dry matter %**
Red clover	2	11	14.6	68.3
	3	8.5	21.3	73.3
Alfalfa	2	10.4	15.6	63.4
	3	10.9	20.7	65.2

Source: SMITH, 1965.

Red clover is the second most valuable and intensively produced leguminous fodder crop in Hungary (KSH, 2021). It is in the constitutional and national interest to preserve Hungary's GMO-free status. The Ministry of Agriculture is working on a national feed protein program to replace imported GMO feed. Red clover is leguminous crops and a rich source of crude protein.

Harvesting date determination

Traditional methods:
1) Methods of harvesting vary widely. In many areas the crop is chemically desiccated and straight combined when the heads are black and the seed ripe.
2) Other growers swath or cut with a mower equipped with a windrowing attachment when the seed is approximately 35% moisture.
At this stage the heads are brown and most of the seeds ripe or tinged with purple. The swaths or windrows are left to dry for 7 to 10 days before being threshed.
It is the timing of each step that can make all the difference between a good yield and a mediocre one. The agronomists decide those actions with personal on-site inspections of the heads. Their decisions rely on random point sampling.

New goals:
A trend has developed with the recent interest in the harvesting time estimation of red clover in seed production to meet the demands of sustainable and precise agriculture. The criteria used for determining the degree of ripeness of red clover are well published but the sampling method i.e. decision making with the help of deep learning technics can be polished soon, and it can be adapted for many agro-technics.

Examination goals
1) Exploring & choosing among different strategies for red clover examination (Classification, Object Detection and Image Segmentation)
2) Computing and using spectral vegetation indices
3) Use deep learning to assess red clover flower heads status
4) Validating the field sampling data with aerial imagery

Material

Study Area and Experiment Layout
This study was undertaken at the Research Centre for Irrigation and Water Management (ÖVKI) in Szarvas (46.852105 N 20.521786 E), Hungary (Figure 3a). The experimental area covers 2,7 ha but we used merely 39.17 m^2 but even 35 m^2 sample area (Figure 3b-c) from it for this pioneer examination was enough.

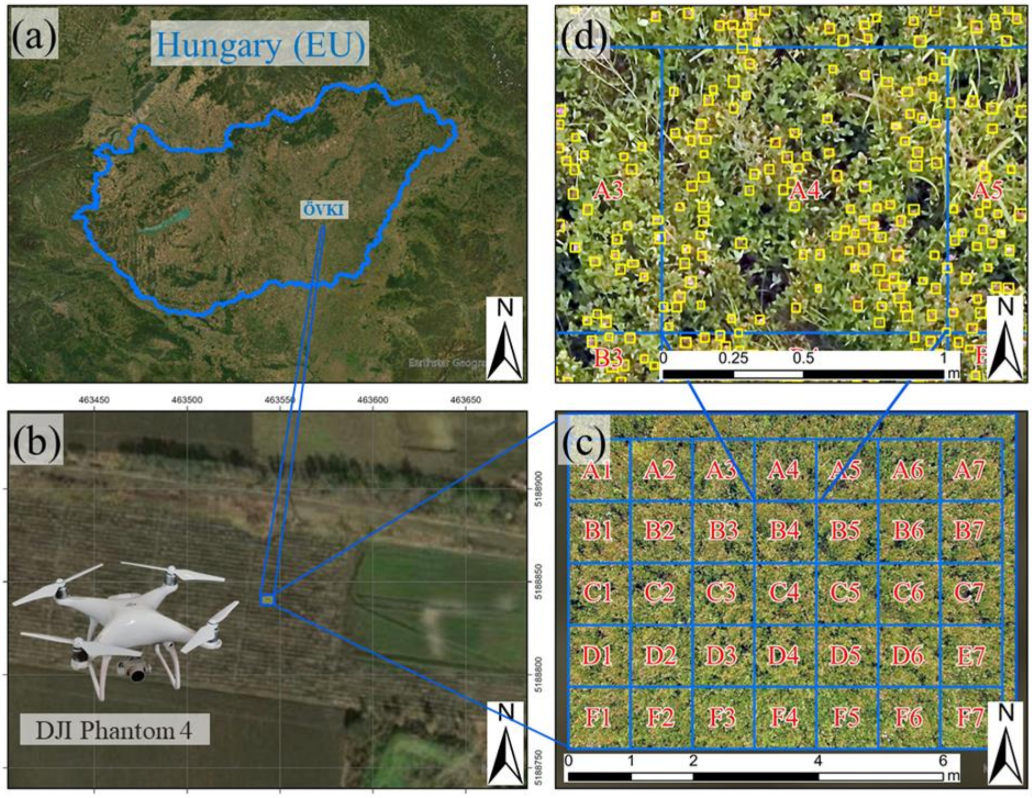


Figure 3. (a) The Research Centre for Irrigation and Water Management (ÖVKI) is situated in Szarvas, Hungary. The sample area locates near to ÖVKI. (b) The DJI Phantom 4 Advanced device was used to capture RGB imaging data with its DJI FC330 camera at ÖVKI's field. (c) The area was divided into square meters with attribute indexes. It speeds up attribute queries on feature classes and tables. (d) The detected red clover heads per one m^2 is identified in yellow bounding boxes.

Image Acquisition
DJI Phantom 4 Advanced “Agro” version was used with DJI FC330 RGB camera (Figure 3/b). Its camera has a 1/2.3” CMOS sensor (effective pixels:12.4 M), lens with FOV 94° 20 mm (35 mm format equivalent) f/2.8 focus at ∞, ISO Range 100-1600 (photo), electronic shutter speed 8 - 1/8000 s and image Size 4000×3000 single shot frame.

System configuration
The processes that are performed when using deep learning take a large amount of memory from your computer. To perform a deep learning process, an NVIDIA GPU with a minimum dedicated memory of 8 GB is recommended.

Image Processing and Orthorectifying
The UAS data was post-processed in ArcGIS Pro using just the exchangeable image file data (EXIF) of the images. This post-process geotagged the UAS images under 1 m error, where the method and accuracy obtained is like and thus less than the one-pixel size in our examination. Pix4D v.4.3.31® software was utilized to process and radiometrically correct (default in Pix4D) the imagery and generate the orthomosaics (Figure 4). These images were used to represent the extent of the experimental area.

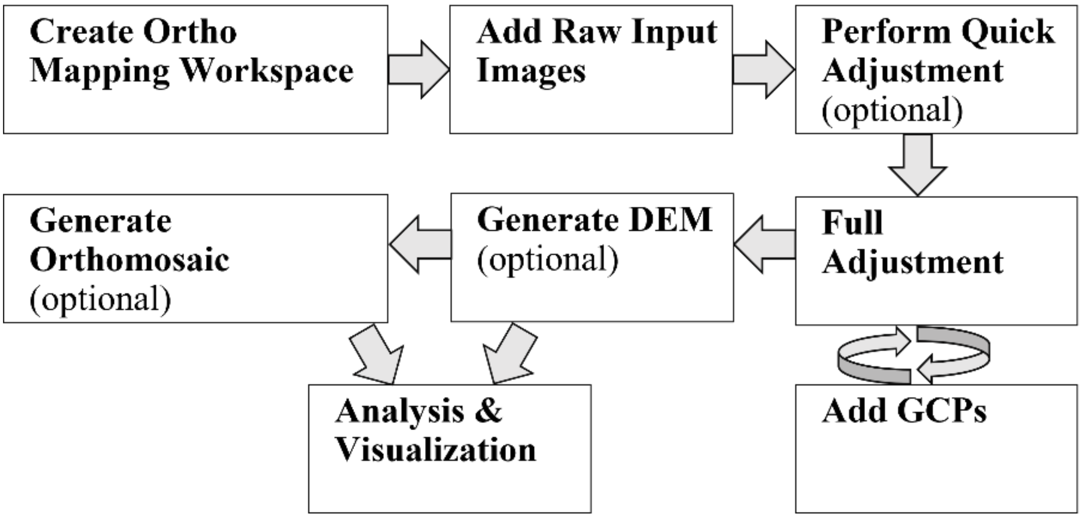


Figure 4. Ortho Mapping workflow

Methods

Data processing steps:

1) Create the project and imagery
2) Create training schema, classes and samples (Label Objects for Deep Learning, Bookmarks)
3) Create image chips
4) Train deep learning model (Model Type is set to SSD)
5) Detect red clover heads (with the created deep learning model package file)
6) Refine detected features (Non-Maximum Suppression)
7) Estimate vegetation health (Visible Atmospherically Resistant Index (VARI); Green Chromatic Coordinate (GCC))
8) Extract indices to red clover heads

1) Create the project and imagery

The first step was to find the UAV imagery that shows red clovers heads and has a fine enough spatial and spectral resolution to identify red clover differences. Accurate and high-resolution imagery is essential when extracting features. The model is only able to identify the red clover if the pixel size is small enough to distinguish heads. Additionally, to calculate heads health, we needed an image with spectral bands that will enable us to generate a vegetation health index. We used the imagery for this study from drone RGB imagery. To begin the classification process, we made an ArcGIS Pro project.

2) Create training schema, classes, and samples (Label Objects for Deep Learning, Bookmarks)

Creating good training samples is essential when training a deep learning model, or any image classification model. It is also often the most time-consuming step in the process. To provide our deep learning model with the information it needs to extract all the red clover in the image, we created features for a number of red clovers to teach the model what the size, shape, and spectral signature of red clover heads may be. These training samples are created and managed through the "Label Objects for Deep Learning" tool.

The "Label Objects for Deep Learning" tool has an "Image Classification" pane where we created a "New schema" and then we created the following classes: 1, purple-; 2, light-brown-; 3 dark-brown flower heads and another schema where we created only one class.

Create training samples (Bookmarks, Image Classification)

To begin the classification process, we made an ArcGIS Pro project containing a few bookmarks to guide us through the process of creating training samples. Those bookmarks are making the process more transparent and faster during creation of training schema. The bookmarks mean on a map or orthomosaic dataset that designate a given portion or zoom of the training locations. To make sure we are capturing a representative sample of clover heads in the area, we digitize features throughout the image. We drew circles around each red clover heads in our current bookmarked display. Circles were drawn from the center of the feature outward, measuring the radius of the feature. The new red clover head records were added in the "Labeled Objects" group of the "Image Classification" pane.

We collected here a few details for help identifying objects:

- We can zoom and pan around the map to make digitizing easier but we need to be sure to digitize as many of the objects within the extent of the bookmark as we can.
- If we are not sure about the exact location of an object, it is OK to skip it. We want to ensure that we create accurate training samples.
- It is OK if the circles we draw overlap.
- Our final model considers the size of the objects we identify, so we need to be sure to mark both small and large objects.

3) Create image chips

The last step before training the model is exporting our training samples to the correct format as image chips. We created a red clover head records for every classes we could to ensure there were many image chips with all the red clover heads marked. These features are read into the deep learning model in a specific format called image chips. Image chips are small blocks of imagery cut from the source image. Once we had created a sufficient number of features in the "Image Classification" pane, we exported them as image chips with metadata. Those chips are special type of image packages in JPG format with connected types of extensions (.jgw;.jpg.aux.xml;.jpg.ovr and .xml) Their numbers depend on the labelled objects but generally many thousands of small size, structured (3-6 KB) images.

4) Train a deep learning model

In ArcGIS Pro 2.9 the Train Deep Learning Model geoprocessing tool uses the image chips we labelled to determine what combinations of pixels in a given image represent red clover heads. We used these training samples to train a single-shot detector (SSD) deep learning model. Depending on our computer's hardware in ArcGIS Pro 2.9, training the model can take more than an hour. It's recommended that the computer be equipped with a dedicated graphics processing unit (GPU).

In ArcGIS Pro 2.9, the name of the geoprocessing tool is “Train Deep Learning Model”. Its pane first asks the previously made imagechips. The imagechips folder contains two folders, two text files, a .json and an .emd file that were created from the “Export Training Data for Deep Learning” tool. The “esri_model_definition.emd file” is a template that will be filled in by the data scientist who trained the model, with information such as the deep learning framework, the file path to the trained model, class names, model type, and image specifications of the image used for training. The .emd file is the bridge between the trained model and ArcGIS Pro.

Before we run the model in ArcGIS, the following steps are set to be on it. First, we created a folder to store our model. Next, we set the number of epochs (50) that our model run. The number of epochs is a hyperparameter that defines the number times that the learning algorithm works through the entire training dataset. An epoch is a full cycle through the training dataset. During each epoch, the training dataset we stored in the imagechips folder were passed forward and backward through the neural network one time.

The model type determines the deep learning algorithm and neural network that we used to train our model. In our case, we used the SSD method because it's optimized for object detection. Next, we set the batch size to 8. The batch size is another hyperparameter that defines the number of samples to work through before updating the internal model parameters. This parameter determines the number of training samples that will be trained at a time. If the model fails to run, reducing the Batch Size parameter can help. We may have to set this parameter to 4 or 2 and rerun the tool. However, this may reduce the quality of our trained model's results.

5) Detect red clover heads

The bulk of the work in extracting features from imagery is preparing the data, creating training samples and training the model. Now that these steps we had completed, we used a trained model to detect red clover throughout our imagery. Object detection is a process that typically requires multiple tests to achieve the best results. There are several parameters that we can alter to allow our model to perform best. To test these parameters quickly, we try detecting red clover heads in a small section of the image. Once we satisfied with the results, we extend the detection tools to the full image. In ArcGIS Pro 2.9, the name of the geoprocessing tool is “Detect Objects Using Deep Learning”. Here we set its parameters and saved the model package file.

6) Refine detected features

Ensuring an accurate count of red clover heads in important. Since many red clover heads have been counted multiple times, we had used the “Non-Maximum Suppression” tool to resolve this. It identifies duplicate features from the output of the “Detect Objects Using Deep Learning” tool as a postprocessing step and creates a new output with no duplicate features. We had to be careful because red clover heads' areas can overlap. So, we removed features that are clearly duplicates of the same heads while ensuring that separate red clover heads with some overlaps are not removed.

It was important to realize that our model's results might not have been perfect the first time. Training and implementing a deep learning model is a process that can take several iterations to provide the best results. Better results can be achieved by doing the following:

- Increasing our initial sample size of features
- Ensuring that our training samples are accurately capturing the features we want to detect
- Making sure our training samples include features of different sizes
- Adjusting the geoprocessing tools' parameters
- Retraining an existing model using the Train Deep Learning Model tool's advanced parameters

7) Estimate vegetation health (Visible Atmospherically Resistant Index (VARI); Green Chromatic Coordinate (GCC)). VARI and GCC can be an effective tool for vegetation mapping when only RGB bands are available, providing approximate vegetation detection and helping with delineating the heads to create training classes.

To assess vegetation health, we calculated the “Visible Atmospherically Resistant Index” (VARI), which was developed as an indirect measure of leaf area index (LAI) and vegetation fraction (VF) using only reflectance values from the visible wavelength (GITELSON et al., 2002):

$$VARI = \frac{(\text{Green} - \text{Red})}{(\text{Green} + \text{Red} - \text{Blue})}$$

VARI values range between -1 and +1. Here are some example values and what they typically represent (GITELSON et al., 2002):

High VARI Values (0.3 to 0.8)

Example: Dense green vegetation, such as forests or healthy crop fields.

Interpretation: High VARI values indicate strong vegetation signals due to high reflectance in the green band and lower reflectance in the red band.

Moderate VARI Values (0.1 to 0.3)

Example: Sparse vegetation, shrubs, or moderately healthy crops.

Interpretation: Moderate values indicate some green vegetation, but it may not be as dense or healthy as areas with higher VARI values.

Low VARI Values (0 to 0.1)

Example: Grasslands, areas with low vegetation cover, or vegetation with stress.

Interpretation: Low VARI values suggest sparse vegetation or vegetation under stress. This may also indicate the presence of non-vegetated areas like bare soil.

Negative VARI Values (-1 to 0)

Example: Bare soil, urban surfaces, water bodies, or areas with minimal vegetation.

Interpretation: Negative values usually indicate non-vegetated surfaces. These surfaces reflect similarly across red, green, and blue bands, resulting in a low or negative VARI value.

Beside the VARI we calculated the “Green Chromatic Coordinate” (GCC) as the ratio of green reflectance to the sum of Red, Green and Blue (RICHARDSON et al. 2007):

$$GCC = \frac{Green}{Green + Red + Blue}$$

GCC values range from 0 to 1. Here’s a rough interpretation of typical values:

High GCC Values (0.3 to 0.5 or higher)

Example: Dense green vegetation, like healthy grasslands, forests, or crops.

Interpretation: High GCC values indicate strong green dominance, which usually correlates with areas that have dense or healthy vegetation cover.

Moderate GCC Values (0.1 to 0.3)

Example: Sparse or mixed vegetation, low-density grass, or areas with partial vegetation cover.

Interpretation: Moderate GCC values suggest vegetation is present but may be sparser or mixed with non-vegetated surfaces.

Low GCC Values (0 to 0.1)

Example: Non-vegetated areas like soil, built environments, or water bodies.

Interpretation: Low GCC values indicate a low proportion of green in the image, typically corresponding to areas without significant vegetation.

8) Extract VARI and GCC to Red Clover Heads

Having a raster layer showing VARI and GCC or other indices are helpful, but not necessarily actionable. To figure out which red clover heads need attention in our case the ripening status, we want to know the average VARI and GCC for each individual heads (Figure 5.). To find the VARI value for each head, we extracted the underlying average VARI and GCC value and symbolize them to show which head are in different ripening status.

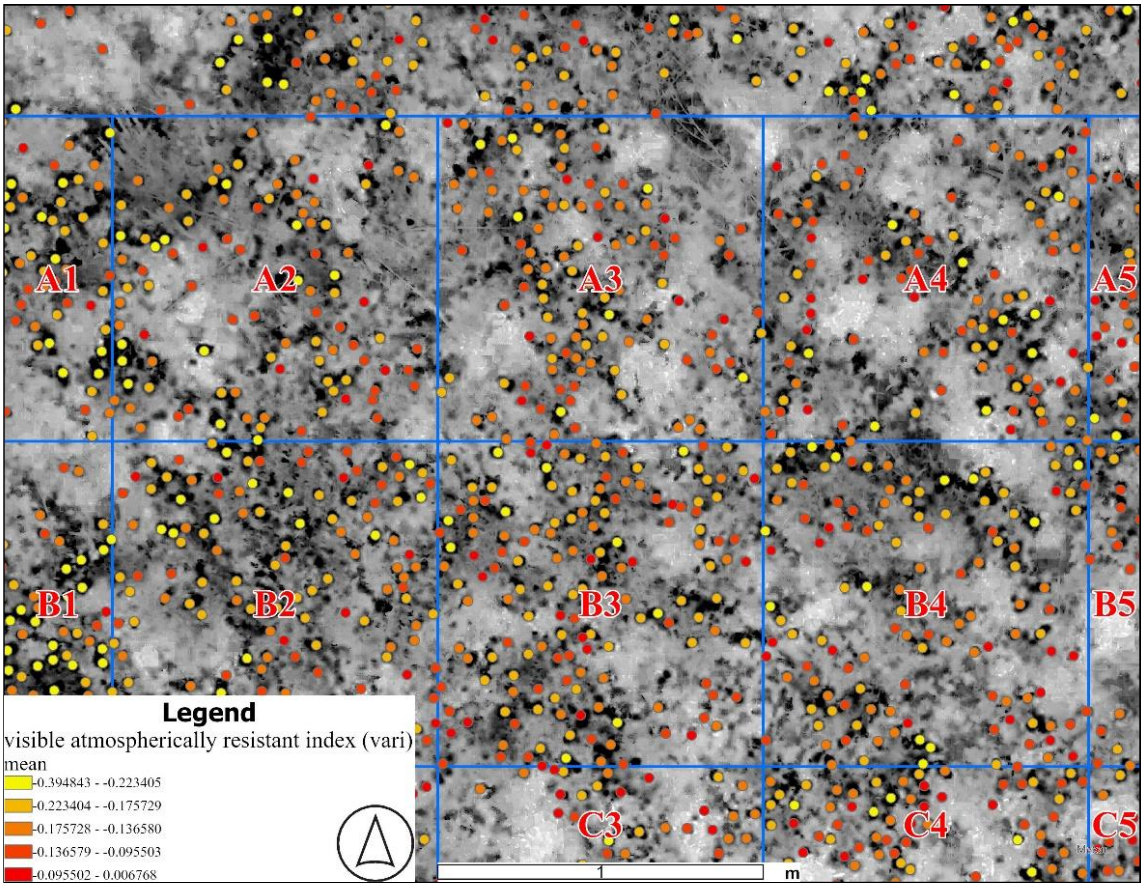


Figure 5. Visible Atmospherically Resistant Index (VARI)

Field data collection (red clover head manual counting)

Before the drone survey, we designated 4 pieces of 1 square meter area in the red clover field. After the UAV survey we manually counted all the red clover heads and classified them into 3 categories (1, purple-; 2, light-brown-; 3, dark-brown flower heads).

Results

Diagnosing Model Behavior

In ArcGIS Pro we had the opportunity to diagnose our model behaviour. We run the model several times with different set of training examples. The shape and dynamics of a learning curve can be used to diagnose the behaviour of our deep learning model and in turn perhaps suggest at the type of configuration changes that may be made to improve learning and/or performance.

There are three common dynamics that we observed in learning curves (ANZANELLO – FOGLIATTO, 2011):

- Underfit. (Underfitting occurs when the model is not able to obtain a sufficiently low error value on the training set.)
- Overfit (Overfitting refers to a model that has learned the training dataset too well, including the statistical noise or random fluctuations in the training dataset.)
- Good Fit. (A good fit is identified by a training and validation loss that decreases to a point of stability with a minimal gap between the two final loss values.)

We made at least 10 trials before we accepted its improvement. The Figure 6. demonstrates 4 of the results from its good fit- (a, d) and slightly overfit (d) and slightly underfit (c) learning curves of our model characteristics.

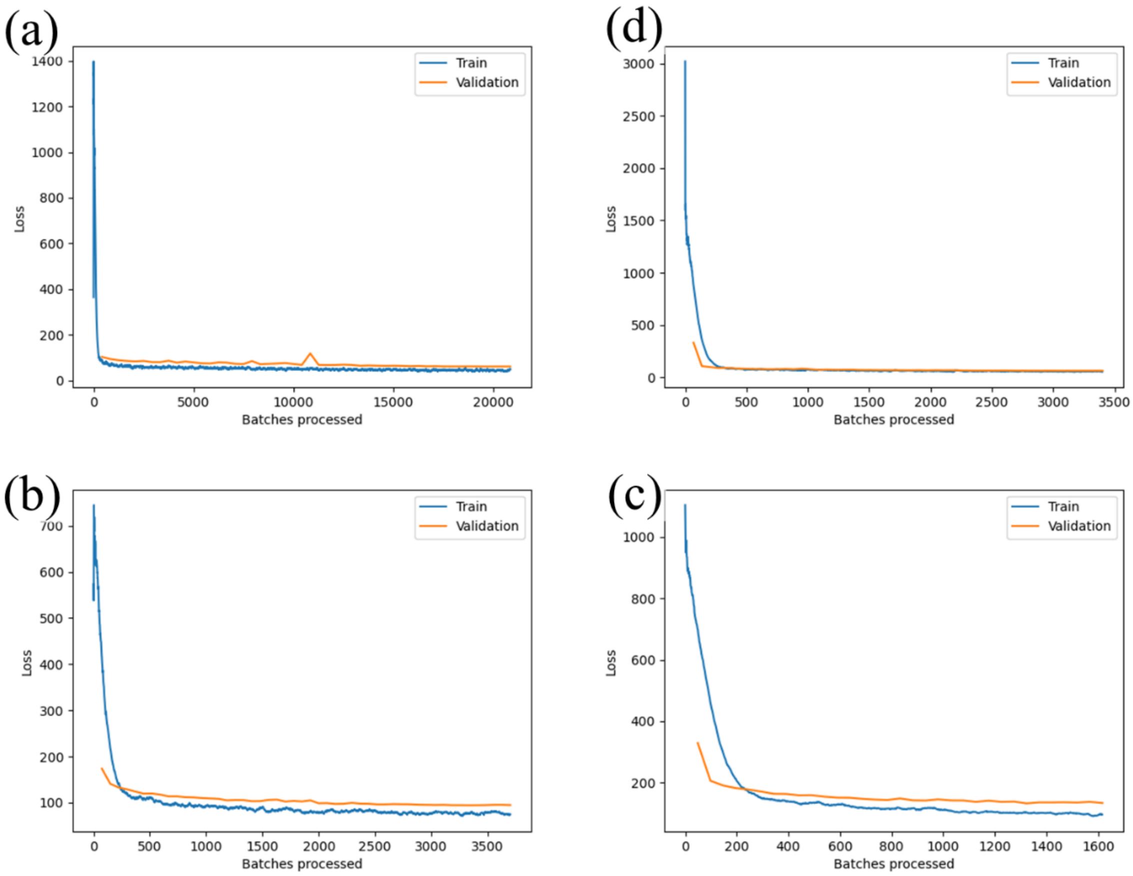


Figure 6. (a) and (d) good fit learning curves-; (c) and (d) overfit learning curves of the model characteristics Source: Own construction

Red clover head detection and classification

With our model, we localized 4793 red clover heads on the 35 m^2 experimental area. We used parallelly 4 classified model results and combined them together in one vector layer.

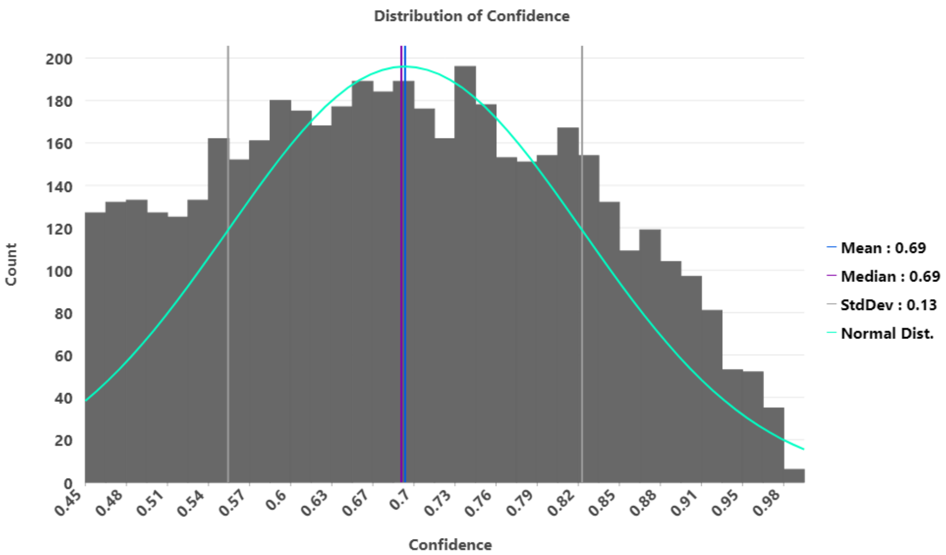


Figure 7. Distribution of confidence (4793) of the detected red clover heads in classes

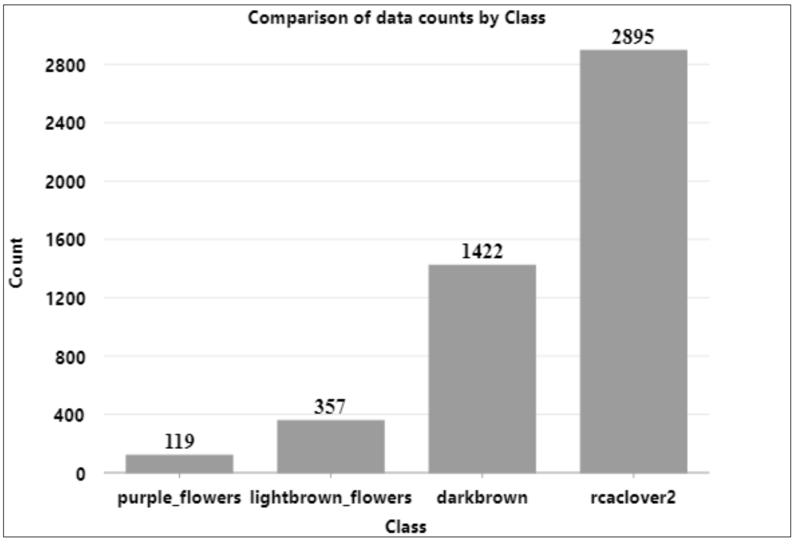
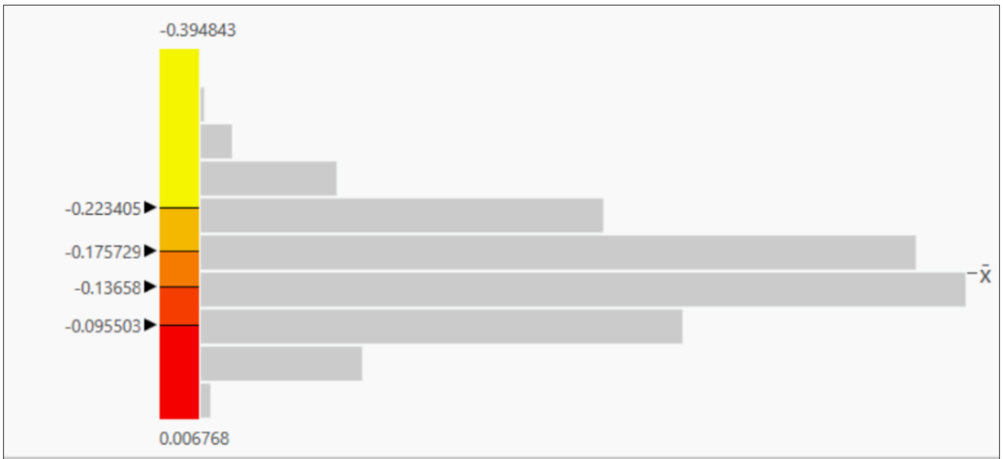


Figure 8. Sum (4793) of the detected red clover heads in classes

Then we refined the detected features with "Non-Maximum Suppression" tool. The sum result is represented in Figure 8. We classified different ripening status of the heads, but the model skipped many heads, and the overall result was complemented by a one-class model (rcaclover2). The heads we could classify were mainly dark brown.
Although the confidence value isn't as convincing as we expected Figure 7.

Results of the estimated vegetation health (Visible Atmospherically Resistant Index (VARI); Green Chromatic Coordinate (GCC))

Even if we did not be able to differentiate all the flower heads' ripening status what we detected was correlated with the VARI. 1422 brown flower heads were detected, and the result of the VARI also showed that feature in its numbers Figure 9 and Figure 10.



Statistics

Count	4793
Minimum	-0.39
Maximum	0.01
Mean	-0.15
Standard deviation	0.05

Figure 9. VARI distribution of mean on the extracted red clover heads

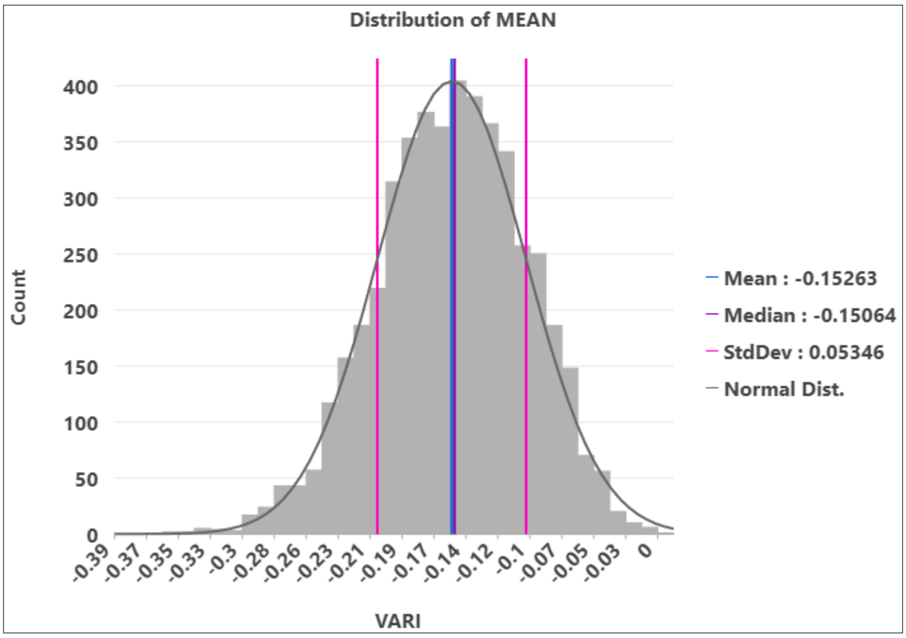
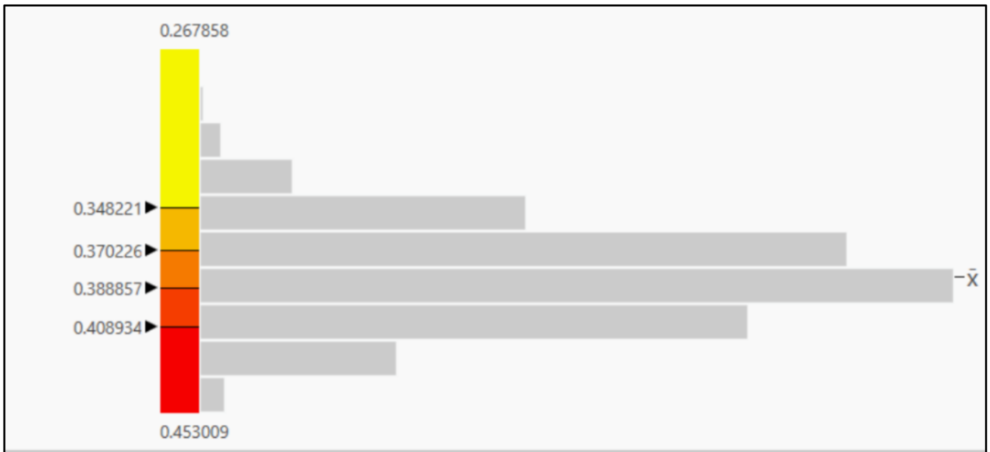


Figure 10 VARI extraction on red clover heads and created 5 classes with Jenks Natural Breaks Optimization (JENKS, 1967)**)**

The Green Chromatic Coordinate (GCC) confirmed the results of VARI in Figure 11 and Figure 12.



Statistics

Count	4793
Minimum	0.27
Maximum	0.45
Mean	0.38
Standard deviation	0.02

Figure 11 GCC extraction on red clover heads and created 5 classes with Jenks Natural Breaks Optimization

The Table 3. shows the differences between the manually counted and the object detected red clover heads. There is a difference because the top view of the red clover experimental area does not show the subsurface heads. The 1-4. samples were counted manually and the rest (A2-E7) was counted by the trained model. The other row contains more what the flower head class model characterized as red clover flower head but it cannot categorized in the 3 classes. The Table 4 show the basics statistical anlalysis.

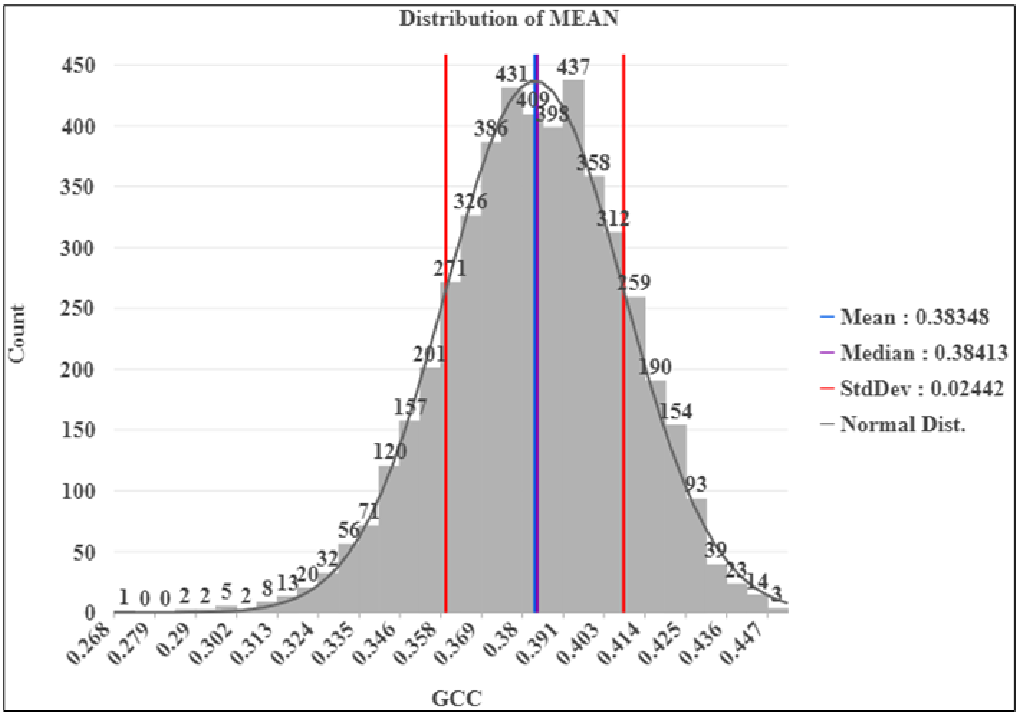


Figure 12 GCC distribution of mean on the extracted red clover heads

Table 3 Comparison with the 4 manually counted and model counted numbers of red clover heads.

2021.09.15														
Flower heads (pcs/sqm)	**1. sample**	**2.sample**	**3.sample**	**4.sample**	**A2**	**A3**	**B3**	**B4**	**C4**	**C5**	**D5**	**D6**	**E6**	**E7**
purple flower	50	101	110	99	2	4	7	2	2	2	1	1	4	0
light brown flower	450	529	375	326	0	10	13	4	20	9	13	6	13	1
darkbrown flowers	275	215	140	218	27	35	47	29	34	32	27	23	43	30
Other					64	56	72	78	95	72	109	88	58	59
Total flowers/sqm	775	845	625	643	145	159	139	113	151	136	150	118	118	90

Table 4. Basic statistics of the manually counted samples (1-4.) and the deep learning samples A2-E7)

Stat.	Purple Flower (Manual)	Purple Flower (DL)	Light Brown Flower (Manual)	Light Brown Flower (DL)	Dark Brown Flowers (Manual)	Dark Brown Flowers (DL)	Other (Manual)	Other (DL)	Total Flowers/sqm (Manual)	Total Flowers/sqm (DL)
Mean	90	2,4	420	8,9	212	32,7	0	75,00	722,00	131,90
Median	100	2	412,5	9,5	216,5	31	0	72,00	709,00	137,50
Min.	50	0	326	0	140	23	0	56,00	625,00	90,00
Max.	110	7	529	20	275	47	0	109	845	159
Std. Dev.	27,09	2,12	88,77	5,86	55,37	7,44	0	17,57	105,81	21,51

Conclusion

The current study showed that the selected object detection model generally needs further improvement and clarification. Although it was just our first trial. With SSD model we can calculated the number of heads on the vegetation surface but to differentiate them (e.g., purple-, light-brown-, dark-brown flower heads) with high confidence, we need further examination, spectral bands or fine adjustments of the model complementing with additional data. The resolution of the used image was noisy as well, but the extracted indices correlated the object detected brown flower heads. Our aims that this forward-looking deep learning technics can be polished, and it can be adapted for many agro-technics.

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