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Relating land-use and plant biodiversity in Scanian semi-natural grazing lands

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Abstract

Climate change and biodiversity loss are amongst the most pressing environmental issues internationally, with far-reaching impacts that place natural and semi-natural habitats at ever greater risk of degradation. My project explores the effects of land-use on plant biodiversity in semi-natural grazing lands using datasets covering Sweden's southernmost region, Scania. Comparative analyses were performed using biodiversity measures and a number of landscape variables. The measures of biodiversity in terms of plant species richness were calculated using a grazing land inventory subset with records from the latest years. These measures were correlated with landscape variables, relating to hydrology and vegetation phenology. Such variables include a Wetness Index and Plant Phenology Index, computed using recent remotely sensed data, namely Sentinel-2 time series data. Land cover data was processed to cluster the study sites into distinct land cover groups which facilitated further correlation analysis between plant biodiversity and the landscape variables. These variables were also analysed at two spatial scales, i.e. at the extent of both the grazing lands and their 1 km buffer zones. Weak negative correlations between the biodiversity measures and vegetation seasonality resulted in the grazing lands with mixed buffer land cover. Grazing lands with open, arable and water-dominated buffers lacked any correlations of significance. Without extrapolating any implications beyond the regional land-use context, overall no statistical dependence was found between plant richness and the multiple landscape variables that delineate land-use.

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List of abbreviations

EVI	Enhanced Vegetation Index
GIS	Geographical Information Systems
GPP	Gross Primary Production
LAI	Leaf Area Index
MODIS	Moderate-resolution Imaging Spectroradiometer
NDVI	Normalised Difference Vegetation Index
PPI	Plant Phenology Index
SR	Species richness

1. Introduction

Grasslands are found naturally on all continents except on Antarctica, with different grasses and related plant species occurring depending on the regional conditions (i.e. ecoregions defined by geography and climate). The grassland habitats found at European northern latitudes are predominantly semi-natural, as both grazing lands (also known as pastures) and meadows are essential for agriculture. With almost 200,000 ha of grassland habitat in Sweden, most are grazing lands (Ihse and Lindahl 2000). Such semi-natural grazing lands are landscapes that are used for domestic livestock, where grasses, herbs and other low-growing plants dominate the vegetation of the habitat. Grazing lands are important for agriculture, specifically animal farming and production. The grazing of these generally open landscapes ensures that these habitats are maintained on an annual basis. Semi-natural meadows are also important for harvesting fodder, which sustains non-grazing animal production. In Europe, semi-natural grasslands are also important for biodiversity conservation, because their relatively low land-use intensity maintains unique habitat features that sustain grassland flora and fauna (WallisDeVries et al. 2002). In fragmented landscapes due to intersecting agricultural and urban infrastructure (e.g. roads and cropland), grazing lands increase the resilience of plants within the habitat. Both plant species diversity and seed dispersal are known to be facilitated by grazing livestock. Kapás et al. (2020) state that the grazing lands and surrounding landscapes help in mitigating climate change and fragmentation.

A number of studies, such as Dainese et al. (2017) and Gámez-Virués et al. (2015), have focused on land-use and its effects on biodiversity at large (plants, insects and other animals like birds). A review by Tscharntke et al. (2005) found that productivity in simple landscapes such as grasslands benefits from plant diversity, and that the presence of specialist species is what often drives the biodiversity-ecosystem functioning in such habitats. In Sweden, an important tool to assess the conservation status of semi-natural grasslands is to monitor grassland indicator species that signify high conservation value of the grasslands, i.e. so-called positive grassland indicator species (Auffret et al. 2018). This term describes the vascular plant species that are typical for Swedish grasslands and attribute ecological benefits to the habitat and its biodiversity. By evaluating landscape variables with plant biodiversity in a manageable area of study, the objective of this project revolves around how the richness of positive indicator species could be associated with land-use, using multiple variables (namely seasonality parameters) for both the grazing lands and their surrounding landscapes.

The loss of biodiversity due to climate change is a global concern, however it is the loss of habitat that poses the foremost threats to biodiversity (Auffret et al. 2018). Habitat loss due to land-use change is impacting habitats at large spatial scales, with open and arable landscapes undergoing significant change through the continued expansion of urban and agricultural activities. While such developments and the landscape they presently occupy can be well-monitored, the plant diversity that support the ecosystem functions and could mitigate some of the negative impacts on their habitat (e.g. biodiversity loss) are less known. Landscapes used for agriculture were found to have high conservation value if the land-use was dynamic and not restricted to monotypic crops (Tschantke et al. (2005). However, the reliability of such studies is impinged by the lack of research on the extent of both the local and landscape management of habitats, and grassland plant diversity is identified as a key player in determining the relative importance of land-use on biodiversity (Tschantke et al. 2005).

A long-standing question in landscape ecology has been to separate how biodiversity responds to land-use intensity (Felipe-Lucia et al. 2020). While land-use depends on how the land is used (forestry, agriculture, grazing, etc.), land-use intensity refers to substantial land cover modifications that increase with the expansion of mostly agricultural production. Estimating land-use intensity can be done using GIS methods, however a key issue has been that available GIS data has been relatively coarse given that most in-situ biodiversity assessments have been based on rather small plots. Remote sensing data can also be useful for estimating land-use intensity. For example, the recent Sentinel-2 satellite mission can reveal fundamental information on the dynamics and productivity of the landscape surrounding grassland habitats and the grasslands themselves (Cai et al. 2021; Jönsson et al. 2018). In this project, I use remote sensing and GIS methods that attempt to disentangle land-use and related landscape variables which could explain patterns of plant biodiversity in Scanian grazing lands.

1.1 Aims

The objectives of this project are encompassed in the following research question, sub-divided into two sub-questions on which the methodology was developed.

What is the relative importance of land-use on plant biodiversity in Scanian semi-natural grazing lands? I. What importance do landscape effects have as a driver of plant biodiversity in grazing lands? II. Which are the most important local effects affecting plant biodiversity in grazing lands?

The results obtained for both sub-questions were evaluated to bring the focus back to the main question of the relative importance of land-use on grazing land biodiversity. While the land-use within the grazing lands (local effects) was expected to be rather uniform, it is the surrounding land-use (landscape effects) that was likely to be more varied (more spatial variability in the landscape due to e.g. fragmentation).

A number of landscape variables related to land-use were studied in terms of their relative importance as drivers of plant biodiversity. This was done using the national TUVA grassland inventory from the Swedish Board of Agriculture (Jordbruksverket) and other landscape variable data processed and provided by The Swedish Environmental Protection Agency's (Naturvårdsverket) and Lund University. The TUVA inventory serves as a vast source of data that informs agricultural and land-use policy, and is highly valuable for landscape ecology and subsequently grassland biodiversity research.

Auffret et al. (2018) state that local effects are the most significant predictors of grassland indicator plant richness, whereas current plant biodiversity is best predicted by the historical landscape. However, their study did not attempt to measure the effect of the current agricultural productivity, which can be used as a land-use intensity proxy, most likely because such metrics have so far not been accessible. In my project, agricultural production in the surroundings of grazing lands was included using the multiple estimated landscape variables.

2. Background

2.1 Grassland biodiversity and land-use

Habitat loss due to land-use change has become an international concern, with semi-natural grasslands on the decline across Europe (Newbold et al. 2016). Following longstanding eras of land-use, the last century has seen grassland habitat reduced further, largely due to the expansion of modern agricultural and urban landscapes, as well as climate warming (Oliver et al. 2017). This is particularly relevant in south Sweden and the Scanian region, which is characterised by highly intensive agriculture (Persson et al. 2010). Such land-use intensity impacts on semi-natural grassland habitat have been studied at both at the local and landscape scales. Auffret et al. (2018) found that historical land-use can explain the present-day plant richness (richness also based on specialist plants defined within the TUVA database, for a larger region of south Sweden than Scania), with local conditions being the best at predicting such species richness. Similar to the decline of old-growth forest habitat across Sweden, grasslands have also experienced degradation compared to historical periods (Auffret et al. 2017;

Auffret et al. 2018). The grassland habitat is designated as semi-natural due to the existing land management of most abandoned agricultural land, meadows and pastures, that is necessary for large areas sustaining crops and livestock.

Being the very basis of any ecosystem, plants are particularly important as they support both under- and above-ground biota in any kind of habitat. In grasslands, it is specifically vascular plants that dominate the land cover. Comprising open landscapes with both meadows and grazing lands, grasslands are an essential habitat for a variety of floral and faunal species (Allan et al. 2014; Duflot et al. 2017). In Nordic countries such as Sweden, it is the grazing lands which occupy much of the open land cover that is not cropland (Ihse & Lindahl 2000). Used as grazing grounds or recently abandoned agricultural land, these semi-natural grasslands host a wealth of biodiversity within their low-lying vegetation. The grasses that characterise this habitat are known to be extensively impacted by land-use. Dainese et al. (2017) found that, in complex landscapes, local plant diversity in semi-natural grasslands had a significant bottom-up effect on butterfly diversity. However, in simple landscapes this effect was not present and suggests that both local and landscape variables impact biodiversity, but to somewhat unknown extents.

Habitat restoration and sustainability measures to limit ecological damage should be based on research that links land-use with biodiversity, and given the national grassland data coverage, it is the diversity of plant species that is most applicable for Swedish grasslands. Available biotic data for Swedish jurisdictions vary, yet it is the TUVA database that is most pertinent for grassland-based studies. Semi-natural grasslands are also directly impacted by agricultural land-use, with the type and intensity of livestock grazing and food crops carrying effects onto the production of the landscape at large, including that of biodiversity in grasslands (Boke Olén et al. 2021). Conserving the biodiversity of rural landscapes requires both environmentally conscious agricultural practices, regulating the intensity and spread of farming, as well as the preservation of semi-natural patches in the landscape (Gonthier et al. 2014). In Scania these semi-natural areas are mainly grazing lands. The conservation of biodiversity in multiple landscape types require not only restoration measures for degraded habitats, but also the appropriate management of those lands, for example maintaining the use of grazing lands to sustain grassland biodiversity (Kuussaari et al. 2009).

Land-use change for forestry, urban infrastructure and agricultural expansion all impact the terrestrial biodiversity, and climate change impacts only add to the threat to biodiversity. Floral and faunal species are at risk of extinction due to both these land-use and climate pressures, especially for sessile species like plants that are not able to migrate to more suitable climatic conditions. The extinction risk for plant species is reduced in fragmented landscapes that include semi-natural areas, often featuring ecological corridors that to some degree mitigate the environmental changes. Grazing lands are known to host a higher species richness than cropland, and this is due to a variety of plant species that are able to endure within them. Even if not at previous abundance levels, the potential extinction is delayed as the plant and the animal diversity they host support each other and allows for a more resilient ecosystem in such habitats (Hodgson et al. 2012).

Manning et al. (2015) state that land-use intensification that increases mowing and fertilising of soils weakens plant richness, while intensification of grazing does not have this effect on plant diversity. Within the limitations of the select taxa for the plant and animal richness that were used, with richness as the main biodiversity indicator, the study suggests that while increased fertiliser use, tilling and mowing decrease the heterogeneity in the landscape, grazing lands have increased habitat heterogeneity. Amongst the spatial (e.g. size of grassland) and landscape descriptors used in the study by Auffret et al. (2018), their focus was on utilising land-use (historical and present) to predict species richness of grassland indicator plants. Investigating more landscape descriptors such as seasonality to better understand the implications of land-use on grassland flora is therefore a gap in knowledge worth exploring.

Biodiversity links to land-use in agricultural landscapes have been studied at large spatial scales using species richness as a measure of diversity of vascular plants, as well as animals (Billeter et al. 2008). Species richness, including that of plants, has been declining in European landscapes, where agricultural intensity is generally increasing. Therefore, no richness measure is understood to be more useful than any other for predicting the richness of the overall biodiversity. It is crucial to investigate how the grassland biodiversity in terms of plant species is affected at large spatial scales, taking into account the relationships that landscape descriptors and variables have with the prevailing land-use, both within and surrounding the grasslands (Auffret et al. 2018). The need to associate land-use with biodiversity remains, particularly in terms of vegetation composition due to agricultural productivity in the landscape. The quality (e.g. presence and occurrence of indicator species) and richness of grassland plants are additional elements to include when analysing plant inventories such as TUVA, which alike any national data repository depends on multiple entities and persons to collect and manage the data. The use of presence-absence data, while not taking species abundance into account, is not based on interpolations or extrapolations of the field data.

Ecosystem services are linked to biodiversity, as well as ecosystem functions derived from the interactions between these components (Felipe-Lucia et al. 2020). A few studies have investigated grassland bee diversity and species richness, showing that specific efforts can facilitate research on species other than plants (Ekroos et al. 2020). However, such research considers the impact on biodiversity and ecosystem services, from various sources. Land-use change and intensity are amongst the major causes cited for negative impacts on biodiversity and ecosystem functioning (Ekroos et al. 2020; Gámez-Virués et al. 2015), and this directly influences the increasingly understood ecosystem services and their benefits to both natural and anthropogenic communities (Felipe-Lucia et al. 2020; Tscharntke et al. 2005). Grassland ecosystems are under threat from factors like land simplification and management intensification, and these changes are disrupting the complex functioning of ecosystems, where the physical habitat and the biota that reside within it are less able to recover from landscape-scale disturbances (Gámez-Virués et al. 2015).

Soil moisture is another important variable related to biodiversity in grasslands (Buchanan et al. 2014). For landscapes dominated by agriculture, the combination of high resolution terrain indices, soil moisture indices and field observations relating to soil type and depth altogether improve the correlation of predicted soil moisture with the patterns of soil moisture observations (Buchanan et al. 2014). The integration of regionally measured soil properties when formulating the indices utilised to estimate soil wetness is not only applicable to agricultural landscapes, but so far has been shown to improve wetness estimated in agricultural land in the United States by Buchanan et al. (2014), in similar topographical settings but at a lower latitude than that of Scania. Various soil wetness predictors have been developed to map the hydrology and wetness of terrestrial habitats, with combinations of soil moisture and terrain indices regularly used to model wetness. The established topographic wetness index and more recent depth-to-water index were found to be the best at predicting soil wetness in Sweden by Ågren et al. (2014). The indices were based on high resolution digital elevation models to map the wetness variations topographically, and their respective suitability depends on the land types being investigated.

For dry sandy grasslands research has clarified that rich biodiversity (often referred to in literature) within these habitats is maintained based on restoration measures that ensure that any red-listed and indigenous vegetation are allowed to flourish (Ödman et al. 2012). While the soil productivity and nutrient content is generally low in such sandy soils, this provides ideal conditions for growth of specific plants and in turn regionally unique fauna that are associated with this variety of plant species. The importance of such grassland habitats is clear when considering that a number of the plant species are habitat-specific, and do not occur in all grassland types. While classifying grasslands using the local environmental conditions of the habitat is conventional, there is also potential in using the landscapes surrounding the habitat to classify grasslands, specifically grazing lands in my project.

2.2 Grassland remote sensing

There are numerous remote sensing applications in ecology, often including the monitoring of biodiversity. Nowadays field observations are frequently coupled with remotely sensed data that has significantly improved the detection of landscape characteristics across large spatial and temporal extents. The use of time series data that is remotely sensed and increasingly free and accessible through a number of satellite missions, is particularly important for the monitoring of vegetation phenology at large spatial scales (Pettorelli et al. 2018). This ability to map vegetation phenology is very useful for monitoring of ecological processes and seasonal fluctuations over time, such as interannual variations in productivity at a continental or more regional scale. The global coverage from most satellite missions is spatially and temporally improving with higher resolution imagery and more extensive time series data (Jönsson et al. 2018).

Different vegetation indices have been developed and extensively utilised, namely the Normalised Difference Vegetation Index (NDVI). NDVI, Enhanced Vegetation Index (EVI) and Plant Phenology Index (PPI) are examples of useful indices that average out across different vegetation types to obtain a net phenology estimate for each pixel in remotely sensed data (Gerard et al. 2020). Therefore, the variation in greenness (i.e. the leaf life cycle) that is captured by remote sensing is based on the phenology of all the vegetation that occurs within a monitored surface. This means that the seasonal greening of vegetation that is used to estimate phenology for a terrestrial habitat, including grasslands and their surroundings, is not species specific.

The use of these indices in multiple geographical locations and using various satellite data has verified the quality and performance of both the datasets and the processing methods for phenological studies (Tian et al. 2021). PPI is an index that has been shown to characterise terrestrial vegetation very well, capturing the dynamics in green leaf area using a radiative transfer equation. It is derived from red and near-infrared reflectance and is also able to estimate canopy foliage, as it is linearly related to the Leaf Area Index (LAI) (Jin and Eklundh 2014).

The Sentinel-2 satellite provides remotely sensed data with higher spatial resolution than most other satellite missions, with an average five-day repeat cycle. This satellite data is captured by the Sentinel-2 Multispectral Instrument, having a total of thirteen spectral bands (including the red and near-infrared bands) and a spatial resolution ranging from 10-60m, depending on which bands from visible and near-infrared to short-wave infrared wavelengths are used. The application of this time series data to compute seasonal parameters to study vegetation phenology, produces a robust analysis of phenology. Tian et al. (2021) tested the Moderate-resolution Imaging Spectroradiometer (MODIS) which has a much coarser resolution than Sentinel-2 data, and it still corresponded well to field measurements of Gross Primary Production (GPP) and LAI.

The monitoring of vegetation phenology, e.g. analysing potential shifts in seasonality is ideally based on the PPI (Jin and Eklundh 2014; Jin et al. 2017; Jin et al. 2019; Tian et al. 2021), but could of course be based other vegetation indices. PPI is closely related to GPP (measured via eddy covariance flux tower sites) in the northern latitudes of Europe (Jin and Eklundh 2014; Cai et al. 2021). The seasonal variations of GPP at these latitudes is linked to the vegetation productivity and therefore the phenology of these terrestrial habitats. PPI has been also been shown to perform better than other indices in estimating phenology, especially due to its consistency with GPP, even when considering snow and cloud-induced data losses, as well as relatively short growing seasons (Tian et al. 2021).

The ability to estimate the spring phenology of vegetation at northern latitudes (above 50˚N) using suitable indices like PPI based on high resolution remotely sensed data is important for investigating climate change impacts on vegetation phenology across ecosystems and habitats at continental scales. For biodiversity studies in grassland habitats, the utilisation of PPI derived parameters as landscape variables has not featured in more ecologically oriented research. The examination of Sentinel-2 and grassland inventory data, at similar temporal resolutions, could demonstrate if land-use within and surrounding Scanian grazing lands is associated with the plant biodiversity of the grazing lands. While vegetation phenology has been studied in terms of such seasonality (Cai et al. 2021; Tian et al. 2021), landscape productivity and land-use intensity have thus far not been analysed using such variables. Using the seasonality variables to describe land-use intensity in Scania is a new approach that uses the extracted variables as indicators that are able to describe vegetation phenology. Such seasonality indicators (e.g. Start of Season) are variables that are mainly capturing the phenology of high productivity land i.e. high land-use intensity due to the extent of cropland in the Scanian region. Most cropland is fertilised land which can influence the growing seasons, e.g. earlier start of season, for those landscapes that are not grassland, forest or abandoned land. The usefulness of the seasonality variables when studying biodiversity in grazing lands is due to the ability to capture this seasonality in the surrounding landscapes, and is intended to reveal more than the typical vegetation indices used, in this case PPI. The advantage of having multiple seasonal variables that are estimated on phenology of the land is not that these capture the vegetation (and hence plant biodiversity) within grazing lands or their surrounding landscape, but rather that the seasonality of the study sites as a whole is estimated.

3. Materials and methods

3.1 Data preparation

The methodological approach to test whether the landscape and/or local variables have any correlation with plant biodiversity in Scanian grazing lands, is shown in Figure 1, in view of the aims of the research question and sub-questions (I) and (II).

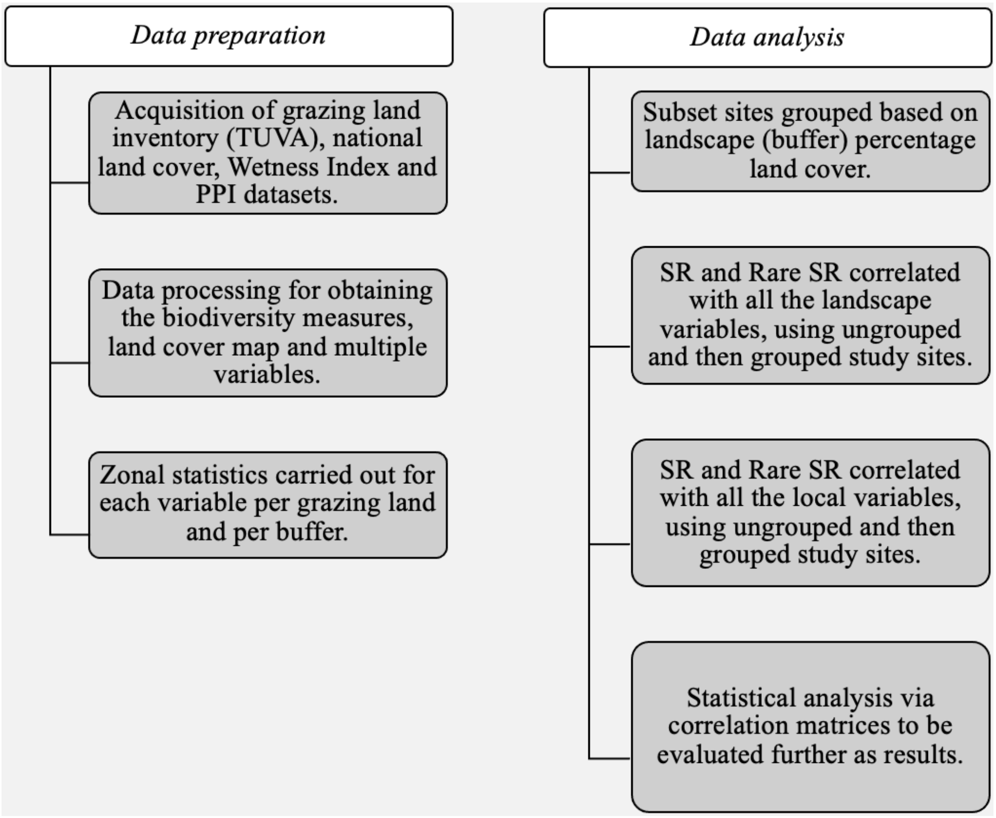

Figure 1. Flowchart of the main methodological stages for data preparation and subsequent analysis. TUVA refers to the national Swedish grassland inventory, while SR and Rare SR refer to two biodiversity measures based on species richness. All the data are further explained in this chapter.

The study area, Scania, is the southernmost county of Sweden, with the North Sea on its western coastline and the Baltic Sea on its southern and eastern coasts. It is adjacent to neighbouring counties towards its northern (Halland and Kronoberg) and north eastern boundaries (Blekinge). The study sites consist of all grazing lands situated within Scania (Figure 2). The TUVA database is central to this project, being the Swedish national plant inventory of semi-natural grasslands compiled by the Swedish Board of Agriculture (Jordbruksverket). From 2002, this grassland and plant database inventoried almost 335,000 hectares nationwide.

A subset of the TUVA database covering the study area was acquired, containing several thousand objects for the Scanian county. Objects classified as meadows were removed from this dataset, retaining 2740 grazing lands that were fully inventoried according to the database protocols. Grazing lands are considered to represent semi-natural grasslands with low vegetation, while meadows are grasslands mown annually for fodder (but not arable land with sown grass for fodder). The vast majority (98%) of the grasslands in the database are indeed grazing lands (Ihse & Lindahl 2000). For any re-inventoried site, the most recent sampling is automatically updated within the TUVA database. Using RStudio, the grazing lands for the subset were selected by extracting all relevant records from 2016 until 2020.

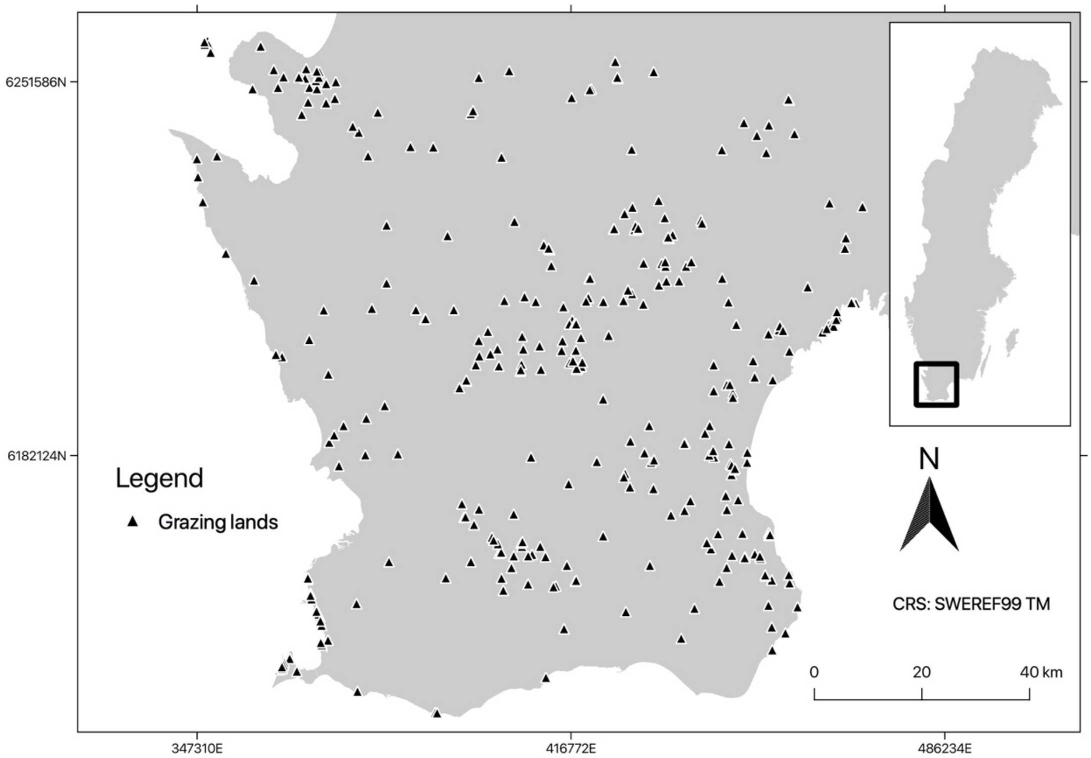

Figure 2. Map showing the southernmost parts of Sweden, mainly Scania county, and the locations of the 315 study sites from the national Swedish grassland inventory (TUVA) subset (all grazing lands inventoried from 2016 to 2020). The map inset shows where Scania is situated in Sweden. The base map is a GIS product provided by The Swedish Environmental Protection Agency (Naturvårdsverket).

The subset resulted in a total of 315 grazing lands spread around the county, with clusters of sites in both coastal and inland areas. This subset is expected to be sufficient for an analysis limited to Scania. It was prepared to obtain an adequate number of sites on which to estimate the biodiversity measures, for a period with a similar timeframe as the rest of the prepared landscape variables. The comparability of this presence-absence data is better between the subset years compared to older periods, when the sampling methods were slightly different and even the number of sites sampled year-on-year differed considerably. The protocols used for the data collection and re-inventorying were adjusted slightly from 2016, and more re-inventorying was done from the year 2016 onward than previous years. An updated positive indicator species list, was used from 2017 onward, however these were mainly taxonomic changes concerning five species. The positive indicator species recorded in the TUVA subset amount to 70 unique species, irrespective of the taxonomical order or nomenclature utilised. The Latin and Swedish names are listed in Appendix A according to the updated species names and taxonomical order. Each species is designated at either the genus or species level (mostly the latter).

Two complementary measures of biodiversity were used based on the positive indicator species: species richness (SR) and the species richness of rare species (Rare SR). Measures of plant biodiversity are limited when one is restricted to presence-absence inventory data. Without being able to estimate species abundance, species richness is a standard approach as a biodiversity indicator. SR was calculated based on the observed positive indicator species in the subset data. Rare SR was used to further analyse the most unique grazing land sites. This measure was estimated based on the occurrence of the positive indicator species, i.e. occurrence of the species as presence-absence data within the 2016-2020 inventory subset. For example the occurrence of *Veronica officinalis* was of 120 out of 315 study sites, while that of *Carex pilulifera* occurred was 11 of 315. The median occurrence was calculated (12) and used as a cut-off for rare species, following the method used by Ekroos et al. (2020) for the rare species richness of wild bees in European grasslands. The result was to classify 37 of the 70 species as rare species, and ultimately used to estimate Rare SR. Next, National land cover data provided by The Swedish Environmental Protection Agency (Naturvårdsverket), as part of the National Land Cover Data (Nationella marktäckedata) was obtained to create a land cover classification map for Scania (Figure 3).

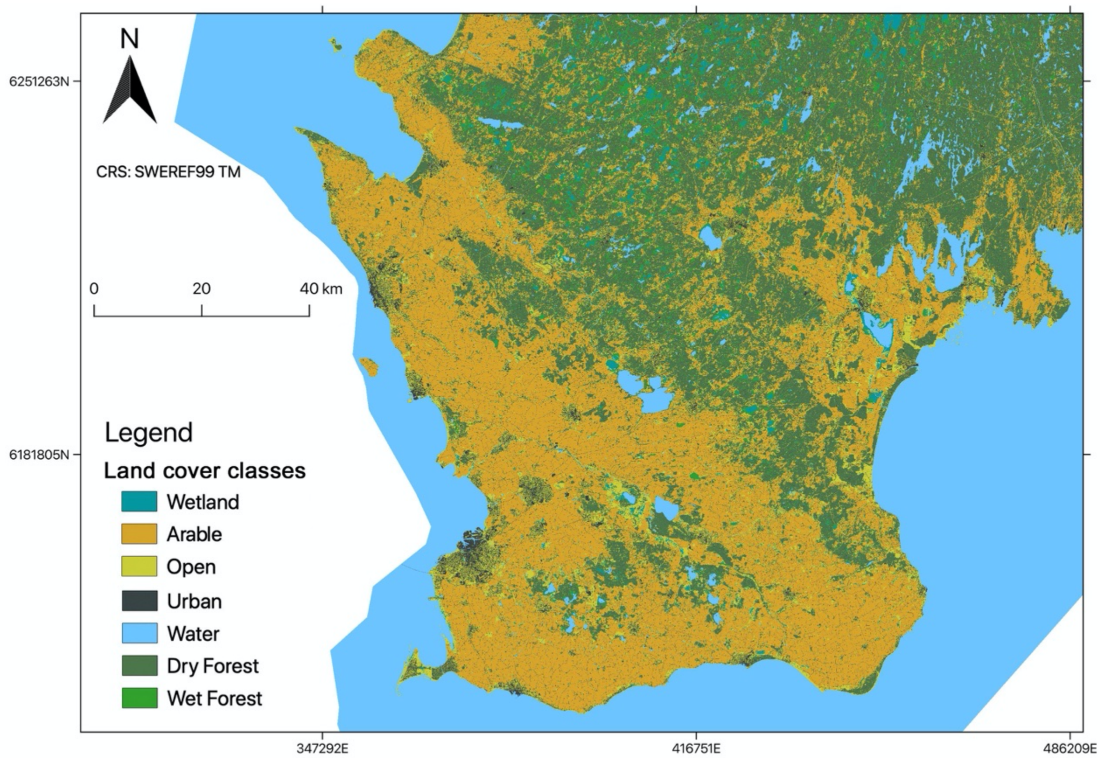

Figure 3. Map showing the land cover classification in Scania (and parts of its neighbouring counties) reclassified into seven land cover classes based on the 2018 National Land Cover Data provided by The Swedish Environmental Protection Agency.

The latest data issued in 2018 was provided at a 10 m resolution, and from two land cover products that are available via the National Land Cover Data portal, the most detailed product was used, with 25 land cover classes. These land cover classes were reclassified into seven main classes for the purpose of this study, ensuring that the land cover raster used is based on the most recent and comprehensive available data. Each of the seven land cover classes created (arable, wetland, dry forest, wet forest, open, urban and water) was based on the original land cover classes that were most closely related. As an example, the water class includes both sea and lake pixels from the original data, wet forest includes all the forest types that are within a wetland (swamp or bog) and dry forest includes all the forest types not within a wetland.

Amongst the soil moisture and wetness indices that exist, an index that forms part of The Swedish Environmental Protection Agency's National Land Cover Data was selected, termed as the Wetness Index and acquired from Miljödataportalen. The Wetness Index consisted of both a soil moisture index and modified topographic wetness index, amongst field observations, soil type and topographical datasets. On processing these altogether the National Land Cover Data generates this Wetness Index. Released in 2019, the 10 m resolution raster for southern Sweden contains pixel values ranging from 0 to 240 (dry to wet), that fall within five classes of soil moisture (i.e. wetness), being dry, mesic, moist, damp and wet. Clipping using QGIS was done to obtain the spatial extent needed to cover the study area, alike the prepared land cover classification map.

PPI raster data covering Scania based on time series of Sentinel-2 satellite imagery was processed and prepared with the help of Lund University researchers, for the years 2017 to 2020. These latest four years cover a similar time period as the other datasets, which is sufficient given my study is more of a geographical than a temporal analysis. It was also decided that using the all the available PPI data, even with the weather events that led to very dry conditions and delayed growing seasons in 2017 and 2018, was preferable to using a shorter PPI time series. The method to obtain the PPI parameters for each year required a number of processing steps. The Sentinel-2 data (Level-2A top of canopy reflectance) was radiometrically corrected using the Sen2Cor software of the Copernicus Scientific Data Hub. Next TIMESAT, a software that facilitates the extraction of all the seasonality parameters from time series Sentinel-2 data (in this case PPI data), was used to extract a set of phenology metrics. These metrics were: Start of Season, Middle of Season, End of Season, Length of Season, Seasonal Amplitude, Small Seasonal Integral and Large Seasonal Integral (Appendix B; Figure A1). These rasterised PPI variables were also processed further to mask the pixels that correspond to water and urban land cover, removing the pixel values that do not represent vegetation in the landscape. The land cover raster (Figure 3) was used for the masking of these variables.

While the extracted seasonality variables were selected as variables, the PPI data itself was not used as a variable. These PPI values could carry some additional information that is revealed in the seasonality variables, however as a time series it consisted of a large number of data files (approximately one every 10 days) which are all correlated, thus redundant. It is also a longer process to analyse all such input data and the bulk of the information in the seasonal data is condensed into the seasonality parameters. The obtained seasonality variables contain the relevant information that relates to productivity of the vegetation (Cai et al. 2021). Therefore, these seasonality variables were chosen over the PPI, producing multiple phenology indicators that constitute the more innovative variables in this study. Although such extracted seasonality variables have not been used before to describe land-use intensity and productivity, this method took advantage of the time series of satellite imagery utilised, also reducing uncertainties due to e.g. cloud cover (Tian et al. 2021).

3.2 Data analysis

To characterise the landscape surrounding each study site, a 1 km (1000 metre) buffer surrounding each grazing land polygon was created, in order to extract zonal statistics at the landscape scale. The grazing land polygons, i.e. sites at the local scale, were obtained from the TUVA database. Following the preparation of the raster datasets (land cover, Wetness Index and seasonality variables all at a 10 m resolution) the zonal statistics for each of the 315 sites at both landscape and local scale were carried out. Using QGIS, the count, mean, standard deviation, minimum, maximum (and more default statistics) were generated per raster. These statistics allowed each variable to be both a landscape and local variable. The percentage cover of each of the seven land cover classes was calculated (using the 'count' as total area of grazing land or buffer), to facilitate the use of land cover as such a variable in the data analysis. The land cover variables are therefore considered as continuous, given each land cover variable is a percentage cover value (out of 100%), even though each variable is only of a single land cover class. The Wetness Index was also considered continuous for similar reasons, as although 'classes' of wetness exist in the obtained data documentation, the pixel values used are continuous in the utilised raster. While the land cover and Wetness Index statistics were based on one raster each, each PPI derived variable equates to a raster per year from 2017 to 2020. This required the averaging of the four years per zonal statistic, for each of the seven seasonality variables. These variables are also continuous, with estimated values ranging across the PPI time series data (Appendix B; Figure A1). Additionally, the plant biodiversity measure SR and the grazing land area were also continuous variables, while the plant biodiversity measure Rare SR was considered as a categorical variable (when converted into a binomial).

Thereafter, the study sites were grouped based on the land cover at the landscape scale, as buffer percentage land cover was more likely to have varying land cover types. On the other hand, the grazing lands were expected to mostly have open land cover and would not be appropriately grouped using the percentage land cover variables. In order to generate the optimal number of groups, a k-means cluster analysis was performed using the percentage land covers per buffer. A centroid clustering algorithm in R was implemented using these percentage land cover variables, and involved a Principal Component Analysis. The number of groups was decided upon the plotting of data into the most distinct groups i.e. four groups (Appendix B; Figures A2 and A3). The group names and the number of study sites per group is shown in Table 1. To account for the main land cover per group, the groups were suitably named e.g. sites with mostly water land cover named as Coastal (only a handful are adjacent to lakes and not sea).

Table 1. Number of sites per land cover group, generated through k-means cluster analysis using percentage land cover within each of the subset's 315 grazing lands. The subset includes all grazing lands inventoried in Scania from 2016 to 2020, from the national Swedish grassland inventory (TUVA).

Land cover group	Number of sites
Open	107
Mixed	64
Arable-dominated open	98
Coastal	46

Correlograms using Spearman's correlation coefficient, for the landscape and local variables (using the ungrouped subset data) were generated to get an overview of relationships between the SR and Rare SR with the variables at both the landscape and local scales. Apart from the biodiversity measures, the area of the grazing lands (derived from the TUVA database) was also utilised as a variable at this stage. Following these two overall correlograms, the landscape and local scale analysis by group followed, i.e. two correlograms per group. These correlation matrices aimed to identify any relationships between the biodiversity measures and the multiple variables.

The zonal statistics generated for all the variables at both the landscape and local scales were then reduced in RStudio, excluding all except the 'mean' zonal statistic per variable. At the landscape scale, the percentage land cover variables with a median cover of less than 10% were excluded in the correlograms, as a threshold to exclude the land cover classes that have very few pixels. At the local scale, the percentage land covers were not used as variables in the correlation matrices (Table 2), as the grouping of sites was based solely on buffer land cover. Several of the seven seasonality variables were moderately correlated with one another (positive correlation coefficient >0.6). A few of these were excluded to reduce redundancy; The Start of Season and End of Season variables were preferred to the Middle of Season and Length of Season; The Seasonal Amplitude was retained; and The Large Seasonal Integral was preferred over the Small Seasonal Integral. The intention was to retain a more unique set of seasonality variables from those at hand.

Spearman's rank correlation coefficient is better suited than Pearson's correlation when using the variables shown in Table 2. The diagnostic plots used for the statistical testing of linearity, normality and homoscedasticity per variable was computed using R (example in Appendix B; Figures A4). Based whether a variable is linear, normal and homoscedastic, Pearson's correlation coefficient (linear correlation) can be used. However, the diagnostic per variable showed that neither of the variables fulfilled these three criteria and Spearman's correlation was consequently used as the correlation method throughout.

Table 2. The plant biodiversity, grazing land area, landscape and local variables, their respective statistical (linearity, normality and homoscedasticity) results and the appropriate correlation coefficient. '✓' = true, '✗' = false.

Variable	Type	Linear	Normal	Homoscedastic	Correlation
SR	continuous	✓	✓	✗	Spearman
Rare SR	categorical	✗	✗	✗	Spearman
Grazing land area	continuous	✓	✗	✗	Spearman
Landscape variables					
Wetness Index	continuous	✗	✓	✗	Spearman
Start of Season	continuous	✓	✓	✗	Spearman
End of Season	continuous	✓	✗	✓	Spearman
Seasonal Amplitude	continuous	✓	✗	✓	Spearman
Large Seasonal Integral	continuous	✗	✗	✓	Spearman
Arable percent cover	continuous	✓	✗	✓	Spearman
Wetland percent cover	continuous	✗	✗	✗	Spearman
Dry Forest percent cover	continuous	✓	✗	✓	Spearman
Wet Forest percent cover	continuous	✗	✗	✗	Spearman
Open percent cover	continuous	✓	✗	✗	Spearman
Urban percent cover	continuous	✓	✗	✓	Spearman
Water percent cover	continuous	✓	✗	✓	Spearman
Local variables					
Wetness Index	continuous	✗	✓	✓	Spearman
Start of Season	continuous	✓	✗	✓	Spearman
End of Season	continuous	✓	✗	✓	Spearman
Seasonal Amplitude	continuous	✓	✗	✓	Spearman
Large Seasonal Integral	continuous	✓	✓	✗	Spearman

A confidence interval of 95% was also used to distinguish which of the correlation coefficients were significant in each correlogram in the Results chapter, without hiding any of the resulting correlations. In the correlograms all relationships were displayed in a graphical format to facilitate the visualisation of all the results, no matter the outcome. Overall landscape and local correlograms were important as an initial correlation analysis, while the group-wise correlograms complemented the initial analysis to study relationships in more detail within specific land cover groups. This indicated if any of the processed landscape and/or local variables could be important drivers of plant biodiversity.

4. Results

4.1 Plant biodiversity

Plant biodiversity refers to the variety of plant species in a particular habitat, being semi-natural grazing lands in this study. The positive indicator species inventoried in Scania summed up to 70 species. Using these positive indicator species as the basis of the biodiversity measures, the highest SR in Scanian grazing lands was of 32 species, while the highest Rare SR was of 9 species. These are the exception as the SR median is 5 species and the Rare SR median is 0 species (Figure 4). The latter result is due to the fact that only 22 of the 315 study sites had a Rare SR greater than 1 species. Therefore, it was decided to consider this biodiversity measure as a binomial (value of 0 or 1), which resulted in 90 of 315 sites (29%) having a value of 1.

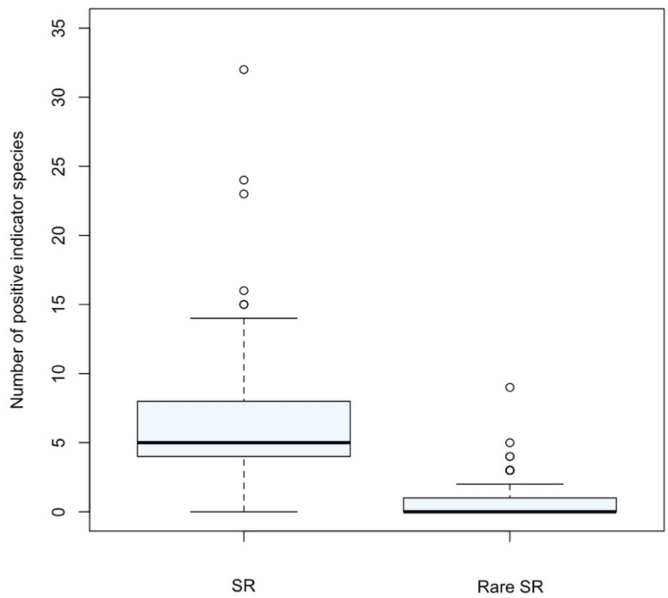

Figure 4. Comparative boxplot of the SR and Rare SR (before being converted into a binomial variable) in the subset grazing lands, based on a subset (all grazing lands inventoried in Scania from 2016 to 2020) of the national Swedish grassland inventory (TUVA). SR and Rare SR refer to two biodiversity measures based on plant species richness.

On mapping SR and Rare SR, a level of spatial aggregation is noticeable in zones where there are many grazing lands close together, particularly for SR, which tends to be higher where clusters of sites are present (Figure 5). However, this phenomenon is less apparent for Rare SR (Figure 6), an exception being in the coastal zone towards the East-North-East. This indicates that overall both SR and Rare SR have a quite random pattern in spatial distribution. Notwithstanding the clusters at the coastal zones and some inland areas that lack study sites, the grazing lands are quite evenly distributed across the study area.

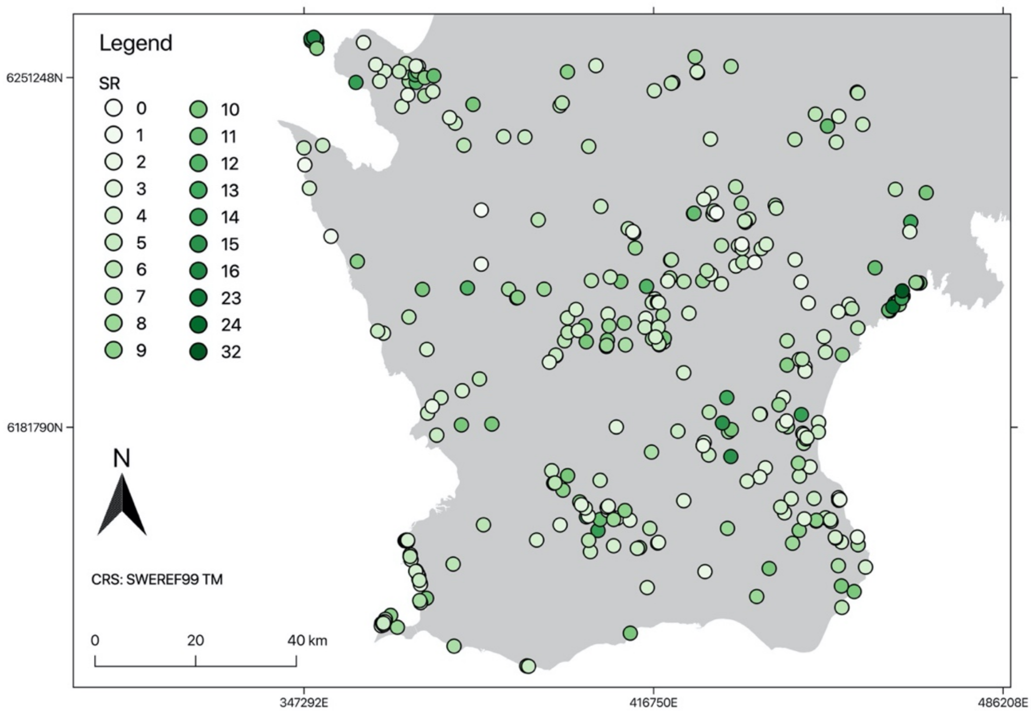

Figure 5. Map of the grazing lands and the SR per site. The grazing lands are a subset (grazing lands inventoried in Scania from 2016 to 2020) of the national Swedish grassland inventory (TUVA). SR is a biodiversity measure based on species richness (all plant species).

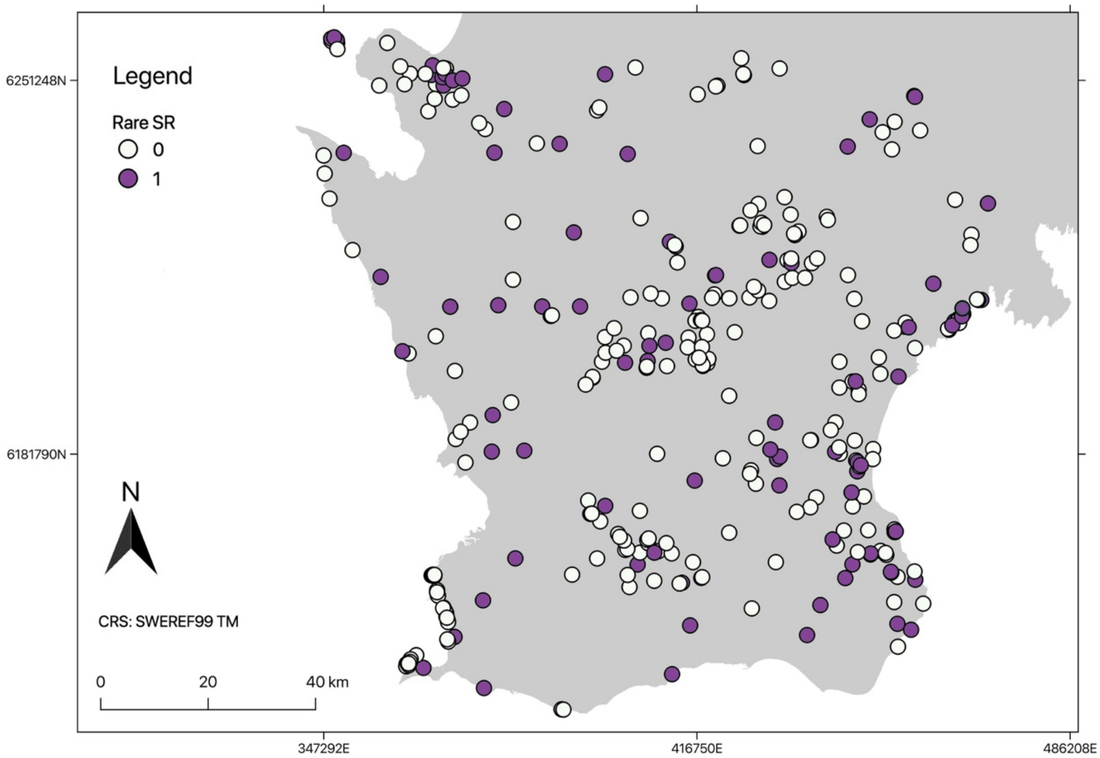

Figure 6. Map of the grazing lands and the Rare SR per site (as a binomial variable, 0=no rare species, 1=at least one rare species). The grazing lands are a subset (grazing lands inventoried in Scania from 2016 to 2020) of the national Swedish grassland inventory (TUVA). Rare SR is a biodiversity measure based on species richness (rare plant species).

4.2 Land cover groups

After completing the land cover classification map as explained in the methods, the percentage land cover was obtained for each grazing land and buffer. The comparative boxplots in Figure 7 show that while the grazing lands are dominated by open land cover, the most prevalent land cover in the 1km buffers is arable land.

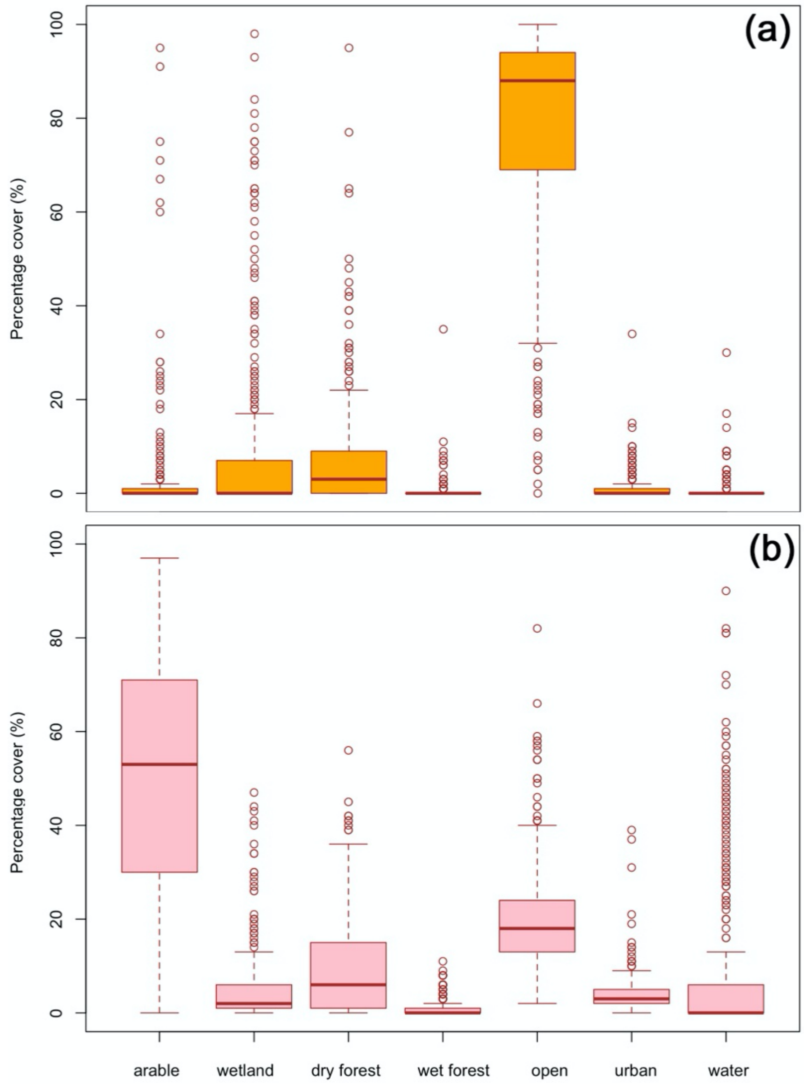

Figure 7. (a) Comparative boxplots of local percentage land cover, i.e. land cover inside the grazing lands. (b) Comparative boxplots of landscape percentage land cover, i.e. land cover inside the buffers. The seven land cover classes are based on the 2018 National Land Cover Data provided by The Swedish Environmental Protection Agency.

Grouping of the study sites by k-means clustering resulted in four distinctive land cover groups, based on the percentage land cover of the buffers. The majority of the sites are in two groups (open and arable-dominated open) with mostly open landscapes as the name suggests, holding 205 of the 315 sites. The rest of the sites are classified into the two other groups, mixed and coastal, 64 and 46 sites respectively. The comparative boxplots for each group display the percentage land cover per group (Figure 8).

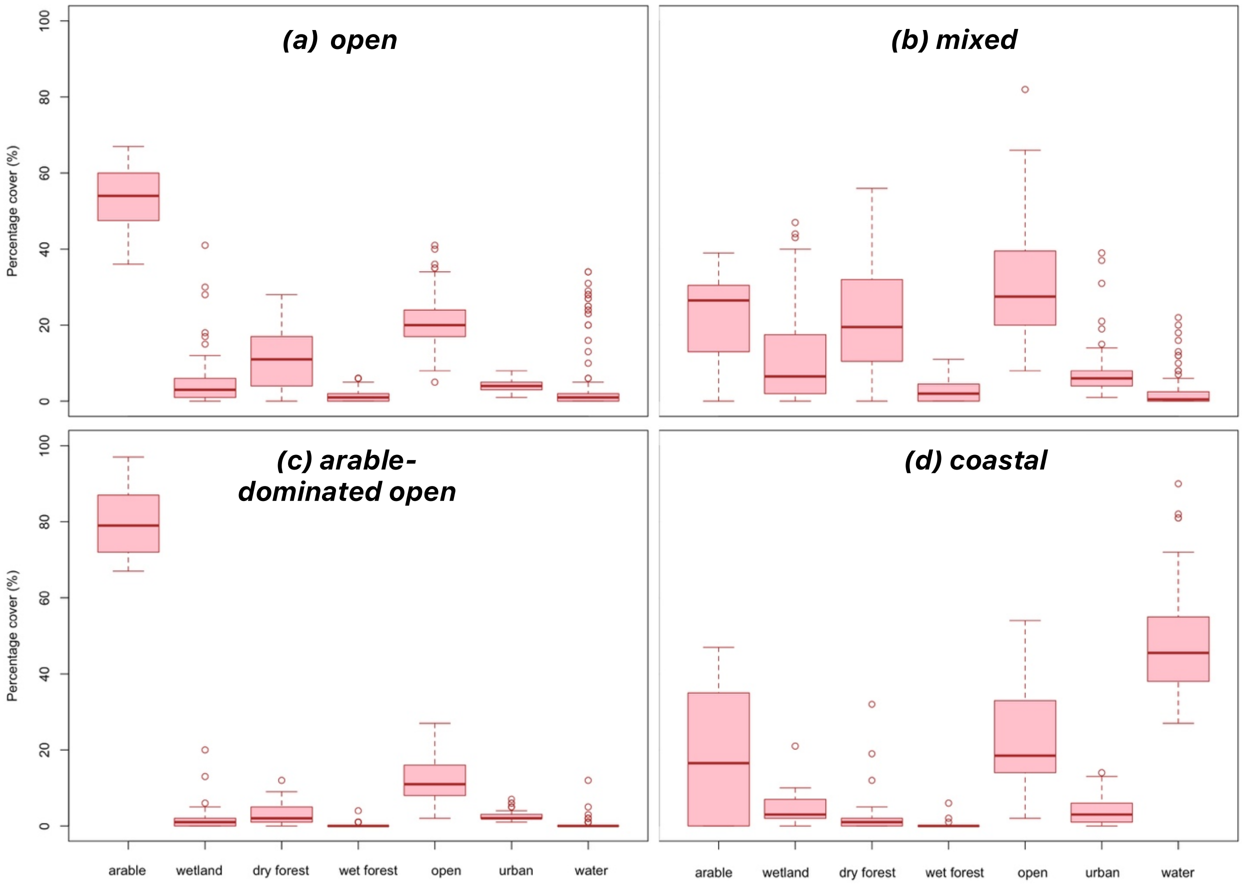

Figure 8. (a) Comparative boxplots showing percentage land cover within the open land cover group. (b) Comparative boxplots showing percentage land cover within the mixed land cover group. (c) Comparative boxplots showing percentage land cover within the arable-dominated open land cover group. (d) Comparative boxplots showing percentage land cover within the coastal land cover group. The seven land cover classes are based on the 2018 National Land Cover Data provided by The Swedish Environmental Protection Agency.

The mixed land cover group has the most evenly distributed land cover, and also the most dry forest cover amongst the groups. Evidently, arable and open land have a substantial percentage cover in each group. The spatial distribution of the sites by land cover group (Figure 9) reveals an expected pattern of land cover that corresponds to the land classification map and the regional land-use, namely the widespread arable and open land cover used for agriculture in Scania. These land cover groups could affect plant biodiversity, e.g. the grazing land ecosystem is likely the most particular in the coastal group. This means that the soil type and some of the plant species that are able to occupy such grazing lands are potentially specific to this group ('endemic' to e.g. sandy soils and high salinity). In the arable-dominated open group the plant biodiversity could be less varied than the open group, due to the predominant arable land cover i.e. not as much varied land cover as in the similar open land cover group. In the mixed group the plant biodiversity is likely to be rather varied (more varied ecosystem types surrounding the grazing land and therefore more potential seed supply of various plant species).

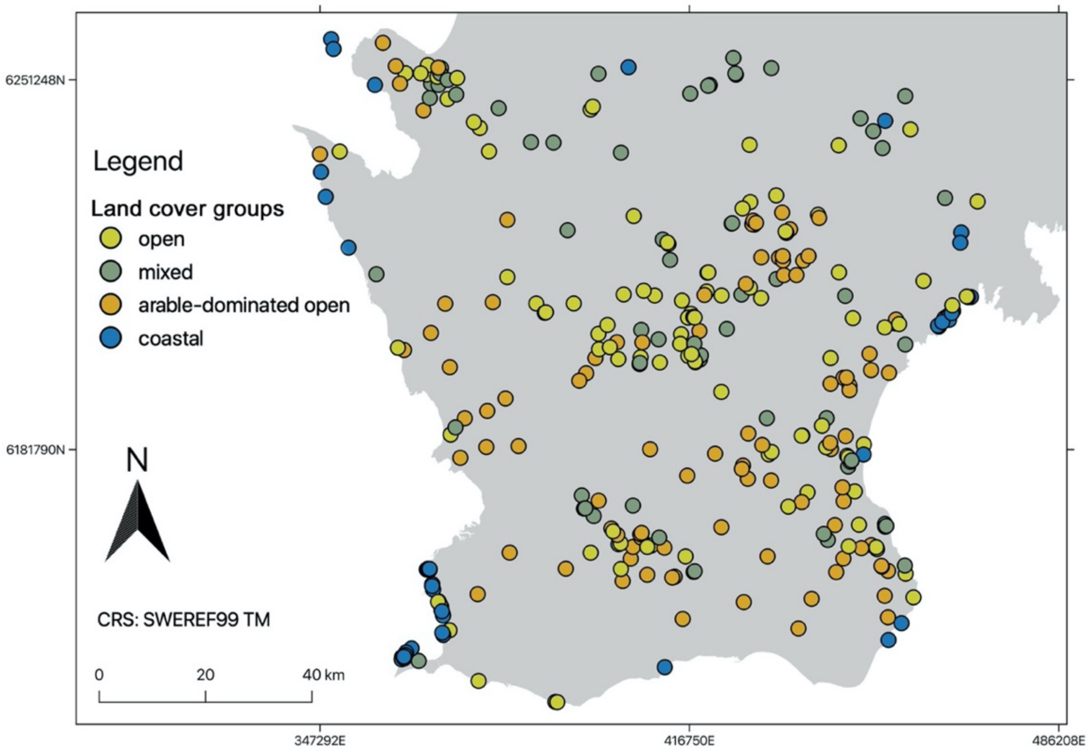

Figure 9. Map showing the spatial distribution of the grazing lands, according to land cover group. The seven land cover classes used to define these land cover groups are based on the 2018 National Land Cover Data provided by The Swedish Environmental Protection Agency. The grazing lands are a subset (all grazing lands inventoried in Scania from 2016 to 2020) of the national Swedish grassland inventory (TUVA).

To visualise the typical land cover in the different groups, three examples of grazing lands and their buffers per group are mapped in Figure 10. While the land cover in the mixed group varies more than in the open and arable-dominated open landscapes, the grouped sites generally have a dominating land cover type. For example this is the case for the coastal sites, where a significant percentage cover of the buffers is water. There are a number of grazing lands that are located very close to each other, having intersecting spatial extents. All the results are based on the 315 grazing lands and 315 buffers, as overlapping sites were not merged or combined.

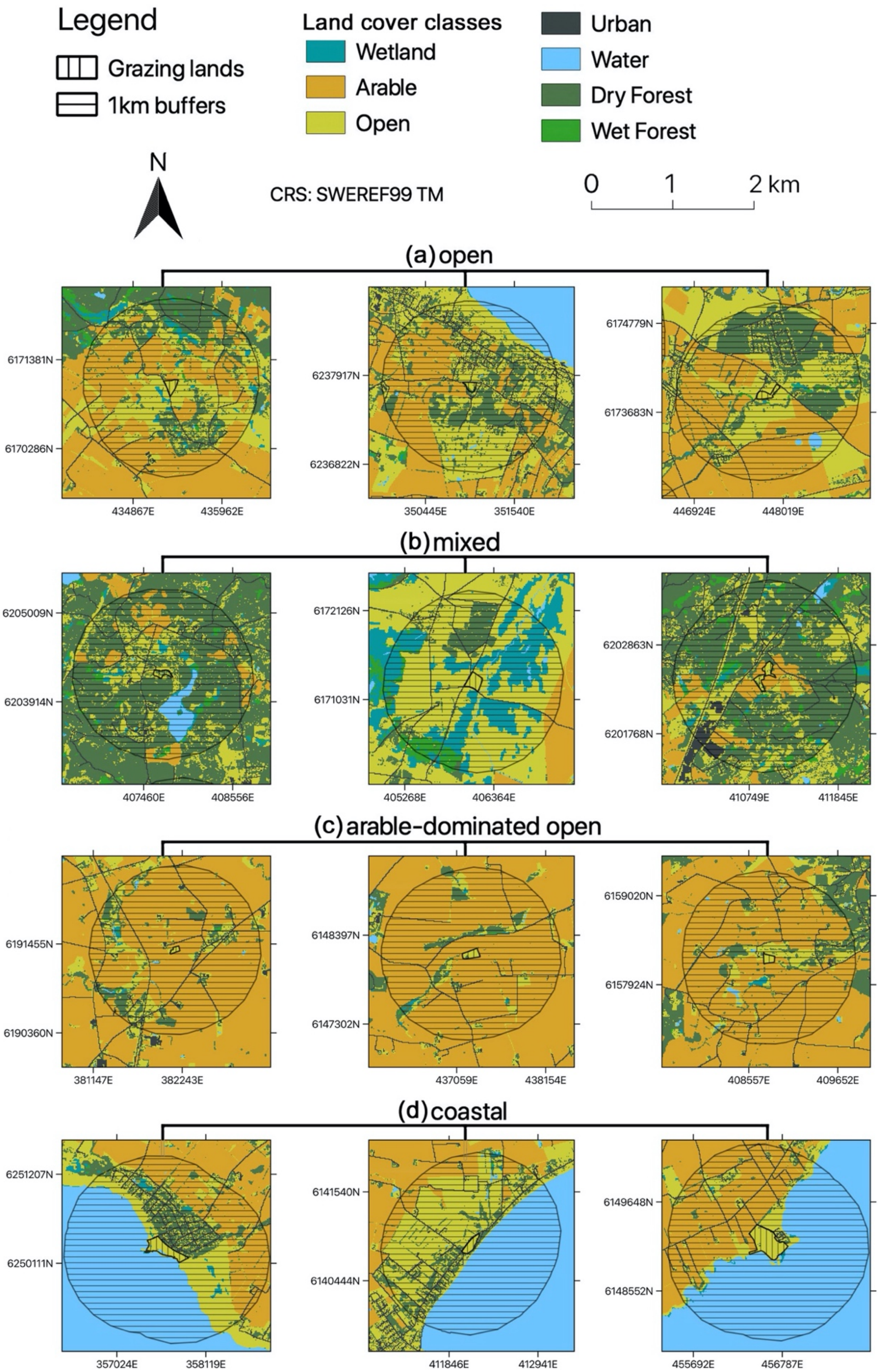

Figure 10. Maps showing three sites per land cover group, showing the land cover within the grazing lands (local scale) and buffers (landscape scale). The groups are based on the buffer percentage land cover. The seven land cover classes are based on the 2018 National Land Cover Data provided by The Swedish Environmental Protection Agency. The grazing lands and buffers are from a subset (grazing lands inventoried in Scania from 2016 to 2020) of the national Swedish grassland inventory (TUVA).

Figure 11 shows group-wise SR comparative boxplots, which indicate that there is very low variability of these measures across the different groups. In the mixed and coastal sites SR (median=6) is marginally higher than that of the two open land cover groups (median=5).

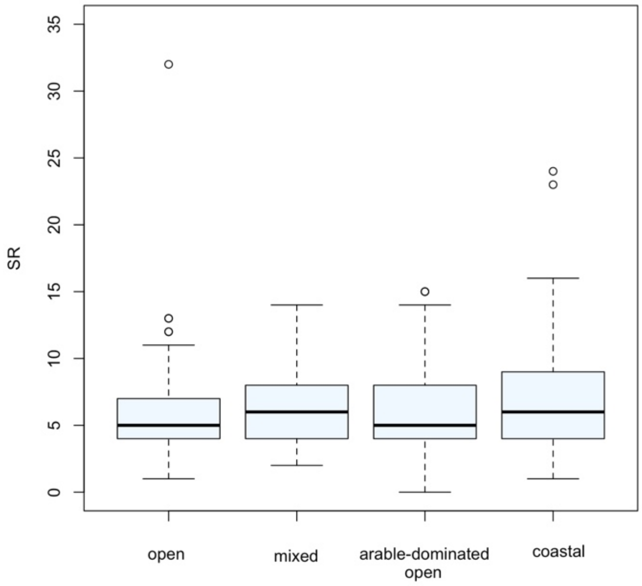

Figure 11. Comparative boxplots of SR by land cover group (SR refers to the biodiversity measure based on plant species richness).

Furthermore, the size of the grazing lands between the groups similarly shows low variability (Figure 12), with coastal sites having a slightly larger median size than the rest. Correlograms were then computed using Spearman's correlation coefficients, for the biodiversity measures against grazing land area, the landscape variables and the local variables (Wetness Index, selected seasonality and land cover variables; using the means across all pixels at the landscape and local scale respectively).

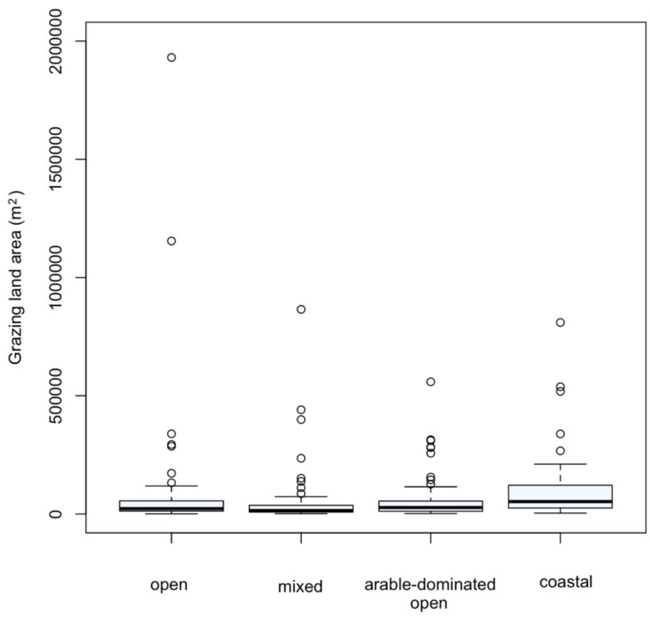

Figure 12. Comparative boxplot of grazing land area (m^2) by land cover group. Grazing land area data were obtained from the TUVA database.

4.3 Landscape variables

The correlogram shown in Figure 13 correlates SR and Rare SR against grazing land area and the multiple independent variables at the landscape scale, based on all the study sites (ungrouped). For each correlogram presented in this chapter, correlation coefficients with a p-value >0.05 are marked with a cross. Hence, all unmarked correlations are considered significant with a 95% confidence interval. SR and Rare SR show almost no correlation with grazing land area and the landscape variables, all of which are not significant (Figure 13).

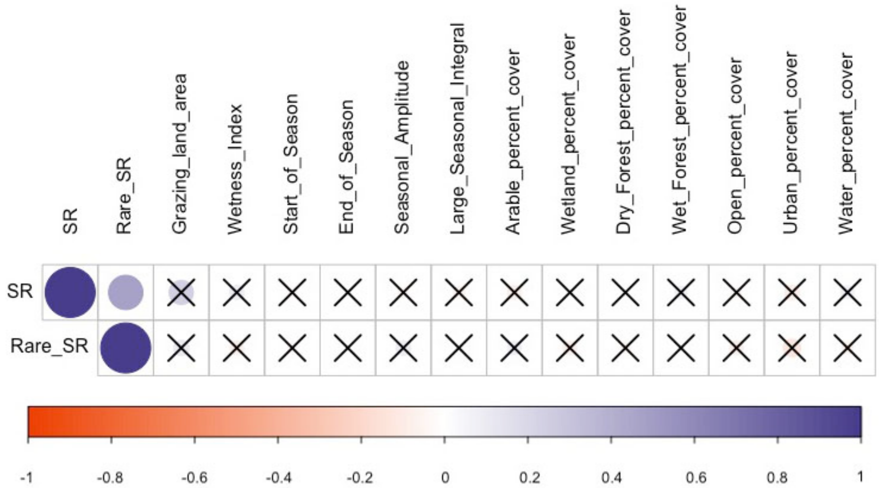

Figure 13. Correlogram of SR and Rare SR with the grazing land area and landscape variables (means). The size of the circles and colour scale portray each correlation coefficient; 1 denotes a perfect positive correlation and -1 is a perfect negative correlation. All correlation coefficients with a p-value >0.05 are marked with a cross (non-significant).

The results using landscape variables per land cover group are shown in the correlograms in Figure 14. There are only a few significant correlations when considering correlations of SR and Rare SR with grazing land area and the landscape variables. In the open land cover group Rare SR and the Start of Season variable show a weak negative correlation (significant), while in the mixed land cover group SR and the seasonality variables also show a weak negative correlation (however, for Start of Season it is not significant). These few weak correlations of SR with the seasonality variables indicate that these variables have the only demonstrable effect, specifically on the plant biodiversity in the grazing lands belonging to the open and mixed land cover groups (landscape land-use is the most varied in the mixed group). In the coastal land cover group the SR shows a moderate positive correlation with the grazing land area. As previously mentioned this land cover group has marginally larger grazing lands than the other groups (Figure 12), which is potentially reflected in this result that contrasts with the rest of the land cover groups. This result is of course replicated in the group-wise correlograms for the local variables (Figure 16), as grazing land area is static per study site.

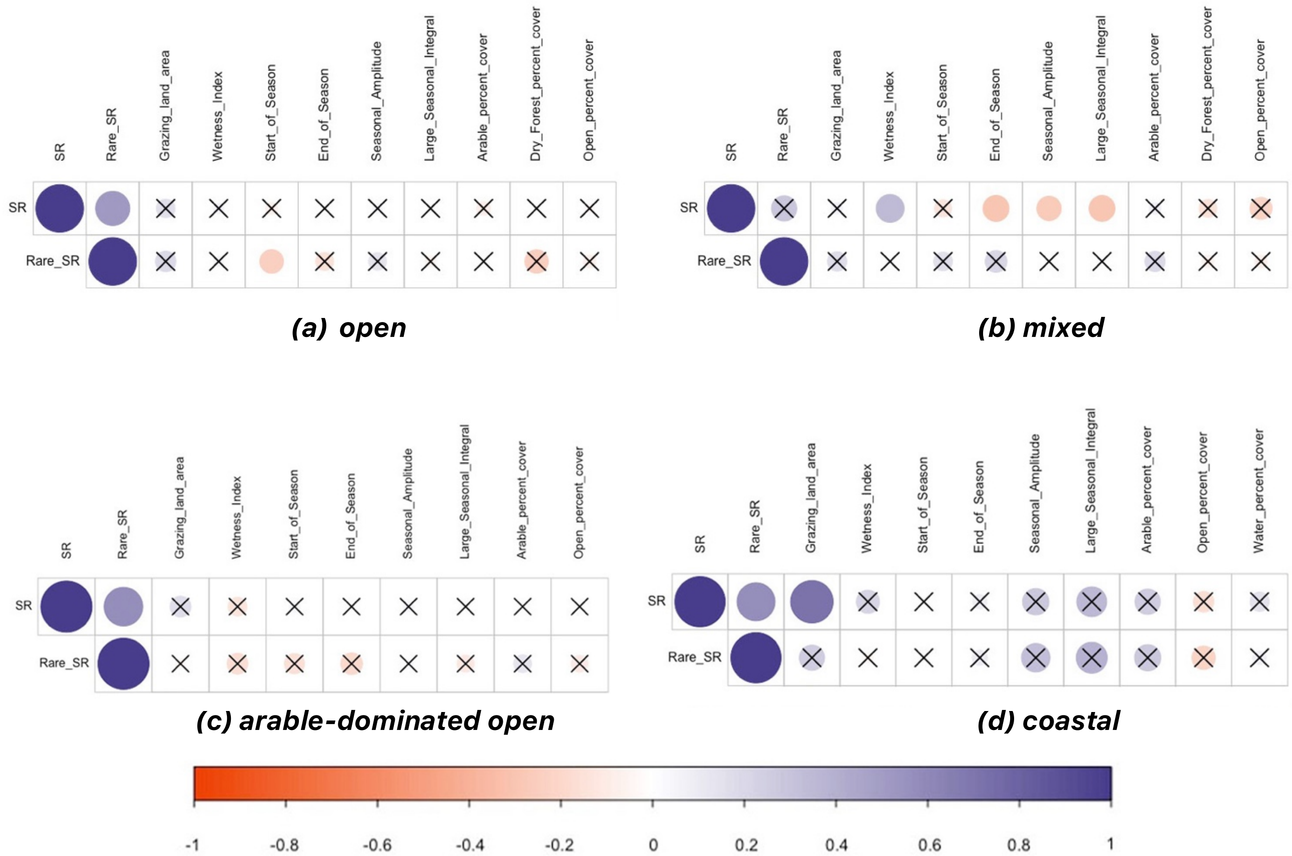

Figure 14. (a) Correlogram of SR and Rare SR with the grazing land area and landscape variables (means) in the open land cover group. (b) Correlogram of SR and Rare SR with the grazing land area and landscape variables (means) in the mixed land cover group. (c) Correlogram of SR and Rare SR with the grazing land area and landscape variables (means) in the arable-dominated open land cover group. (d) Correlogram of SR and Rare SR with the grazing land area and landscape variables (means) in the coastal land cover group. The size of the circles and colour scale portray each correlation coefficient; 1 denotes a perfect positive correlation and -1 is a perfect negative correlation. All correlation coefficients with a p-value >0.05 are marked with a cross (non-significant).

Although not significant correlations, the seasonality variables (particularly the Seasonal Amplitude and Large Seasonal Integral variables) in the coastal land cover group have a weak positive correlation with both SR and Rare SR. To a certain extent, this shows a contrary relationship of SR with the seasonality at the landscape scale when compared to the weak negative correlations of SR with these variables in the mixed group.

4.4 Local variables

SR and Rare SR are correlated against grazing land area and all the variables at the local scale in Figure 15, based on all the study sites (ungrouped).

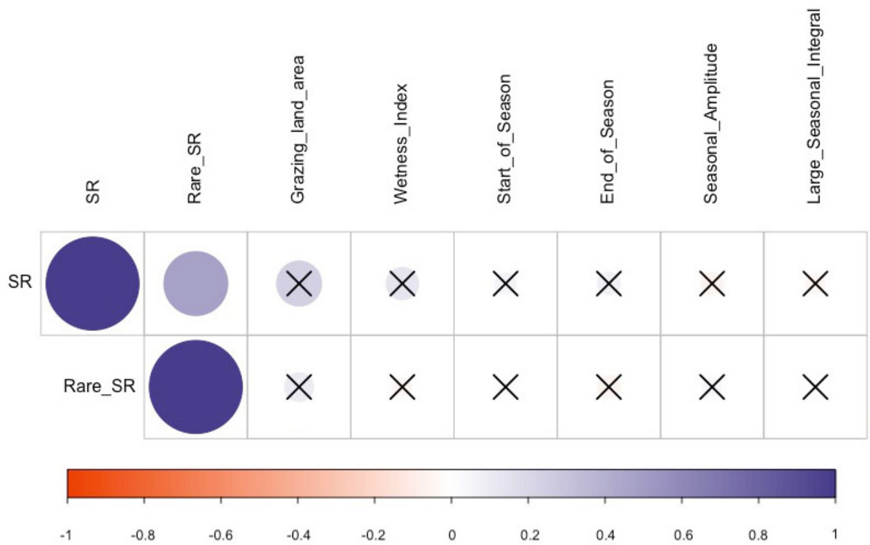

Figure 15. Correlogram of SR and Rare SR with the grazing land area and local variables (means). The size of the circles and colour scale portray each correlation coefficient; 1 denotes a perfect positive correlation and -1 is a perfect negative correlation. All correlation coefficients with a p-value >0.05 are marked with a cross (non-significant).

For the local variable correlograms by group, the majority of correlation coefficients are not significant (Figure 16). Less variables are included in the correlograms using local variables (Figures 15 and 16) as the percentage land cover variables are excluded. This allows for less correlations per group and in turn less opportunity of finding positive or negative relationships between variables as with the landscape variables. Four weak negative correlations in the coastal land cover group are shown, with SR and Rare SR both having a weak negative correlations (that are significant) with the Wetness Index and Start of Season variables.

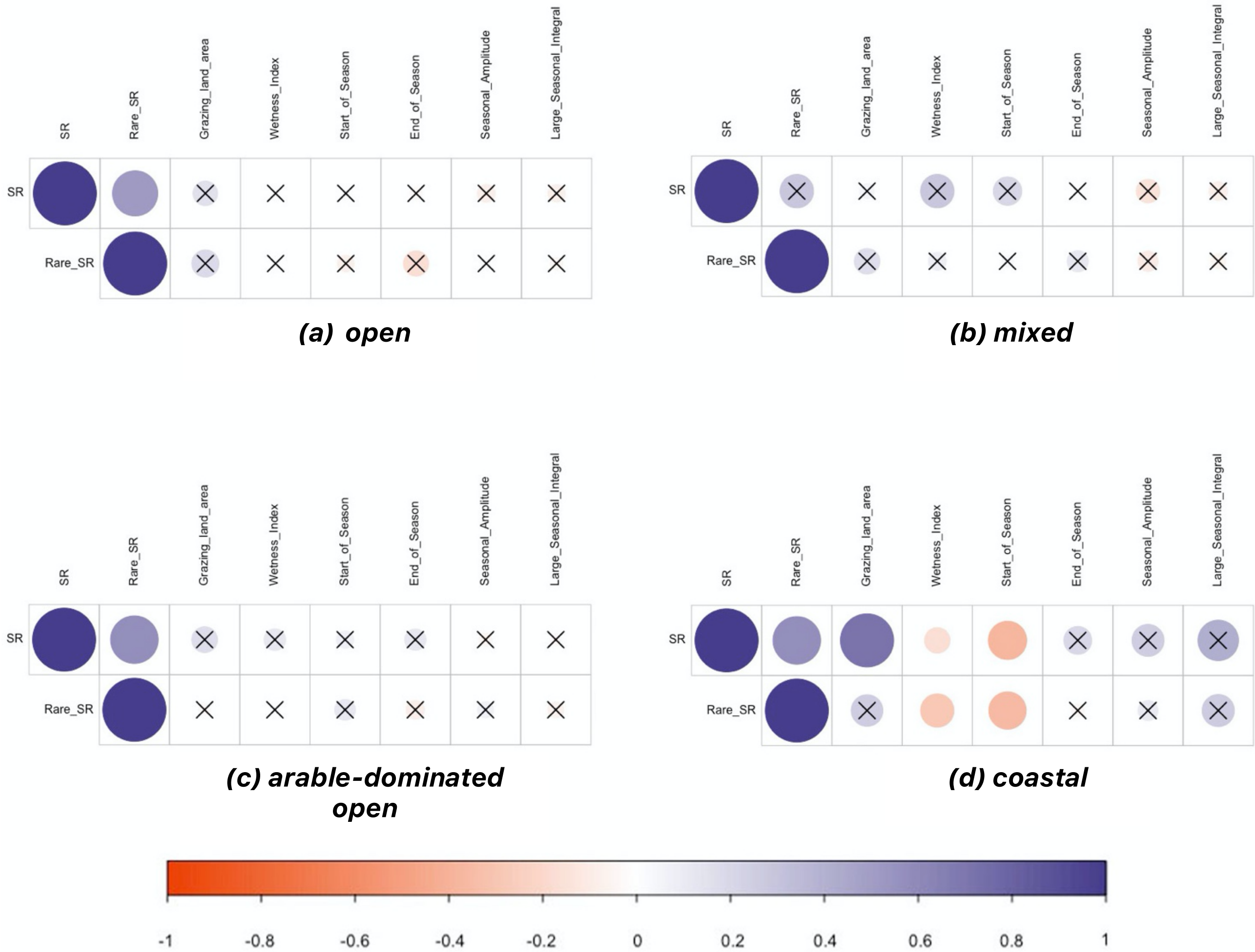

Figure 16. (a) Correlogram of SR and Rare SR with the grazing land area and local variables (means) in the open land cover group. (b) Correlogram of SR and Rare SR with the grazing land area and local variables (means) in the mixed land cover group. (c) Correlogram of SR and Rare SR with the grazing land area and local variables (means) in the arable-dominated open land cover group. (d) Correlogram of SR and Rare SR with the grazing land area and local variables (means) in the coastal land cover group. The size of the circles and colour scale portray each correlation coefficient; 1 denotes a perfect positive correlation and -1 is a perfect negative correlation. All correlation coefficients with a p-value >0.05 are marked with a cross (non-significant).

Overall the data analysis at both landscape and local scales shows that very few positive and negative weak correlations can be observed between plant biodiversity and the multiple, mainly remotely sensed seasonality variables. Group-wise analysis of the study sites identified these weak correlations, only some of which are considered as significant.

5. Discussion

5.1 Main findings

Following the initial results relating to the plant biodiversity measures used, the correlation matrices provide the more substantial results that can be interpreted to answer the research questions. The correlograms presented in Figures 13 and 15 show no correlation between SR and Rare SR with grazing land area, landscape variables and local variables, respectively. This part of the analysis, while delivering an overall result, shows that none of the land-use related variables can be clearly associated with the biodiversity measures. The grouping of the sites was devised to investigate further, classifying the grazing lands according to land cover at the landscape scale. This group-wise analysis was initially a spatial assessment, to check that the sites were distinct enough in their surrounding land cover (Figure 9). The typical landscape per land cover group shown in Figure 10 complements the comparative boxplots of land cover presented in Figure 8. The number of sites per group is another aspect that was also taken into consideration when interpreting the SR and Rare SR by group (Figure 11). The low variability of the SR by group suggests that these are overall not dependent on the location or size of the grazing land (Figure 12).

The productivity in mixed group is expected to be higher due to more varied vegetation (e.g. wetland and dry forest land cover) at the landscape scale, when compared to the open and arable landscape land covers of the two main groups. This could explain why the richness of specialist plants in such grazing lands with more varied landscape land cover show a weak negative correlation with the seasonality variables at the landscape scale (Figure 14). Although the weak positive correlations of SR with the seasonality variables are not significant in the coastal land cover group (using 5% significance), this suggests an opposite effect of the land-use to that found in the mixed group. While productivity may be highest in a mixed land-use, this gives an expected indication that there is less productivity in the landscape of coastal grazing lands. The extent of water cover surrounding coastal sites would explain this lower productivity, yet the SR and Rare SR are relatively high in some coastal grazing lands (Figures 5 and 6). The coastal sites may harbour particular species that occur less or do not occur inland (and to a less extent, conversely, inland sites may host species that coastal sites do not) and therefore a number of the positive indicator species could be somewhat exclusive to the coastal grazing lands (e.g. different types of soil and salinity conditions compared to the other land cover groups). The slightly larger size of some coastal sites could also allow more of the plant species to occur, yet SR and Rare SR are rather evenly distributed across the different land cover groups.

When evaluating the local scale group-wise correlograms, the only significant correlations suggested are in the coastal group (Figure 16). SR and Rare SR were shown to have a weak negative correlation with the Start of Season variable, and an even weaker negative correlation with the Wetness Index variable. These results suggest that to some extent there is an association between SR and Rare SR with an earlier start of season, possibly due to different growth timing of the positive indicator species with other vegetation in the grazing lands. A similar association specifically in these coastal sites is indicated for SR and Rare SR when considering the Wetness Index, where higher soil moisture could limit the plant biodiversity in these grazing lands. Overall it can be deduced that none of the local variables can be strongly associated with the plant biodiversity measures, and that SR and Rare SR are overall not associated on the land-use at this scale.

Relating the results back to the research question and sub-questions, the results at the landscape scale show that SR and seasonality variables show weak negative correlations in the mixed land cover group, while Rare SR shows a weak negative the Start of Season variable. On the whole, the lack of measurable correlations at this scale could be due to the variables tested being completely independent. However, it could also be due to the variable data being unsuited to observe significant correlations (even though the appropriate correlation coefficients were used). Similarly, the local scale results show that SR and Rare SR are generally not correlated to the multiple variables, with only few correlations of significance found in the coastal land cover group. At both local and landscape scales, association of the multiple variables (relating to land-use, aside from the grazing land area variable) with the plant biodiversity in Scanian grazing lands was not possible to determine with significant correlations. The very few correlations that can be revealed between the selected variables and the biodiversity measures studied indicates that while the results point towards no correlation, it is possible that the analysis method itself and/or the processed variables are not able to reveal correlations of significance (i.e. the lack of association between the variables does not conclusively exclude the possibility of such associations across different methods and spatial scales). In practice, the sub-research questions (I) and (II) are not answered in any certain terms following the analysis and nature of the results obtained at both the landscape (sub-question I) and local (sub-question II) scales. In turn, the answer to the main research question is a negative results, that plant biodiversity and land-use are not associated, within the context of the variables used to describe land-use (the Wetness Index, seasonality and land cover variables).

5.2 Data quality and validity of results

When considering the spatial and temporal qualities of the inventory data utilised and the analysis carried out, the SR and Rare SR results should be interpreted as a snapshot of the vegetation biodiversity situation in Scanian grazing lands. The use of TUVA-defined specialist plants was ultimately done to ensure that the measures of plant biodiversity are estimated on sites that are managed and have had long-term land-use as grazing lands. The subset data used is essential for the relevance of the results, using the most recent field inventory records, although there are limitations when using a subset with 315 grazing lands. My sample of grazing lands uses data almost 10% of the 2734 grazing lands inventoried regionally over the past two decades. However, the distribution of these grazing lands is assumed to be adequate, taking into account that there is a suitable balance between the number of inland and coastal sites (Figures 2 and 3). Therefore the distribution of these grazing lands is assumed to be adequate.

With the utilisation of the most recent datasets for these partially and fully-remotely sensed variables, the remote sensing data could introduce artefacts in the results obtained, potentially related to interannual weather variability affecting satellite imagery. Land cover data is perhaps the least to vary significantly between years and the data used provided expected land cover results, with agricultural land types having a prevalent percentage cover in most study sites. The Wetness Index that relates to soil moisture and other terrestrial indices, also provided expected results, substantiated in the resulting correlograms that for example indicate negative correlations between Wetness Index and Dry Forest percent cover, and positive correlations with Water percent cover (Figures 13 and 14). Contrary to the Wetness Index and land cover data, the seasonality variables are likely the most influenced by variability of weather between the years. The averaging of the 2017-2020 seasonality raster layers was done to avoid selecting a year and subjectively influence the seasonality parameters. A number of positive and negative correlations between the PPI variables is present and also expected, suggesting that the seasonality variables used to capture the phenology of the growing season behave as anticipated throughout the data analysis.

The relatively small size and cover of the specialist species in the grazing lands would not be expected to heavily influence any of the remotely sensed data (satellite imagery) used to derive the Wetness Index, seasonality variables and land cover utilised as land-use variables. This is ultimately why the landscape scale is used more in my analysis, utilising the remotely sensed data across differing land covers and vegetation types, in larger areas than the grazing land extents.

While all the variables used incorporate remote sensing derived data, it is the Sentinel-2 data (on which seasonal variables were derived using PPI) which exclusively uses remotely sensed data. Apart from the quality of the source data (fine resolution of 10m), it is the use of PPI and its capability to capture the vegetation phenology in northern latitudes (Tian et al. 2021) that reinforces the application of the derived parameters as seasonality variables. Applying such PPI data is consistent with what the literature identifies as the best performing vegetation index given the study area. Moreover, the PPI source data and the processing methods implemented are very similar to those used by Tian et al. (2021).

Successional stages of grasslands have been also been classified via remote sensing techniques, however this is based on remote sensing techniques using hyperspectral imagery. Mockel et al. (2014) developed methods that are able to discern grassland age-classes, related to the length of time of grazing management. Such grassland successional stages could be implemented in biodiversity research to classify grasslands, enabling the monitoring of biodiversity with respect to group-wise grazing periods (age-classes) instead of using land-use. Although hyperspectral data is often used in biodiversity research, it is not as easily obtained as satellite data and thus would now be very applicable in determining seasonal ecosystem productivity that was I was aiming for in my study.

Other vegetation indices were not implemented in my study, which would have allowed for more validation of the PPI-related results of this project. Additionally, more topographical variables would allow for more correlation analyses, furthering research on land-use and its effects on grassland plants. Finally, the land-use effects that potentially drive plant biodiversity in Scanian grazing lands, in terms of the other landscape and local variables (not tackled in this project) require further research. More advanced analysis and modelling could be implemented in larger scope studies, however the first steps in investigating land-use and its effects on biodiversity could utilise the methodology presented. This would incorporate more remote sensing techniques and allows for relatively large scale studies, depending on the data in use. Throughout the project I strived to balance this biodiversity-related research using methods from both landscape ecology and physical geography approaches.

Whilst an adequate number of grazing land records were utilised in this project, both regional and national grassland studies could benefit from larger quantities of up-to-date records. An increased inventorying effort of grasslands would enlarge the number of sites available for recent years in the TUVA database. This could improve the biodiversity measures. Re-inventorying efforts for sites with rather old records (e.g. those collected in the early 2000s when the TUVA surveying was initiated) has been carried out but could be prioritised to generate further contemporary data.

The SR and Rare SR measures using TUVA-defined positive indicator species are in line with ecological standards in biodiversity research. However, one could also select the inventoried plant species that are red-listed and use this as an additional biodiversity measure. Although not widely used, future research could incorporate such a method and assess how it compares to the measures of this project.

5.3 Implications of study

The few weak correlations found at both the landscape and local scales do not provide much room for further investigation of any dependencies between these scales, when using the variables selected for this study. Historical land-use is therefore said to be the best explanation for the current specialist plant richness, meaning that the plant biodiversity mostly depends on the long-standing land-use of the grazing land habitat itself (Auffret et al. 2018). For grazing lands, this underpins the importance of this habitat and the vegetative diversity that is maintained by conserving the sites, and biodiversity as a whole would benefit as a result of maintaining the plant biodiversity found to occur in this semi-natural habitat. Biodiversity in terms of both plant and animal species are able to thrive in such grazing land habitat, and the conservation of such grasslands to avoid further land-use change is imperative to safeguard biodiversity at large (Allan et al. 2014).

The correlograms for the grouped sites at the landscape scale imply weak to no correlation between the biodiversity measures and the landscape variables (Figure 12). Using a 95% confidence interval, the biodiversity measures and grazing land area show a weak association in the coastal land-use group. The only other correlation of significance are those between SR and the four seasonality variables, which indicate a weak negative correlation, in the mixed land-use group. All the correlograms (reduced correlograms presented in the Results chapter, showing correlations for the multiple variables against SR and Rare SR only) helped in validating the results, as they included all the data utilised and showed other correlations between the multiple variables.

It is crucial to repeat that the resulting lack of correlations at both landscape and local scales indicate that the biodiversity within grazing lands is not seemingly dependent on the multiple variables related to land-use. Even with a limited regional context and biodiversity measures based on plant richness, the suggestion in recent literature that historical land-use drives biodiversity in grasslands can to some degree be supported by the results of this study (Auffret et al. 2018; Allan et al. 2014; Dainese et al. 2017). Extinction debt is another phenomenon that could provide insights into how the habitat fragmentation of the Scanian landscape in modern times could have a delayed effect on biodiversity (Kuussaari et al. 2009), that is applicable to grazing lands and the positive indicator species considered in my study. As pointed out in the literature, the use of species richness as a biodiversity metric appears to be the most simple but insensitive measure (Dainese et al. 2017). The use of SR and Rare SR (and similar richness metrics) is therefore the best practice so far, to capture any cascading extinction events with the loss of particular species in grassland ecosystems.

The land-use change in Scania has increased from historical levels, especially due to agriculture. Crop production from arable land and grazing livestock on grazing lands are increasingly managed according to the modern agricultural operations (Kapás et al. 2020). This impacts land-use intensity and adds to the stress on land resources, contributing to the decrease in semi-natural grazing land across Sweden in recent years. While not all grazing activities benefit wildlife, grazing lands remain important for many flora and fauna, as the habitat is maintained in a more natural state than if used as arable (ploughed) land.

6. Conclusions

Whereas the use of specialist species is conventional in estimating species richness, it is the use of the Wetness Index and the seasonality variables as estimations of landscape productivity and phenology that distinguishes my study from previous land-use and biodiversity research. Although the correlation analyses between plant richness and the multiple variables indicate a lack of statistical dependency, the conservation of grazing land habitat as well as the surrounding buffers remains imperative for the habitat-specific biodiversity. At the landscape scale, only very weak negative correlations of plant richness with seasonality were discovered. Subsequently, none of correlations between the biodiversity measures and multiple variables were found to be significant at the local scale. Further analysis using land cover groups revealed a few weak correlations, however the research goal of finding associations between the plant biodiversity and land-use in Scanian grazing lands could not be met and is therefore a negative result in terms of finding correlations of significance.

Following the use of standard biodiversity metrics and multiple landscape descriptors, the importance of present land-use for plant biodiversity patterns in Scanian grazing lands could not be established (at both the landscape and local scales). Whilst avoiding unnecessary complexity in my attempt to relate land-use with biodiversity, the results and implications are in agreement with recent literature suggesting that rather than the present land-use, the grassland plant biodiversity is due to historical land-use to a greater extent than the current landscape and local land-use. Historical land-use remains a valid explanation of present-day plant richness in grazing lands as most landscape and local effects cannot be associated with biodiversity (with statistical significance).

As a semi-natural habitat, grazing land should be protected and its loss to increasing land-use change or land-use intensity should be mitigated. The potential for further research into grazing land biodiversity and land-use could involve an increased landscape scale (greater than a 1 km landscape scale buffer) in future analysis and compared to the results of this study. Finally, habitat restoration and conservation measures to limit ecological damage should be based on research that considers land-use intensity and productivity when assessing biodiversity, including grazing land plant biodiversity.

7. References

Allan, E., O. Bossdorf, C. F. Dormann, D. Prati, M. M. Gossner, T. Tscharntke, N. Blüthgen, M. Bellach, et al. 2014. Interannual variation in land-use intensity enhances grassland multidiversity. *Proceedings of the National Academy of Sciences of the United States of America* 111: 308–313. doi:10.1073/pnas.1312213111.

Auffret, A. G., A. Kimberley, J. Plue, H. Skånes, S. Jakobsson, E. Waldén, M. Wennbom, H. Wood, et al. 2017. HistMapR: Rapid digitization of historical land-use maps in R. *Methods in Ecology and Evolution* 8: 1453–1457. doi:10.1111/2041-210X.12788.

Auffret, A. G., A. Kimberley, J. Plue, and E. Waldén. 2018. Super-regional land-use change and effects on the grassland specialist flora. *Nature Communications* 9. Springer US. doi:10.1038/s41467-018-05991-y.

Billeter, R., J. Liira, D. Bailey, R. Bugter, P. Arens, I. Augenstein, S. Aviron, J. Baudry, et al. 2008. Indicators for biodiversity in agricultural landscapes: A pan-European study. *Journal of Applied Ecology* 45: 141–150. doi:10.1111/j.1365-2664.2007.01393.x.

Boke Olén, N., F. Roger, M. V. Brady, C. Larsson, G. K. S. Andersson, J. Ekroos, P. Caplat, H. G. Smith, et al. 2021. Effects of farm type on food production, landscape openness, grassland biodiversity, and greenhouse gas emissions in mixed agricultural-forestry regions. *Agricultural Systems* 189. doi:10.1016/j.agsy.2021.103071.

Buchanan, B. P., M. Fleming, R. L. Schneider, B. K. Richards, J. Archibald, Z. Qiu, and M. T. Walter. 2014. Evaluating topographic wetness indices across central New York agricultural landscapes. *Hydrology and Earth System Sciences* 18: 3279–3299. doi:10.5194/hess-18-3279-2014.

Cai, Z., S. Junttila, J. Holst, H. Jin, J. Ardö, A. Ibrom, M. Peichl, M. Mölder, et al. 2021. Modelling Daily Gross Primary Productivity with Sentinel-2 Data in the Nordic Region – Comparison with Data from MODIS: 1–18.

Clough, Y., J. Ekroos, A. Báldi, P. Batáry, R. Bommarco, N. Gross, A. Holzschuh, S. Hopfenmüller, et al. 2014. Density of insect-pollinated grassland plants decreases with increasing surrounding land-use intensity. *Ecology Letters* 17: 1168–1177. doi:10.1111/ele.12325.

Dainese, M., N. J. B. Isaac, G. D. Powney, R. Bommarco, E. Öckinger, M. Kuussaari, J. Pöyry, T. G. Benton, et al. 2017. Landscape simplification weakens the association between terrestrial producer and consumer diversity in Europe. *Global Change Biology* 23: 3040–3051. doi:10.1111/gcb.13601.

Duflot, R., A. Ernoult, S. Aviron, L. Fahrig, and F. Burel. 2017. Relative effects of landscape composition and configuration on multi-habitat gamma diversity in agricultural landscapes. *Agriculture, Ecosystems and Environment* 241. Elsevier B.V.: 62–69. doi:10.1016/j.agee.2017.02.035.

Eklundh, L. and Jönsson, P., 2017, Timesat 3.3 Software Manual, Lund and Malmö University, Sweden.

Ekroos, J., D. Kleijn, P. Batáry, M. Albrecht, A. Báldi, N. Blüthgen, E. Knop, A. Kovács-Hostyánszki, et al. 2020. High land-use intensity in grasslands constrains wild bee species richness in Europe. *Biological Conservation* 241. Elsevier: 108255. doi:10.1016/j.biocon.2019.108255.

Felipe-Lucia, M. R., S. Soliveres, C. Penone, M. Fischer, C. Ammer, S. Boch, R. S. Boeddinghaus, M. Bonkowski, et al. 2020. Land-use intensity alters networks between biodiversity, ecosystem functions, and services. *Proceedings of the National Academy of Sciences of the United States of America* 117: 28140–28149. doi:10.1073/pnas.2016210117.

Gámez-Virués, S., D. J. Perović, M. M. Gossner, C. Börschig, N. Blüthgen, H. De Jong, N. K. Simons, A. M. Klein, et al. 2015. Landscape simplification filters species traits and drives biotic homogenization. *Nature Communications* 6. doi:10.1038/ncomms9568.

Gerard, F. F., C. T. George, G. Hayman, C. Chavana-Bryant, and G. P. Weedon. 2020. Leaf phenology amplitude derived from MODIS NDVI and EVI: Maps of leaf phenology synchrony for Meso- and South America. *Geoscience Data Journal* 7: 13–26. doi:10.1002/gdj3.87.

Gonthier, D. J., K. K. Ennis, S. Farinas, H. Y. Hsieh, A. L. Iverson, P. Batáry, J. Rudolphi, T. Tscharntke, et al. 2014. Biodiversity conservation in agriculture requires a multi-scale approach. *Proceedings of the Royal Society B: Biological Sciences* 281: 9–14. doi:10.1098/rspb.2014.1358.

Hodgson, J. A., C. D. Thomas, C. Dytham, J. M. J. Travis, and S. J. Cornell. 2012. The Speed of Range Shifts in Fragmented Landscapes. *PLoS ONE* 7. doi:10.1371/journal.pone.0047141.

Ihse, M., and C. Lindahl. 2000. A holistic model for landscape ecology in practice: The Swedish survey and management of ancient meadows and pastures. *Landscape and Urban Planning* 50: 59–84. doi:10.1016/S0169-2046(00)00080-3.

Jin, H., and L. Eklundh. 2014. A physically based vegetation index for improved monitoring of plant phenology. *Remote Sensing of Environment* 152. Elsevier Inc.: 512–525. doi:10.1016/j.rse.2014.07.010.

Jin, H., A. M. Jönsson, K. Bolmgren, O. Langvall, and L. Eklundh. 2017. Disentangling remotely-sensed plant phenology and snow seasonality at northern Europe using MODIS and the plant phenology index. *Remote Sensing of Environment* 198. Elsevier Inc.: 203–212. doi:10.1016/j.rse.2017.06.015.

Jin, H., A. M. Jönsson, C. Olsson, J. Lindström, P. Jönsson, and L. Eklundh. 2019. New satellite-based estimates show significant trends in spring phenology and complex sensitivities to temperature and precipitation at northern European latitudes. *International Journal of Biometeorology* 63. International Journal of Biometeorology: 763–775. doi:10.1007/s00484-019-01690-5.

Jönsson, P. and Eklundh, L., 2002, Seasonality extraction and noise removal by function fitting to time-series of satellite sensor data, IEEE Transactions of Geoscience and Remote Sensing, 40, No 8, 1824 – 1832.

Jönsson, P., and L. Eklundh. 2004. TIMESAT - A program for analyzing time-series of satellite sensor data. *Computers and Geosciences* 30: 833–845. doi:10.1016/j.cageo.2004.05.006.

Jönsson, P., Z. Cai, E. Melaas, M. A. Friedl, and L. Eklundh. 2018. A method for robust estimation of vegetation seasonality from Landsat and Sentinel-2 time series data. *Remote Sensing* 10. doi:10.3390/rs10040635.

Kapás, R. E., J. Plue, A. Kimberley, and S. A. O. Cousins. 2020. Grazing livestock increases both vegetation and seed bank diversity in remnant and restored grasslands. *Journal of Vegetation Science* 31: 1053–1065. doi:10.1111/jvs.12956.

Kuussaari, M., R. Bommarco, R. K. Heikkinen, A. Helm, J. Krauss, R. Lindborg, E. Öckinger, M. Pärtel, et al. 2009. Extinction debt: a challenge for biodiversity conservation. *Trends in Ecology and Evolution* 24: 564–571. doi:10.1016/j.tree.2009.04.011.

Manning, P., M. M. Gossner, O. Bossdorf, E. Allan, Y. Y. Zhang, D. Prati, N. Blüthgen, S. Boch, et al. 2015. Grassland management intensification weakens the associations among the diversities of multiple plant and animal taxa. *Ecology* 96: 1492–1501. doi:10.1890/14-1307.1.

Mockel, T., J. Dalmayne, H. C. Prentice, L. Eklundh, O. Purschke, S. Schmidtlein, and K. Hall. 2014. Classification of grassland successional stages using airborne hyperspectral imagery. *Remote Sensing* 6: 7732–7761. doi:10.3390/rs6087732.

Oliver, T. H., S. Gillings, J. W. Pearce-Higgins, T. Brereton, H. Q. P. Crick, S. J. Duffield, M. D. Morecroft, and D. B. Roy. 2017. Large extents of intensive land use limit community reorganization during climate warming. *Global Change Biology* 23: 2272–2283. doi:10.1111/gcb.13587.

Persson, A. S., O. Olsson, M. Rundlöf, and H. G. Smith. 2010. Land use intensity and landscape complexity-Analysis of landscape characteristics in an agricultural region in Southern Sweden. *Agriculture, Ecosystems and Environment* 136: 169–176. doi:10.1016/j.agee.2009.12.018.

Pettorelli, N., H. Schulte to Bühne, A. Tulloch, G. Dubois, C. Macinnis-Ng, A. M. Queirós, D. A. Keith, M. Wegmann, et al. 2018. Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. *Remote Sensing in Ecology and Conservation* 4: 71–93. doi:10.1002/rse2.59.

QGIS.org, 2021. QGIS Geographic Information System. QGIS Association. http://www.qgis.org

RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/

Swedish Board of Agriculture, 2013. “Utvärdering av ängs- och betesmarksinventeringen och databasen TUVA”. Accessed on 11 February 2021 from: https://www2.jordbruksverket.se/webdav/files/SJV/trycksaker/Pdf_rapporter/ra13_32.pdf

Swedish Board of Agriculture, 2017. “Ängs- och betesmarksinventeringen. Metodik för inventerering från och med 2016”. Accessed on 11 February 2021 from: https://www2.jordbruksverket.se/download/18.48a7452e15c7b4a5a65a3a6b/1496908244029/ra17_9.pdf

Swedish Environmental Protection Agency, 2019. “Rikstäckande information om markens fuktighet”. Accessed on 3 February 2021 from: https://metadatakatalogen.naturvardsverket.se/metadatakatalogen/GetMetaDataById?id=8853721d-a466-4c01-afcc-9eae57b17b39

Swedish Environmental Protection Agency, 2020. “Nationella marktäckedata 2018 basskikt”. Accessed on 3 February 2021 from: https://www.naturvardsverket.se/upload/sa-mar-miljon/kartor/NMD-Produktbeskr-NMD2018Basskikt-v2-2.pdf

Newbold T., L. Hudson, A. S. Arnell, S. Contu, et al. 2016. Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. Science 353: 288–291. doi: 10.1126/science.aaf2201.

Tian, F., Z. Cai, H. Jin, K. Hufkens, H. Scheifinger, et al. 2021. Calibrating vegetation phenology from Sentinel-2 using eddy covariance, PhenoCam, and PEP725 networks across Europe. *Remote Sensing of Environment* 260. Elsevier Inc.: 112456. doi:10.1016/j.rse.2021.112456.

The National Land Cover Database (from Swedish Environmental Protection Agency). Retrieved on 3 February 2021 from: http://www.swedishepa.se/State-of-the-environment/Maps-and-map-services/National-Land-Cover-Database/Download-the-National-Land-Cover-Database/

Tscharntke, T., A. M. Klein, A. Kruess, I. Steffan-Dewenter, and C. Thies. 2005. Landscape perspectives on agricultural intensification and biodiversity - Ecosystem service management. *Ecology Letters* 8: 857–874. doi:10.1111/j.1461-0248.2005.00782.x.

TUVA database (Swedish national survey of semi-natural pastures and meadows). Retrieved on 2 February 2021 from: https://jordbruksverket.se/e-tjanster-databaser-och-appar/e-tjanster-och-databaser-stod/tuva

TUVA database (Swedish national survey of semi-natural pastures and meadows) shapefiles. Retrieved on 2 February 2021 from: https://jordbruksverket.se/e-tjanster-databaser-och-appar/e-tjanster-och-databaser-stod/tuva

WallisDeVries, M. F., P. Poschlod, and J. H. Willems. 2002. Challenges for the conservation of calcareous grasslands in northwestern Europe: Integrating the requirements of flora and fauna. *Biological Conservation* 104: 265–273. doi:10.1016/S0006-3207(01)00191-4.

Wetness Index data (Markfuktighetsindex). Retrieved on 3 February 2021 from: https://gpt.vic-metria.nu/data/land/NMD/Markfuktighetsindex_NMD_del9.zip

Ågren, A. M., W. Lidberg, M. Strömgren, J. Ogilvie, and P. A. Arp. 2014. Evaluating digital terrain indices for soil wetness mapping-a Swedish case study. *Hydrology and Earth System Sciences* 18: 3623–3634. doi:10.5194/hess-18-3623-2014.

Ödman, A. M., T. K. Schnoor, J. Ripa, and P. A. Olsson. 2012. Soil disturbance as a restoration measure in dry sandy grasslands. *Biodiversity and Conservation* 21: 1921–1935. doi:10.1007/s10531-012-0292-4.

8. Appendices

8.1 Appendix A

Alphabetical list of the 70 positive indicator species inventoried in Scanian semi-natural grazing lands. All these plant species were used to calculate SR, while the 37 species annotated with a (*) were used to calculate Rare SR.

	Latin name	Swedish name
*	*Ajuga pyramidalis*	Blåsuga
*	*Antennaria dioica*	Kattfot
	Armeria maritima	Trift
	Arnica montana	Slåttergubbe
*	*Botrychium lunaria*	Låsbräkenarter
	Briza media	Darrgräs
	Campanula persicifolia	Stor blåklocka
	Cardamine	Ängs- och kärrbräsma
*	*Carex hostiana*	Ängsstarr
	Carex panicea	Hirsstarr
*	*Carex pilulifera*	Pillerstarr
*	*Carlina vulgaris*	Spåtistel
	Centaurium	Aruner
*	*Cirsium heterophyllum*	Brudborste
	Corynephorus canescens	Borsttåtel
*	*Crepis praemorsa*	Klasefibbla
*	*Dactylorhiza incarnata*	Ängsnycklar
*	*Dactylorhiza maculata*	Fläcknycklar
	Danthonia decumbens	Knägräs
	Dianthus deltoides	Backnejlika
*	*Epipactis palustris*	Kärrknipprot
*	*Erica tetralix*	Klockljung
*	*Euphrasia*	Ögontröster
	Filipendula vulgaris	Brudbröd
	Galium saxatile	Stenmåra
	Galium verum	Gulmåra
*	*Gentiana pneumonanthe*	Klockgentiana
*	*Gymnadenia conopsea*	Brudsporre
*	*Helianthemum*	Solvändor
*	*Helictotrichon pratense*	Ängshavre

*	*Hypochaeris maculata*	Slåtterfibbla
	Juncus squarrosus	Borsttåg
*	*Leontodon hispidus*	Sommarfibbla
	Leucanthemum vulgare	Prästkrage
*	*Linum catharticum*	Vildlin
	Luzula	Ängsfryle/blek-/svartfryle
	Lychnis flos-cuculi	Gökblomster
	Nardus stricta	Stagg
*	*Narthecium ossifragum*	Myrlilja
*	*Odontites litoralis*	Strandrödtoppa
*	*Ophioglossum vulgatum*	Ormtunga
*	*Orchis mascula*	Sankt Pers nycklar
*	*Parnassia palustris*	Slåtterblomma
*	*Pedicularis palustris*	Kärrspira/nordspira
*	*Pedicularis sylvatica*	Granspira
	Pimpinella saxifraga	Bockrot
*	*Pinguicula vulgaris*	Tätört
	Plantago maritima	Gulkämpar
*	*Plantago media*	Rödkämpar
	Platanthera bifolia	Nattvioler
*	*Poa alpina*	Fjällgröe
	Polygalaceae	Jungfrulinväxter
	Potentilla erecta	Blodrot
*	*Primula farinosa*	Majviva
	Primula veris	Gullviva
	Pulsatilla	Pulsatillor (backsippa, fältsippa, mosippa, nipsippa)
	Rhinanthus	Skallror
	Scorzonera humilis	Svinrot
	Sedum	Fetknoppar
*	*Selaginella selaginoides*	Dvärglummer
*	*Serratula tinctoria*	Ängsskära
	Succisa pratensis	Ängsvädd
*	*Thalictrum simplex*	Backruta/nordruta
	Thymus serpyllum	Backtimjan
*	*Trifolium fragiferum*	Blåsklöver
	Triglochin maritima	Havssälting
	Triglochin palustris	Kärrsälting
*	*Trollius europaeus*	Smörboll
	Veronica officinalis	Ärenpris
*	*Veronica spicata*	Axveronika

8.2 Appendix B

Additional figures cited in the Materials and methods chapter.

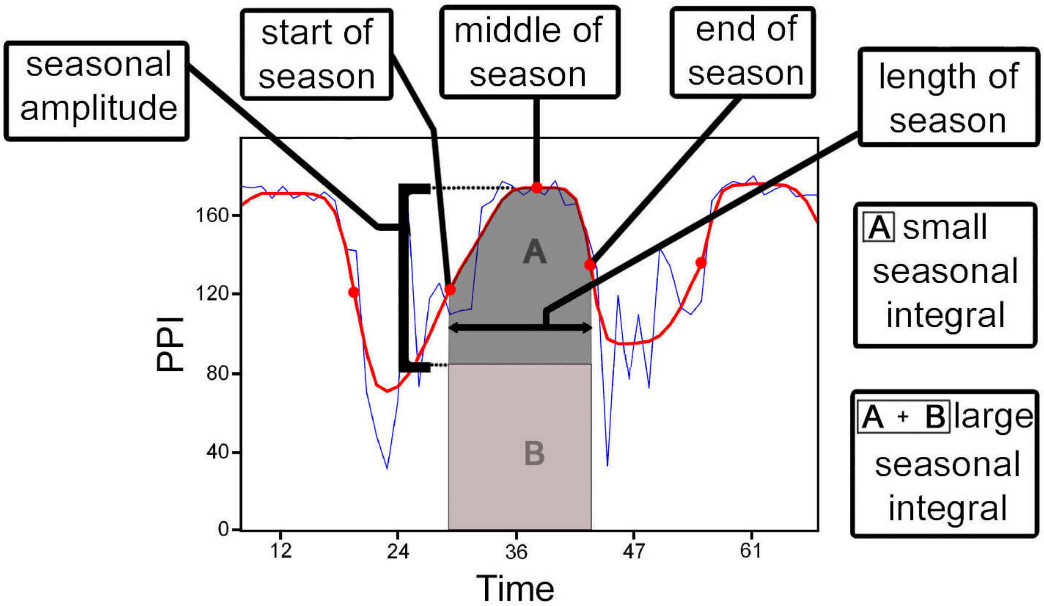

Figure A1. Plot showing the seven seasonal parameters based on TIMESAT processing, through which the PPI derived seasonality variables were obtained. The extracted phenology values were estimated using the smoothed data (denoted by the red line). Modified from Jönsson and Eklundh 2004.

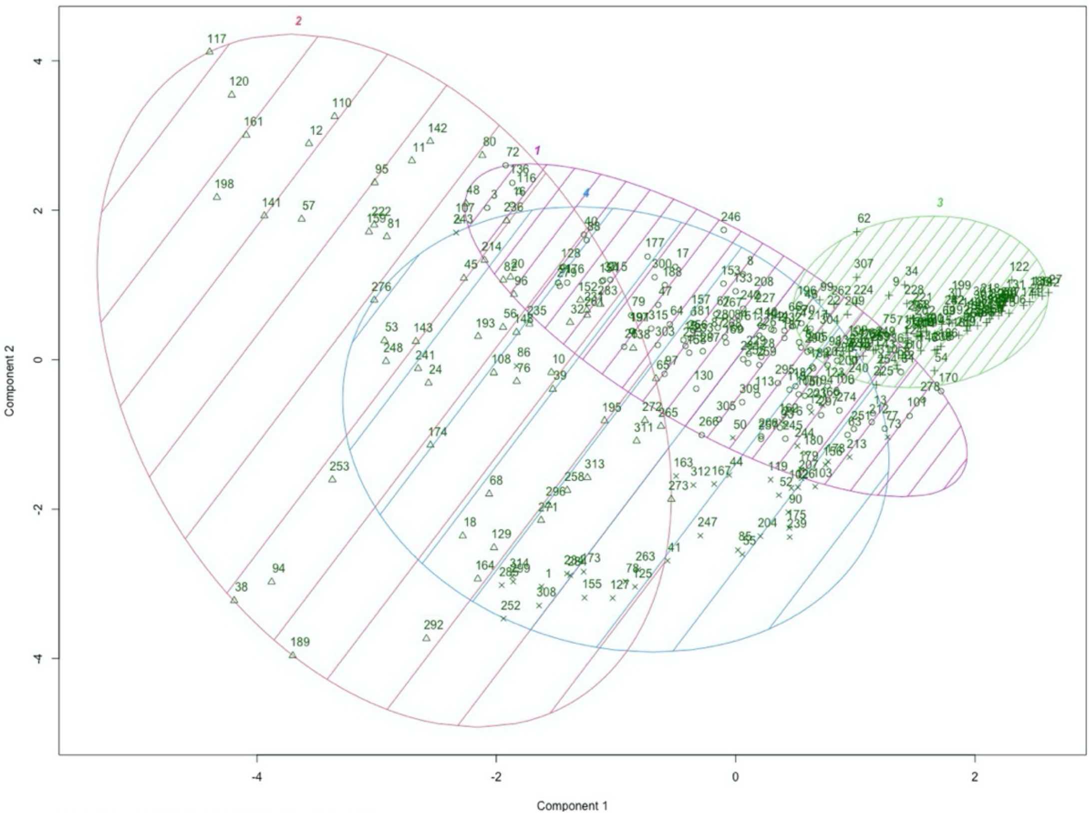

Figure A2. Cluster plot against the first two principal components used in the k-means clustering performed using R (these two components explain 61.34% of the point variability). The four groups (labelled 1-4 in this plot) were based on the percentage land cover variables of the 1 km buffers (landscape scale).

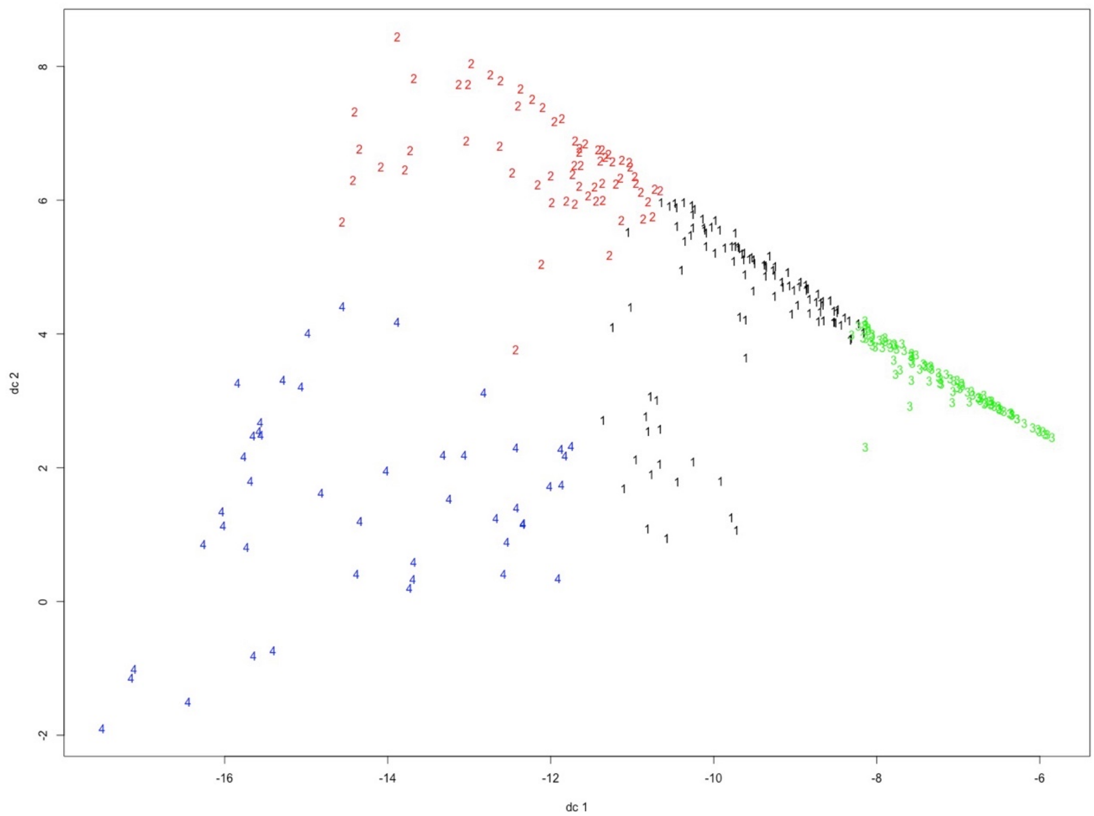

Figure A3. Centroid plot against the first two discriminant functions, used in the k-means clustering performed using R. The four groups (labelled 1-4 in this plot) were based on the percentage land cover variables of the 1 km buffers (landscape scale).

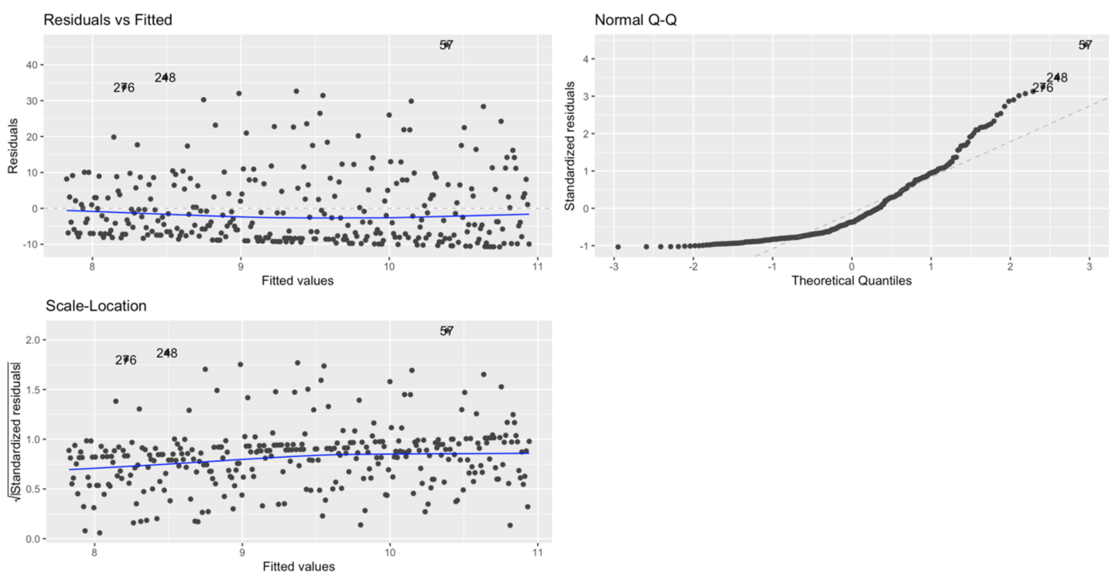

Figure A4. Example of statistical diagnostic results for the Dry Forest percent cover variable (as a landscape variable). Linearity test (Residuals vs Fitted), normality test (Normal Q-Q), homoscedasticity test (Scale-Location).