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Dit rapport is een verkenning naar de mogelijkheden van remote sensing voor natuur monitoring, met nadruk op Natura 2000 gebieden. In de beschikbaarheid en processing van hoge resolutie satelliet- en drone beelden is de afgelopen jaren een enorme vooruitgang geboekt, waardoor de toepassingsmogelijkheden voor allerlei beleids- en natuurbeheervraagstukken toenemen. We tonen aan dat remote sensing veel toegevoegde waarde kan hebben voor zowel de monitoring in de verspreiding van habitats als de habitatkwaliteit over een breed scala aan natuurgebieden. We tonen ook aan dat een hogere ruimtelijke resolutie van remote sensing beelden vaak resulteert in een betere classificatie nauwkeurigheid. Deep learning-technieken worden nu ook populair omdat ze ook de contextuele informatie in aanmerking nemen en niet alleen de spectrale informatie van de beelden voor het classificeren en/of identificeren van objecten (van habitat typen tot individuele plantensoorten). De hoeveelheid trainingsgegevens kan echter een grote invloed hebben op de classificatienauwkeurigheid, veel meer dan voor meer conventionele classificatie technieken. Het betekent dus ook een grote investering in het verzamelen van in-situ (veld)data. Een andere bevinding is dat het opnemen van LiDAR en hyperspectrale gegevens de gedetailleerde habitatkartering en monitoring aanzienlijk kan verbeteren. Samengevat, de bron van remote sensing data en technieken dient gekozen te worden afhankelijk van de relevante natuurtypen, onderzoeksvragen en natuurdoelen op een specifieke lokale, regionale of landelijke schaal. Het vereist meer communicatie tussen teledetectie onderzoekers en ecologen. Als de natuurdoelen en remote sensing-mogelijkheden in een vroeg stadium bij elkaar worden gebracht, zijn er veel toepassingen mogelijk. Voor Nederland zou de remote sensing gemeenschap zich vooral moeten richten op het monitoren van structuur en functie van habitattypen. En een grootschalig en langdurig remote sensing monitoring programma zou onderdeel moeten worden van een nationaal natuurmonitoringprogramma.

This report is the result of a review on the possibilities of remote sensing for applications in the nature domain, with emphasis on Natura 2000 habitat monitoring. In recent years, enormous progress has been made in the availability and processing of high-resolution satellite and drone images. This increases the potential application for answering all kinds of policy and nature management questions. We demonstrate that remote sensing can have much added value for the monitoring of habitat distribution and habitat quality across a wide range of nature areas. We also demonstrate that higher spatial resolution of remotely sensed imagery often results in better classification accuracies. Deep learning techniques are also becoming popular since they are able to consider the contextual information and not only the spectral information from the imagery in classifying or identifying objects (from habitats to individual plant species). However, the amount of training data can have a large impact on classification accuracies, much more than for more conventional classification methods. This, then, requires a large investment in the collection of in-situ (field) data as well. Another finding is that including LiDAR and hyperspectral data can significantly improve detailed habitat mapping. In summary, the resource of remote sensing data and techniques should be selected depending on the relevant nature types, research questions and nature targets at a specific local, regional or national scale. It requires more communication between remote sensing researchers and ecologists. If nature goals and remote sensing technologies are brought together at an early stage, many applications will be possible. For the Netherlands, the remote sensing community should focus especially on monitoring the structure and function of habitat types. Also, such large-scale and long-term remote sensing monitoring should become part of a national nature monitoring programme.

Keywords: remote sensing, natura 2000, habitat function and structure, habitat area, machine learning, deep learning, Lidar, drones, in-situ data.

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Photo cover: Drone monitoring campaign with LiDAR Ricopter in the dunes on the Dutch coast on 28th of May 2020 to detect changes in vegetation structure and dune morphology (Photo made by Sander Mücher)

Contents

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Wageningen Environmental Research (WENR) values the quality of our end products greatly. A review of the reports on scientific quality by a reviewer is a standard part of our quality policy.

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Summary

This report is the result of a review on the possibilities of remote sensing for applications in the nature domain, with emphasis on Natura 2000 habitat monitoring. In recent years, enormous progress has been made in the availability and processing of high-resolution satellite and drone data, which increases the potential application for all kinds of policy and nature management questions. Relevant developments are, among other things, an enormous decrease in the costs of satellite data, the better availability and accessibility of remotely sensed imagery, including drone images, the better CPU and GPU power of computers for processing the imagery, and the emergence of artificial intelligence (AI) techniques, such as machine learning (ML) and deep learning (DL), to interpret remotely sensed imagery with regard to specific themes. The objective of this report is the exploration of the possibilities of state-of-the-art remote sensing techniques and how they can be applied to nature policy and management tasks. A previous evaluation of remote sensing techniques for nature monitoring dates back to 2015 (Mücher et al., 2015), and the present report can be considered as a follow-up. Next to literature research on the current state of remote sensing techniques for nature monitoring, we have elaborated four use cases to demonstrate the use of remote sensing for nature surveys and monitoring. These elaborated use cases demonstrate the use of satellite time series analysis on the habitat function (quality), as well as on the mapping of habitat types with DL techniques and the monitoring of changes in vegetation structure with LiDAR data that will now become available on a three-yearly basis for the entire Netherlands. A lot of remote sensing data sources with much higher spatial, spectral and temporal resolution have become available that can now better support nature monitoring in the Netherlands (and in other regions). In particular, drone techniques are developing fast and can contribute to the monitoring of specific areas as well. They have a limited coverage compared to other platforms (spaceborne and manned airborne), but are flexible to use (making it appealing for targeted tasks).

The literature demonstrates that higher spatial resolution of remotely sensed imagery often results in better overall accuracy. Machine learning has become a proven and robust technique to classify the remote sensing images, of which Support Vector Machine (SVM) and Random Forest (RF) have the best performances. Deep learning techniques are now also becoming popular since they are able to consider the contextual information and not only the spectral information for classifying or identifying objects (from habitats to individual plant species). However, the amount of training data can have a large impact on classification accuracies, much more than for the more conventional classification algorithms. This, then, means a large investment in the collection of in-situ (field) data as well. Another finding of the literature review is that including LiDAR and hyperspectral data can significantly improve detailed habitat mapping. This can bring earth observation and vegetation experts closer together in monitoring Natura 2000 with a combination of remotely sensed imagery and field data.

With regard to the mapping and monitoring of habitat quality there are also a lot of studies which show that remote sensing can play an important role. A strength of remote sensing (RS) is that one can analyse time series of satellite imagery for any Natura 2000 site to detect changes, and data are often freely available in historic satellite archives. In addition to the use of satellite time series as indicators for changes in habitat quality, they are also being used to identify specific events, such as the mowing of grasslands. In addition, RS-enabled Essential Biodiversity Variables (RS-EBVs) were proposed in 2015 by Skidmore et al. to the biodiversity community to improve the harmonization of biodiversity data into meaningful metrics from space. The RS-enabled EBVs can play a role in the monitoring of the quality of the habitats, in addition to the mapping and monitoring of habitat types. Nevertheless, much effort still has to be put in place to translate these remote sensing variables into useful information for ecologists in terms of habitat quality. Since the literature review does not reveal many deep learning techniques for nature monitoring, we can give some examples of their use in identifying specific plant species and habitat types.

In summary, the resource of remote sensing data and techniques should be selected depending on the relevant nature types, research questions and nature targets at a specific local, regional or national scale. It requires more communication between remote sensing researchers and ecologists. If the aims of nature conservation agencies and the possibilities of remote sensing technologies are brought together at an early stage, many applications will be possible.

For the Netherlands, the remote sensing community should focus especially on monitoring the structure and function of habitat types (like in use case study 3), including identifying specific species. The focus of remote sensing should be on monitoring large areas (provinces or regions, like in case study 2) over long time periods (like in case study 1). Especially relevant are indicators that relate to climate change, like phenology, biomass production, changes in land cover and inundation. Such large-scale and long-term remote sensing monitoring should become part of a national monitoring programme.

1 Introduction

1.1 Background

This report is the result of a review on the possibilities of remote sensing for applications in the nature domain, with emphasis on Natura 2000 habitat monitoring. In recent years, enormous progress has been made in the availability and processing of high-resolution satellite and drone data, which increases the potential application for all kinds of policy and nature management questions. Relevant developments are, among other things, an enormous decrease in the costs of satellite data, the better availability and accessibility of remotely sensed imagery, including drone images, the better CPU and GPU power of computers for processing the imagery, and the emergence of machine learning (ML) / artificial intelligence (AI) to interpret remotely sensed imagery with regard to specific themes.

Monitoring of nature in protected sites has been done for a long time and for various purposes, such as nature conservation reports in relation to targets from the Birds and Habitats Directives. Although most monitoring of Natura 2000 sites has been done by field surveys, remote sensing provides new opportunities to monitor, among other things, the structure and function of nature reserves (Diaz-Delgado and Mücher, 2019; Mücher et al., 2017, Mücher et al., 2015; Skidmore et al., 2015). The reason to carry out an updated review of possible applications in nature policy and management is based on the current rapid development in remote sensing imagery and drone technology—including very high resolution satellite imagery with a spatial resolution of up to 30 cm (see for example SuperView in https://www.satellietdataportaal.nl), open-source Copernicus Sentinel satellite images with high temporal resolution, Airborne LiDAR 3D imagery (AHN.nl), and a wide array of drone imagery—in combination with other data sources and machine learning / deep learning techniques. The use of these remote sensing techniques could improve nature monitoring in the Netherlands and provide additional and actual information to policymakers and conservation site managers.

1.2 Objectives

This report concerns an exploration of the possibilities of state-of-the-art remote sensing techniques and how they can be applied to nature policy and management tasks. A previous evaluation of remote sensing techniques for nature monitoring dates back to 2015 (Mücher et al., 2015), and the present report can be considered as a follow-up.

The goals of the report are:
- To provide the latest state of knowledge in the field of remote sensing of nature, linked to the policy objectives of the Ministry of Agriculture, Nature and Food Quality.
- To define indicators (especially focussed on Natura 2000 habitat types) that can be detected in remote sensing imagery and used for nature monitoring.

We aim to achieve these results through literature study and the results of four case studies:
1. Monitoring biomass in semi-natural grasslands in relation to climate changes based on high resolution satellite imagery.
2. Classifying intensively and extensively used grasslands using time series of satellite data.
3. Detection of changes in the vegetation structure on the island Terschelling in the Wadden Sea using public and freely available airborne 3D LiDAR data and very high-resolution satellite imagery.
4. Mapping habitat types using remote sensing, field data on vegetation plot records and deep learning techniques for National Park De Hoge Veluwe.

1.3 Outline of the report

The report has eight chapters. Chapter 1 is the introduction with information on the background and objectives of the study. Chapter 2 gives a short overview of recent developments in remote sensing and drone technology. Chapter 3 describes a summary of the literature research on peer reviewed articles in relation to 1) mapping and monitoring of habitat areas and 2) mapping and/or monitoring of habitat quality. Due to the fact that the peer reviewed literature is still very limited in publications with regard to deep learning techniques and nature monitoring we provide some of our own experiences with regard to the detection of specific plant species from drone imagery with deep learning techniques. Chapters 4 – 7 concern four use cases that demonstrate the use of remote sensing for nature surveys and monitoring. Case study 1 concerns the detecting of biomass change in semi-natural grasslands in relation to climate change based on time series of satellite data. Case study 2 concerns the classification of intensive and extensive grasslands using time series of satellite data. Case study 3 concerns the detection of changes in the vegetation structure on the island Terschelling using LiDAR data. Case study 4 concerns the mapping of habitat types with deep learning techniques using high resolution satellite imagery in combination with vegetation plot observations from the Dutch Vegetation Database (LVD) for part of the Veluwe. The last chapter, Chapter 8, is the synthesis of the suitability of remote sensing for nature management.

2 Recent developments in RS technology

2.1 New high resolution satellite sensors and drones

Compared to a decade ago, many more remote sensing data sources, with a much higher spatial and temporal resolution, have become available that can support nature monitoring. There are roughly three types of imaging platforms: the ground-based camera platforms, in which the sensor is mounted on a mast or held manually above the ground, airborne platforms (including aircraft, helicopters, balloons and Unmanned Airborne Vehicles (UAV), better known as drones), and spaceborne platforms, read satellites. The observations from the different platforms are often integrated for upscaling and downscaling the measurements and derived information (Figure 2.1). In particular, the use of drones is rapidly increasing for biodiversity monitoring, with spectral, spatial and temporal resolution often adjustable, but with limited coverage compared to other platforms.

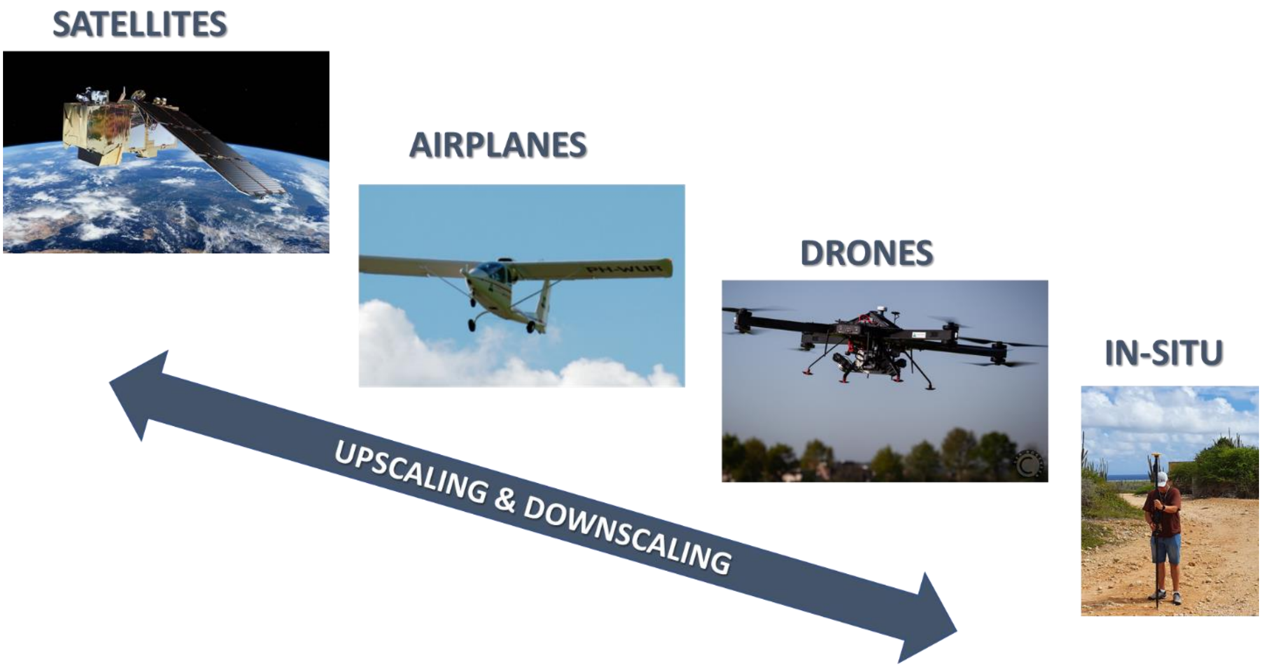


Figure 2.1 *Multi-scale sensing approach with different remote sensing platforms: spaceborne, airborne and ground-based.*

Below is a broad overview of remote sensing platforms and applications related to nature monitoring.

Table 2.1 *Remote sensing platforms & applications.*

RS platform	Scale	Applications	Aspects of habitat conservation status that can be measured
MODIS	250 m pixel size	Global monitoring and monitoring large areas. Typical MODIS products are: surface reflectance, surface temperature and emissivity, land cover, vegetation indices, e.g., NDVI, thermal anomalies /active fraction of photosynthetically active radiation (FPAR) / leaf area index (LAI), evapotranspiration, gross primary productivity (GPP) / net primary productivity (NPP), water, burned area, snow cover, sea ice, sea surface temperature	• habitat area • habitat structure and **function** (quality), • **changes** in area and quality (structure and function)
Landsat TM	30 m pixel size	Regional studies and recently also global studies, such as Global Forest Watch and Global Water Surface Explorer. Typical Landsat products are: surface reflectance, spectral indices such as NDVI, vegetation and moisture measurements, surface temperature, dynamic surface water extent, fractional snow-covered area, burned area	• **habitat area** • habitat structure and function (quality), • **changes** in area and quality (structure and function)
Sentinel	10 m pixel size	Regional and global studies Typical Sentinel products are: surface reflectance, land cover, vegetation indices, e.g., NDVI, leaf area index (LAI), water	• **habitat area** • habitat structure and function (quality), • **changes** in area and quality (structure and function)
Very high-resolution satellite imagery such as Worldview, Pleiades, Superview, etc.	30–300 cm pixel size	Local and regional studies. Typical products are: surface reflectance, land cover, vegetation indices, e.g., NDVI and leaf area index (LAI). But new products are added on almost a monthly basis	• **habitat area** • habitat structure and function (quality), • **changes** in area and quality (structure and function)
Aerial photos	7-25 cm pixel size	Local and national studies, typically used for topographical surveying.	• **habitat area** • habitat **structure** and **function** (quality), • **changes** in area and quality (structure and function)
Drone imagery: RGB, hyperspectral, LiDAR, thermal	A few cm to a few mm	Local studies such as specific Natura 2000 sites. Typical UAV (drone) LiDAR products are for example: canopy height model	• **habitat area** • habitat **structure** and **function** (quality) • **changes** in area and quality (structure and function)

The spatial resolution of most multispectral spaceborne sensors (~ 0.3 m - 250 m) is insufficient to detect the presence of individual plants. However, most airborne sensors have a sufficiently high spatial resolution (pixels of 25 cm – 5 cm) to register small-scale variation in the vegetation. Spaceborne systems have the advantage of coming over at fixed intervals (ranging from daily acquisition to a few weeks). This means that a new recording can be made regularly, so that the phenology can be visualized as well.

An even higher spatial and temporal resolution than with airborne or spaceborne systems can be achieved with the use of UAVs. However, this also depends on the type of camera used. Different types of UAVs, like multicopters and fixed wing airplanes, have different capacities (camera load, flight time, easiness to manoeuvre) (Figure 2.2). They can be equipped with different sensors (passive and active). The use of drones that can carry a LiDAR camera is a more recent development. Lately, the use and adoption of UAVs as a flexible sensor platform for monitoring has evolved rapidly. Examples of potential application domains are agriculture (phenotyping of individual plants), coastal monitoring, archaeology, live inspection of infrastructure (power lines, railway tracks, pipelines), topography, geomorphology, and construction site monitoring (surveying urban environments), as well as forestry and vegetation monitoring.

Figure 2.2 *Multicopter with hyperspectral and LiDAR camera, Nano Hyperspec (Left) and a EBEE fixed wing drone with multispectral camera (Right).*

Until recently it was not possible to have a LiDAR camera on a UAV since the cameras were too heavy. LiDAR measurements were made previously only from manned helicopters or airplanes. Attaching a LiDAR sensor to a moving UAV platform allows 3D mapping of larger surface areas (Mücher et al., 2017b). The big advantage of the use of a UAV is its flexibility to be used in space and time. The major limitation, compared to manned airborne laser scanning, is in its restricted areal coverage. This is due not only to the technological capabilities but also to aviation regulations which do not allow, in most cases, for the vehicle to be flown beyond the line of sight. The use of unmanned airborne LiDAR Scanning (ULS) certainly has advantages compared to the more static terrestrial laser scanning (TLS) or large-scale systems using manned platforms (Mücher et al., 2017b): UAVs are more flexible in their use, and ULS allows both a larger area to be covered and a better timing of (repeated) data acquisition. However, at the moment, only a limited number of manufacturers can provide such integrated UAV-LiDAR systems (Mücher et al., 2017b). See Figure 2.3 as an example of ULS.

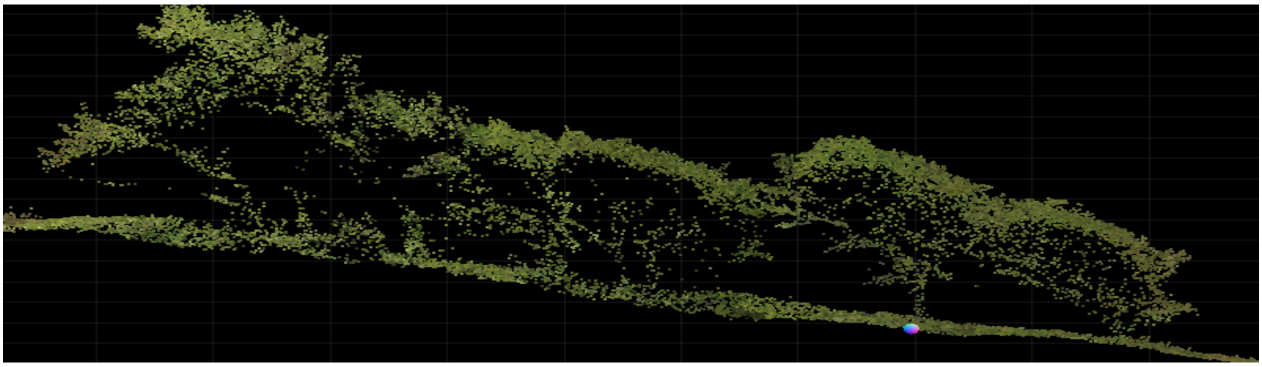


Figure 2.3 *Example of a line transect through a LiDAR point cloud, visualized in 3D, as taken by an UAV LiDAR camera (Acquired with VUX-SYS camera mounted on a RiCOPTER).*

LiDAR drones will be very useful to assess vegetation structure, which is crucial information to assess habitat status.

3 Literature research: current state of remote sensing for nature monitoring

3.1 Introduction

Nature policy and management is based on a cycle in which monitoring data forms are one of the stages (Figure 3.1). What kind of monitoring data needs to be collected depends on the topic that one aims to monitor. In most cases relevant information concerns the topic of landscape (patterns), vegetation patterns (types and extent, including habitats of species), plant populations and animal populations, and abiotic conditions and processes.

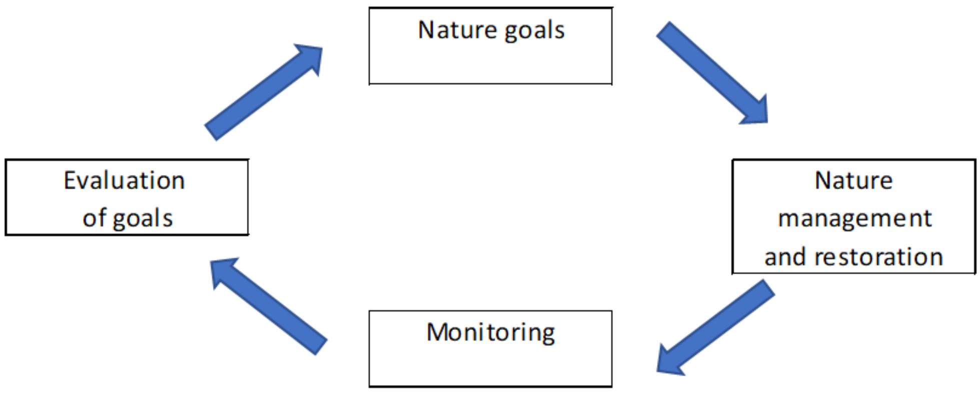


Figure 3.1 *Cycle of nature management practices, based on reaching certain goals, and evaluating of reaching those goals by monitoring data.*

In this report we focus on nature monitoring with an emphasis on Natura 2000 habitat types. For this topic three more general groups of indicators are relevant:

- The location and area of habitat types;
- The quality of habitat types, more specifically, their structure and functioning;
- The species composition of habitat types.

These three groups of indicators are required for the six-yearly national reporting on the conservation status of habitat types (DG Environment, 2017, Janssen et al., 2019). They are also relevant at a local scale (see Bijlsma & Janssen, 2021) for evaluating site measures, management and restoration and for reporting on Natura 2000 sites through the so-called Standard Data Forms (Janssen et al., 2014).

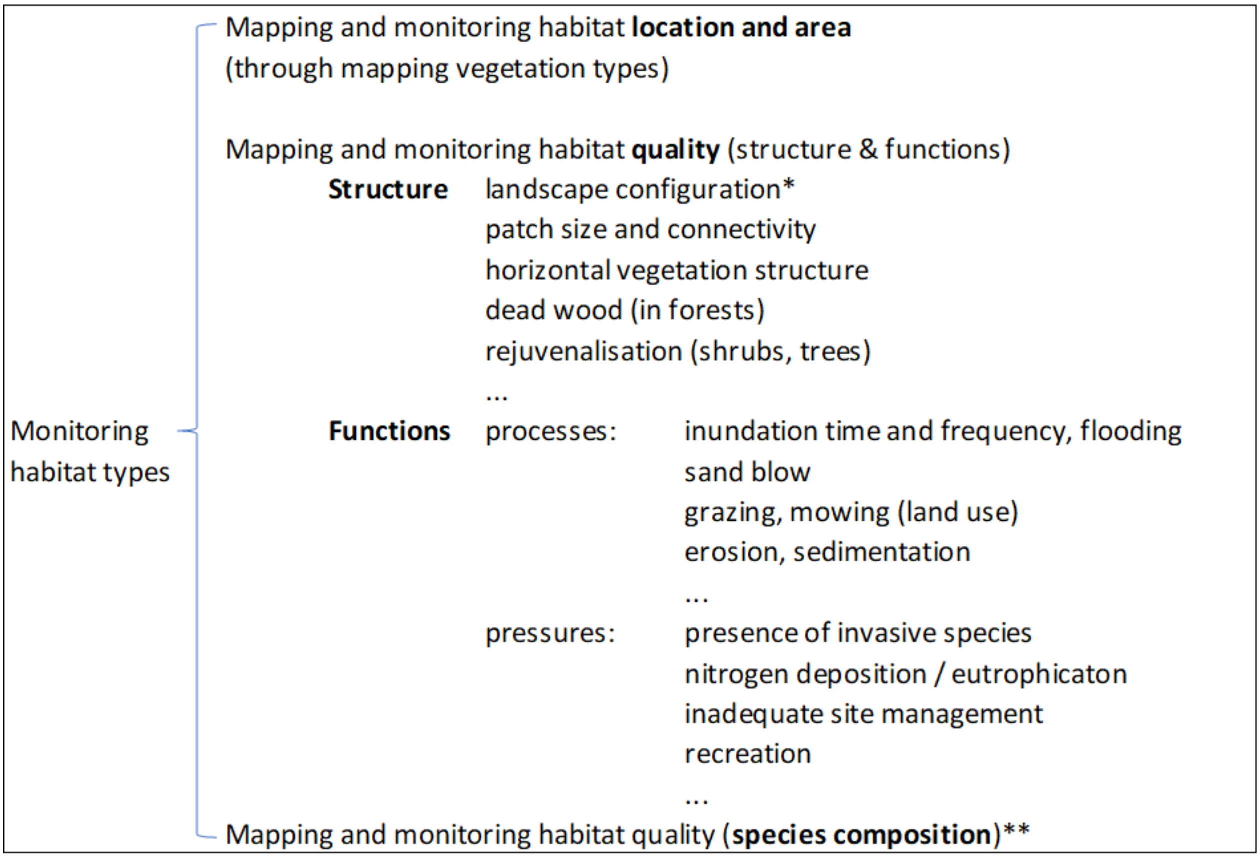
In Figure 3.2 the three relevant groups of indicators are listed, and the habitat quality is elaborated in more detail, with a main division in structure and functioning.

For monitoring habitat structure, several indicators may be used, depending on the specific habitat type. Some examples are: the landscape configuration (the mosaic of different habitats in a landscape), the size of habitat patches and their connectivity (as this determines the populations of characteristic fauna species), the vertical vegetation structure (the tree layer, shrub layer, herb layer, moss layer), the presence of standing or lying dead wood (in an old forest), the population structure and rejuvenation of shrubs or trees, and the encroachment of shrubs or trees in a grassland or heathland.

For habitat functioning, indicators may be used that provide information on processes. Some examples are: fluctuation in water level (as indicator for flooding and seepage), amount of bare soil (as indicator for erosion and sedimentation), presence of herbivores (as indicator for grazing intensity), changes in productivity (as indicator for mowing practices or eutrophication, etc.). Pressures may also be assessed under functioning.

Examples of indicators are the presence of invasive species, the presence of species indicating eutrophication, and number of people or density of footpaths as indicator for recreation pressure.

The species composition is very important, as it is what nature conservation aims at: protecting and restoring high diversity and rare or endangered species through managing the structure and functioning. Trends in characteristic species can be considered an overall indicator for the structure and functioning (Bijlsma & Janssen, 2021).



* may be considered under functions

** trends in species composition may be considered an overall indicator of habitat quality

Figure 3.2 *Relevant indicators of Natura 2000 habitat types at national or local scale.*

The selected articles from the literature research are reviewed and are discussed in two major sections:
1. Mapping and monitoring habitat location and area
2. Mapping and monitoring habitat quality (structure and function)

For mapping plant species we have added two practical examples. To identify relevant peer reviewed articles related to nature monitoring and remote sensing we used the following search term in Scopus: TITLE-ABS-KEY (“remote sensing” AND “Natura 2000” AND “monitoring”). This resulted in 83 articles, of which 62 articles were identified as very relevant and were available in Dutch or English and reviewed by us.

3.2 Mapping and monitoring habitat location and area

The traditional way of monitoring habitats by field surveys is effective but time-consuming and labour intensive. This mapping and monitoring of habitat areas might be supported by interpreting Very High Resolution (VHR) imagery obtained with UAVs (Unmanned Aerial Vehicles), airplanes and/or satellites. In the article of Vanden Borre et al. (2011), the authors argued that the integration of remote sensing with Natura 2000 habitat monitoring could be improved by harmonising and standardising the monitoring approaches, developing readily available remote sensing products, comparing and validating traditional and remote sensing methods and exchanging ideas and results among research communities. Currently, the European Commission does not have guidelines on how to monitor habitats for the six-yearly reporting under Article 17 of Habitats Directives. Monitoring experts consider the thematic accuracy of remote sensing to be the most important aspect, but the accuracy is barely above 80% and results are therefore seen as somewhat unreliable. Field-based maps are not, per definition, better.

However, a lot of new studies have been made during the last 15 years on the mapping and monitoring of habitat types and habitat areas with remote sensing data (Bock et al., 2005; Förster et al., 2008; Alexandridis et al., 2009; Vanden Borre et al., 2011a; Vanden Borre et al., 2011b; Nieland et al., 2014; Modica et al., 2016; Zlinszky et al., 2016; Haest et al., 2017; Buck et al., 2018; Regos et al., 2018; Agrillo et al., 2021; Osińska-skotak et al., 2021; Szporak-Wasilewska et al., 2021 & Sittaro et al., 2022). Within these studies different data and methods are used, such as segmentation or machine learning methods. This has resulted in different classification methods and a variation in classification accuracies. To get a better overview of the different data and methods used, this review study will be useful in seeing what is currently researched and what has good potential in monitoring and mapping habitat types or habitat areas.

First of all, the data which is used to monitor and map habitats ranges in the studies from satellite, aerial photography and UAV data, where sometimes a combination of platforms are used. Satellite data is being used in most studies reviewed. The satellite data is covering mostly large areas, and mostly open-source and has a revisit time of a few days or a few weeks. The resolution and the number of spectral bands acquired can be quite different. For example, Landsat has a 30-meter spatial resolution, Sentinel-2 data has a spatial resolution between 10-60 m, RapidEye has a spatial resolution of 5 m, while SuperView data has a spatial resolution of 0.5 m (pan-sharpened). However, the Sentinel-2 revisit time is five days, which provides a lot of data, while SuperView images are occasionally available. For QuickBird, with a spatial resolution ranging between 0.61 to 2.8 meters, the revisit time is between 1 and 3.5 days depending on the area. VHR satellite imagery, such as SuperView or QuickBird, can be used to monitor habitats in Natura 2000 sites. However, most studies looked at still make use of multispectral Sentinel, Landsat or RapidEye.

Also, data retrieved from airplanes is used to map and monitor habitat types and habitat areas. The resolution reaches centimetre level and the data is especially used with regard to Natura 2000 habitats such as heathlands, shrublands or wetlands (Hufkens et al., 2010, Haest et al., 2017; Thoonen et al., 2012; Osínska et al., 2021; Szporak-Wasilewska et al., 2021). Both hyperspectral and LiDAR data were gathered to map Natura 2000 habitats with different classification methods. Hufkens et al. (2010) used a linear discriminant least squares classification from Matlab to classify the heathlands on different levels of habitat classes with hyperspectral airborne data. This resulted in an overall accuracy (OA) of 85.66% and a kappa value of 0.84 for level 2 and 3 (e.g., respectively dry heathland and Calluna-dominated heathland). For even more specific habitat types at level 4, the accuracy was still 80.44% with a kappa value of 0.79. Also, in the study of Haest et al. (2017) good accuracies were found with imagery from aircraft, but using a different classification method. In this study the airborne hyperspectral imagery was also gathered to map Natura 2000 heathland patches. The method consisted of a multi-step mapping approach, in which a land/vegetation type (LVT) classification was made first with supervised classification. It was then reclassified to a patch map and then the Natura 2000 habitat types were identified. OA reached 83% and 92% for the LVT mapping. However, direct heathland habitat mapping is limited by high spectral intra-variability of habitat patches of the same habitat type, and a relatively low spectral intra-variability of habitat patches of different heathland habitat types. This result matches the current field-based results of N2000 sites. Also, the machine learning method 'Random Forest' was used to map biodiversity and identify Natura 2000 habitats. Szporak-Wasilewska et al. (2021) found that with Random Forest, classification accuracies are improved for wetland habitats when combining hyperspectral products with airborne laser scanner data and statistical products. Zlinszky et al. (2016) showed that LiDAR-derived proxies had a very strong potential for biodiversity mapping. It was successfully identified for all biophysical parameters requested by the field monitoring manual and showed an OA of 80% for the Natura 2000 conservation status. It is demonstrated that the synergetic use of hyperspectral and LiDAR data can be used in mapping and monitoring Natura2000 wetland habitats (Szporak-Wasilewska et al., 2021). However, Natura 2000 monitoring with remote sensing will still require labour-intensive ground truth data, and is more of a tool for extending the findings of fieldwork outside the reference plots (Zlinszky et al., 2016). Also, the data retrieved is mostly done only a few times a year since airborne systems have to be deployed each time to gather imagery of the areas of interest, whereas satellite data is automatically acquired in a repeating pattern. Therefore, using data gathered with aircraft is expensive and time-consuming. This explains why only a few studies found in the literature review used aircraft imagery for habitat mapping and monitoring.

UAVs are able to map and monitor Natura2000 areas and are more flexible to use than manned airplane flights. Spatial resolution can reach under centimetre accuracy, which means UAVS can make very detailed images. These, in turn, result in good mapping and monitoring of habitat areas. In the study of Gonçalves et al. (2016), UAVs are used to collect VHR imagery with a spatial resolution of 6 cm to produce a DSM of 10 cm of a Natura 2000 site. A pixel-based random forest classifier was used to create a habitat map for the study area. Validation results showed an overall accuracy of 0.89 for habitat types 4020, 4030, and 6230. Habitat type 6230 (Nardus grasslands) reached a result of 0.96 for producer accuracy and 0.91 for user accuracy. Habitat type 4020 (wet heathlands) reached a result of 0.68 for producer accuracy and 0.77 for user accuracy. These results are promising for future advances in UAV platforms. However, almost the same accuracies for heathland mapping are found with aerial photography and satellite imagery. In the study of Hufkens et al. (2010), an overall accuracy of 85.66% was found for mapping dry heathlands with aerial imagery and in a study of Förster et al. (2008) a knowledge-based method on satellite data had classification accuracies reaching 88 to 90% within dry heathland areas. As Calleja et al. (2019) showed, coarser spatial resolution tends to decrease because of an increasing mixture of pixels. As explained in the study, larger pixel sizes may be modifying the variance to the point at which classes are spectrally separated. This can also be the case for UAV imagery, meaning that coarser resolutions of aerial photographs or satellites does not necessarily decrease the overall accuracies found with classifications. Also, for mapping and monitoring large habitat areas, UAVs have their limitations. It is time consuming and expensive since flight spans are less than one hour for commercial drones (for multi-rotor drones it is even lower at approximately half an hour). Therefore, UAVs are not used much in large scale studies, and the focus is mostly on studies using satellite data or aerial photographs for habitat mapping and monitoring.

As already mentioned, most of the studies use satellite data in monitoring and mapping habitats because of the high frequency, open access, cost-efficient monitoring of large habitats and the increasing spatial resolution. Different classification methods used for research with satellite data range from object- and pixel-based classifications, Maximum Likelihood Classification (MLC), Random Forest (RF) decision trees, Support Vector Machine (SVM) and even deep learning (DL) techniques. Many studies reviewed made use of segmentation and object-classification techniques (Bock et al., 2005; Förster et al., 2010; Buck et al., 2011; Franke et al., 2012, Chan et al., 2010; Nieland et al., 2014; Rapinel et al., 2014, Buck et al., 2018), while others used MLC (Förster et al., 2008; Modica et al., 2016; Pesaresi et al., 2022), or SVM (Schuster et al., 2015; Calleja et al., 2019; Buck et al., 2015), or RF machine learning classification techniques (Raab et al., 2018; Agrillo et al., 2021). And recently, new methods, such as deep learning, are also being used in the mapping of habitat types (Mikula et al., 2021). Choosing and using a classification method is dependent on the amount and sort of data, the desired results, and the research goal. As mentioned before, a lot of different methods are used which are evaluated by their achieved accuracies. Some studies also used several classification methods on the same dataset. It is interesting to view differences in results per classification method (Regos et al., 2018; Sittaro et al., 2022). First, studies are discussed and compared using different classification methods. Then the studies with more classification methods on the same dataset are discussed.

A popular software for mapping and monitoring habitats or vegetation is eCognition which is used in several studies (Bock et al., 2005; Förster et al., 2010; Buck et al., 2011; Franke et al., 2012). This software is developed by Trimble, a software, hardware, and service technology company based in California, USA. eCognition is an advanced analysis software for geospatial applications and is designed to transform analysis of remote sensing and geodata into geo information. In most of the studies, RapidEye data was used as input for classification of habitats or vegetation types (Förster et al., 2010; Buck et al., 2011; Franke et al., 2012). In the study of Förster et al. (2010), a multi-temporal approach was performed with RapidEye and TerraSAR-X data from 2009 which was used to monitor different vegetation types and habitats, especially heathlands, dry grasslands and wetlands. The data was processed with a multi-scale segmentation method within the eCognition software using an object-oriented approach, and images were classified with nearest neighbour algorithm. With five images from RapidEye, the object-based classification was performed for 31 different combinations. The overall accuracy for monitoring Natura2000 habitats was above 85%. Adding images from August and September increased the accuracy to 88%. Buck et al. (2011) also makes use of multi-temporal object-based eCognition software, as in the article of Förster et al. (2010). GeoEye and RapidEye scenes were used to detect tree habitats and mask them out to focus on the non-forest habitats, such as heath, sand, and grasslands. A stratified random sampling of 100 points, with at least ten points in each class, resulted in an overall accuracy of 68% and a kappa coefficient of 0.563. The producer accuracy reached 92% and 97%. However, the user accuracy stayed at, respectively, 70% and 63%. It shows that grassland detection is mostly correct but not adequately complete. Removing forest areas in advance does not increase the accuracy of grassland classification since this was performed in the study of Förster et al. (2010). Also, in the study of Franke et al. (2012), the software eCognition was used on multi-temporal RapidEye imagery to do object-based classifications. This study showed that this approach was suitable for an assessment of grassland use intensity per management plot over a large area. Accuracies reached 85.7% using a combination of five multi-temporal scenes, the same accuracy as in the study of Förster et al. (2010). Other software was used in the study of Stenzel et al. (2014) in which the maximum-entropy based classification approach Maxent was used to map four habitat types in Germany. Maxent is a machine learning method using a one-class classifier. 125 ground reference points, along with multi-seasonal RapidEye satellite imagery, were used. Maxent does not need a lot of training data. The results of each class were merged, resulting in a multi-class classification which had an overall accuracy of 73% for training data and 70% for test data. In comparison with studies using eCognition, Maxent accuracies are lower. Not a lot of data is needed for classification, however if more data is used, perhaps higher overall accuracies can be achieved.

In the study of Chan et al. (2010) hyperspectral satellite imagery was preferred above multi-spectral satellite imagery. Hyperspectral data is more effective for mapping different vegetation types. The first method performed was a direct classification of the habitats with object detection. The second method resulted in two steps: during the first step the vegetation was divided into 24 vegetation types, and in the second step the vegetation patches were merged into habitat types using predefined rules. Both methods reached a classification accuracy of around 63%. Other object- and pixel-based classifications were performed by Förster et al. (2008), Nieland et al. (2014), Rapinel et al. (2014), and Buck et al. (2018). In the study of Förster et al. (2008), a knowledge-based classification was used which carries out a pixel-based classification and resolves the results in an object-based dataset. This combining of the pixel- and object-based classifications to better reflect the habitats is useful for monitoring or mapping habitats. Within heathlands, the knowledge-based method had classification accuracies reaching 88 to 99%, while the object-based method had a classification accuracy ranging from 71 to 77%. However, the object-based method was used for forest monitoring, which is a more challenging task compared to monitoring heathlands. In the study of Nieland et al. (2014), it is shown that automated delineation of heathland habitats using a spatial reclassification method based on classification results with remote sensing is feasible. The data used consisted of aerial imagery but was resampled to 2.5m x 2.5m. For some habitats results were poor due to very small resulting objects such as for Habitat 4030 (heathland) which had an accuracy of 17.8%. Habitat codes 2330 (inland dunes) and 31xx (all standing waters) showed good classification results (respectively 84.8% and 90%). Moreover, the study of Rapinel et al. (2014) showed that Worldview-2 data (with a higher resolution of ~0.5 m, can map vegetation at different levels reaching 95% accuracy for a land cover classification map. Their method consisted of a combination of pixel- and object-based classification, in which a supervised pixel-based classification was first applied, and, in a second step, improvements were made with object-based classification integrating the shape and texture. This resulted in good classifications for mapping and monitoring vegetation. At a coarser level, major vegetation types, such as crops, forests etc., were classified with 88% accuracy and for vegetation formation types, including different types of forests and grasslands, a 76% accuracy was reached. Multi-temporal monitoring and LiDAR integration could considerably improve results for forests classes. It shows that satellite data can achieve better results than resampled aerial imagery, meaning that spatial resolution is an important factor.

Other results for monitoring and mapping habitat maps or woodlands are obtained with e.g. Maximum Likelihood Classification (MLC), which shows high overall accuracies in the studies of Modica et al. (2016) and Pesaresi et al. (2022). In the study of Modica et al. (2016), Landsat-8 data was used to map the presence of cork oak woodlands. The study focussed on the characterization and separability of the spectral signatures of cork oak woodlands in different seasonal periods. 55 GCP ground truths were used. Maximum likelihood classification and minimum distance (MD) algorithms were applied to choose the best option. The highest achieved classification accuracy was over 85%. It should be considered that MLC is a powerful classification technique, but sensitive to variations in quality of training data in comparison to other supervised techniques. In the study of Pesaresi et al. (2022), Sentinel-2 time series data is used to generate habitat maps using supervised classification. The method used was Functional Principal Component Analysis. On OA of 85.58% was obtained using vegetation index time series, topography and lithology data. Both studies show high classification accuracies using supervised classification on satellite imagery.

Using Support Vector Machine (SVM) for mapping Natura 2000 habitats or shrub species showed very high overall accuracies. In the study of Schuster et al. (2015), the key to mapping small-scale semi-natural vegetation habitats, such as Natura2000 habitats, is to acquire interannual time series from satellites that provide high spatial and temporal resolution. Schuster et al. used time series of multi-spectral RapidEye and synthetic aperture radar (TerraSAR-X) satellite data to differentiate seven grassland classes with a Support Vector Machines classifier. It was shown that very dense time series resulted in high accuracy classification of over 90% for small scale vegetation types. With TerraSAR-X, more scenes were needed to reach higher accuracies. In the study of Calleja et al. (2019), Landsat-8 and Sentinel-2 images are compared to determine which platform is best in mapping a shrub *Baccharis halimifolia*. Also, three classification approaches are used to find the best combination, namely: pixel-based, object-based and a combination of both. Pixel-based classification was done using a Support Vector Machines algorithm. Object-based classification was done using Meanshift Segmentation algorithm (MSS). The combination of both was done in two steps: first the area for the shrub was found with object-based classification, and afterwards SVM was used. The Landsat image had better accuracy (highest 88%) due to the coarse spatial and spectral resolution, which tend to increase the variance of the image. However, the Sentinel image had higher accuracies of classifying the shrub class because of higher spatial and spectral resolution, which suited the mapping of the shrub better. Pixel-based detection was best for shrub classification in all cases. In the study of Buck et al. (2015), a segmentation and several classification approaches were tested, starting with the segmentation algorithm implemented in eCognition with RapidEye data (as used by the previous articles). For the classification approaches, Maximum likelihood (which is a supervised classification method) was performed on RapidEye data. For complex landscapes, SVM was used since it may provide better results. All approaches reached overall accuracies above 80%. The highest reached was with SVM at 89%. Cropland and maize are well discriminated, as are intensive grasslands, but classification of natural grassland habitats is very weak. Also, here is stated, as with the article of Rapinel et al. (2014), that LiDAR can improve grassland classification, and hyperspectral data can discriminate habitat features such as: lignin composition, presence of soil and senescent matter or litter. This can bring earth observation and vegetation experts closer together in monitoring Natura 2000 with remote sensing.

Machine learning can improve classifications when enough data is available for habitat classes. Natura 2000 or EUNIS habitat levels can be classified with Random Forest (RF). In the study of Raab et al. (2018), a remote sensing-based monitoring framework, making use of the RF algorithm, is presented for a Natura 2000 site with heterogenous composition of different grassland communities. Automated training data selection was used and OAs were found ranging from 77.5 to 86.5% using RapidEye data. Imagery used of vegetation from pre-spring, spring, late summer and first autumn were important phenological phases for mapping these semi-natural grasslands. In the study of Agrillo et al. (2021), 24 forest habitats are classified and mapped using a Supervised machine learning model (SMLM) with Sentinel-2 data. This is done with a combination of a vegetation plot database and spectral and environmental predictors. The procedure includes forest habitat data from Sentinel-2 and environmental data parameterizing a Random Forest classifier. OA was 87% at EUNIS II level classes and 76.14% at EUNIS III level. Broadleaved evergreen forests had the highest OA of 91%, needle leaved deciduous forest had 76%, and broadleaved deciduous forest had 68%. This study found that EUNIS habitat categories can be mapped with the proposed methodology. In both studies, almost the same overall accuracies are achieved. However, with SVM accuracies were higher with the same practice of mapping e.g. Natura 2000 areas as in the study of Schuster et al. (2015) compared to the study of Raab et al. (2018).

Summarizing, the above studies show generally good results in mapping and monitoring habitat types. However, as mentioned before, different datasets are used with different methods. Detection of heathlands can be done accurately with e.g. an RF classifier and RapidEye imagery, whereas the same heathlands can be done with e.g. an MLC classifier and Landsat data, but less accurately. Whether heathlands are accurately classified depends on the method and the data used. Therefore, studies testing multiple methods for the same habitats with the same data can provide useful insights regarding the accuracy of different methods. In the study of Regos et al. (2018), supervised classification was carried out on the remote sensing data with ten classification algorithms (e.g., RF, SVM Partial Least Squares and k-NN). The habitat maps, also involving semi-natural grasslands, which were derived from the classification approaches—SVM in both cases—showed an OA of 94% on 2003 data and 95% on 2016 data. In 2003 SVM with the 'amdai' classifier showed slightly better results, while in 2016 SVM with linear kernel achieved the highest accuracy. Despite all the current advantages within the classification methods, detailed habitat mapping could require more advanced technologies, such as hyperspectral or LiDAR data, to avoid spectral similarity of the land covers. This is in line with the assumptions of both Rapinel et al. (2014) and Buck et al. (2015). In the article of Sittaro et al. (2022), a modelling framework for habitat monitoring was introduced using MODIS surface reflectance data. Supervised classification models were developed that allocate semi-natural areas based on similarity with natura 2000 habitat types. Three machine learning classifiers were used: SVM, RF and C5.0 decision trees. SVM and RF obtained better OA (SVM 0.72-0.93 and RF 0.72-0.94) in comparison to C5.0. This study has shown that with these machine learning methods it is possible to represent the distribution of natural areas comparable with Natura2000 habitats.

In general, we have seen that higher spatial resolution often results in better overall accuracy, although this is not always the case (as was explained before by the study of Calleja et al. (2019)). Reviewing all the studies, it is clear that SVM gives the best results, even when using different satellite data. The studies of Agrillo et al. (2021), Schuster et al. (2015), Raab et al. (2018), Buck et al. (2015) and Calleja et al. (2019) have shown that using SVM to classify habitats gives high, or even the highest, accuracies compared to other techniques. In addition, RF achieved almost similar results to SVM, as was seen in the study of Sittaro et al. (2022), in which RF had almost identical overall accuracies with the same dataset.

Another finding of this literature review is that including LiDAR and hyperspectral data can improve detailed habitat mapping and help to prevent spectral similarity of different land cover and habitat types (Rapinel et al., 2014; Buck et al., 2015; Regos et al., 2018). This can bring earth observation and vegetation experts closer together in monitoring Natura 2000 with remote sensing.

In a study by Maxwell et al. (2018), a review on the machine learning literature was done which is in line with what is done in our study. It was found by Huang et al. (2002), that training sample sizes had a larger impact on classification accuracies than the used methods, such as MLC, SVM, ANNs and Decision trees. Also, machine learning has been shown to provide better classification performance for remote sensing classifications than MLC or any other parametric technique. Maxwell et al. (2018) stated that RF is a good tool since it is robust to the parameter settings used. Our findings around SVM methods achieving high accuracies are in line with the review of Maxwell et al. (2018) in which SVM can achieve high accuracies if training samples sizes are large enough.

3.3 Mapping and monitoring habitat quality

With regard to the mapping and monitoring of habitat quality there are a lot of studies that show that remote sensing can play an important role in this domain (Spanhove et al., 2012; Mücher et al., 2013; Vaz et al., 2015; Zlinsky et al., 2015; Neuman et al., 2015; Schmidt et al., 2017a; Schmidt et al., 2017b; Schmidt et al., 2018; Marcinkowska-Ochytra et al., 2018; Radecka et al., 2019; Matas-Granados et al., 2022; Cavender-Bares et al., 2022). Nevertheless, more studies focus on habitat structure (Mücher et al., 2013; Schmidt et al., 2018; Marcinkowska-Ochytra et al., 2018) than on habitat function (Schmidt et al., 2017a; Radecka et al., 2019; Matas-Granados et al., 2022). Although important studies also focus on grass, shrub and tree encroachment in heathlands (Mücher et al., 2013; Marcinkowska-Ochytra et al., 2018; Kopeć and Sławik, 2020), which can be considered as monitoring the habitat function. Especially with airborne LiDAR, the possibilities for mapping vegetation structures are endless (Ficetola et al., 2014; Kathman et al., 2022) at a very detailed spatial level.

An important strength of remote sensing is that one can analyse time series of satellite imagery (which are often freely available in historic satellite archives) for any Natura 2000 site. For example, Matas-Granados et al. (2022) quantified changes in the normalized difference vegetation index (NDVI) over the past 35 years across locations with threatened plants in Natura 2000 protected areas. The approach demonstrates how long-term remote sensing (Landsat) monitoring can help to assess the effects of both slow processes and drastic landscape transformation events on priority plants in a comprehensive and rapid manner. RS-enabled Essential Biodiversity Variables (EBVs) identify measurable variables to allow the rate and direction of change to be quantified for some aspect of the biodiversity state over time and across space, and they may belong to different frameworks, such as ecosystem structures and functions (Skidmore et al., 2015; Pettorelli et al., 2016). Matas-Granados et al. (2022) states 'Remote sensing technology has great potential for use in monitoring and building global indicators of change (O'Connor et al., 2015; Pasquarella et al., 2016), but conservation biologists need to engage in "joined-up thinking" to effectively respond to clearly oriented questions (Lindenmayer et al., 2018)'. This is one of the current weak points: that RS experts and ecologists have not yet operationalized how RS-enabled EBVs can explicitly help the monitor changes in structure and function of habitats. Once such a link is established, it can be applied on a global scale for any nature area and will be complementary to unevenly distributed in-situ species monitoring. At this moment, long time series of satellite imagery are affiliated with: MODIS, at 250-meter spatial resolution from December 1999 till today (daily scenes are often processed to ten-day or monthly products), and Landsat, at 30-meter spatial resolution from July 1972 till today. With a data archive spanning over 40 years, Landsat provides the longest and most sophisticated record of high spatial resolution satellite imagery (Roy et al., 2014). However, many tropical countries have very limited coverage or no observations at all available for the 1980s and 1990s due to a non-global observation strategy (Goward et al., 2006) and a lack of available ground receiving stations in the past (Arvidson et al., 2006). But since the mid-1990s a number of optical and C- and L-band SAR satellite constellations have provided an additional source of time-series data (Reiche J., 2015). Since the launch of the European radar satellite Sentinel-1 on 3 April 2014 and the European optical satellite Sentinel-2 on 23 June 2015 (both series of satellites within the framework of the Copernicus programme) it has become possible to build historic time series with a high spatial resolution of 10 m. The latter will be especially interesting for analysing fine-scale trends (e.g., in the Netherlands).

In addition to satellite time series being used as global indicators for changes in habitat quality, they are also being used to identify specific events, such as mowing of grasslands (Schuster et al., 2011). In Schmidt et al. (2018) the remote sensing-based mapping of heathland conservation status showed an overall agreement of 76% with field data. Transferring the approach in time (applying a second set of Sentinel-1 and -2 data) caused a decrease in accuracy to 73%. Their findings suggest that Sentinel-1 SAR data contains information about vegetation structure that is complimentary to optical Sentinel-2 data and, therefore, relevant for nature conservation.

Airborne hyperspectral data is often used for measuring the habitat quality at a detailed resolution in centimetres, especially with regard to heathlands (Spanhove et al., 2012; Mücher et al., 2013; Schmidt et al., 2017a; Schmidt et al., 2017b). However, these airborne hyperspectral data are only used on a case-by-case basis, since new spaceborne hyperspectral satellite sensors, such as PRISMA and ENMAP, have a relatively low spatial resolution of 30 m. Nowadays, hyperspectral and LiDAR cameras are becoming easier to implement on UAVs and will have many operational applications for monitoring habitat area and quality for targeted areas.

In addition, Essential Biodiversity Variables (EBVs) were proposed in 2015 by the biodiversity community to improve harmonization of biodiversity data in order to produce meaningful metrics (Skidmore et al., 2015; Petorelli et al., 2016). The proposed EBVs have been grouped into six classes: genetic composition (not yet perceivable with remote sensing data), species populations, species traits, community composition, ecosystem structure, and ecosystem function (see Figure 3.3). This concept has taken root within wide segments of the theoretical and applied ecology communities. The idea behind the original EBV concept was that at least one EBV per class should be monitored, while keeping the set of EBVs limited in order to assure the usefulness of the EBV concept. Possible EBV's that capture biodiversity change on the ground and can be monitored from space range from leaf nitrogen and chlorophyll content to seasonal changes in floods and fires (Skidmore et al., 2015).

The RS-enabled EBVs can play a role in the monitoring of the quality of the habitats in conjunction with the mapping and monitoring of habitat types. Nevertheless, much effort still has to be put in place to translate these remote sensing variables into useful information for ecologists in terms of habitat quality. For example, Vaz et al. (2015) collected field data on five habitat quality indicators in vegetation plots from woodland habitats of a landscape undergoing agricultural abandonment. Their findings strongly suggest that some features of habitat quality, such as structure and habitat composition, can be effectively monitored from EO data, combined with field campaigns, as part of an integrative monitoring framework for habitat status assessment.

Because many elements of biodiversity remain unseen or unknown when measuring global biodiversity change, Skidmore et al. (2021) prioritize feasible and relevant biodiversity products that could be generated from satellite remote sensing with high accuracy, thereby filling data gaps in the spatial and temporal coverage of in-situ biodiversity observations.

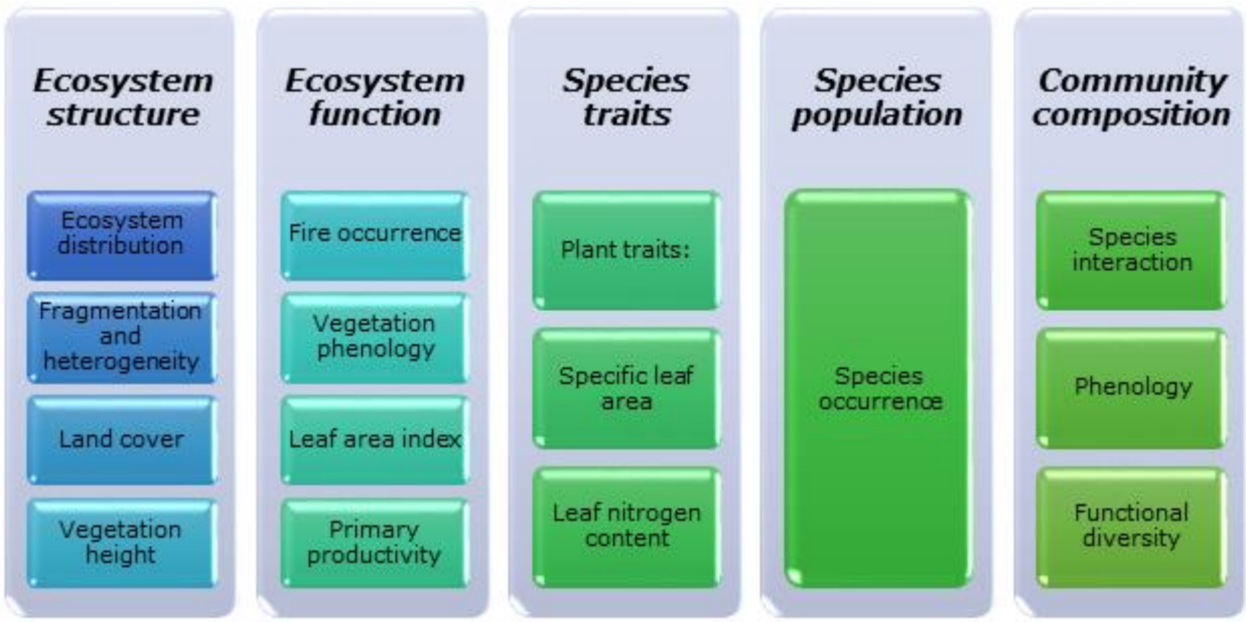


Figure 3.3 *A selection of proposed Remoted-Sensing-Enabled Essential Biodiversity Variables (RS-EBVs) – Skidmore et al. (2015), modified by E. Neinavaz.*

3.4 Mapping plant species

Since the literature review did not directly result in peer reviewed articles with regard to deep learning techniques to detect plant species, we will give two examples from our own experiences in which we exploited drone images for: 1) the detection of marsh marigold in the wetland forest the Biesbosch and 2) the detection of sea grass in the Province of Zeeland.

3.4.1 Detection of marsh marigold (*Caltha palustris)*

The exploitation of machine learning/deep learning, or artificial intelligence (AI), has improved with the increase in computational power. It now provides the basis for more complicated image classifications that enable the recognition of objects such as human individuals. This capacity provides opportunities to map individual plant species (in the case of larger plants with distinct features). In general, deep learning explores patterns and regularities within the data in order to make predictions based on what is learnt by analysing available known data. Since the accuracy can be improved with experience, deep learning performs the best when it can incorporate large training datasets.

Below is an example of a deep learning approach to identifying marsh marigold (*Caltha palustris*) from RGB drone imagery over the wetland forest Biesbosch National Park in the Netherlands (Figure 3.4). The study (Alkema, 2019) attempts to get species recognition from UAV images in order to potentially assist or replace field inventories. The bright yellow flowers of marsh marigold and reflective leaves allow for relatively easy recognition in the field, and as an indicator species, its presence or absence gives insight in the status of the surrounding swampy habitat.

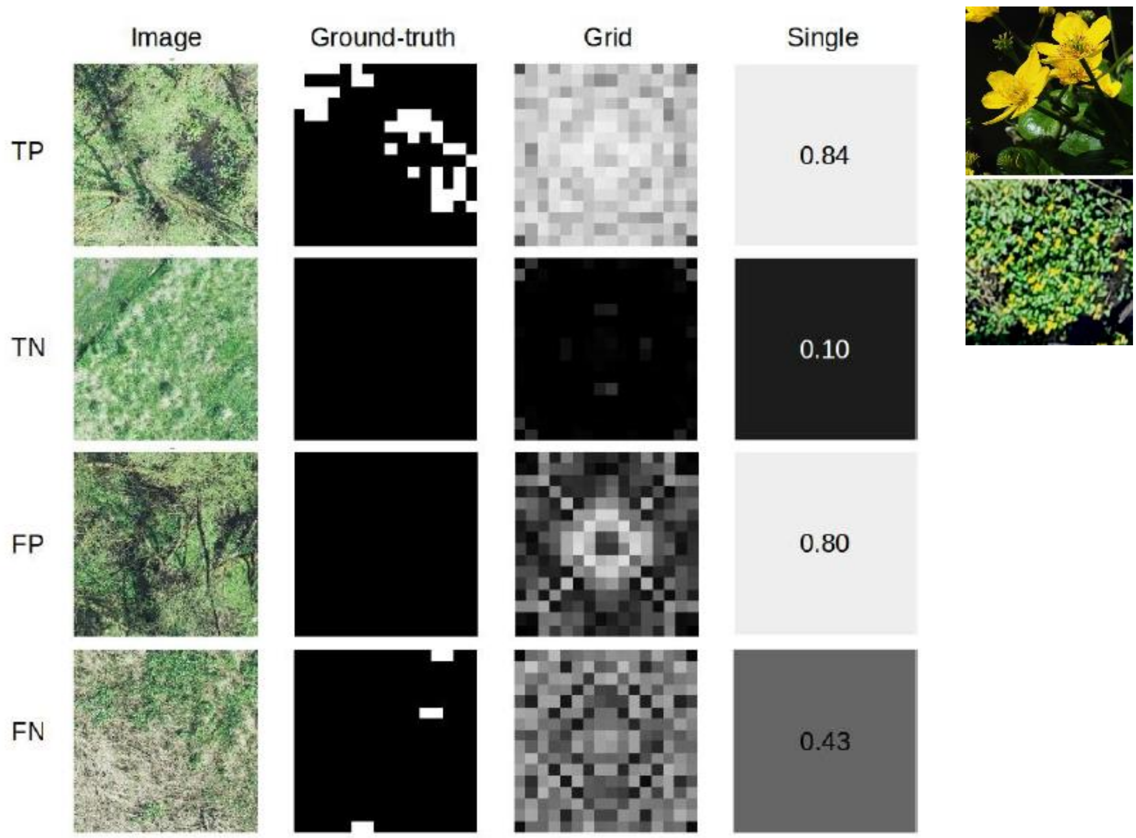


Figure 3.4 *Examples of correct and false predictions of the grid (3rd column) and single prediction models (4th column). True positive (TP), true negative (TN), false positive (FP) and false negative (FN) outputs are depicted next to the corresponding UAV images and ground-truth masks, given a threshold of 0.5.*

3.4.2 Detection of sea grass (Zostera spp.)

Within this pilot case study, we examined to what extent it is possible, based on different types of UAV imagery, to accurately distinguish between dwarf eelgrass (*Zostera noltii)*, common eelgrass (*Zostera marina)*, beaked tasselweed (*Ruppia maritima)* and other types of cover such as algae and bare soil (Mücher et al., 2020). Coverage of seagrass could then be determined based on these classifications. This innovative method may eventually be used to support or replace the traditional regular field surveys.

Two study sites in Oosterschelde, the Netherlands were selected: an area of 32 hectares near Krabbendijke (where *Zostera noltii* occurs in different cover classes, Figure 3.5) and an area of 18 hectares at Plaat van Oude Tonge (where we can find *Zostera marina* and sporadic *Ruppia maritima*, albeit on a small scale and in a very low cover). RGB and multispectral UAV imagery was acquired on 21 July 2020 under favourable weather and tide conditions (wind 3bft NNW, 23° C, cloud 1/8). In the same week, a conventional field survey took place by Eurofins (Mücher et al., 2020).

Figure 3.5 *Study area of Krabbendijke with Zostera noltii.*

Two types of UAVs were tested. With a fixed-wing eBee-X RTK, images were taken with two modular camera types: an RGB camera (Sensor Optimised for Drone Applications - S.O.D.A.) and a multispectral camera (Parrot Sequoia) measuring reflections in 4 spectral bands: Green (530-570 nm), Red (640-680 nm), Red Edge (730-740 nm) and Near Infrared (770-810 nm). From a height of approximately 60 m, these sites were sampled in a pre-programmed flight plan in squares with a 70-80% overlap. This generated orthomosaics with a pixel resolution of about 1.5 cm for the RGB and about 5 cm for the multispectral images (Mücher et al., 2020).

In addition, a Phantom 4 Pro (multicopter) was used for the RGB recordings of the Plaat van Oude Tonge. On the 3 mm resolution images of the Phantom 4 (10 m height), different vegetation types (sea grasses, algae and bald mud) were visually located to be used for both training and validating the classification, along with the RGB orthomosaic. This arrangement assured the optimal thematic accuracy, georeferencing and ground-truthing (Mücher et al., 2020).

This training dataset was used in the deep learning module of ENVI software. The reason for this choice of deep learning algorithm over the often-used OBIA was that the segmentation process within OBIA is so computationally demanding that segmenting images at the given level of detail (such as for large seagrass and ruppia) for large areas was not considered workable. Deep learning techniques were expected to serve the purpose more efficiently.

To test the results of the deep learning classification (Figure 3.6), a validation was performed for Krabbendijke based on independently collected ground truth data (manually interpreted points based on 3 mm resolution detail Phantom UAV images at 10 m height at 414 locations). The classification accuracy for small eelgrass at Krabbendijke was good for high abundances but dropped with lower coverage (Table 3.1). For the other test site, common eelgrass (not present in Krabbendijke) did not reach good results since it only occurred at a few locations, and therefore the amount of ground truth data was too limited with only eight observations for running a deep learning model. Overall, the deep learning techniques performed better on 1.5 cm RGB orthomosaics than on 5 cm multispectral orthomosaics. Obviously, spatial resolution outperformed the spectral one (Mücher et al, 2020).

Table 3.1 *Confusion matrix of deep learning eelgrass classification in Krabbendijke (the Netherlands).*

In-situ	**Classification**								
	Brown seaweed	**Green seaweed**	**Bare soil**	**D. eelgrass 1-25%**	**D. eelgrass 26-50%**	**D. eelgrass 51-100%**	**Sea lettuce**	**Total**	**User Accuracy**
Brown seaweed	**46**		1	1		4	2	54	85%
Green seaweed	3	**0**					1	4	0
Bare soil			**98**	16				114	86%
Dwarf eelgrass 1-25% cover	2		15	**31**	19	2	12	81	38%
Dwarf eelgrass 26-50% cover	1			5	**36**	10	10	62	58%
Dwarf eelgrass 51-100% cover	4				3	**43**		50	86%
Sea lettuce	3			4		2	**2**	11	18%
Total	59	0	114	57	58	61	27	**376**	
Producer Accuracy	78%	0%	86%	54%	62%	70%	7%		**68%**

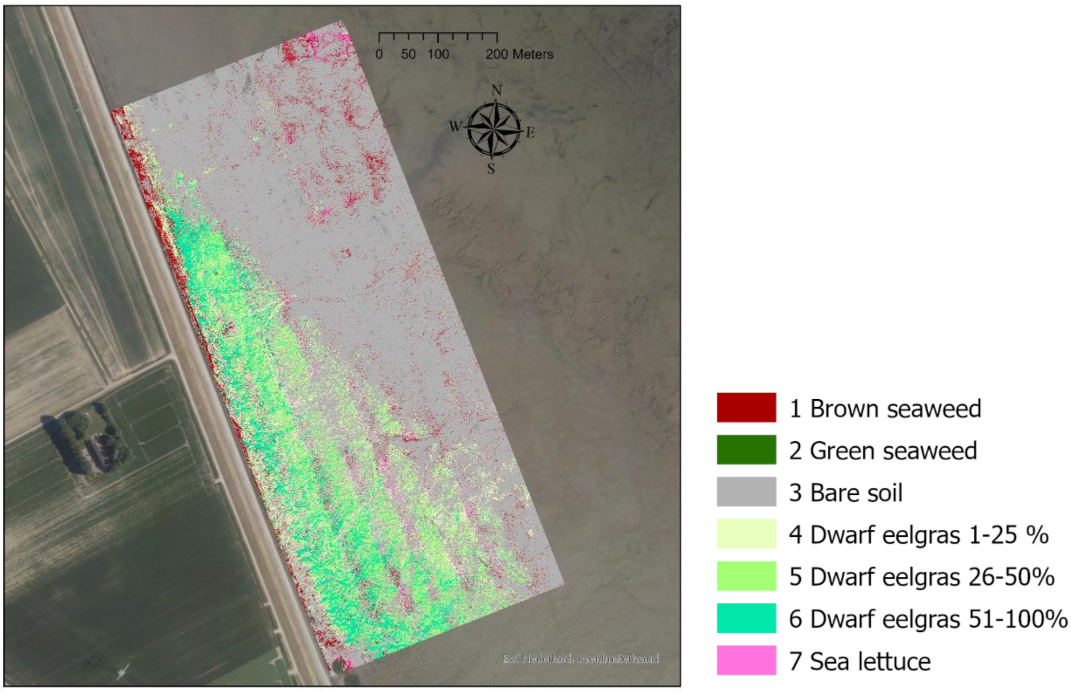


Figure 3.6 *Deep learning classification of sea grass on Dutch sea coast (Mucher et al., 2020).*

4 Case study 1: Detecting biomass change in semi-natural grasslands in relation to climate change based on time series of satellite data

4.1 Introduction

This case study discusses the application of remote sensing for detecting changes in biomass for semi-natural grasslands (hay meadows and calcareous grasslands) based on Sentinel-2 data from groenmonitor.nl. We would like to relate these changes in biomass to changes in climate. The background is that there is a growing concern among nature managers that climate change causes a longer growing season and therefore higher productivity in grasslands, which may require more (and more expensive) management.

The climate is changing, causing things such as a rise in sea level, increasing river discharge and temperature changes (KNMI, 2022; Bresser et al., 2005; IPCC, 2022). The expectation of the changing climate is that extremely hot and dry summers will occur more often, and more frequent extreme precipitation is expected, which can cause flooding. These climate changes also affect nature in the Netherlands. Dry and warm summers can hinder plant growth and may require adaptation of water management. Warmer winters and an increase in precipitation on an annual basis may increase biomass production and therefore may require adaptation of management practices in short vegetation types, e.g. grasslands and heathlands.

Remote sensing is useful for monitoring historical changes in biomass production of vegetation. Satellite images from the open-source Copernicus Sentinel-2 satellite are available on a weekly basis, and with a cloud-free image, this data can be used to monitor vegetation development throughout the year and over several years. For longer historical time periods, other imagery from Landsat or MODIS satellites are freely available. Sentinel-2 data is suitable for monitoring semi-natural grasslands, grasslands that are managed with extensive mowing management or light grazing.

This case study focuses on two semi-natural grassland types, namely hay meadows (Natura 2000 habitat type 6510A) and calcareous grasslands (Natura 2000 habitat type 6120). We studied the relationship between changes in biomass and changes in climate. From groenmonitor.nl we collected Sentinel-2 data since 2013, and for the available images the NDVI (Normalized Difference Vegetation Index) has been calculated. The NDVI is an indicator of vegetation or crop biomass (the amount of leaf biomass present).

4.2 Method

In this case study, time series of Sentinel-2 satellite images from groenmonitor.nl were examined in order to observe the development of biomass within the hay meadows and calcareous grasslands. The hay meadow and calcareous grassland plots were supplied in the form of a shapefile. The analysis was carried out on the basis of those plots. Sentinel-2 data has a resolution of 10 m, so it was decided to only use plots larger than 1 hectare in order to have enough information for each plot. The BRP (basic registration of parcels of the Netherlands) was used to link the hay meadows and calcareous grasslands to data from the AgroDataCube (ADC, a collection of data for agricultural applications, offered by WENR), which also contains the data from groenmonitor.nl. Each year, each plot in the Netherlands is assigned a unique "field ID". These "field IDs" were collected for the years 2013 to 2020. For each available image between these years, the NDVI time series was used to calculate an average per year. In addition to the NDVI, the number of mowing moments can also be determined since 2018, which can be used to see whether an increase in biomass can be detected. An increase in biomass due to a change in the climate can result in an increase in the number of mowing events because the production of the semi-natural grasslands has also increased.

If results from groenmonitor.nl show that the time period is too short (and therefore not sufficient), another method using Google Earth Engine can be used to access data from Landsat or MODIS satellites. Landsat 5 Thematic Mapper (TM) has a resolution of 30 m for the used bands (RGB and NIR infrared) and collected data from 1984 to 2012. Landsat 7 Enhanced Thematic Mapper Plus (ETM+) also has a resolution of 30 m for the used bands and collected data from 1999 to the present day. This data combined can give a same indication of the NDVI curve over almost 40 years for the same parcel by picking a pixel in the Landsat archive which corresponds with hay meadow grasslands or calcareous grasslands.

MODIS data can also be used to give an indication on the NDVI curve over the last 22 years. However, the MODIS satellite data, and most importantly the RGB and NIR infrared bands, have a spatial resolution of 250 m which is not as accurate as Sentinel-2 or Landsat data. Therefore, this data can only be used if parcels of hay meadow grasslands or calcareous grasslands are large enough so that one pixel covers all, or almost all, of the grasslands. Since this pixel size is too coarse for the calcareous grasslands, we will focus on the Landsat time series.

4.3 Results and discussion

The results will be discussed for each type of semi-natural grassland investigated in this case study. First, we will discuss the results of the hay meadows and then the calcareous grasslands.

4.3.1 Hay meadows

The supplied shapefile with hay meadows for the Netherlands covers 262 features. After the selection of plots larger than 1 hectare, there are still 71 features left. The hay meadows that were supplied were sometimes not completely overlapping with the BRP or not present in the BRP, which is why it was decided to leave out plots that cover less than half of the BRP plots in the study. This results in 52 hay meadow plots that are included in the study. After coupling the plots with the ADC, the NDVI time series for one year can be determined (see Figure 4.1).

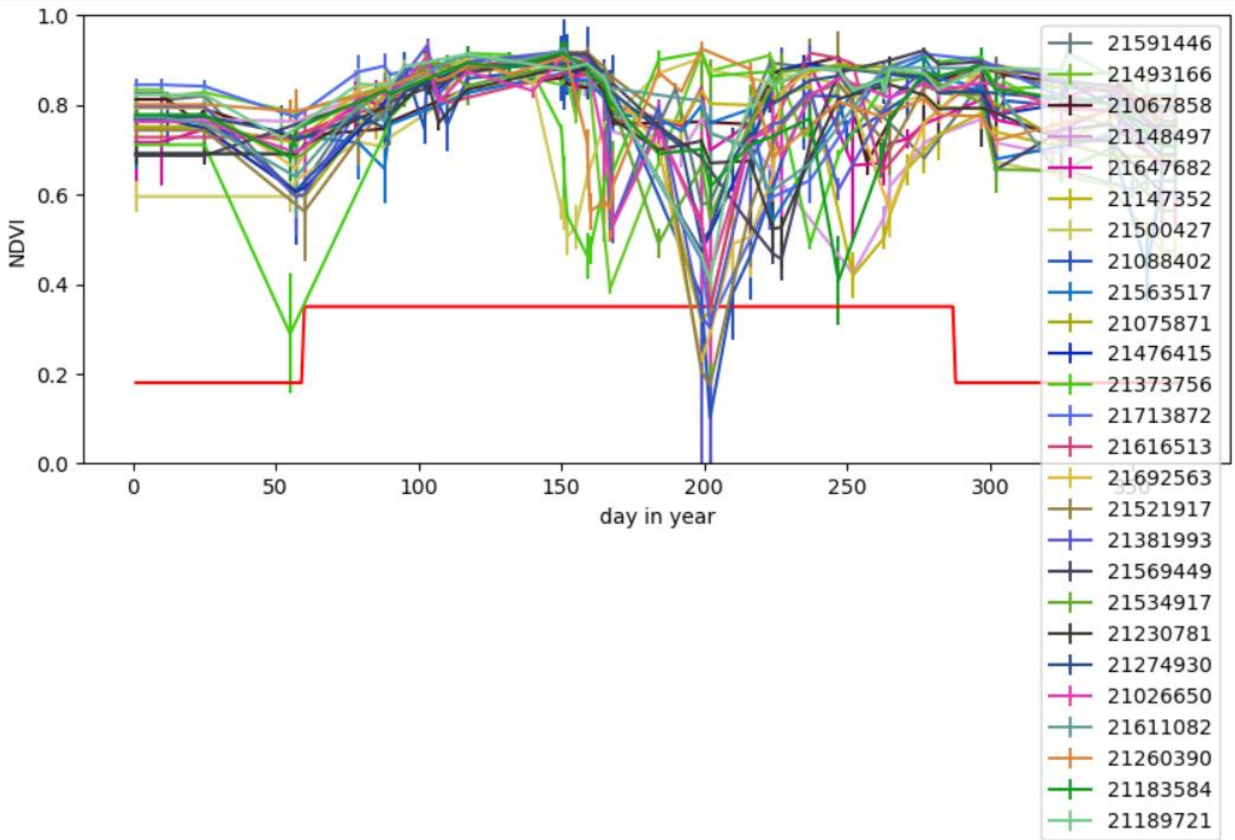


Figure 4.1 *NDVI time series for some of the parcels in 2020.*

In Figure 4.1, only half of the hay meadow plots are made visible, with a great deal of difference between the plots and the NDVI. To make this more transparent, we determined an average NDVI for all years and plotted this in a box plot to show the difference. For the years 2013 to 2016, lower values were calculated by other atmospheric corrections of the satellite image at that time. Therefore, a correction of 9% has been applied to make the years 2013 to 2021 more comparable. Figure 4.2 shows the box plot from 2013 to 2021.

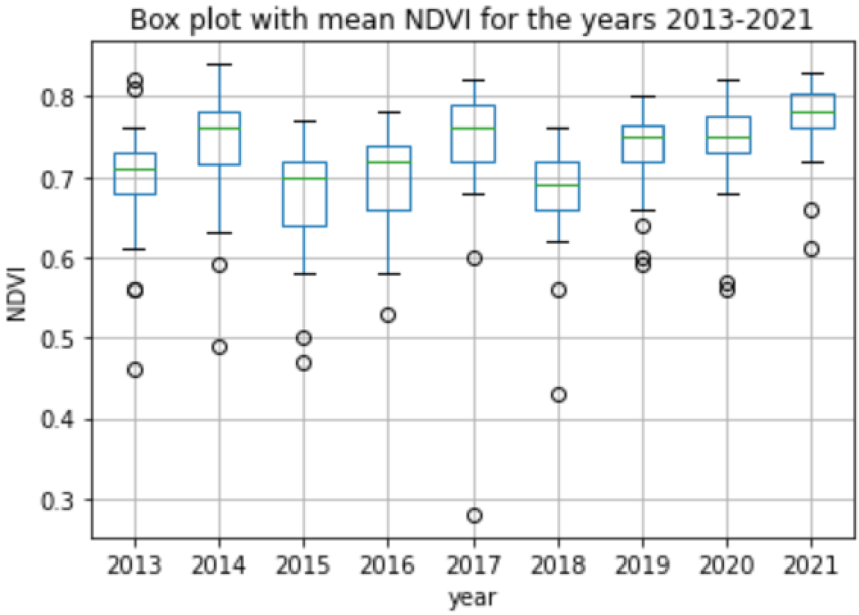


Figure 4.2 *Box plot of the mean NDVI for the available images.*

The figure shows differences between the years in the NDVI average, but there is no visible trend that the average in NDVI has increased significantly over the years. The lower values of the boxplots in 2015 and 2018 correspond with dry years with little precipitation, resulting in a visible drop in production (see section 4.3.3 on temperature and precipitation). The number of mowing events from 2018 can also be determined. With an increase in biomass, it is expected that the number of mowing events to remove the biomass will increase. Table 4.1 shows the mowing frequency from 2018 to 2021.

Table 4.1 *Mean of mowing events for hay meadows.*

Year	Mean of mowing events
2018	1.69
2019	1.47
2020	1.63
2021	1.45

No significant increase is visible for the average number of mowing times over the years; the average fluctuates, but a trend cannot be determined. Four years of information is too little to see a change.

Since the groenmonitor.nl data has a 9-year range, data from Landsat and MODIS were also analysed in the Google Earth Engine providing data for a range of over 20 years for both satellites. For Landsat data the following time series of the NDVI curve could be retrieved from the online database by selecting a pixel in hay meadows (see Figure 4.3).

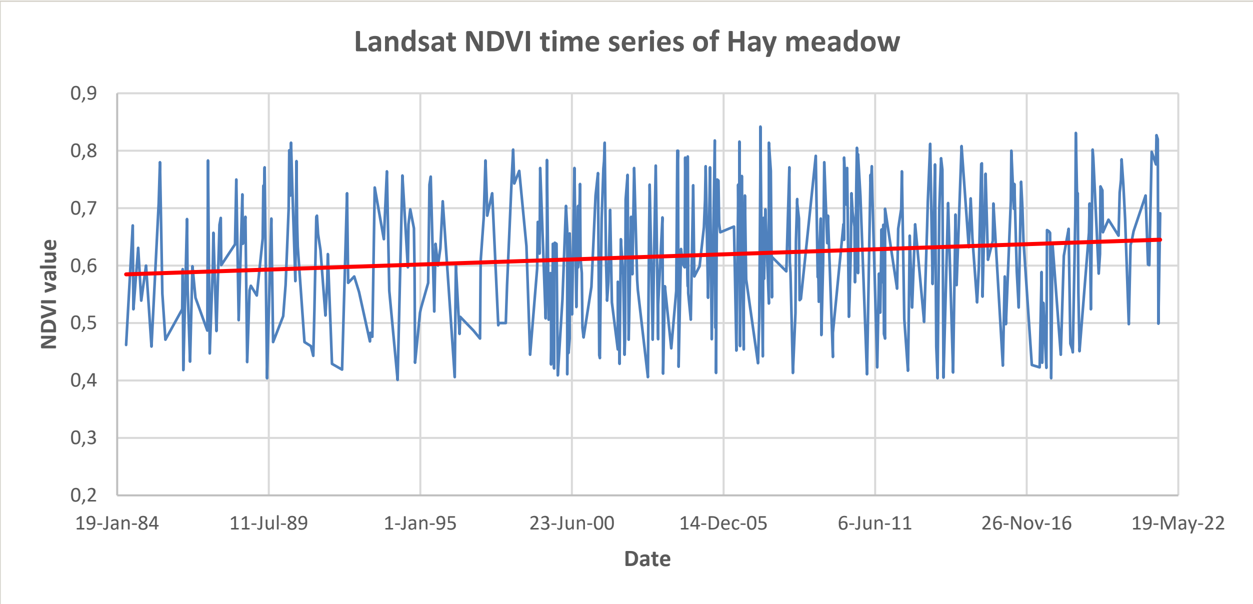


Figure 4.3 *Landsat NDVI time series of a hay meadow in Amerongen between 1984 and 2021.*

With the trendline it is visible that the mean NDVI is slightly increasing over the years indicating that through the years the NDVI values are getting higher. Figure 4.3 is for a pixel in Amerongen, however other pixels pinpointed in hay meadows show the same kind of trend in the time series. The NDVI values under 0.3 are removed from the data since NDVI values below 0.3 correspond with snow, water and clouds, as well as low density vegetation. This does not represent grasslands, which have a dense vegetation throughout the year. An increase in the mean NDVI could be an effect of climate change and an increase in the biomass production of these hay meadows. A correspondence with increasing nitrogen deposition from the air is also possible, but this was not studied.

4.3.2 Calcareous grasslands

The supplied shapefile with calcareous grasslands for the Netherlands consists of 64 features. After the selection of plots larger than 1 hectare, there were 20 features left. The calcareous grassland plots that were supplied sometimes did not completely overlap with the BRP or are not present in the BRP, so that it has been decided to also omit plots that cover less than half of the BRP plots in the study. This results in 14 calcareous grassland plots that are included in the study. After coupling the plots with the ADC, the NDVI time series for one year can be determined (see Figure 4.4).

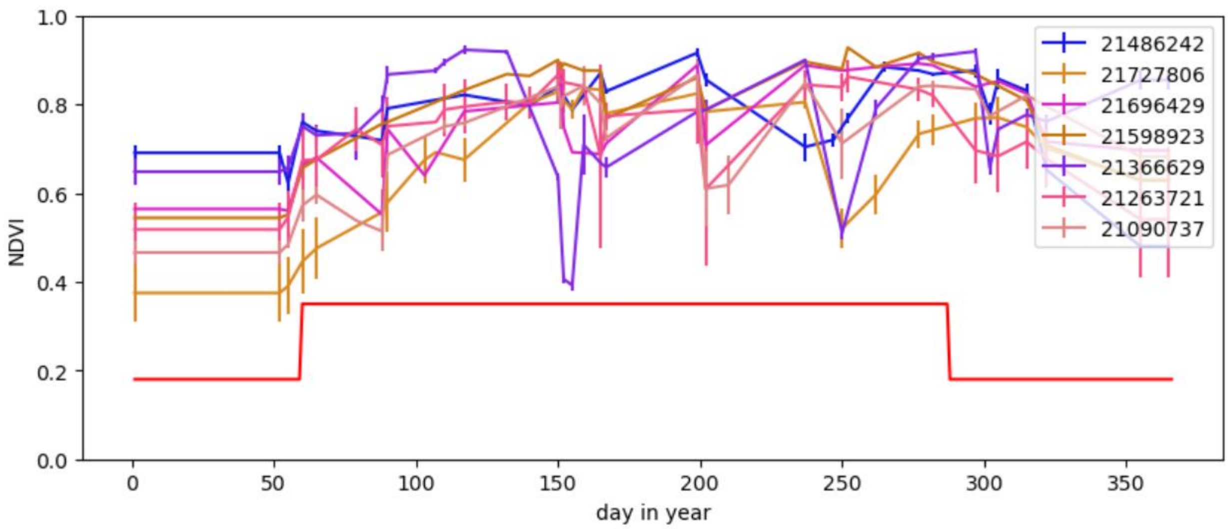


Figure 4.4 *NDVI time series for some of the parcels in 2020.*

In Figure 4.5 the calcareous grassland plots are made visible, showing a great deal of difference between the plots and the NDVI. To make this more transparent, we determined an average NDVI for all years and plotted this in a box plot to show the difference. For the years 2013 to 2016, lower values were calculated by other atmospheric corrections of the satellite image at that time. Therefore, a correction of 9% has been applied to make the years 2013 to 2021 more comparable. Figure 4.5 shows the box plot from 2013 to 2021.

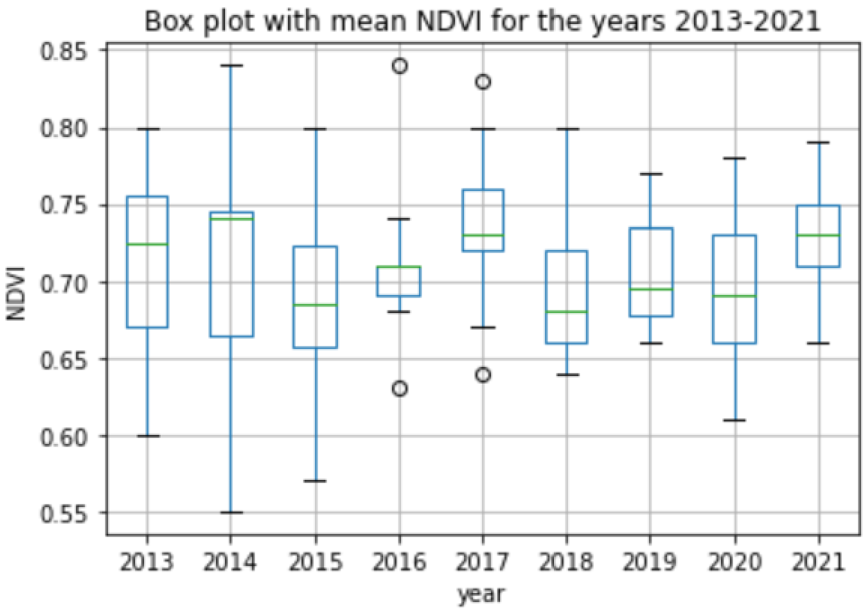


Figure 4.5 *Box plot of the mean NDVI for the available images.*

The figure shows differences between the years in the NDVI average, but a trend is not fully visible. The NDVI values have been somewhat lower in the last three years instead of increasing on average over the years. The lower values of the box plots cannot be fully explained by the drier years, such as 2015 and 2018, because production is also lower in 2016, 2019 and even 2020, which were not exceptionally dry years.

The number of mowing events from 2018 can also be determined. With an increase in biomass, it is also expected that the number of mowing events to remove the biomass will increase. Table 4.2 shows the mowing times from 2018 to 2021.

Table 4.2 *Mean of mowing events for calcareous grasslands.*

Year	Mean of mowing events
2018	1.62
2019	1.30
2020	1.30
2021	1.36

No significant increase is visible for the average number of mowing times over the years. It fluctuates over the years, but a trend cannot be determined. Four years of information is too little to see a change.

The calcareous grasslands data from Landsat and MODIS were also analysed in the Google Earth Engine, providing data for a range of over 20 years for both satellites. For Landsat data the following time series of the NDVI curve could be retrieved from the online database by selecting a pixel in hay meadows (see Figure 4.6).

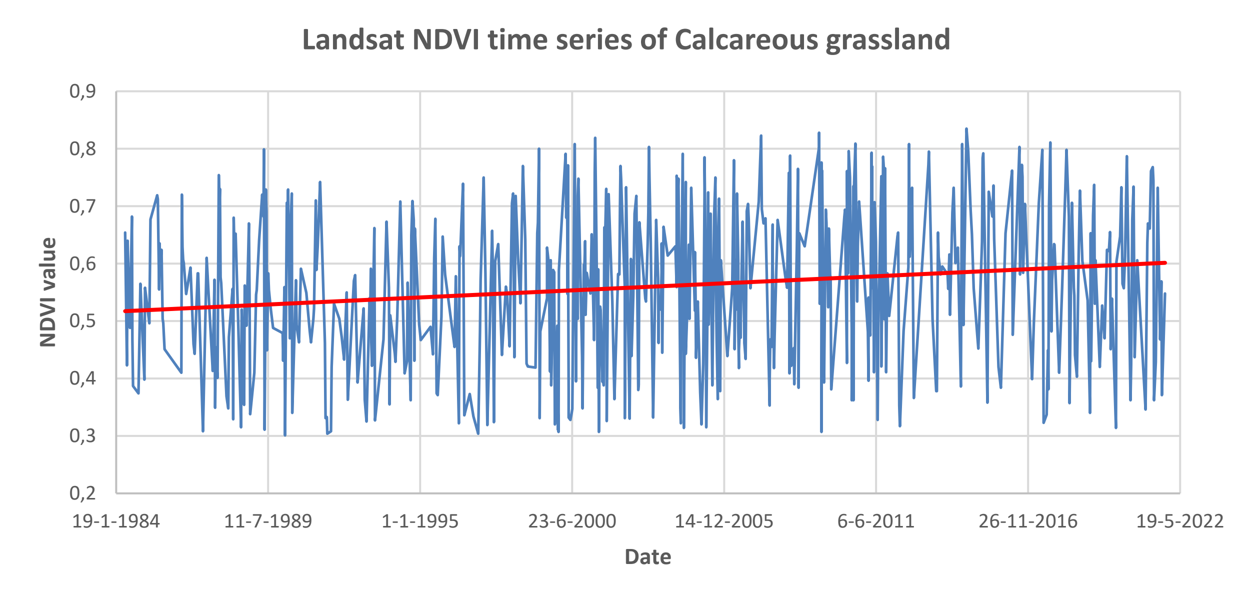


Figure 4.6 *Landsat NDVI time series of a calcareous grassland in Wijlre between 1984 and 2021.*

With the trendline it is visible that the mean NDVI is slightly increasing over the years, indicating that through the years the biomass is getting higher. Figure 4.6 is based on a pixel at Wijlre, however other pixels pinpointed in calcareous grasslands show the same kind of trend in the time series. The NDVI values under 0.3 are removed, the same as for the hay meadow. For these semi-natural grasslands, an increase in the mean NDVI could also be an effect of climate change, but other causes should be considered as they may play an (additional) role, like changes in nitrogen deposition from the air and natural succession. The latter is relevant, as several calcareous grasslands have been restored from arable land.

4.3.3 Temperature and precipitation data

We see a clear decrease in the Sentinel-2 boxplot figures for 2018 compared to the year before and the year after, especially in the hay meadows. The year 2018 was an exceptionally dry and quite warm year. As a result, the productivity of the hay meadow has fallen sharply. To make it more transparent what the average temperature and precipitation were from 2013 to 2021, they are shown in the graphs below.

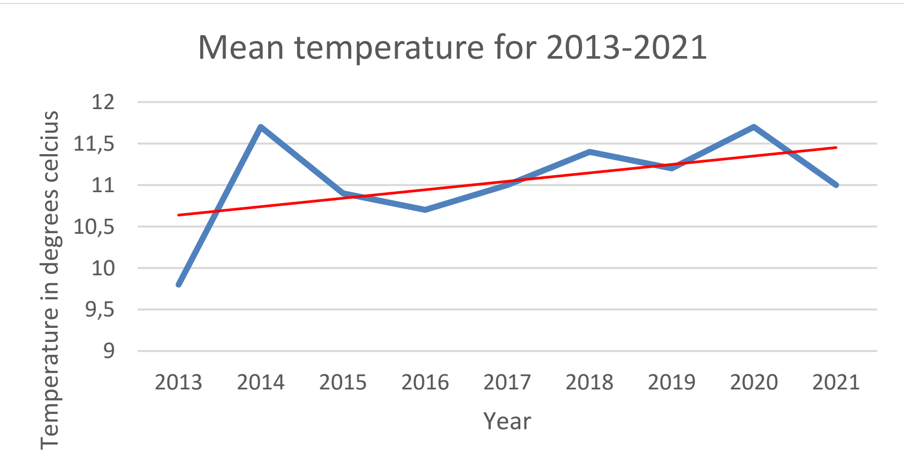


Figure 4.7 *Mean temperature for the years 2013 until 2021.*

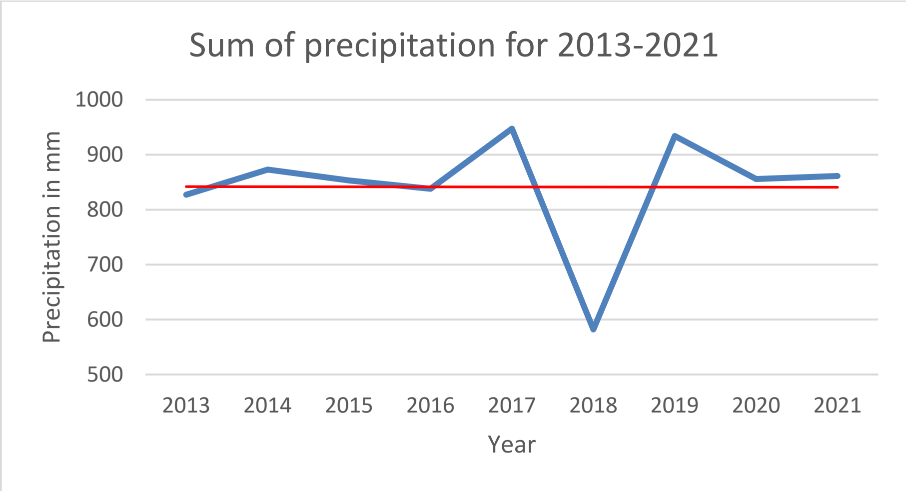


Figure 4.8 *Sum of precipitation for the years 2013 until 2021.*

For Landsat data the drop in the precipitation in 2018 is difficult to read from the data since the data range is longer and individual years are hard to extract from the figures. Therefore, a figure is made to show the change in temperature between the years 1984 and 2021 to give an idea of the trendline through these years (See Figure 4.9).

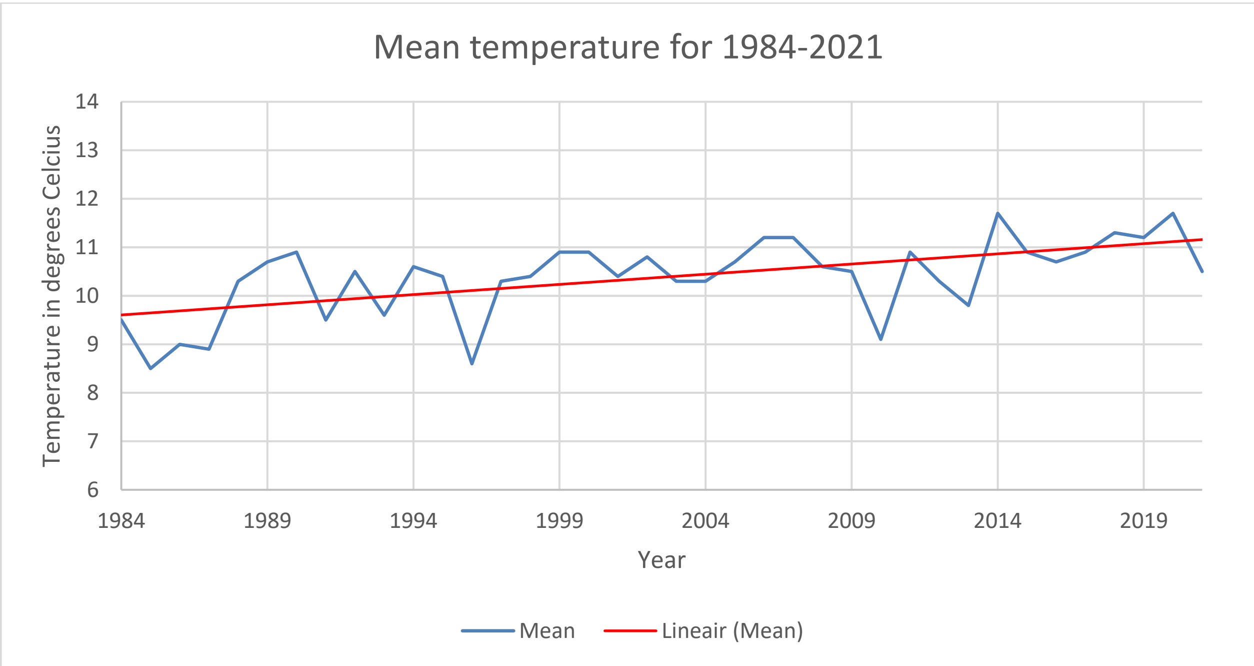


Figure 4.9 *Mean temperatures over the years 1984 to 2021.*

In the above figure it is clear that the temperature is increasing, which is also confirmed by e.g. the IPCC report (IPCC, 2022). In 1984 the mean temperature was 9.5 degrees Celsius. In 2021 this increased to 10.5 and, where the trend line is exceeding, a mean of 11 degrees Celsius. This could be the reason that the biomass is increasing since warmer temperatures cause grass to increase their growth rate. This would explain why NDVI values are higher in recent years than 20 years ago.

For the precipitation there is less of a trend, although there is a slight increase in the sum of precipitation since 1984 which is visible in Figure 4.10.

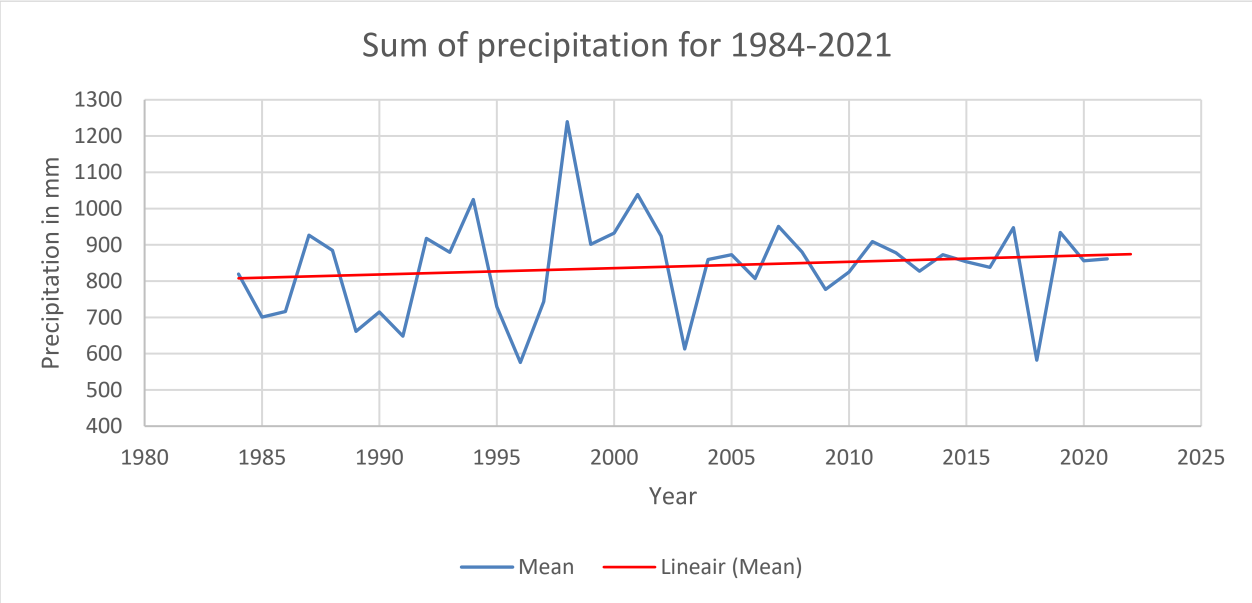


Figure 4.10 *Sum of precipitation over the years 1984-2021.*

4.4 Conclusion

It can be concluded from the results that for both types of semi-natural grasslands (hay meadows and calcareous grassland) no clear trends in biomass in the short period from 2013 to 2021 were visible in the processed Sentinel-2 data. Some years show a peak and others low values in the NDVI curves, but these yearly fluctuations can be explained by a precipitation shortage or temperature changes in that specific year. The time series is too short to analyse long-term effects of climate change, but it may serve as a baseline for such a study.

In order to analyse effects of climate change, it is necessary to look at the biomass development over a longer time period. On sites where hay meadows or calcareous grasslands have been present for 20 years or more, we see an increase in biomass based on Landsat satellite images. These images are dating from 1984 to today. Combined Landsat 5 and 7 data give an NDVI time series for a period of almost 40 years. The trendline shows an increase in the NDVI value which may be caused by climate change, but other causes may be of relevance as well, like nitrogen deposition and natural succession.

Summarising, in the future, Sentinel-2 imagery might provide detailed information for monitoring biomass effects due to climate change, while current long-term Landsat data already show an increase in biomass, which corresponds with temperature increases between 1984 and 2021.

5 Case study 2: Classifying intensively and extensively used grasslands using time series of satellite data

5.1 Introduction

Another feature that can be derived from groenmonitor.nl is whether a grassland is intensively or extensively used. Grassland is the most common form of agricultural land use in the Netherlands (almost 500,000 plots exist, with an area of approximately 1 million ha). Grasslands may also have nature goals, such as pasture management for breeding birds or classifying as Natura 2000 habitat types. Such grasslands, in general, require a relatively extensive use with low productivity and low mowing numbers during the year. In this case study we localize grasslands that have such extensive use, and therefore are potentially suitable for nature restoration or nature targets.

In order to achieve nature goals, provinces prepare and execute nature management plans, which include measures with regard to agricultural grassland management, often in association with agricultural nature associations (ANV). However, very little information is available about current grassland management for large areas, such as when, where and how often grasslands are mown. To answer these questions, Wageningen Environmental Research (WENR) has developed a grassland monitoring service within groenmonitor.nl. It uses satellite images to monitor the land surface of the Netherlands with a resolution of 25 m since 2012, and 10 m since 2017. A satellite image is available three to four times a week. A biomass index (NDVI) can be determined from these recordings when no clouds are visible on the image. The NDVI measures how green the surface is, and therefore is an indicator of the amount of green biomass.

5.2 Method

With the available data in groenmonitor.nl, we can distinguish the grasslands as intensive or extensive with the help of four grassland markers. These four markers consist of: 1) first mowing event, 2) number of mowing events, 3) winter greenness and 4) heterogeneity.

The first two markers are determined by detecting the mowing cuts. The mowing management of grassland is clearly visible on successive satellite images as a sudden drop in the green index, since the biomass (grass) is mown and then removed from the pasture. By means of smart algorithms it is possible to determine the number of mowing cuts and when these take place. In Figure 5.1 shows how the mowing moment detection algorithm works. The graph shows the NDVI green index development of a grassland parcel in 2018. Four abrupt decreases in the signal are very clearly visible. These are the cuts, where the blue dot is defined as the start of the cut (the mowing itself) and the green dot as the end of the cut (the removal or ensiling of the grass). The graph also shows an initial slight decrease in the signal around day 75. However, this decrease is caused by a colder period in March, and not the result of mowing. When reference is made to a mowing cut in the further text and graphics, this means the end of the mowing cut (i.e., the green dots in the graph).

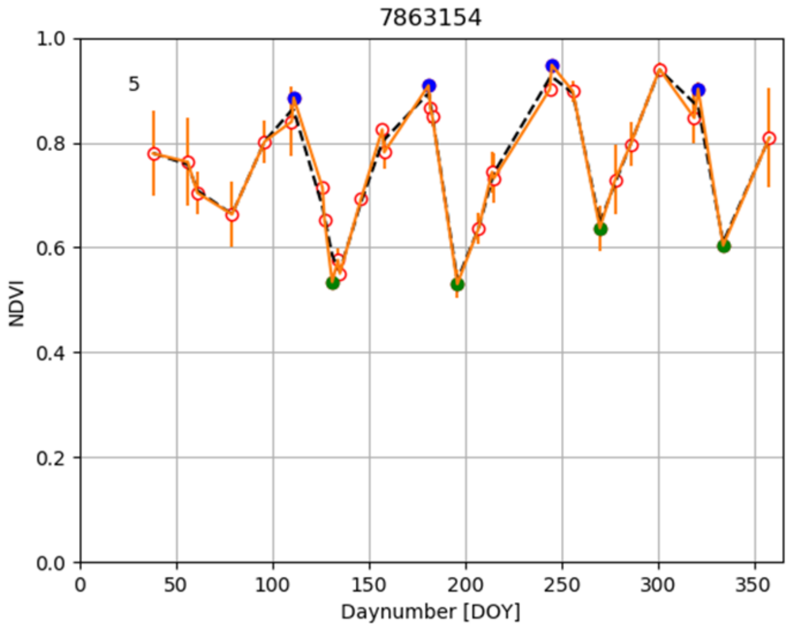


Figure 5.1 *Practical example of the mowing moment detection algorithm. The graph shows the NDVI green index development of a grassland parcel in 2018. Four abrupt decreases in the signal are very clearly visible. These are the mowing cuts, with the blue dot defined as the start and the green dot as the end of the cut.*

A condition for a good and complete mowing detection is that: 1) sufficient (partially) unclouded satellite images are available in time and 2) that the cloud cover and associated cloud shadows are completely filtered out. In order to have sufficient snapshots in time, groenmonitor.nl uses several satellites from ESA and NASA, which are mutually calibrated so that the signal is uniform and comparable. The clouds and shadows are removed with artificial intelligence algorithms, after which a final manual check takes place. This is the only way WENR can guarantee sufficient images of sufficient quality for this service.

5.3 Results detection indicators

The mowing cut algorithm annually detects the mowing cuts and the associated mowing date. This allows both spatial and temporal analysis to be performed. In addition, an indication is also given of how extensively or intensively the grassland is managed. Below are some examples of the possibilities of this new information.

5.3.1 First mowing event

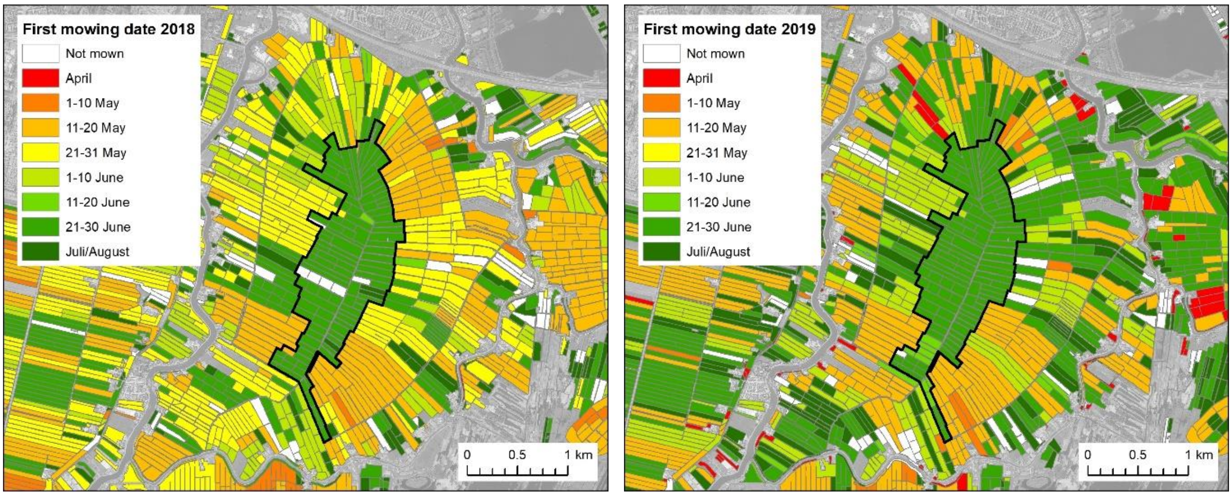


Figure 5.2 *The first mowing date per grassland plot in 2018 and 2019 for the Amstelland area just below Ouderkerk a/d Amstel. The black-lined area is the Ronde Hoep reserve with special meadow bird management measures, such as deferred mowing management.*

First, the first mowing date is visualized for the grassland plots for the Amstelland area just below Ouderkerk a/d Amstel. This also includes the De Ronde Hoep meadow bird sanctuary (black border in the figures) with deferred mowing management. It is very clearly visible that mowing management only takes place at the end of June. Outside this area the picture is much more diverse, the first mowing cuts mainly takes place in May and June. In this way, second and later cuts can also be viewed.

5.3.2 Number of mowing events

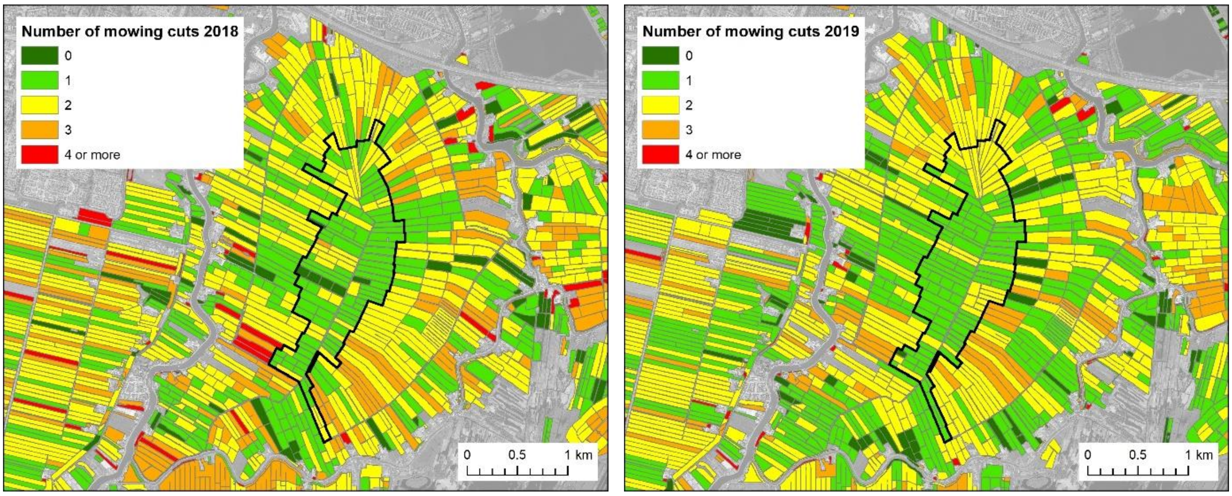


Figure 5.3 *The total number of cuts per grassland plot in 2018 and 2019 (until 31 August) for the Amstelland area just below Ouderkerk a/d Amstel.*

The total number of cuts is an important indicator of how intensively or extensively the grassland is used. In the Amstelland area, most grass will be mowed one to three times in 2018, with peaks of mowing 4 times. In the meadow bird reserve De Ronde Hoep, the grassland is used more extensively with one or two mowing cuts at the most.

5.3.3 Winter greenness

The first mowing date and the number of mowing cuts already say something about how intensive or extensive the grassland management is. However, an additional grassland management indicator has been developed based on the NDVI green index value of early spring (before the first mowing cut). The principle behind this is that intensively managed grassland is often much greener in winter, because it receives much more fertilizer during the year. In addition, the drainage of these plots is often optimized, resulting in a higher NDVI green index value.

5.3.4 Heterogeneity

The last marker is about the heterogeneity of the grassland. Intensively used grassland consists of perennial ryegrass which is the same in the entire parcel. This results in a similar NDVI value throughout the parcel for intensively used grasslands. For extensive grasslands, a more diverse set of grass and flowering species results in a variability in the NDVI values retrieved throughout the parcel. This results in a higher standard deviation which is visible at parcel level and which is shown below. The green borders around the NDVI line define the difference in NDVI within the same plot. This is indicative of an extensively used grassland.

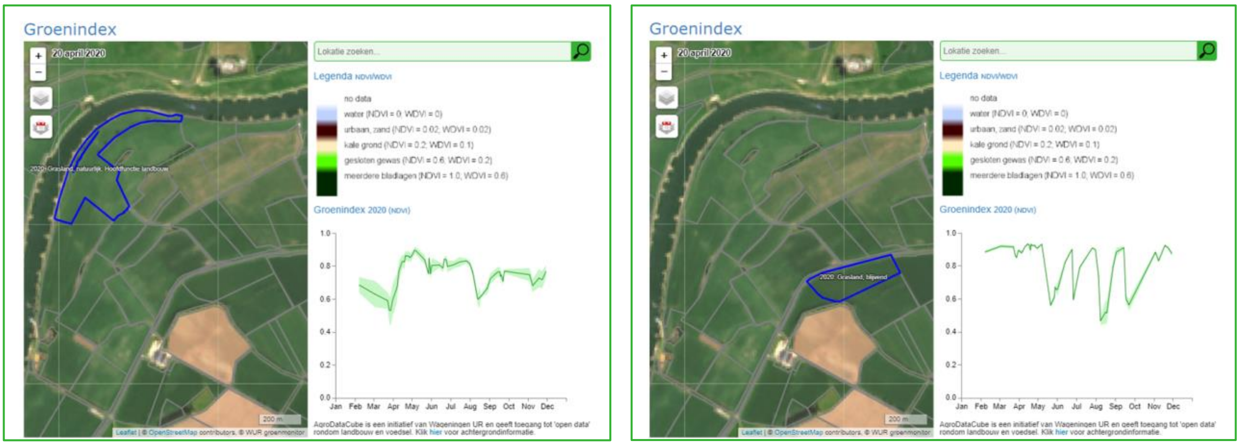


Figure 5.4 *Difference between extensively used grassland (left) and intensively used grassland (right), where all four markers are visible within the NDVI curve (green line).*

5.4 Conclusions

The grassland monitoring service has now been rolled out for the whole of the Netherlands and includes the following components:

- Monitoring period: 1 April to 1 December
- Cutting detection
- Indicator indicating the degree of intensive or extensive grassland management
- Grassland crack detection
- Weekly mowing management update containing a mowing management label for all grassland plots:
  - Mowing moment
  - No mowing moment
  - No satellite recording available for detection
- Satellite image processing is done near real-time with a processing speed of up to three working days from the moment of satellite image availability to mowing cut detection
- An aggregated mowing management map containing the number of mowing cuts and the dates of these mowing cuts per plot
- If desired, a form of mowing management statistics for a certain region and/or certain plots (e.g., agricultural versus natural grasslands)

6 Case study 3: Detecting changes in vegetation structure using LiDAR

This chapter concerns the detection of changes in the vegetation structure for the island Terschelling using public and freely available airborne 3D LiDAR (laser scanning) data that are being recorded for the entire Netherlands on a regular basis (source: AHN.nl).

6.1 Introduction

Since LiDAR campaigns are now organized in the Netherlands on a regular basis (in the future this might even be every three years), we want to show how point clouds from the digital elevation map (*Actueel Hoogtebestand Nederland,* AHN) can be used for monitoring changes in vegetation structure. This method has been previously explored in the nature reserve Meijendel (Mücher et al., 2017) but with older data and with less specifications. The 2014 (AHN3) and 2020 (AHN4) LiDAR point clouds have similar technical specifications and make it more robust and easier to analyze changes in vegetation structure. Both AHN3 and AHN4 datasets are provided with a classification label for ground points, making it easier to calculate the vegetation height. Analyzing vegetation structure in 3D point clouds from two different dates is an interactive process on a detailed scale, as well as an intensive process. However, it is much faster than field surveys. Areas where vegetation height changes occur can be identified by calculating a vegetation height change map, but it is still sometimes difficult to interpret. By viewing the various locations of changes in vegetation height in detail within the 3D point cloud, it becomes clearer what the change in vegetation structure is. The method of this approach is described in this chapter with specific examples.

6.2 Method

To monitor changes in vegetation structure over a six-year period, the AHN point cloud from 2014 (AHN3) and 2020 (AHN4) were used. A detailed description of the point cloud data specification and the collection method can be found on the AHN website (AHN, 2022). The short technical description is that the point cloud data can be used for detection of objects with a size of at least 23 centimetres. For both years, the vegetation height was calculated by computing the relative height of each point above the ground. The points that are used for the AHN Digital Terrain Model (DTM) construction are labelled in the AHN point cloud as ‘ground’ while all points above the ground are labelled as ‘not classified’. The vegetation height was calculated by subtracting the height of the ground from the height of a ‘not classified’ point with the lasheight tool of the lastools suite (Rapidlasso, 2022). The output is also a point cloud where the original absolute height is replaced by the relative object height. Now all points that are part of the ground class have a height value of 0 and all other points have the value of the height above the ground. This point cloud was converted into a 50 cm grid with the lasgrid tool from the lastools suite where the value of the gridcel is the maximum relative point height within the 50 by 50 cm gridcel. For the ground, this is 0; for vegetation and other objects on the ground, this is the height above the ground. Figure 6.1 shows an example of a Digital Terrain Model (DTM), a Digital Surface Model (DSM) and an Object Height Model (OHN).

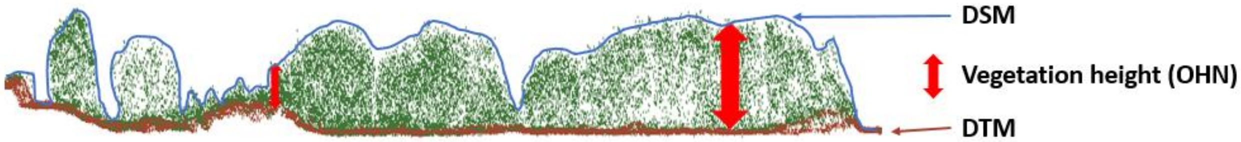


Figure 6.1 *AHN point cloud (brown: classified as ground, green: ‘not classified’) with indication for terrain (DTM), surface (DSM) and vegetation height (OHN).*

The changes in vegetation height over the period of 2014-2020 can be calculated by subtracting the 2014 OHN from the 2020 OHN. However, this only gives an indication of the absolute changes in vegetation height and is not necessarily an indication of significant changes in vegetation structure. A tree can have grown a few meters, but it still remains a tree. In order to be able to identify the relevant changes in vegetation structure, a class division has been made with five different vegetation height classes (Figure 6.2). This can be changed to other height classes if required (like vegetation height classes for very low vegetation, grasses, low shrubs, high scrubs and trees). Changing the height classes has an impact on the changes in classes found.

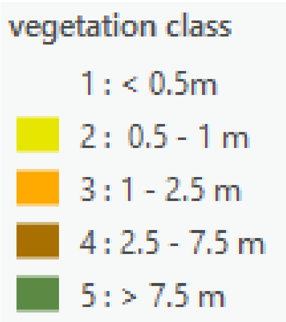


Figure 6.2 *Vegetation height classes.*

The vegetation height classes have been applied to OHN 2014 and OHN 2020 and provide the distribution of the height classes for the island Terschelling for both years. The changes in vegetation height classes can also be calculated. A mask was used in which all changes (decreases and increases) in vegetation height of less than half a meter were excluded from the analysis. The assumption here is that a slight change across the boundary of a class is not relevant and that the interpretation of the patterns of change in vegetation structure is easier explained if all small changes are masked. Masking of the small changes did not occur on a large scale.

The LiDAR data also contains buildings, but these were not removed from the analysis because most buildings were outside the areas of interest.

The vegetation structure change map can be used to identify places where significant changes in vegetation structure have occurred. The original 3D point clouds from the AHN dataset can be used to visualize the actual change in vegetation structure for specific locations. This provides the terrain manager with a clear overview of the vegetation structure changes for the entire area of interest and also provides details about the actual vegetation change pattern.

The definition of vegetation height classes can be changed, as mentioned before, but here it provides a proof of concept. For a specific analysis, the boundaries of the height classes can easily be adjusted. A new reclassification must then be performed from the source data, after which the change map and table are updated. The vegetation height maps (OHN) are rasters with 50 x 50 cm grid cells.

Next to the changes in vegetation height, the terrain height has also changed in some areas in the period 2014–2020. To get an overall impression, the difference in terrain height was calculated based on the AHN Digital Terrain Model (DTM) for 2014 and 2020 (Annex 1).

6.3 Results

Figure 6.3 and 6.4 show the calculated vegetation height for 2014 and 2020, respectively, on Terschelling as they are calculated from the AHN3 and AHN4 data, and the maps show the distribution according to five different vegetation height classes.

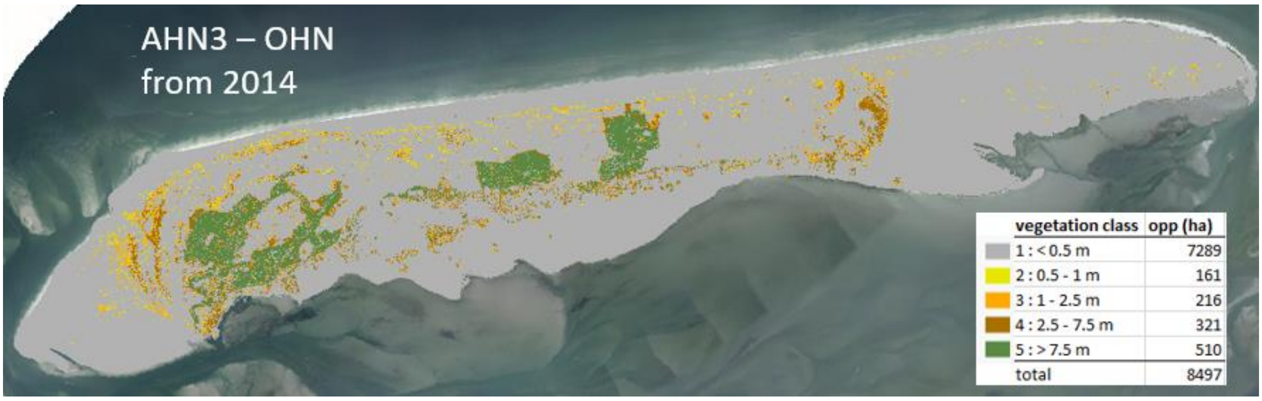


Figure 6.3 *Vegetation height map 2014 with area per height class.*

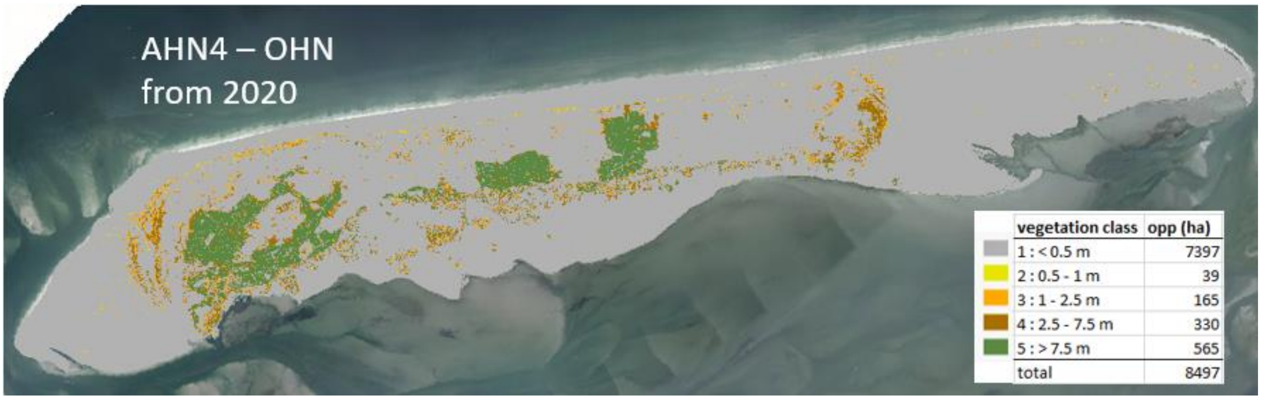


Figure 6.4 *Vegetation height map 2020 with area per height class.*

In Figure 6.5, the change in vegetation height between 2014 and 2020 is shown in two classes, decrease and increase in vegetation height, over the six-year period. The exact change per 50 cm cell is calculated, but this is too detailed to depict in the map on this scale. With an interactive viewer, the detailed changes can be viewed in more detail.

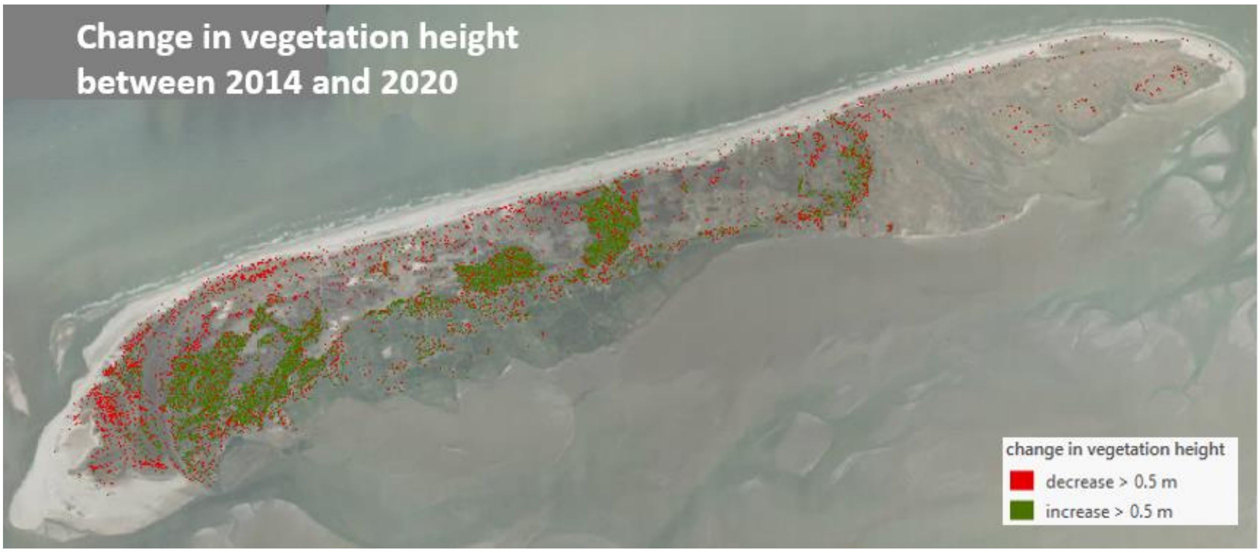


Figure 6.5 *Change in vegetation height between 2014 and 2020.*

The amount of change between vegetation classes is calculated from the two maps and is shown in Table 6.1.

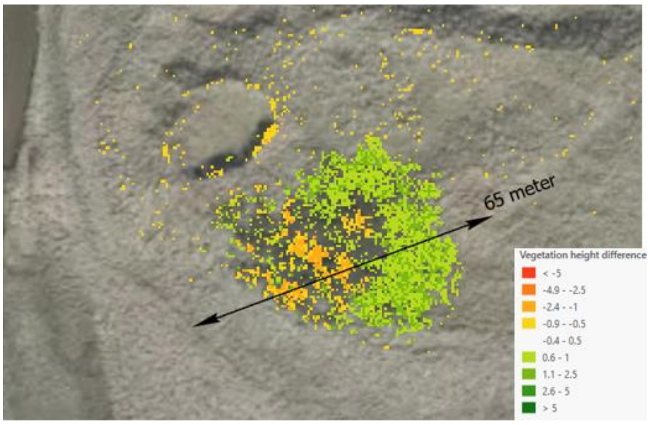
Table 6.1 *Change in vegetation height classes between 2014 and 2020.*

Area (ha)	**Vegetation height (OHN4 – 2020)**					
OHN3 (2014)	**1) < 0.5 m**	**2) 0.5 - 1 m**	**3) 1 - 2.5 m**	**4) 2.5 - 7.5 m**	**5) > 7.5 m**	**Total**
1) < 0.5 m	7144	17	47	48	32	7289
2) 0.5 - 1 m	129	11	15	6	1	161
3) 1 - 2.5 m	81	10	79	41	5	216
4) 2.5 - 7.5 m	25	1	21	225	48	321
5) > 7.5 m	18	1	3	10	479	510
Total	7397	39	165	330	565	8497
	stable	decrease	increase			

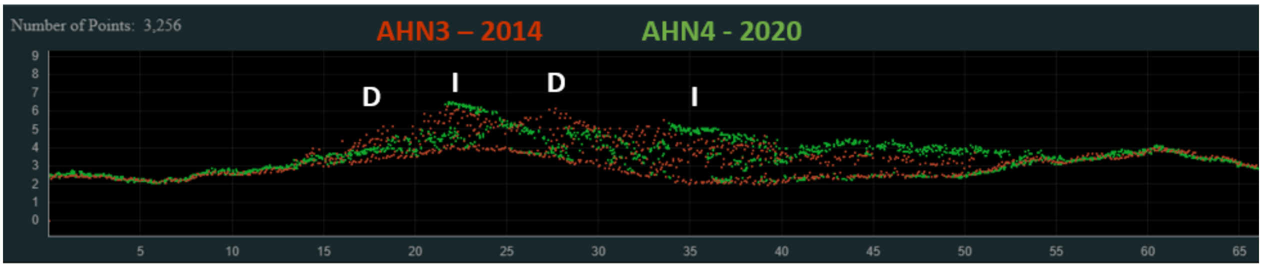
A change from class 1 to class 4 or 5 seems illogical in six years' time, but can be easily explained. This is namely caused by e.g. a tree whose crown expands in its width. The vegetation class of the adjacent area to the tree (for example grass with a height of 40 cm) then changes abruptly from class 1 to class 4 or 5. Decrease is cause by disappearance of vegetation.

Changes in vegetation structure can be better seen when viewing the change map at a more detailed scale. The height changes then reveal patterns of changes. Figure 6.6 shows an example of changes in a patch of vegetation that is located on the eastern part of the island (a) where part of the vegetation has decreased and a part has increased (b). The profile (c) shows the cross section of the AHN point clouds with 2014 in red and 2020 in green. The aerial photos from 2014 and 2020 (d) do show the expansion of the vegetation but not the internal changes in structure that can be seen in the profile.

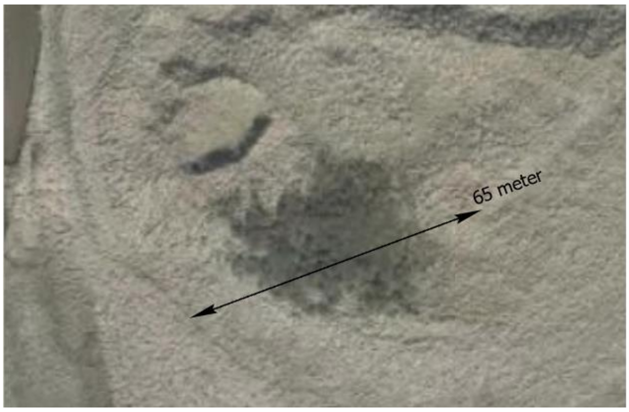
a: *location of the vegetation patch*



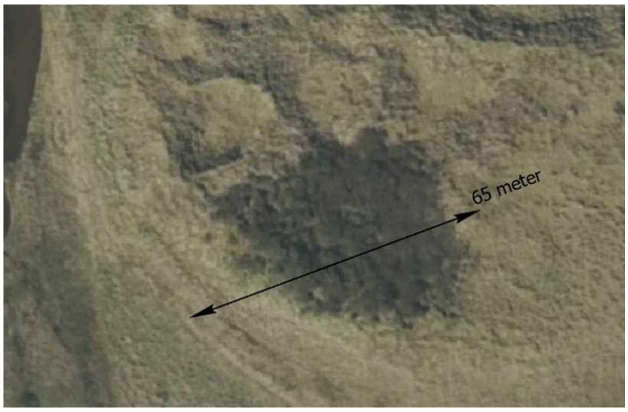
b: detailed view of the vegetation patch with changes in vegetation height between 2014 and 2020 and location of the cross section as shown below



c: cross section showing a strip of 1 meter wide from the AHN point clouds from 2014 in red and 2020 in green



d: aerial photo 2014



aerial photo 2020

Figure 6.6 *height and structure changes in vegetation between 2014 and 2020.*

More examples of changes in vegetation structure are shown in Annex 2.

6.4 Conclusions

The results show that changes in the vegetation height and structure can be detected for the entire Netherlands based on LiDAR data from AHN. The AHN 3D point cloud captures the actual state of the vegetation which allows monitoring of the area, in this case Terschelling. From 2019 the interval of acquired AHN data is three years instead of six years. It therefore becomes an excellent basis for frequent monitoring of the vegetation structure. From the AHN point cloud, the vegetation height maps can be derived, and from these maps the changes in vegetation height can be calculated. This can be either an absolute height change per cell or changes between vegetation height classes (e.g., a change from grasses into shrubs) as is shown in Table 2. These height classes can be adjusted to the needs of the topic/research in question. This can be used to identify hotspots of vegetation changes which can then be viewed in more detail with interactive 3D views of the point clouds from both years (2014 and 2020). This will give insights in the actual changes of the vegetation structure (see Figure 6-5). The meaning of this should be addressed and evaluated by the experts involved in this area, e.g. a terrain manager.

The results shown are general changes in vegetation height for the entire study area of Terschelling. However, to do this in a more structured way, improvements can be made by focusing on specific areas or specific vegetation types. For example, if the research is focused on unmanaged areas, the managed areas in the study area can be excluded from the results by providing a mask. This can be done for any specific area as long as there is a database available that contains the area of interest.

It is shown that this method provides much information about changes in vegetation height and structure, but to answer specific research questions the method needs to be tailored to the needs of the clients.

7 Case study 4: Mapping habitat types using deep learning techniques

Mapping habitat types using remote sensing and deep learning techniques, in which we exploit the recorded vegetation plots in the Dutch Vegetation Database (LVD) for National Park de Hoge Veluwe.

7.1 Introduction

Habitat types are an important feature in monitoring Nature 2000 sites. They are one of the elements that identify whether the status of the area meets the nature management objectives and also form an indicator for desired or undesired changes by mapping an area in time. Habitat type maps are constructed using fieldwork, which is labor and time consuming. A habitat type is usually a combination of several vegetation types in which a specific vegetation type is dominant. When classifying vegetation in satellite images, the classification is generally based on land cover using the maximum likelihood method. Land cover classes can be distinguished spectrally in multispectral satellite images (Mücher et al., 2017). Deep learning classification methods use the spectral information, but also the contextual information, from the satellite images. Using context information, such as spatial patterns of vegetation, can make it possible to distinguish habitat types with deep learning classification methods. This project explores the applicability of deep learning methods for habitat type classification.

When using DL models for classification it is important that there is enough ground truth data to train the model. There are no references about what is enough, but in practice it is known that the performance of a DL model improves if more in-situ data is used for training a model. Brownlee (2019) shares online some insights on how to deal with this. The bottom line is that the required amount depends on the application and the result achieved. Therefore, it is important to properly interpret the available resources, such as the model metrics that are available from the DL model training. But the map with the classification result also gives insight on how good the DL model has performed. With the classification of habitat types, both the class label and the spatial pattern of the class are important features to consider.

7.2 Method

The Deep Learning Geoprocessing tools from ArcGIS Pro 2.9.x (ESRI inc., 2021) were used for the classification with U-NET convolutional neural network (Ronneberger, 2015; ESRI inc., 2021) as the deep learning model. in 2021 it became apparent by testing that U-NET is a useful model, as one of the many convolutional neural networks for pixel-based classification of RS imagery. The test area was located within the national park De Hoge Veluwe, between Otterloo, Hoenderloo, airport Deelen and Wolfheeze. Vegetation plots were recorded in the field and translated into habitat types. These were used as training points. Additional training points were digitized based on visual interpretation of points with a corresponding spectral appearance in the image nearby recorded field plots.

Collecting training points in the field and digitizing additional points on screen is time-consuming. Therefore training data were drawn from an existing information source, the Dutch national Vegetation Database (LVD) (Hennekens et. al., 2016). A selection of points was made with relevant classes which are not older than ten years in the area of the National Park De Hoge Veluwe.

Summer images from SuperView (Figure 7.1) and Sentinel (Figure 7.2) were used in the period that the vegetation is fully developed and can best be captured by the satellite sensor. SuperView satellite data has a spatial resolution of 0.5 m and is available several times a year on satellietdataportaal.nl. Sentinel 2 data has a spatial resolution of 10 m but is more frequently available (a revisit time of around five days). A time series of seven images from Sentinel and four images for SuperView in 2020 were available and used for the DL classification. This time series covers a large part of the growing season and better represents the different types of vegetation than a single image because it also includes the seasonal variation. Both satellite images are used for a DL classification and the results are compared.

Figure 7.1 *Sentinel 31-07-2020, False colour.*

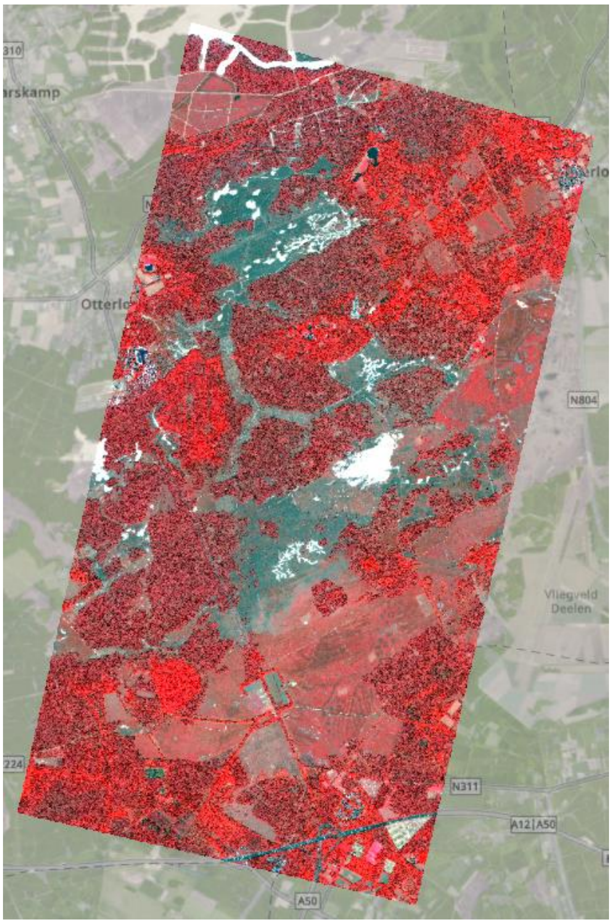


Figure 7.2 *SuperView 12-08-2020, False colour.*

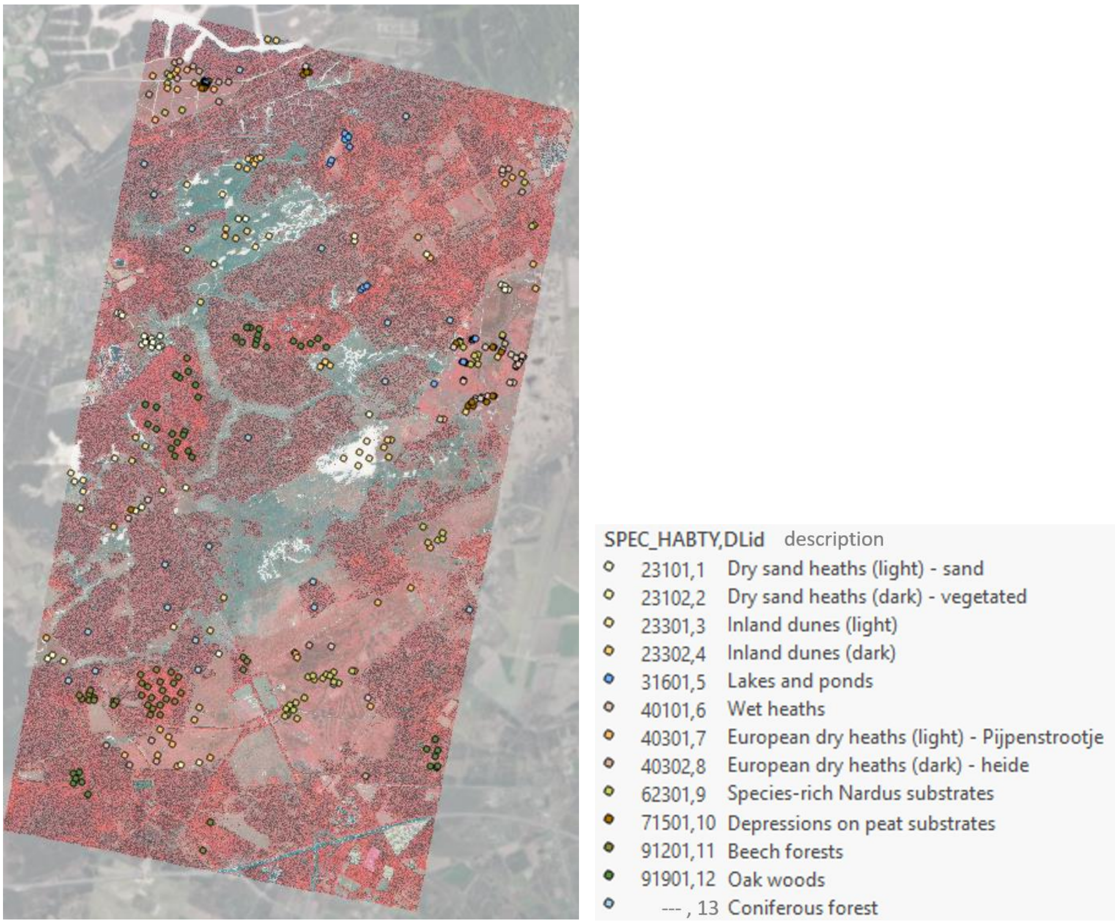


Figure 7.3 *Selected LVD points in De Hoge Veluwe test area (with legend LVD points).*

The selected LVD points were first checked on validity, as the classification of older points may have changed over time. The exact location of the point was also visually checked. The measured location in the field often has a geometric accuracy of several meters, and when points are measured on the edge of a habitat type the measurement can be located wronlgly in the satellite image. For example, a point measured in a heath area but next to a forest area can have a GPS coordinate located in the forest due to its inaccuracy in the GPS measurement. The preferred position of a point is in the centre of a homogeneous patch in the image. If the satellite image clearly showed that the registered habitat type was no longer correct, the point was removed from the training dataset.

The habitat types Dry sand heaths (2310), Inland dunes (2330) and European dry heaths (4030) were divided into two spectral subclasses, namely in a lighter and darker spectral appearance (due to differences in species composition and vegetation cover). These spectral differences must be included as separate training classes in order to train the deep learning model accurately. A class for coniferous forest was added since it is quite common in the area, however it is not a habitat type.

Only four LVD points were available for class 3 (Inland dunes (light)). First runs of the deep learning model gave poor results, so additional points for this class were added by visual interpretation of the satellite imagery to achieve a more even distribution of training points. Table 7.1 shows the selected training points with the count.

Table 7.1 *LVD training points with count.*

Nr	Habitat class name	Count
1	Dry sand and heaths (light)	19
2	Dry sand and heaths (dark)	16
3	Inland dunes (light)	16
4	Inland dunes (dark)	33
5	Lakes and ponds	28
6	Wet heaths	39
7	European dry heaths (light)	35
8	European dry heaths (dark)	19
9	Species-rich nardus substrates	37
10	Depression on peat substrates	33
11	Beech forest	37
12	Oak woods	44
13	Coniferous forest	21
	Total	377

The workflow used in ArcGIS Pro consists of the following steps:
- Prepare training data
- Train the model
- Apply the trained model
- Validate the results

Prepare training data
The ArcGIS Pro 2.9.x (ESRI inc., 2021) geoprocessing tool "Export Training Data For Deep Learning" was used to create training data that is used to train the deep learning model. The metadata format "Classified Tiles" was selected as output, as this is required for pixel-based deep learning classification. This tool converts labeled vector data into deep learning training datasets using the satellite image. The output is a folder of image chips and a folder of metadata files in the "Classified Tiles" format.

Train the model
The geoprocessing tool "Train Deep learning Model" was used for training the deep learning model using the U-Net model type. The output of this tool is a trained model that can be used to classify a satellite image with the same characteristics. It also provides model metrics in the form of a table with performance statistics, like precision and recall, and a graph of the learning curves for both training and validation.

Apply the trained model
The geoprocessing tool "Classify Pixels Using Deep Learning" was then used to classify the image with the trained model. Input was derived from the model definition created in the previous step and satellite image. The result is a thematic raster containing the habitat type classes values.

Validation
Validation is preferably performed with an independent dataset, but this is not available at the moment. It was decided to carry out the validation with the available training points. This does give an idea of how well the classification based on the trained model works. The classification result is linked to the training points, and from this a confusion matrix is calulcated. In addition, a visual validation with the available habitat type map was also performed.

7.3 Results

An example of updating the LVD points is shown in Figure 7.4. The points are shown on the SuperView image of 28 March 2020. The examples show the moving points with class 8 (European dry heaths (dark)) from the edge into the middle of the vegetation strip in the upper part of the image and the addition of a few points on locations with the same image features in the right part of the image. Also, points with class 7 (European dry heaths (light)) are moved from light red areas into light grey areas. The light red areas in the false-color SuperView image are vegetated, and dry heath does not have this spectral signature in March. This is more likely class 9 (Species-rich Nardus substrates), and these points have also been updated. A point with class 13 (Coniferous forest) has been added in the right upper part of the image. Points with the classes 5 (Lakes and ponds) and 10 (Depressions on peat substrates) have been updated to match the image features.

Figure 7.4 *Updating LVD training points based on visible image features in the SuperView image. Left image: original version of LVD training points. Right image: updated version of LVD training points.*

This example already shows the challenge of using habitat types. Classes 7 and 8 belong to the same habitat type (European dry heaths) but are spectrally very different. That is why they are divided into two training classes. And when heathland changes into grassy heathland, the spectral signature changes more into the signature of grass. The habitat type has therefore changed and should no longer be used as a source for training on that habitat type. But it can still be used by moving the point into an area that does match the spectral features of dry heath. It remains important to have enough correct training points for training the DL model. All available training points have been checked in this way and corrected where necessary (but caution is needed).

The deep learning model was trained separately for the SuperView and Sentinel images and then used to classify the respective satellite images. Results are shown in Figure 7.5.

Figure 7.5 *Classification result from three different inputs. Left: SuperView 12-08-2020 with 50 cm resolution. Middle: Sentinel 31-07-2020 with 10 m resolution. Right: Sentinel multi-temporal with 10 m resolution.*

The classification result of the high resolution SuperView image gives a better overall impression when focusing on spatial patterns of bare soil (2310, 2330), heaths (4010, 4030), grasslands (6230) and forest (9120, 9090, coniferous). In the single date Sentinel result, many different small patterns of heath are visible on the edges of larger areas. There is also a great deal of confusion between the forest classes. The multi-temporal Sentinel result gives a much better overall impression for all classes, lacking the edge effects than can be seen in the single date result, and offers forest patterns that are comparable with the SuperView classification result. This impression is supported by the data from the validation crosstabs (tables 7.2, 7.3, 7.4).

The Sentinel images offer better options than the SuperView images for performing a classification for the whole of the Netherlands. A SuperView image covers an area of 15 x 15 km and can cover multiple areas in the North-South direction during the satellites overpass. But this is not always the case as the satellite sensor is not always recording directly underneath the satellite but can be directed sideways if required. Full coverage during the growing season (March–October) for the Netherlands is attempted every six weeks (source: Spaceoffice.nl). But with many cloudy days in the Netherlands, this is not always possible, or only with many different acquisition dates for neighboring areas.

A Sentinel image covers an area of 290 x 290 km (source: ESA), capturing a large part of the Netherlands at one time. This can of course be disturbed by cloud cover, but with an average revisit time of five days, Sentinel has a better chance of making good recordings for large areas.

Table 7.2 *Validation Sentinel 31-07-2020 result with input training points (LVD).*

		classification result											
LDV training points	**HABITATTYP**	**2310**	**2330**	**3160**	**4010**	**4030**	**6230**	**7150**	**9120**	**9190**	**coniferous forest**	**total**	**producer accuracy**
dry sand and heaths	2310	17	11		1	2	3				1	35	49%
inland dunes	2330	7	40	1				1				49	82%
lakes and ponds	3160			24		3	0	1				28	86%
wet heaths	4010	3	2		5	10	5	13			1	39	13%
european dry heaths	4030		7	5	3	16	17	3		1	2	54	30%
species-rich nardus substrates	6230	1	4	3	1	11	10	4	1	2		37	27%
depression on peat substrates	7150	4	1	5	4	1	1	17				33	52%
beech forest	9120								36	1		37	97%
oak woods	9190			1					31	10	2	44	23%
coniferous forest	13						2			7	12	21	57%
	Grand total	**32**	**65**	**39**	**14**	**43**	**38**	**39**	**68**	**21**	**18**	**377**	
	user accuracy	53%	62%	62%	36%	37%	26%	44%	53%	48%	67%		**50% overall accuracy**

Table 7.3 *Validation SuperView 12-08-2020 result with input training points (LVD).*

		classification result											
LDV training points	**HABITATTYP**	**2310**	**2330**	**3160**	**4010**	**4030**	**6230**	**7150**	**9120**	**9190**	**coniferous forest**	**total**	**producer accuracy**
dry sand and heaths	2310	27	2			5	1					**35**	77%
inland dunes	2330		48				1					**49**	98%
lakes and ponds	3160			28								**28**	100%
wet heaths	4010				32	2		5				**39**	82%
european dry heaths	4030				3	47	4					**54**	87%
species-rich nardus substrates	6230	2	1		0	5	29					**37**	78%
depression on peat substrates	7150				3			30				**33**	91%
beech forest	9120								35	2		**37**	95%
oak woods	9190								3	40	1	**44**	91%
coniferous forest	13										21	**21**	100%
	Grand total	**29**	**51**	**28**	**38**	**59**	**35**	**35**	**38**	**42**	**22**	**377**	
	user accuracy	93%	94%	100%	84%	80%	83%	86%	92%	95%	95%		**89% overall accuracy**

Table 7.4 *Validation Sentinel multi-temporal with input training points (LVD).*

		classification result											
LDV training points	**HABITATTYP**	**2310**	**2330**	**3160**	**4010**	**4030**	**6230**	**7150**	**9120**	**9190**	**s forest**	**total**	**producer accuracy**
dry sand and heaths	2310	23	5		1	1	5					35	66%
inland dunes	2330	3	42		1		2	1				49	86%
lakes and ponds	3160			26	1			1				28	93%
wet heaths	4010	1			27	7		4				39	69%
european dry heaths	4030	1			4	40	9					54	74%
species-rich nardus substrates	6230				3	5	28			1		37	76%
depression on peat substrates	7150				10	2		21				33	64%
beech forest	9120								34	3		37	92%
oak woods	9190						1		1	42		44	95%
coniferous forest	13										21	21	100%
	Grand total	**28**	**47**	**26**	**47**	**55**	**45**	**27**	**35**	**46**	**21**	**377**	
	user accuracy	82%	89%	100%	57%	73%	62%	78%	97%	91%	100%		**81% overall accuracy**

Producer accuracy: the number of points that are correctly classified as class A divided by the total number of points with a reference class A

User accuracy: the number of points that are correctly classified as class A divided by the total number of points that are classified as class A.

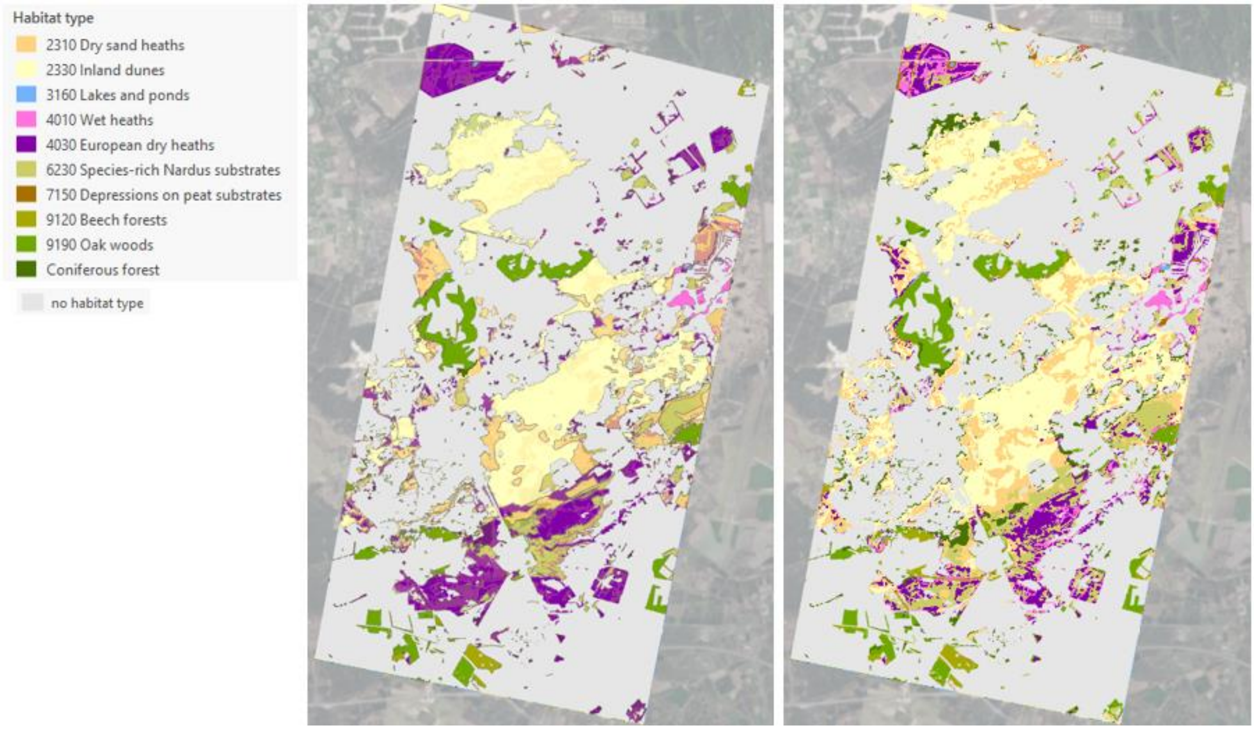


Figure 7.6 *Visual validation of classification result with an existing habitat map (used as a reference). Left: habitat type map (ground truth). Right: classification result Sentinel multi-temporal.*

Figure 7.6 shows the existing habitat type map and the classification result for only the area that is covered by the original habitat type polygons. The area outside the habitat type polygons is masked in grey. The original habitat type polygons contain one class value each, whereas the classification result contains a class value for every 10 x 10 m gridcel. The overall patterns do match, but a mutual change occurs between the bare soil classes (2310, 2330) or between heath (4010, 4030) and grassland (6230). This might be a real change as the habitat type map from 2021 also contains data from previous years, but exact dates/years are not known. The classification result is derived from satellite imagery from 2020.

Next, the deep learning model was expanded from the National Park to the entire Veluwe region (see Figure 7.7). The upscaling was done to show that the DL models can also be used for larger areas without much difficulty. It takes more computing time, but if all classes are included in the original area used for training, the upscaling to the area with the same imagery can be done without re-training for the larger area (assuming that the number of habitat types has not changed).

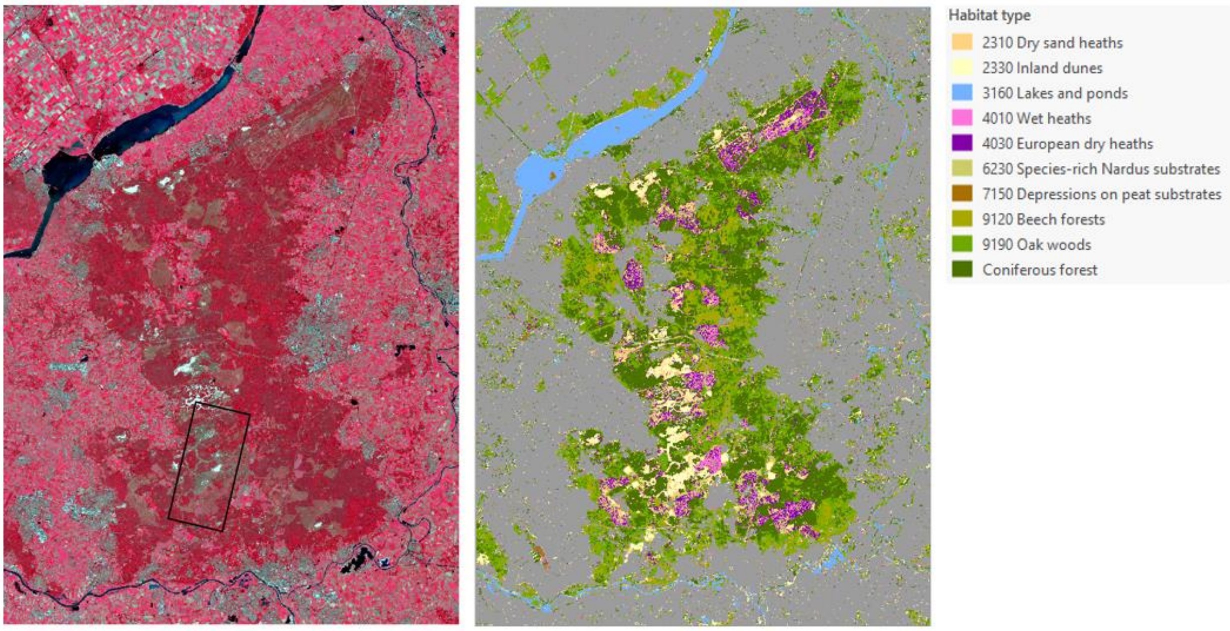


Figure 7.7 *Expanded study area. The black box shows the smaller study area around the Ginkelse Heide. In the right image the results outside nature areas are masked in gray.*

7.4 Conclusions

The results show the potential of habitat classification by using DL. The training is the most important step since the amount of training data defines the accuracy of the classification of the DL model. SuperView satellite images show a higher overall accuracy than the Sentinel 2 images. However, SuperView data is limited by having only a few images per year (cloud free) and being available for smaller areas. This makes SuperView less useful for national habitat classification. However, for small areas it can be a useful option when images are available.

The multi-temporal Sentinel classification had an overall accuracy of 81%. This is much better than the single Sentinel image used for habitat classification which only resulted in 50% overall accuracy. This shows the potential of Sentinel imagery for habitat classification on a national scale. However, it requires an extensive amount of training data. Potentially, this is available in the LVD, but the preparation of this data is a time-consuming task. A methodology should be developed for a semi-automatic quality check of the training data, preferably based on an existing dataset (e.g., LGN).

8 Synthesis: suitability of remote sensing for nature management

8.1 Match or mismatch

Whether remote sensing data are suitable for application in nature management is determined by the match between the characteristics observed in a remote sensing image and the relevance of these characteristics as an indicator for nature management (see paragraph 3.1). It therefore depends on the type of platform and sensor, the weather conditions, site specific characteristics and nature management questions or aims, such as targeted scale or spatial details. Skidmore et al. (2015) argue in a comment in Nature that remote sensing researchers and ecologists should agree on standard essential biodiversity variables that are used, in order to improve the application of remote sensing for worldwide monitoring of biodiversity.

However, the fact that they discuss it, also indicates that in many cases there is a mismatch between remote sensing and application in nature management. From the remote sensing side this mismatch is caused by:
- Availability and costs of images
- Spatial scale, spectral scale, and temporal scale
- Digital processing resulting in raster images which cannot always be easily read by users in nature management and policy (see Figure 8.1)
- No unique reflection patterns of species or plant communities, as these are dependent on season, growing stage, atmosphere, sensor, etc.

From the nature management side mismatch is caused by:
- Changes of definitions and typologies of nature types, including differences in typologies amongst countries
- Different species compositions within one habitat type in different regions
- Changes in relevance of pressures over time (e.g., N-deposition, drought from climate change)
- Different approaches used by surveying companies (also depending on requirements of site manager).

In general, one can conclude that there is still a lack of communication between remote sensing researchers and ecologists, which sometimes complicates the application of remote sensing for biodiversity monitoring. And in cases where the habitat type is also determined by specific plant species that are not very abundant in their coverage, the application of remote sensing remains restricted and needs field work.

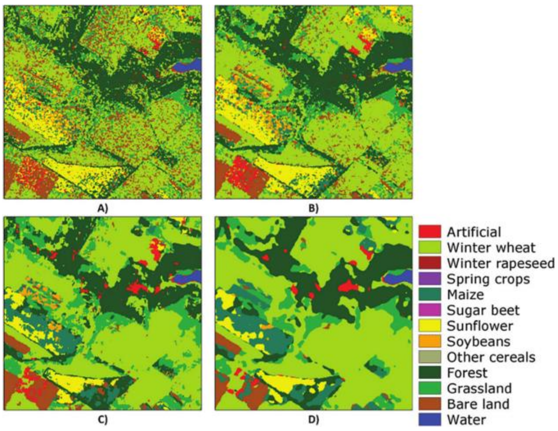


Figure 8.1 *Processing of a remote sensing image with many speckles (A) in three steps towards a picture that is more easily read by users (D) (Lukin et al. 2019). And, by the way, deep learning techniques are much less hampered by these speckles as shown in case study 4.*

Skidmore et al. (2015) proposed a top ten list of RS-enabled essential biodiversity variables (RS-EBVs) as standards in nature management and policy. We have listed them here and have indicated seven of these with an asterisk (*). These are the ones that we consider most promising for application of remote sensing in the Netherlands. The monitoring of vegetation height and primary production have been discussed in the case studies. The other 'promising' ones will be discussed in more detail below, in relation to monitoring of habitat types.

Species population
- Species occurrence*

Species traits
- Plant traits (leaf area, nitrogen area)

Ecosystem structure
- Ecosystem distribution
- Fragmentation, heterogeneity*
- Land cover*
- Vegetation height*

Ecosystem function
- Fire occurrence
- Vegetation phenology (variability)*
- Primary production and leaf area index (LAI)*
- Inundation*

Species occurrence
Monitoring species occurrence is relevant for habitat type monitoring in different ways. In the first place, as a way of mapping habitat types that are dominated by one (or a few) shrub or tree species. Examples are the *Juniperus communis* scrub (habitat type 5130) and the *Cladium mariscus* marshes (type 7210). It may also be used for monitoring indicators of the functioning/quality of the habitat types, like population sizes of grazing animals, shrub and tree encroachment, or the spread of invasive plant species. For some habitat types (forests, heathlands) grazing by large herbivores is a relevant factor. Remote sensing, for example through drones, may be applied for providing accurate estimates of mammal populations (Hodgson et al., 2018). Too large populations may form a threat to some habitats, like the grazing by fallow deer (*Dama dama*) in dune grasslands. Also, in case of such pressures remote sensing can be applied to measure the population size. Applications of remote sensing for monitoring shrub and tree encroachment in grassland and heathlands are numerous (see section 3.3). In the same way encroachment of invasive species can be mapped and monitored, like *Prunus serotina*, *Quercus rubra* or *Robinia pseudoacacia* in forest habitats (see Rusnák et al., 2022), *Rosa rugosa* in dune grasslands and scrub (Hantson et al., 2012), *Impatiens glandulifera* in tall herb habitats, and *Crassula helmsii* or *Hydrocotyle ranunculoides* in water bodies. An example of an image with an invasive species on the Caribbean island Sint Eustatius is shown in Figure 8.2.

Figure 8.2 *Near-infrared image of a part of the island Sint Eustatius with patches of the invasive Coralita (Antigonon leptopus) in bright pink.*

Ecosystem distribution
Ecosystem distribution is monitored in the Netherlands in a traditional way through vegetation mapping, which forms an important part of nature monitoring in the Netherlands (as basis for SNL-types and Natura 2000 habitats mapping). The traditional way in vegetation mapping is through a combination of visual interpretation of aerial photographs and field surveys. In general, we do not think that this method will be easily replaced in the Netherlands by remote sensing methods, because of the small size of the country and the way it is intensively monitored by field surveyors (moreover, at the moment it is even mandatory that the habitat maps are derived from field-based vegetation maps). The main reason for this is that the required detail in the Netherlands, that is derived from the combination of field work and visual interpretation of aerial photographs, is not easily met by remote sensing techniques. Although traditional vegetation mapping by field work and visual interpretation of aerial images is time-consuming and has its limitations for monitoring, after many decades of digital remote sensing, this method still forms the basis for vegetation mapping in the Netherlands. However, this will not hold for most other European countries which are too large for traditional vegetation surveying. In a European perspective there is much need for habitat mapping with remote sensing and deep learning techniques as mentioned in case study 4. So, perspectives differ in other countries, especially in cases where very large areas and/or rather inaccessible regions have to be mapped and sites cannot be visited easily for field work; in these places, digital processing of images may be a good alternative. On the other hand, the Netherlands is an ideal country to test new techniques, such as deep learning techniques, on high resolution satellite imagery since independent vegetation surveys can be used as a validation source at a very detailed scale.

Landscape fragmentation and heterogeneity
Mapping fragmentation of landscapes is a relevant indicator for monitoring the so-called basic quality nature (*basiskwaliteit natuur*). A monitoring program is currently under development for urban areas, farmland and other areas outside protected nature sites. In cases that include the standardized mapping of landscape elements, like hedges, pools and small forests, this may best be carried out through remote sensing.

Land cover and inundation
Land cover and inundation are variables that are becoming more and more relevant in relation to climate change. Land cover is relevant as a variable that shows processes of sand drift, erosion and sedimentation, while inundation (flooding time and frequency) is relevant for understanding changing abiotic processes in

rivers and brooks. These variables can be mapped very well with remote sensing techniques (including time series analysis).

Vegetation phenology
Monitoring vegetation phenology is also relevant for climate change, being a pressure to many habitat types, especially in case climate change causes mismatches between flowering time (providing nectar) of plants and visiting of insects. Remote sensing is an outstanding technique for measuring vegetation phenology, and it would be interesting to test remote sensing techniques at a local or regional scale (also between general vegetation phenology and e.g. flowering of specific species).

8.2 Conclusions

The source of remote sensing data and techniques should be selected depending on the relevant nature types, research questions and nature targets at a specific local, regional or national scale. Using this data requires more communication between remote sensing researchers and ecologists. If the nature aims and remote sensing possibilities are brought together at an early stage, many applications are possible.

For the Netherlands the remote sensing focus should be especially on the complementary information for structure and functioning of habitat types (like in case study 3), including specific species, rather than on mapping habitat types (for which the traditional methods still work fine; but new methods can be tested, see case study 4). Focus should be on monitoring large areas (provinces, regions, like in case study 2) and over long time periods (like in case study 1). Indicators that relate to climate change are especially relevant, like phenology, biomass production, changes in land cover and inundation. This is particularly true if historic time series can be included. Such a large-scale and long-term remote sensing monitoring should become part of a national monitoring programme.

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Annex 1 Changes in terrain height between 2014 and 2020

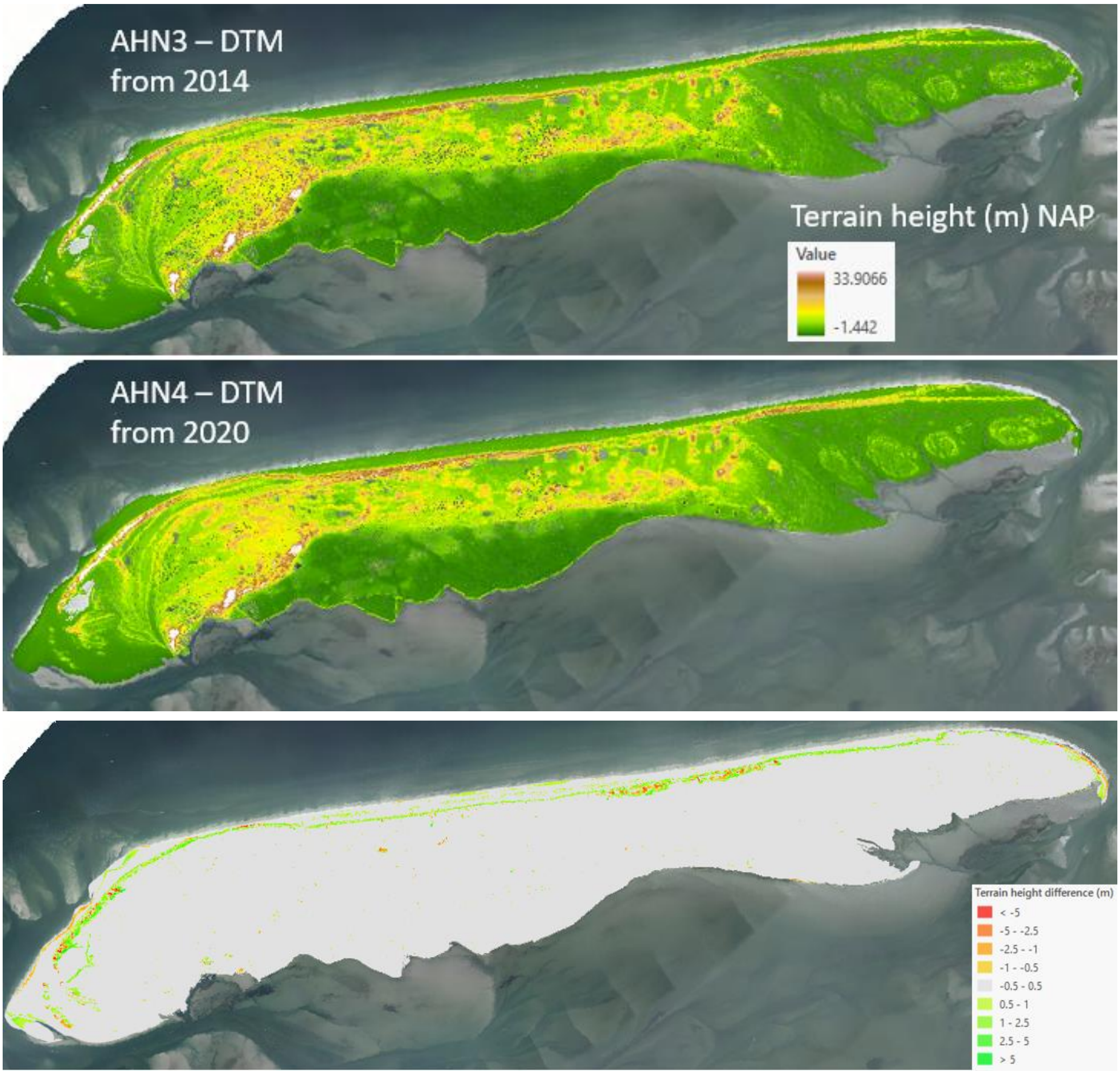

Figure A1.1 *AHN4 DTM – AHN3 DTM: Decrease (red) and increase (green) of terrain height (m).*

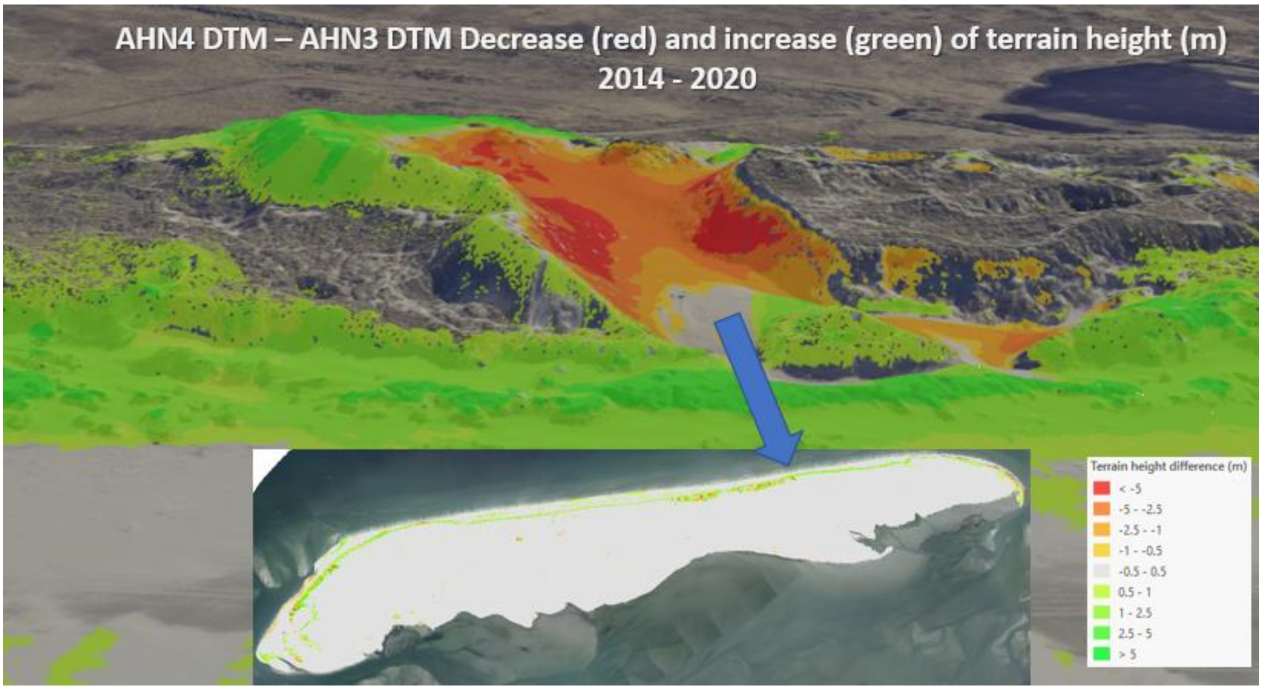

Figure A1.2 *Detail in 3D of the decrease and increase of terrain height in dunes along the coastline.*

Annex 2 Examples of 2D and 3D changes in vegetation structure

The images below show snapshots of the interactive exploration of the vegetation structure changes in a 3D point cloud with a cross section indicated by the red line. (AHN3 2014 = red points, AHN4 2020 = green points)

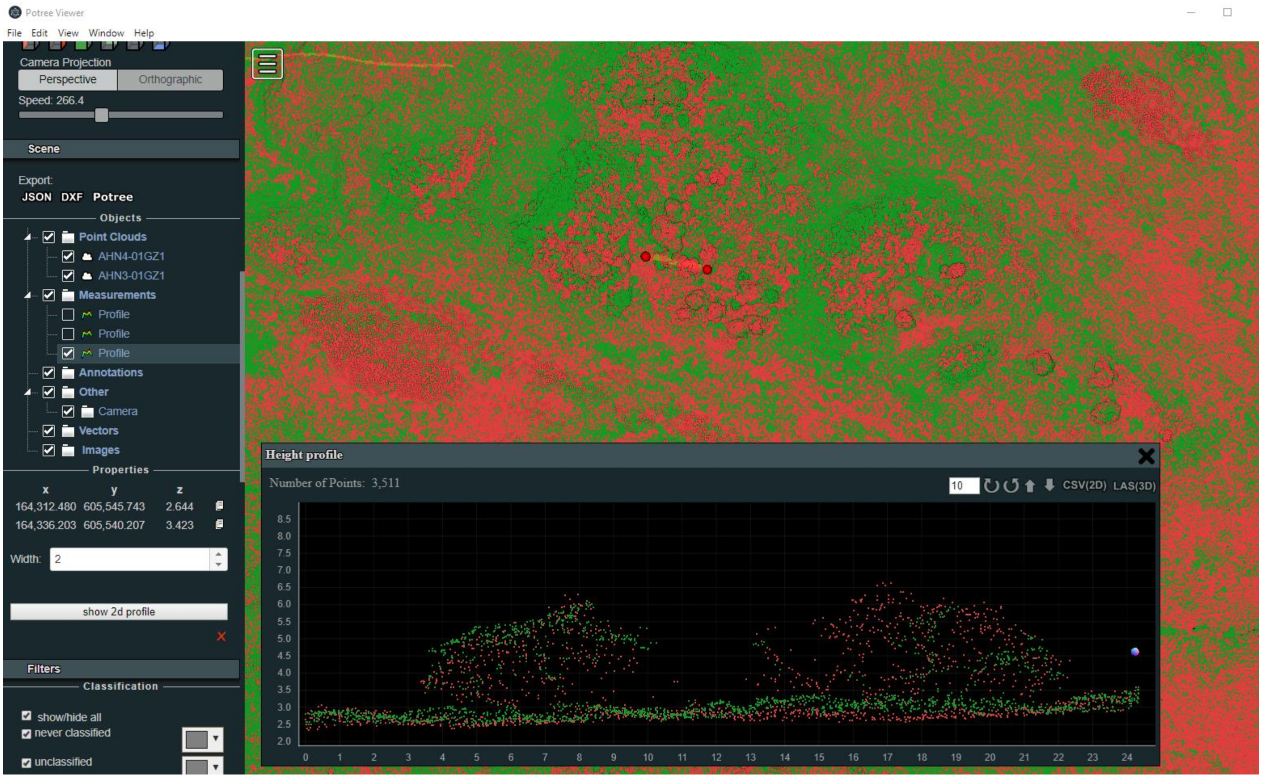

Figure A2.1 *Visible vegetation height changes in an area with trees. In the cross section on the left an increase of the tree object is visible and on the right a decrease.*

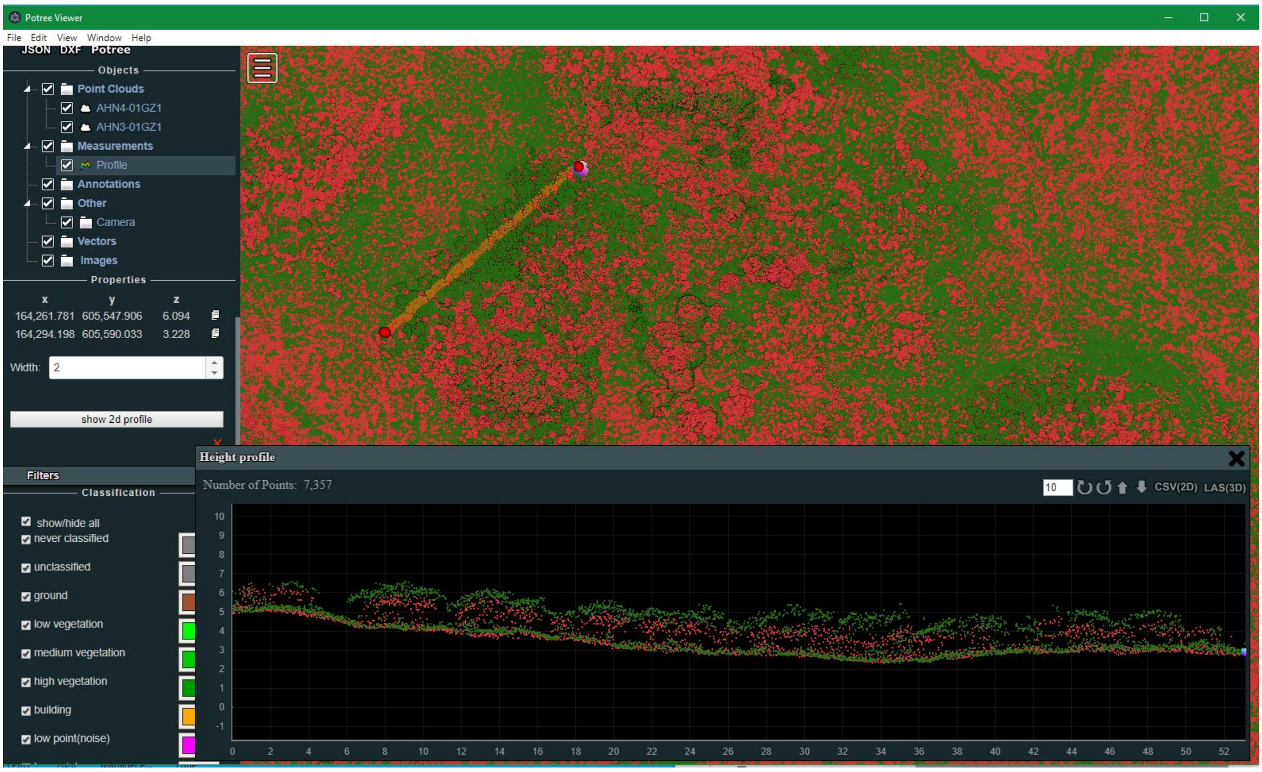

Figure A2.2 *An overall increase of shrubs.*

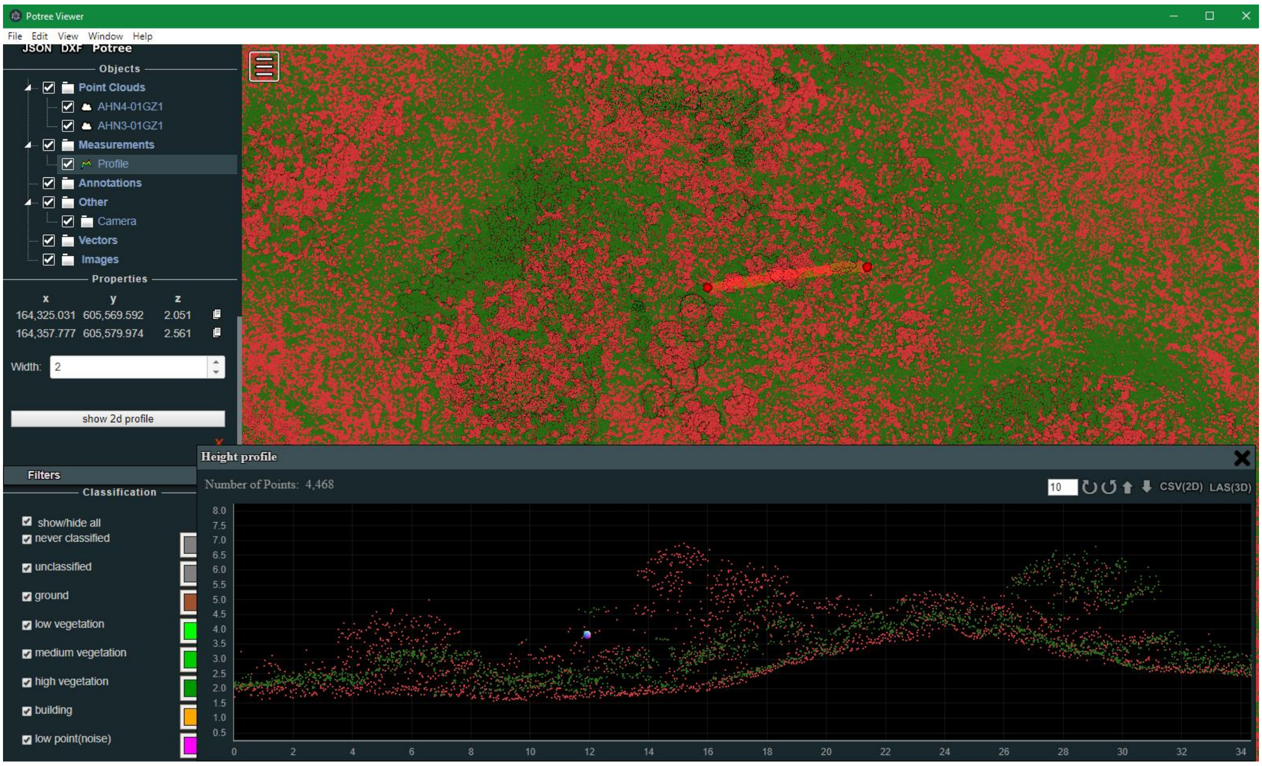

Figure A2.3 *An overall decrease of combined vegetation.*

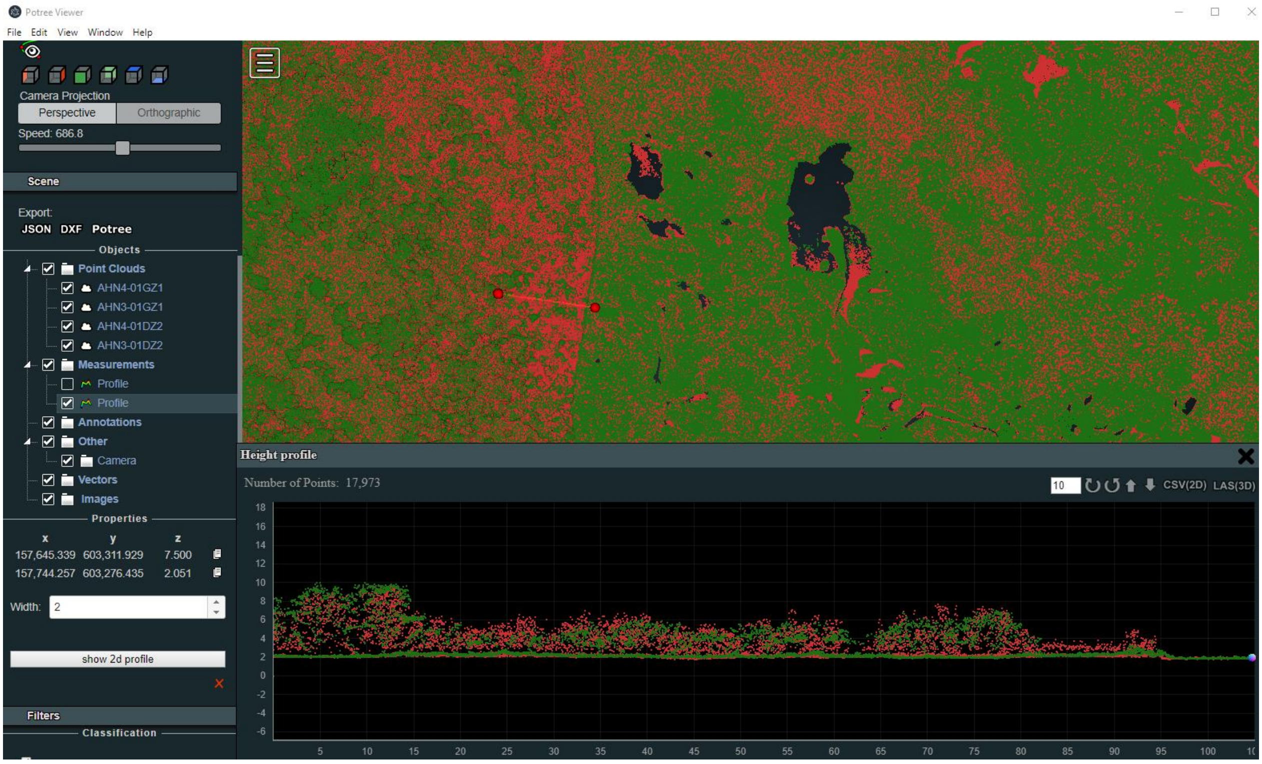

Figure A2.4 *The difference between managed and unmanaged areas, for the managed areas on the right in the cross section no change have occurred.*

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