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Detection, identification and posture recognition of cattle with satellites, aerial photography and UAVs using deep learning techniques

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ABSTRACT

To obtain specific information about cattle in extensive production systems, the usual labor intensive work done by the farmer to find and visit cattle herds in large pastures can be replaced by using UAVs. UAVs are capable of assessing traits in cows, like distinguishing individuals and postures. Although these traits and the detection of cattle, do not represent resilience and efficiency directly, these may contain information associated to resilience. We performed a feasibility study of remotely sensed imagery (using datasets from satellites, manned aircrafts, and UAVs), and deep learning techniques to detect, count, identify and characterize posture of individual cows in grassland production systems. With these techniques, we focused on : (1) automatic detection of cattle locations and animal counting; (2) cow postures like standing, grazing or lying; and (3) individual cow identification. Data were collected during three field trials in the Netherlands and Poland. Artificial Intelligence was used to classify the objects (cattle) in the drone imagery. Classification accuracies of >95% were obtained for detecting cows. Accuracies of ~91% were obtained for identifying individual cows, and accuracies of ~88% were obtained for cow postures. These results make camera-mounted drones a promising new technology for monitoring extensive beef production systems.

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1. Introduction

The evolving developments in the detection of animals with remotely sensed imagery using Artificial Intelligence (AI), is becoming a promising method for farmers to efficiently monitor their cattle herds in especially extensive and remote beef production systems. Understanding parameters such as resilience and efficiency for cattle, could tell more about the status or wellbeing of cattle. For dairy cattle, sensors were used to investigate whether lifetime resilience and productive life span of dairy cows can be predicted (Adriaens et al. 2020). However, dairy cattle come to the farm daily which allows farmers to retrieve data from the sensors. For extensive beef cattle production systems, cattle should first be detected to find the locations of the herd before understanding their individual status.

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This feasibility study investigates whether remotely sensed imagery from satellites, manned aircrafts or UAVs can contribute to efficiently monitor the parameters resilience and efficiency for cattle. Remotely sensed imagery can support farmers by locating their cattle herds in an efficient and low-cost way compared to the traditional locating and counting which is a labour-intensive field trip. Current research focuses especially on Unmanned Aerial Vehicles (UAVs) in detecting cattle herds (Shao et al. 2020; Barbedo et al. 2019; Xu et al. 2020). Also VHR satellite imagery and aerial photographs can be used to detect animals in extensive herds (Yang et al. 2014). In this study, three different remote sensing platforms, namely very high-resolution satellite imagery, aerial photography and UAVs, were analyzed for detecting cattle. Especially, automatic or semi-automatic detection with pixel-based or object-based image analysis are mostly used in literature (Rivas et al. 2018; Barbedo et al. 2019). Convolutional Neural Networks (CNNs) as AI technology proved to be effective in object-based detection of cattle in large datasets (Kellenberger, Marcos and Tuia 2018). Standardized remote sensing software such as ENVI (Exelis 2019), Nanonets (ilink1) and YOLO (Redmon et al. 2016; Redmon and Farhadi 2018) are now also making use of CNN in their deep learning tools, and are therefore used in this study, also because the first two have user-friendly interfaces. These methods can provide a model, which can automate future analysis of detecting livestock from imagery. However, manual annotation (creation of training data by labelling or categorizing objects or pixels for the deep learning classification) of imagery is still time-consuming since large training datasets are needed. At the same time, machine learning, e.g. CNN, can provide faster processing (Kellenberger 2020) than conventional classification methods, e.g. visual image interpretation. However, the different platforms also have limitations in monitoring cattle in extensive production systems. For example, UAVs have limitations in battery life, drone regulations and weather conditions. For VHR satellite imagery and aerial photographs, it is difficult to monitor resilience or efficiency of individual cattle since beef cattle have the same appearance and are difficult to distinguish from higher heights. Therefore, in addition to our research on the detection and counting of cattle with various remotely sensed imaging platforms, we also focussed on the identification of individual cows and their posture with UAV imagery due to the required spatial resolution and to distinguish individuals. Monitoring their posture such as standing, grazing and lying ought to be useful as proxies for resilience and efficiency. A comparison of the advantages and disadvantages of the different platforms for the detection of cattle is discussed as well.

2. Study areas and materials

2.1. Study areas

Field trials were executed in the period 2018–2019 at the research facility CARUS of Wageningen University (WU) in the Netherlands and the Juchowo biological farm in Poland (see Table 1).

Wageningen research facility CARUS provides high-tech research equipment such as climate respiration chambers, high-speed cameras and adaptable rooms, as well as providing accommodation for a wide range of animals, from fish to companion animals to cattle. Research for cattle can be done indoors, as well as outdoors in the surrounding meadows.

Table 1. Field trials, location and use of equipment for gathering imagery with UAVs.

Field Trial	Date	Location	UAV	Camera
1	1-10-2018	Carus (NL)	Phantom	RGB
	2-10-2018	Carus (NL)	Phantom	RGB
	3-10-2018	Carus (NL)	Phantom	RGB
	4-10-2018	Carus (NL)	Phantom	RGB
	5-10-2018	Carus (NL)	Phantom	RGB
2	20-5-2019	Carus (NL)	Phantom	RGB
	20-5-2019	Carus (NL)	Phantom	RGB
	20-5-2019	Carus (NL)	Phantom	RGB
	20-5-2019	Carus (NL)	Phantom	RGB
	21-5-2019	Carus (NL)	Phantom	RGB
	21-5-2019	Carus (NL)	Phantom	RGB
	21-5-2019	Carus (NL)	Phantom	RGB
	21-5-2019	Carus (NL)	Phantom	RGB
3	4-6-2019	Juchowo (PL)	Phantom	RGB
	5-6-2019	Juchowo (PL)	Phantom	RGB
	5-6-2019	Juchowo (PL)	Phantom	RGB

Juchowo biological farm is an organic farm in North-Western Poland, near Szczecinek. It was established in 2000, operating on nearly 2,000 ha of land, of which approximately 1,450 ha of arable land, 340 ha of grasslands, 140 ha of forests and trees outside forests and 7.5 ha of vegetables garden. The main source of income for the farm is the production and sale of organic milk produced by a herd of approximately 700 cows.

2.2. Materials

For the *detection and counting* of cattle, three platforms were explored. First, the use of very high resolution (VHR) satellite imagery. A SuperView RGB image from April 2019 was used for an area in Friesland with a spatial resolution of 50 cm (pan-sharpened multi-spectral imagery). In total, 260 annotations were made on a part of this SuperView image. Other parts of the image were used as test dataset for the trained model.

Second, a dataset from 2019 consisting of national aerial photographs was provided to us by the Rijksdienst voor Ondernemend Nederland (RVO), which is an agency for the ministry of economic business and climate. The dataset consists of 1,000 RGB images from a manned aircraft with a spatial resolution of 7.5 cm. Five hundred images were captured in the east of the Province of Gelderland (Netherlands) and another 500 images were captured at the eastern side of the Province of Friesland (Netherlands). Cattle were not present in all images since it was a dataset of connected areas in the Netherlands and on some images there were simply no cattle present. Still 10 images with cattle were used to acquire 200 annotations of cows.

Third, the UAV was used for capturing RGB imagery and videos with a multirotor DJI Phantom 4. This drone weighs 1,4 kg and has a RGB camera mounted which captures imagery with a spatial resolution of approximately 1 cm. Flights have been performed at 30 m altitude, while flights at higher altitudes (60, 90 and 120 m) were not suitable for cow identification since patterns were difficult to distinguish. For the *detection and counting* of cattle with UAVs, we had 3,373 annotations in 734 images, collected during a field trial in October 2018 at CARUS. Another 1,339 annotations were made in 226 images, collected in June 2019 at Juchowo farm. For the detection of cows in video streams we used 100

Table 2. Data collection of the used platforms at different field experiments.

Platform	Model aim	Material	CARUS 2018	CARUS 2019	Juchowo 2019
Satellite					
Detecting		Images	-	1 image 260 annotations	-
Manned aircraft					
Detecting		Images	-	10 images 200 annotations	-
UAV					
Detecting		Images	734 images 3,373 annotations 4 cows	-	226 images 1,339 annotations 6 cows
Detecting and counting		Video	100 annotations	-	-
Identifying		Images	706 images 706 annotations 4 cows	89 images 89 annotations 6 cows	-
Posture		Images	2,932 images 1,106 annotations	-	-

annotations of cows from UAV imagery in addition to an existing YOLO (You Only Look Once) model version 3 (Redmon et al. 2016; Redmon and Farhadi 2018). Detection in a HD video is performing at about 14 fps on a NVIDIA GeForce GTX 2080 graphics card. It uses Darknet as its neural network model. For counting cows, video streams have been used which were made with a DJI Phantom at CARUS farm in 2018. For the *identification* of individual cows, the same imagery was used. An additional labelling exercise with LabelImg was implemented with all nicknames of the individual cows. Four cows were selected in 2018 ('Smallspot', 'Whitey', 'Bigblack', 'Redneck') and six cows were selected in 2019 ('Femke', 'Sylvana', 'Louise', 'Annemarie', 'Erica', 'Sarah') for this experiment based on different patterns and colors of their skin, which helps to distinguish the cattle. A total of 706 individual cow annotations from 706 images were made in the 2018 dataset. The 2019 dataset contained 89 images and annotations from CARUS. For the *posture* of cattle, a total of 2,932 annotations were made in 1,106 images collected at the 2018 field trial at CARUS. In total 'standing' has been annotated 954 times in 363 images, 'lying' has been annotated 827 times in 263 images, and 'grazing' has been annotated 1151 times in 480 images. The data that was collected for the different field experiments are viewed in Table 2.

The spatial resolution, and here with the cow visibility, of the three platforms (VHR satellite imagery, aerial imagery and UAV imagery) are visualized in Figure 1.

3. Methods

The deep learning methods (Nanonets API, ENVI 5.4 deep learning module, and YOLO v3) used to analyze data collected at different experimental sites are explained in this chapter. The methods are divided into two sections. The first section explains the methods used for automatic detection and counting of cattle, the second section explains the methods used to identify individual cattle and their posture

Figure 1. Cow visibility on different platform imagery. Left to right: SuperView VHR satellite imagery (50 cm), Aerial (7.5 cm) and UAV (~1 cm).

3.1. Methods for automatic detection of cattle

Most deep learning software tools make use of Convolutional Neural Networks (CNN) such as Shao et al. (2020) for cattle detection and counting in UAV imagery, or make use of adjusted forms such as the use of Mask R-CNN for livestock classification and counting in UAV imagery by Xu et al. (2020). However, more standardized remote sensing software such as ENVI, Nanonets and YOLO are also making use of CNN in their deep learning tools, and therefore are exploited here. AI tools we used for detecting cattle and animal counting were Nanonets API, ENVI 5.4 deep learning module, and YOLO. All deep learning software tools, which we used for the automatic detection of cattle in satellite, aerial and UAV imagery are described below.

3.1.1. Deep learning with Nanonets

Nanonets API is a machine learning software, which has a user-friendly structure to upload images and annotations to train a model. Annotation is, as mentioned before, the process of creating training data by labeling or categorizing objects or pixels for the deep learning classification. The trained model can then be implemented wherever necessary. Annotations can be made within Nanonets itself or with the LabelImg tool, which allows the user to create polygons around the Region Of Interest (ROI). Both LabelImg and Nanonets are only able to annotate with polygons, and not with points to identify ROI in each image. This imposes the risk of adding noise because the polygons will also include background, e.g. pasture, that will be used in training the model. After creating a.xml with all the ROIs, this file can be used for training a deep learning model. The labeling exercises are laborious and time-consuming and Nanonets requires a substantial amount of annotated images to train a model, however with every training set the deep learning iteration models are becoming better. At least 50 images are needed as input into Nanonets, with the affiliated annotations as.xml file in order to start training the model.

In our study, the UAV images were annotated with LabelImg tool and a prediction model in Nanonets was made for detecting cattle. Since Nanonets requires a high spatial resolution of the imagery for training the model, it was only used to analyze UAV imagery. The spatial resolution of the VHR satellite imagery and aerial photographs were too low for Nanonets. For these platforms, therefore, the deep learning module of ENVI was used.

3.1.2. Deep learning with ENVI

ENVI 5.4 is a geospatial image analysis software, which uses deep learning methods to detect objects. ENVI has been mentioned as good software for the detection of animals already by Larue et al. (2015). It has a lot of capacity to intricately analyze images and parse images via OBIA (Object-Based Image Analysis). Since ENVI was also used in studies of Gray et al. (2018) and Larue et al. (2015) to analyze satellite data, it was assumed that it would work for aerial photographs as well as VHR satellite imagery.

First, the deep learning models for detecting cattle were created using a training image, for example an aerial image with several cattle present which were annotated. The image with annotations is used to make a label raster. The labeling can be done with points or polygons. Both approaches were tested in the current study. The next step is to train a model with the image and annotations so that the model can be used to detect cattle in other unseen aerial images. ENVI provides a random classification iteration process, which means that several models were created which had automatically different parameter settings. Fifteen iterations with different parameter settings were done. The different parameters were: patch sampling, solid distance, blur distance, class weight and loss weight. Adjusting these parameters gives different output models as a result. The predicted class activations from the 15 different models were visually checked and the model with the best results in terms of the amount of classified cows in another test image was used to further finetune the parameters. This finetuning existed of making small changes to the parameter settings to see if the model could be further improved. The finetuned model will be capable of detecting cattle in the best way possible based on other images where cattle is present. The parameters that are used for the evaluation of the model are the commission and omission errors. Commission errors mean that something is classified as a cow, while it is not a cow. Omission errors occur when a cow has not been detected by the classification method (Lillesand, Kiefer and Chipman 2015). Also the users and producers accuracy are used as a parameter to evaluate the detected cattle with a confusion matrix. This matrix shows a determined set of points, in this research we created 5,000 random points, whether the pixels of the ground truth (pixel belonging to a cow which by visual checks) is the same as the classified pixel (pixel belonging to the cow according to the model). The results can be evaluated based on users and producers accuracy. Users accuracy (commission) describes the probability that a class, in this case cattle, on the classification image is correct compared to ground truth (Lillesand, Kiefer and Chipman 2015). Producers accuracy (omission) describes the amount of the class, so the random points, correctly classified on the classification image. In a short explanation users and producers accuracies can be calculated in the following way:

Users Accuracy = 100% - Commission Error –> commission error = 1–0.09 = 0.91

producer accuracy = 100% - Omission Error –> omission error = 1–0.88 = 0.12

3.1.3. Deep learning with YOLO

You Only Look Once (YOLO) is a state-of-the-art, real-time object detection system. Object detection in YOLO is framed as a regression problem to spatially separated bounding boxes and associated class probabilities. A single neural network predicts bounding boxes and class probabilities directly per photo in one evaluation. Since the whole detection pipeline is a single network, it can be optimized directly in detection performance. YOLO v3 is the current version used for object detection in video streams from UAVs. Satellite and aerial photographs were not used since YOLO required video input.

3.2. Methods to identify posture, and identify individual cattle

Deep learning software Nanonets was also used to identify individual cows on UAV imagery at experiments performed in 2018 and 2019 at CARUS. The individual cows have been photographed in the field with mobile phones from all sides, including collar number, to be used for labeling the UAV imagery in a later stage. The individual cows were given a nickname and these nicknames were used to label them in open software LabelImg. RGB UAV images were annotated in 2018 and 2019 with the individual cows as a tag that has been used to train the cattle detection model in Nanonets.

The same software Nanonets was used to identify cow postures on RGB drone imagery in three different classes: namely standing, lying and grazing. LabelImg software has been used to label poses of cattle on 2932 UAV images from an experiment performed in 2018 at CARUS farm in terms of standing, lying and grazing.

4. Results

The results are divided into two sections. The first section is on detection of cattle and the second section on identifying individual cattle and their posture. Results can be divided in what is achievable per platform (Table 3).

4.1. Detection of cattle

The results for VHR satellite, aerial and UAV imagery to detect and count cattle are discussed per platform.

4.1.1. Satellite imagery

The ENVI deep learning model based on SuperView VHR satellite imagery is shown in Figure 2 with the most accurate cow detection results. Commission errors were made due to the fact that each cow is described by a few pixels, while ENVI software detects many times multiple cows and direct surroundings as one object. Omission errors were rare. The omission and commission errors are visible in Figure 3.

Table 4 shows the 5,000 random points used to compare the ground truth with the classified pixels. Although the overall accuracy is high (OA = 0.99), the user's accuracy of 0.09 is very low due to inclusion of classified grasslands surrounding the cows. In fact, the user's accuracy is the most important factor for this research since it represents correctly classified cattle. Of the 80 pixels classified by the model as cattle, only 7 pixels were really cattle, while the other pixels that were classified as cattle were in fact grassland.

Table 3. Possibilities to reach per platform.

Results	Satellite	Manned aircraft	UAV
Detect cattle	X	X	X
Counting cattle		X	X
Identifying poses			X
Identify individual cows			X

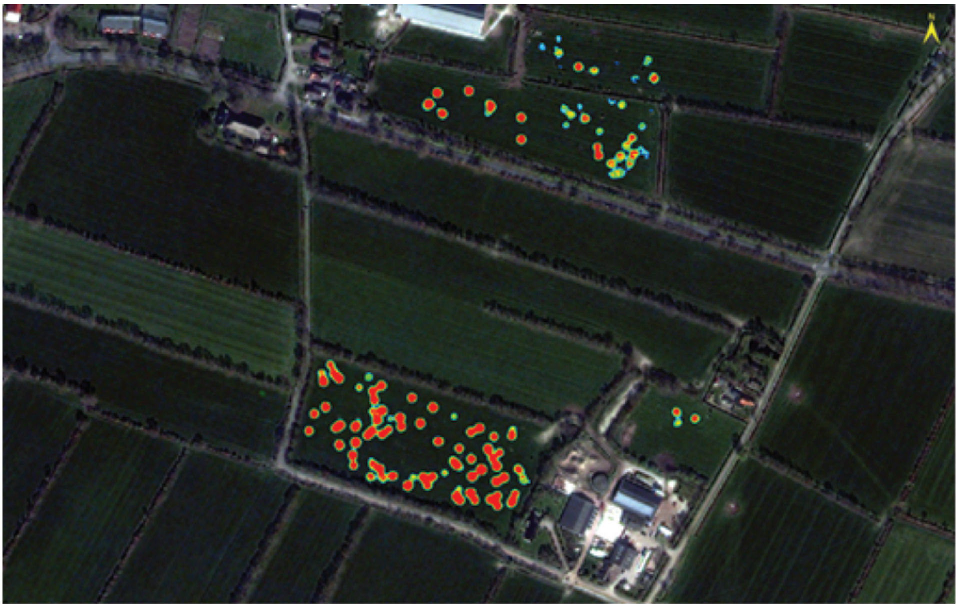

Figure 2. Classified image of object detection with ENVI deep learning module on basis of SuperView VHR satellite imagery. Livestock is present and detected well in specific parcels which is confirmed by visual interpretation.

4.1.2. Aerial photographs

The ENVI model with parameter settings in Table 5 produced the best results (made visible in Figure 4).

Still some errors of omission and commission were made which are also clearly visible in Figure 5. Some bright parts of the farm are still detected as cattle, while some cattle were not detected at all. In total 56 of the 58 cattle were detected, which is a better result comparable to those using VHR satellite imagery (see Table 6). At the same time, 22 commission errors were made (cattle detected where no cattle was really present).

4.1.3. UAV imagery

The performance of the AI model in Nanonets for detecting cattle on UAV imagery is summarized in Table 4. The accuracy 95.0% using data from CARUS from 2018, and increased to 96.2% using data from CARUS from 2019. At Juchowo biological farm we detected all cattle in full sunlight in 2019 with 99.9% accuracy, but when we included cattle in shadows of trees as well, the accuracy dropped to 97.3%. Cattle within the forest/under the trees were not detected at all.

In Figure 6, examples of detected cattle and the script defining the score of the model is shown at the right side.

With YOLO video streams analysis, a maximum accuracy of 80% was reached, but the accuracy greatly depended on the distance of cattle from the video camera (Figure 7).

Figure 3. Presence of omission and commission errors. on the left side 3 red circles represent omission errors (cattle not detected where there is actual cattle present) and on the bottom right side a commission error is present (no cattle were visually detected on that spot).

Table 4. Confusion matrix of cattle detection from a model made with ENVI.

# 5000 random pixels	Ground truth			
Classified	No cattle	Cattle	Total	**Users accuracy**
No cattle	4919	1	4920	0.99
Cattle	73	7	80	0.09
Total	4992	8	5000	
				OA
Producers accuracy	0.99	0.88		0.99

Table 5. Parameter settings used in ENVI for result of Figure 4 with point annotations.

Parameter setting	Value
Number of Epochs	25
Patches per Epoch	300
Patches per Batch	8
Sampling Rate	16
Solid Distance	17.5
Blur Distance	0.625; 13.125
Class Weight	1.75; 2
Loss Weight	0.625

4.2. Results for identifying individual cattle and their poses

An example of the output of Nanonets for identification of individual cows with the accuracy score for identification per individual cow is seen in Figure 8.

Figure 4. Detection of cow with 74% accuracy. 22 errors of omission and 2 errors of commission are made.

Figure 5. On the left image, cattle are detected except for one (see red circle). on the right image, some silo's, roof tiles and a white car are classified as cattle by the model (see red circles as false positives).

Table 6. Accuracy analysis of ENVI deep learning cattle detection model.

Cattle present	Cattle detections	No cattle detections	Error of omission	Error of commission	Overall accuracy
58	56	22	3%	38%	74%

The overall accuracy for identifying individual cows at CARUS was 87.6% in 2018 and 91.3% in 2019. For the first time, the deep learning classification with Nanonets in 2018 was performed, an accuracy of 56.0% was reached. Later on, accuracies improved to 87.6% with the same data set of 2018, indicating that models of Nanonets had been improved as well.

Figure 6. Detection of cattle in Nanonets with an overall accuracy of 99.9% in full sunlight at Juchowo biological farm in 2019, and dropping to an overall accuracy of 97.3% with cows in the shadows. Cows standing under the trees or in the forest were not detected at all.

Figure 7. Counting cattle in video streams with YOLO software. Yellow counting label visible in upper left corner of the video stream has been scripted by WR, and sums the total amount of cows in this particular frame which have a confidence threshold of 10% before counting the object as a cow (can be adjusted manually). the blue boxes indicate the probability for the individual cows in terms of detection.

AI software Nanonets has been used as well to identify cow postures on RGB drone imagery in three different poses: namely ''standing', 'lying' and 'grazing'. An example of the output of Nanonets with the accuracy score per individual posture is seen in Figure 9. Overall precision scores for identifying individual poses of cows at CARUS was 88.7% in 2018. However, 'standing' pose could not be differentiated from 'grazing' pose, due to the fact that from above it is difficult to see whether the head is on the ground grazing or above the ground. This was already sometimes a problem during the annotation process.

The overall summary of the results on the accuracy assessment of UAV imagery are reported in Tables 7 and 8.

Figure 8. A result from deep learning software Nanonets with an accuracy of 91.3% with on the right side the score for the identification of the individual cows at CARUS in 2019.

Figure 9. A result of deep learning software Nanonets with accuracy of 88.7% and on the right side the score for individual cow poses that have been recognized at CARUS in 2018.

Table 7. Overall results on accuracy assessment for UAV imagery on detecting and counting cattle.

Characteristics to be measured	Nanonets (Photos)	Yolo (video)
Automatic detection of location and animal counting	CARUS 2018: 95.0% CARUS 2019: 96.2% Juchowo 2019: 99.9% en 97.3%	CARUS 2018: 80.0%

Table 8. Overall results on accuracy assessment for UAV imagery on individual cows and their posture.

Characteristics to be measured	Nanonets (Photos)
Poses: Standing, grazing or lying	CARUS 2018: 88.7%
Individual cow identification	CARUS 2018: 56.0% CARUS 2018 new: 87.6% CARUS 2019: 91.3%

5. Discussion

Although our field experiments were applied with dairy cattle and not with beef cattle, the results shows the current potential of VHR satellite imagery, aerial photographs and UAVs as a promising new technology in monitoring cattle herds. This can be interesting to provide specific information useful as proxies for resilience and efficiency. Despite VHR satellite imagery and aerial photographs were only capable of detecting cattle, UAVs were additionally capable to detect and assess traits on individual cows. Although all these traits from different platforms do not represent resilience or efficiency directly, these may contain information associated to resilience or efficiency. Future research should focus on improving the detection of specific behavior and how to associate that with resilience and efficiency. This means that detecting, counting and identification can tell something about the resilience of cattle in varying and remote environments. It can be of interest to identify cattle and their posture to monitor their behavior and wellbeing. If a cow is identified and their posture or behavior is peculiar, a farmer can visit the cow for further health checks which will improve resilience and efficiency of cattle. However, one must first locate the cattle in large pastures in order to retrieve different traits. For VHR satellite imagery there is still a gap in spatial resolution which can provide accurate results for detecting and counting cattle. It was shown that areas can be detected were cattle was present. However, the detection exists of clustered pixels representing multiple individuals. Results of VHR satellite imagery showed high values for the confusion matrix. However, the overall accuracy of 0.99 was reached since few pixels of cow were present and mostly surrounding pixels were part of the detection. This makes it difficult to make a proper accuracy assessment and to count cattle with AI techniques and the current spatial resolution of VHR satellite imagery. The direct detection and counting of individual animals for population purposes was also discovered to still be problematic by Hollings et al. (2018). Manual locating and counting individuals (>0.6 m) has shown to be possible what was also discussed in the paper of Wang, Shao and Yue (2019). Future developments in both spatial and temporal resolution of satellite imagery will improve detection and counting of cattle with AI techniques and make it an useful and fast method to apply at extensive beef production systems. Aerial photographs could be used to detect cattle (~74%) although software used was based on pixel-based detection and not on objects itself which makes counting more difficult.

However, software related developments could shift to object-detection which improves detection and counting of cattle. The results of UAVs used for detection (>95%), counting (~80%), and postures (~88%) can be applied directly on extensive beef production systems, however this is not possible for identification of individual cows. Results showed accuracies of ~91% for identifying dairy cattle. However, beef cattle are in general more alike than dairy cows. The latter group, often Holstein Frisian breeds, have distinct color patterns that the models use to identify individual cows. Since beef cattle are more alike, cow identification is expected to be more difficult, particularly in large groups. The desired accuracy of the model for different traits for practical value has yet to be determined and is different for every situation. Yet, around 90% accuracy for all traits shows high potential for using UAVs to monitor different cattle traits. Future developments of used software, as was seen with increasing accuracies of Nanonets from 2019 to 2020, could also provide more potential for use of UAVs in detecting, counting and identifying postures and individuals even for beef cattle. Moreover, ENVI has recently released a new version of their deep learning module with object detection instead of a pixel-based classification which could improve the detection and identification of cattle as well. Besides, other standardized software such as ArcGIS PRO has now also a deep learning classification chain that is improving constantly, while former versions were not working sufficiently well. Both ENVI and ArcGIS make use of the opensource TensorFlow library for their deep learning modules. The big advantage of software tools such ENVI, ArcGIS PRO and Nanonets is that they have user friendly interfaces that makes the complete processing chain easier to implement.

The difference in software is that Nanonets requires a high spatial resolution of the imagery for object classification, so it was only used to analyze UAV imagery with very high resolution (a few cm detail). The spatial resolution of the VHR satellite imagery and aerial photographs were too low for Nanonets. For these platforms, therefore, the deep learning module of ENVI was used since it makes use of a pixel-based classification. While YOLO software was used for analyzing video streams.

Another feasibility study also investigated the use of trackers and sensors for extensive beef cattle to monitor their posture as proxies for resilience and efficiency (Noldus 2021). Results showed a performance between 0.78 and 0.95 for the Noldus cow trackers sensors using RumiWatch to track the behaviour of cattle in the field. However, limitations such as battery life and data storage should be dealt with in the future.

All the platforms are discussed with their advantages and disadvantages, which we came across during the research. They are summarized in Table 9.

Table 9. Advantages and disadvantages of different platforms.

Platform	Advantage	Disadvantage
Satellite	• Available on national scale (for the Netherlands). • Relatively cheap compared to other platforms. • SuperView images of 50 cm resolution make it possible to detect few pixels corresponding to cattle.	• Only possible to detect cattle, not separate species. • Cloud cover hampers analysis • Fixed revisit times.
Manned aircraft	• Available on a national scale (for the Netherlands). • Time of acquisition can be determined for research purposes.	• Data gathering expensive for small areas.
UAV	• High-resolution images make detecting of cattle accurate. • Possible to detect different traits of cattle. • Every day data can be gathered on preferred timestamps.	• Difficult to obtain images in no-fly zones (around airports). • Weather conditions need to be good (no rain or too much wind)

For use as proxies for resilience and efficiency, satellite imagery and manned aircraft showed not to be useful since species cannot be separated nor identified as individuals. UAV imagery has a lot of advantages, mainly because of the spatial resolution. However, several other disadvantages for the use of UAVs exist of a short battery life of around 30 minutes for multirotor UAVs and 1 hour for fixed wing UAVs. Also, data acquisition is expensive since a small area can be measured per flight. Only certain weather conditions allow for flying UAVs, for example no rain should be expected and the wind cannot exceed certain speeds. At last, UAV regulations are determined to only fly at locations which are not forbidden due to certain 'drone no-fly zones'. This makes it hard to gather data on all possible locations at the desired days.

6. Conclusion

In this study, we applied AI techniques to detect and count cattle with different remote sensing platforms (VHR satellite imagery, aerial photographs and UAV imagery) and additionally identify individual cattle and their poses with UAV imagery as proxies for resilience and efficiency. Detection, identification, and monitoring the posture of cattle with remotely sensed imagery is possible to some extent. However, high accuracies in detecting cattle are not reached with all platforms. UAVs are most suitable and are able to accurately detect, identify and monitor their posture. Aerial photographs and VHR satellite imagery are only able to detect and potentially count cattle. Future developments in VHR satellite imagery are promising since they can provide higher spatial resolutions (pixels smaller than 30 cm) which also improves the detection of cattle. Satellite data has the advantage that it can be made available almost on a daily basis and covers large areas, which is not possible with UAV technology.

The current results show that UAV imagery gives the highest accuracy in the detection of cattle (>95%) due to the high spatial resolution of the images with pixel size of a few centimetres. Satellites or manned aircraft are not the primary choice in the detection of cattle although future improvements in e.g. spatial resolution and the availability of data could provide the location of the herd from images, if not already provided by the use of collar mounted cow tracker sensors. The result from this feasibility study shows that drones with RGB cameras are best to use for detecting and identifying cattle in pastures. It seems feasible to detect, identify and monitor behaviour of individuals cows based on conducted experiments with Holstein dairy cows and therefore get more knowledge of cattle in terms of resilience and efficiency within researched production systems. Further research is required to show the results for extensive beef production systems and for practical usage on results.

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