Universiteit Utrecht

High-resolution ecotope characterization of a Dutch river floodplain using OBIA

- MSc THESIS -

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SUMMARY

Ecotope maps, representing vegetation communities, are a versatile tool in the Netherlands for calculations on floodplain roughness and monitoring biodiversity. Current ecotope maps show low accuracies regarding grass and brushwood ecotope types and are often produced on a low resolution (smallest units 20 x 20 m). Considering fauna ecology and biodiversity, the current resolution of classification is too low to monitor habitats of small floodplain fauna. Important patch characteristics, such as area and shape; and vegetation patterns such as patch connectivity and heterogeneity have yet not been monitored on meter - decimetre scales. Therefore, in this research floodplain ecotope maps are improved, using high resolution UAV images and object based image analysis (OBIA). These approaches are used to divide the landscape in segments which are homogeneous according to a threshold which is determined with trial and error. Results showed that standard deviations, vegetation height and NDVI are valuable object feature variables for extracting patches on a meter scale. The used method leads to (1) overall classification accuracies of almost 90% regarding grasses and brushwoods, (2) extraction of the most ecologically relevant patch characteristics and (3) (temporal) patterns for small floodplain fauna. OBIA with high resolution images is therefore recommended for future ecotope classification cycles.

1. Introduction

Floodplains serve as a buffer zone for peak river discharge and as the habitats for several fauna species. The amount and type of vegetation determines the maximum discharge capacity (Van Velzen et al., 2003). Vegetation communities determine what types of habitats are available for floodplain fauna. Ecotope maps, containing an overview of vegetation communities of within riverine areas, can be used to visualize floodplain roughness and ecology. For example, an ecotope map can be used by ecologists to determine the suitability of the area for threatened fauna species.

The dynamic character of floodplain areas is enforced by the current change in Dutch river management strategies towards 'working with nature', which aims at nature development (Schasfoort et al., 2013), ecological restoration and more spatial variation in floodplain vegetation and increasing the number of habitats for floodplain fauna. The natural dynamic character, along with less intensive management, cause a continuous change in vegetation communities, which can result in different vegetation patterns within a month time (e.g. sudden sprout of new vegetation, inundations). Change in vegetation patterns and therefore discontinuity in habitat types and surroundings has impact on native fauna species and should therefore be closely monitored.

Vegetation analysis becomes increasingly important as flood risks significantly increased over the last 40 years (Straatsma & Huthoff, 2010). A goal of improved monitoring is to gain accurate safety levels and more adapted management so that economic damage (residential, infrastructure, crops) can be better controlled. Especially for this, the current ecotope maps of the Netherlands have been developed. However, the impact of increased discontinuity on fauna and possible changes in the food web of floodplain areas remains underexposed. To monitor biodiversity from the vegetation cover in a high dynamic area, more accurate and more frequent vegetation classifications are needed.

Ecotopes are described as, or as a derivative of: *'Spatial landscape units that are homogeneous as to vegetation structure, succession stage and the main abiotic factors that are relevant to plant growth'* (Rademakers & Wolfert, 1994), or are sometimes referred to as vegetation patches (Forman, 1995b). Definitions do not include scales, but ecotope classification formerly used minimum mapping units of 20 m width (Bergwerff et al., 2003; Houkes, 2008; Straatsma & Huthoff, 2010), and are performed with airborne imagery on 1:10,000 scales (Maas et al., 1997; Houkes, 2008; Straatsma & Huthoff, 2010).

Floodplain flow resistance research is often performed on a relative high resolution (1:5000; van Velzen et al., 2003). Straatsma and Huthoff (2010) additionally state that the median ecotope unit size was 5000 m² while the largest ecotope covered over 3 km². Such sizes are too large and heterogeneous as ecotopes functioning as a habitat for birds and small mammals, which are low on the food chain, often lie within these units. Monitoring their habitat requires mapping on a meter scale.

Digitizing aerial imagery is often performed manually, which is an expensive and time consuming method (Straatsma, 2006; Geerling et al., 2009). Houkes (2008) provided an ecotope map of floodplains along the river Rhine that was mapped both manually and digitally. Ecotope delineation in the manual method is done by visual interpretation by the authors only, while the digital mapping includes ecotope boundaries of a preceding survey as starting point. New lines are drawn where boundaries of a scanned aerial photograph are not within ten meters of the old object boundaries. The threshold of ten meters illustrates the low resolution on which ecotope mapping in the Netherlands takes place. Furthermore, it is proven that manual classification of ecotopes is not reliable as it depends on interpretations which are not uniform among the persons analysing them (Jansen & Splunder, 2000). Using high-resolution data, drawing boundaries manually becomes too time-consuming and high-resolution vegetation maps are therefore not available.

The classification accuracy remained too low to distinguish between grassland and herbaceous vegetation (Jansen & Splunder, 2000; Houkes, 2008), due to their spectral and structural similarity on a low resolution, floodplain scale. Depending on the spatial scale, objects of an ecotope map may be pure herbaceous, pure grass or a mix. Generalizing these types of vegetation is a problem, especially for herbaceous vegetation, as it is an important factor in floodplain roughness (Straatsma, 2006) and ecology. Therefore, herbaceous vegetation should be distinguished from other communities where possible and should have the highest classification accuracy of the ecotopes in the maps produced for those purposes (Straatsma & Hothoff, 2011). However, when grassland and herbaceous vegetation are studied on a smaller scale, focussing at object sizes of a few meters, spectral and structural differences become observable with high-resolution remote sensing (RS) techniques as these ecotopes often contain several species (van Velzen et al., 2003). This provides new insights in terms of spatial arrangements of floodplain vegetation on a meter scale and thus information on habitats of small floodplain fauna. Using airborne imagery with a spatial resolution of 5 cm collected with an unmanned aerial vehicle (UAV) allows for analysis of vegetation patches of the suggested maximum size of a few meters. Object based image analysis (OBIA) is based on a technique which automatically identifies objects (vegetation patches) at any scale. This method has become increasingly popular in the last decade within large scale research (Addink et al., 2007) and has become feasible due to increasing computation capacities. Also, data derived with UAVs is relatively cheap and thus the frequency of collecting (multi-temporal) data can be increased.

For the Dutch floodplain ecotope maps, herbaceous vegetation and grassland vegetation are distinguished by their height only. Herbaceous vegetation is higher (> 70 cm) than grassland vegetation (< 70 cm) and a digital elevation model provides valuable information during high resolution classifications. Ultimately, maps derived from high-resolution data give a more detailed view of ecotope spatial variation and characteristics, relevant for (small) floodplain fauna.

With an optimized OBIA-based classification more accurate temporal patterns could be revealed. As 'Room for the River' (Schasfoort et al., 2013) allows for more dynamic floodplain areas (Peters & Kurstjens, 2011), frequent data collection should reveal more information on floodplain dynamics. Nowadays, the mapping routine applied by Dutch river managers exists of an eight-year renewal cycle (Geerling et al., 2009). This frequency is not high enough for temporal pattern analysis relating to an individual fauna species, as it does not fit most floodplain fauna's lifetime. A higher frequency is of special interest regarding high resolutions, as the smallest units have the highest rate in change in vegetation composition. However, mapping on an individual flora species scale has been expensive and probably takes too much effort to describe and determine it roughness (van Velzen et al., 2003) in the past.

Working with nature influences the patterns of habitats for floodplain fauna. As the habitat of floodplain fauna in the Netherlands is often relatively small, the methods used for developing the current ecotope maps are too inaccurate, both over space and time, to monitor potential habitats and therefore the biodiversity in dynamic floodplains. Due to the low resolution, heterogeneous areas such as grasslands and herbaceous vegetation, suitable for small fauna appear homogeneous on current maps and more detailed maps are necessary to investigate the spatial and temporal vegetation patterns. Using OBIA and high resolution UAV images, more detailed analysis on vegetation, ecotopes and therefore habitats, could become available and at the same time human errors are minimized by semi-automatization of the classification process. Such ecotope maps have high potential to lead to improved monitoring of dynamic floodplains, which allow for better adapted management and ultimately to higher biodiversity.

1.1 Objectives

The objectives of this study were to identify and map herbaceous and grassland vegetation in dynamic floodplains and to assess which spatial- and temporal patterns can be recognized on a meter scale within one year, using high resolution UAV imagery. More detailed maps are necessary with regards to ecology, as the current mapping scales oversize the habitats of small floodplain fauna. The objective was attempted to achieve by exploring different OBIA techniques on combinations of input data layers, such as digital elevation models and spectral information from UAV imagery. These techniques demonstrated that the process of ecotope mapping can be automatized. This was done for a floodplain during three different seasonal vegetation stages in a single year. In addition, the vegetation patterns emerging from this technical approach were evaluated and characterised regarding their resemblance to how the patterns are described in literature, and the usability for mapping purposes regarding small floodplain fauna. The following research questions are addressed:

Q1: Which vegetation patterns can be identified and analysed and are relevant regarding small floodplain fauna (from literature)?

Q2: What combination of criteria in OBIA is needed to distinguish between objects of grasses and herbaceous vegetation on a high resolution, meter scale?

Q3: What are the feature characteristics of the objects that can be identified in terms of area, shape and structure?

Q4: How do feature characteristics and patterns change throughout a year?

1.2 Study area

The study area forms a small part of one of Europe longest river systems, the Rhine river. This river has its source in the Swiss Alps and flows via borders of Liechtenstein, France and Germany towards The Netherlands. Here it splits into the IJssel, a branch of the Rhine and the Waal. These are all meandering branches but have been normalized and embanked for flood protection. The study was carried out in the Breemwaard floodplain and is situated along the southern bank of the Waal River, approximately five kilometres west of the city of Zaltbommel (Figure 1). This 116 ha area is predominantly under management of the state's forestry (81 ha) but some parts are privately owned and managed (Peters & Kurstjens, 2011).

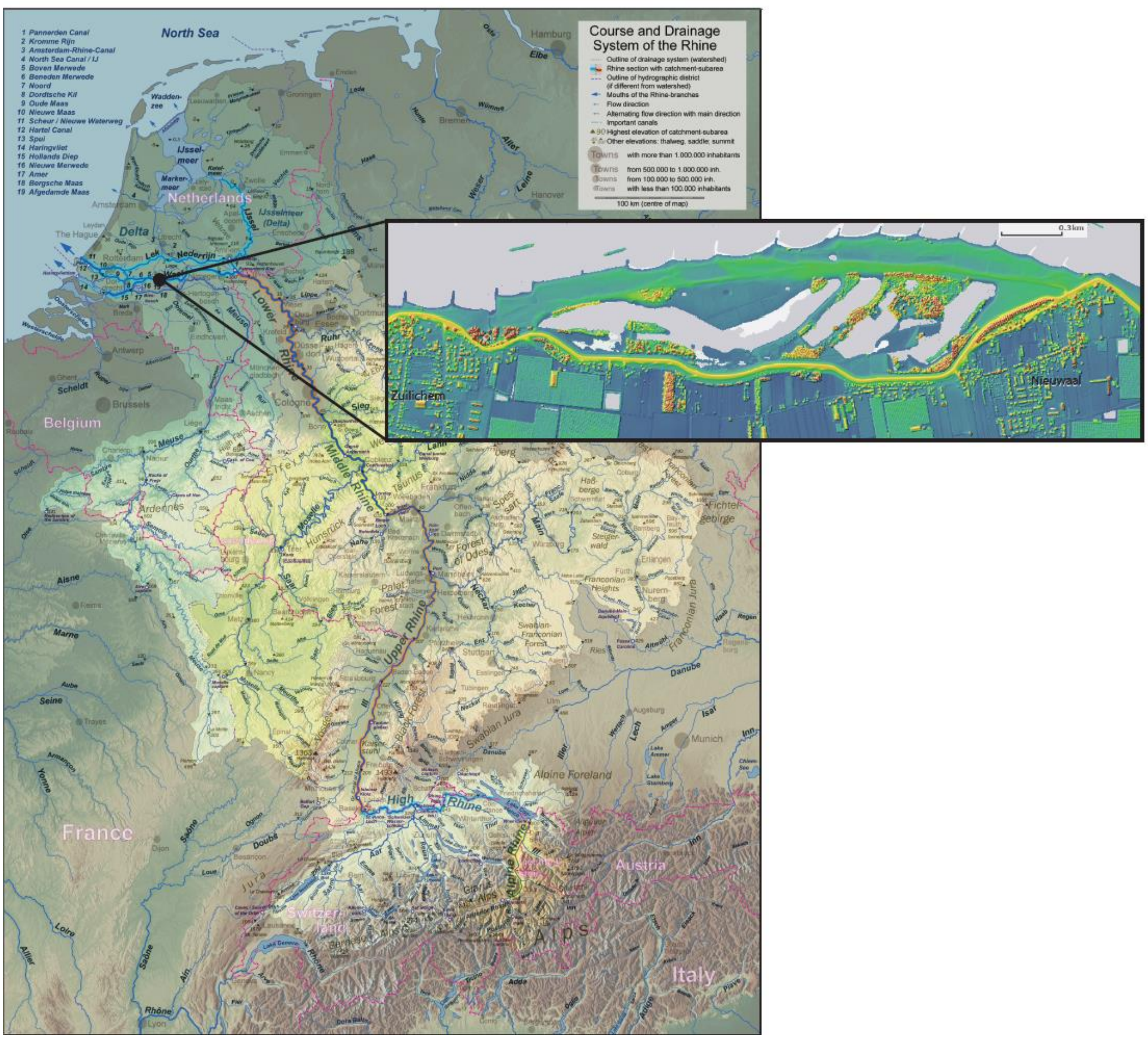

Figure 1. Overview of the Rhine catchment and Breemwaard floodplain as a DSM layer (AHN, 2012).

Since 1996, an area of approximately 100 ha has become nature reserves as a result of floodplain lowering due to clay extraction. Until the end of the nineteenth century, the Breemwaard floodplain functioned as a river bank and had a dynamic character (Peters & Kurstjens, 2011). After groynes were placed along the river in the early twentieth century, more sedimentation took place and the dynamic character decreased. Clay and sand were extracted from the Breemwaard, leaving several small lakes. As cultivation was reduced, a divers natural landscape occurred. There was again a high need of clay after the floodings in 1995, causing the Breemwaard to become an area of both clay extraction and nature development (Peters & Kurstjens, 2011). The ground level was lowered and a large channel was constructed to function as a buffer. North of this channel, in the centre of the Breemwaard, a large structure with ditches and small dikes is present. Along the minor embankment, north from these structures, a higher, sandy embankment was constructed which functions as a dry area for fauna during inundation (Peters & Kurstjens, 2011). This spatial planning resulted in the presence of beavers since 2007.

Around 30% of the area is used as production grassland (east side). Several other parts of the floodplain are extensively grazed by cows and ponies, while reed- and willow fields occur as well. The remaining areas are managed by state forestry and also grazed (Peters & Kurstjens, 2011). Due to the variety in management, a diverse area in terms of grassland and herbaceous species and structures has developed, which makes it a suitable area for classification of different types of grasslands and herbaceous vegetation.

The process of obtaining accurate ecotope maps which distinguish between grass- and herbaceous vegetation on a meter scale and being able to do identify patterns in the objects found which are relevant for floodplain fauna consists of several steps. This research starts with a literature overview of the most important ecotopes consisting of low vegetation and a description of the spatial patterns and patch characteristics important for two fauna species. Furthermore, the process of obtaining the most accurate ecotope maps using OBIA is described followed by an extensive pattern analysis.

2. Ecotopes

In The Netherlands, ecotope maps are made by Rijkswaterstaat (RWS), which is part of the Dutch Ministry of Infrastructure and the Environment. The maps are produced with an emphasis on floodplain morphology instead of vegetation communities as this defines where most of the water is discharged during inundation. For example, Jansen and Van Splunder (2000) use the 'RES' (River Ecotope Scheme) and Houkes (2008) uses the adherent 'RWES' (State Water Ecotope Scheme) method. The RES and RWES classifications both use geomorphology (i.e. levee, channel, floodplain) and the type of vegetation. The latter includes ecotopes such as '*floodplain brushwoods*'. Maas et al. (1997) give examples of river ecotopes such as '*sandy secondary channel*' and '*levee with river dune formation*', derived from the river-ecotope-system (RES) found by Rademakers & and Wolfert (1996), but those ecotopes are not relevant for this research. For classification of ecotopes on a small scale, the type of vegetation is most important. The classification of van Velzen et al. (2003) is based on vegetation types or vegetation communities which develop according to the type of management present. Therefore, this classification is used as a guideline and summarized in Table 1.

Former ecotope classifications were made by using an interpretation key for the interpretation of airborne imagery (Houkes, 2008). By answering several questions in a classification key (including height and structure) a label is assigned to an object. As the current research is also based on the vegetation structure, it still meets some of the same criteria as former classifications. As the interpretation key has to be followed for every object, automatization of the process would save a lot of time and avoid (possible) mistakes.

2.1 Floodplain vegetation

Van Velzen et al. (2003) give a comprehensive description of ecotopes and their vegetation structure. Ecotopes and vegetation structure types consisting of low vegetation are summarized below. These 'structure types' are described in terms of origin, development, management and flow resistance. Pioneer vegetation, three types of grasslands, along with five types of herbaceous vegetation and six types of swamp vegetation can be expected in the Breemwaard.

Figure 2. Dry pioneer vegetation settled on a sand bank in June 2015 (Breemwaard, plot 8).

The first ecotope is **pioneer vegetation**. This type of vegetation can consist of a wide variety of species, and the species which finally settle depend on the environment. These vegetation types appear in high energetic environments where vegetation has difficulties to settle permanently. This can be both wet (riverbanks) and dry (sandy) bear grounds (Figure 2).

Figure 3. Homogeneous production grassland (A, plot 26) and natural grass- and hayland (B, plot 25) in June.

Grasslands are divided in three categories. The first, **production grasslands**, is an intensively managed ecotope. The grasslands, which can contain relatively few grass species, are sowed and grazed or mowed when livestock is absent. This results in a homogeneous ecotope in terms of species, height and density (Figure 3A). The second type, **natural grass-and hayland,** is less intensively managed and therefore forms a less homogeneous ecotope (Figure 3B). It has a higher species diversity and depending on the topographical height it has silverweed-, foxtail-, oat-grass-, crested dog's-tail- and river-valley as dominant species. These grasslands are being grazed and sometimes hayed in addition. The last type, **roughened grassland**, has a low management intensity which results in tall vegetation, dominated by foxtails- and oat-grasses and herbaceous vegetation. These grasslands are grazed with a low intensity which results in a mosaic of patches and corridors. With even less intensive grazing these types of grasslands can evolve to brushwoods/ herbaceous vegetation.

Figure 4. Overview of brushwood ecotopes in June. A) Creeping thistle- nettle brushes (plot 28) B) Dry brushwoods (plot 18) C) Dewberry brushwoods, mixed with nettles (plot 14) and D) Reed brushwoods (plot 6).

Brushwoods are subdivided in five ecotopes (Figure 4). First of all, the **creeping thistle- nettle brushes** (short: 'nettle brushwood') usually occur after a change in management, for example after grassland is taken out of production. After some time without management, grasslands will be dominated by other more herbaceous vegetation such as **Dry brushwoods.** This ecotope exist of a variety of communities such as tansy, bushgrass and mugwort. It has a low grazing intensity and at places where no grazing occurs, higher herbaceous vegetation (such as nettle brushwood) can develop. **Dewberry brushwood** is dominated by the dewberry. This type develops in the least grazed parts of the floodplain and is therefore common on riverbanks rich in basalt stones. During winter other herbs, such as nettles, tansy, hairy willowherbs, couch- and rough-meadow grasses get the opportunity dominate. **The hairy willowherb brushwoods** can contain, besides hairy willowherb, species as docks, broad-leaved ragwort and late goldenrod. These brushwoods often occur on dried swamps or sludge rich, ungrazed areas. Further development results in softwood brushwood or forest ecotopes. **Reed brushwood** contains more than 25% reed. Reed is the dominant community but is interrupted by other swampy vegetation types as holy rope, *Angelica* and hedge bindweed. The soil is too dry to develop to a fully reed-dominated area but too wet to become hairy willowherb brushwood.

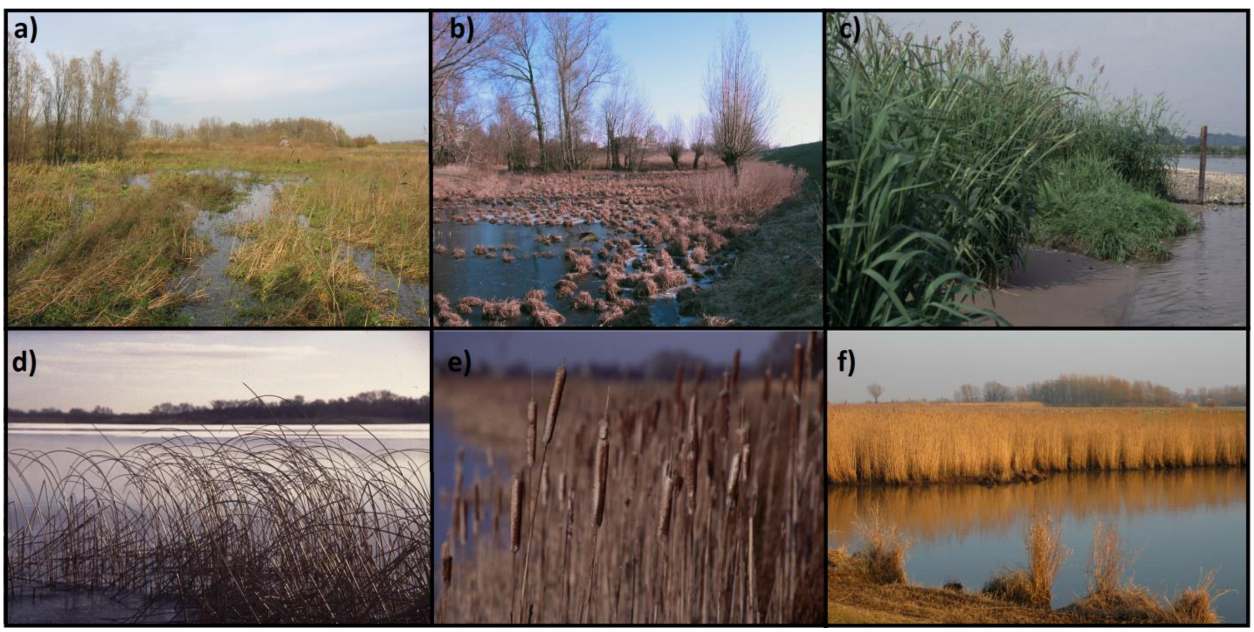

Figure 5. Swamp vegetation ecotopes. A) Wet brushwood (November; P. Jesse) B) Sedge (February; P. Jesse) C) Reed grass (June; H. Coops) D) Rushes (October; H. Coops) E) Bulrush (October; H. Coops) F) Reed (January; T. Slingerland)

Swamp vegetation (Figure 5) includes vegetation types which grow on wet soils with a (semi-)steady water level. Most vegetation types are sensitive to grazing and some ecotopes can therefore best survive in continuously wet environments so that it has protection from grazers. The first ecotope described is **wet brushwood**, which can consist of species like meadowsweet, great manna grass, common meadow-rue, purple loosestrife and watermint. These species disappear in winter and species which lignify (such as reeds and hairy willowherb) are absent. As these species depend on a wet environment, this ecotope is common at edges of gullies and lakes. **Sedge** is an ecotope which includes slim- and greater pond sedges. Sometimes it can easily be recognized as it grows in large tufts. When they are close together it can form a homogeneous field. **Reedgrass** ecotopes mainly consist of reedgrasses with a possible low amount of other brushwoods and occurs both on wet and dry soils. Typically, they grow on riverbanks, old river gullies and areas of former sand extraction. **Rushes** are common in places where the water levels are too high for reed to settle. In the Netherlands, the most common species are common-club rush and great bulrush. **Bulrush** is an ecotope including two species: common bulrush and lesser bulrush. Bulrush typically occurs in the same environments as reeds. It prefers a stable, wet environment and is commonly seen in the diked parts of the floodplain. **Reeds** occur in areas where there is no to little summer inundation and groundwater levels are high. It could form homogeneous fields but can also be present in patches as migrating fauna leave corridors within the fields. Common co-occurring species are the great yellowcress, slim sedge and yellow loosestrife.

Table 1. Summary of used ecotopes and structure types with accessory definitions, after van Velzen et al. (2003).

Ecotope	Structure-type	Definition
Pioneer vegetation	Pioneer vegetation	Variety of plant communities on high dynamic (bare) soils.
Grassland	Production grassland	Homogeneous cultivated grassland, dominated by a few species.
	Natural grass- and hayland	Cultivated grasslands.
	Roughened grassland	Least cultivated grasslands with high vegetation.
Brushwood	Creeping thistle- nettle brushes	Present on disturbed circumstances and sensitive to grazing.
	Dry brushwood	Variety of (transition-) brushwood communities on dry substrate.
	Dewberry brushwood	Brushwood dominated by dewberry brushwood.
	Hairy willowherb brushwood	Brushwood dominated by hairy willowherb brushwood.
	Reed brushwood	Brushwood dominated by reed (>25%).
Swamp vegetation	Wet brushwood	Variety of vegetation present on wet substrates.
	Sedge	Dominated by tufts of sedge on wet substrates.
	Reedgrass	Brushwood dominated by reedgrass.
	Rush	Occurs in wet environments which are too deep for reed to settle.
	Bulrush	Occurs near reeds in slightly deeper waters.
	Reed	Homogeneous fields of reeds in relative low dynamic environments.

River dynamics and grazing result in a floodplain with a diversity of objects which are highly variable (in species occurrence, height, and density) from year to year (van Velzen et al., 2003). To integrate the observed changes into floodplain ecology, it is required to determine what ecotope characteristics are most important and how spatial variation or spatial changes are commonly described.

3. Patterns and ecology

Accurate vegetation analysis is of importance for floodplain ecology as vegetation patterns are directly linked to ecological processes. Especially at local scales (within floodplains), variables such as patch area, connectivity, vegetation type, productivity and land use are important (Goetz et al, 2007), where the influence of a variable like climate might be dominant on regional scales. Floodplain vegetation patterns have been extensively studied in the past decennia (Bayley, 1995; Hupp & Osterkamp, 1996; Alvarez-Cobelas et al., 2008; Arierira et al., 2011; Zhao et al., 2014), but these mainly focused on the effect of overbank flooding on patterns on a regional scale, significantly larger than intended in this research. To understand what patterns are relevant for small floodplain fauna, it is necessary to understand some basic pattern principles.

3.1 Patch characteristics

Ecotope patterns relate to patch characteristics, the spatial arrangement of patches or the temporal variation of a patch. The first is of importance in patch recognition. Forman (2011) describes patches (or ecotopes) in terms of:

- Shape (e.g. curvilinear boundaries, narrow lobes);
- Size and edge;
- Density; and
- Connectedness

as a measure for the amount of disturbance and fragmentation. For example, human-disturbed patches have a simpler shape (square), are more isolated and decrease in size or disappear. Shape and size also influence the edge of a patch, which is the boundary between patches. Turner (1989) highlights the importance of edge habitats, as these are areas of movement of biota. Furthermore, such a transition zone might increase vegetation heterogeneity of the patch and benefit its inhabitants. In Addition, Lillesand et al. (2014) define ‘feature characteristics’ of individual patches. These include (1) shape (form, configuration or outline and height in stereoscopy), (2) size (scale), (3) tone (brightness), (4) texture (tonal change within an object, also smoothness or coarseness), (5) shadows (the shape or outline can help identify the profile of the object), (6) site (location, certain species have a distinct preference for a certain topographical or geographical location), (7) association (surrounding elements make suggestions about the objects identity), (8) resolution and (9) patterns. Here, ‘patterns’ describe the spatial arrangement of patches. The repetition of appearance at expected locations make it possible for the viewer to recognize an object from a certain pattern. For example, structured arrangement of trees in an orchard makes it perfectly distinguishable from natural trees in woodland by its lined pattern. Therefore, a distinction is made between feature characteristics, regarding an individual patch, and patterns emerging from multiple patches (spatial and temporal).

3.2 Spatial arrangement of patches

The patch-corridor-matrix model (Forman 1995a) is an example of a model developed to describe patterns in its spatial form. It takes into account the extent and configuration of three types of landscape elements. It describes the arrangement or structural patterns in terms of patches, corridors and a matrix, in which the latter represents the dominant vegetation type (Figure 6). In landscape ecology, it can be used to describe potential flows and movements of fauna through the landscape and the changes of patterns and processes over time. Landscape resistance (for example barriers, deforestation) is a measure for mobility of a species. Therefore, by studying the spatial arrangement of landscape elements will provide insight in fauna migration as migration can be a measure for the viability of a fauna species.

Forman and Godron (1981) define a patch as: ‘A community or species assemblage surrounded by a matrix with a dissimilar community structure or composition’. In 1995b, Forman refines the definition in the patch-corridor-matrix model to: ‘discrete areas of relatively homogeneous environmental conditions where the patch boundaries are distinguished by discontinuities … or relevant to the organism or ecological phenomenon under consideration’. Furthermore, patches are dynamic and can differ on a variety of spatial and temporal scales. The smallest considered scales are on the ‘grain-size’, which is a level on which the patch becomes so fine that individual fauna stops responding to it. Naturally this scale is different for different species and therefore a patch must be defined according to the species investigated. In practice, the smallest patch size which can be studied with RS is limited by the resolution of the imagery.

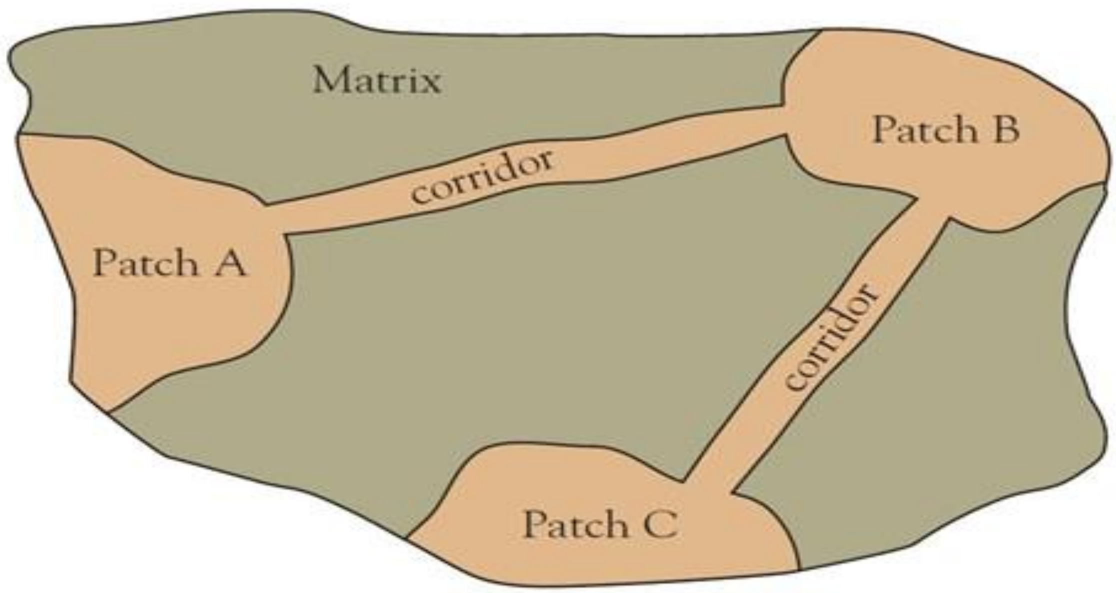

Figure 6. Illustration of the patch- corridor- matrix model. Landscapes consist of multiple patches within the dominant feature (matrix) and corridors that connect the patches (Barnes, 1999).

McGarigal (2014) mentions four ways of describing patterns spatially. The first is object based, i.e. that every object is converted into a point, and every point has a location and a name. In this way it can be visualized whether or not the points are more clustered than expected. The second is network based, as linear networks such as borders are mapped while the matrix is often not considered. With these types of analyses, network connectivity is monitored. Thirdly, surface patterns are often continuous and can for example represent biomass, LAI or elevation. This analysis of continuous patterns can for instance be used to measure density. Last of all, categorical map patterns, often referred to as ‘patch mosaic’, is a way of analysis in which patches represent discrete and relative homogeneous areas in which environmental conditions are equal. Patch boundaries are abrupt and therefore easily distinguished. Therefore, this last type of analysis will be most suitable in patch pattern recognition.

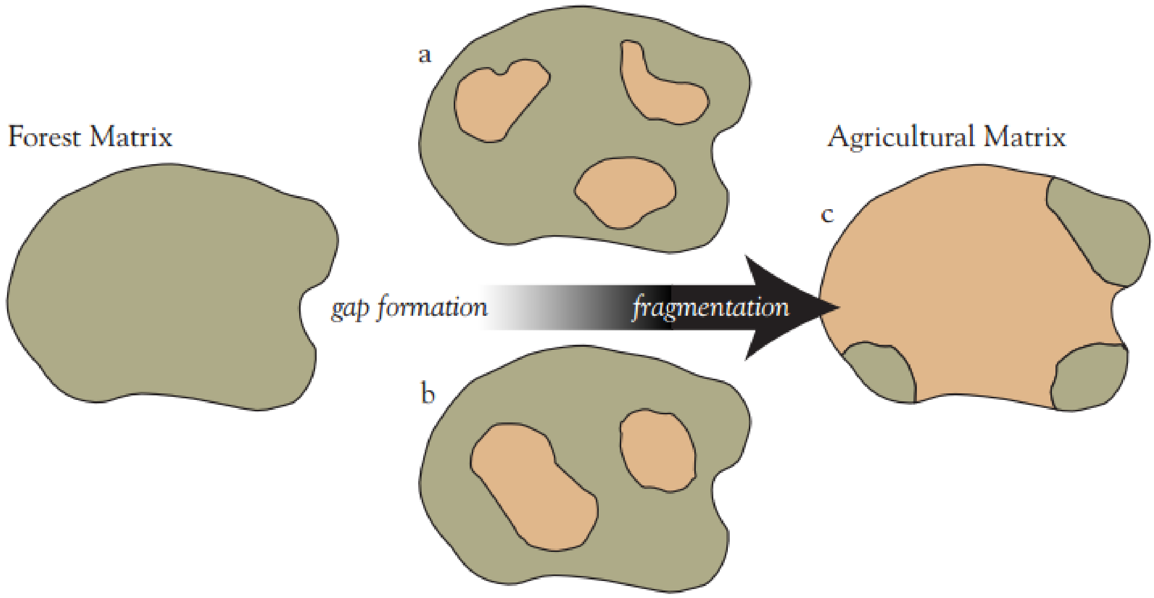

Figure 7. Visualization of types of aggregation. A) relative high dispersion, relative low interspersion; B) relative low dispersion, relative low interspersion; C) Fragmentation of forest matrix resulting in patch isolation. After Barnes, 1999.

McGarigal (2014) gives a second approach of describing patterns in the landscape. First of all, patterns can be described in terms of composition: the variety and the number of patch types in the landscape (or landscape occupation). This includes proportional or relative abundance of each class (evenness); the richness, or the number of classes; and diversity, which is a composite measure of evenness and richness. Second, patterns can be described in terms of spatial configuration. This refers to the spatial character and arrangement, position, or orientation of patches within the class or landscape. Terms used here are patch size, shape (complexity), contrast and aggregation. Again these terms can be separated in patch characteristics (size, shape) and spatial patterns. Contrast is a diversity measure as it describes the difference between two classes. For example, a grassland next to pioneer vegetation shows less contrast than a grassland next to a forest. Aggregation involves dispersion, interspersion (mixing) and isolation (Figure 7). Interspersion is the mixing of different ecotope classes, dispersion the spatial arrangement of patches of a single class. Aggregation is sometimes referred to as the landscape texture (McGarigal, 2014).

Forman (1995a) also describes six spatial patterns (Figure 8):

1) Large-patch landscapes consist of large patches within a matrix. This type probably overlaps single floodplains, as it should be able to sustain viable populations of large-home range vertebrates.
2) Small patch landscapes are the smaller scale variant of the large patch landscape, and could inhabit small-home range vertebrates.
3) Dendritic landscapes, having the imprint typical multi-branching tree-like form.
4) Rectilinear landscapes, having the imprint of a network of straight corridors like agricultural landscapes have.
5) Checkerboard. This pattern represents landscapes without extensive stretches of matrixes or patches. Such patterns could be the result of landscape fragmentation. When large patch size is ecologically important, checkerboard fragmentation has a negative effect on fauna. On the other hand, diversity in the area increases.
6) Interdigitated. Two types of ecotopes are locked together, like grasslands at the edge of a forest.

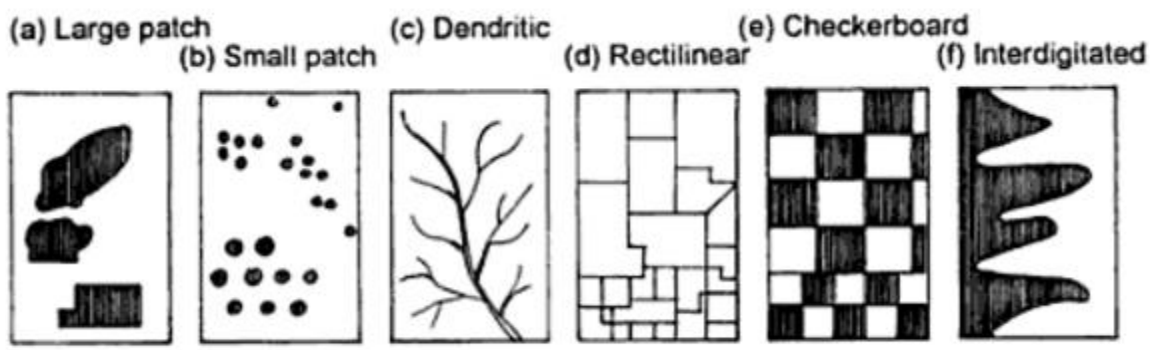

Figure 8. Six types of spatial landscape patterns, categorized based on the predominant pattern (Forman, 1995a).

Turner (1989) states that environmental patterns strongly influence ecological processes. Alike, McGarigal (2014) indicate that changes in patterns influence ecological flows, i.e. changes in patterns mean change in the structure of the landscape and therefore influence the migration of flora and fauna. But in addition, McGarigal (2014) state that it is not always clear on what level mapping and measuring of patterns should be done to be ecologically relevant and depends on the fauna species under investigation.

Landscape ecology considers the development and dynamics of spatial heterogeneity; interactions and exchanges across a heterogeneous landscape and the influences of spatial heterogeneity on biotic and abiotic processes (Turner, 1989). Research on vegetation patterns in a floodplain could therefore contribute to landscape ecology on several levels. For example, feature characteristics give insight on individual habitats of fauna, while pattern analysis provides information on spatial heterogeneity and connectivity of the landscape. To find out what feature characteristics or patterns are most relevant in landscape ecology in this research, it is necessary to know which are most important for floodplain fauna.

First of all, every species has a minimum habitat area (or home range), which has to be considered during this research. Besides the fact that single plant species are too difficult to determine with the current remote sensing technology, ecotopes much smaller than the minimum habitat area are of less relevance in analysing feature characteristics. Patch size is ecologically important, since populations are more successful when vegetation patches in which they live (habitats) are larger and when there are many spatial connections between patches (Goetz et al., 2007). In other words, isolated patches are less viable and small patches have a higher extinction rate for fauna. Habitat connectivity, a spatial vegetation pattern, is therefore of importance for floodplain ecology. For example, poor habitat connectivity, which one could interpret as large distance between similar vegetation objects, seems to slow down decolonization of the floodplain after inundation (Wijhoven et al., 2005). Most animal species use different habitats to feed and find shelter, and therefore a divers and heterogeneous environment (low evenness) is most suitable for those species (Goetz et al., 2007; Rocchini et al., 2010) and often a precondition (de Lange et al., 2012). Also relatively heterogeneous areas can host more diverse fauna due to the greater number of available niches. Therefore, habitat heterogeneity is considered to be one of most important spatial characteristics concerning biodiversity. Also, on a supra-species level, the Spectral Variation Hypothesis states that the greater the habitat heterogeneity, the greater the species diversity (Rocchini et al., 2010).

Heterogeneity is hard to measure using field-based data collection (Rocchini et al., 2010) as it is labour intensive, difficult to map in detail and inaccurate when extrapolated. As remote sensing can deliver images with resolutions of centimetres and contrast in pixel information can be used for separation of groups of pixels that are alike, it might be a powerful tool for solving this problem. Furthermore, if the process is accelerated, analyses on multiple time-steps could reveal changes in patch characteristics and spatial patterns. These (relative) changes, or temporal patterns, can provide information on viability of habitats over a longer period of time. Altogether, partial automatization of the classification could help finding spatial and temporal vegetation patterns within the floodplain.

4. Object Based Image Analysis

Object Based Image Analysis, also referred to as OBIA or GEOBIA (Addink et al., 2012), is a relatively new method of image analysis and classification. This method has been widely adopted within the remote sensing community in recent years. Traditionally, the most common approach has been the per-pixel analysis (Addink et al., 2007), which is based on the values of individual pixels to make classifications. However, important spatial information is not caught by pixel-by-pixel classification algorithms (van der Sande, 2003). For example, a natural vegetation patch will hardly ever be square, so the spatial information that can help to identify an observed unit (i.e. edge, shape) will not be fairly represented by a square pixel. The larger the scale of the object, the less influence the square size of the pixels have. Also, recognizing individual pixels is not important in this research, as the pixels are part of a larger unit which can represent a habitat, not the pixel by itself. Therefore, Addink et al. (2007) recommend the use of OBIA for classifications with high resolution input data for spatial unit recognition.

OBIA is based on segmentation before classification. This method clusters neighbouring pixels, depending on the individual pixels' characteristics and within-group similarity. These sets of similar neighbouring pixels form segments, representing (parts of) the observed units with defined boundaries instead of a direct per-pixel classification based on spectral behaviour. Pair-wise merging of pixels continues until homogeneity thresholds are reached (Smith et al., 2008) or a discontinuity is perceived (Figure 9). Not only spectral behaviour is taken into account; the user can also define the criteria for size, texture and shape of the segments. The scale can be decreased when the size of the segments are considered to be too large, as scale controls the amount of spectral variation (or texture) within the segments and therefore the resulting segment. The shape-parameter is a weighted measure between the segments shape and its spectral colour, whereas if = 0 only colour is considered and often result in fractal shapes. Last of all, the compactness parameter describes the closeness of pixels clustered in a segment compared to a circle. A low compactness will therefore allow more elongated segments. After a perfect segmentation, every segment covers a patch of one vegetation community, with internal homogeneity, which is referred to as an object. It is possible that one homogeneous patch consists of two or more segments, due to e.g. shade or edge, but the segments are assigned to the same ecotope. These segments are referred to as objects after classification and merging.

When using a pixel-by-pixel analysis on small scales, a different coloured leaf in a tree crown could be wrongly classified (Smith et al., 2008), while the pixel will be assigned to the three when using OBIA. Therefore, the use of OBIA will further increase with the increasing availability of high resolution imagery (<5.0 m) (Hay & Castilla, 2006).

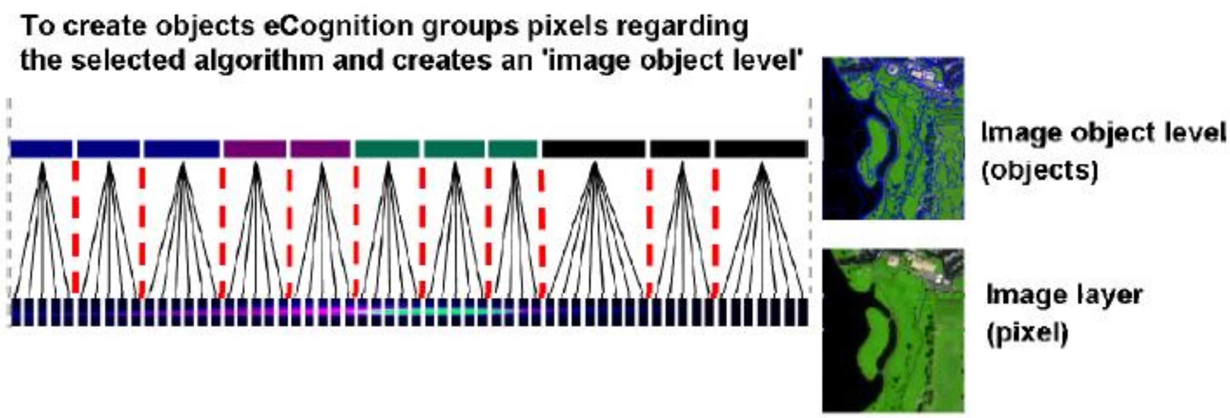

Figure 9. Visualization of the segmentation process, from the pixel- to object level (eCognition, 2010).

Other drivers for the development of OBIA are the developments in computing capacities, which become more widely available and affordable. Besides spatial information of objects as edge and shape, OBIA can recognize texture and context of objects, making it a more comprehensive classification method. Last of all, in monitoring, modeling and management of the environment multi-scalar approaches are necessary for which object-based methods are very suitable (Hay & Castilla, 2006).

As the OBIA method has the potential to detect ecotopes and their boundaries on a meter scale using high resolution images, it is considered a good method for finding spatial and temporal vegetation patterns within the Breemwaard floodplain.

5. Methods and materials

Dynamic floodplains have the potential to bear multiple habitats for small floodplain fauna. Pattern analysis can be done to describe the suitability of a habitat. However, every fauna species has its own niche and therefore has different habitat requirements. To evaluate the patch characteristics and spatial patterns over time, two target species were selected. To prove the broader applicability of the methods, both species have different home ranges (starting from 125 m^2) to illustrate two kinds of habitat on two different scales. Furthermore, their habitat includes former hard to determine ecotopes such as grasslands and brushwoods. Using UAV high-resolution images and ground truths, the spatial characteristics and organization of their habitats were analysed over one year. The analyses were done with the use of aerial near-infrared images (Appendix A-C) and elevation models. These functioned as input layers for eCognition Developer, able to perform OBIA, to extract ecotope objects. FRAGSTATS v4 (McGarigal et al., 2012) software was used to determine feature characteristics, patterns and landscape heterogeneity. The results, including maps of February, June and November with objects on different scales, were compared to the habitat characteristics preferred by the target species.

5.1 Target species

Greater white-toothed shrew

The Greater white-toothed shrew (*Crocidura russula,* Figure 10) is a small mammal belonging to the family of white-toothed shrews. It mainly inhabits grasslands, hedgerows and woodlands, but it is also found in shrublands and cultivated fields, as long as there is abundant ground covered by vegetation (Aulagnier et al., 2008). An extended and more applied research on small floodplain fauna was done by Wijnhoven et al. (2005), who indicated rough herbaceous vegetation, grazed – and ungrazed grassy vegetation as most suitable habitats for *C. russula* in Dutch river floodplains.

Wijnhoven et al. (2005) placed traps on 40 different plots representing a wide range of vegetation structures (11 variables). The number of trapped shrews per plot was assumed to indicate their habitat preferences. The species was found to be especially related to shrubs and rectangular shaped objects, situated on (dry) inland areas (Figure 11). Rectangular shapes were described as homogeneous shapes bordered by linear structures, typical for agricultural landscapes and therefore the 'rectangular shapes' are considered to be straight as well, instead of 'elongated'. Other suitable ecotopes that are present in the Breemwaard as well are mowing land (hayland), nettle brushwood and (rough) herbaceous vegetation.

Figure 10. ***Croicidura russula*, or Greather white-toothed shrew within grassy vegetation.**

Pairs defend territories about $100m^2$ (Favre et al., 1997), which is in accordant to Wijnhoven et al. (2005), who set the home range to $125m^2$ and calculated an action diameter of 12.6m assuming a circular patch.

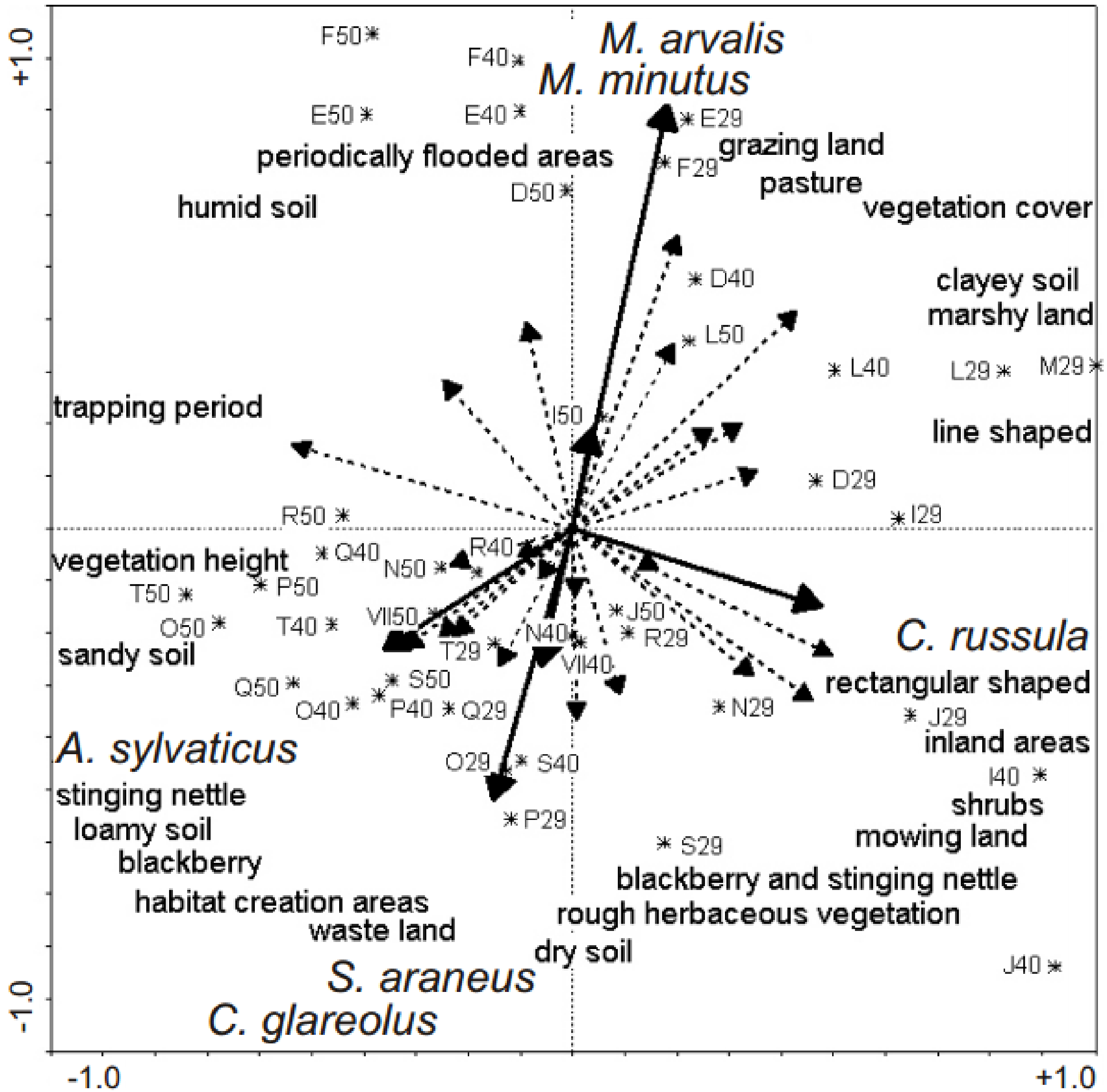

Figure 11. Redundancy Analyses of trapping results of six small mammal species related to environmental variables (Wijnhoven et al., 2005).

The preference for dry inland area's covered with dry brushwood or mowing land with a patch size of 125 m^2 make small patches of dry brushwood, natural grass- and hayland and nettle brushwood the most suitable ecotopes for this species.

Common whitethroat

Figure 12. *Sylvia communis,* or Common whitethroath fledglings within nettle – and dewberry brushwood (picture by Ed Tooth)

The second target species is the common whitethroat (*Sylvia communis*, Figure 12), a small bird species occurring in the Breemwaard, especially in the most western areas where there is lot of (nettle) brushwood (Peters & Kurstjens, 2011). Therefore, this species might profit from the decreased amount of management in the area. According to MacDonald (1979), whitethroats occupy habitats with dense shrubs with spikes, such as brambles, raspberries and roses accompanied by nettles. This is supported by Mason (1976) who states that *S. communis* is a shrub breeding species. He also mentions bramble and nettles as the predominant nesting vegetation types. Halupka et al. (2002) found that tall herbage, bramble and sparse woody vegetation are the best habitat vegetation types for breeding in a floodplain and as nest surrounding. Figure 13 illustrates that whitethroats prefer a more than average available amount of tall herbage vegetation within 10-50 meters from their nests. However, they mention that these types of vegetation were not desirable for foraging.

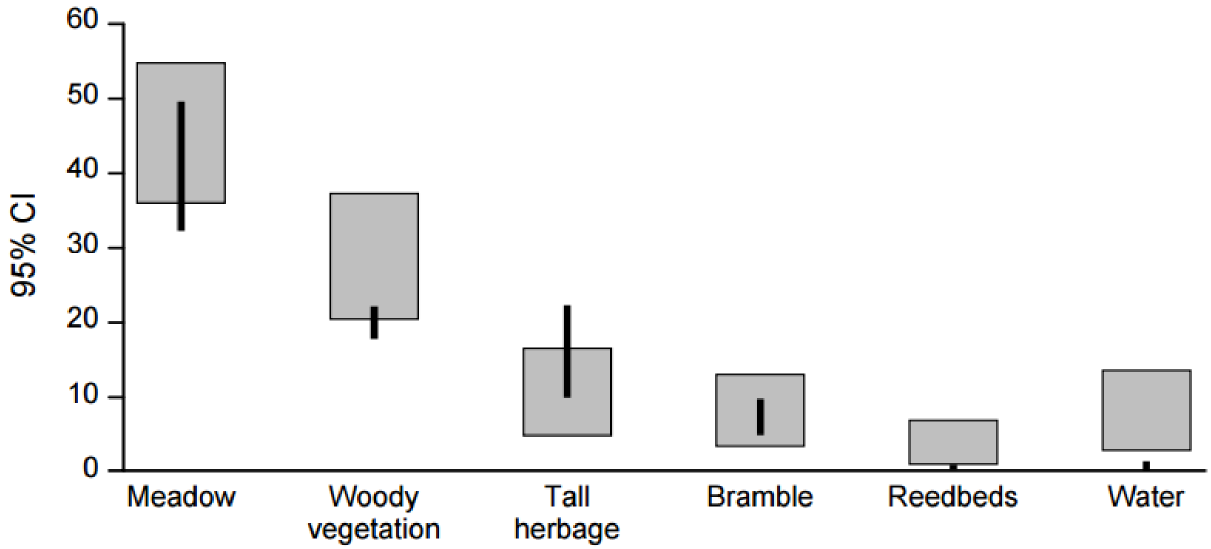

Figure 13. 95% Confidence intervals (CI) for the percentage of various vegetation types in the researched area (shaded) with black lines representing median proportions of each type of vegetation within 10-50 m from nests (n = 46 nests) (Halupka et al., 2002).

MacDonald (1979) mentions a habitat size of 0.10-0.54 ha. The territories were mainly defined by the song posts which consisted of narrow strips (100-150m). The width was restricted to less than 100m. A similar range was found by Halupka et al. (2002) which determined a territory size of 0.04 to 0.65 ha, with a mean size of 0.2 ha. They also compared this result with five more (including that of MacDonald (1979)) studies, which also average ~0.2 ha. Additionally, MacDonald (1979) mentions that adults rarely went further away than 50m from their nest to find food for their nestlings. Halupka et al. (2000) found that this species was foraging within 30 meters from its nest.

For this species the main focus is on all types of present brushwood ecotopes with an area ≥ 0.2 ha and which are preferably long-shaped.

5.2 Field data

Plots were set up to sample vegetation during each flight to serve as ground reference (28 in total, Appendix D). Data extracted from the plots include vegetation height (H_v), density and species occurrence. The vegetation plots were analysed on species occurrence using the Transley vegetation scale in August 2015. Former plots were classified as 'pioneer vegetation', 'grasslands', 'herbaceous vegetation' and 'helophytes', which is on the level of vegetation types rather than specific species. Therefore, the plots were manually classified on a more detailed level with the ground truth vegetation height and species occurrences into the ecotopes described by van Velzen et al. (2003). The plots had areas between 150 and 250 m^2, oversizing the habitat of *C. russulla* and thus multiple ecotopes within a plot were allowed. The plot data will be used to train and evaluate the classification method obtained with the OBIA.

5.3 Material information

During six previous surveys stereoscopic airborne images of the Breemwaard were collected using a UAV (Swinglet CAM). The surveys took place in February, June and November (2015).

Table 2. UAV imagery information

Data provider	**HiView**
UAV	Swinglet CAM by Sensefly
Camera	Canon IXUS 125 HS
Sensor resolution	16 megapixel
Ground resolution	5 cm
File format	JPEG
Acquisition height	~150 m

The UAV was equipped with a GPS, altimeter, wind meter and a Canon IXUS 125 HS camera (Table 2). The images were georeferenced using ground control points (GCPs). By placing 40 white vinyl markers measured with dGPS in the study area as GCPs, the data was georectified.

5.4 Image processing

From the stereoscopic photographs, Digital Surface Models (DSM) were derived by a conversion into point cloud data using a Structure-from-Motion workflow (SfM) in the software package Agisoft PhotoScan Professional version 1.1 (Agisoft, 2014). With spring and summer conditions, when vegetation grows towards detectable heights, the DEM represents a Digital Surface Model (DSM). During low vegetation cover (winter conditions); the Digital Elevation Model (DEM) is close to a Digital

Terrain Model (DTM). The difference between the DSM and DTM should result in the vegetation height, but some vegetation types, especially trees and reeds, are still detected with photogrammetry. Therefore, LiDAR data was used (AHN) which gives the ground level, even in vegetated areas. The AHN is based on dense laser data points and multiple returns of one laser makes it possible to derive the ground level and filter out vegetation or buildings (van der Zon, 2013). After normalisation of the DSM, the predicted vegetation height (hereafter referred to as DEM), was used as an input layer for ecotope classification. Horizontal accuracy of the dGPS was determined at 0.015 m; vertical accuracy at 0.02 m. Standard error of the DEMs was 0.22 m.

All pictures obtained from one UAV flight were merged into a single picture. This was done by selecting tie points which are present on overlapping pictures. As the pictures were made on different angles, it is difficult to determine tie points within waterbodies and therefore ever-present waterbodies were masked. In this research, masking was done manually by drawing polygons overlaying these land cover types within ArcMap 10.3.1. (ESRI 2014) and export the raster data by the selected graphics (clipping).

5.4.1 Segmentation

The software used for image classification is *eCognition Developer*, which is able to segment the image into objects and classify them using OBIA. This subdivision of an image into unclassified separate regions forms the 'image object primitives' (eCognition, 2010). Multiple segmentation algorithms are available, including multi-resolution segmentation. This type of segmentation starts at pixel level and the values of pairs of neighbouring pixels are compared and merged to form a single segment if they satisfy multiple heterogeneity conditions. These conditions are designed to minimize the heterogeneity of the segments across the image and thus maximize the individual segment homogeneity. First of all, the four input layers (near infrared, green, blue and DEM) are weighted. As spectral differences for different types of brushwood and grasslands do not allow direct visual distinction between those ecotopes, it is chosen to put extra weight on the digital elevation model (layer values set at 1,1,1,2).

Second, the scale parameter, determining amount of heterogeneity and therefore the size of the object was set. Addink et al. (2007) found a scale parameter of 15 most appropriate for their classification, but mention that the parameter depends on both the size of the objects of interest and the homogeneity of the landscape. For this research it was important to find a scale suitable for the habitats of the two target species. For this purpose, the image of June is selected as it was expected to have most spectral contrast and height variation. Subsets including meter-scale brushwood patches suitable for small floodplain fauna were used to determine the scale, and the scale parameter was considered optimal when one segment comprises a small (diameter of ~ 10m, considering the smallest of the two fauna species) brushwood patch (Figure 14). A scale parameter of 110 was considered most successful using the default values for compactness and shape (0.5 and 0.1).

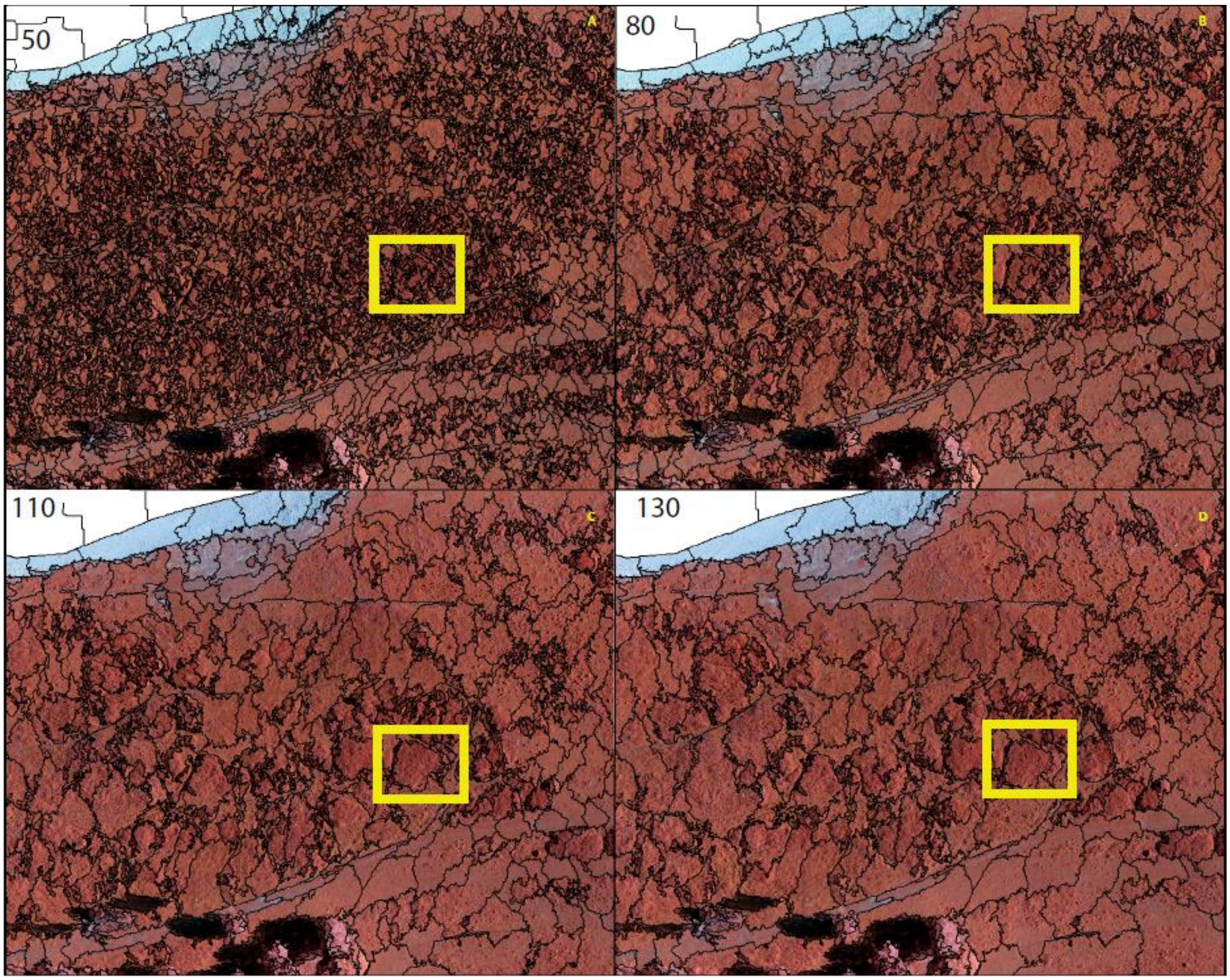

Figure 14. Results of segmentation with different scale parameters. Used parameter is displayed in the top left corner (A-D). The yellow boxes show the reference patch, containing nettle brushwood according to the plot, and has a diameter of ~12 meters. The yellow box is situated at X,Y = 138980, 424980.

Last of all, these two weighted values for compactness and shape (default at 0.5 and 0.1) were refined. Three meter-scale patches, appearing as homogeneous brushwood vegetation (validated for the largest, plot 21) were selected as they were assumed to be potential habitats for the smallest fauna species, *C. russula*. Combinations of values for these variables were tested on this subset and the best combination, resulting in a low number of segments which follow the patch' edges with little overlap, was used. The patch' edge depends on how much variation is allowed within a patch, but here the edge is defined by visual assessment.

5.4.2 Classification

Besides the segmentation rules, additions to the rule set (set of processes) are necessary to obtain a refined classification. These classification rules have an 'assign class' algorithm. The classes, or ecotopes, are listed in the 'class hierarchy', which is developed by the user. The rules were established by an interactive process of trial and error. Every rule was tested separately before adding another.

To start with, 10 plots containing vegetation with H_v < 2 m were selected to function as training plot (Appendix D). Segments within these plots which have the same visual appearance and are predominant were then selected. The feature values of these segments were compared and generalized, leading to one or more threshold conditions. As an example, the data of the DEM was used to classify trees (≥ 3 m). One threshold condition can be previewed within the 'Feature View' window in eCognition Developer (Figure 15), highlighting every segment meeting the threshold condition.

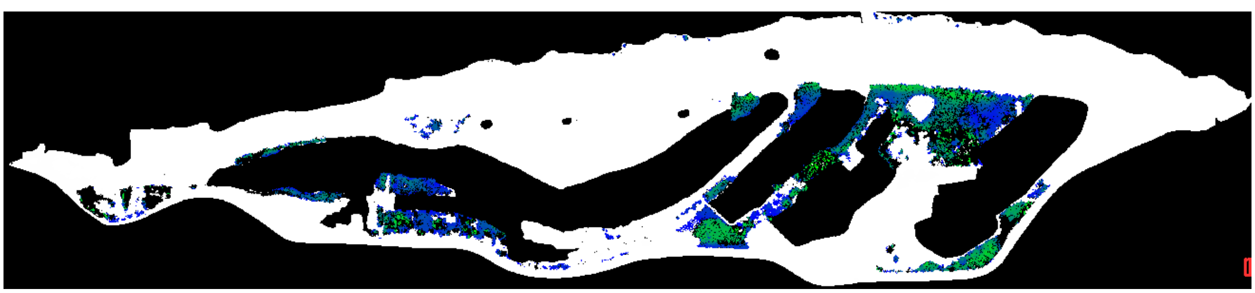

Figure 15. Feature view of threshold condition DEM ≥ 3 m and ≤ 20 m in November image. Blue colours represent segments which have values approaching the threshold values, while green segments have values in the heart of the range.

Besides elevation values, every segment has 'object features' (layer values, shape, position), scene features (brightness) and class-related features (context information about neighbours) (eCognition, 2010). Object features include mean layer values of NIR, green and blue but also brightness and SD values. To generate extra information on vegetation from the layer values, a customized NDVI object feature was created, according to the formula used by Rouse et al., (1974):

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \quad (1)$$

As the NIR image used as input in eCognition Developer includes a NIR band instead of the visible red band as in RGB imagery, the formula was converted to:

$$NDVI = \frac{(Mean\ NIR - Mean\ Blue)}{(Mean\ NIR + Mean\ Blue)} \quad (2)$$

By comparing different segments which belong to the same ecotope class according to the reference plot, the range of these features for this specific ecotope was determined and added to the rule set. After running the process, segments meeting the criteria of the rule were coloured according to the colour set for the specific class in the class hierarchy.

The classification needed further refinement as some segments had the same features in one of the layers but belong to a different class. For example, spectral similar segments were separated by adding height data as an extra threshold. Also variability in height was used as a measure of homogeneity by using a threshold including standard deviation. A dense shrub will have a lower standard deviation than a more open one, for example. The other way around, there were segments which did belong to the already classified object but bore different object features as the object core was often different from the edge. In these cases the classification was refined by using context information. For example, segments which had a high common border to the classes already classified were assumed that they also belonged to the class they shared the common border with. Such context information was also used for pioneer vegetation, as this ecotope often occurs on the borders of sand bodies. Also, shape information was used to generalize objects or separate them by size. After the classification segments are merged to become objects and an area threshold was set to leave out small internal segments (< *x* pixels) not belonging to the larger object.

The last step in the process was to export the categorical map (algorithm ‘export vector layer’) as a shapefile, containing all classes. Then the shapefile was converted to a GeoTIFF raster layer using ArcMap 10.3.1. and further (pattern) analysis was done.

5.4.3 Pattern analysis

Pattern analysis was performed with FRAGSTATS freeware (McGarigal et al., 2012). This software is developed to perform analysis on a patch-, class- and landscape scale. To start with, a FRAGSTATS model was created, containing all information necessary for performing an analysis. As FRAGSTATS is unable to allocate enough memory for the analysis of a complete categorical map, the three largest areas (sub-landscapes bordered by waterbodies, trees or artificial borders) containing both grasslands and brushwoods were taken as subsets to do three separate analyses (Figure 16). After the extraction in ArcMap 10.3.1., the first layer was imported in FRAGSTATS.

Figure 16. Reference map to indicate the sites of the different sub-landscapes.

The next step was to create a class descriptors table. This table is used to specify a description for each numeric class value. This value is equal to the class value given in ArcMap and can be found in the table as 'ID'. As the research includes connectivity, additional information is needed. This spatial pattern is calculated by using a threshold distance, the distance within patches are considered to be connected. In this case, that threshold was set according to the possible migration range of the two fauna species. These values were derived from the home ranges, the area in which an animal lives and moves, of the two fauna species. A patch was considered square as FRAGSTATS equals a square shape to 1 and the value increases with increasing irregularity. Furthermore, an animal was considered to act from the centre of its habitat and thus never crosses it diagonally (which is the action diameter). Therefore, the maximum migration range was chosen to be equal to one side of the square, being 11 and 45 meters, respectively (~ $\sqrt{125}$; ~ $\sqrt{2000}$).

The metrics calculated by FRAGSTATS were carefully selected according to the known habitat preferences of the two target species. In terms of patch characteristics, area and shape were calculated from FRAGSTATS (Table 3). For spatial patterns such as landscape heterogeneity and fragmentation; class area, relative abundance, number of patches, and Connectance index were calculated on a class-level, and two diversity metrics were selected to calculate biodiversity on a landscape scale. Shannon's Diversity Index (SHDI) is a popular measure used in community ecology (McGarigal, 2014). It is based on the theory that the more classes present, and the more equal their proportional abundances are, it is harder to predict a pixel's class and diversity increases. It is calculated as follows (Shannon 1948):

$$SHDI = -\sum_{i=1}^{m} (P_i * \ln P_i) \qquad (3)$$

Where P_i = the proportion of the landscape occupied by class *i*. If the landscape is completely homogeneous, i.e. is only containing one class, SHDI = 0. As SHDI ≥ 0 without limit, it can be used as a relative measure to compare different time-steps.

Simpson's Diversity Index (SIDI) is another popular diversity measure in community ecology (McGarigal, 2014). This measure represents the probability that two randomly selected pixels would belong to the different ecotopes and is calculated as follows (Simpson, 1949):

$$SIDI = 1 - \sum_{i=1}^{m} P_i^2 \qquad (4)$$

The range of this value is between 0 (considering a landscape with one class) and 1, where an increasing SIDI relates to a more proportional distribution of area among ecotopes, becoming more equal in size. This measure is, as opposed to SHDI, both a relative and absolute measure as it represents a probability.
Furthermore, total landscape area was calculated to correct for relative metrics of the three sub-landscapes before summing them up.

Table 3. Used patch-, class- and landscape metrics from FRAGSTATS and their symbology, description and the reason of use.

Patch	**What?**	**Why?**
PID	ID of the patch	For linking shape objects to data
AREA	Area of patch (ha)	To filter out patches > 125 & 2000 m^2, to find pattern on patch size
SHAPE	Shape index a patch, range ≥ 1	Finding patch shape pattern

Class	**What?**	**Why?**
CA	Total class area (ha)	Finding patterns as evenness, heterogeneity
PLAND	Percentage of the landscape	Finding patterns as evenness, heterogeneity
NP	Number of patches per class	Spatial arrangement, fragmentation
CONNECT	Connectance index (%)	Spatial arrangement. Gives percentage of patches that is connected within the migration range.

Landscape	**What?**	**Why?**
TA	Total area	Calculating relative areas of the three sub-landscapes.
SHDI	Shannon's Diversity index	Landscape heterogeneity, biodiversity
SIDI	Simpson's Diversity index	Landscape heterogeneity, biodiversity

Connectance index is a percentage that represents the extent in which the patches of classes are linked. This index equals 100% if all possible joinings between patches of the corresponding patch type are within the threshold distance of each other. If the distance between two patches is larger than this threshold, the connection index decreases. Beside the Connectance index another connectivity measure was calculated, as this index is a relative measure for the connectivity within a class. Finding connectivity of the landscape for fauna species which inhabit multiple ecotopes and therefore be able determine possible migration required an extra step. A shapefile containing all objects from a sub-landscape was filtered on area ArcMap 10.3.1., leaving only all brushwood objects with AREA ≥ 0.0125 or 0.2 ha. A search radius, set to 11- or 45 m, determines if there is a possible migration route between two objects if they are situated within this range from each other.

To compare, data of different time steps were plotted to visualize spatial and temporal patterns, as well as the temporal behaviour of patch characteristics. Temporal patterns provide useful information on the temporal behaviour of patch characteristics as trends in patch area have direct influence on the landscape occupation. These patterns were related to floodplain fauna and their preferences, to be able to determine the habitat suitability.

5.5 Evaluation

5.5.1 Evaluation of segmentation

Following Geerling et al. (2009), segmentation was considered successful when the segments fully cover the ecotope (i.e. does not cover parts outside the ecotope) and the number of segments patch is low

(Figure 17). Results where every patch was captured by a single segment without overlapping areas outside the patch were not encountered.

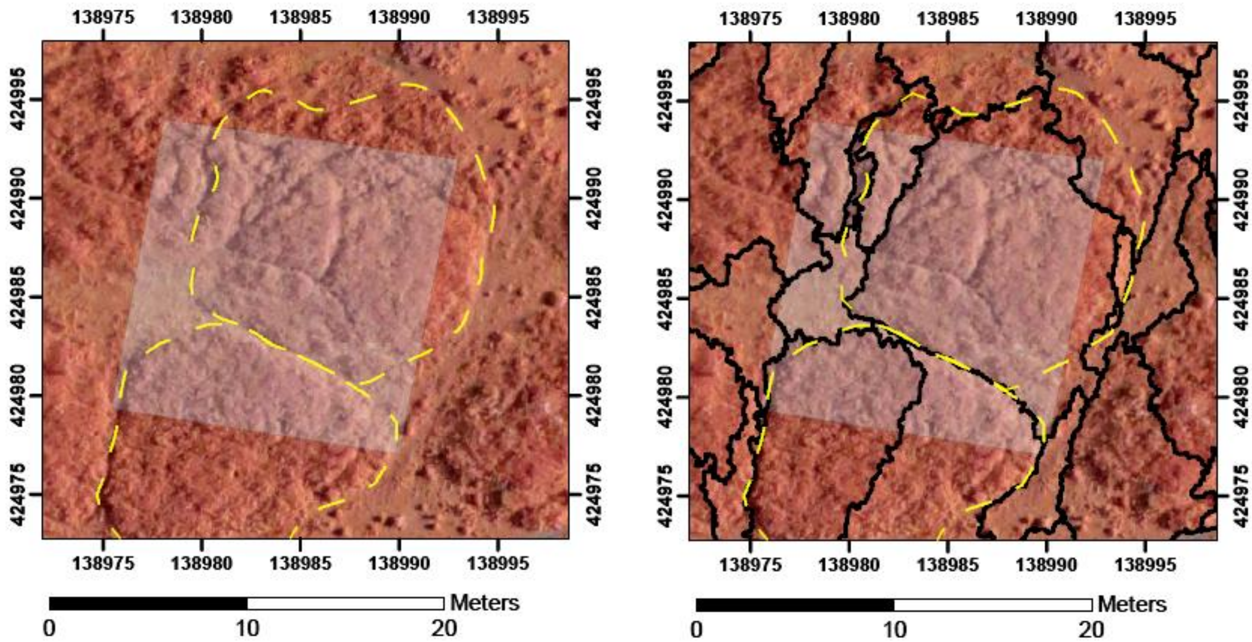

Figure 17. Visualization of a successful segmentation as used for classification of the June image. Two patches (yellow dashed lines) are captured within 5 segments, with little overlap. The white washed areas represent plot 21.

5.5.2 Evaluation of classification

Natural grass- and hayland is recognized by a relatively homogeneous matrix with many small clumps of low herbaceous vegetation. Brushwood has darker colours in the NIR imagery during June; but is relatively grey during winter conditions. The inserted rule, applied to one class at a time, should only classify these visually separable areas. As the rules are based on ground truth data, the classification was considered successful when this visual control satisfied. Furthermore, objects should be obtained according the size of the habitats of the species of interest. The objects were compared to the data in the plots (those which have not been used to classify), to determine the classification accuracy. To do so, the classified segments of five plots, containing natural grass- and hayland and brushwoods were exported and compared to the NIR image of the same time-step. This image provides (sometimes necessary) additional visual information on ecotope variation within the plot (from the ground truth), as some plots are not homogeneous. The use of plots results in an accurate validation; regularly used point measurements do not represent a patch due to internal heterogeneity (Straatsma & Huthoff, 2011). Every classified segment present in the plot was compared to this ground truth information and it was determined whether the classification was correct. This information was summarized in a confusion matrix, containing accuracy and reliability. Accuracy represents the fraction of correct classified segments with regards to all segments of ground truth class and is also referred to as producer's accuracy. Reliability (also known as user's accuracy) is the fraction of segments classified correctly with regards to all segments classified as this class in the image. Last of all, the overall accuracy represents the fraction of correctly classified segments with regards to the total number of segments. Furthermore, the obtained map was compared to other validated Dutch ecotope maps and the latest (unpublished and invalidated) version of the ecotope map published by RWS (fourth cycle, 2012).

To summarize, when monitoring (potential) habitats of small floodplain fauna, the first step is to obtain field data. Next, high resolution images taken by a UAV were processed so that pixels are grouped into segments representing small homogeneous areas. The field data was then linked to the segments and a phase of trial and error determined what feature values are the most useful for specific ecotope classification. After classification, the obtained maps were used to derive most important patch characteristics (vegetation type, area and shape) and patterns (landscape heterogeneity, connectivity). Last of all, using multiple time steps the viability of the landscapes was analysed over a one-year period.

6. Results

6.1 Segmentation

First of all, the right scale parameter had to be found (Figure 12). The scale parameter of 15 used by Addink at al. (2007) is too small as too many segments comprise single ecotopes. The same applies to scale parameters 50 and 80 (Figure 18A and 18B). A scale parameter of 110 seemed to suit the small brushwood patches (Figure 18C), while a slightly larger scale does not improve this fit (Figure 18D). The number of segments is smaller, but the scale parameter of 110 was selected as the possibility to classify smaller objects is kept.

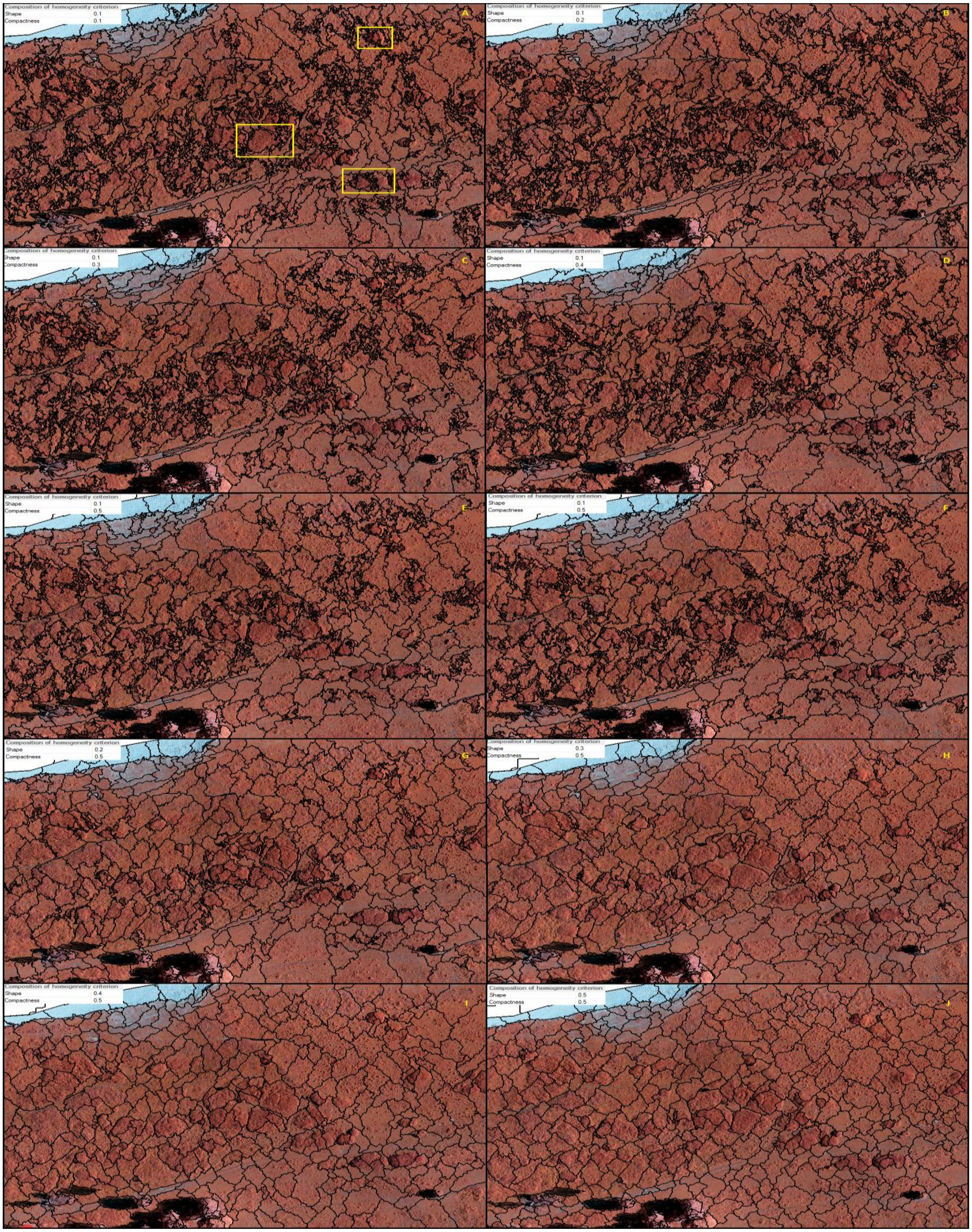

Figure 18. Segmentation results (A-J) within a subset selection (situated in the centre) of the floodplain. Segmentation settings are displayed in the top left corner. Three patches within the yellow boxes were used for segmentation analyses. The most left yellow box is situated at X,Y = 138980, 424980.

A segmentation was considered successful when the number of segments per patch is small, and the coverage of segments per patch is high (i.e. segments do not cover area outside the ecotope). The default values (shape = 0.1; compactness = 0.5) result in many segments per ecotope. First of all, the value for compactness was increased (Figure 19 & 20). There is no explicit trend in the number of segments per ecotope, but the segments better follow the patch' outlines as the number of segments exceeding the underlying perimeter decreases, with the least number of overlaps at value 0.5. The number of segments was also lowest here, and the segments seem to become less irregular (Figure 18 A-E).

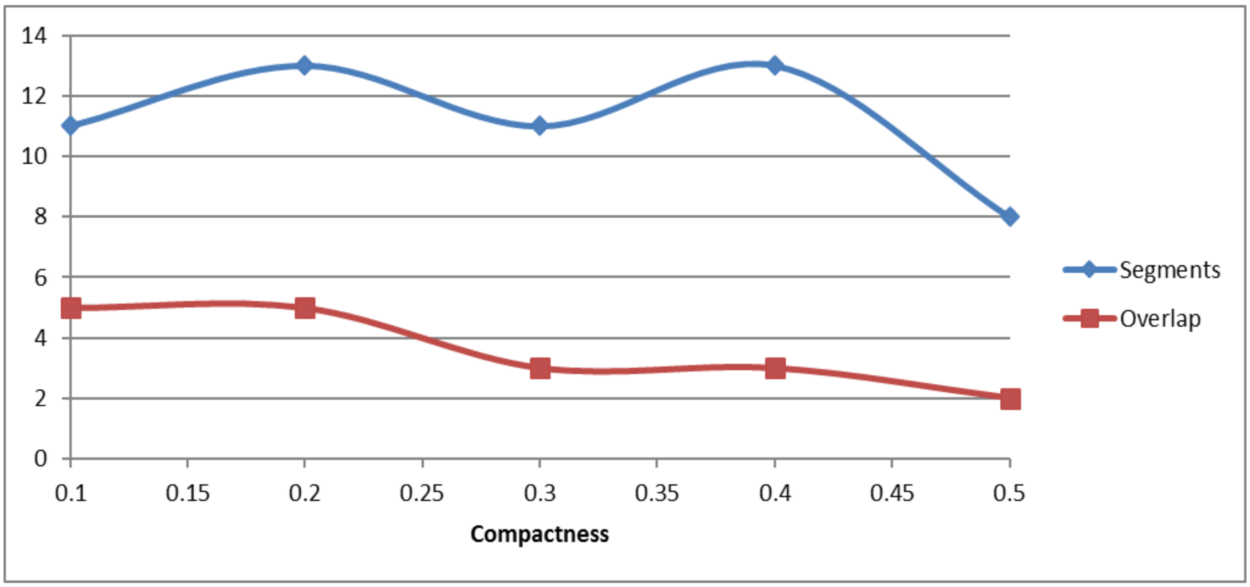

Figure 19. Number of segments within the three patches and number of overlaps (y-axis) for the five compactness values.

Next the value for shape was increased (Figure 18 F-I), while maintaining the value for compactness fixed at 0.5. The number of segments had likewise changes as seen with increasing compactness, but the lowest number of segments was found at value 0.3 (Figure 20). When the shape value increases, the fit is of lower quality and the number of overlaps increases.

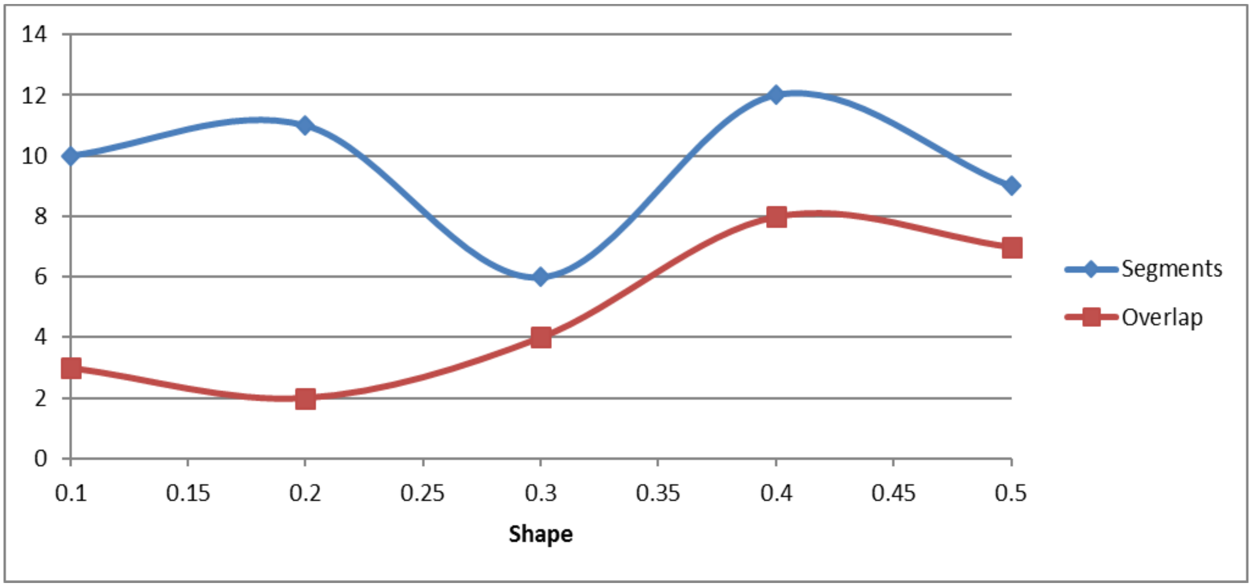

Figure 20. Number of segments and number of overlaps (y-axis) for the five shape values.

For the image of June, the segmentation settings of Figure 18H (shape = 0.3; compactness = 0.5) were selected as this results in the lowest number of segments per patch. When comparing this to the other settings (Figure 18F & G), the number of overlaps is lower, but the total number of segments is substantially higher. For the other images (November, February) the values where set default, as there is less contrast in those images due to the loss of vegetation during winter and thus the value of shape could be decreased. This results in more segments per object, but the segments do follow the visible patch edges.

6.2 Classification

6.2.1 Feature selection

In general, the order of classifications within the classification tree was similar for every time step. First of all, sand was classified using the blue layer values and segments sharing a high relative border with sand were included as these form a transition between sand and pioneer vegetation. Second, water was classified as it has characteristic low or negative NDVI values. Trees are characteristic as they have high (and also negative in the used layer) DEM values. These three classes were classified according to field observations and visual interpretation. Reed was classified according to its height (DEM; > 0.9m). Pioneer vegetation was classified by assuming that this ecotope is always present at the borders of sand bodies, if those bodies are not already classified as water. Segments with low NDVI values were also classified as pioneer vegetation. Production grassland was classified using low standard deviations, due to uniformity of this ecotope in all spectral layer values and in the DEM. Nettle brushwood contains more vegetation species and can reach relatively high values in the DEM, resulting in a relative high internal heterogeneity. Therefore, these segments were assigned to nettle brushwood using the high standard deviations of the DEM (Figure 21). The classification of this ecotope was refined using the mean difference in the DEM of neighbouring segments, i.e. positive values of these surrounding segments indicate higher DEM values and do not belong to the nettle brushwood class. Additionally, for the February and November images, high brightness values were used as the dead, woody vegetation occur bright. The most homogeneous ecotope left is natural grass- and hayland, as it contains grasses and some herbs, instead of a variety of brushwood vegetation. This ecotope was assigned to the unclassified segments with a low standard deviation value in the DEM feature. Furthermore, segments within the plots used for classification had low values (< 10) in the NIR layer and a specific range of blue during summer. Leftover dark, unclassified segments were assigned to the shade class using their low values in the blue layer. Last of all, dry brushwood was classified using combinations spectral values (blue, brightness, NIR) and was refined using the mean difference of the DEM to neighbouring segments.

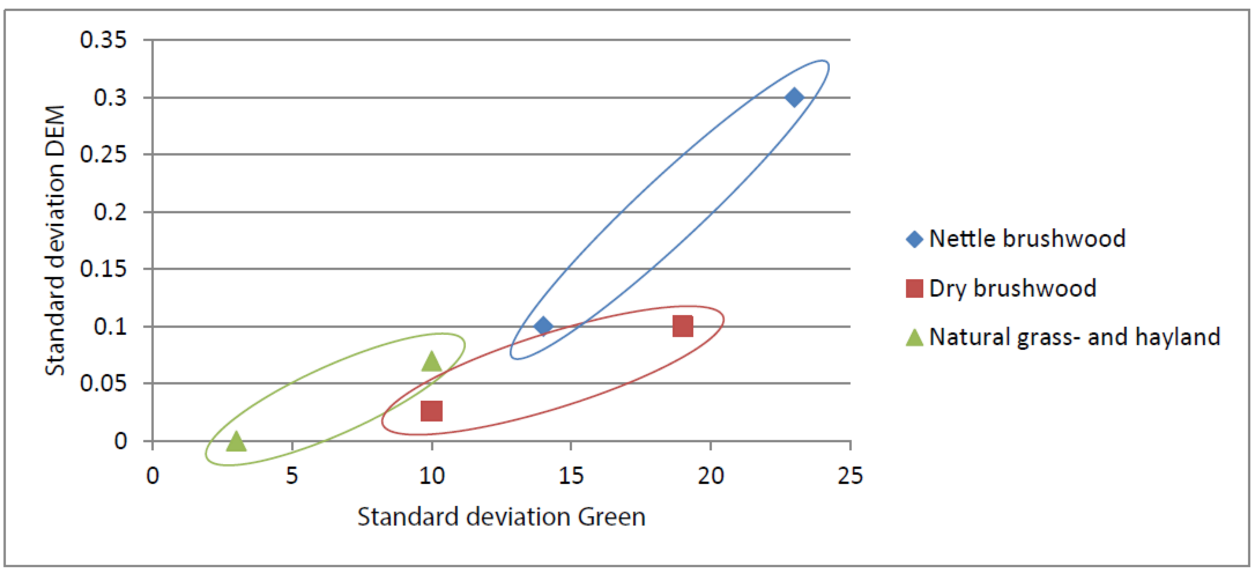

Figure 21. Feature space showing natural grass- and hayland, nettle- and dry brushwood with their ranges for SD DEM and SD green, in June.

As most ecotopes share several spectral values it is hard to determine the right combination of parameters and there are multiple possibilities, as also ecotope composition changes. First of all, the SD values of the green- and DEM layer provided enough information to separate the brushwood ecotopes and natural grass- and hayland (Figure 21). The combination of these two is the only one found which could almost fully separate these three ecotopes with two criteria during this time-step. Second, NDVI in combination with blue layer values is a good combination for separating nettle brushwood from spectral similar ecotopes in June (Figure 22). In practice, after using DEM for classification of the brushwood patch cores, relations to neighbours were used to define the edges. For further, more detailed classifications, or for images with less contrast, an extra criterion is welcome.

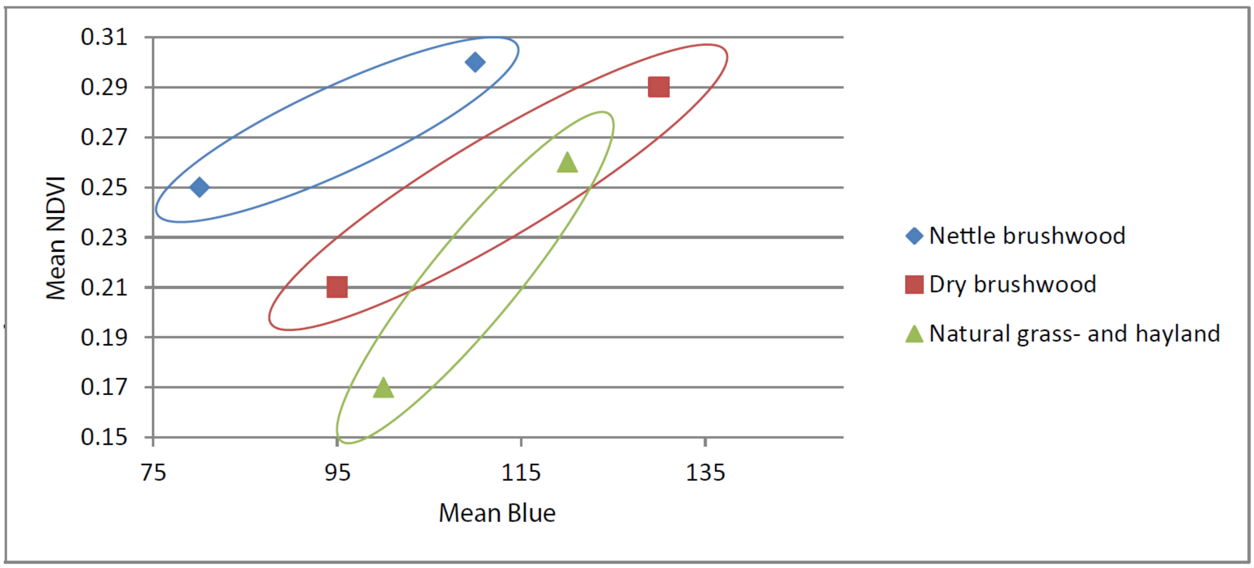

Figure 22. Feature space showing natural grass- and hayland, nettle- and dry brushwood with their ranges for mean NDVI and mean blue, in June.

To summarize, some ecotopes were classified by using only one feature. Most used features were the mean layer values (blue, DEM, NIR, brightness). Additionally, standard deviations were used to classify most homo- and heterogeneous patches and relations to neighbours were used to refine or define boundaries. For most classes, one parameter is not sufficient to classify the whole class. The right combination of object features needs to be found in order to make a satisfying classification. Also the layer values have to be adjusted for new images which could lead to an overlap in values with another class.

6.2.2 Classification accuracy and reliability

The accuracies for the three produced ecotope maps, based on the vegetation plots, are expressed in average accuracy, average reliability and overall accuracy (Table 4-6).

Table 4. Confusion matrix of Natural grass- and hayland (NGH), Dry- (DB) and Nettle brushwood (NB) segments in February. Rows correspond to the classes in the ground truth, columns to the classes in the classification result. Accuracy (ACC) represents the producer's accuracy; reliability represents the user's accuracy.

		Classification Results			
		NGH	DB	NB	ACC
Ground truth	NGH	**32**	0	0	1
	DB	0	**0**	0	-
	NB	3	4	**5**	0.42
	REL	0.91	0	1	

Average accuracy = 70.8 %

Average reliability = 63.8 %

Overall accuracy = 84.1 %

No segments were classified as dry brushwood, so the accuracy is solely dependent on the other two classes. While ecotope nettle brushwood has a low accuracy, the reliability is high. Furthermore, the accuracy of natural grass- and hayland is perfect. NB is both classified as NGH and DB.

Table 5. Confusion matrix of Natural grass- and hayland (NGH), Dry- (DB) and Nettle brushwood (NB) segments in June. Rows correspond to the classes in the ground truth, columns to the classes in the classification result. Accuracy (ACC) represents the producer's accuracy; reliability represents the user's accuracy.

		Classification Results			
		NGH	DB	NB	ACC
Ground truth	NGH	**11**	2	0	0.85
	DB	1	**24**	1	0.92
	NB	0	3	**22**	0.88
	REL	0.92	0.83	0.96	

Average accuracy = 88.3 %

Average reliability = 90.0 %

Overall accuracy = 89.1%

Average accuracy and reliability are highest for the classification of June. The same accounts for overall accuracy. The reliability of DB is lowest in this classification and is both confused with NGH and NB.

Table 6. Confusion matrix of Natural grass- and hayland (NGH), Dry- (DB) and Nettle brushwood (NB) in November. Rows correspond to the classes in the ground truth, columns to the classes in the classification result. Accuracy (ACC) represents the producer's accuracy; reliability represents the user's accuracy.

		Classification Results			
		NGH	DB	NB	ACC
Ground truth	NGH	**21**	4	0	0.81
	DB	5	**4**	0	0.44
	NB	0	5	**40**	0.89
	REL	0.81	0.31	1	

Average accuracy = 78.6 %

Average reliability = 70.5 %

Overall accuracy = 82.3%

The classified map of November shows misclassifications in every ecotope. One out of five NGH segments was classified as DB, while more than half of DB segments were classified as NGH. NB was confused with DB during classification. The overall accuracy is slightly lower than the overall accuracy of February but the map has a higher average accuracy and reliability.

Of all three maps, the overall accuracy is higher than 80%. The ecotopes used to calculate accuracies and reliabilities were proven to be hard to distinguish in former ecotope classifications and their accuracies remained low. However, the method used in this research resulted in accuracies and reliabilities of 88 & 90% for the month of June, the period in which the ecotope mapping of RWS is also performed.

6.2.2 Ecotope maps

The ecotope map derived from the UAV imagery of February (Appendix E) mainly consists of the ecotope natural grass- and hayland. This matrix is interrupted by small patches of dry- and nettle brushwood. The northern boundary consists of sand bodies with pioneer vegetation, alternated with small waterbodies and single trees. Production grassland on the east side of the map is separated by natural grass- and hayland.

The second ecotope map (Appendix F), derived from imagery from June 2015, is dominated by large dry brushwood objects. Production grassland forms one object and is bordered by two objects of natural grass- and hayland. Those two objects were also present in February, although they are now more interfered by patches of brushwood. Within the dry brushwood matrix, the pattern (N-S) of ditches and dikes is visible in the centre of the Breemwaard, bordered by two long corridors of natural grass- and hayland (W-E). One leads to the western part of the floodplain, which consists of a large area of nettle brushwood, surrounded by natural grass- and hayland. Altogether, this map has the most even distribution of ecotopes in terms of landscape occupation (Figure 23).

In November, the amount of natural grass- and hayland has increased at the expense of dry brushwood (Appendix G). When compared to the ecotope map of June, the two (widened) corridors and the pattern of ditches and dikes in the centre of the floodplain are still visible. The nettle brushwood ecotope in the western part of the floodplain seems unaltered.

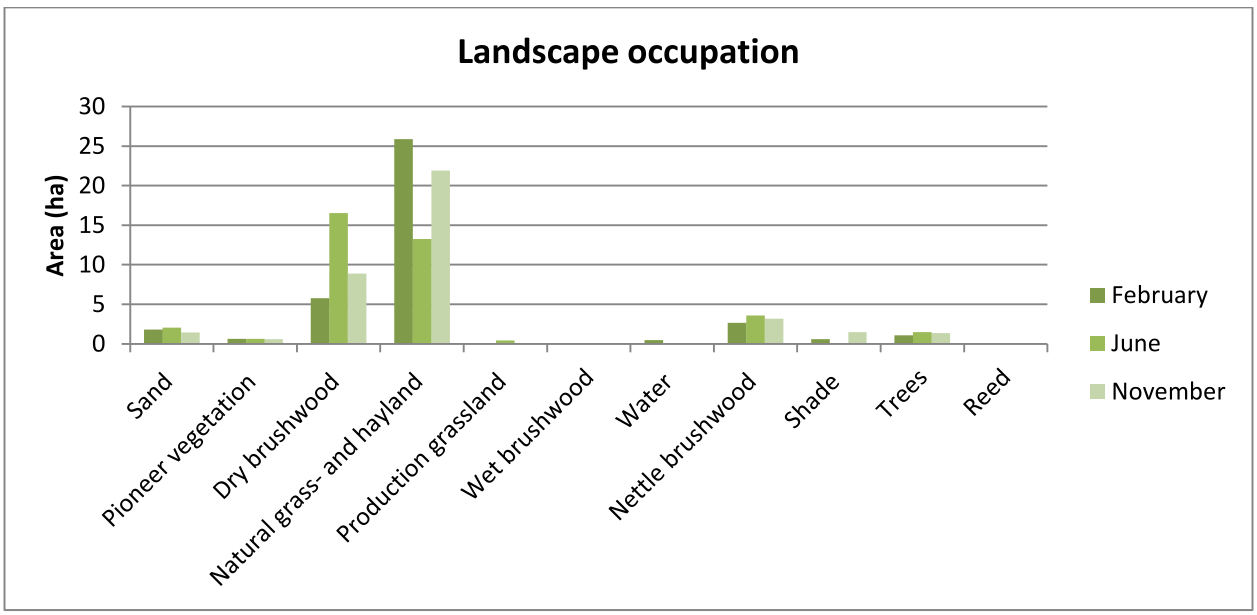

Figure 23. Landscape occupation of sub-landscapes in hectares per ecotope.

From figure 23, it becomes clear that towards summer, natural grass- and hayland is replaced by 1) dry brushwood 2) nettle brushwood and 3) sand bodies (Figure 23). In November, the amount of brushwood decreases and natural grass- and hayland is dominant. This trend is continued towards February, although the trend attenuates.

From February to June, the number of dry brushwood patches decreases (Figure 24), as this ecotope becomes the matrix in June and forms one large patch. The same but reversed process occurs towards

November. The matrix decreases in size and fragments, and underlying grasslands become visible on the aerial photographs. This results in a matrix of grass- and hayland and the number of brushwood patches increases. The other way around, the number of natural grass- and hayland patches decreases, although it reaches its optimum in February. Nettle brushwood is never the dominant ecotope and the total area of this ecotope decreases after the summer. Also the total number of patches is lowest in November. A decrease in the number of patches could be the result of some patches disappearing instead of being fragmented.

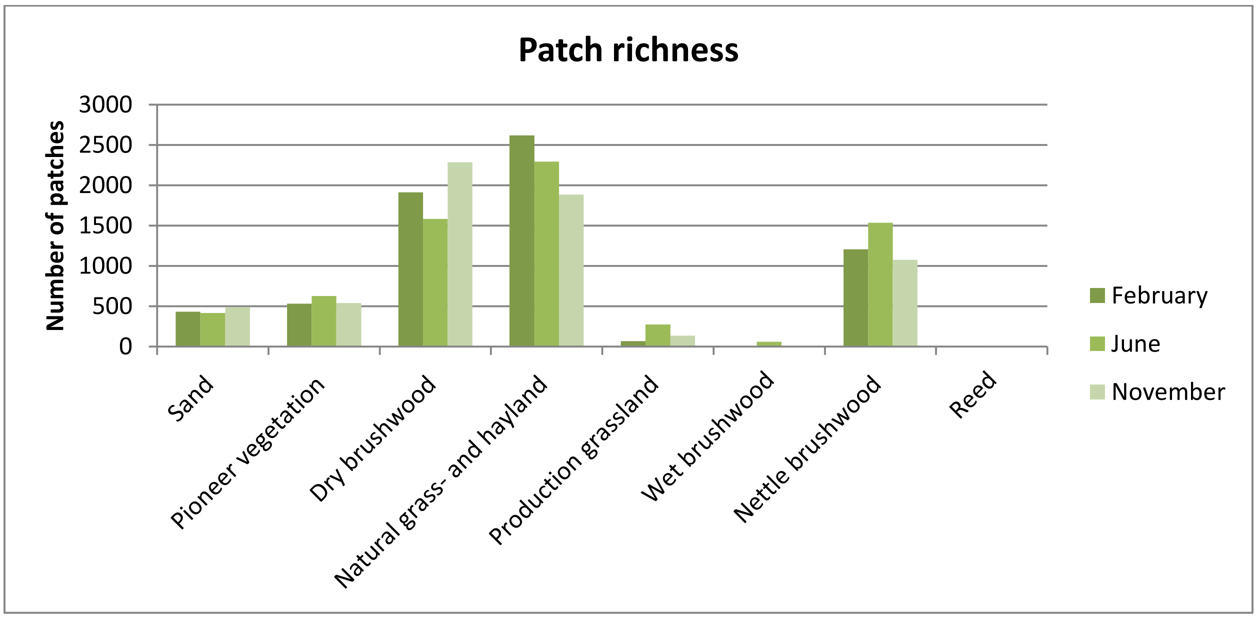

Figure 24. Number of patches of sub-landscapes per ecotope.

6.3 Ecotope patterns

6.4.2 Patch-level patterns

Patch area

The first important feature characteristic is the size of a patch. As area is one of the limiting factors in habitat suitability, it is of interest to monitor the number of large patches (≥ 0.0125 ha). To understand the development of such patches, also the smaller patches are considered (Figure 25).

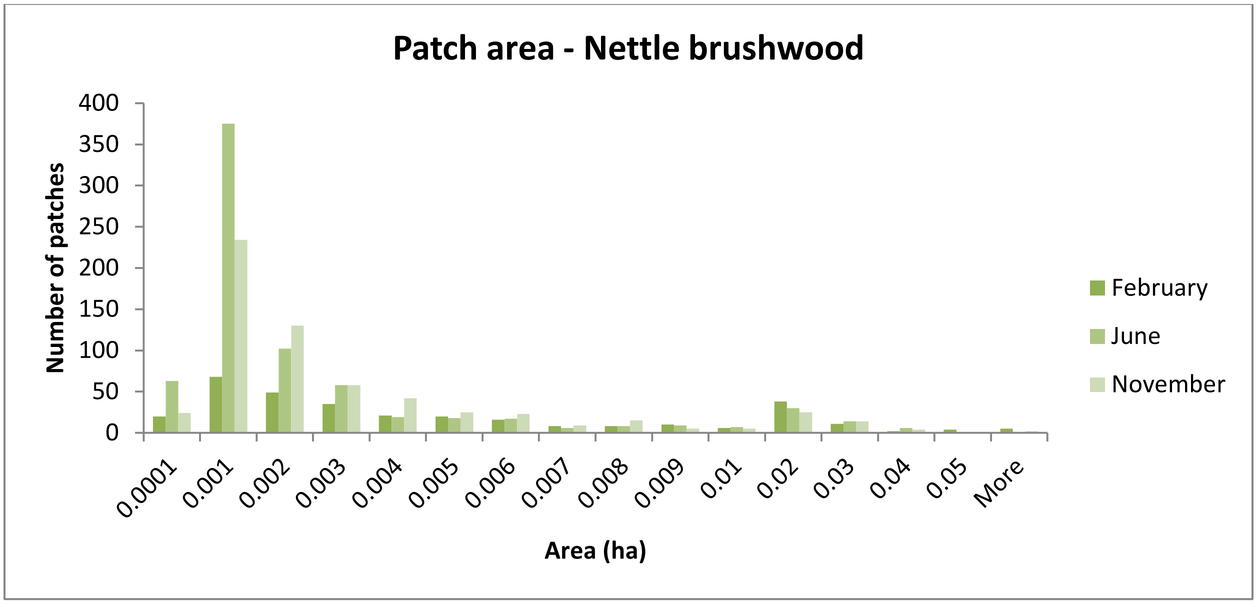

Figure 25. Patch area of nettle brushwood in three time-steps. Vertical axis gives the number of patches in the histogram bin (range of area). Note: bin-distribution is not uniform.

In all three months, most nettle brushwood patches are within the second smallest category (0.0001-0.001 ha). From this point, the number of patches decline exponentially. February has the lowest number of patches, while most patches are present in June. The total numbers of patches > 0.0125 ha are respectively 47, 53 and 33; with corresponding average areas of 0.04, 0.05 and 0.06 ha. This indicates that the smallest patches in this range disappear from June to November. In all three time steps one patch > 0.2 ha (‘more’, figure 25) is present. This patch, situated in the western part of the Breemwaard, shows the same temporal pattern as it expands from February to June (0.6 – 0.7 ha) and reaches its optimum in November (1.1 ha).

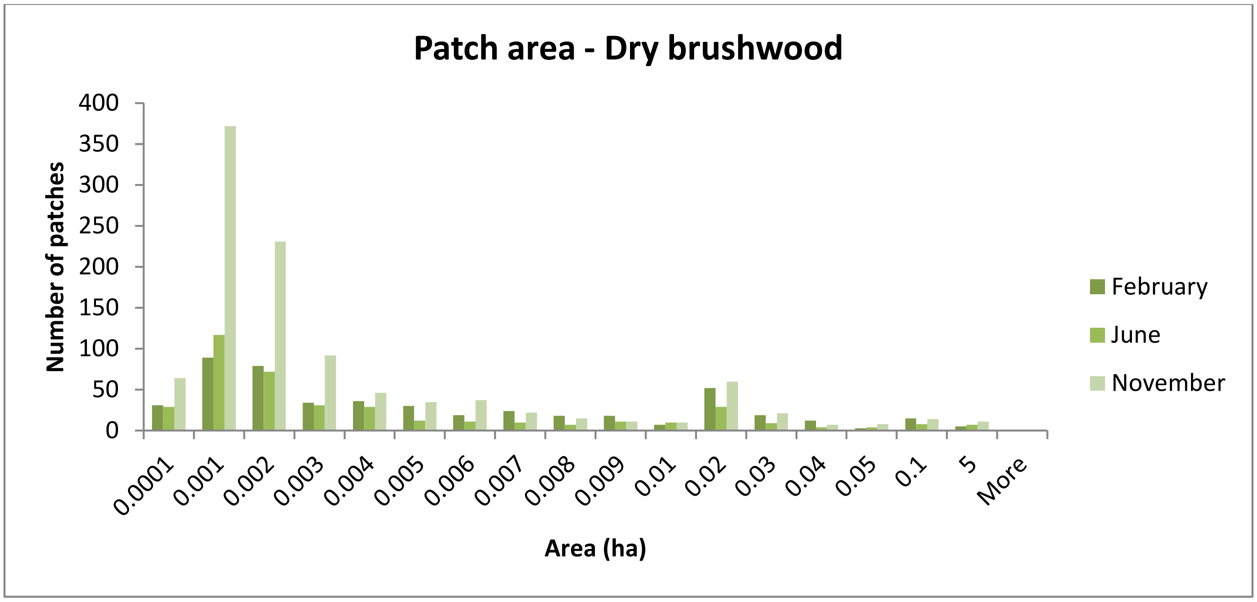

Figure 26. Patch area of dry brushwood in three time-steps. Vertical axis gives the number of patches in the histogram bin (range of area). Note: bin-distribution is not uniform.

Patch areas of dry brushwood in November have an alike distribution as nettle brushwood (Figure 26). However, February and June have a relative even distribution of patch areas. Additionally, more patches are within the range of > 0.2 ha (Table 7) and June has the largest patches (and average area) as dry brushwood is the ecotope forming the matrix at this time step. Consequently, the number of patches is lowest in June, while it is highest in November. These temporal patterns might relate to fragmentation of dry brushwood as matrix after the summer, increasing the number of patches and decreasing average size. There could also be a link between the loss in patches of nettle brushwood towards November and the increase in dry brushwood in the same time-step.

Table 7. Number of viable patches for both fauna target species, in terms of area.

	≥ 0.0125 ha			**≥ 0.2 ha**		
	February	June	November	February	June	November
Dry brushwood	86	51	104	4	5	5
Nettle brushwood	47	53	33	1	1	1
Total	133	104	137	5	6	6

Shape

Second, the Shape index gives an indication of how complex the patch form is. A value of 1 equals a standard (square) shape, while higher values are an indication of more irregularity. Shape index is calculated by the formula:

$$SHAPE = \frac{.25 * P_i}{\sqrt{a_i}} \tag{5}$$

Where P_i equals the patch perimeter and a_i the patch area, in meters (McGarigal, 2014).

The average Shape index values of nettle brushwood do not change significantly throughout the seasons (Figure 27). In November the patch shapes are most irregular, while the average Shape index in June and February is comparable. However, the range of the Shape index of February is larger than that of June, which indicates as a higher variability in patch shapes in February.

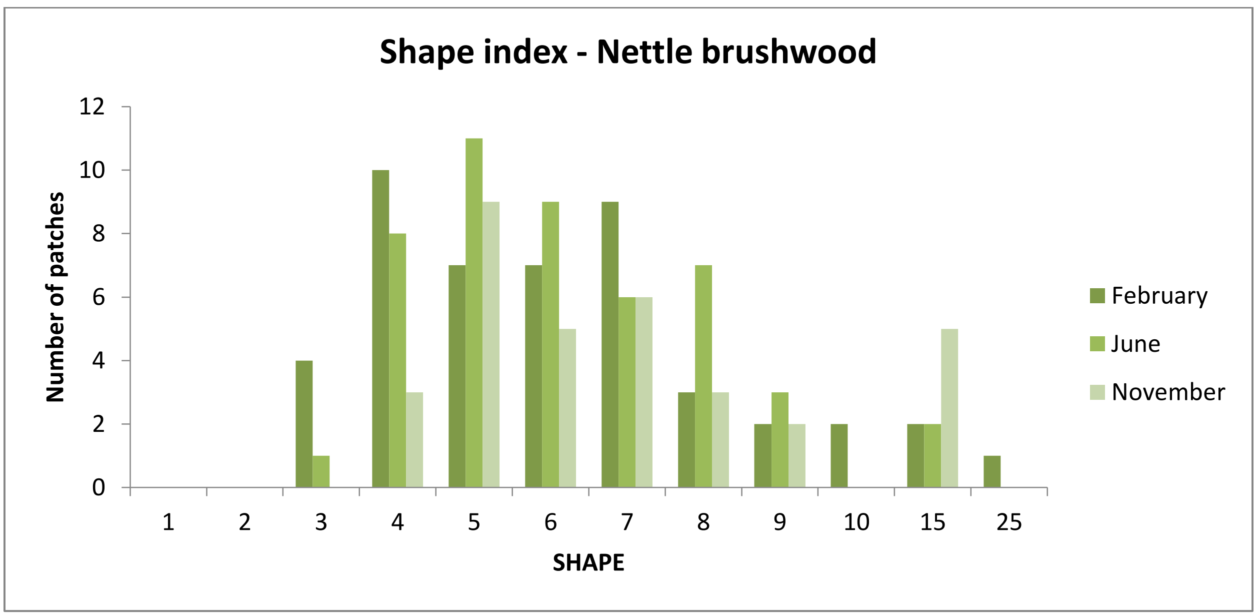

Figure 27. Shape index of nettle brushwood patches (≥ 0.0125 ha) in three time-steps. Vertical axis gives the number of patches in the histogram bin (range of SHAPE values).

Dry brushwood patches are more irregular than nettle brushwood patches, as the average values are higher and the range is bigger (Figure 28). This could be related to the number of patches or the average patch size, which are larger for dry brushwood. As large patches have more edge, irregularity becomes more likely. As seen with nettle brushwood, the shape of dry brushwood is also most irregular in November. The average Shape index is lowest in February.

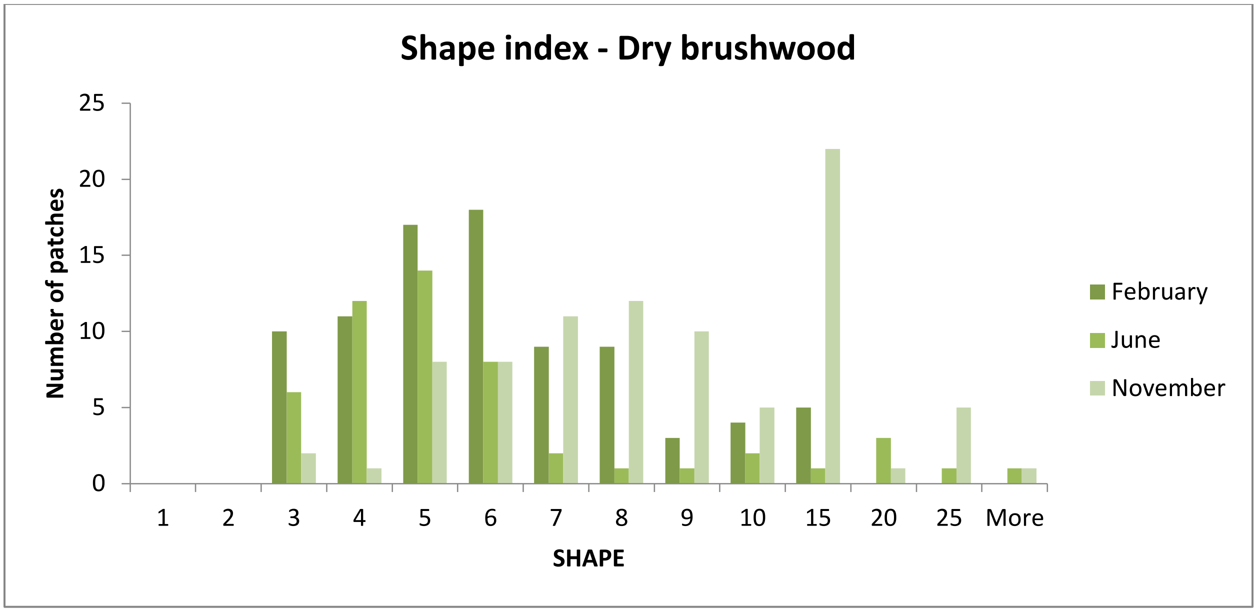

Figure 28. Shape index of dry brushwood Patches (≥ 0.0125 ha) in three time-steps. Vertical axis gives the number of patches in the histogram bin (range of SHAPE values).

The largest brushwood patches (> 0.2 ha) show a similar temporal pattern as is seen in figure 28. Average Shape indexes of the available patches indicate that most irregular patches are present in November (SHAPE ≈ 22), although June has a similar average (≈ 21). February however has significantly more regular shaped large patches (≈ 15), as is also seen in figure 28.

6.4.3 Spatial arrangement and connectivity

The Connectance index can be used as a measure of class connectivity as the threshold represents the migration distance of fauna species. However, this measure does not include patch area. As the threshold for the Whitethroat is higher than for the shrew, the Connectance index of the brushwood ecotopes is also higher for this species (7-15 % versus 1-3 %). For brushwood, the Connectance index is highest in February (Figure 29). The opposite is true for grass- and hayland.

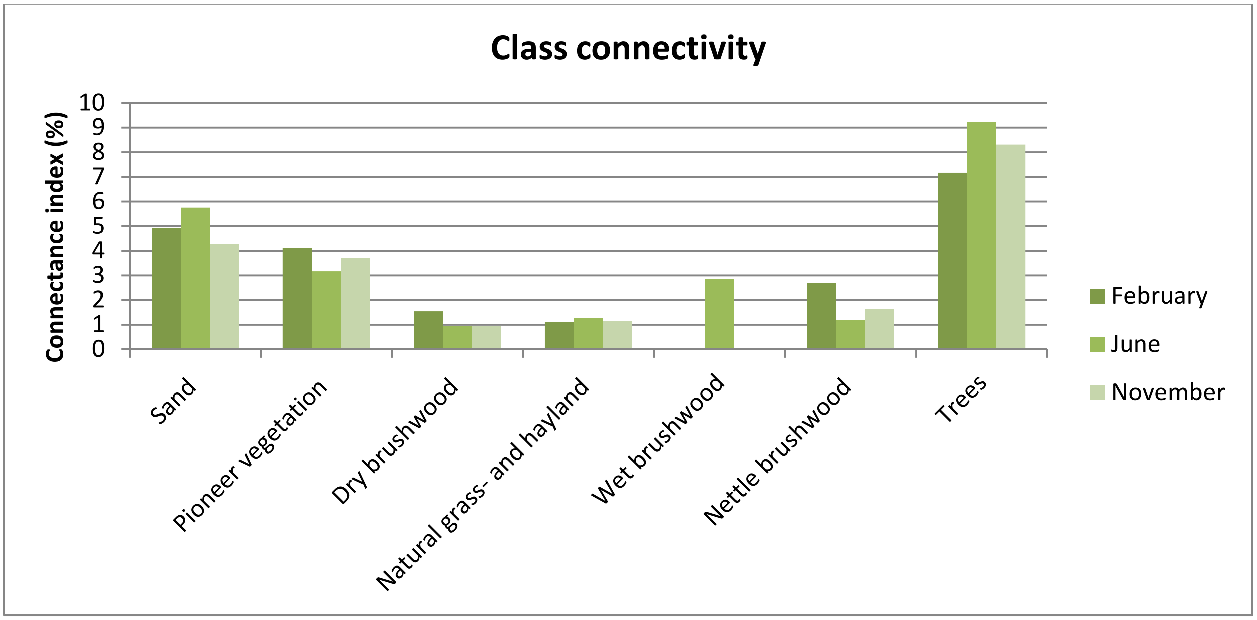

Figure 29. Mutual connectivity (Connectance index) of ecotopes in the three sub-landscapes, considering a 11-meter threshold.

The high Connectance index of February can be explained by both the number of patches (NP) of a class and the class area (CA). For example, the CA of nettle brushwood is highest in the June image (Figure 23). The lower CA in February and November could mean the disappearance of patches as well as fragmentation of a single patch. However, the number of patches decreases towards November, which rules out the latter. Figure 30 illustrates how this can positively influence the Connectance index.

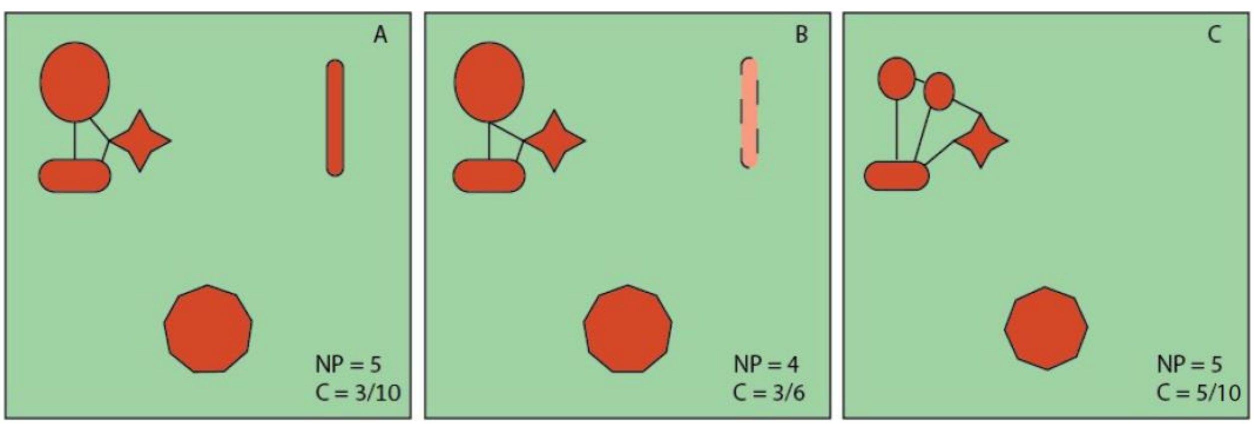

Figure 30. Schematic overview of Connectance index (C) development. A) Situation in June, B) November C) February. A) In this situation there are 10 possible migration routes. However, only three of them fall within the 11-meter threshold. B) With one patch disappearing (dashed line) four possible migration routes are lost, increasing C. C) Due to fragmentation of the round patch the number of patches (NP) increases, the class area decreases but C increases.

Figure 30A shows the situation in June. The Connectance index increases in November due to the decrease in number of patches, also resulting in a smaller CA, while the number of connections stays constant. In February, the number of patches is higher compared to November while the CA is lowest. This is probably the effect of fragmentation, which increases the Connectance index as this measure does not include a minimum patch area. This is supported by the pattern seen in large patches (≥ 0.2 ha), as the number of large nettle brushwood patches is constant over time (= 1) while the Connectance index is highest in the February image. As this patch' size is lowest in this time step, fragmentation of this large patch and disappearance of other small patches could have caused increase the class connectivity.

Patch connectivity is an important factor in species migration and thus species viability, but a patch has to satisfy certain requirements. For *C. russula*, a patch should have a minimum area of 125 m^2. For this purpose, nettle- and dry brushwood are combined.

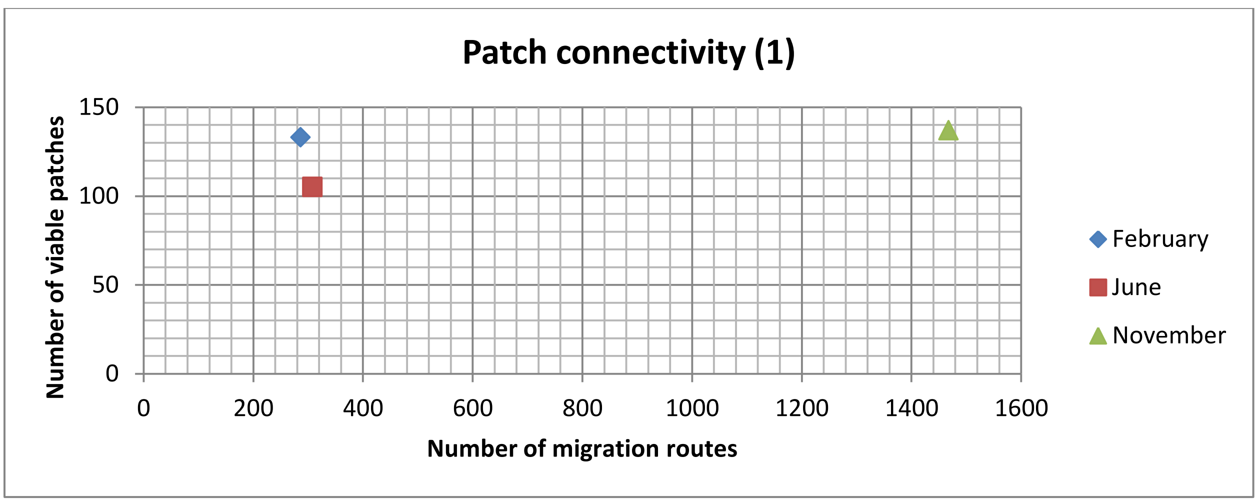

Figure 31. Patch connectivity which is expressed in the number of migration routes (within 11 meters) between viable patches.

When this threshold is applied, the number of possible migration routes in November is highest by far (Figure 31). To identify the source of this high number, the connectivity was separated into sub-landscapes (Figure 32), showing that the high number is related to sub-landscape 2. A few explanations are possible. The first one is fragmentation, which follows the same principle as shown in Figure 30. However, the number of viable patches does not increase significantly (Table 7). Another explanation lies within the distribution of the patches in the landscape, i.e. patches might become isolated and lose connections. However, this would probably occur towards winter instead of vice versa. The last explanation would be the decrease in average patch size. Towards the winter, small patches (around the threshold value) would decrease in size and are excluded. Fragmentation of larger patches would compensate for the number of viable patches. Large patches that fragment into many viable smaller ones create more possible connections (among themselves, Appendix H) than the number of connections that is lost from distant patches that opt out. To validate this, a histogram was computed from viable patches in sub-landscape 2 (Table 8).

Table 8. Histogram data with patch area (Bin) and the frequency of patches ≥ 0.0125 ha.

	February	**June**	**November**
Bin	Frequency	Frequency	Frequency
0 - 0.1	57	53	47
0.1 - 0.2	0	3	3
0.3 - 0.4	1	0	0
0.4 - 0.6	0	1	0
0.6 - 0.8	1	1	1
0.8 - 1.2	0	3	1

The data in Table 8 shows small differences in patch size between June and November. The only major differences can be found in patches ≥ 0.8 ha. In June, the count is three, while this is one in November. These patch areas together are 3.1 and 1.1 ha, respectively.

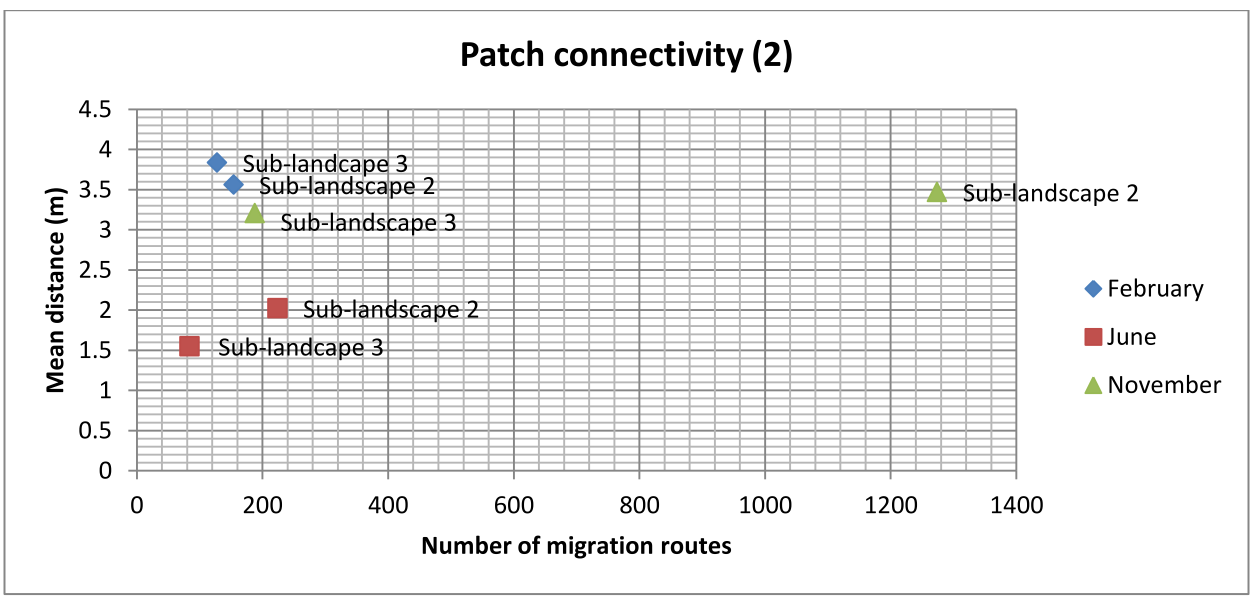

Figure 32. Patch connectivity expressed in number of possible migration routes and mean distance. Sub-landscape 1 is excluded as it includes too little viable patches to form reliable data.

The fragmentation of two of these large patches into some small ones would significantly increase the number of migration routes, as there is a new core which can connect to all its former edges. When one patch divides into two, the number of migration routes could more than double (Figure 33). Also the route works both ways, further catalysing the effect. To illustrate; 100 links form 200 migration routes, while 200 links form 400.

Both the Connectance index and patch connectivity will increase when the migration distance threshold is increased. For example, a landscape is more connected ragarding a larger floodplain mammal or bird with a larger home range (and the same habitat patch area).

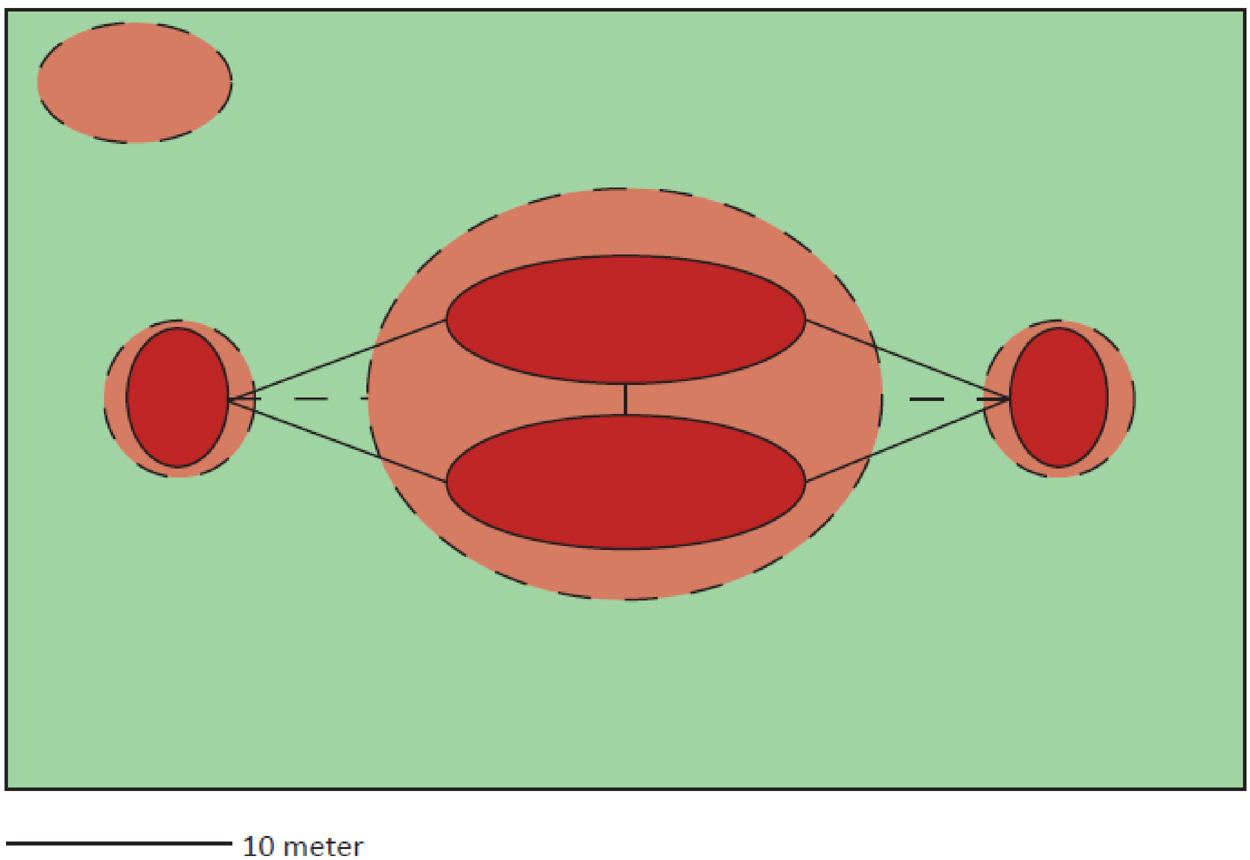

Figure 33. Illustration of increasing patch connectivity with shrinking and divided patches. Dashed lines represent former patch outlines (light red), present patches in dark red. Former migration routes are represented by straight dashed lines, present in straight black lines.

The average length of the migration routes is highest in February (Figure 32). This could be the result of the loss of patch edges and accessory change in angle of the migration routes, which is illustrated in Figure 33. The average patch size and number of migration routes are lower in February compared to November, while the number of viable patches remains unchanged. Such a temporal pattern might be the result of increasing distance between patches (Figure 33), due to the loss of edge, causing loss of patch connections and an increase in mean migration route distance. The same applies to the number of migration routes between large patches (≥ 0.2 ha). Here, the trend in average patch area, the number of large patches (Table 8) and average length of the migration route is similar and might be devoted to changes in patch's edges.

6.4.4 Landscape homogeneity

The outcomes of SHDI and SIDI are similar. Both diversity measures show the same temporal trend (Figure 34). The landscape shows the highest diversity during June and the lowest in February. The peak in June might be related to the presence of wet brushwood, which is absent in the other time-steps. The peak diversity or heterogeneity of the landscape in June is supported by the landscape occupation in this time-step (Figure 23).

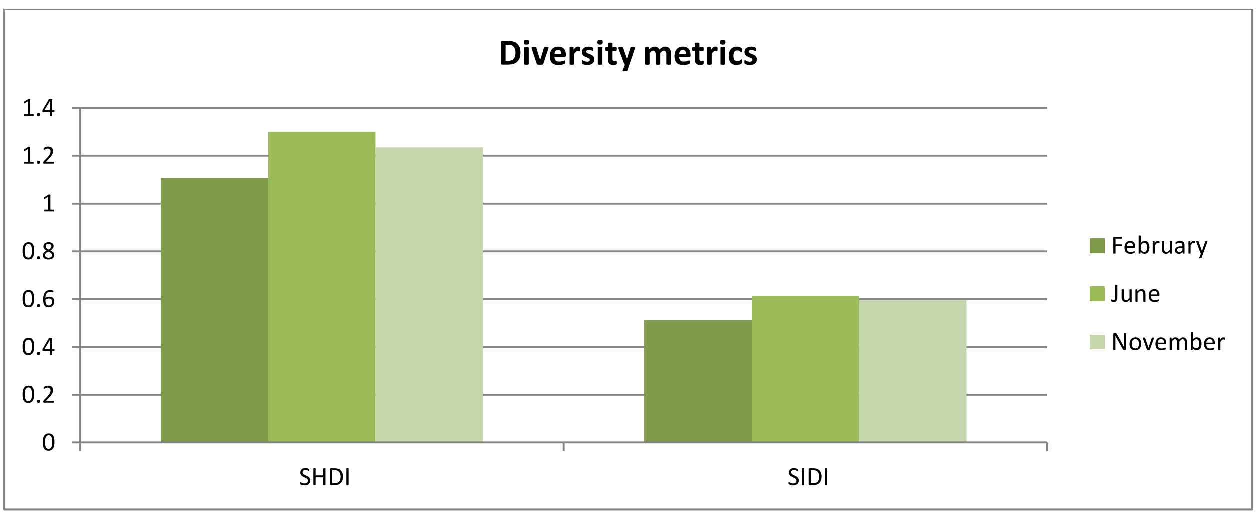

Figure 34. Diversity metrics SHDI and SIDI for the three time-steps.

7. Discussion

There is an extensive list of feature characteristics and patterns that can be identified and analysed. Most pattern analyses are done on a low resolution, including a high level of internal ecotope heterogeneity. Not all patterns used to describe such large objects seem to be relevant for landscape ecology and small floodplain fauna. One of the main questions in literature was on what scale mapping should be done to be ecologically relevant. This research has shown that mapping on a meter scale using high resolution data is possible and becomes ecologically relevant as multiple patterns have been successfully extracted. Moreover, distinctions between grassland and brushwood have been successful on a floodplain scale, using OBIA, as overall accuracies ranging from 82 to 89% have been obtained. The Breemwaard floodplain is part of a nature development project designed to lead towards more spatial variation. Also, natural vegetation is likely to be patchier than the present day vegetation (Straatsma et al., 2013) which is influenced by (former) cultivation. Such areas are dynamic (variable in height, management and flora) and likely to evolve into more natural vegetation. More accurate classifications will be necessary and the methods used here have high potential to solve this problem, with high efficiency.

7.1 Method

7.1.1 Segmentation

This research required the extraction of patches with a minimum size of 125 m^2 and segmentation was based on three brushwood patches having this approximate size. Segmentation was applied in such way that these patches were incorporated in the least possible number of segments with the least amount of overlap, however, there is always a segmentation error. For classification of these patches, potential habitats of *C. russula,* the segmentations were successful as high classification accuracies were obtained. However, segmentation depends on size, shape and compactness, parameters that can differ per ecotope. If this method is to be used for determining future habitat suitability, it is recommended to make a segmentation with the use of ecotopes of interest.

Second, the segmentations resulted in multiple segments per ground truth plot. As plots are meant to represent one ecotope, they are assumed to be homogeneous. In practice, most plots existed of multiple ecotopes. Therefore, the accuracy calculations demanded supervision using the NIR and ground truth data, to eliminate the possibility of a segment being misinterpreted. For example, plot 28 contains 10% natural grass- and hayland besides nettle brushwood (Figure 35). According to the ground truth, this plot is nettle brushwood and therefore every segment which is classified differently is considered a misclassification. Visually, the segment in the lower left corner of the plot in Figure 35 is natural grass- and hayland and is correctly classified. To eliminate supervision, plots could be decreased in size, e.g. one segment incorporates one plot, but the problem of internal plot variation remains. Another solution would be to lay out the plots in such way that they represent a homogenous area. With regards to floodplain fauna ecology, it would be recommended that a plot would be established within an object of interest, which would be a patch of brushwood of ~125 m^2 for *C. russula* in this particular research. Overall, the use of plots favours the outcomes of this research, as former point validations do not cover full patches and are therefore not representable as habitats.

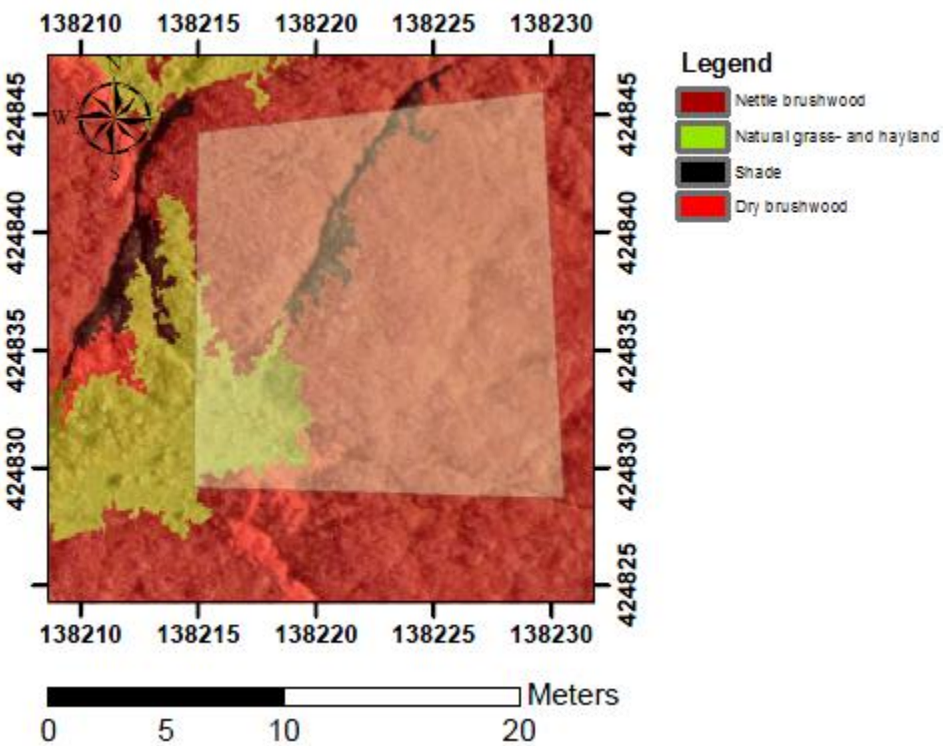

Figure 35. Transparent subset of the produced ecotope map (June) as an overlay on the NIR layer. Plot 28 is visualized as the transparent quadrate.

7.1.2 Classification

Feature selection

The criteria used for classification, as well as for segmentation, were different for every time-step. This means that a developed rule set is not applicable on other time steps without supervision. As the seasons change the structure and colour of ecotopes, their spectral values, height and standard deviations change. It is possible to preserve the same rule, although the feature values have to be adjusted for most classes and there is a risk of more overlap in the feature space. Some ecotopes are easy to distinguish from others (water, forest) as they have unique feature values (NDVI, vegetation height). Others share many common features and multiple thresholds have to be incorporated within the rule, but most of the former hard to classify ecotope patches were distinguished by a combination of only two variables.

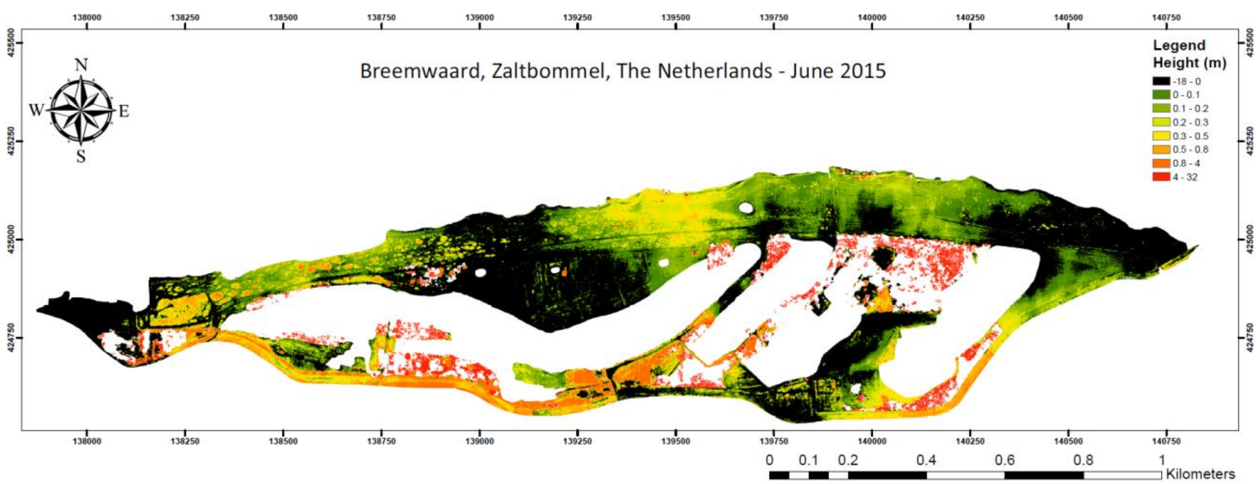

Figure 36. Visualisation of errors within the DEM of June. Black coloured parts are negative in height, which means that these parts have incorrect values and could not be classified using the DEM. Legend values are in meters.

The criteria DEM and standard deviations have shown to be able to separate natural grass- and hayland and brushwoods and are therefore recommended to use when making ecotope maps on meter scales. Standard deviations of the green layer might also be a powerful tool for analysing internal patch heterogeneity. Figure 21 shows that grass- and hayland has the lowest SD, which is, as expected, a more homogeneous ecotope than brushwood. Last of all, a more accurate digital elevation model (the current model has a standard error of 0.22 m) will increase the accuracy as it is a powerful tool for separating ecotopes, especially for summer images as the height differences increase. The current data included some inaccuracies (Figure 36) but these mainly occur on natural grass- and hayland and sometimes on dry brushwood. Nettle brushwood still has positive values and the DEM can be used as a classification criterion for this ecotope. A more accurate DEM will decrease the number of necessary classification criteria, making OBIA easier to apply on a supra-floodplain scale. For example, the AHN provides LiDAR data of the filtered points, representing vegetation, with a maximum error of 0.05 m (van der Zon, 2013).

Accuracy

As mentioned by Jansen and Splunder (2000) and Houkes (2008) grasslands are hard to separate from brushwoods. This research has shown that the separate classification of these ecotopes was possible and their accuracies (82-89 %) were within the typical range (70-90 %, Straatsma & Huthoff, 2010) of most ecotope maps. Moreover, user- and producer accuracies for the two types of brushwood are higher in this research (June) than that of Houkes (2008) (respectively 63.8 and 64.9 %). Also grassland has higher accuracies for the ecotope maps of February and June. However, overall accuracy (70.7 % in Houkes, 2008) might even be higher as ecotopes besides natural grass- and hayland, dry- and nettle brushwood were not included in the accuracy calculations in this report. A visual scan initiates classification accuracies of 100 % for the ecotopes water and trees, while production grassland was also well defined. Furthermore, the lowest derived accuracies and reliabilities originate from the lowest number of segments (i.e. two segments, one classified incorrect). To illustrate this: the lowest user/producer accuracies (< 45 %) originate from an average of 9.5 segments, while the highest accuracies (> 90 %) originate from an average of 24.7 segments. More evaluation plots may therefore increase these accuracies.

Comparison to National ecotope maps

The most recent ecotope mapping done by RWS resulted in a map (Figure 37) similar to the map produced in this research. For example, the dry brushwoods found in the western part of the floodplain are similar and also the production grassland is present in both maps. However, the dewberry brushwood ecotope is present in the map produced by RWS, although ground truths present in this study mark the upper-middle part as dry brushwood. Furthermore, the extent of production grassland is larger in the ecotope map of RWS which suggests that grassland ecotopes are sensitive to confusion. There is no distinction made between dry – and nettle brushwood and the map contains less detail due to the relative small scale (smallest unit 5x5 m). Therefore, this map might be of use for floodplain ecology when considering large floodplain fauna, but for small fauna the amount of detail is too low. Unfortunately, the accuracy of this map remains unknown.

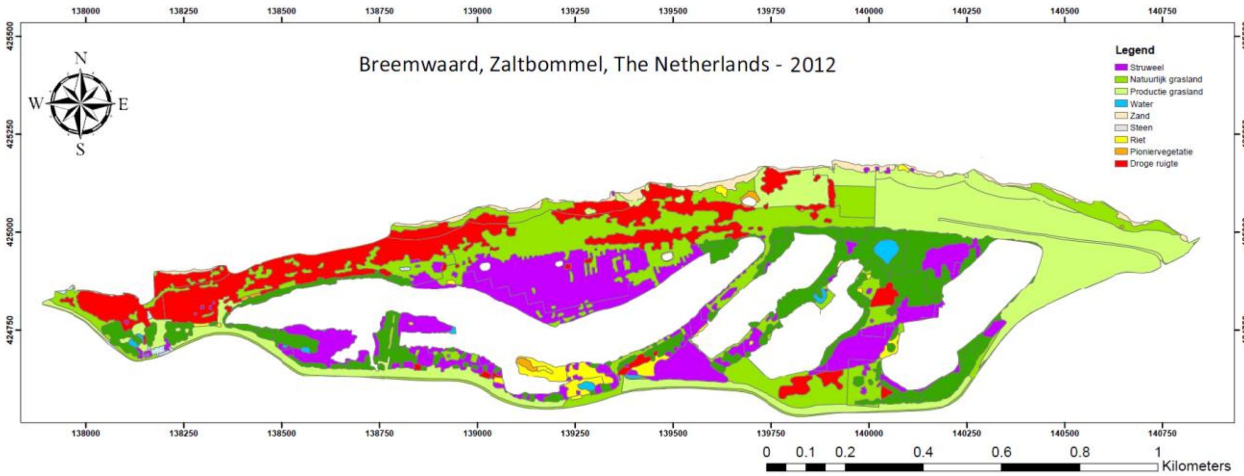

Figure 37. Adjusted Ecotope classification of Breemwaard according to RWS (4th cycle, unpublished, 2012). Ecotopes are merged in such way that ecotopes do not include morphology.

To compare the results with validated Dutch ecotope maps, a table was produced which includes the accuracies of the second ecotope mapping cycle (Table 9). The map produced in this research has the highest accuracies when compared to all five maps of the second national ecotope mapping cycle, except for the producers' accuracy of grassland and the users' accuracy of brushwood, where it has the second-best accuracies. When the accuracies of nettle brushwood are added, the user's accuracy of brushwood is also highest for this map.

Table 9. Overview of User- (U) and producer (P) accuracies of the second cycle of ecotope mapping for the Dutch river-systems. Marked in green are the highest accuracies found. Grassland and brushwood is a group of ecotopes in the other studies, while it represents respectively natural grass- and hayland and dry brushwood in this study. *Straatsma et al. (2008) derived the overall correct classifications (A) of the second ecotope mapping cycle. Numbers represent percentages.

	Maalderink, 2016		Rijn-Maasmonding 2006 (RWS)		Rijntakken oost 2005 (RWS)		Maas 2004 (RWS)		Ijsselmeer 2004 (RWS)		Volkerak Zoommeer 2005 (RWS)		Straatsma et al. (2008)*
	P	U	P	U	P	U	P	U	P	U	P	U	A
Grassland	84.62	91.67	86.34	86.07	82.64	83.80	76	81	74	88	69.07	75.28	43
Brushwood	92.38	82.76	70.12	85.82	63.79	64.91	39	48	35	23	57.41	62.00	53
Nettles	88	95.65											

Straatsma et al. (2008) converted the ecotopes to the division as proposed by van Velzen et al. (2003) and made a summary of the second ecotope mapping cycle. They conclude that overall natural grass- and hayland and dry herbaceous vegetation accuracies are as low as 43 and 53 %, respectively, proving the method used in this study to be a significant improvement.

Unmappable vegetation types

The only major ecotope which has been identified in some vegetation plots but was not distinguishable from other types of brushwood was dewberry brushwood. Its structure, height and layer values are almost identical to that of nettle- or dry brushwood, while species composition is also similar. The applicability of this method on studies considering fauna having this specific ecotope as their only habitat is therefore uncertain. As *S. communis* has multiple brushwood ecotopes as a potential habitat, classification of dewberry as another brushwood type does not influence the results. A similar problem occurred with reed brushwood, which is almost identical to reed. Using imagery with an even higher resolution might enable distinction. Purple loosestrife was added as an extra ecotope in June based on field observations, but could not be classified in the other time steps. The same accounts for wet brushwood. As this ecotope includes purple loosestrife, the two might be easier to identify when added together. Other ecotopes listed by van Velzen et al. (2003) have not been identified in the vegetation plots and are therefore absent in the produced ecotope maps of the Breemwaard.

Applicability and recommendations

The OBIA method used for this research is recommended to be used when considering other floodplain fauna; only the scale of segmentation can be adjusted to the size of the objects of interest, if desired, and habitat characteristics should be known. When multiple time-steps are made within the same year, it is important to update the ground truths. This problem is encountered with for example nettle brushwood. Nettle brushwood can reach to high heights, but when height reduces towards to winter, it could switch to a dry brushwood ecotope. If the ground truth still labels it as nettle brushwood the accuracy decreases while the classification might be correct. A similar problem is encountered with the incorporation of management in an ecotope. The area where plots 1-5 (Appendix D) are situated belongs to the ecotope natural grass- and hayland, as it is mowed several times a year. However, after a period of growth the area evolves into dry brushwood (van Velzen et al. 2003). Then the classification might also be correct while the ground truths mark it as incorrect.

7.2 Identifiable patch characteristics and patterns

Vegetation type, patch area and shape are the most important patch characteristics for (small) floodplain fauna. Furthermore, on a spatial scale, connectivity between patches and landscape heterogeneity are patterns important to extract and monitor on a temporal time scale. Grasslands and brushwoods have low accuracies in Dutch ecotope maps, but function as a habitat for small floodplain fauna. The study of Wijnhoven et al. (2005) reported that these types of ecotopes were important habitats for *C. russula*, as Mason (1976), MacDonald (1979) and Halupka (2002) did for *S. communis.* After accurate classifications of these ecotopes, most important habitat conditions could be identified and analysed using FRAGSTATS. Furthermore, it was possible to do analyses on a patch scale suitable for this specific fauna species. Texture is a feature characteristic which was not extracted with FRAGSTATS, but might be of importance for future analyses as it could be seen as a measure of patch's internal heterogeneity. The standard deviations of segments could be interpreted as such measures. However, after classification the segment loses its feature values.

7.2.1 Patch-level patterns

Patch area was easy to extract using this method and shows temporal variation throughout a year which reflects fragmentation and loss and gain of edge. During February the landscape consists of many small dry brushwood patches. However, the least number of dry brushwood patches is present in June, while the average patch area is also largest here, indicating merging of patches. The total number of patches increases towards November as fragmentation takes place. The highest number of nettle brushwood patches is in June, while the size seems to increase towards November. This pattern could be related to a difference in growing season between the two types of brushwood, e.g. nettle brushwood might have an offset when compared to dry brushwood. This growth is also illustrated in the ecotope maps (Appendix E-G). Such a temporal pattern might be beneficial for *C. russula*, as the timespan of suitable vegetation cover increases.

Shape is the second important feature characteristic for the two target species, according to Wijnhoven et al. (2005) which caught most individuals in rectangular-shaped patches; and MacDonald (1979) mentions long-shaped territories for *S. communis*. A reason for this preference could be the relative high amount of edge, increasing heterogeneity. The Shape index values of brushwood patches throughout the year seem to suit these species, as a Shape index value of 1 represents a square patch and the average Shape index values found range between 5.7 – 9.3 (dry brushwood) and 5.7 – 6.6 (nettle brushwood). Such values could be interpreted as elongated shapes, although multiple (irregular) shapes could be imagined here. The lowest average Shape index value was found in June for both types of brushwood and highest in November.

A patch consisting of one pixel is assigned a Shape index value of 1. Two pixels always have a Shape index value of 2; 3 pixels range between 3/8 and 3. Four pixels could have a Shape index of 1, but range up to 4. To determine the relationship between area and shape, regression analyses were plotted in Appendix I. There is a positive linear relationship, which is most apparent in June. This means that large patches have a higher Shape index, which has positive effects on both fauna species. However, average patch area decreases in November while average Shape index peaks. Fragmentation and loss of edges seem to change the natural (round) patch shape into more irregular forms; smaller patches being most regular. This is also illustrated in Figure 33 and Appendix H.

7.2.2 Spatial arrangement and connectivity

Patterns, or spatial arrangements, have been extracted from the data on a high resolution. The patch-corridor-matrix model was used as basic knowledge to relate spatial patterns to fauna species migration. Only in this research the matrix is not different from the corridor, as corridors are described as 'linear landscape elements' (McGarigal, 2014), and those particular elements were not extracted. Therefore, corridors have been described as 'possible migration routes'. As the focus was on extracting small patches which form a habitat for small floodplain fauna, small corridors were merged with the matrix as they become harder to recognize, but corridors are likely to be classified on an even higher resolution. Natural grass- and hayland forms the matrix in most time steps. This research mainly focused on the separation and classification of two types of brushwood (patches) and natural grass- and hayland (matrix). However, in one time step dry brushwood becomes the matrix, which might have consequences on fauna migration. Corridors normally covered by (high) grasses are now covered in brushwood. It remains unknown what the required vegetation cover is for *C. russula* to migrate from one brushwood patch to another, although it is mentioned that this species needs 'enough vegetation cover' in its habitat (Aulagnier et al., 2008). *S. communis* is not concerned here as it migrates by air. Patch connectivity is a useful measure to determine the possibility of species migration and the number of migration routes identified in the different time steps (at least 286 for *C. russula,* February) suggest that there are enough opportunities for small floodplain mammals to migrate. For further improvement, a future model should include an extent (lifetime home range); as the possibility remains that an individual is not able to make use of all possible migration routes during its lifetime. The opposite is true for *S*. *communis*. As it only has two connections between viable patches in February, the viability of the studied area is low. However, a larger study area including more floodplains connected to the Breemwaard might influence this observation as *S. communis* has a relative large homerange.

The two patch based metrics mentioned by McGarigal (2014) were also obtained in this research: 1) composition, consisting of the proportional abundances of each class; 2) richness, the number of classes and diversity, in the forms of SHDI and SIDI. The second involves spatial configuration, which refers to patch area and shape. Core area, contrast and aggregation were not taken into account here. Subdivision and isolation of patches was examined using patch connectivity and number of possible migration routes. Two classes of landscape patterns mentioned by McGarigal (2014) were used during this research; the surface patterns (digital elevation model, for classification) and the categorical map patterns (as an input for FRAGSTATS).

Forman (1995a) mentions six types of patterns, of which two can be integrated in the produced maps. The first one, small patch landscape pattern, applies to all three maps as classification is done on a floodplain scale. Second, the checkerboard pattern can be found in the map of November, after landscape fragmentation. This can be seen visually when comparing the June categorical map to the one of November, but can also be seen in patch area, number of migration routes and landscape occupation. The increase in small brushwood patches illustrates fragmentation after summer, leading to an increase in possible migration routes. The landscape occupation of dry brushwood decreases after summer and fragmentation is one reason for this (beside loss of edge) as the number of patches increases. Forman (1995a) relates the checkboard pattern to an increase of diversity but in this case it is hard to determine what diversity or homogeneity is.

Homogeneity of the landscape is mentioned as an important condition for habitat suitability and biodiversity. According to Forman (1995a), fragmentation leads to diversity while the two diversity metrics, SHDI and SIDI decrease during fragmentation. Also the landscape occupation is more balanced during June, where dry brushwood forms the matrix. An important additive should be the spatial configuration of patches. To visualize the problem of landscape homogeneity as a measure, this is illustrated in Figure 38.

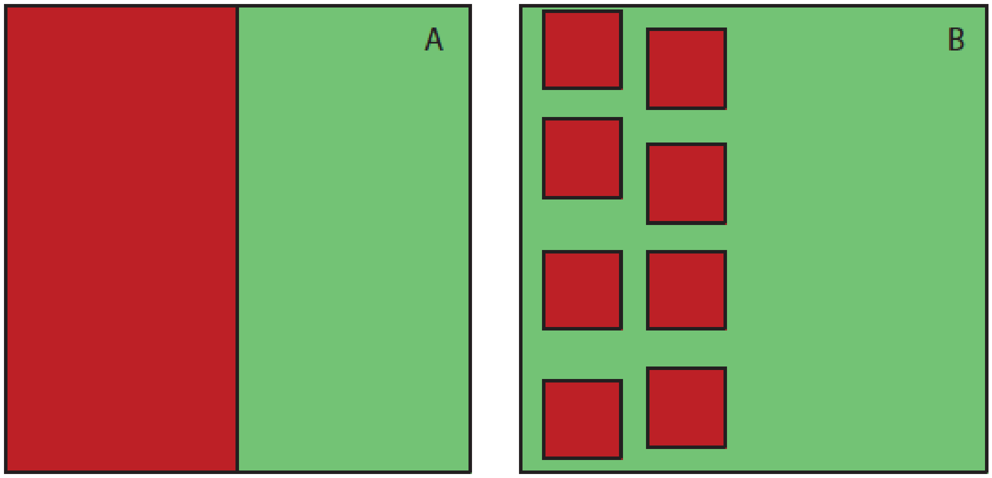

Figure 38. Illustration of the homogeneity problem.

In Figure 38A, the landscape is in balance in terms of class area, which should be labelled heterogeneous as there is maximum diversity. After fragmentation, the diversity decreases as one class gains more area. On the other hand, the spatial configuration of the fragmented class causes the landscape to become more heterogeneous. It depends on the scale whether or not a (sub-) landscape is heterogeneous. The fragmented landscape is still homogeneous for a small fauna species having its migration range within a single patch. The diversity measures SHDI and SIDI do not include home ranges which make them more applicable to larger floodplain fauna; however, these measures can give an indication of the larger scale homogeneity. All these measures do not indicate the spatial configuration of patches. As the fragmented landscape in Figure 38B could be seen as a heterogeneous landscape for small fauna if the distance between two patches is within the migration range, a combination of the amount of viable patches and corridors might be an indicator for landscape diversity. Additionally, average migration route length could indicate aggregation. Figure 38 shows an increase in patch connectivity (formation of more possible migration routes), which was also seen in the period June-November for *C. russula*. This means that November is probably the most suitable situation for *C. russula* as the number of viable patches remains constant but the possibilities of migration increase. Furthermore, poor connectivity slows down the re-colonisation after inundation as mentioned by Wijnhoven et al. (2005). Larger floodplain fauna may be more beneficial in June, when SHDI and SIDI peak. This also accounts for *S. communis*, as June has the most viable patches and the highest number of migration routes, although the number stays low. The loss of connections after the summer is in accordance with the fact that *S. communis* is a migrating species and winters in Africa south of Sahara

(Fransson, 1998). Furthermore, the number of viable patches in June (8) is similar to the average number of breeding birds (12.3) found in the whole Breemwaard area (one-third of the area was analysed, another one-third consists of waterbodies) in the period of 2003-2008 (Peters & Kurstjens, 2011), and might increase if more (types of) brushwood becomes available.

This method can be applied in research on connectivity and calculating the number of migration routes for other fauna, as only the home-range has to be adjusted. The number of migration routes in this study might even be higher, as the landscape was divided in three parts, which results in the loss of some possible migration routes. Several argumentations were proposed for understanding the temporal patterns in class connectivity (Connectance index) and patch connectivity, but only tracking of individual patches could verify these theories. New methods on individual patch monitoring and simultaneous homogeneity analyses are therefore required.

8. Conclusion

OBIA is a promising method regarding classification of relative homogeneous objects in floodplain vegetation mapping. Former manual classification methods-, which lose reliability due to human interpretations, are time consuming and are done on a low resolution, -seem to have become outdated. This research has shown that it has become possible to discriminate between grasses and brushwoods and habitat characteristics most important to floodplain fauna, connectivity and homogeneity can successfully be extracted using OBIA in combination with high resolution data on a meter scale. Furthermore, combining data resulted in recognition of fragmentation and matrix formation. The use of UAV data is relatively cheap in comparison to manned aerial flights and can increase classification cyclicity, intensifying the amount of monitoring. Standard deviations of layer values and relations to neighbouring segments are effective parameters for distinguishing grasslands and brushwoods. Especially DEM layers, representing vegetation height, have potential to contribute to future ecotope classifications. The users-, producers- and overall accuracy are highest for natural grass- and hayland and the two brushwood ecotopes in the ecotope map of June. Therefore, it is recommended to take images during or close to this month. For fauna studies, only small adjustments in the workflow have to be made to determine the habitat suitability in terms of patch shape, area and migration possibilities. Homogeneity analysis lacks high resolution information but gives a good indication of the overall landscape homogeneity. For individual patch homogeneity another measure should be introduced, such as individual patch tracking with a measure for object texture, shape analysis or standard deviation.

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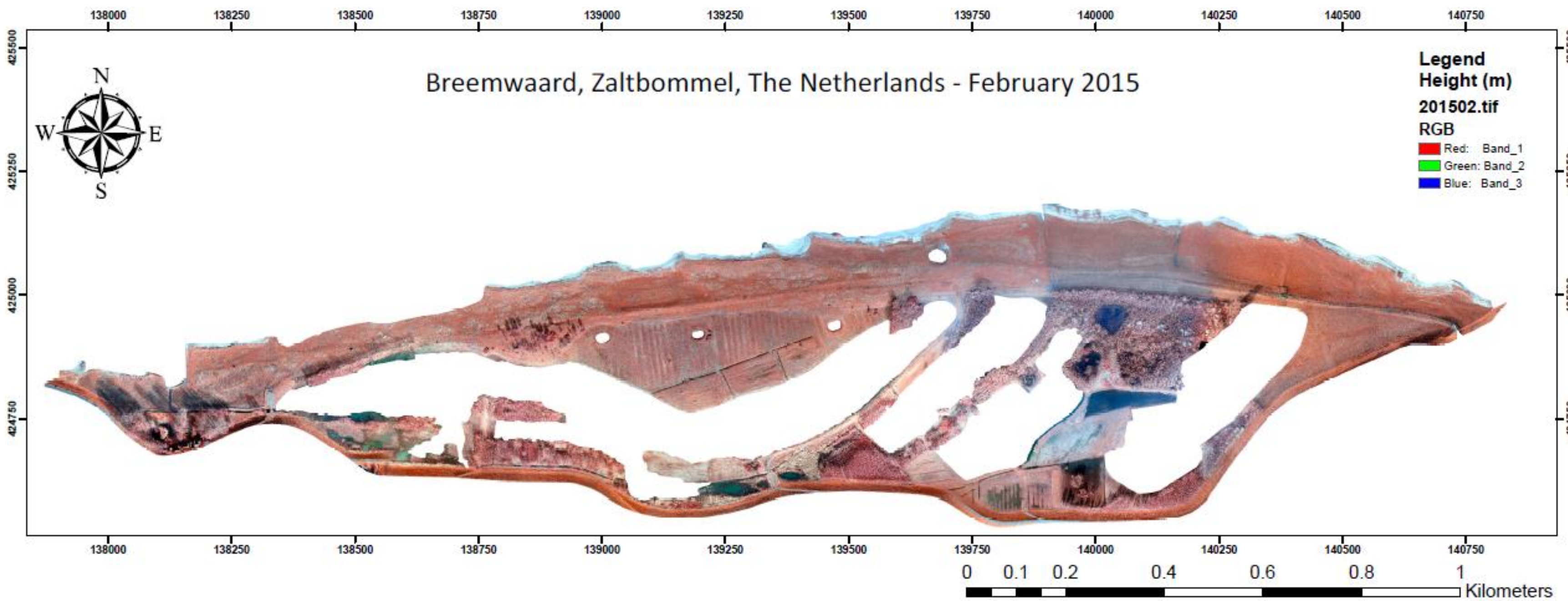
10. Appendix

Overview

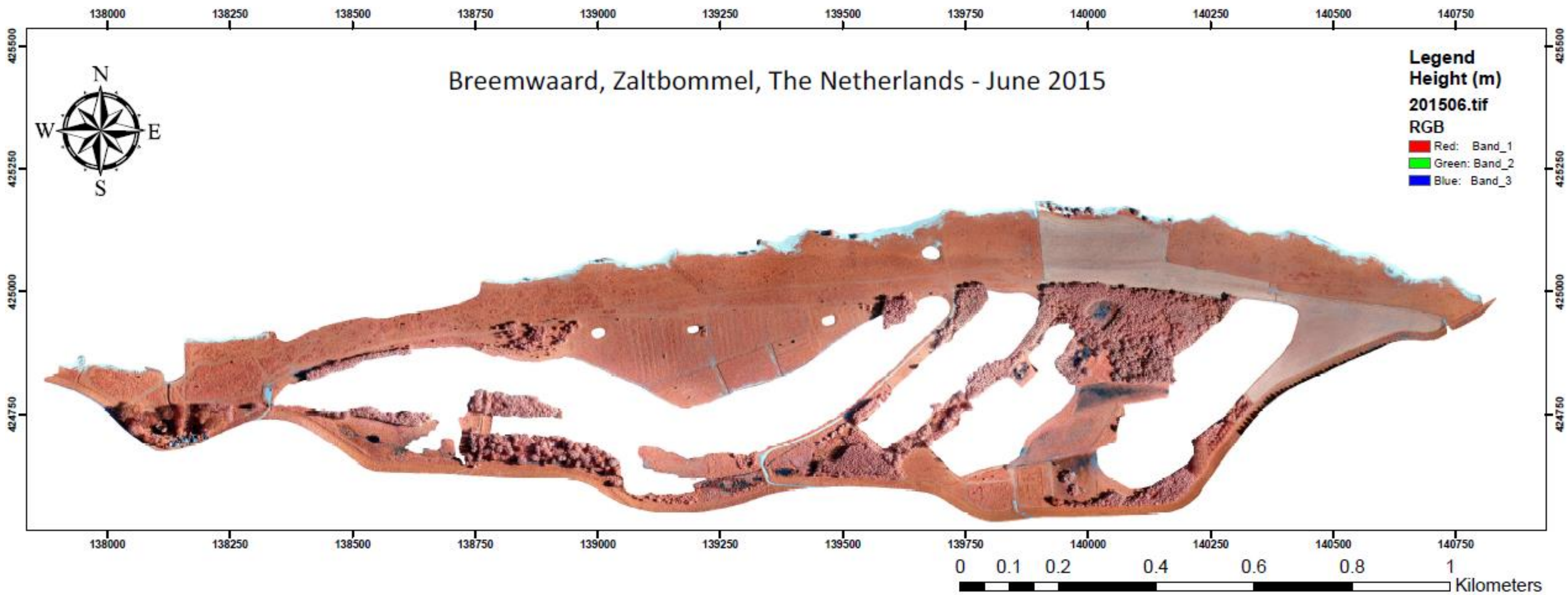
Appendix A

NIR image of February



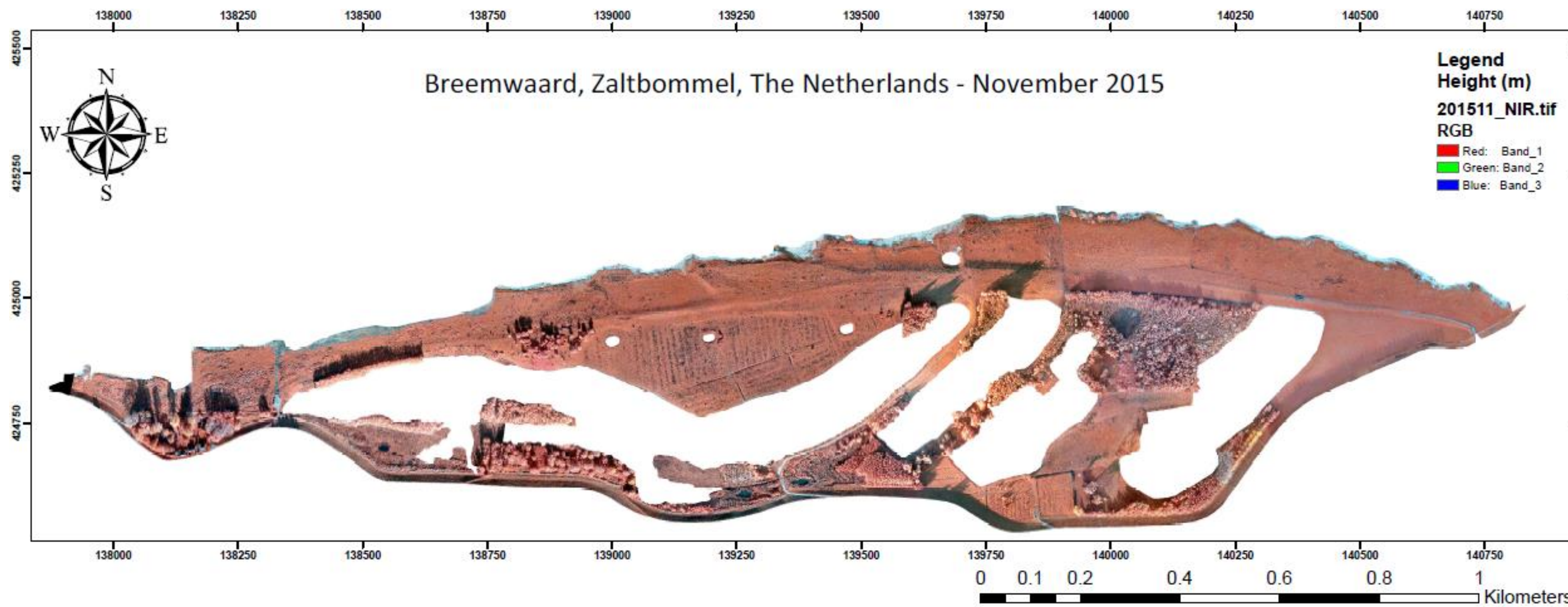
Appendix B

NIR image of June



Appendix C

NIR image of November



Appendix D

Overview of plot locations

Appendix E

Ecotope map of the Breemwaard floodplain – February 2015

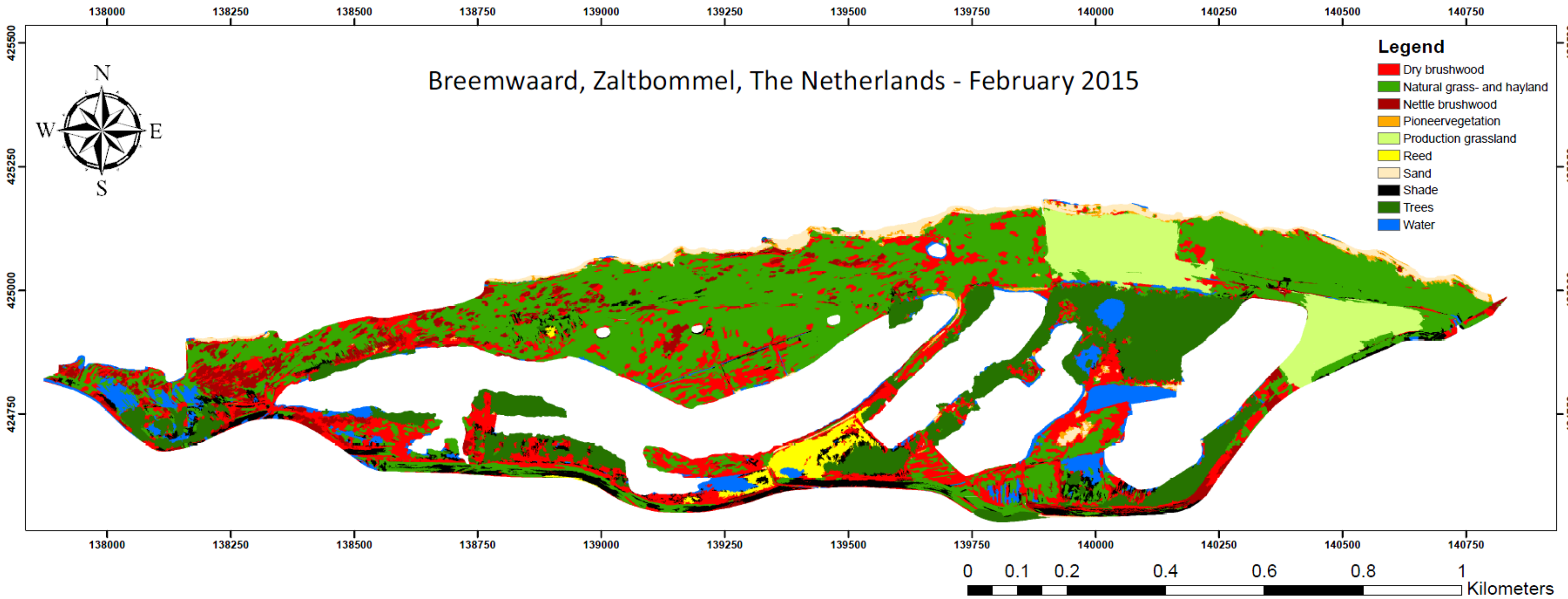


Table E1

Summed class area (ha) of three sub-landscapes in February, per class.

CA (ha)			
Sand	1.8082	**Water**	0.4842
Pioneer vegetation	0.6113	**Nettle brushwood**	2.6643
Dry Brushwood	5.7621	**Shade**	0.5959
Natural grass- and hayland	25.8856	**Trees**	1.0809
Production grassland	0.0772	**Reed**	0.0294

Appendix F

Ecotope map of the Breemwaard floodplain – June 2015

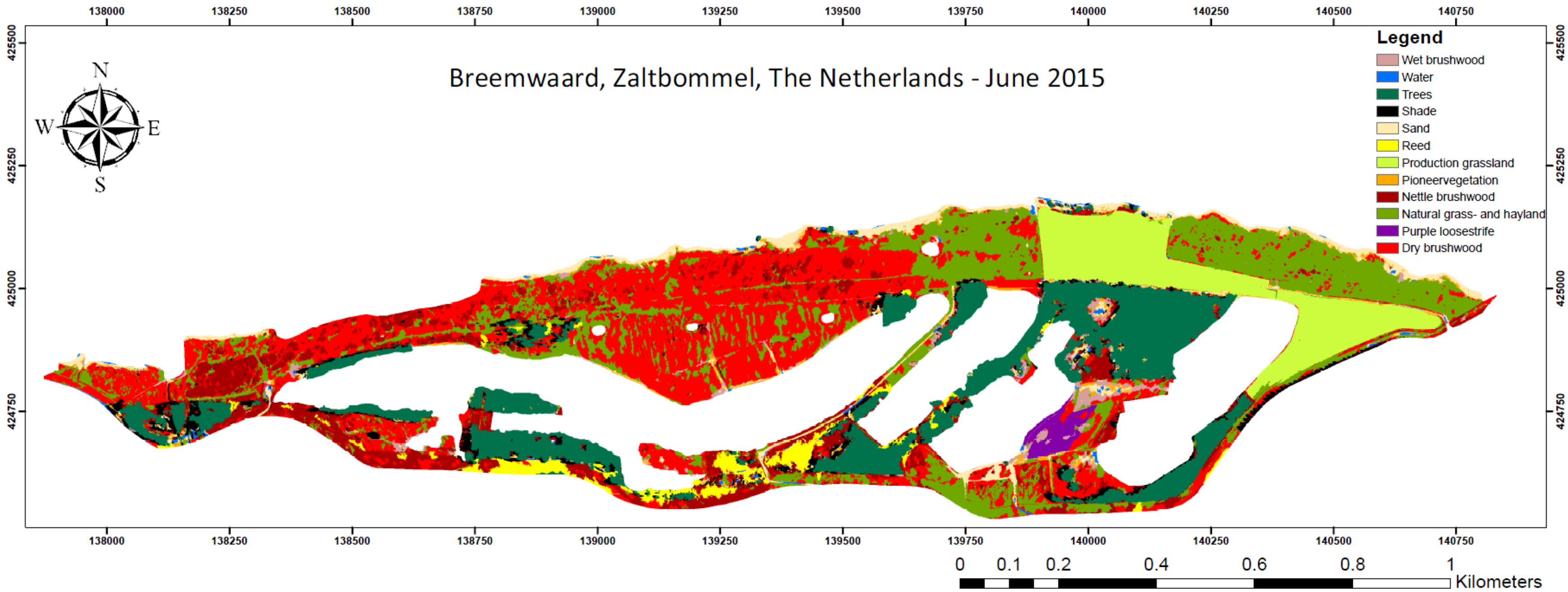


Table F1

Summed class area (ha) of three sub-landscapes in June, per class.

CA (ha)				
	Sand	2.0545	**Wet brushwood**	0.0012
	Pioneer vegetation	0.6345	**Water**	0.1004
	Dry Brushwood	16.5459	**Nettle brushwood**	3.5799
	Natural grass- and hayland	13.2429	**Trees**	1.485
	Production grassland	0.4429		

Appendix G

Ecotope map of the Breemwaard floodplain – November 2015

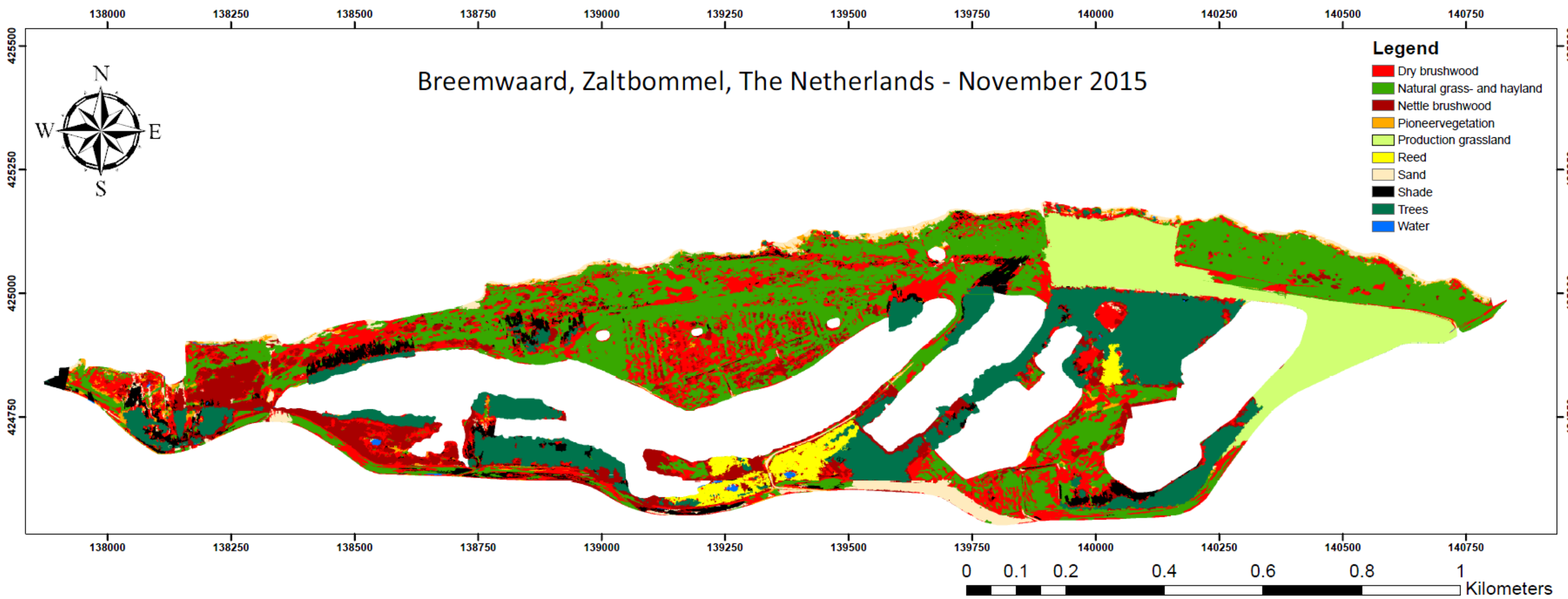


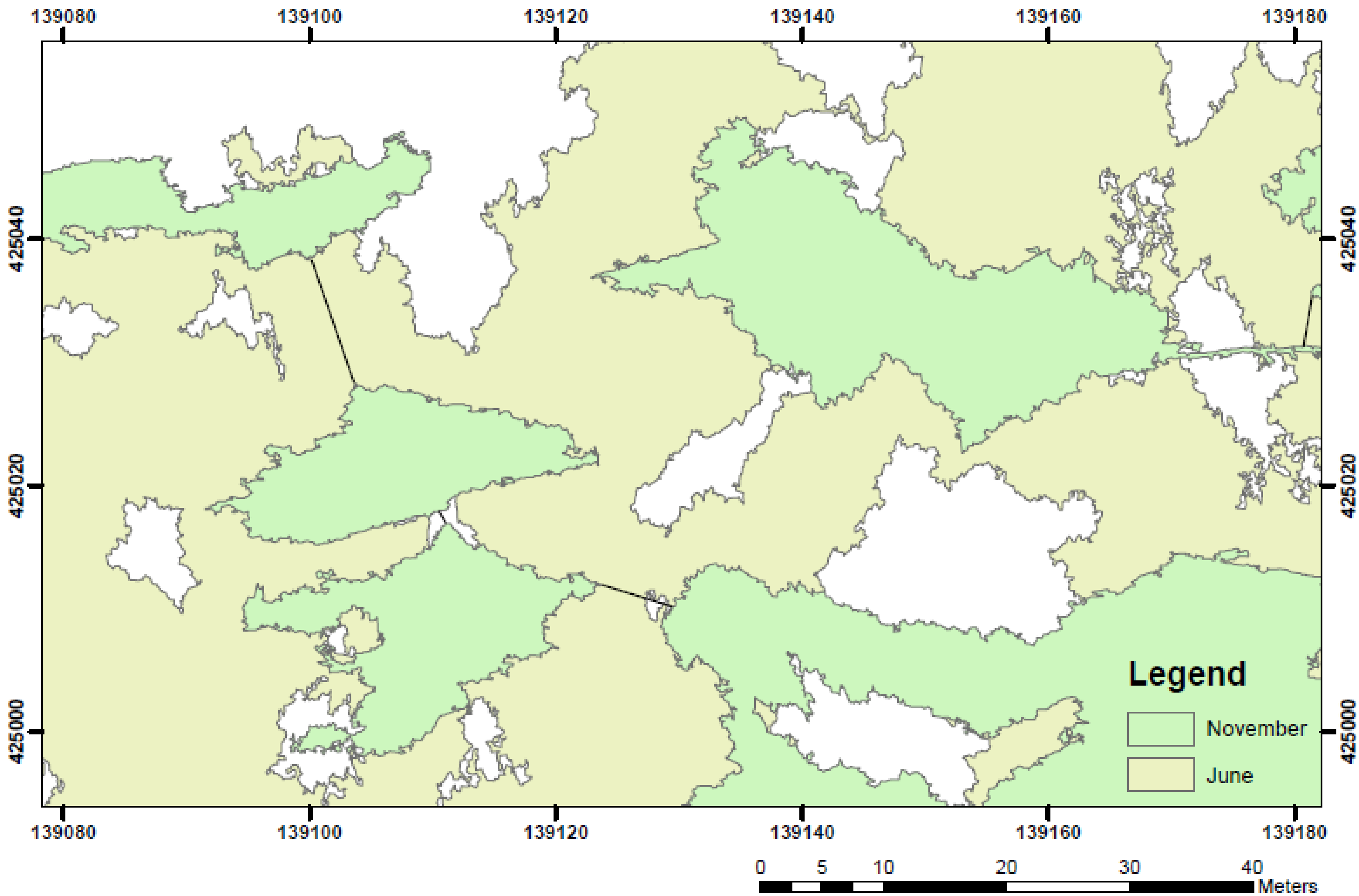
Table G1

Summed class area (ha) of three sub-landscapes, per class.

CA (ha)			
Sand	1.4377	**Water**	0.01
Pioneer vegetation	0.5688	**Nettle brushwood**	3.1927
Dry Brushwood	8.8795	**Shade**	1.4919
Natural grass- and hayland	21.9226	**Trees**	1.3396
Production grassland	0.0378		

Appendix H

Matrix fragmentation and migration route formation in period June – November



Appendix I

Regression analysis