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Assessing the Spectral Diversity of Managed Grassland in the Lower Engadin

GEO 511 Master's Thesis

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Abstract

Biodiversity in grasslands is decreasing, worldwide as well as in the Swiss Alpine regions, which is why effective monitoring methods are needed. Remote sensing can provide broader spatial coverage, potentially addressing the limitations of conventional field surveys. This study investigated whether the spectral diversity of agriculturally managed plots in the Lower Engadin could serve as a proxy for biodiversity. Leveraging an object-based approach, it analysed the spectral diversity on plot level and related it to the management type. Remote sensing data (AVIRIS-NG, SwissImage RS and Sentinel-2) and agricultural plot data were processed, different data aggregation techniques and different quantification methods were tested. Most applications revealed significant differences between management types, but the results were not consistent across all datasets. However, consistent results could be achieved at different spatial and spectral resolutions. Important findings revealed that pastures exhibited higher spectral diversity than artificial meadows, most likely due to structural elements. Large differences were observed between mown and unmown plots, which suggests that a multitemporal analysis of the different conditions might be useful. Furthermore, the analysis highlighted the significance of dataset selection, aggregation, and applied spectral metrics. The study showed there is potential for spectral diversity to serve as a proxy for certain biodiversity parameters in alpine grasslands. While the object-based approach is feasible, careful interpretation and consideration of local conditions are essential. Overall, this research contributes to understanding spectral diversity's utility in assessing biodiversity and underscores the complexity of ecological relationships.

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List of Abbreviations

AVIRIS-NG	AVIRIS Next Generation
CV	Coefficient of Variation
FD	Functional Diversity
m asl	Meters above sea level
NDII	Normalized Difference Infrared Index
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
PC	Principal Component
PCA	Principal Component Analysis
SNP	Swiss National Park
SNR	Signal-to-noise ratio
SR	Species Richness
SVH	Spectral Variation Hypothesis
SWIR	Short-Wave Infrared
TGI	Triangulated Greenness Index

1 Introduction

1.1 Motivation

The grassland biodiversity is declining worldwide (Brondízio et al., 2019; IPCC, 2022). This trend is also observable in Swiss alpine grasslands (BAFU, 2016; Graf et al., 2014). To mitigate this decline, comprehensive monitoring of the affected ecosystems is essential. The coverage of traditional field surveys is often limited by logistical and financial constraints. Modern remote sensing systems bear the potential to close the gap produced by a limited availability of plant surveys on grasslands. Therefore, remotely sensed data may offer the opportunity to provide information about the biodiversity of grasslands at large spatial scales. Biodiversity can be understood ambiguously and is quantified in different ways, which also offers a wide range of methods to measure it (e.g., Andermann et al., 2022; Pimm, 2023; Tilman et al., 1997). One promising method for remote measurement of biodiversity exploits the spectral diversity of the recorded data. This means trying to translate the variability in the reflectance of the measured wavelengths into insights about different aspects of biodiversity. In the last years, the spectral diversity has been increasingly recognized as a valuable indicator for different facets of plant diversity (Gholizadeh et al., 2019; Homolová et al., 2013). But up to date, most applications are limited to experimental plots (Gholizadeh et al., 2019; Rossi et al., 2020, 2022). The spectral diversity is calculated on areas with regular and uniform shapes and sizes, e.g., 20 m × 20 m, 60 m × 60 m window or polygons (Gholizadeh et al., 2019; Rossi et al., 2020).

When studying the spectral diversity at larger spatial scales, the use of regular areas is restricted to natural grasslands, where no anthropogenic structure is present, or when the plots are defined manually. Agricultural landscapes exhibit a distinctive mosaic-like spatial structure which includes field boundaries, roadways, and fields at different phenological and management phases, all of which contribute to the inflation of spectral diversity measurements. Hence there might be a high spectral diversity, besides a low biodiversity. Therefore, when studying the spectral diversity in agricultural areas, the spatial units underlying the analysis need to be defined differently.

So, to study the spectral diversity of agricultural areas, spatial units need to be defined, that represent the local management structures. For the study area, the Lower Engadin Valley in the Swiss mountains, the Canton of Grisons provides a spatial dataset containing the agricultural plots with their respective management types. A large part of the agricultural plots of the Lower Engadin is split up into very small areas of the size of only a few dozen square meters. Plots of sizes this small are not suited to be analyzed with the available data. Therefore, the original plot dataset must be processed to group plots together so that they exceed a certain minimum size. The refined dataset allows to study the spectral diversity of the Lower Engadin agricultural land plot by plot and also provides reference data in the form of the management types. Hence, spectral diversity is calculated for individual agricultural plots, thereby characterizing the plant diversity unique to each plot. We refer to this plot analysis method, as object-based approach.

For this study, the data of different sensors is used, each with distinctive spatial and spectral resolution. AVIRIS-NG has high spectral resolution and medium spatial resolution (Jet Propulsion Laboratory, 2022a), SwissImage RS a very high spatial resolution, but only four spectral bands (Bundesamt für Landestopografie (Swisstopo), 2023b) and Sentinel-2 the lowest spatial resolution and medium spectral resolution (Sentinel Hub, 2023). It is essential to understand the differences between these sensors and to examine their capability to measure the spectral diversity.

1.2 Objectives

The overall objective of this thesis is to assess whether the previously presented object-based approach can be successfully applied to alpine grassland. In the course of this, different remote sensing datasets varying in spectral and spatial resolution are considered (AVIRIS-NG, SwissImage RS and Sentinel-2) and assessed for suitability. For these datasets, several methods of data aggregation and means to quantify spectral diversity are tested. The aim is to identify differences between different management types and to relate them to factors relevant to biodiversity. The purpose of this work is to investigate the potential of remote sensing data for studying the biodiversity of alpine grassland. Different methods and approaches for assessing the spectral diversity of alpine grassland will be explored and promising methods will be proposed.

1.3 Research Question

These objectives are investigated by answering the following questions.

1) Is it possible to study the spectral diversity of agriculturally managed plots in the Lower Engadin using an object-based approach?

The first question concerns the data aggregation, especially for the plot data, which needed refinement. It asks whether plot data and remote sensing data can be brought in relation and whether the available reference data is useful.

2) How can the spectral diversity of agriculturally managed plots of the Lower Engadin serve as a proxy for biodiversity measures?

The second research question relates to how remote sensing data can best be used to measure biodiversity. Thus, to answer this question, it is necessary to observe which biodiversity parameters can potentially be predicted, which data sets need to be used and how the data need to be aggregated and analyzed.

1.4 Outline

This thesis is structured as follows: The literature review explains how biodiversity and remote sensing data can be related and what approaches have been taken so far. In the material section, the study area and the used datasets are introduced. The method section presents the applied methodologies, while the emerging findings are presented in the result section. The discussion shows major limitations and tries to provide explanations for the observed phenomena. Finally, the conclusion summarizes the most important findings.

2 Literature Review

For a better understanding of this chapter, the most important definitions of biodiversity:

- *Ecosystem: the complex of living organisms, their physical environment and all their interrelationships in a particular unit of space*(Britannica, 2023).

- *Biodiversity (also called biological diversity): The variety of life found in a place on earth or the total variety of life on earth* (Pimm, 2023). *Biodiversity can be understood and studied in different ways. This is because the concept of biodiversity offers a range of perspectives and approaches to quantify it. For example, the taxonomic diversity studies the richness and abundance of species* (Le Bagousse-Pinguet et al., 2019), *while the genetic diversity refers to the the range of different inherited traits within and among species* (Finlay & Cooper, 2015). *Biodiversity is not only understood globally but also locally or regionally. Because of its versatility, summarizing this complex and multidimensional concept in a single measure is problematic. Multiple mathematical indices have been proposed for this purpose, but these can provide contradictory results leading to misleading or incorrect conclusions about a community's diversity* (Daly et al., 2018).

- α - *Diversity: Alpha diversity refers to diversity on a local scale, describing the species diversity (richness) within a community* (Andermann et al., 2022).

- β - *Diversity: Beta diversity describes the amount of differentiation between species communities* (Andermann et al., 2022).

- *Functional Diversity: Describes the range of things that organisms do in communities and ecosystems* (Petchey & Gaston, 2006). *Therefore, it is the quantification of biological diversity that accounts for functional and phenotypic differences* (Cadotte et al., 2011). *FD is also described as the number of functionally different roles represented in an ecosystem* (Tilman et al., 1997). *FD has effects on the properties of an ecosystem, which are directly relevant to ecosystem services* (Díaz et al., 2007). *On grassland, structural elements like trees, hedges, bushes, or stone- or brush piles increase functional diversity. The reason for this is that they contribute functions on their own or provide a habitat for species that contribute functions that are not present in plain grassland.*

- *Species Richness: A common measure of biodiversity, it counts the number of species in an area* (Pimm, 2023).

- *Plant Traits: Describe the morphological, anatomical, physiological, biochemical and phenological characteristics of plants and their organs* (Kattge et al., 2011).

- *Plant Functional Diversity: The variation of plant traits* (Rossi et al., 2020).

- *Spectral Variation Hypothesis: States that the spatial variability in the remotely sensed signal is related to environmental heterogeneity and could therefore be used as a powerful proxy of species diversity* (Rocchini et al., 2018).

- *Ecosystem Services: The outputs, conditions, or processes of natural systems that directly or indirectly benefit humans or enhance social welfare* (Johnston, 2018).

- *Environmental Factor: Any factor, abiotic or biotic, that influences living organisms* (Gilpin, 1996). *For this study, it is understood as factors without direct human impact (e.g., through infrastructure or agricultural management)*

2.1 Global State of Biodiversity

According to the Living Planet Report (WWF, 2022), between 1970 and 2018 there has been a worldwide decline of monitored wildlife of 69%. This number indicates that global biodiversity is endangered. Biodiversity can be described as the variety of life and the interactions between organisms at all levels. This includes life in terrestrial, freshwater and marine ecosystems. These ecosystems provide various ecosystem services like oxygen, food and medicines and therefore are crucial for human living on earth. Furthermore, they regulate the climate, air quality, quality and quantity of fresh water, soils, ocean acidification, pollination and the dispersal of seeds and diseases (WWF, 2022). Different reports show that various kinds of ecosystems are under pressure (Brondízio et al., 2019; IPCC, 2022; Secretariat of the Convention on Biological Diversity, 2020; WWF, 2022). The major forces putting ecosystems under pressure are changes in land and sea use, the overexploitation of plants and animals, pollution, invasive alien species and climate change. Due to these pressures, it is estimated that the local biodiversity intactness has already been reduced beyond its planetary boundary on more than half of the world's surface (Newbold et al., 2016).

The loss of ecosystems and biodiversity is not equally dispersed over the planet. To understand the trends in different regions, the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (Brondízio et al., 2019) divided the world into different geographic regions (North America, Latin America and the Caribbean, Europa and Central Asia, Asia and the Pacific and Africa). This segmentation shows that between 1970 and 2020, the biodiversity loss in Latin America and Africa was much more severe than in Europe and North America. But still, the State of Nature in the EU – report (European Union. European

Environment Agency., 2020) shows some alarming signals regarding the condition of biodiversity. Even though there have been significant efforts across the member states of the European Union, biodiversity is still declining in wide parts of Europe (European Union. European Environment Agency., 2020). As the main pressures on ecosystems are still present, most of the protected areas in the EU are in poor condition (European Union. European Environment Agency., 2020).

Also in Switzerland, biodiversity is not in a satisfactory state. 47% of all 160 types of habitats in Switzerland are under pressure. On a species level, 36% of all evaluated animal, plant and fungus species are categorized as threatened on the Red Lists (Federal Office for the Environment FOEN, 2014). Habitats in Switzerland are disappearing particularly in agricultural areas, in areas that are used for settlement and transport and where land use is becoming more and more intensive (Federal Office for the Environment FOEN, 2014).

In recent years, there has emerged a more profound understanding of biodiversity and its importance for human living on earth. Also, there is now a better understanding of which policies, practices, technologies and behaviors can lead to the conservation and sustainable use of biodiversity (Brondízio et al., 2019). Consequently, at the Nagoya Biodiversity Summit in 2010, the United Nations introduced the Aichi Biodiversity Targets (Convention on Biological Diversity, 2020). These targets provided an overarching framework on biodiversity for the years 2011 until 2020 with the vision that by 2050 biodiversity should be valued, conserved, restored and wisely used. Ecosystem services should be maintained, and a healthy planet sustained. 20 strategic goals were defined that targeted the societal perception of biodiversity, aimed to reduce the direct pressures on biodiversity and enhance the benefits of all from biodiversity. Globally, there has been positive progress for only a small majority of the targets, while for most of the targets, there has been poor progress (Brondízio et al., 2019). The targets that were reached mostly concerned the understanding of biodiversity loss and developing strategies against it. The targets concerning actual protection mostly have been missed, so the Aichi Biodiversity Targets have not led to a change in the declining trend.

The Swiss attempts to implement the Aichi Biodiversity Targets led to progress addressing public awareness of biodiversity and the conservation of the genetic diversity of cultivated plants and farmed animals. The Swiss government tried also to achieve further targets, for example, to eliminate incentives that are harmful to biodiversity. However, the measures taken have not led to a more sustainable use of resources, a reduction in pollution or the creation of sufficiently large and contiguous protected areas. (Federal Office for the Environment FOEN, 2014).

2.1.1 Decline of Grassland Biodiversity

The alpine meadows of the lower Engadin belong to the surface class of temperate grasslands. Temperate grasslands comprise steppes, prairies and pampas, high-altitude steppes, forest steppes and wood pastures (Brondízio et al., 2019). They cover globally an area of 13 million km², which makes 5 - 10% of the global terrestrial surface. Temperate grasslands often show a high biodiversity of mammals and birds and are also important for global carbon storage (Brondízio et al., 2019). Globally, temperate grasslands belong to the habitats that show the highest plant species richness (Wilson et al., 2012). This richness is endangered, as no other biome has experienced the level of degradation and conversion as temperate grasslands (Brondízio et al., 2019). In the last century ca. 60% of the temperate grasslands have been converted. In North America and Europe, less than 10% remains intact while the decline is continuing. In the member countries of the EU, 49% of grassland areas show a bad conservation status (European Union. European Environment Agency., 2020). Therefore, grassland belongs to the habitats with the highest share of areas in a bad conservation status (European Union. European Environment Agency., 2020). Over the last century, most of the grassland habitats have been lost. Most often this is due to an intensification of agricultural cultivation and land use. That agriculture is a major pressure on biodiversity is evident from recent trends in agricultural habitats. Only 8% of agricultural habitats show improving trends, whereas 45% are assessed as deteriorating (European Union. European Environment Agency., 2020).

Alpine grasslands provide ecosystem services that are of important value for stakeholders in alpine regions like farmers, other local residents and tourists. Important ecosystem services for those stakeholders are e.g., fodder production, prevention of snow gliding, cultural heritage, habitat for pollinators or the maintenance of soil fertility (Díaz et al., 2007).

Swiss agricultural habitats are also under major pressure. Due to the intensification of agriculture, habitats have decreased in size and of many habitats there are only very small areas remaining (BAFU, 2016). The pressure by intensification of the agriculture is increasing especially in mountain areas of Switzerland. Extensively cultivated areas often show characteristics of structural diversity. This means that these meadows and pastures are intersected by a diverse range of landscape components (e.g., hedges, stone- or brush piles), which can be valuable habitats for animal- and plant species and soil. Diverse landscape components can interfere with intensive agricultural management. To facilitate management, landscape components are removed. This leads to a decreased structural diversity. Practices that lead to this effect are the removal of landscape components, the draining of wet areas, the irrigation of dry meadows or the fertilization of nutrient-poor areas. Amongst the most endangered habitat types in Switzerland are dry meadows and pastures. Between 1900 and 2010, dry meadows and pastures have lost around 95% of their size in Switzerland (BAFU, 2016). A negative development is observed especially in mountain areas.

A large share of meadows and pastures in the Engadin are classified as dry meadows. A previous study has revealed that 20% of the former area of unimproved grassland types has disappeared and was mostly transformed into fertile habitat types (Graf et al., 2014). Unimproved grassland accounts for grassland that has not been artificially fertilized, plowed or reseeded and therefore often is exceptionally rich in species. Moreover, nutrient-poor meadows lost one-third of their former area mainly to fertile meadows and nutrient-poor pastures lost 17% to fertile pastures and abandonment. Extensively used agricultural land lost 15% and intensively used land increased by 21% during the examined timespan. In 1987/1988, extensive land covered 60%, intensive land 33% of the agricultural area; in 2009/2010, the share of extensive land decreased to 51% and intensive land increased to 40%. The loss of extensively used areas was mainly due to intensification and much less due to abandonment. This shows a transition of either unimproved grassland towards cultivated grassland or from extensively used agricultural land towards intensively used agricultural land. Furthermore, several studies conducted on alpine grasslands in Switzerland revealed that the intensification of the management of agricultural grasslands is a major threat to biodiversity (Boch et al., 2021; Humbert et al., 2021).

2.2 Assessing Biodiversity

Biodiversity is crucial for the ecosystem services that an ecosystem can provide. The impact of biodiversity on ecosystem services can be assessed by identifying the key characteristics through which organisms affect ecosystem properties (Bello et al., 2010). The delivery of ecosystem services is directly modulated by the FD of biological communities (Díaz et al., 2007). Common biodiversity concepts are the α - Diversity and the β - Diversity, which were described earlier. As for this study, diversity is not studied on a species level, the applied approach comes closer to examining the characteristics of the β - Diversity. I expect that when studying the spatial heterogeneity of ecosystems, the obtained results might represent the diversity of traits (e.g., functional diversity) better than the diversity of species (similarly to e.g., Schneider et al., 2017. This is because FD consists of elements of different spatial scales. Some features that impact FD on grasslands have sizes that small so they cannot be examined with the available datasets, whereas this is possible for other features (e.g., trees, large stones, hedges). FD is a term that can be interpreted in different ways. In a general interpretation, it is understood as the phenotypic diversity of organisms. More recent definitions have focused on the value and range of organismal traits that influence ecosystem functioning (Petchey & Gaston, 2006). FD can be linked to other biodiversity – concepts. For example, Naeem & Wright (2003) have found a positive relationship between FD and species richness. The FD of an ecosystem can influence various of its processes (Tilman et al., 1997). Results even suggest that the number of functionally different groups present in an ecosystem may even be a stronger determinant of ecosystem processes than the total number of species (Tilman et al., 1997). To get meaningful conclusions from measurements of FD, it should be the goal to define traits that are important for the functioning of ecosystems. Various studies have shown that locally, ecosystem functions are linked to functional diversity (Bello et al., 2010; Díaz et al., 2007; Rossi et al., 2020). The dominant mechanisms by which this is done are the mass ratio, niche complementarity and buffering capacities, but are strongly dependent on the functional attributes of the local ecosystem (Balvanera et al., 2006; Díaz et al., 2006, 2007). According to Petchey and Gaston (2006), measuring FD should ideally meet the following standards:

- Appropriate functional information (traits) about organisms should be included in the measure. Irrelevant information should be excluded.

- Traits should be weighted according to their relative functional importance.

- The statistical measure of trait diversity should have desirable mathematical characteristics.

- The measure should be able to explain and predict variation in ecosystem-level processes.

Among ecosystem traits are plant traits. Plant traits are structural, physiological, biochemical or phenological features, e.g., plant height, photosynthesis rate, nitrogen content or leaf phenology (Homolová et al., 2013). Ecologists have identified hundreds of plant traits (Homolová et al., 2013). They are measured at the level of individual plants but also on the canopy level (Homolová et al., 2013). The diversity of plant traits affects the properties of an ecosystem and thus also the ecosystem services it provides. Plant traits determine how primary producers respond to environmental factors, affect other trophic levels and influence ecosystem processes and services (Kattge et al., 2011). Additionally, they provide a direct link from functional diversity to species richness (Kattge et al., 2011).

Due to the large logistical effort and being time intensive, field measurements of plant trait data are limited to small areas, to a certain moment in time and to a certain number of species only (Homolová et al., 2013). Remote sensing techniques offer the potential to solve these constraints. They can provide spatially contiguous information, cover larger areas and allow repeated measurements without disproportional efforts. Furthermore, remote sensing techniques are very well suited to extract spatial variation, which is an important characteristic of biodiversity (Rocchini et al., 2018). For this study, specific traits (greenness, chlorophyll content and water content) are assessed, but also the entire spectral signature of plants and communities. In heterogeneous environments, these traits can vary spatially. Areas with highly heterogeneous environments can host more species due to their higher number of available niches (Rocchini et al., 2010). Heterogeneous environments can be expected to have a high structural diversity. Extensively managed areas host a higher structural diversity (BAFU, 2016) than intensively managed, this information provided by the agricultural plot dataset is exploited to find a relationship between spectral diversity and environmental heterogeneity.

2.3 Assessing Biodiversity Using Remote Sensing Techniques

2.3.1 Introduction to Vegetation Measurements

Interactions between incident radiation and canopy elements are described by three main physical mechanisms: absorption, reflection and transmission. Radiation is emitted by the sun and interacts with the atmosphere, the canopy and the radiation reflected by the canopy can be retrieved by remote sensing instruments. The solar reflected radiation in the range between 380 and 2500 nm is commonly used in vegetation studies because most of the diagnostic absorption features of green vegetation are located in this part of the spectrum. The reflectance of vegetation canopies depends on the radiative properties of leaves, other non-photosynthetic canopy elements and their spatial arrangement (Homolová et al., 2013).

Remote sensing measurements are characterized by their spatial resolution (addressing the pixel size), temporal resolution (addressing the temporal intervals, in which the measurement is repeated) and spectral resolution (addressing the sample of the electromagnetic spectrum that is covered). For each pixel of the resulting image, the incoming radiation is detected at one or more wavelength ranges and measures the mean reflection within the ground ranging distance of this pixel. When obtaining grassland data, with a decreasing spatial resolution (i.e., increasing pixel size), more and more individual plants occur within a single pixel. This leads to spectral signatures of several species to be detected combined together by the sensor. Grassland plants have smaller canopies than many other vegetation types. This means that space- or airborne measurements are almost always on canopy level and not on plant or even leaf level. Consequently, pixels do not contain a pure signal of single plants but a mixed signal of multiple plants.

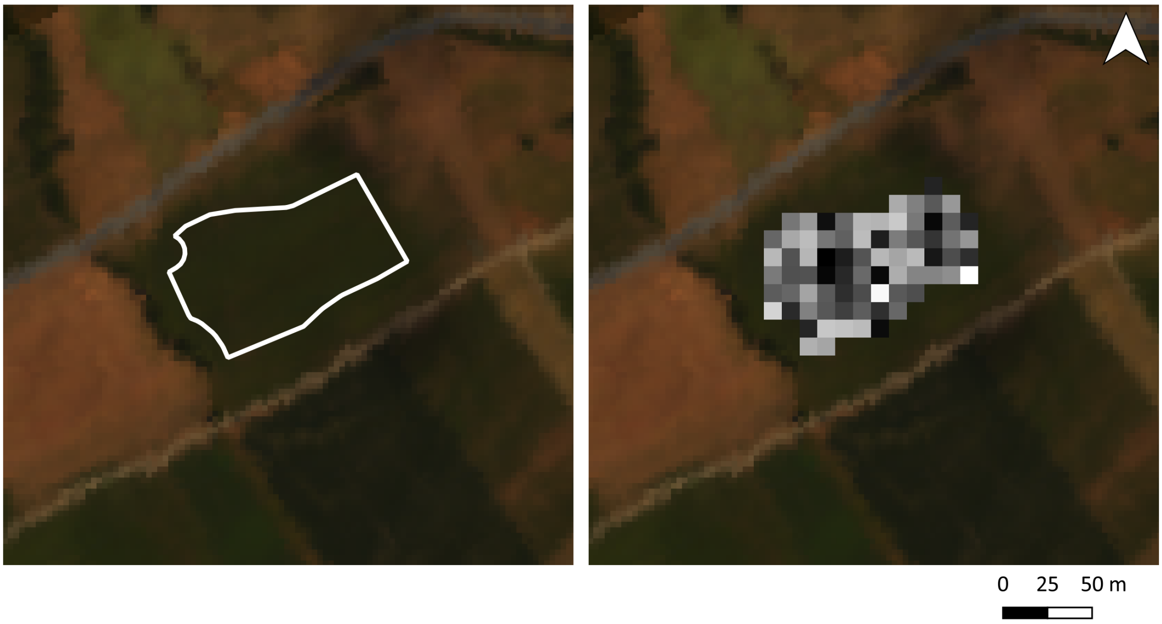

Figure 1: Illustration of the Spectral Diversity of a Plot (white polygon, left image). The color of each pixel within the plot represents the reflectance value of the pixel (right image). The visualized values are randomly generated for visualization purposes and do not represent measured values. The spatial resolution of the generated raster has a lower spatial resolution than the AVIRIS-NG and SwissImage datasets, therefore the clipped raster areas of these datasets do match the area of the polygon more precisely.

The environmental diversity is transferred to measurable variables on plot level in the following manner: For each pixel, the reflectance properties are measured as a mean reflectance value. As illustrated in Figure 1, each plot consists of a variable number of pixels. Using measures of variability, the spectral diversity of one plot can be calculated. Then, the spectral diversity of different plots can be compared (Figure 2). Similar to the metrics of α and β diversity, Cavender-Bares et al. (2017) labeled differences in spectra among pixels within a plot as alpha spectral diversity and among plots as beta spectral diversity.

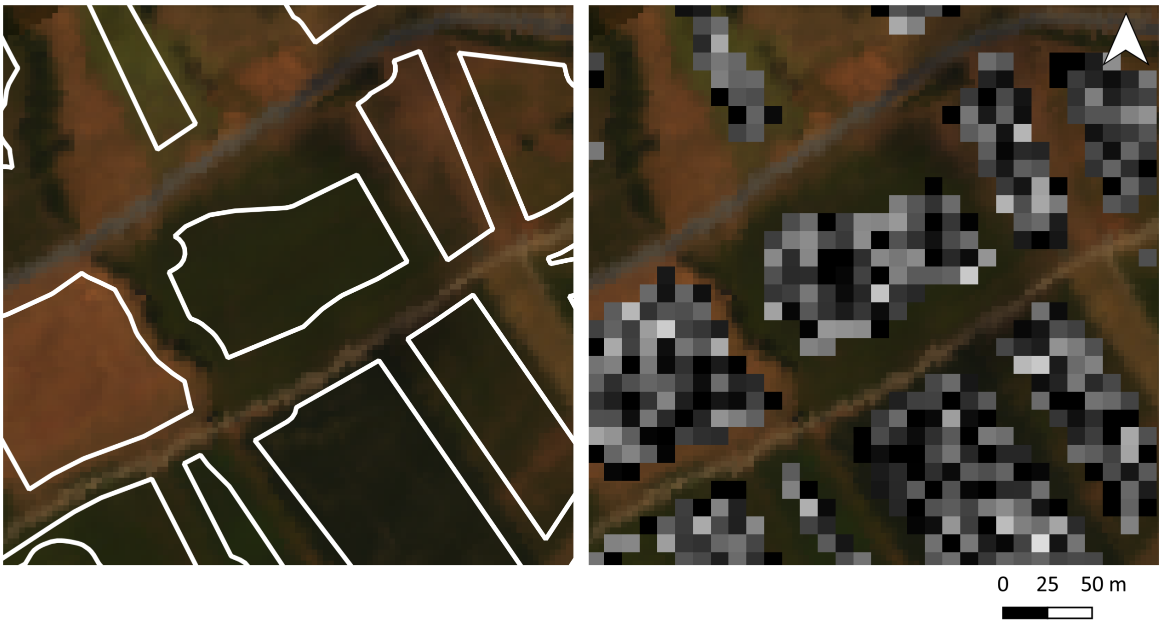

Figure 2: Illustration of the Spectral Diversity of several neighboring Plots (white polygons, left image). Each Plot has a spectral variability, that can be compared between plots. The visualized values are randomly generated for visualization purposes and do not represent measured values.

2.3.2 Assessing Biodiversity with Remotely Sensed Data

Applications of remotely sensed data for assessing the functional diversity of ecosystems build on the underlying assumption that higher spectral variation in canopy reflectance is caused by either variation in habitats, plant communities with their specific optical community traits or in the species themselves with their specific optical traits (Fassnacht et al., 2022). This link between spectral variation and plant biodiversity is also referred to as the Spectral Variation Hypothesis, which predicts a link between spectral heterogeneity and biodiversity (Palmer et al., 2002). The environmental heterogeneity is most often assessed by studying the variation of plant traits. For that, a wide range of plant traits are considered. When working with coarse spatial and spectral resolution data, plant traits are studied as properties of the entire canopy. For these applications, among others vegetation indices are used to quantify the variation of plant traits (Homolová et al., 2013; Turner et al., 1989). The emergence of instruments with high spectral resolution allows a more detailed estimation of plant traits (Homolová et al., 2013). Very specific traits were measured like this, e.g., single plant pigments and leaf fluorescence (Blackburn, 2007; Homolová et al., 2013; Ustin et al., 2009).

The interpretation of the link between spectral variation and actual environmental heterogeneity depends on multiple factors and is often ambiguous. A major challenge in measuring plant characteristics with remote sensing data is the structure of the canopy. Taking measurements on the canopy level has a negative impact on the retrieval accuracy of single biochemical traits (Homolová et al., 2013). This is because an average value is measured, neglecting the small-scale variations. A further issue that is important to be considered is that the spectral variation caused by species or functional traits is often subtle in comparison to other factors, that are present in a study area (Fassnacht et al., 2022). The exposure of bare soil or plant litter can for example affect the measured environmental heterogeneity significantly (Gholizadeh et al., 2018; Hauser et al., 2021). Filtering of pixels detecting bare soil improves the performance of spectral diversity metrics but can be difficult, especially for sensors with coarse spatial resolution (Gholizadeh et al., 2018). A further restriction is the selection of plant traits. Using empirical data often lacks a causal relationship (Homolová et al., 2013). This means that when working with airborne or spaceborne imagery, the applied metric often does not directly represent a specific plant trait. Consequently, the emerging statistical relationships are often less robust and transferable, as they are usually site and time specific (Homolová et al., 2013). Additionally, it is important to be aware that potential insights can be superimposed by effects that are not specifically studied. Accordingly, Hauser et al (Hauser et al., 2021) showed, that properties of the vegetational cover (canopy architecture, exposure of bare soil, plant litter) can veil potential variations of FD. When analyzing the environmental heterogeneity of grassland, it is important to be aware of these methodological constraints.

2.3.3 Scale Effects

The first issue with scale is that the exact relationship between species counts and area depends on the characteristics of the ecosystem that is analyzed (Fassnacht et al., 2022). This issue refers to the size of the examined area and is independent of the remotely sensed data acquisition.

Further scale effects refer to effects related to the spatial extent of the study area in relation to the spatial grain (pixel size, ground sampling distance or spatial resolution) of the remotely sensed data. When calculating local spectral heterogeneity for local species diversity estimates, pixels should be smaller than the sampling units (Rocchini et al., 2010). This is a further restriction that limits the available data.

Finally, there is an impact of the spatial resolution on the performance of spectral diversity metrics (Gholizadeh et al., 2018; Wang et al., 2018a). It can be assumed, that the coarser the spatial grain of a remotely sensed data set is at a given location, the more species occur within an individual pixel. However, as this diversity lies within one pixel, the diversity cannot be measured using remote sensing techniques and is only represented by a mean reflectance value. This means that a smoothing of the original diversity happens when a coarse resolution is used. Consequently, it can be expected that the coarser the spatial grain of the remotely sensed data is, the smaller the overall spectral variation across all pixels of a given area (Fassnacht et al., 2022; Rocchini et al., 2010). Statistically, the spatial variability of reflectance values should reach its maximum, when the spatial grain of each pixel is equal to the size of the objects under examination (Rocchini et al., 2010). As grassland plants are usually of the size of a few millimeters to centimeters, working with high spatial resolution data should reveal the most precise predictions. But there are also contradicting effects, which can corrupt the performance of high-resolution data. For example, when pixels with a very high spatial resolution (e.g., a ground spatial distance of ~1 to 5 m) are used, shadows can create a higher spatial heterogeneity among spectra (Rocchini et al., 2010). As this heterogeneity does not come from a high environmental diversity, these impacts can lower the quality of the predicting metrics. Accordingly, several studies have shown that the relationship between spectral diversity and species richness is not consistent across scales (Gholizadeh et al., 2018; Wang etal., 2018). Wang et al. (2018) stated that the optimal pixel size for plant-biodiversity studies varies depending on the size of the individual organisms. Contrastingly, Gholizadeh et al. (2018) claim, that the performance of the quantification decreases with increasing pixel size. To study grassland biodiversity both suggest working with a higher spatial resolution than when studying the biodiversity of a forest canopy. Therefore, the spatial resolution should be adapted to the ecosystem under analysis. Wang et al (2018) propose a pixel size of 1mm to 10cm as optimal to predict prairie biodiversity.

2.3.4 Temporal Variations

Ecosystems show temporal variations, which are also captured in the spectral signal. These variations consist of daily, seasonal and irregular variations. Examples of daily variations are the photosynthetic activity or the leaf orientation of plants (Chávez et al., 2014). This variation needs to be considered especially when data acquisition does not always happen at the same time of the day. Seasonal variation can have a strong impact on the spectral signal. So has the relationship between field- and remote sensing-based α- and β-diversity detected to weaken towards the end of the growing season (Gholizadeh et al., 2020). Flowering events that occur seasonally also have a large impact on the spectra signal (Fassnacht et al., 2022). A way to get a better understanding of seasonal effects is to conduct repeated measurements throughout the season. The irregular variation stands for the impacts of temporary stresses and disturbances, that do not occur regularly (e.g., mowing events, drought and effects of wind and rain) (Fassnacht et al., 2022).

Because of these temporal variations, species can have unique spectral signatures at one time but less pronounced differences at another time (Fassnacht et al., 2022). This leads to a variation in the measured environmental heterogeneity. So, it can be difficult to establish a stable relationship between spectral variation and biodiversity metrics in areas with a pronounced temporal dynamic (Fassnacht et al., 2022). To use spectral variation as a reliable predictor for biodiversity, it is crucial to identify suitable time windows or to include the temporal dimension into the applied spectral variation measure (Fassnacht et al., 2022). An important temporal variation especially on managed grassland is mowing. After a mowing, the spectral signal of a meadow can completely change from one day to another. Therefore, it is important to keep track of mowing events as well as to analyze their implications on spectral diversity measurements.

2.4 Spectral Metrics

Spectral diversity metrics are applied to predict environmental heterogeneity by quantifying the variation in spectral data. They are calculated based on the distance between pixel values in a multidimensional spectral space. The position of a pixel in the multidimensional spectral space is given by its reflectance value of each band. If all pixels of a sample have similar reflectance values, they build a small and dense point cloud. Pixels with large differences in reflection values at different wavelengths result in dispersed point clouds.

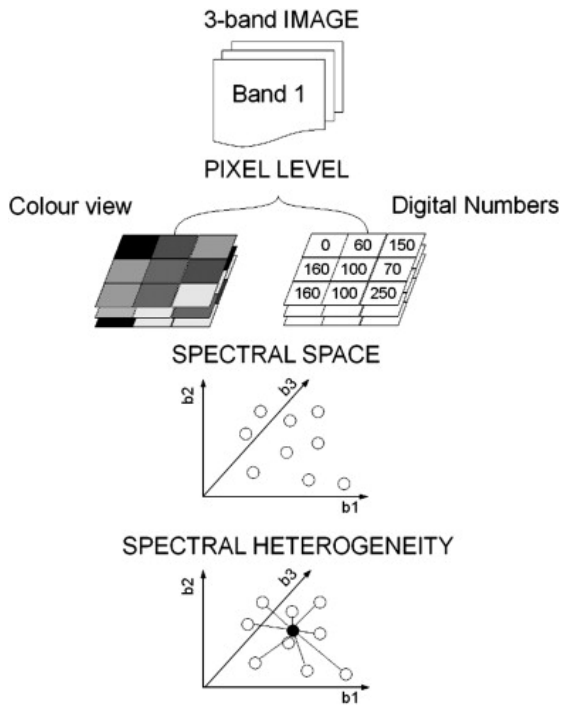

Figure 3: With multispectral remote sensing, a value (digital number) is recorded per pixel and band. Spectral metrics quantify the dispersion of the pixel values in the spectral space. Figure from Rocchini et al. (2010).

There is a wide range of diversity metrics in use and their performance can vary significantly depending on various factors (e.g., spatial resolution and exposure of bare soil) (Gholizadeh et al., 2018). The metrics can be calculated to quantify variation over the entire spectra of the acquired data, but also to quantify specific characteristics. Metrics that performed well on grassland applications are the Variance (Dahlin, 2016), Standard Deviation, Coefficient of Variation (CV) and Spectral Angle Mapper (Gholizadeh et al., 2019). Another commonly used metric on grassland and agricultural areas is the Rao's Q diversity index, which addresses the abundance and the pairwise spectral distance among pixels (Rocchini et al., 2017, 2018; Tassi et al., 2022). The algorithm calculates the expected difference in reflectance values between two pixels drawn randomly with replacement from the considered evaluated pixels set and is often applied to the NDVI (Tassi et al., 2022). It is important to emphasize that the performance of those metrics strongly depends on the local circumstances and measurement parameters. Hence, only because they performed well in a hereby presented application, does not mean that they lead to meaningful results in other applications.

2.5 Similar Studies

Directly neighboring to the research area is the Swiss National Park (SNP). The SNP is a protected mountain area in the canton of Grisons, which is unique in Switzerland because it has not been managed for the last 100 years (Rossi et al., 2020). The SNP was founded in 1914 and belongs to the category with the highest protection according to the International Union for Conservation of Nature (IUCN) (Schweizerischer Nationalpark, 2023). On an area of 170 km^2 habitats and natural processes can develop protected from human influences

(Schweizerischer Nationalpark, 2023). Studies on grassland biodiversity were conducted in this area (Rossi et al., 2020, 2022). Its grassland areas differ from the grassland areas in the lower Engadin, as they are not managed. Due to the management, the methodologies to study spectral diversity need to be adapted to areas that are managed, which will be described in more detail in the methods section.

Not only were studies conducted on a similar field and on a neighboring area, but also with similar data. Rossi et al. (2022) also included data acquired with AVIRIS-NG in July 2018 in their analysis. Further applications in related fields of AVIRIS hyperspectral data are Blackburn (2007) (using a predecessor instrument) and Dahlin (2016). Sentinel-2 data have been used for biodiversity studies on grassland (Hauser et al., 2021; Ma et al., 2019; Rossi et al., 2020).

3 Materials

3.1 Study Area

The Engadin is an inner-alpine valley in the canton of Grisons, which reaches from Maloja to Martina at the border Swiss-Austrian border. The examined data reaches from the village Martina up to the village Lavin over 30 km. The Lower Engadin is situated adjacent to the SNP, the largest and oldest protected area of Switzerland.

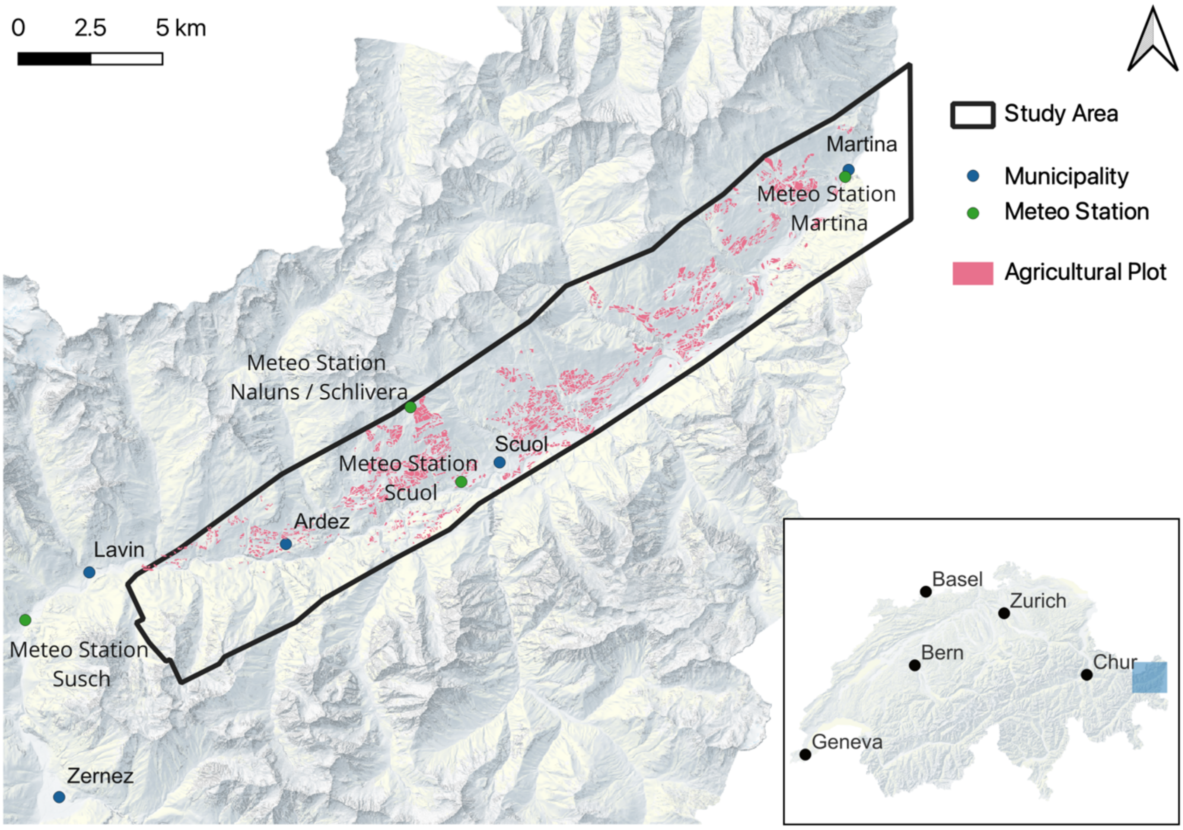

Figure 4: Study area and MeteoSwiss meteo stations in the Lower Engadin Valley.

The Lower Engadin belongs to the mountain area of the Eastern Central Alps. The slopes on both sides of the valley end up in prominent mountain ridges with peaks reaching heights of 3400 m asl. The elevation of the valley ground ranges from 1035 m asl (Martina) to 1387 m asl (Lavin). The landscape of the valley is characterized by a northern slope with medium steepness, a steep and mostly forested southern slope, and the river Inn at the bottom of the valley. Most of the villages are located on the northern slope of the valley. As there are rather shallow gradients and many sun-exposed areas, most of the agriculturally used areas are also on the northern slope. Most plots are meadows and pastures. At the few flat areas, most located at the bottom of the valley, there are also a few field crops.

The inner-alpine location leads to a dryness that is characteristic of the climate of the Engadin. The mean annual precipitation of the Engadin is between 700 and 1000 mm (MeteoSchweiz, 2023b). This is about half the amount of other areas of Switzerland (e.g., the Central Plateau) (MeteoSchweiz, 2023b). To get more detailed knowledge about the climatic conditions and the weather conditions in the months before the data acquisitions, I retrieved the available climate data from four stations in or near the study area from 1990 to 2023. This data is freely available for research on the Data Portal for Education and Research (IDAWEB) (MeteoSchweiz, 2023a). When available, precipitation, temperature and duration of sunshine are aggregated to annual averages.

Table 1: Annual Averages of the Meteo Stations in the Lower Engadin.

Station	Mean Annual Precipitation [mm]	Mean Annual Temperature [°C]	Mean Annual Duration of Sunshine [hour]
Martina (1043 m asl)	729.48		
Scuol (1305 m asl)	709.00	5.9	1803.65
Naluns / Schlivera (2382 m asl)		0.7	1803.39 (Data availability only 2011 – 2020)
Susch (1418 m asl)	825.19		

The Lower Engadin has a long agricultural history. The first mentions of settled farmers reach back to the 2nd century BC (Clavuot, 2014). For a long time, the valley's economy was agrarian-oriented. Since the 1950s, tourism has also become an important economic sector (Clavuot, 2014). Today, local agriculture is mostly focused on an extensive management of the areas with high ecological value (ARE Graubünden & ALG Graubünden, 2016). Only at the bottom of the valley, there are also conventionally managed areas (ARE Graubünden & ALG Graubünden, 2016). There is generally low pressure on agricultural areas, which is limited to land-use conflicts with conservation areas to preserve ecologically valuable landscapes (ARE Graubünden & ALG Graubünden, 2016). In contrast to most areas of the lower areas of Switzerland, the Engadin still harbors a great biodiversity on farmland (Graf et al., 2014). However, this biodiversity hot spot is getting under pressure. Between 1988 and 2010, unimproved areas (i.e., grassland which has not been artificially fertilized, ploughed or reseeded), which are crucial for maintaining a high biodiversity, lost 20% of their covered area (Graf et al., 2014).

3.2 Agricultural Plot Data

Crucial for a successful application of the object-based approach are ground data of good quality. The approach would not work using regular or random areas. All cantons of Switzerland provide agricultural land use plans which are available on the data portal "Geodienste.ch" (Geodienste.ch, 2023). The land-use areas correspond to the agriculturally used areas according to the Swiss Ordinance on Agricultural Terms (LBV) derived by the confederation and cantons (geocat.ch, 2023).

This study is based on the agricultural land use plan of the canton of Grisons from 2021. Earlier versions are not available according to the Swiss Federal Office for Agriculture. The unprocessed dataset contains 162’802 agricultural plots, of which 9413 are within the study area. The plots within the study area make up an entire area of 29.368 km^2, with a mean plot size of 3119.931 m^2. The following cultures among others are included: Crops (Barley, Wheat, Oats, Rye), Potatoes, Maize, Meadows (Artificial meadows, less intensively used meadows, extensively used meadows), pastures and areas to explicitly support biodiversity. Validity information and extensive metadata for the dataset are not available, so it is difficult to make conclusions about the correctness and the spatial precision of the dataset. However, as the dataset is provided by a local authority (canton of Grisons), one can expect satisfying data quality. For permanent types of agricultural cultivation, a high degree of accuracy of the dataset can be expected, while for crop rotation areas the dataset is not up to date. Spatial precision can be assessed using spot checks, for example by comparing the border of a plot directly adjacent to streets or other landscape elements using satellite imagery. These checks showed a high spatial precision of the data.

To link biodiversity to spectral diversity, assumptions need to be made about the different management types. For extensively managed areas one can expect a higher plant- and functional diversity than for intensively used. This is because intensively managed plots have the main purpose of leading to a maximized harvest, while extensively used plots are often able to provide other services. Intensively managed areas are fertilized, leading to the proliferation of only a few species, primarily nutrient-demanding grasses. Pastures are expected to show a higher functional diversity than meadows, as they host more structural elements such as hedges, trees or dry-stone walls. The highest functional diversity one can expect is on plots that are labeled to promote biodiversity. The scientific background for these assumptions is given by Boch et al. (2021) and Humbert et al. (2021), who showed that intensive management of alpine grasslands in Switzerland has negative implications for biodiversity.

3.3 Land Cover Classes

The agricultural plot dataset includes forested areas. As the following analysis will only include grassland, these forested areas had to be excluded. This was done using the WordlCover Dataset provided by ESA (Zanaga et al., 2022). This freely available dataset provides land cover information at a spatial resolution of 10 meters based on Sentinel-1 and Sentinel-2 data (ESA WorldCover, 2023). It contains 11 land cover classes (including tree cover) with a global overall accuracy of about 75% (ESA WorldCover, 2023).

3.4 Remote Sensing Data

3.4.1 AVIRIS-NG

3.4.1.1 Data Characteristics

The Airborne Visible InfraRed Imaging Spectrometer-Next Generation is a NASA Earth Science airborne sensor developed and operated by Jet Propulsion Laboratories (JPL) (Jet Propulsion Laboratory, 2022b). The sensor is a pushbroom spectral mapping system with a high signal-to-noise ratio (SNR), designed for high-performance spectroscopy (Chapman et al., 2019). It is the successor of AVIRIS-Classic, which has been in operation since 1989, mainly used for ecology sciences (Jet Propulsion Laboratory, 2022b). AVIRIS-NG measures the reflected radiance of the solar spectrum with 425 spectral bands at a wavelength range from 380 nm to 2510 nm with 5 nm sampling (Jet Propulsion Laboratory, 2022c). Potential uncertainties emerge from natural and irreducible measurement noise or calibration uncertainties arising from systematic optical and electronic imperfections in the instrument (Chapman et al., 2019). Scientific application areas are among others:

- Ecology: composition, function, chlorophyll, pigments, etc.
- Geology and soils: mineralogy and soil type
- Coastal and inland waters: chlorophyll, plankton, dissolved organics, sediments, etc.
- Snow and Ice Hydrology: snow cover fraction, grain size, dust, impurities, melting
- Atmosphere: water vapor, clouds properties, aerosols, absorbing gases
- Environmental hazards: contaminants, geological substrate
- Agriculture: crop type, crop health, nitrogen, leaf water, soil composition, soil salinity, soil carbon

Geometrically- and atmospherically corrected datasets are openly available via the AVIRIS-NG Data Portal (Jet Propulsion Laboratory, 2023). On 1 July 2018, 28 flight strips were recorded in the areas of the Lower Engadin, the SNP and Val Müstair. The airplane carrying the sensor flew at an altitude of 4.8 to 5.5 km. Most flight strips have a cloud cover of 10 – 30%, some even up to 50%. So, the data was not acquired at optimal conditions, consequently, some areas needed to be masked out due to the cloud cover. The spatial resolution of the flight strips varies between 2.6 and 3.4 meters for the entire area. An issue with the AVIRIS-NG dataset related specifically to the mountainous area of the lower Engadin and the SNP is the poor quality of the georeferencing of the data. Especially in steep areas, the position of the pixels does not exactly match the ground truth. This can be observed when comparing the data to other, more accurately referenced datasets or when comparing overlapping flight strips with each other.

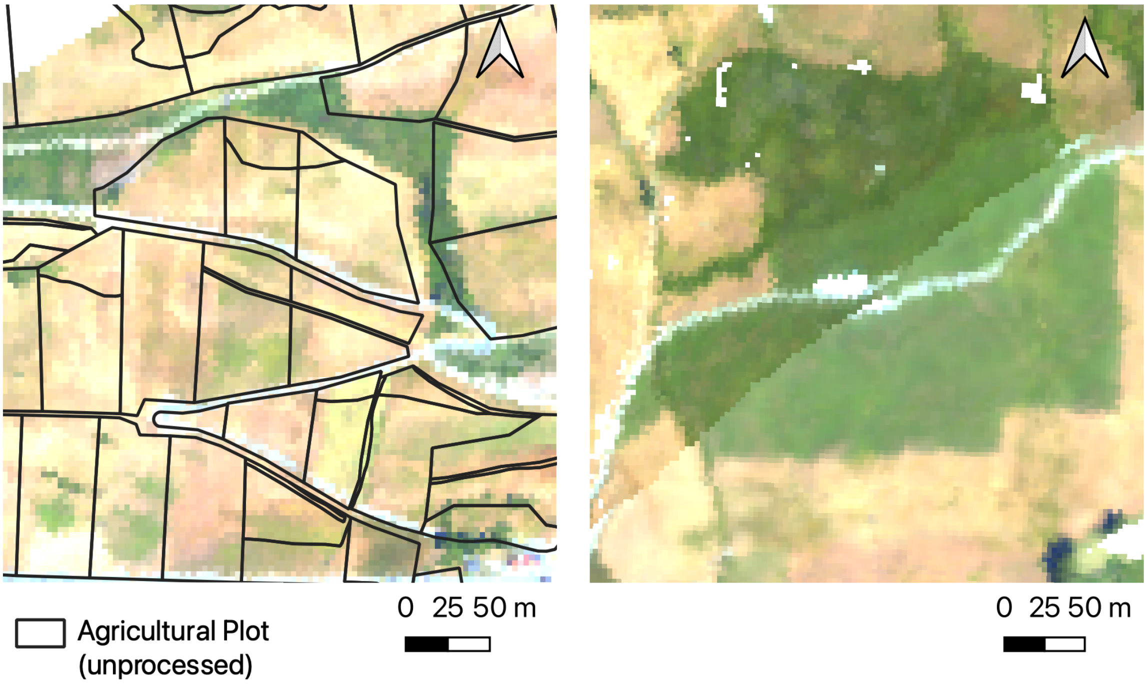

Figure 5: Examples of the geographic impreciseness of the AVIRIS-NG dataset. Left Image: Impreciseness visualized by plotting unprocessed agricultural plots over the AVIRIS-NG product. The roads can be seen in the plot data as stripes between the plots. These stripes do not match the roads visible in the AVIRIS-NG scene. Right Image: Impreciseness is visualized by analyzing the border of two flight strips. The street should be continuous but has a significant offset.

To cover the study areas, three flight strips were selected, all collected on July 1, 2018. They cover most of the managed areas of the Lower Engadin as well as alpine pastures and meadows on the northern slope of the valley. The study area could have been further expanded, but this would have come with storage- and processing issues, as the amount of data already reached a critical maximum working with only three flight strips.

3.4.1.2 Pre-Processing

The first processing steps are already conducted before the download of the data (georeferencing and atmospheric corrections). The data are provided in the ENVI format with an associated ASCII header file containing important information about the imagery data. To reduce the size of the datasets and to preserve the original pixel values, the datasets are provided in a rotated grid. This means that pixels are not aligned in a north-south direction but in the direction of the flight path. For the Engadin and SNP data acquisition, the flight strips were rotated by -58 degrees. The original coordinate reference system of the dataset is WGS84/UTM zone 32N (EPSG: 32632).

In a first step, the flight strips were rotated and then merged. The north-eastern part of the data covered areas in Austria and Italy. As the study focuses on the Engadin, this part was cut off. The rotated, merged and clipped dataset was ready for manual image registration. In areas with simpler terrain, or if the georeferencing by the data provider had been more precise, this step would not have been necessary. As reference data served the SwissImage 10cm dataset from 2019 provided by the Swiss Federal Office of Topography (Swisstopo) (Bundesamt für Landestopografie (Swisstopo), 2023a). The SwissImage 10cm is a freely available RGB product with a spatial resolution of 10 cm in the lower parts of Switzerland and 25 cm in the Alps. It is acquired every three years (Bundesamt für Landestopografie (Swisstopo), 2023a). In contrast to the AVIRIS-NG datasets, it has a higher spatial precision also in steep and mountainous areas.

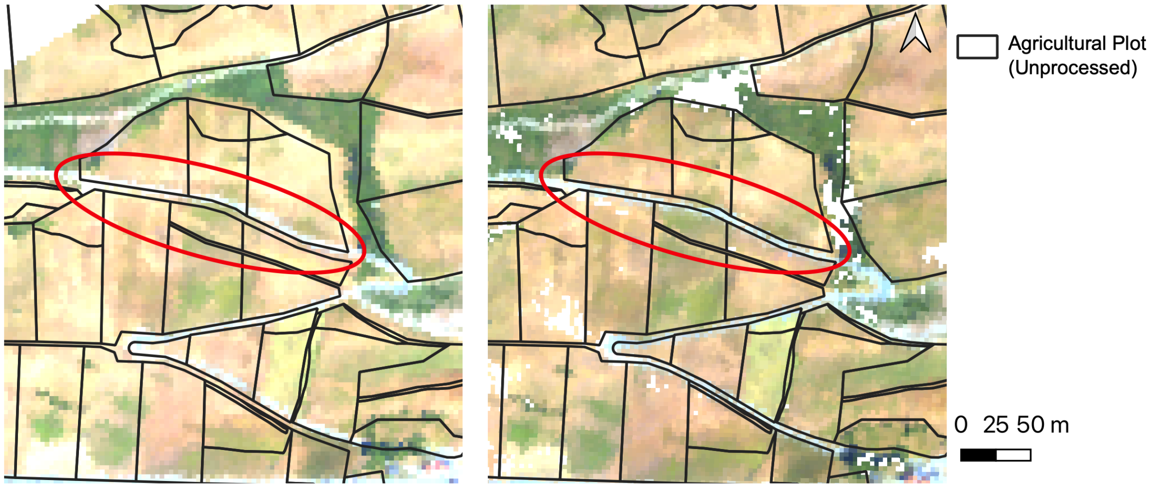

Figure 6: AVIRIS-NG product before (left image) and after (right image) image registration. Again, the streets serve as a reference in comparison to the agricultural plots. They should lie between plots; this is mostly the case in the image on the right side but not on the left side.

As there are large areas covered with clouds, carefully conducted cloud filtering was necessary. Multiple methods were tested (cloud indexes, supervised classification) but it was difficult to find a satisfying working method. This is because several types of clouds are apparent in the scene, which were difficult to catch using one single approach. Approaches proposed in the literature did not lead to satisfying results either (Marshak et al., 2000; Sentinel Online, 2023). By inspecting the Principal Components (PCs), which were calculated for further analysis, I discovered that PC Band 5 showed very distinctive values for clouds. Especially the cirrus and nearly opaque clouds, which were rarely detected by the other approaches were well distinctive using this method. The center regions of the big clouds were not detected by this band, but as these regions are well distinctive on several original bands this was not an issue. So, a threshold was applied on PC Band 5 and original Band 2 (at 381 nm) of the original dataset and combined to a cloud mask. The cloud masking methodology slightly tends to exclude pixels that are not clouds but was the most reliably performing method.

The 425 spectral bands of AVIRIS-NG result in a relatively large dataset, which makes operations on the dataset computation-intensive and long-lasting. As many of the spectral bands are strongly correlated, I performed a data dimensionality reduction on the cloud-masked dataset. I applied one of the most common and simple methods of dimensionality reduction which is to extract spectral features with a principal component analysis (PCA) (Wold et al., 1987). PCA is a multivariate statistical technique that is used to extract information from spectral data and transform the data into a set of orthogonal variables called principal components (Prospere et al., 2014). This procedure reduces irrelevant information from the original inter-correlated variables and allows to extract the valuable information. The method has already been applied in other ecology-related studies using remote sensing data (e.g., Prospere et al., 2014). This data dimensionality reduction is applied either to reduce the computational effort but also because analyzing all 425 bands comes with the risk that the relevant data are superimposed and therefore hidden by a lot of irrelevant data.

The first three PCs explain together 99.88% of the variance within the AVIRIS-NG data. The first PC explains 92.34%, the second explains 7.09% and the third only 0.36%. All other PCs explain less than 0.01% of the Variance, hence they were discarded.

3.4.2 SwissImage

The SwissImage RS is a high-resolution remote sensing product provided by Swisstopo (Bundesamt für Landestopografie (Swisstopo), 2023b). It has a spatial resolution of 10 cm in the lower parts of Switzerland and 25 cm in the Alps. In contrast to the formerly introduced SwissImage 10cm, it has an additional NIR – Band. It is available upon requested at Swisstopo. The four bands cover the following wavelengths:

- Band 1: NIR [808 - 882 nm]
- Band 2: red [619 - 651 nm]
- Band 3: green [525 - 585 nm]
- Band 4: blue [435 - 495 nm]

The data acquisition in the study area was done in September 2019 (4. - 29.). The SwissImage RS is geometrically corrected, so no further processing was necessary for this dataset. As the data was acquired on clear days, there was no need for cloud filtering. In regions with complex topographies, the geometric deviation can be 3 - 5 meters, otherwise, it is below 0.25 meters (Bundesamt für Landestopografie (Swisstopo), 2023b). As the entire dataset is very large, it is delivered in 1 km × 1 km tiles. For the mowing classification of SwissImage RS, which was a preliminary step for the main spectral diversity analysis, the high spatial resolution was not necessary, but a continuous dataset was needed. To obtain this, the tiles were resampled to a spectral resolution of 10 meters and then merged. The main spectral diversity analysis was performed using the original resolution.

3.4.3 Sentinel-2 Data

The MultiSpectral Instrument (MSI) onboard both Sentinel-2 satellites provides a set of 13 spectral bands (4 visible bands, 6 Near-Infrared bands, and 3 Short-Wave Infrared bands) with a revisit time of 5 days (Sentinel Hub, 2023). Four bands have a spatial resolution of 10 m, six bands of 20 m and three bands at 60 m spatial resolution. Sentinel-2 products are available, e.g., via Google Earth Engine (Harmonized Sentinel-2 MSI: MultiSpectral Instrument, 2023).

3.4.3.1 Mowing Classification for Plot aggregation

Sentinel-2 scenes were used for the processing of the agricultural plots. A supervised classification using a random forest classifier, based on 200 training points that were manually selected, was performed on scenes from June 2018 to August 2018 to categorize pixels as mowed and not recently mowed.

3.5 Software

Most of the image processing operations of the AVIRIS-NG data were done in ENVI (Exelis Visual Information Solutions, 2017). Further operations on remote sensing data and data analysis were conducted in a Python environment using Rasterio (Gillies, 2023)and Xarray (Hoyer & Hamman, 2017). The processing of the agricultural plots was also done in Python using Geopandas (Jordahl et al., 2020). Using Seaborn (Michael L. Waskom, 2021) and Matplotlib (Hunter, 2007), the visualizations were done. The Python libraries Scikit (Pedregosa et al., 2011) and Scipy (Virtanen et al., 2020) were used to perform the statistical analysis of the spectral diversity data. For geographical visualizations, I used QGIS (QGIS Development Team, 2022).

4 Methods

4.1 Processing of Agricultural Plots

Before the spectral diversity of the agricultural areas could be calculated, the agricultural plots that formed the basis for the calculations had to be processed to resolve some issues that would have significantly affected the results. A major issue was the size of the plots in the initial dataset. Because of the common agricultural heritage practices, the agricultural plots had become increasingly fragmented over time. In some areas, the plot size had become too small for a meaningful analysis. So, these plots needed to be merged sensibly. The plots were merged based on two criteria. The first criterion addressed the type of agricultural management of a plot. In the Lower Engadin, one can find a wide range of management types (e.g., artificial meadows, intensively- and extensively used meadows, intensively- and extensively used pastures, areas to support biodiversity, etc.). All plots of the land-use dataset have been attributed to one of these categories. The second criterion was not contained in the original dataset. It builds on the assumption that if a plot was mowed within the same few days as a neighboring plot, it may be one single plot and managed as one by the local farmer. Based on the Sentinel-2 time series of June to August 2018, each scene and each plot was checked if the plot was recently mowed or not. If the majority of the pixels of a plot were categorized as mown, the plot was also categorized as such. From this, the date of the first mowing was extracted for each plot and served as the second criterion. Adjacent plots were merged when the date of the first mowing and the management categories were equal. This step reduced the number of plots from 13’210 to 9762 and increased the mean size from 2909 m^2 to 3936 m^2.

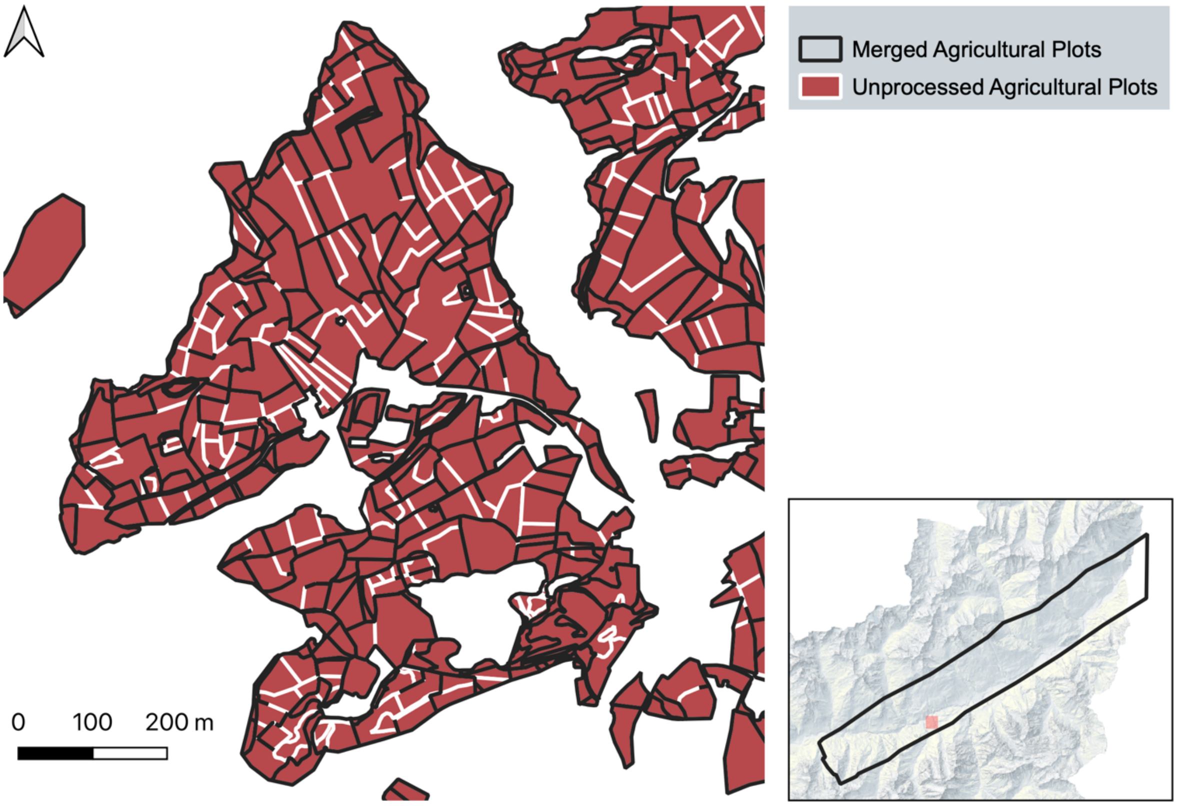

Figure 7: Example of the agricultural plots before and after the merging. The black-colored borders show the borders of the merged plots. The white lines show the borders of the unprocessed dataset that were dropped while merging.

The next step was the exclusion of forested areas based on the WorldCover dataset. Furthermore, the plots were buffered by 10 meters. This made sure that the potentially relatively large spatial diversions between remote sensing data and agricultural plot data do not lead to negative impacts when analyzing the data. After that, plots that still have a size of more than 2000 m^2 were selected. After these processing steps, the dataset was considered ready for analysis and had the following properties:

- Number of Plots: 1777
- Mean Area: 7318 m^2
- Cumulated Area: 13’004’242 m^2

Table 2: Compilation of the management types that are present within the study area (Green: selected for further analysis, Red: not selected).

Original German Definition	English Definition (translated and abbreviated)	Number of Plots per Management Type	Cumulative Area per Management Type [m²]
Übrige Dauerwiesen (ohne Weiden)	Permanent meadows	751	5’907’755
Wenig intensiv genutzte Wiesen (ohne Weiden)	Low-intensity meadows	192	1’192’209
Extensiv genutzte Wiesen (ohne Weiden)	Extensively used meadows	458	3’546’575
Regionsspezifische Biodiversitätsförderfläche (Grünflächen ohne Weiden)	Region-specific biodiversity area	162	1’068’137
Extensiv genutzte Weiden	Extensively used pastures	52	390’997
Waldweiden (ohne bewaldete Fläche)	Wooded pastures	2	21’291
Weiden (Heimweiden, übrige Weiden ohne Sömmerungsweiden)	Pastures	7	26’350
Übrige Flächen innerhalb der LN, nicht beitragsberechtigt	Other areas, not eligible for contributions	3	6572
Kunstwiesen (ohne Weiden)	Artificial meadows	128	764’661
Sommerweizen (ohne Futterweizen der Sortenliste swiss granum)	Spring wheat	2	5055
Sommergerste	Spring barley	16	59’680
Futterweizen gemäss Sortenliste swiss granum	Fodder wheat	2	9539
Getreide siliert	Silage Cereals	1	2638
Hanf	Hemp	1	2783

Table 3: Definition and Description of the management types that are objects of the study.

Management Type	Description
Permanent meadows	Areas that are mown at least once a year for forage production. Permanent meadows have existed for more than six years as such (Bundesamt für Landwirtschaft BLW, 2017).

Low-intensity meadows	Low-intensity meadows are lightly fertilized meadows on dry to wet sites. They can have a high plant diversity (Forschungsinstitut für biologischen Landbau FiBL et al., 2023d). In the canton of Grisons, there are defined different mowing periods, based on the location of the meadows. In the valley region, mowing is allowed from June 15, and in the more alpine areas from July 1, or July 15. (Amt für Natur und Umwelt, 2017).
Extensively used meadows	Extensively used meadows are unfertilized meadows on dry to wet sites. They provide an important habitat for many plant and animal species (Forschungsinstitut für biologischen Landbau FiBL et al., 2023c).
Region-specific biodiversity areas	A wide range of cultivations with the aim to promote biodiversity (includes extensively used areas, not harvested strips on fields, hedges or dry stone walls) (Forschungsinstitut für biologischen Landbau FiBL et al., 2023a)
Extensively used pastures	Extensively used pastures are low in nutrients, mostly of large areas and on uneven terrain. They are characterized by diverse vegetation and ecologically valuable structures (Forschungsinstitut für biologischen Landbau FiBL et al., 2023b).
Artificial meadows	An artificial meadow is an area sown as a meadow and cultivated within a crop rotation for at least one growing season (Bundesamt für Landwirtschaft BLW, 2017).

Table 2 shows that not all management types are sufficiently present in the study area to be included in the analysis. Only management types with a cumulative area of more than 100’000 square meters were selected for the analysis. Furthermore, certain management types did not represent grassland and therefore needed to be excluded from the analysis. As in the Lower Engadin, meadows and pastures are the dominant type of cultivation, several present types of cultivation do not meet the two criteria and are therefore excluded (Wooded pastures, Pastures, Areas not eligible for contributions, Spring wheat, Fodder wheat, Silage Cereals, Hemp). Remaining are six different types of management, all differently managed pastures and meadows.

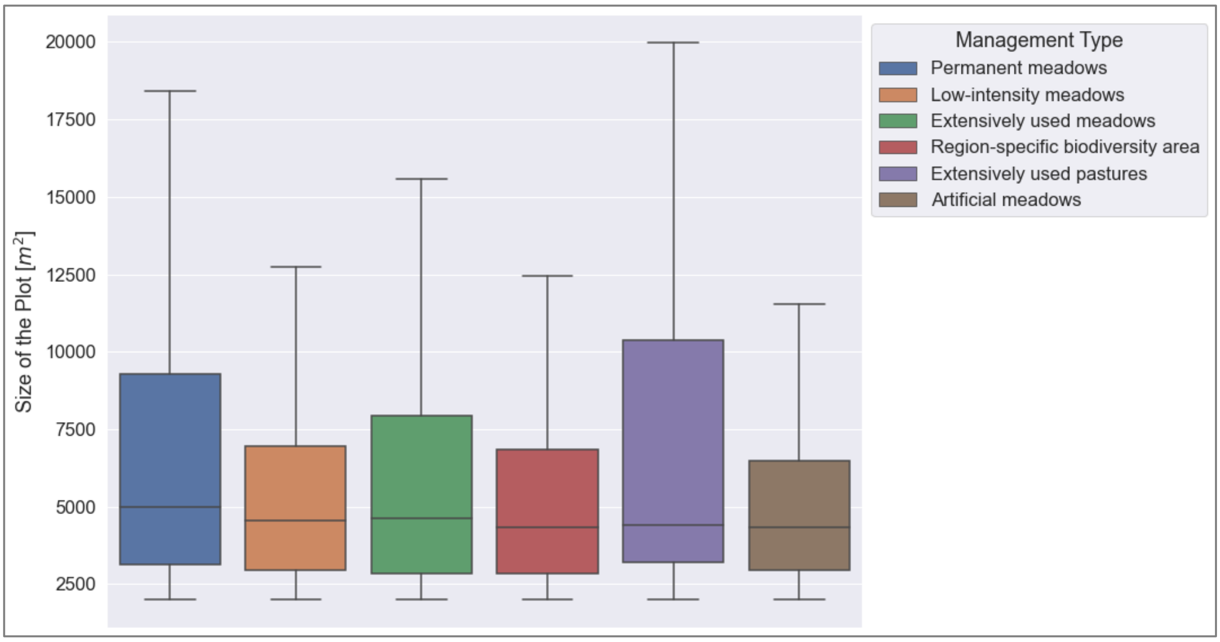

Figure 8: Area distribution of the selected management types.

Figure 8 shows that the plot sizes of the selected management types are similarly distributed. The median plot size is around 5000 m^2 for all categories. All management types contain outliers that are not shown in Figure 8, the largest plot covers an area of more than 200'000 square meters.

A last selection of agricultural plots is done after the analysis of the spectral diversity metrics. Plots with exceptionally high spectral diversity values were individually manually checked for multiple management types within the plot and other effects distorting the diversity metrics. Plots with very high diversity that could not be attributed to species richness or functional diversity were excluded.

4.2 Spectral Diversity Analysis

4.2.1 Theoretical background of the applied Methods

To analyze functional diversity, plants offer a wide range of traits that can be the subject of the examination. To develop predictive measures of functional diversity, the choice of functional traits with which organisms are distinguished is crucial (Petchey & Gaston, 2006). It is also important to find a meaningful way to summarize the trait information (Petchey & Gaston, 2006). This study exploits the fact that plant traits can be scaled to canopy level, not only plant level (Homolová et al., 2013). The functional traits that were studied were determined by the available data the study was conducted with. As the study was done using optical remote sensing data, the functional diversity was assessed only by analyzing the reflectance properties of the plants. But as the AVIRIS-NG dataset offered a very wide range of detected wavelengths, this can be done very extensively. Hence, for this study, there was no critical selection of plant traits, but just a selection of plant traits that were possible to analyze with remote sensing data. To find the most accurate prediction of the environmental heterogeneity, different spectral metrics were tested and if possible, applied to different datasets. Scale and spatial resolution have a significant impact on the success of a spectral metrics analysis (Gholizadeh et al., 2018). To examine this impact, this study tested three datasets, all with significant differences in spatial resolution and covered spectral range.

4.2.2 Object-based Approach

There is a large number of studies in the ecology field addressing biodiversity assessments calculating spectral diversity based on regular plots (e.g., Fassnacht et al., 2022; Rocchini et al., 2018; Rossi et al., 2022). When working with a moving window (Rocchini et al., 2018) or randomly placed plots (Fassnacht et al., 2022), covering an extended area, the approach relies on the assumption that the diversity of the remote sensing signal is driven by ecological factors. Therefore, this approach is limited to areas where ecological factors are expected to be the main determinants of spectral diversity (e.g., forested areas or untouched grassland). If other factors contribute to diversity, the spectral metrics do not only quantify the ecological diversity. Anthropogenic influences, such as roads or settlements, can also become evident, affecting spectral diversity. Agricultural land management practices can also be significant anthropogenic influences. Management leads to severe differences in reflectance properties. For example, a recently mown meadow looks completely different compared to a neighboring meadow that has not been mown for several weeks, although they may be very similar from an ecological perspective. When working with random regular areas or a moving window, such areas would likely be analyzed within the same spatial unit. The spectral dissimilarity between the two areas would return very high spectral diversity values, primarily attributable to differences in land management practices. Consequently, the results of studying grassland diversity would depend stronger on the dissimilarity of the management and not on the ecological diversity. An alternative to tackle this issue would be to draw the analyzed units manually, but this would be hardly applicable when trying to cover large areas.

Figure 9: Examples of managed and untouched grassland. On the left side a scene near Scuol within the study area. The scene is not suited to measure spectral diversity with a moving window approach, as the diversity would be strongly influenced by the dissimilarity of management (top-left and bottom-right corners), streets and settlements. The scene on the right side lies within the Swiss National Park, there has been no management for decades. Here it would be an option to assess spectral diversity using a moving window, as the diversity is mainly driven by environmental factors.

Therefore, to study ecological parameters, it was important to analyze grassland independent of the current state of management. To achieve this, this work is grounded on an object-based approach. This describes the approach of analyzing grassland at the level of agricultural plots, without variations of management within the plot. Like this, it can be assumed that the spectral diversity of the signal was only driven by ecologic factors within certain sub-regions of a surface. The plots were not given by a moving window or otherwise randomly placed within a study area. They were defined by the land-use dataset of the canton of Grisons and then processed.

4.2.3 Evaluation of the Entire Spectrum

To explore the entire spectrum of AVIRIS-NG, the first three PCs were analyzed. For the SwissImage RS and Sentinel-2, no PCA was performed, because only a few bands were available. To quantify the spectral diversity, the variance and the Coefficient of Variation

(CV) of different products of AVIRIS-NG, SwissImage RS and Sentinel-2 were calculated. The variance is a common statistical measure for dispersion and has also been applied to quantify spectral diversity (Dahlin, 2016; Laliberté et al., 2019). Very similar to the standard deviation, it measures how far a set of numbers of a dataset is spread out from the mean value. Given a sample of data of size the sample variance is calculated as follows:

$$s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$$

The coefficient of variation (CV) is a measure that is widely applied in studies concerning the spectral diversity of remote sensing data (Gholizadeh et al., 2019; Hauser et al., 2021; Rossi et al., 2022; Wang et al., 2016, 2018b). The CV calculates the ratio between the standard deviation (square root of formerly introduced variance) and the mean of the reflectance value at a specific wavelength (Rossi et al., 2022). The resulting values of the CV can also be negative (when the mean value is negative). To cover the entire spectrum, the CV can be averaged over all measured wavelengths, when working with PCs, a weighted average of specific PCs can also be applied. When the mean value, with which the CV was calculated, could have negative values, the CV delivered chaotic results. This is the case because there is no linear relationship to the standard deviation. Therefore, the CV is only presented when applied on the NDVI in the results section, the results of the other products can be found in the appendix.

The analyzed bands were clipped for each plot and the Variance and the CV were calculated. For the AVIRIS-NG PC analysis, several ways to summarize the resulting values were tested (inspired by Dahlin (2016)). The number of analyzed PCs was varied between one to ten. I also tested whether a weighting of the diversity values retrieved per PC would enhance the result. In the end, calculating the mean Variance and CV of the first three PCs led to the most meaningful result. When working with the original SwissImage RS and Sentinel-2 bands, the average of all bands was calculated.

4.2.4 Working with specific Plant Traits

Working with empirical, not specified data often lacks a causal relationship (Homolová et al., 2013). Analyzing the spectral diversity of the full spectrum bears this risk. The issue can be overcome when analyzing specific plant traits. Another advantage of this approach is that comparing the results of the different datasets is possible, as only a small fraction of data, that is common to all datasets, is used. This can be done for example using the Normalized Difference Vegetation Index (NDVI). The NDVI is a widely used index for analyzing vegetation, as it quantifies its greenness and productivity and helps understand its density (USGS, 2023). It has been applied in several studies regarding biodiversity (e.g., Gholizadeh et al., 2019). It is calculated as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

For the AVIRIS-NG dataset, I calculated the NDVI using Band 57 (662nm) as RED and Band 91 (832nm) as NIR. For the SwissImage RS, I used the Red Band at 619 - 651 nm and the NIR band at 808 - 882 nm to calculate it. The spatial variability of the NDVI I quantified in the same way as when exploiting the entire spectrum using variance and CV. The only difference was that no mean value was calculated, as there was only one resulting layer per plot. For Gholizadeh et al. (2019) the standard deviation of the NDVI worked as a good predictor of biodiversity. The NDVI was calculated from AVIRIS-NG, Sentinel-2 and SwissImage RS imagery.

Another plant trait that is widely used in ecology studies is the plant chlorophyll content (Homolová et al., 2013; Hunt et al., 2012). An index that shows good results in detecting chlorophyll is the triangular greenness index. It relies only on the RGB-Bands and performs well also on canopy scale. It is calculated as follows:

$$TGI = -0.5\, [(\lambda_r - \lambda_b)(R_r - R_g) - (\lambda_r - \lambda_g)(R_r - R_b)]$$ (Raymond Hunt et al.,2011)

Where $\lambda_{r,\ g,\ b}$ is the wavelength of the specific bands in nanometers and R_λ is the spectral reflectance of the band.

e.g., for AVIRIS-NG:

$$TGI = -0.5\, [(632 - 437)(R_{632} - R_{547}) - (632 - 547)(R_{632} - R_{437})]$$

Vegetation-related indexes using only RGB bands are rare, as most use either a NIR or a red-edge band (Hunt et al., 2012). Indices specifically designed for chlorophyll detection mostly use narrow bands of the red-edge region of the spectrum (e.g., Leaf Chlorophyll Index (Datt, 1999) and Normalized Pigment Chlorophyll Index (Peñuelas et al., 1994)). Since NDVI already covers the red edge, I explored an index that only covers the RGB region to assess whether significant results can be achieved using this region alone. The TGI can be determined with narrow bands but also using broad-band multispectral sensors or digital cameras (Raymond Hunt et al., 2011).

To also explicitly analyze the SWIR region, a further index was introduced. The normalized difference infrared index (NDII) is an index that detects canopy water content, and therefore can also potentially detect differences between plots. The index values increase with increasing water content. Applications include crop agricultural management, forest canopy monitoring, and vegetation stress detection (NV5 Geospatial, 2023). On AVIRIS-NG it was calculated using Band 89 (817 nm) and Band 255 (1649 nm).

4.2.5 Mowing Detection

An important property of a grassland canopy, that has a very large impact on the reflectance, is the recent mowing status of a grassland surface (see Figure 10). A recently mowed meadow is in most cases distinguishable from a neighboring meadow that has not been mowed. In an RGB band display, the recently mowed meadows appear brighter and less intense green. At very dry conditions, they appear in light brownish and yellow tones, while most unmown meadows stay green.

Differing mowing statuses of meadows have the potential to lead to distorted results of the spectral metrics analysis. To solve this issue, within a category of management types, the spectral metrics can be compared by distinguishing between recently mowed and unmown plots. Additionally, knowing the mowing status of plots allows to compare results overall categories of management types.

Classifying the plots on mown and not mown I have done by training a classifier and performing a Minimum Distance Classification. The minimum distance technique uses the mean vectors of each endmember, which is obtained using training areas. Then it calculates the Euclidean distance from each unknown pixel to the mean vector for each class. Pixels are assigned to the nearest class (Richards, 1999).

4.3 Plot Refinement based on Spectral Diversity Values

The original dataset providing the agricultural plots and the processing steps performed on the dataset ultimately did not provide plots that perfectly represented the actual management structures in the Lower Engadin. There were still plots, which contained more than one management type or where the borders did not match the change of management observed by the remote sensing data. These plots resulted in extreme values in the spectral diversity analysis. As they would have distorted the result of the analysis, these plots needed to be excluded, which was done very carefully.

When analyzing the plot with outliers in the different diversity metrics, it became clear that these values mostly came from plots containing multiple management types or the border of a shadowed area, so there were areas with high and areas with low illumination. In some cases, the border of different AVIRIS-NG flight strips passed through the plot, which also led to outlier values. This step was done by hand, to ensure that the proper plots were excluded from the analysis, and not plots that had high values because of their high functional diversity.

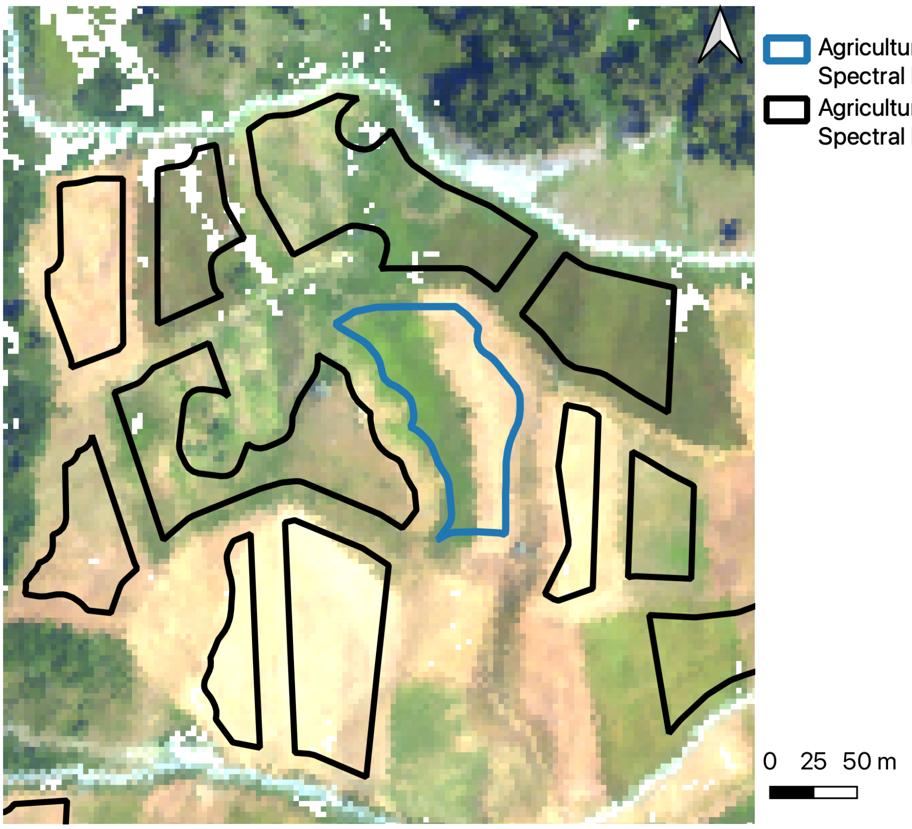

Figure 10: AVIRIS-NG scene and agricultural plots near the village Ardez. The plot in blue was not used in the spectral diversity analysis, as the border of the plot did not correspond with the actual management practice. This was well visible as the border from green to yellow was very well recognizable and passed along a clear line, that indicated this is not a natural border, but a border caused by management. Also, other plots showed changes, but they were less clear and therefore may had other reasons than management.

4.4 Overlapping SwissImage Tiles

As the SwissImage RS tiles had overlapping areas, the plots that were analyzed multiple times needed to be aggregated. This was done by calculating the mean of each spectral diversity metric over the number of observations. The original values deviated only marginally from each other per plot.

4.5 Statistics and Visualization

The results of the spectral diversity analysis are presented using boxplot diagrams. Boxplot diagrams show the 25th to the 75th percentile of the data range with a box. The bar within the box represents the median value. Whiskers show the minimum and maximum values without outliers. To test for significant differences in spectral diversity between the plots of different management types, statistical tests were performed. The first test involved two variables: the management type as a group variable and the diversity metric as the dependent variable, which was being examined for differences. As the results of the spectral diversity analysis were not always normally distributed, this led to the usage of the Kruskal-Wallis test (UZH Methodenberatung, 2023b). A Kruskal-Wallis test is used to examine the differences in the central tendency of a variable between more than two independent samples. The dependent variable does not have to be normally distributed. The objective of the test is to determine whether there is a statistical difference between the medians of at least three independent groups. The null hypothesis usually states that there are no significant differences between the medians of the data groups. The alternative hypothesis states that the median is not equal for all the data groups. The test returns a p-value, if the p-value is lower than 0.05, one can reject the null hypothesis (UZH Methodenberatung, 2023a). The Kruskall-Wallis test only gives information if there are differences between the data groups, but not between which groups. A post-hoc test needs to be performed, to find out which groups differ significantly. As performed after the Kruskall-Wallis test, the Dunn-Bonferroni test was applied (UZH Methodenberatung, 2023a). The null hypothesis and alternative hypothesis were the same as for the Kruskal-Wallis test and the same level of significance was needed. The test returned a matrix of p-values, from which one can read which groups do differ significantly.

The statistical analysis of the mowing condition I have done using the Mann-Whitney-U test, which tests for differences between two samples (UZH Methodenberatung, 2023b).

When comparing the results of different sensors or underlying methods, I calculated the coefficient of correlation (Pearson's r) to describe correlations. It is a measure of the strength of a linear association between two variables.

5 Results

5.1 AVIRIS-NG data

As the main focus of this study is on the AVIRIS-NG dataset, the dataset is analyzed in more detail than the SwissImage RS - and Sentinel-2 data.

5.1.1 Analyzing the Entire Spectrum

Several ways to evaluate the results of the spectral diversity derived by the AVIRIS-NG PCs were tested (only first PC, mean of PC 1 to 3, weighted mean of PC 1 to 3). The most promising results, statistically and by visual interpretation, were obtained when the mean of the applied diversity metrics was calculated across the three first PCs. As the aim of the study is to observe differences in the spectral diversity of different management types, results were regarded as convincing when these differences were evident in the data. The Kruskal-Wallis test for the mean Variance of the three first PCs returned a p-value of <0.001 indicating strong evidence that different management types indeed had distinct median values of the spectral variance.

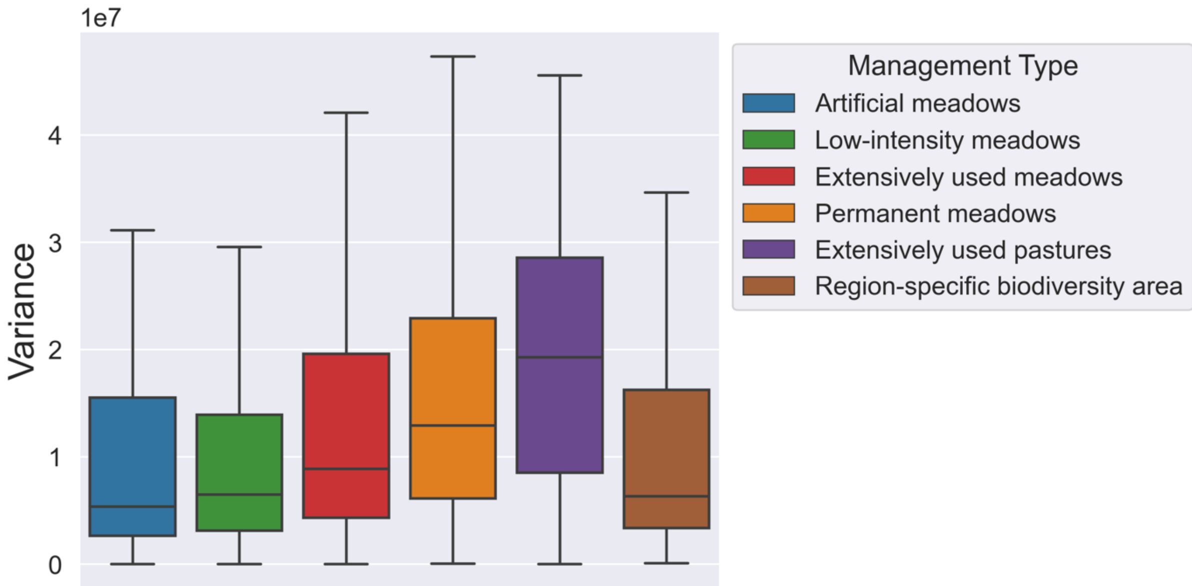

Figure 11: Boxplot of the mean Variance of the first three AVIRIS-NG PCs, grouped by the different management types.

Table 4: P-Values of the Dunn-Bonferroni post-hoc test of all management types of mean Variance of the first three AVIRIS-NG PCs.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1	0.51389	0.00278	0	0.00007	0.35761
Low-intensity meadows	0.51389	1	0.0186	0.00001	0.00028	0.7777
Extensively used meadows	0.00278	0.0186	1	0.00431	0.00974	0.04613
Permanent meadows	0	0.00001	0.00431	1	0.11279	0.00003
Extensively used pastures	0.00007	0.00028	0.00974	0.11279	1	0.00056
Region-specific biodiversity area	0.35761	0.7777	0.04613	0.00003	0.00056	1

Amongst the meadows, the artificial meadows had the lowest Variance. Extensively used- and permanent meadows showed significantly higher values than the other two types of meadows. Especially for artificial meadows, a low spectral diversity could be explained by the absence of structures that enabled intensive management and fertilization, which made a low plant diversity very likely. Another reason for the low spectral diversity may be the rotational farming, applied on artificial meadows. This may hinder local developments, that would be distinctive in the data. On the other hand, pastures often are rich in structures (e.g., trees or hedges), which increased the spectral diversity, especially at the spatial resolution level of AVIRIS-NG. Consequently, pastures differed significantly from all other management types except permanent meadows.

5.1.2 Analyzing AVIRIS-NG NDVI

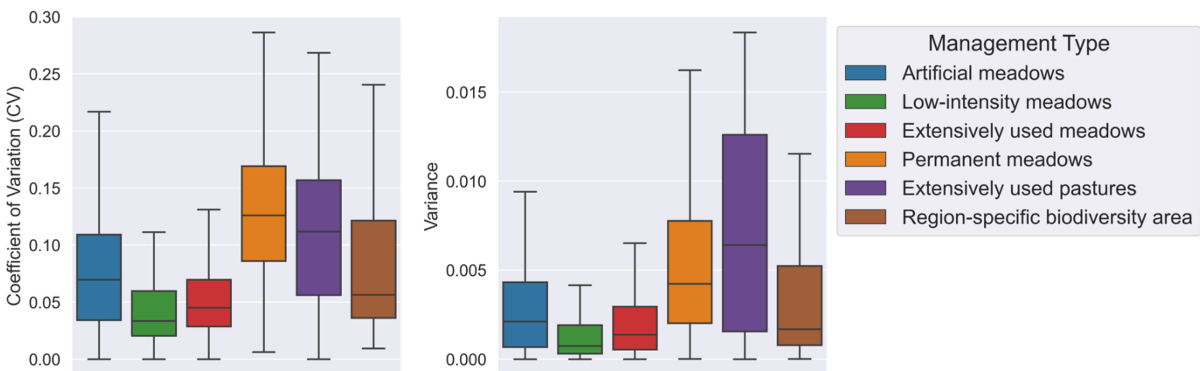

Figure 12: Boxplot of the mean Variance (right image) and CV (left image) of the NDVI of AVIRIS-NG, grouped by the different management types.

Using the NDVI, the spectral metrics aimed to quantify differences in vegetation productivity and density. The spectral metrics calculated using the NDVI produced similar results to using the full spectrum. The value range of the CV differed from the calculation using the PCs, there were no negative values. This was because negative values of the NDVI would show clouds or water surfaces. These elements were not present within the studied areas, as clouds were masked out and the agricultural plots did not contain water surfaces. In both measures, there were significant differences between the management types. (p-value <0.001 for both metrics). The low values of artificial, low-intensity and extensively used meadows may have resulted from homogenous vegetation covers. As in Figure 11, extensively used pastures strongly differed from other management types (e.g., artificial meadows). But unlike the use of the entire spectrum, permanent meadows showed similar values that did not differ significantly.

Table 5: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the Coefficient of Variation of the NDVI of AVIRIS-NG.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.00001	0.00056	0	0.04736	0.89255
Low-intensity meadows	0.00001	1	0.05529	0	0	0.00001
Extensively used meadows	0.00056	0.05529	1	0	0.00004	0.00056
Permanent meadows	0	0	0	1	0.07118	0
Extensively used pastures	0.04736	0	0.00004	0.07118	1	0.03626
Region-specific biodiversity area	0.89255	0.00001	0.00056	0	0.03626	1

Table 6: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the Variance of the NDVI of AVIRIS-NG.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.00006	0.03624	0	0.00382	0.94371
Low-intensity meadows	0.00006	1	0.00522	0	0	0.00002
Extensively used meadows	0.03624	0.00522	1	0	0.00002	0.02247
Permanent meadows	0	0	0	1	0.85452	0
Extensively used pastures	0.00382	0	0.00002	0.85452	1	0.00392
Region-specific biodiversity area	0.94371	0.00002	0.02247	0	0.00392	1

5.1.3 Analyzing AVIRIS-NG TGI

The Triangular Greenness Index detects the chlorophyll content of the canopy, the spectral metrics applied on TGI therefore quantified the spatial variation of the chlorophyll content. Unlike the NDVI, the TGI produced also negative average values within the studied plots. When the green reflectance was less than the red-blue line, for example, for reddish soils, then the TGI was negative. (Raymond Hunt et al., 2011). Therefore, the CV did not produce reliable results and is not presented here.

The variance showed similar tendencies as when looking at the entire spectrum and the NDVI. There were significant differences in both spectral metrics between the different management types (p-value <0.001), but not as strong differences as for the NDVI.

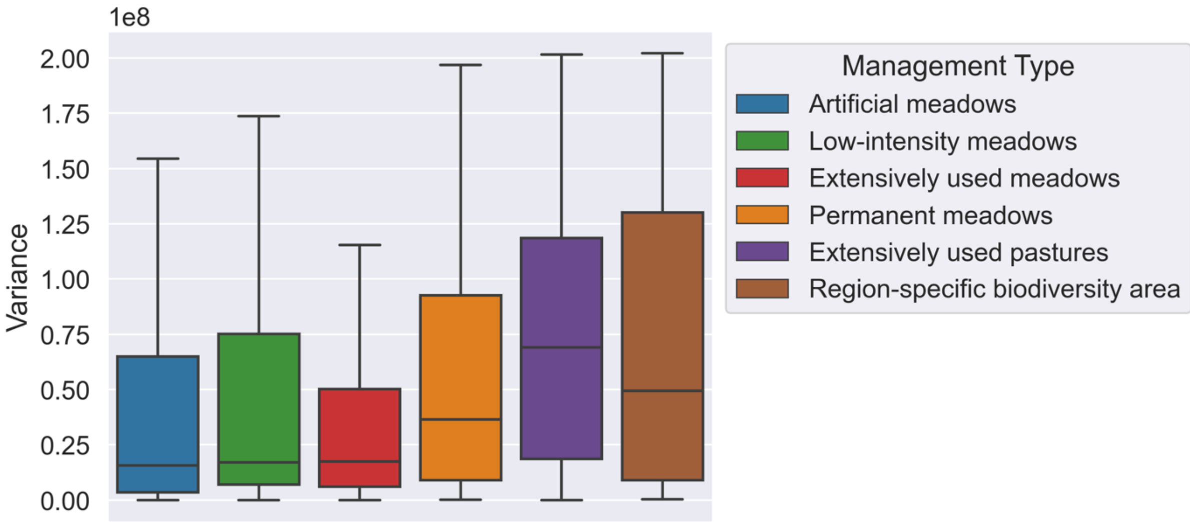

Figure 13: Boxplot of the mean Variance of the TGI of AVIRIS-NG, grouped by the different management types.

Table 7: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of the TGI of AVIRIS-NG.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.18083	0.64417	0.00238	0.0011	0.00008
Low-intensity meadows	0.18083	1	0.23987	0.14428	0.01352	0.00669
Extensively used meadows	0.64417	0.23987	1	0.00015	0.00115	0.00001
Permanent meadows	0.00238	0.14428	0.00015	1	0.05508	0.045
Extensively used pastures	0.0011	0.01352	0.00115	0.05508	1	0.41677
Region-specific biodiversity area	0.00008	0.00669	0.00001	0.045	0.41677	1

This was also evident when looking at the p-values of the Dunns-Bufferoni test. The differences were generally smaller, only a few were significant. Again, permanent meadows and pastures did differ significantly from the other meadows, they also showed a broad range of variance values. The TGI was the single method of data aggregation, that produced high values in the variance of biodiversity areas.

5.1.4 Analyzing AVIRIS-NG NDII

To cover also specifically the SWIR region of the AVIRIS-NG spectrum, I performed a spectral diversity analysis on the NDII. The NDII produced also significant differences between management types. The results resembled those obtained using the full spectrum and the NDVI.

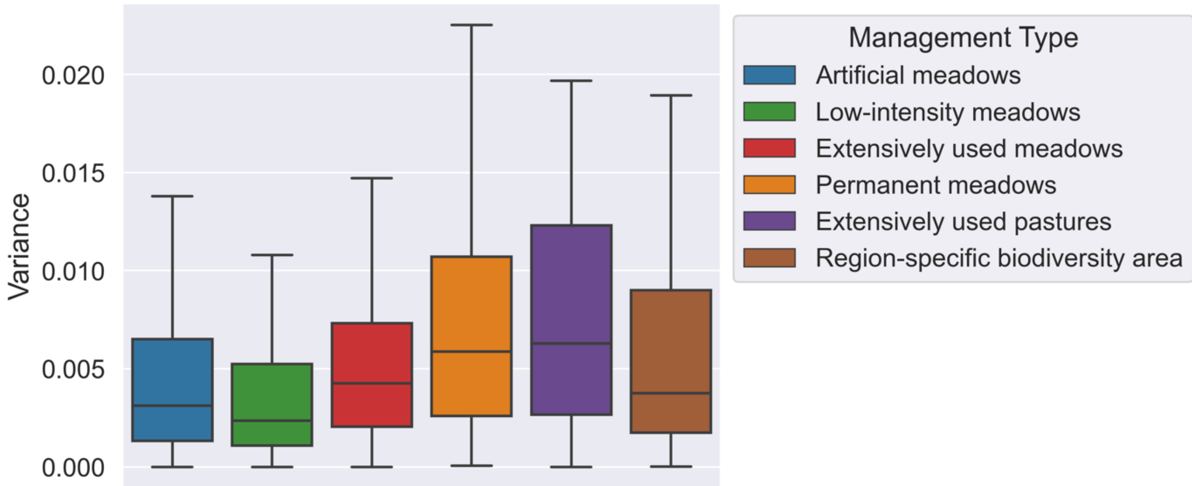

Figure 14: Boxplot of the mean Variance of the NDII of AVIRIS-NG, grouped by the different management types.

Table 8: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of the NDII of AVIRIS-NG.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.1526	0.07904	0.00001	0.00944	0.09065
Low-intensity meadows	0.1526	1	0.00028	0	0.0004	0.0012
Extensively used meadows	0.07904	0.00028	1	0.00007	0.07291	0.79776
Permanent meadows	0.00001	0	0.00007	1	0.71736	0.0107
Extensively used pastures	0.00944	0.0004	0.07291	0.71736	1	0.11956
Region-specific biodiversity area	0.09065	0.0012	0.79776	0.0107	0.11956	1

5.1.5 Analyzing the Effect of Mowing on AVIRIS-NG data

For the analysis based on the mowing status of the plots, the pastures were not included, as pastures did generally not get mowed but grazed. Six pasture plots were classified as mown in the AVIRIS-NG scenery. These plots appeared like they had been grazed in the days before the data acquisition and therefore visually appeared similar to mowed areas.

For the AVIRIS-NG data, mown and not mown plots were distributed among the different management types in the following way:

Table 9: Mown and not mown plots per management type, classified on AVIRIS-NG.

Management Type	**Mown plots**	**Not mown plots**
Artificial meadows	27	68
Low-intensity meadows	8	103
Extensively used meadows	12	164
Permanent meadows	346	145
Region-specific biodiversity area	27	81
Total	**420**	**561**

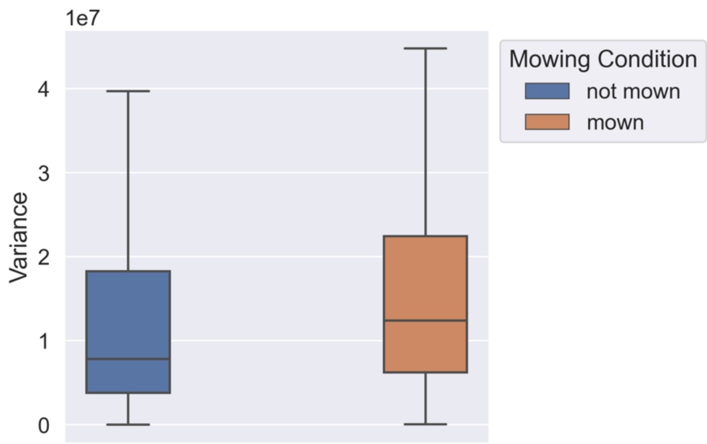

Figure 15: Boxplot of the Variance, derived from the three first AVIRIS-NG PCs, separated in mown and not mown plots.

Across management types, the Variance did differ between mown and not mown areas (p-value (p-value <0.001). The spectral diversity of the mown plots was higher than that of the unmown plots, which could also be observed with the other sensors and types of data processing. A possible explanation for this may be the exposition of bare soil, which was more prominent in recently mown areas. This factor could increase spectral diversity, its influence has been described by Gholizadeh et al. (2018).

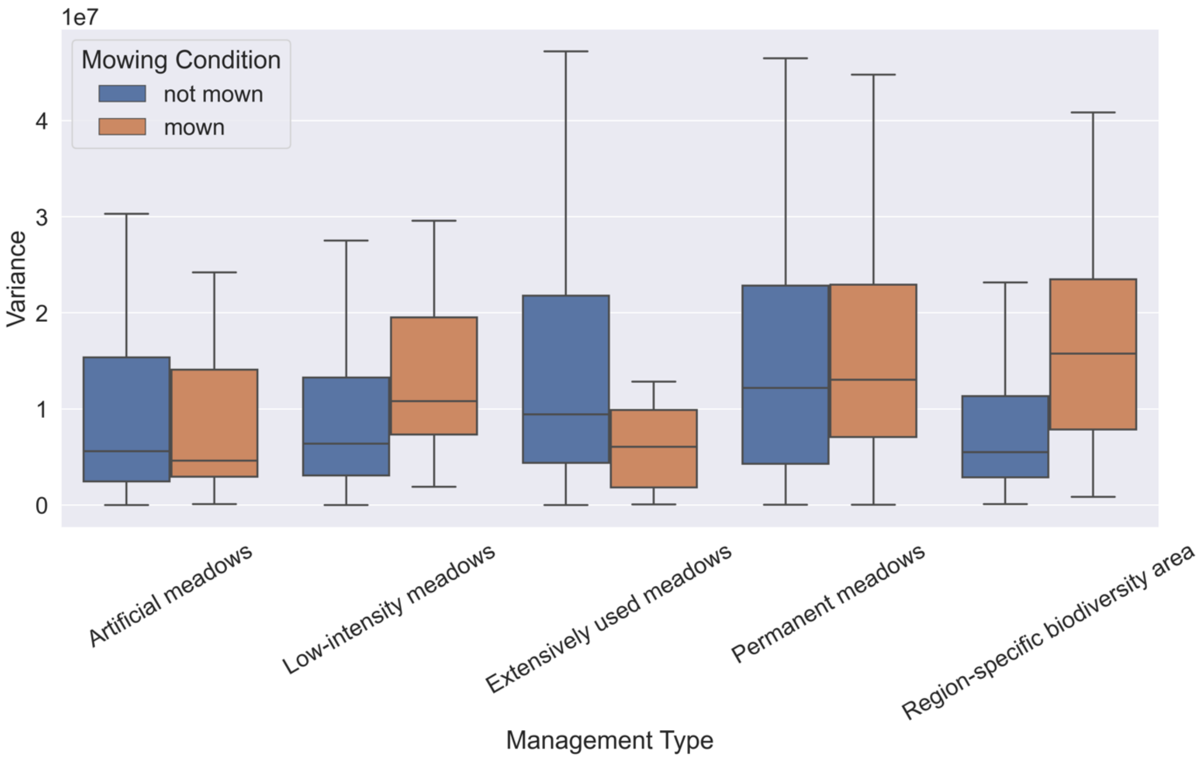

Figure 16: Boxplot of the Variance of the different management types, separated in mown and not mown plots, derived from the three first AVIRIS-NG PCs.

The differences between mown and not mown plots per management type changed with the management type, there was also a management type (extensively used meadow) with a significantly lower variance at mown plots.

Table 10: P-values resulting from the Mann-Whitney-U test, testing for significant differences between the Variance of mown and not mown plots of each Management Type. Input dataset: AVIRIS-NG first three PCs.

Management Type	p-value
Artificial meadows	0.8917
Low-intensity meadows	0.1762
Extensively used meadows	0.0237
Permanent meadows	0.2198
Region-specific biodiversity area	0.0003

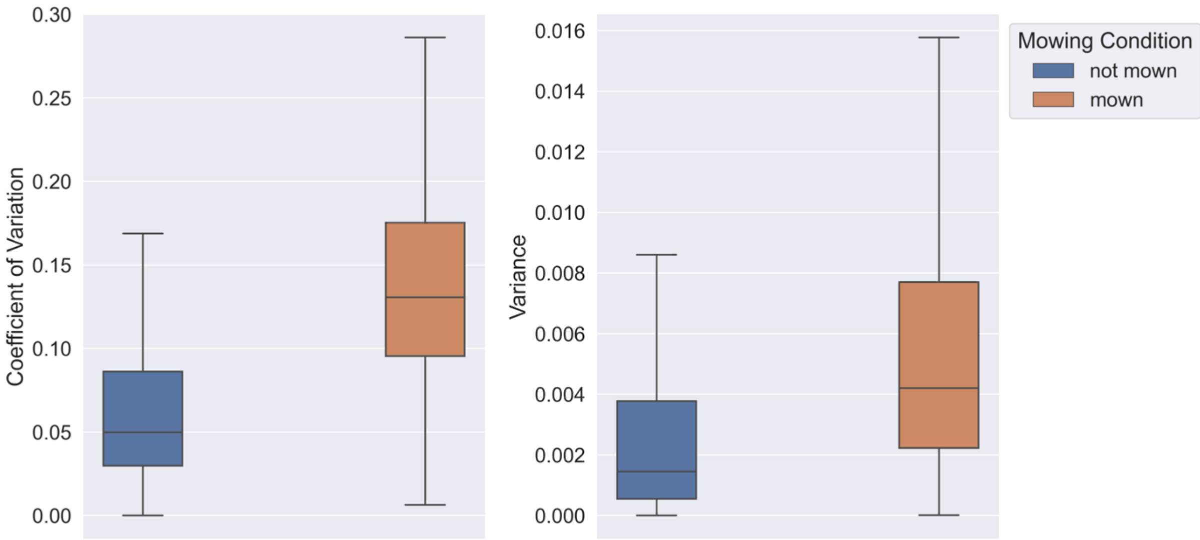

Figure 17: Boxplot of CV and Variance, separated in mown and not mown plots, derived from the NDVI of AVIRIS-NG.

The NDVI of AVIRIS-NG produced a more distinct separation between mown and non-mown areas. This was the case for the Variance and the CV. The exposition of bare soil may play an even more important role, as this may lower the NDVI. The level of significance was higher than when studying the entire spectrum (p-value <0.001 for both metrics). With the NDVI, all management types showed a higher CV at mown areas, most even significantly.

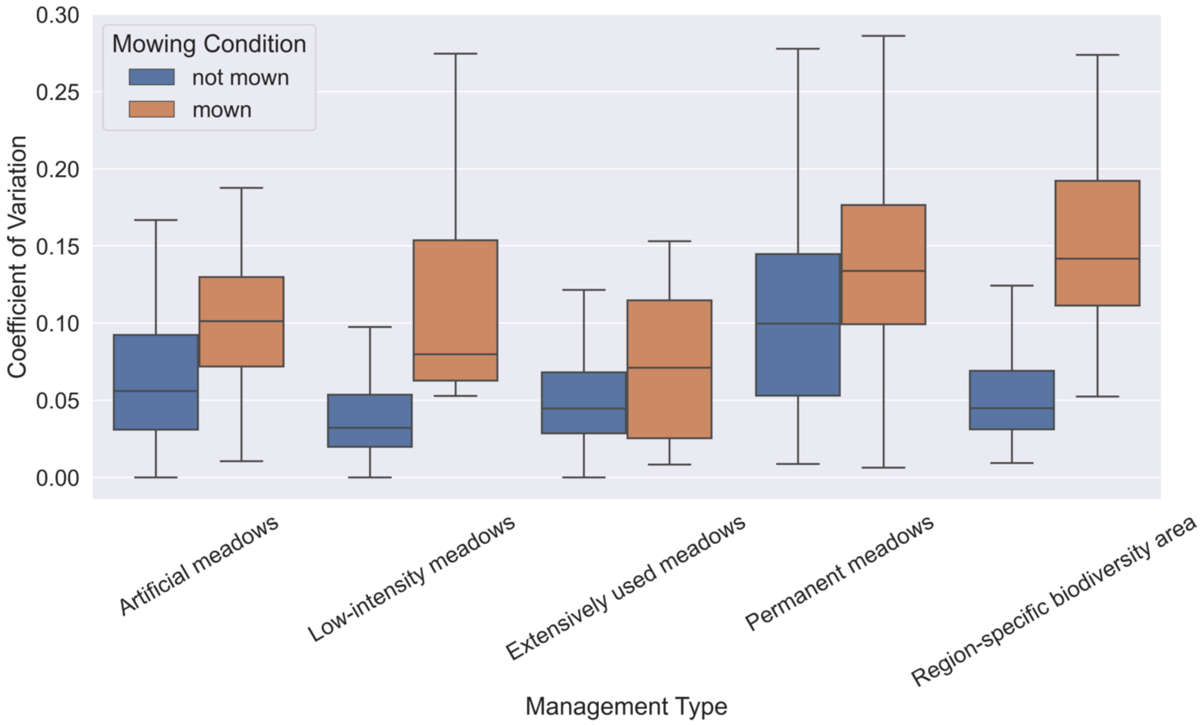

Figure 18: Boxplot of the CV of the different Management Types, separated in mown and not mown plots, derived from the NDVI of AVIRIS-NG.

Table 11: P-values resulting from the Mann-Whitney-U test, testing for significant differences of the CV between mown and not mown plots of each Management Type. Input dataset: AVIRIS-NG NDVI.

Management Type	**p-value**
Artificial meadows	0.0002
Low-intensity meadows	0.0000
Extensively used meadows	0.3738
Permanent meadows	0.0000
Region-specific biodiversity area	0.0000

The same tendency was also observed when looking at the TGI, although the difference between mown and non-mown plots derived from the TGI Variance is the lowest observed with AVIRIS-NG data (p-value Variance 0.002).

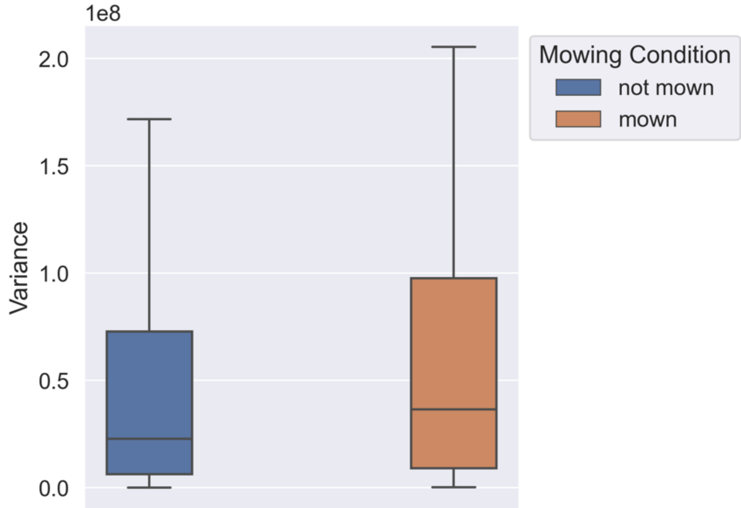

Figure 19: Boxplot of the Variance across all management types, separated in mown and not mown plots, derived from the TGI of AVIRIS-NG.

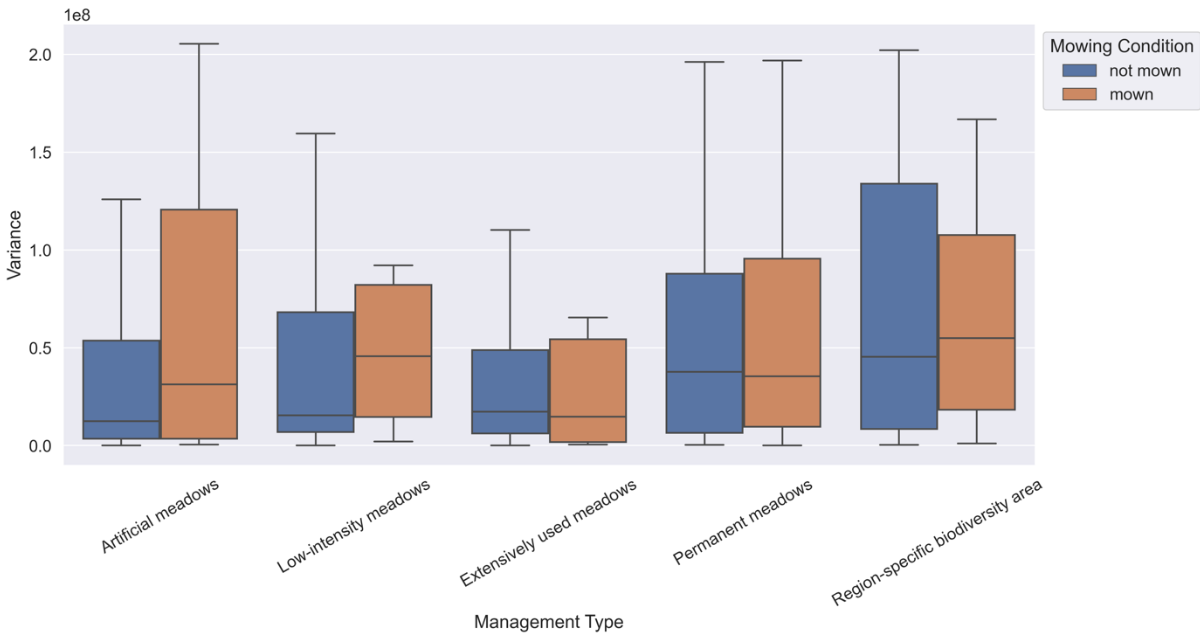

Figure 20: Boxplot of the CV of the different Management Types, separated in mown and not mown plots, derived from the TGI of AVIRIS-NG.

Table 12: P-values resulting from the Mann-Whitney-U test, testing for significant differences of the Variance between mown and not mown plots of each Management Type. Input dataset: AVIRIS-NG TGI.

Management Type	p-value
Artificial meadows	0.1721
Low-intensity meadows	0.3962
Extensively used meadows	0.5553
Permanent meadows	0.3803
Region-specific biodiversity area	0.9830

The TGI showed no consistent relationship for the different management types between mown and non-mown plots. The p-value showed that there are no significant differences detectable between mown and non-mown plots for all management types.

5.1.6 Cross-Comparison of the AVIRIS-NG data

To find a correlation within the four tested methods to aggregate AVIRIS-NG data, the Variance of the methods was plotted against each other and the Coefficient of Correlation was calculated. Every data point within the plots represents an agricultural plot. Correlation could be observed between certain methods of data aggregation when looking at the Variance. Comparing the NDVI and NDII showed the highest correlation, while comparisons to the TGI resulted in low values. Compared to the variance full spectrum, the NDII showed the highest correlation. The variance did not correlate stronger, because different regions of the spectrum were used for the calculations.

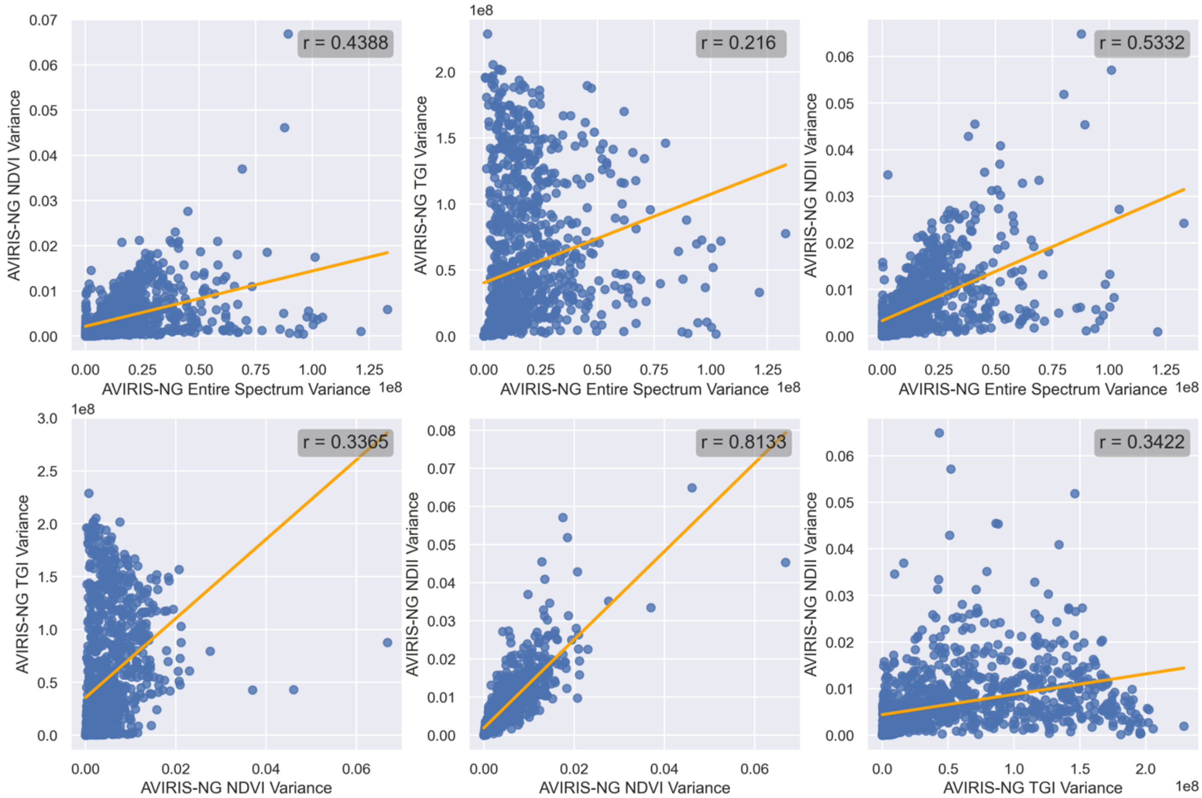

Figure 21: The Variance per plot of the full AVIRS-NG spectrum plotted against the Variance per plot of the three applied indexes (upper row). In the lower row, the Variance per plot of the three indexes plotted against each other.

5.2 SwissImage RS data

When working with SwissImage RS data (spatial resolution: 0.25m in mountainous areas) it is likely to obtain different results than when using AVIRIS-NG data. This is because the performance of spectral metrics is dependent on spatial resolution. Due to a smaller pixel size, the SwissImage RS data can detect more details and smaller structures, which may be of advantage when studying the spectral diversity of grassland. The SwissImage RS has been recorded more than a year after AVIRIS-NG, so both products have different local conditions and the observed plots and their management may have changed in the meantime.

5.2.1 Analyzing All SwissImage RS Bands

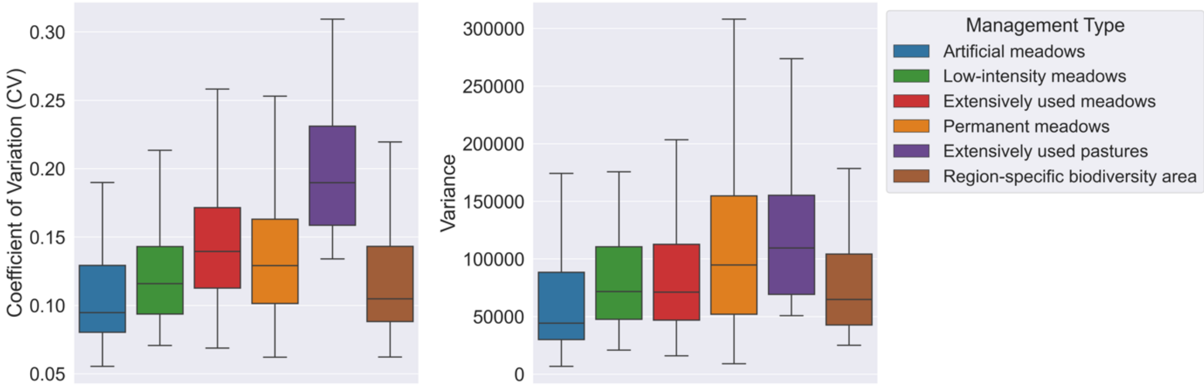

Figure 22: Boxplot of the mean Variance and CV of all SwissImage RS Bands, grouped by the different management types.

The result of analyzing the entire SwissImage RS spectrum resembled the result of the analysis of the full AVIRIS-NG spectrum, especially for the Variance. Figure 38 also showed that the use of the entire AVIRIS-NG spectrum, by exploiting the PCs, and the four SwissImage RS bands led to similar results. These two methods showed a slight correlation ($r = 0.3271$). For both spectral metrics, there were significant differences between the management types (p-values <0.001).

The value distribution of the CV was noticeable. Extensively used meadows, which are expected to have a high species richness, have the second-highest median value of all management types. Whether this value was actually due to the high species richness or to other effects could not be assessed based on the available data.

Table 13: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean CV of all bands of the SwissImage RS.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.00347	0	0	0	0.06414
Low-intensity meadows	0.00347	1	0	0.01857	0	0.27687
Extensively used meadows	0	0	1	0.00031	0.00013	0
Permanent meadows	0	0.01857	0.00031	1	0	0.0002
Extensively used pastures	0	0	0.00013	0	1	0
Region-specific biodiversity area	0.06414	0.27687	0	0.0002	0	1

Table 14: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of all bands of the SwissImage RS.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1	0.00033	0.00001	0	0	0.00339
Low-intensity meadows	0.00033	1	0.84954	0.00776	0.00832	0.5098
Extensively used meadows	0.00001	0.84954	1	0.00054	0.007	0.32918
Permanent meadows	0	0.00776	0.00054	1	0.13681	0.0005
Extensively used pastures	0	0.00832	0.007	0.13681	1	0.0024
Region-specific biodiversity area	0.00339	0.5098	0.32918	0.0005	0.0024	1

5.2.2 Analyzing SwissImage RS NDVI

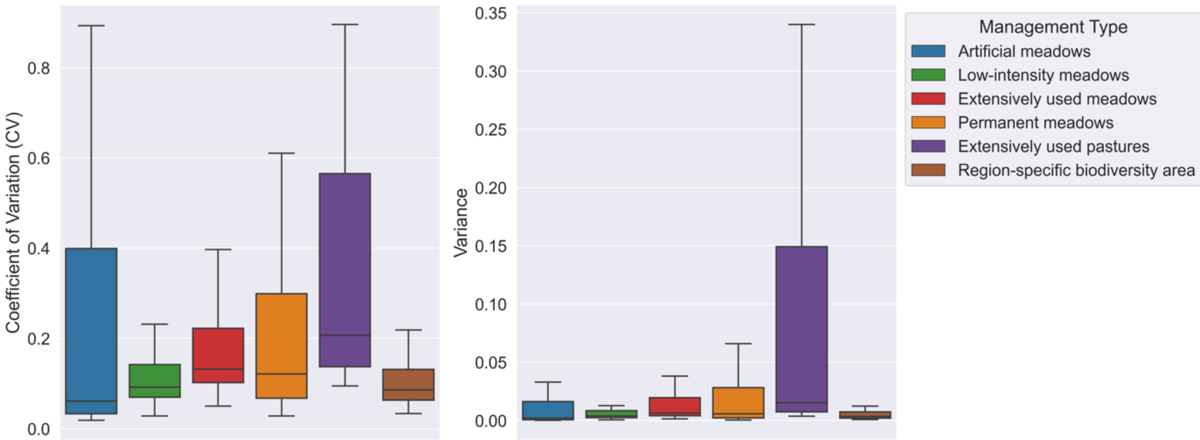

Figure 23: Boxplot of the Variance and CV of the NDVI of the SwissImage RS, grouped by the different management types.

Both spectral metrics showed large values and also a large range of values for extensively used pastures. There were significant differences observable between the management types (p-values <0.001), extensively used pastures did differ from all other management types significantly at both spectral metrics. A reason for this may be that the NDVI was very sensitive to structures introduced by grazing (e.g., trampling damage) and that the pixel size of the SwissImage RS was small enough the detect these structures. This would have explained that the difference between extensively used pastures and all other management types was the largest here compared to all other methods and datasets.

Table 15: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean CV of the NDVI of SwissImage RS.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1	0.19962	0	0.00002	0	0.45191
Low-intensity meadows	0.19962	1	0.00002	0.01282	0.00004	0.5919
Extensively used meadows	0	0.00002	1	0.00189	0.04869	0
Permanent meadows	0.00002	0.01282	0.00189	1	0.00151	0.0012
Extensively used pastures	0	0.00004	0.04869	0.00151	1	0.00001
Region-specific biodiversity area	0.45191	0.5919	0	0.0012	0.00001	1

Table 16: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of the NDVI of SwissImage RS.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1	0.07788	0	0.00001	0	0.22854
Low-intensity meadows	0.07788	1	0.00041	0.04679	0.00008	0.56894
Extensively used meadows	0	0.00041	1	0.00817	0.02721	0.00002
Permanent meadows	0.00001	0.04679	0.00817	1	0.00118	0.00558
Extensively used pastures	0	0.00008	0.02721	0.00118	1	0.00002
Region-specific biodiversity area	0.22854	0.56894	0.00002	0.00558	0.00002	1

5.2.3 Analyzing SwissImage RS TGI

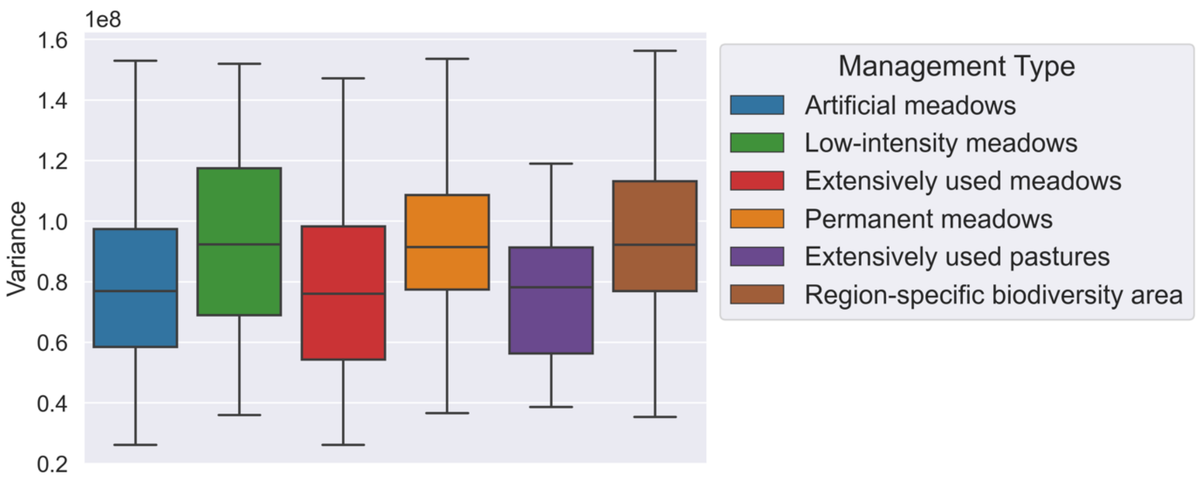

Figure 24: Boxplot of the mean Variance of the TGI of the SwissImage RS, grouped by the different management types.

The Variance of the TGI did produce significant differences (p-value <0.001), but it did show different patterns as the other methods applied to the SwissImage RS. The reasons for this remained unclear. Similarly, as for the AVIRIS-NG data, the Variance of biodiversity areas was high, which could not be observed when studying the full spectrum of the other sensors or the NDVI.

Table 17: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of the TGI of SwissImage RS.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.00196	0.78343	0.00001	0.72423	0.00012
Low-intensity meadows	0.00196	1	0.00004	0.49723	0.02231	0.43961
Extensively used meadows	0.78343	0.00004	1	0	0.82217	0
Permanent meadows	0.00001	0.49723	0	1	0.00486	0.75486
Extensively used pastures	0.72423	0.02231	0.82217	0.00486	1	0.00594
Region-specific biodiversity area	0.00012	0.43961	0	0.75486	0.00594	1

5.2.4 Analyzing the Effect of Mowing on SwissImage RS Data

Table 18: Mown and not mown plots per management type, classified on SwissImage RS.

Management Type	**Mown**	**Not Mown**
Artificial meadows	29	71
Low-intensity meadows	40	71
Extensively used meadows	220	60
Permanent meadows	209	292
Region-specific biodiversity area	34	75
Total	**532**	**569**

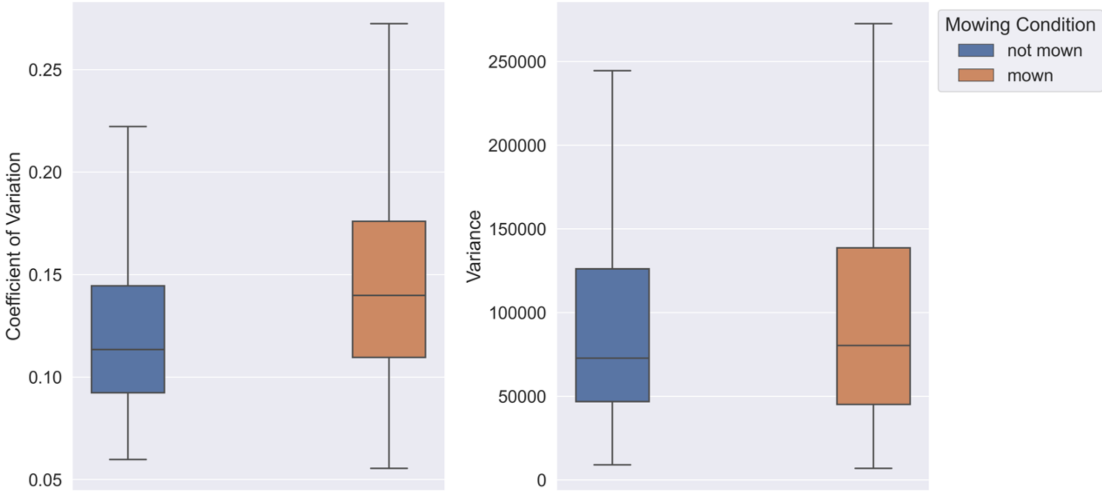

Figure 25: Boxplot of CV and Variance, separated in mown and not mown plots, derived from all SwissImage RS Bands.

As observed in the AVIRIS-NG data, mown plots showed a higher spectral diversity compared to areas not mown. But when analyzing the entire AVIRIS-NG spectrum, the effect was more pronounced, here only the CV was significant (p-value CV <0.001; p-value Variance: 0.35). The earlier observed tendency for high CV values for mown areas could again be observed across management types, for most management types at a significant level.

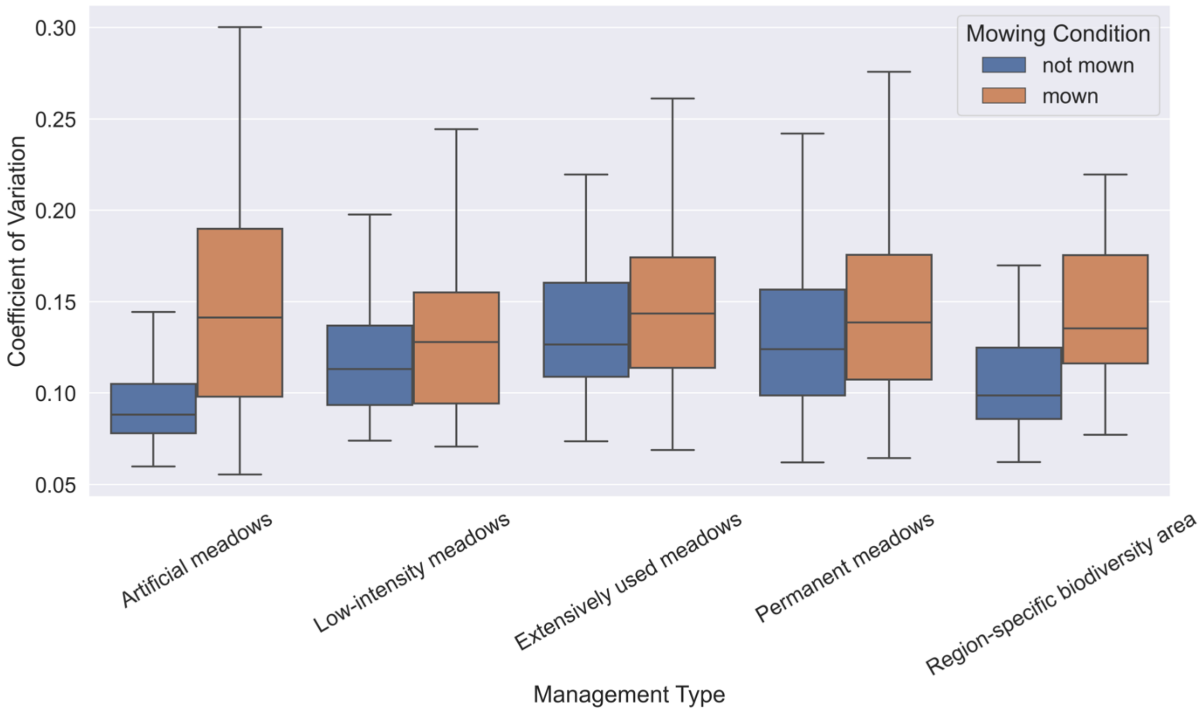

Figure 26: Boxplot of the CV of the different Management Types, separated in mown and not mown plots, derived from all SwissImage RS Bands.

Table 19: P-values resulting from the Mann-Whitney-U test, testing for significant differences between mown and not mown plots of each Management Type. Input dataset: All SwissImage RS Bands.

Management Type	**p-value**
Artificial meadows	0.0000
Low-intensity meadows	0.2298
Extensively used meadows	0.0555
Permanent meadows	0.0021
Region-specific biodiversity area	0.0000

Using the NDVI, this tendency was also visible. For the AVIRIS-NG data, the tendency was stronger at the NDVI than when exploiting the entire spectrum, this is also the case for the SwissImage RS. The differences are strongly significant for both spectral metrics (p-value <0.001)

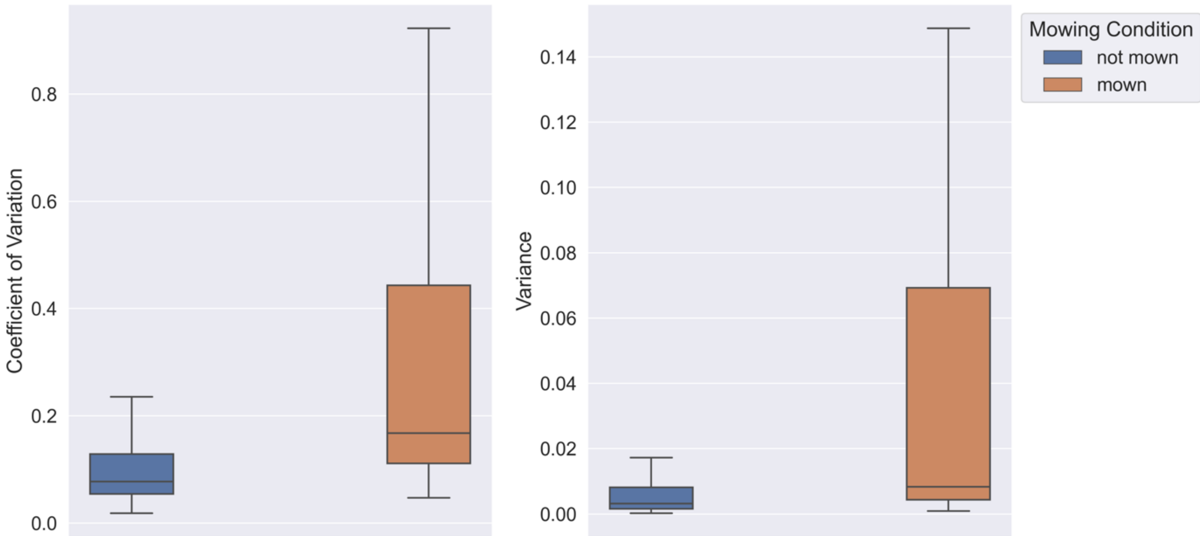

Figure 27: Boxplot of CV and Variance, separated in mown and not mown plots, derived from the NDVI of the SwissImage RS.

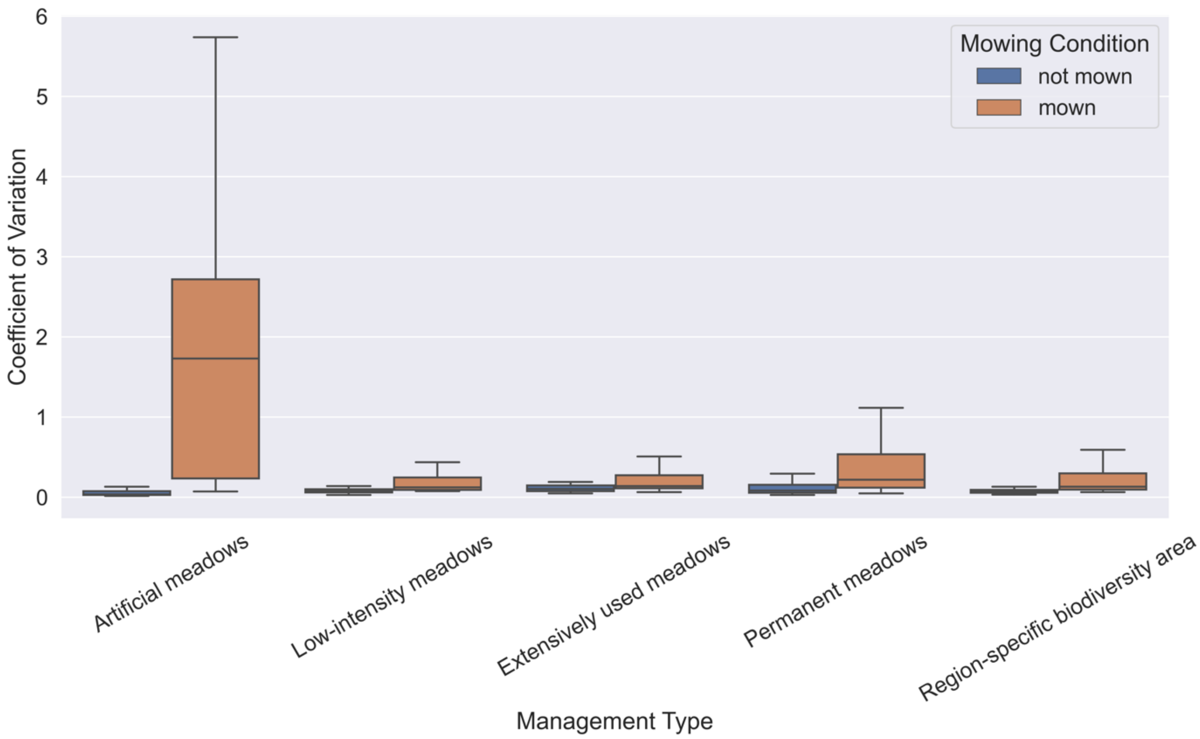

Figure 28: Boxplot of the CV of the different Management Types, separated in mown and not mown plots, derived from the NDVI of SwissImage RS.

The Mann-Whitney-U test returned significant p-values between mown and not mown plots of all management types.

Figure 23 shows that the CV was highest at Artificial Meadows and Permanent Meadows. These high values mostly originated from mown plots, as we can see in Figure 28. The plots that were not mown showed relatively uniform values.

5.3 Sentinel-2 data

5.3.1 Analyzing Sentinel-2 High-Resolution Bands

Only the results of the analysis of the high-resolution bands and the indices are presented. The calculations were done based on high-resolution bands with a spatial resolution of 10 m × 10 m. Working with pixel sizes of 20 m x 20 m would not have made much sense to exploit diversity within the already small-scale agricultural structures of the Lower Engadin.

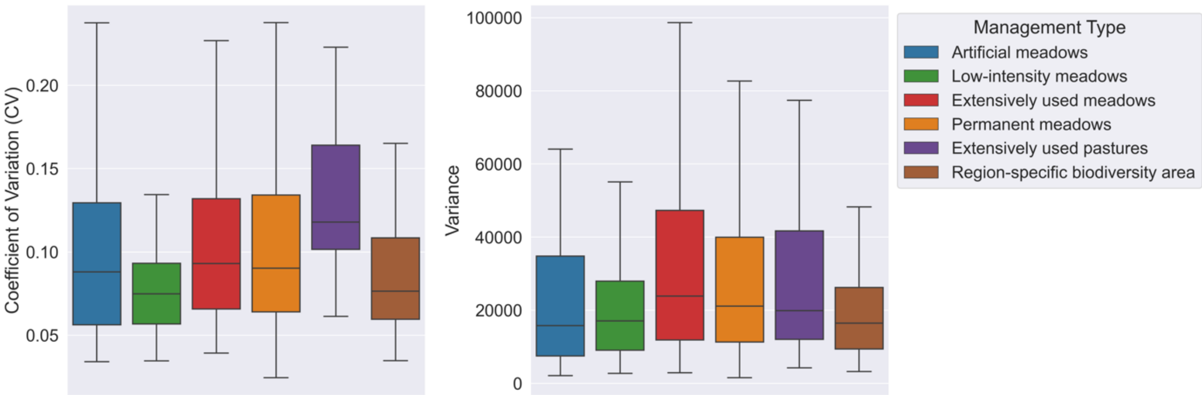

Figure 29: Boxplot of the mean Variance and CV of the Sentinel-2 high-resolution Bands, grouped by the different management types.

Significant differences between the different types of management could also be identified using the Sentinel-2 data for both spectral metrics (p-value <0.001). For the variance, the earlier observed tendencies were not very distinct, but again a higher diversity was calculated for extensively used and permanent meadows and pastures, also with significant differences to artificial meadows. The CV showed large differences between pastures and meadows, which also have been observed using other methods.

Table 20: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean CV of the high-resolution bands of Sentinel-2.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.03141	0.40998	0.30185	0.0015	0.10062
Low-intensity meadows	0.03141	1	0.00045	0.00009	0.00001	0.60962
Extensively used meadows	0.40998	0.00045	1	0.81675	0.00324	0.00414
Permanent meadows	0.30185	0.00009	0.81675	1	0.00358	0.00128
Extensively used pastures	0.0015	0.00001	0.00324	0.00358	1	0.00002
Region-specific biodiversity area	0.10062	0.60962	0.00414	0.00128	0.00002	1

Table 21: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of the high-resolution bands of Sentinel-2.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1	0.97218	0.00075	0.01588	0.11319	0.91758
Low-intensity meadows	0.97218	1	0.00052	0.01309	0.11421	0.88695
Extensively used meadows	0.00075	0.00052	1	0.08524	0.85573	0.00031
Permanent meadows	0.01588	0.01309	0.08524	1	0.66037	0.00842
Extensively used pastures	0.11319	0.11421	0.85573	0.66037	1	0.09654
Region-specific biodiversity area	0.91758	0.88695	0.00031	0.00842	0.09654	1

5.3.2 Analyzing Sentinel-2 NDVI

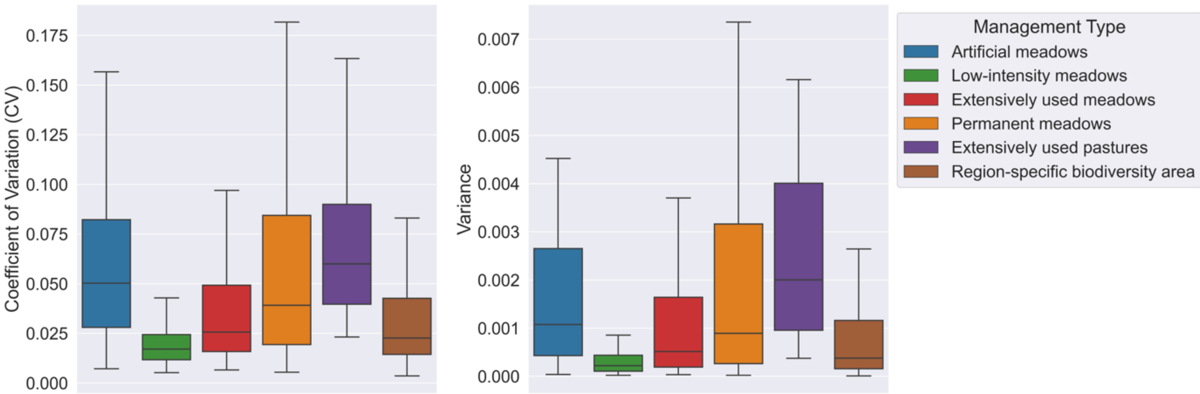

Figure 30: Boxplot of the mean Variance and CV of the Sentinel-2 NDVI, grouped by the different management types.

With the NDVI of Sentinel-2, different management types also could be discriminated (p-values <0.001). The observed differences between management types were more distinct than when using the full spectrum. Remarkable was that the values of artificial meadows were similar to the values of permanent meadows and pastures, which show large differences in the other datasets. A possible explanation may be that greenness and vegetation density appear similar when studied at the spatial resolution of 10 m.

Table 22: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean CV of the NDVI of Sentinel-2.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1.00000	0.00000	0.00000	0.07522	0.14097	0.00000
Low-intensity meadows	0.00000	1.00000	0.00000	0.00000	0.00000	0.00174
Extensively used meadows	0.00000	0.00000	1.00000	0.00000	0.00002	0.17664
Permanent meadows	0.07522	0.00000	0.00000	1.00000	0.01055	0.00000
Extensively used pastures	0.14097	0.00000	0.00002	0.01055	1.00000	0.00000
Region-specific biodiversity area	0.00000	0.00174	0.17664	0.00000	0.00000	1.00000

Table 23: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of the NDVI of Sentinel-2.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1.00000	0.00000	0.00069	0.29071	0.03629	0.00002
Low-intensity meadows	0.00000	1.00000	0.00000	0.00000	0.00000	0.00321
Extensively used meadows	0.00069	0.00000	1.00000	0.00018	0.00004	0.08754
Permanent meadows	0.29071	0.00000	0.00018	1.00000	0.00438	0.00001
Extensively used pastures	0.03629	0.00000	0.00004	0.00438	1.00000	0.00000
Region-specific biodiversity area	0.00002	0.00321	0.08754	0.00001	0.00000	1.00000

5.3.3 Analyzing Sentinel-2 TGI

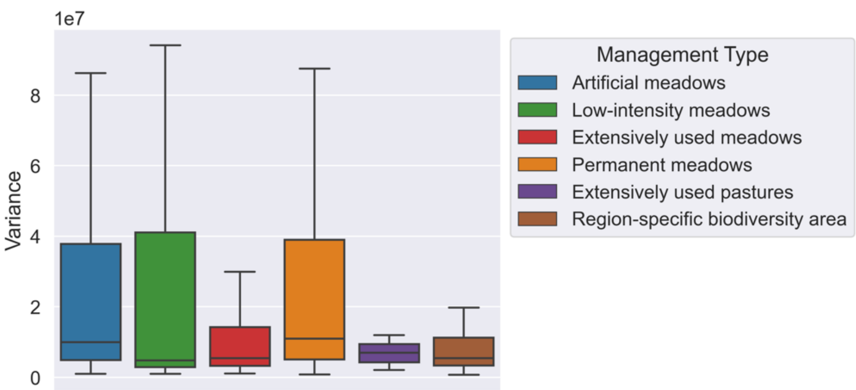

Figure 31: Boxplot of the mean Variance of the Sentinel-2 TGI, grouped by the different management types.

Similar to the examination of the AVIRIS-NG and SwissImage RS data, the results of the TGI were not in line with the results of using the entire spectrum and the NDVI. The TGI of

Sentinel-2 led to significant differences between management types (p-value <0.001) but it was difficult to find possible explanations for the results.

Table 24: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the mean Variance of the TGI of Sentinel-2.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1.00000	0.00752	0.00026	0.52512	0.22490	0.00053
Low-intensity meadows	0.00752	1.00000	0.60565	0.00003	0.66309	0.40393
Extensively used meadows	0.00026	0.60565	1.00000	0.00000	0.46046	0.62776
Permanent meadows	0.52512	0.00003	0.00000	1.00000	0.09615	0.00000
Extensively used pastures	0.22490	0.66309	0.46046	0.09615	1.00000	0.34673
Region-specific biodiversity area	0.00053	0.40393	0.62776	0.00000	0.34673	1.00000

5.3.4 Analyzing the Effect of Mowing on Sentinel-2 Data

The area distribution between mown and non-mown areas showed a large difference to the distribution at the AVIRIS-NG and SwissImage RS datasets. This could be explained by the date of the Sentinel-2 data acquisition (June 16, 2018). For example, on low-intensity meadows, mowing is only permitted in valley regions as of June 15. In more alpine areas it is not yet permitted by this date. Consequently, only 5 of 112 plots were classified as mown. The other management types were also mostly not mown at this time, only artificial and permanent meadows showed balanced ratios between mown and not mown plots.

Table 25: Mown and not mown plots per management type, classified on Sentinel-2.

Management Type	**Mown**	**Not Mown**
Artificial meadows	63	37
Low-intensity meadows	5	107
Extensively used meadows	46	237
Permanent meadows	225	276
Region-specific biodiversity area	31	78
Total	**370**	**735**

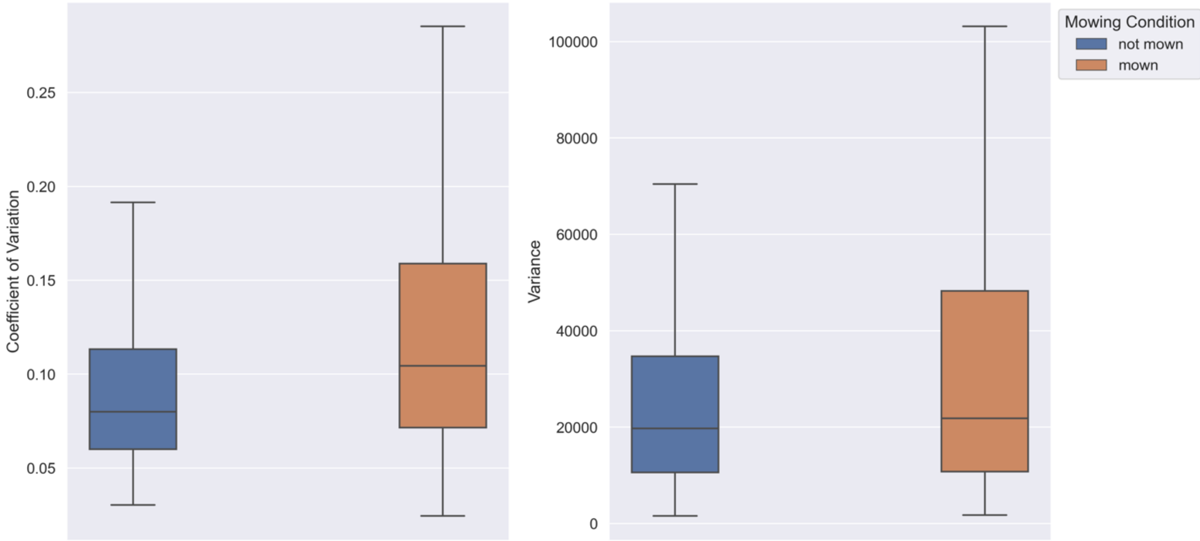

Figure 32: Sentinel-2 CV and Variance of the high-resolution Bands, divided between mown and not mown plots.

The CV showed significant differences between mown and not mown plots (p-value CV <0.001; p-value Variance: 0.07), and as for AVIRIS-NG or SwissImage RS, mown plots had a higher spectral diversity than not mown plots. This was also the case on a significant level for all management types, except artificial meadows.

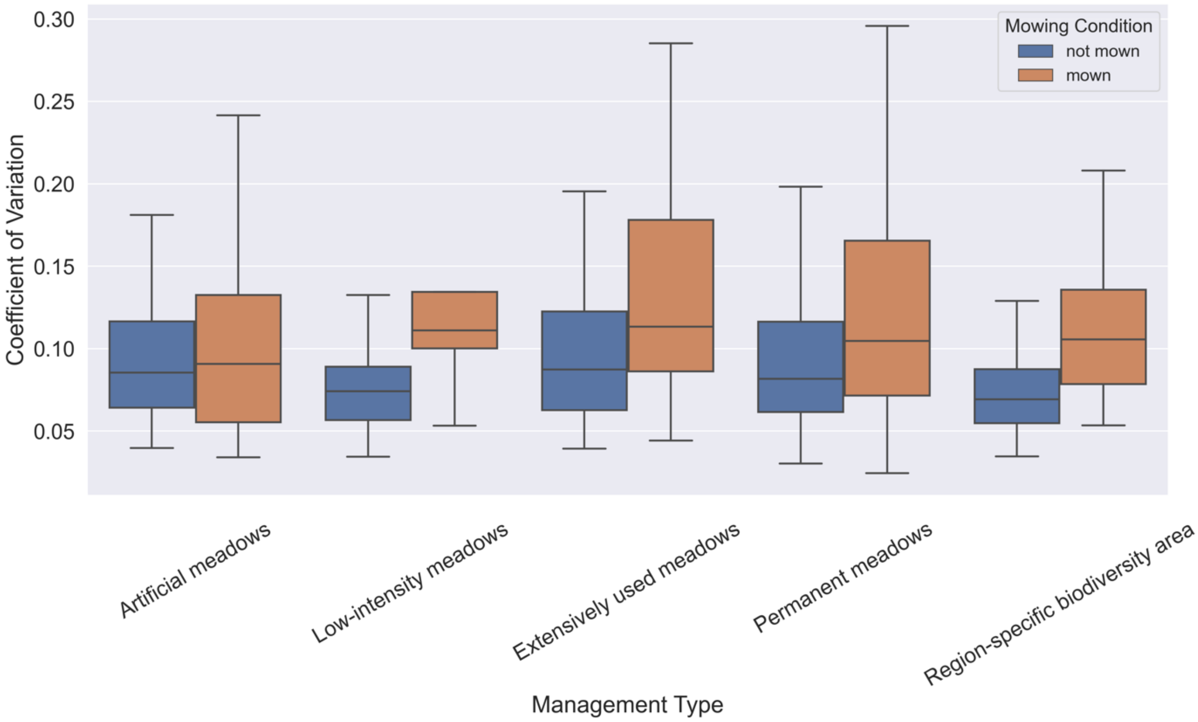

Figure 33: Sentinel-2 CV of the high-resolution Bands, divided between mown and not mown plots per Management Type.

Table 26: P-values resulting from the Mann-Whitney-U test of the CV, testing for significant differences between mown and not mown plots of each Management Type. Input dataset: Sentinel-2 High-Resolution Bands.

Management Type	p-value
Artificial meadows	0.9374
Low-intensity meadows	0.0682
Extensively used meadows	0.0001
Permanent meadows	0.0000
Region-specific biodiversity area	0.0000

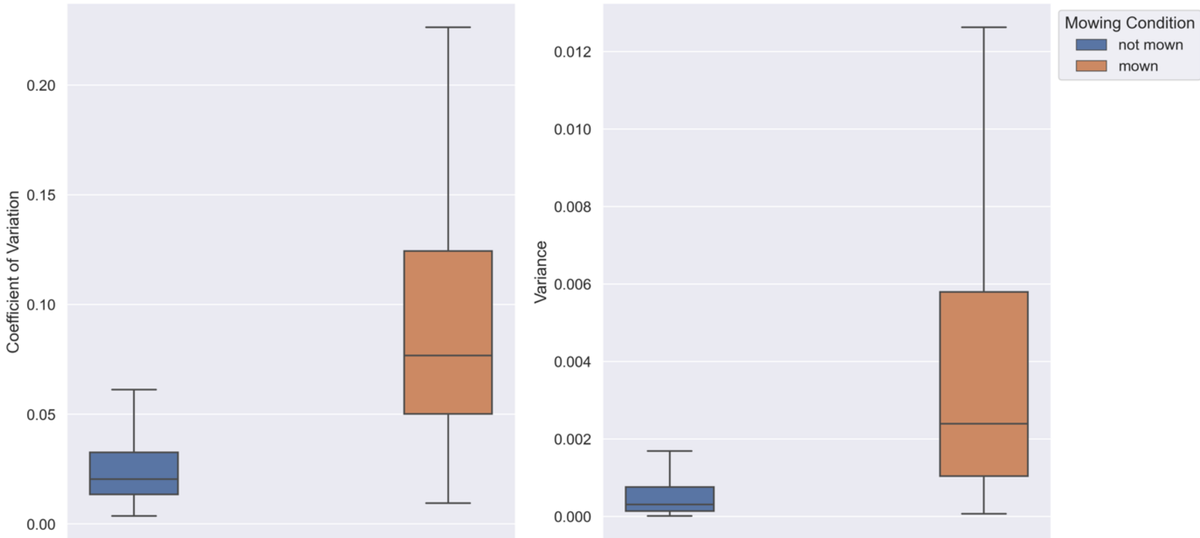

Figure 34: Sentinel-2 CV and Variance of NDVI, divided between mown and not mown plots.

The same tendency is also apparent for the NDVI, again, the differences are more distinct and significant for both spectral diversity metrics (p-values <0.001).

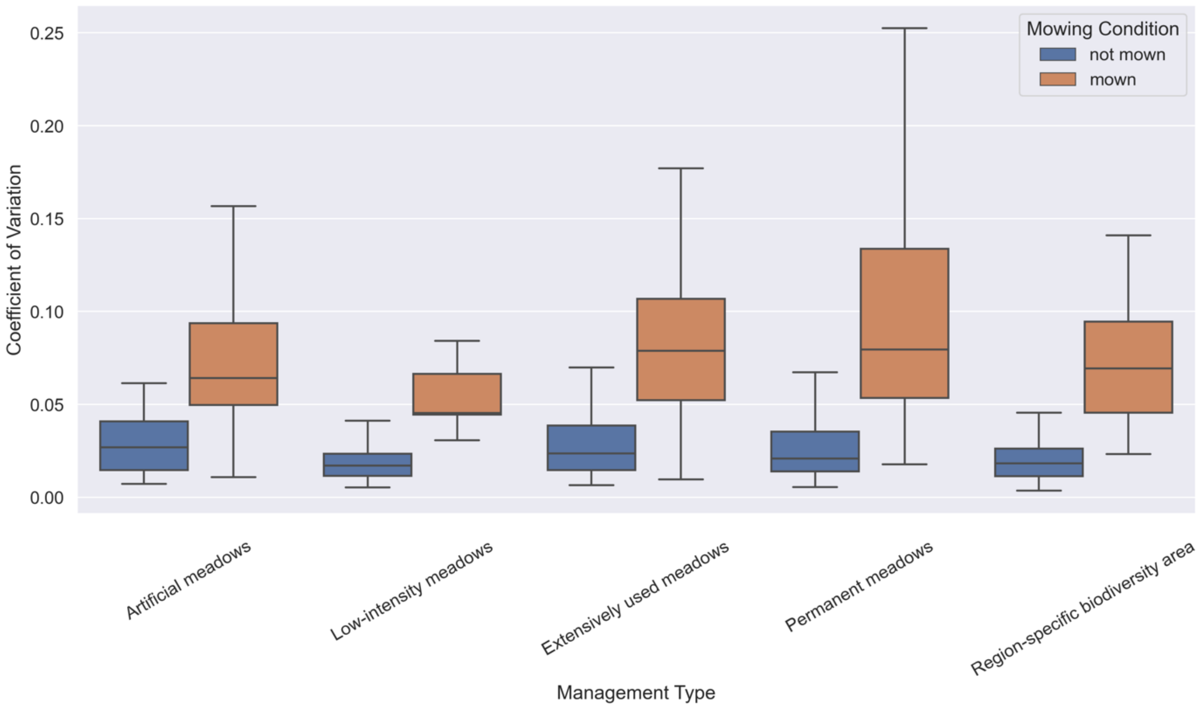

Figure 35: Sentinel-2 CV of NDVI, divided between mown and not mown plots per Management Type.

The Mann-Whitney-U test showed significant differences between all management types.

5.4 Cross-Comparison between different Sensors

Comparing the values resulting from applying the same methods on different sensors revealed whether the measurements were consistent across the different sensors. Looking at the CV of the NDVI revealed that the SwissImage RS did not correspond with the other sensors, while AVIRIS-NG and Sentinel-2 did correlate on a medium level. This made sense, as AVIRIS-NG and Sentinel-2 measurements were taken only two weeks apart, while the SwissImage RS was obtained more than a year later (AVIRIS-NG: start of July 2018, SwissImage RS: September 2019, Sentinel-2: middle of June 2018). The medium correlation between AVIRIS-NG NDVI and Sentinel-2 NDVI showed that the difference in spatial resolution did not result in uncorrelated values. The effect of the different spatial resolutions of AVIRIS-NG and SwissImage could not be studied isolated, as the effect of the temporal offset was not assessable.

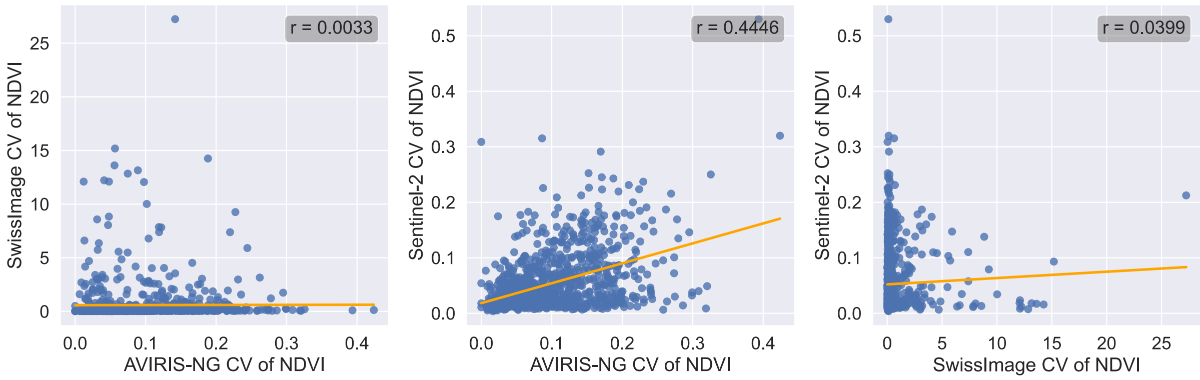

Figure 36: Cross-comparison of the CV of the NDVI, derived using AVIRIS-NG-, SwissImage RS - and Sentinel-2-data.

The TGI showed no correlation between the sensors. The TGI never showed consistent results, so it was not surprising, that no correlation could be seen for this variable.

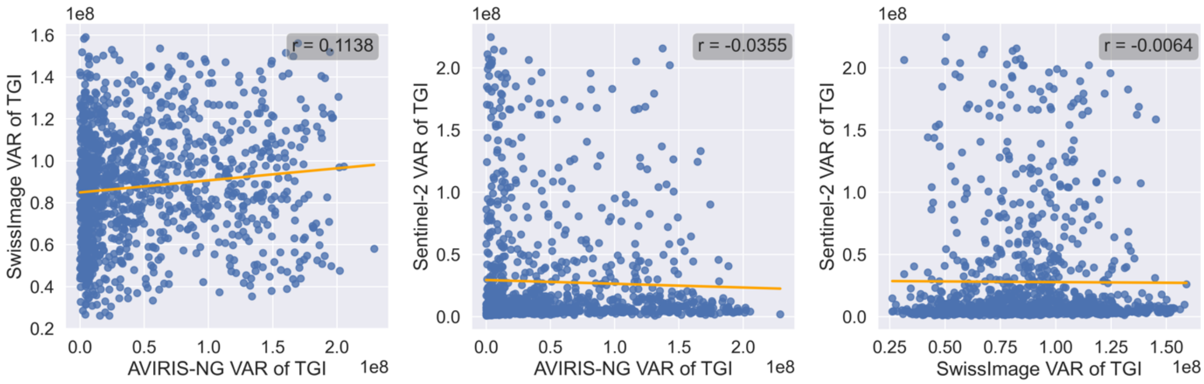

Figure 37: Cross-comparison of the Variance of the TGI, derived using AVIRIS-NG-, SwissImage RS - and Sentinel-2-data.

A higher correlation between AVIRIS-NG and SwissImage RS was observed when looking at the results of exploiting the full spectrum. This was also in line with the similar results between AVIRIS-NG and SwissImage RS data presented in Figure 11 and Figure 22. A reason for the higher correlation in comparison to the NDVI may be that here the focus was not on specific vegetation properties, but on all structures present within the plots. The vegetation properties might have changed significantly between the dates of the data acquisition, while other structures were more constant. Therefore, using the full spectrum may be a method that is more robust for temporal changes.

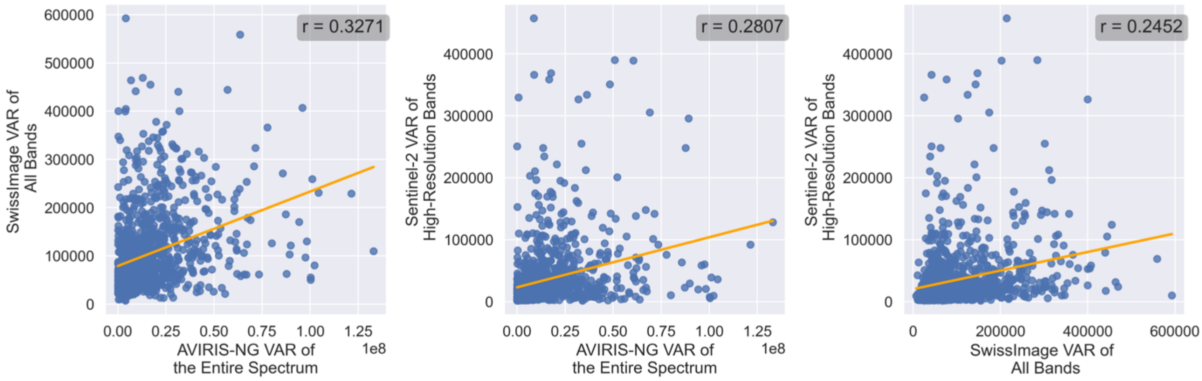

Figure 38: Cross-comparison of the Variance when exploiting the entire spectrum, derived using AVIRIS-NG PCs, SwissImage RS - and Sentinel-2-data.

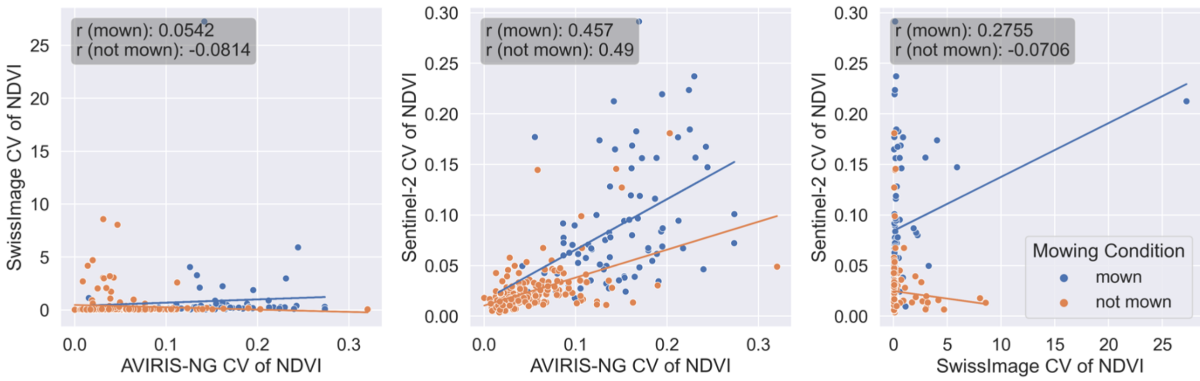

Figure 39: Cross-comparison of the CV NDVI, divided into mown and not mown plots, derived using AVIRIS-NG-, SwissImage RS - and Sentinel-2-data.

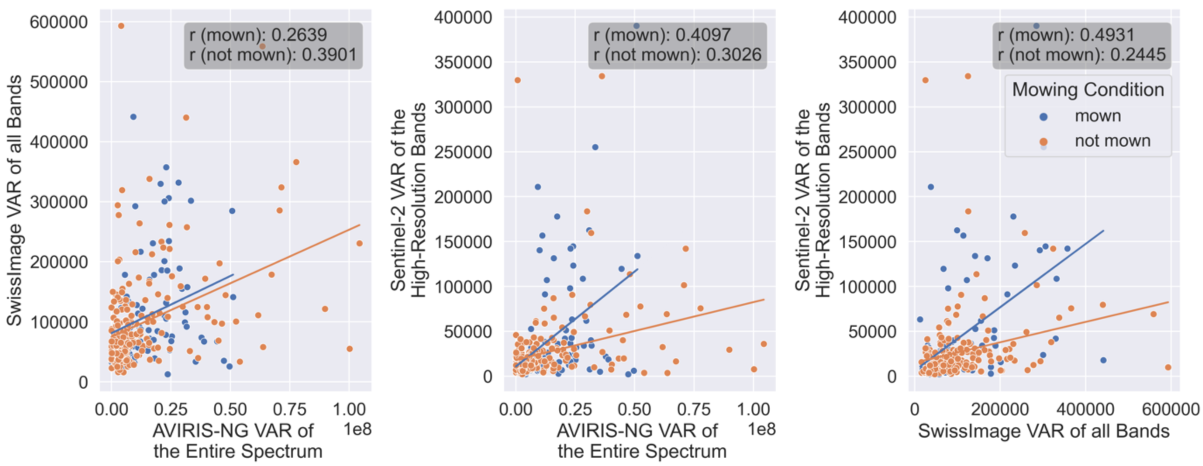

Figure 40: Cross-comparison of the Variance when exploiting the entire spectrum, separated between mown and not mown plots, derived using AVIRIS-NG-, SwissImage RS - and Sentinel-2-data.

Figure 39 and Figure 40 showed that the correlation was in most cases higher on mown plots than on plots, that were not recently mown. One reason for this could be that the grassland is brought into a uniform condition by mowing and therefore effects that lead to temporal differences are less significant.

6 Discussion

The results presented so far show that differences in spectral diversity can be detected when investigating agricultural areas in the Lower Engadin with AVIRIS-NG, SwissImage RS and Sentinel-2 data. Correlating results between different sensors were obtained, which might indicate the robustness of the approach and might offer a transferability of the applied methods. A strong effect of mowing on the spectral diversity has been observed, which could be an indicator to test an adapted methodology for further applications, discriminating between mown and not mown plots. In this chapter, I will provide a more detailed perspective on these insights. Additionally, I will share the most important issues and limitations and will discuss the differences observed between sensors, data aggregation methods and spectral metrics.

6.1 Impact of Plot Size

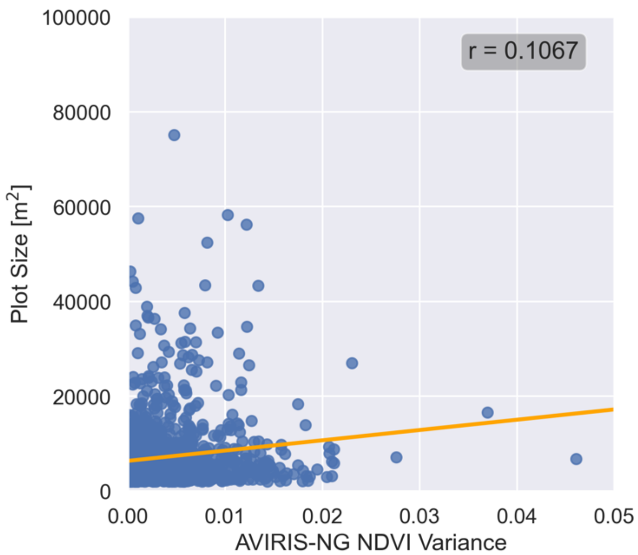

Figure 41: The Variance of the NDVI of AVIRIS-NG plotted against the size of the respective plots.

When calculating the Variance of a sample, the variation between observations is divided through the number of observations. For the calculation of the spectral variation, this means that the differences between pixels are divided by the number of pixels of a plot. Therefore, the values resulting from the calculations of the spectral metrics should be independent of the plot size. This was confirmed by Figure 41, which shows that there is only a very slight correlation between the Variance of the AVIRIS-NG NDVI and the plot size.

6.2 Performance of the Spectral Metrics

Due to the absence of strong validation data, it could not clearly be said which of the applied spectral metrics did perform better. In earlier applications, there was not necessarily a best-performing spectral metric, as the performance of spectral metrics depended on several factors (e.g., spatial resolution, exposure of bare soil (Gholizadeh et al., 2018)). Therefore, I also needed to assess for each application which metric works better. To make predictions whether a spectral metric performs better or worse for a specific application remains difficult. Figure 42 shows distributions that support this finding. For the NDVI of AVIRIS-NG, CV and Variance correlate strongly, while when exploiting the PCs of AVIRIS-NG, this correlation cannot be found. This shows that the two metrics can behave very similarly but can also differ completely. The CV has proven as a useful spectral metric but could only be applied when the input pixel values are positive. Otherwise, negative average values can lead to chaotic and inconsistent results. For this study, only an indirect link between the CV of different sensors and data products and FD could have been established. However, the CV has also proven useful in creating a direct relationship between remote sensing datasets and biodiversity measures (e.g., to species richness on grassland (Gholizadeh et al., 2018)).

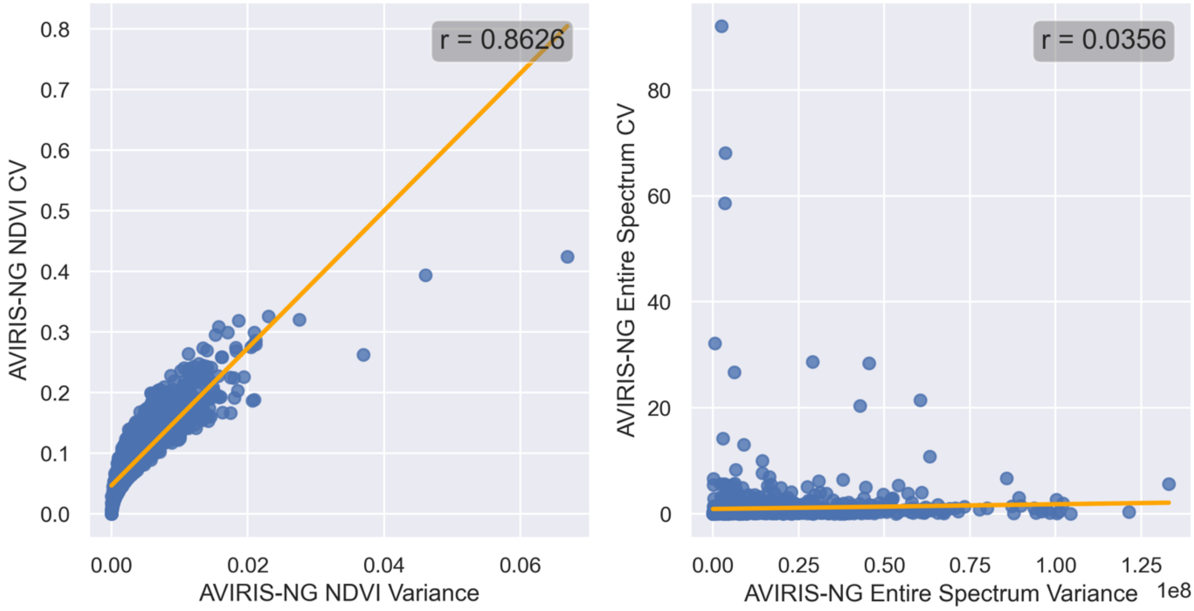

Figure 42: Variance plotted against CV of the NDVI of AVIRIS-NG (left plot) and of the Entire Spectrum of AVIRIS-NG (right plot). To make the CV of the Entire Spectrum of AVIRIS-NG better comparable, the absolute values were calculated.

When studying the value distributions of the spectral metrics across all applications (e.g., Figure 37), the results indicate that the variance is more robust to outliers. Hence, when examining and comparing the results of the different methods applied to the AVIRIS-NG data, the variance seems to produce more robust results across different applications using data of the same sensor.

6.3 Indices vs. Full Spectrum

The analysis of the AVIRIS-NG products revealed that using the full spectrum (PCs for AVIRIS-NG), NDVI and NDII obtained similar results, especially when using the variance. This can be seen Figure 11, Figure 12 and Figure 14, which showed that the variance revealed the same relationships between the management types. This was also supported when looking at the correlations (Figure 21), the analysis of the full spectrum showed a medium correlation to NDVI and NDII. Interestingly, NDVI and NDII did strongly correlate, although they were calculated using different regions of the spectrum. The TGI did only correlate at a very low level with the results obtained using the full spectrum. Also to NDVI and NDII, correlation is relatively low. Although the NDII also revealed promising results, the index of interest for further discussion is the NDVI as it allows comparisons between AVIRIS-NG and SwissImage RS.

6.4 Spectral- vs. Spatial Resolution

When working with AVIRIS-NG data, features are visible that are not visible in the SwissImage RS because of the larger spectral coverage. On the other hand, in the AVIRIS-NG scenery features remain hidden that are present in the SwissImage RS, because the SwissImage RS has a smaller pixel size. Thus, natural features such as small bushes, stones or fine meadow structures, but also anthropogenic features such as mowing patterns or power lines are recognizable.

To answer the question of whether data with a high spatial resolution or with large spectral coverage and high spectral resolution, the applied methodology did not produce answers. Studying specific traits (e.g., vegetation density using NDVI) did produce meaningful results in this study but also in earlier studies ((Gholizadeh et al., 2019)). To find an optimal spatial and spectral resolution, methods should have been used that look at this problem in a more isolated way, despite the optimal resolutions might change between different applications. For example, by comparing the original spatial resolution of the SwissImage compared to a resampled product with lower spatial resolution. Wang et al. (2018) searched in this way after optimal pixel size for distinguishing α-diversity on grassland, they found out that using a very high spatial resolution of 1mm to 10cm works best. Figure 38 showed that there is a correlation on a low level when comparing the Variance of the AVIRIS-NG PCs to the four SwissImage RS bands. This indicates that a similar result can be obtained even when using data sets with strongly different spatial and spectral resolutions. For the other shown comparison between AVIRIS-NG data and the SwissImage RS, this correlation cannot be found. The temporal gap between the data acquisitions is likely the most important reason for this.

The NDVI allowed for a coarse isolated analysis of the effects of the spatial resolution, as the same regions of the spectrum were used. When studying the results obtained per management type for the NDVI (Figure 12, Figure 23 and Figure 30), no major differences in the results became apparent. All three datasets revealed significant differences between the datasets and the resulting Variance and CVs stood in similar relations to each other. The differences revealed in the analysis were difficult to explain with the available data. Comparing the results of the NDVI of the three sensors (Figure 36) showed a medium correlation ($r = 0.44$) between Sentinel-2 and SwissImage RS, but no correlation between AVRIS-NG and SwissImage RS and AVIRIS-NG and Sentinel-2. This outcome was difficult to interpret, as a correlation between SwissImage RS and Sentinel-2 is the least expectable (large temporal gap and largest difference in spatial resolution).

For the often observed difference between artificial meadows and extensively used pastures, the SwissImage products revealed a higher level of confidence as for their AVIRIS-NG counterparts. This could be due to the different spatial resolution but would need further investigation to be confirmed.

Table 27: P-values of the Dunn-Bonferroni post-hoc test resulting from comparing artificial meadows to pastures. The test searches for differences between the distributions of the Variance and the CV of the presented applications. In all cases, the extensively used pastures showed larger diversity values.

	CV	Variance
AVIRIS-NG Entire Spectrum	0.0001	0.0207
AVIRIS-NG NDVI	0.0474	0.0038
SwissImage RS All Bands	0.0000	0.0000
SwissImage RS NDVI	0.0000	0.0000

An advanced insight into how the values of the spectral diversity emerged offers Figure 43. It showed that variations that were not or only very slightly recognizable in the RGB scene were well visible when looking at false color images, consisting of the PCs. This was the case for the high-diversity scene, but also for the low-diversity scene where small variations became apparent, that were not observable in the RGB bands. The compilation showed that slight spectral variations were best visible when the full AVIRIS-NG spectrum was exploited by using the PCs, as variations were observed that cannot be seen with the NDVI. This indicated that important variations of grassland were happening beyond the spectral range of the NDVI, which was considered a solid measure of vegetational properties. Therefore, it could be advantageous to have a wider spectral range available as RGB and NIR, e.g., a spectral coverage like AVIRIS-NG or at least a SWIR band. This showed that products like AVIRIS-NG can offer additional insights in comparison to products with a small spectral coverage like SwissImage RS. On the other hand, the scene also revealed the advantages of the high spatial resolution of the SwissImage RS. For both plots, one could observe small structures like stones, hedges and small trees. This led to different results when assigning the plots a spectral diversity rank (ranked high to low after values of the variance). For example, the plot that had a low spectral diversity on the AVIRIS-NG products had a rather high diversity when examined with the SwissImage RS. This was because the fine structures were visible due to the improved spatial resolution. Furthermore, Figure 43 shows the importance of considering temporal effects. The SwissImage RS observation of the plot shown in the bottom row is inflated by the shadows cast by the neighboring trees and is therefore hardly comparable to the AVIRIS-NG scene. This is because the scenes were taken on different days of the year and at different times of day.

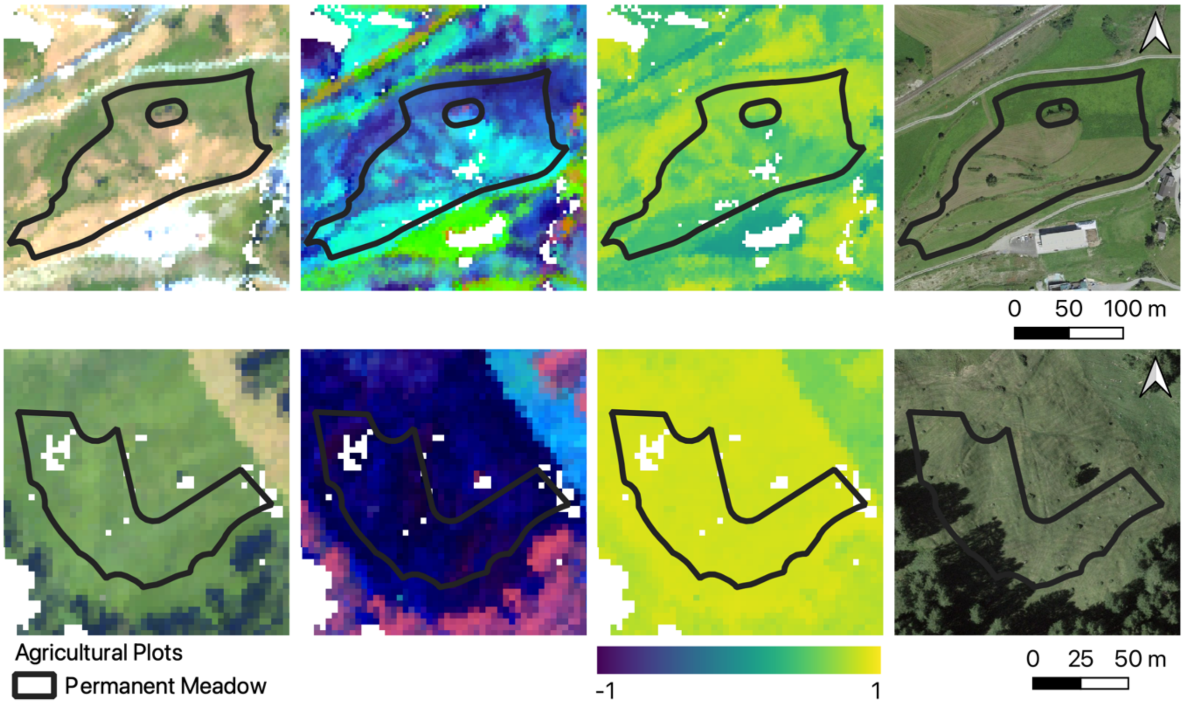

Figure 43: The upper row of Images shows different products of a plot with generally high spectral diversity. The lower row shows a plot with a low diversity. From left to right the images show: AVIRIS-NG RGB, AVIRIS-NG First 3 PCs, AVIRIS-NG NDVI, SwissImage RS RGB. (High-diversity plot: AVIRIS-NG Entire Spectrum Variance Rank (from high to low): 232, AVIRIS-NG NDVI Variance Rank: 43, SwissImage All Bands Variance Rank: 25, SwissImage NDVI Varienca Rank: 252; Low-diversity plot: AVIRIS-NG Entire Spectrum Variance Rank: 747; AVIRIS-NG NDVI Variance Rank: 1099, SwissImage All Bands Variance Rank: 175; SwissImage NDVI Variance Rank: 7)

A closer look shows that this difference between PCs and NDVI can be observed in many plots. Figure 44 illustrates this phenomenon, as several plots that appear very homogenous in the NDVI show well-visible variation in the false color composite of the PCs.

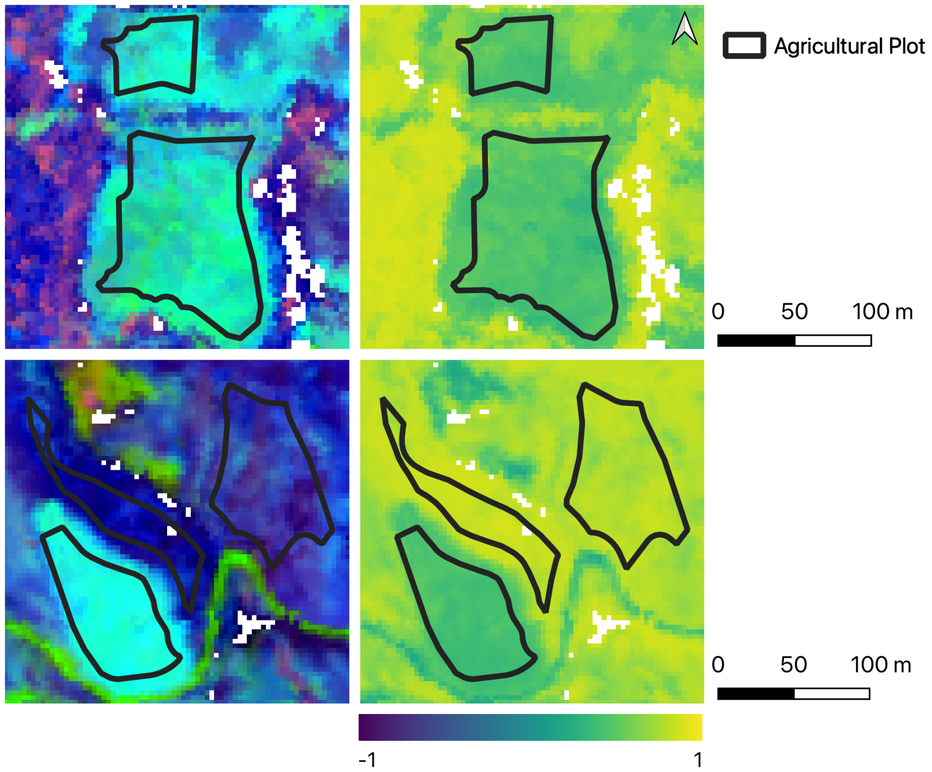

Figure 44: PC False Color Scenes on the left side and the NDVI on the right side.

6.5 Differences between Management Types

The most noticeable observation across almost all applications and all sensors is the distinction between artificial meadows and extensively used pastures (Table 27 shows the respective p-values for the difference between the two management types). This relationship is interesting, as it corresponds to the expectation in almost all cases (Significantly higher variance of extensively used pastures for all AVIRIS-NG measures and all SwissImage RS measures except the TGI). Figure 45 shows exemplary plots with the management types of extensively managed pastures and artificial meadows. Even when only looking at the RGB bands, one can see clear differences between the two management types in AVIRIS-NG and SwissImage RS. In the SwissImage RS scene, finer structures are visible, but also in the AVIRIS-NG scene, variations are clearly detectable. In many cases, the variation within the plot is even more distinct, as extensively managed pastures often contain trees and bushes. The richness of these structures is likely to be related to a high FD, as the structures offer niches and habitats, that are not present on plain grassland. The artificial meadows also show slight variations but are less pronounced than the presented pastures. Again, the variations are detectable using AVIRIS-NG and SwissImage RS data.

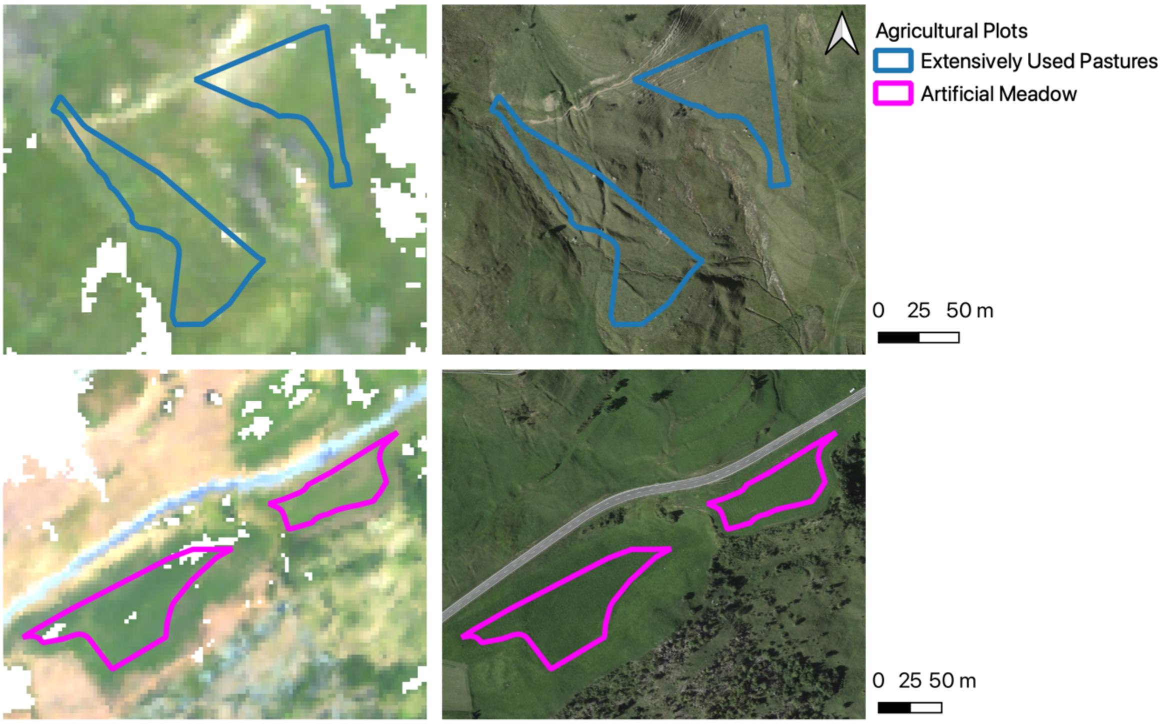

Figure 45: AVIRIS-NG- (left side) and SwissImage RS scenes (right side). The scenes illustrate the different appearances of artificial meadows and pastures.

6.5.1 TGI

Figure 13 and Figure 24 revealed that the TGI did not produce results that matched those of the other applications. The TGI revealed pronounced variations that were difficult to attribute to specific causes. The abrupt variations did not emerge along features, that were observable at other products. This is illustrated in Figure 46. This may be an explanation for the very low correlation between TGI and the other products (PCs, entire spectrum and NDVI). The abrupt variations are most likely coming from the earlier described change from positive to negative values when the green reflectance is less than the red-blue line. The phenomenon discussed and the values obtained lead to the conclusion that the use of the TGI is not a suitable method to aggregate remotely sensed vegetation data based on which spectral diversity metrics should reveal meaningful differences in the spectral variation of different management types.

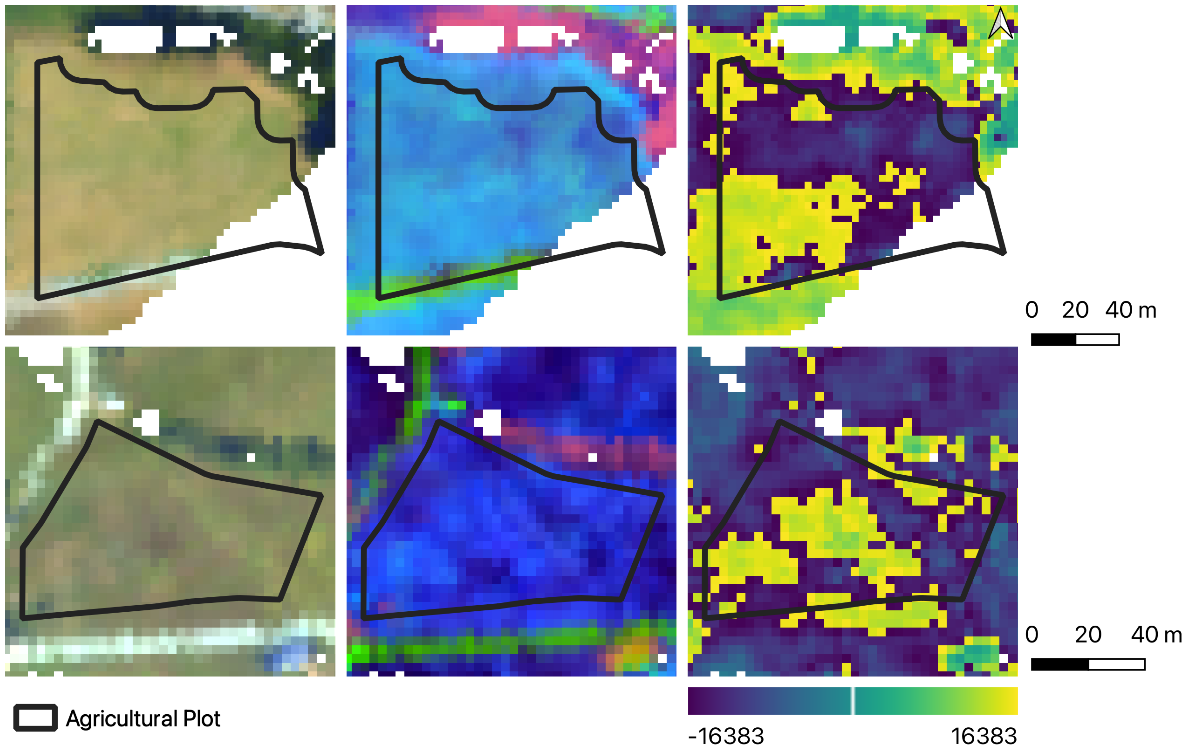

Figure 46: Two exemplary plots with a high TGI, plotted on different AVIRIS-NG products. Left side: RGB, middle: PC false-color image, right side: TGI.

6.5.2 The Issue with the Biodiversity Areas

The TGI did not deliver results that matched those of the other applications. In the case of biodiversity areas, however, it delivered results that corresponded more closely to the originally expected values than the other products. Therefore, it is exciting to take a closer look at these biodiversity plots. While the difference between artificial meadows and pastures is not as pronounced as in the other applications, the TGI derived from AVIRIS-NG and SwissImage RS provided significant differences between artificial meadows and biodiversity plots. Those differences could not be observed in the other applications. A closer examination of biodiversity plots (including the plots presented in Figure 46) with high diversity values of the TGI reveals that the plots mostly look like meadows with regular vegetation and without structural elements. Therefore, the examined plots look very similar to artificial meadows, they do not look like they offer a great diversity of niches and therefore one can expect a low FD. This is surprising as biodiversity areas should explicitly host elements such as hedges, groves and other small structures to provide such niches (Agridea, 2023). The randomly appearing structures produced by the TGI appear across all management types, the reason why they lead to significant differences between management types remains unclear. Visual inspection of the biodiversity plots indicates that the results obtained using the full spectrum and the NDVI of AVIRIS-NG and SwissImage RS are much more valid. Therefore, one can expect biodiversity areas to generally have a low FD. When analyzing them on plant level to study the species richness, different insights may emerge.

6.6 The Effect of Mowing

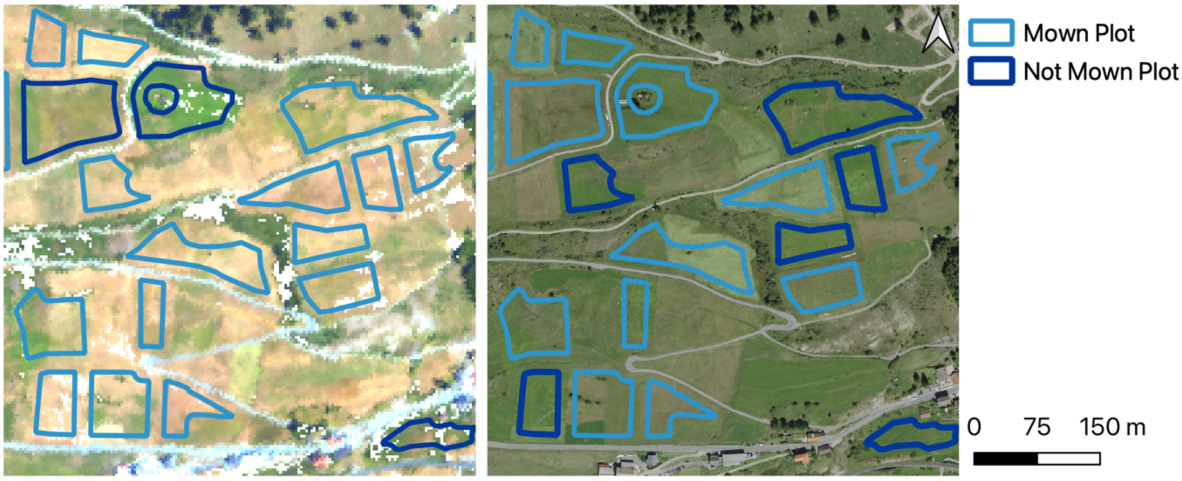

Figure 47: Mown and not mown plots, calculated and plotted on AVIRIS-NG (right side) and SwissImage RS (left side).

Before the differences between mown and unmown plots can be analyzed, the quality of the underlying classification must be verified. As no reference data is available, this cannot be done quantitatively, but only by visual inspection. Figure 47 and the study of other areas lead to the conclusion that the classification of AVIRIS-NG was done with a high degree of correctness, while the classification of SwissImage RS was often more difficult and therefore less accurate. Because of the dry conditions in the weeks before the data acquisition, the AVIRIS-NG was simpler to classify. The vegetation in the AVIRIS-NG scene was very dry and appeared brownish when mown, therefore it was well distinguishable. The SwissImage RS was acquired at less dry conditions, so the differences between mown and unmown plots were less pronounced.

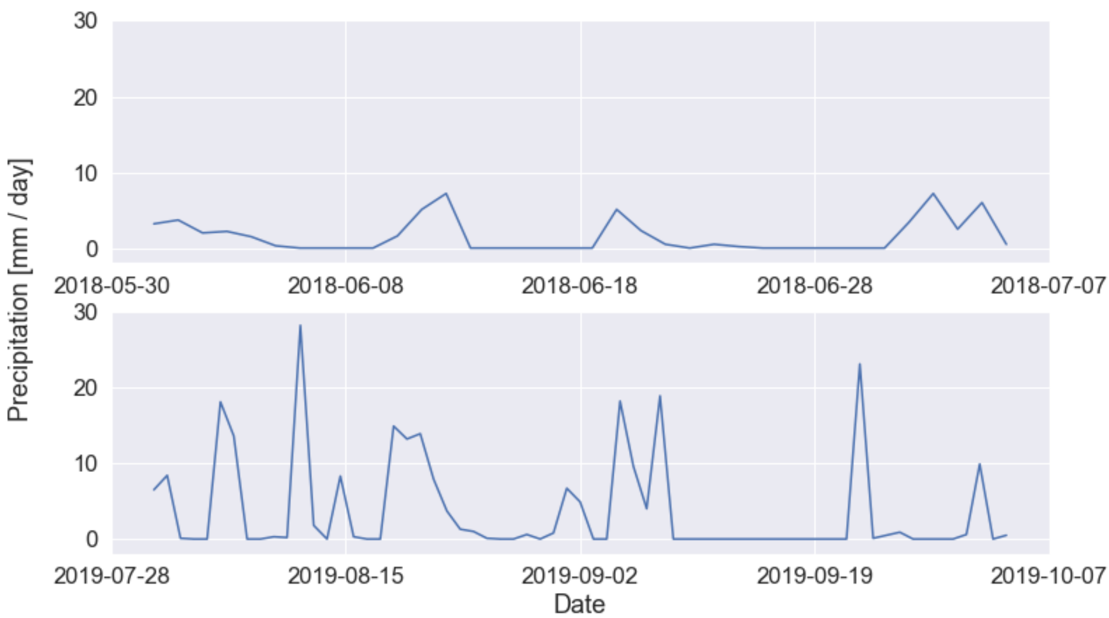

Figure 48: Daily precipitation in Scuol in the month before the AVIRIS-NG data acquisition (upper, data acquisition on 1 July 2018) and SwissImage RS data acquisition (lower, data acquisition on 4 – 29 September 2019) (Source: MeteoSchweiz, 2023a).

The distribution of mown and unmown plots for AVIRIS-NG, SwissImage RS and Sentinel-2 suggests that the classification methods worked satisfactorily for all sensors. The Sentinel-2 scene was recorded earliest in the year and only one-third of the plots were classified as mown. This makes sense as mowing is not allowed at this time of the year for some management types. AVIRIS-NG was recorded as the second, two weeks after Sentinel-2. More than 40% of the plots were classified as mown. SwissImage RS was recorded latest in the year and almost half of the plots are mown. A detailed compilation of the classification results can be found in Table 9, Table 18 and Table 25.

The most striking finding of the analysis of the spectral diversity of mown and unmown areas was that mown areas had across almost all applications a significantly higher spectral diversity. A reason for this may be the exposition of bare soil, which could possibly increase the spectral diversity. The exposition of bare soil is more likely to occur at mown plots. As bare soil has a substantially different reflectance from vegetation, it can increase spectral diversity (Gholizadeh et al., 2018; Lucas & Carter, 2008). Another reason may be that at mown plots, the spectral difference between structures that are unaffected by the mowing (e.g., bushes, hedges, trees) and the surrounding grassland increases. This would increase the spectral diversity of mown plots containing such structures in comparison to unmown plots containing such structures. This hypothesis is supported by the differences between management types obtained by AVIRIS-NG. Permanent meadows which often contain distinctive structures show a higher spectral diversity than artificial meadows on AVIRIS-NG application. For the SwissImage RS applications, the result looks different, artificial meadows result in higher spectral diversity on mown plots than permanent meadows. However, this result does not seem valid, as only 29 artificial meadows were classified as mown and the high values were mostly coming from plots where the borders did not match the actual management structure.

The difference between mown and non-mown plots was stronger when using the NDVI than when using the entire spectrum. This was the case for all three sensors. The reason for this may be that the NDVI was more sensitive to vegetational changes and may be stronger affected by the exposition of bare soil. As there were considerable differences between mown and unmown plots, it might be useful for future applications to use a more precise classification method and to carry out separate analyses for mown and unmown plots.

6.7 Results in the Context of Further Literature

According to current knowledge, no similar studies have yet been conducted that have investigated the spectral diversity of agricultural grassland using an object-based approach that directly coupled remote sensing data with local plot data. So, there is no data available that is directly comparable. The most comparable study has been conducted by Rossi et al. ((2020)), who examined plant traits on plot level with a PROSAIL inversion using Sentinel-2.

Although processing the remote sensing data differently and examining different plant traits, they also retrieved significant differences between plots that were mowed and plots that were grazed. This outcome may have a similar reason as the differences between artificial meadows and pastures observed in this study. The diversity metrics applied by Rossi et al. also observed differences between mown and non-mown management types. But with the relationships being conflicting, it is critical to draw comparisons.

In the SNP, neighboring the study area, the spectral diversity of untouched grassland has been examined, also using the data of AVIRIS-NG (Rossi et al., 2022). Comparing the CV and Convex Hull Volume of AVIRIS-NG to in-situ measured plant species richness within 5m × 5m plots, no correlation could be found. While AVIRIS-NG did deliver meaningful results in this study predicting FD, it might have an inappropriate spatial resolution to study the species richness of grassland on such a small spatial scale.

6.8 Issues and Limitations

During the conduct of this study, several problems and limitations arose. These potentially limited the validity of the presented results. It is important to be aware of these issues when assessing the results and drawing conclusions. The first major limitation arose from the dataset, which contained the agricultural plots of the canton of Grisons. The dataset did not very accurately represent the agricultural structures and practices of the Lower Engadin at the time of each remote sensing data acquisition. This is because of expected inaccuracies when the dataset is obtained, but also due to the time lag between the collection of the plot dataset and the collection of the remote sensing datasets. A second problem of the plot dataset was the fine parcellation in certain regions, that needed to be refined. As the refinement was done based on the Sentinel-2 mowing classification, the accuracy of this process was constrained by the Sentinel-2 revisit time and the quality of the mowing classification. The refinement was done for Summer 2018, so the resulting plot dataset was more accurate for AVIRIS-NG and Sentinel-2 than for SwissImage RS.

A further limitation was the data quality of the AVIRIS-NG dataset, which showed significant spatial offsets, especially in steep regions. For the plot dataset nor AVIRIS-NG detailed error information was available, so I could only broadly estimate the influence of these inaccuracies. These issues could be expected to be apparent over the entire study area and all management types, so they should not have concerned certain areas or management types specifically. A small bias may exist between plots on the valley ground and plots on higher elevations. This was first because the spatial imprecision of AVIRIS-NG is lower in flat terrain. Second, the plots in the valleys are less fragmented, so fewer refinements were required in these regions. This introduced mainly a spatial bias but could also have impacts of different severity on the different management types. This is because artificial meadows can mainly be found on the ground of the valley, while extensively used meadows and pastures are mostly at higher elevations. To verify that the elevation of the plots did not have a severe impact on the spectral diversity, Figure 49 shows the variance of the NDVI of AVIRIS-NG plotted against the elevation above sea level of the respective plots. There is no correlation between the spectral diversity measure and the elevation of plots, which shows that the elevation of the plots did not introduce a bias. Due to these issues, it can be expected that the significance of the results is reduced, but they should not have led to biases that may resulted in false findings. Table 27 shows the different levels of significance between AVIRIS-NG and SwissImage RS. These differences may be partly explainable by the differing data quality but as one can see do not lead to conflicting results.

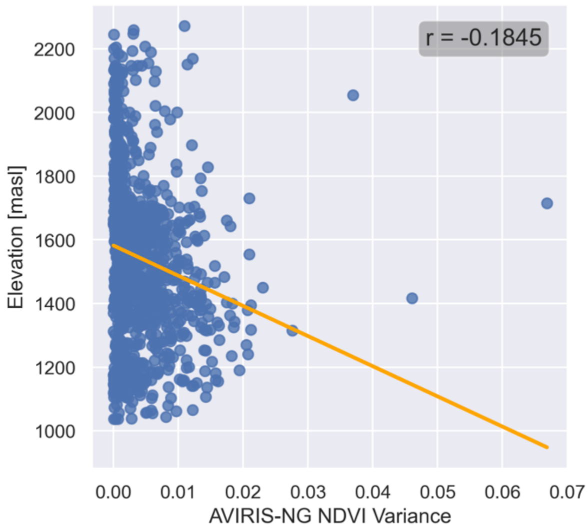

Figure 49: The Variance of the NDVI of AVIRIS-NG plotted against the Elevation of the respective plot. The slightly negative correlation can be explained by the fact that the more intensively managed plots are mainly located in the valley areas, while the extensively farmed plots are more often located at higher altitudes.

A further issue present in the AVIRIS-NG products was related to cloud extraction. To retrieve meaningful results, plots with a size smaller than 2000 m^2 were excluded from the analysis. However, there were still areas whose spectral diversity values resulted from a very small number of pixels. This was the case because in some areas a large part of the pixels within a plot had been cloud-masked. The areas with only a few analyzed pixels resulted in very low diversity values. This problem occurred across all management types and therefore did not lead to a distortion of results, but it should be solved differently in future work.

A further limitation, especially for the analysis based on the SwissImage RS was that the agricultural plots were refined for summer 2018. As the agricultural management practices seem to be dynamic, in several regions of the study area, the borders between different managements have changed between summer 2018 and September 2019. This can be observed when examining the SwissImage RS concerning the refined agricultural plots. Again, this effect is expected to be uniformly distributed over the entire study area and all management types and therefore should not have led to a bias towards a certain management type.

Figure 50: Left side: AVIRIS-NG scenery; Right side: SwissImage RS 2019 scenery. On the left side, the borders of the agricultural plots correspond relatively well to the changes in management visible in the scene. On the right side one can see borders between different management passing through plots.

Generally, examining the spectral diversity of grassland on a large spatial scale remains difficult, because no clear cause-effect relationships can be drawn. Possible insights can be superimposed by effects that were not the subject of the examination (Hauser et al., 2021). However, the discussion of the obtained results and comparison to similarly conducted studies showed that SwissImage RS and AVIRIS-NG are successful in detecting structures within agricultural managed areas, which may promote functional diversity. This worked using the full spectrum provided by the respective sensors, but also when using the NDVI. Especially the difference between intensively managed (fertilized and mown) and grazed management types was present across several datasets, data aggregation methods and quantifications of variability. The applied spectral metrics detected significant differences in the reflectance properties across all applied datasets. As the spectral metrics only quantified these differences but did not provide the underlying reasons, the reasons for these differences remained unclear in many cases. To draw more specific conclusions about the potential of predicting FD from remote sensing data, the reasons for the observed results would need to be explored in more detail. This could be done by studying specific observed phenomena isolated and on a smaller scaler. For example, the impact of structural elements or bare soil on the different products could be studied in small test plots. Another approach would be to study the effects of different spectral and spatial resolutions by resampling certain scenes, again at small test plots where detailed reference data would be available.

7 Conclusion

7.1 Summary

For this study, three remote sensing datasets were studied in the context of an agricultural plot dataset containing management data. The analysis focused on the AVIRIS-NG hyperspectral dataset, which was recorded in July 2018. This dataset and the agricultural plot data needed vast processing, which introduced several issues, limiting the validity of the analysis. From the original remote sensing datasets, several data products were analyzed: the full spectrum (AVIRIS-NG: first three PCs, explaining more than 99% of the variance; SwissImage RS: all four bands, Sentinel-2: all four bands with a spatial resolution of 10 meters), the NDVI, TGI and NDII (only for AVIRIS-NG). From these products, the CV and the Variance were calculated for each plot. A classifier to detect mown plots was run over the datasets, to discriminate between mown and not mown plots in the analysis. Both spectral metrics returned significant differences between management types for all analyzed products. However, the results vary strongly, only a few consistent relationships were observed. For many observed phenomena, it is difficult to find meaningful explanations. To draw more certain conclusions, the observed phenomena and the expected underlying explanations would need to be tested isolated. A relation observed several times was between artificial meadows and pastures, with the latter showing a higher spectral diversity in almost all applications. Most likely this was due to structural elements, that were often present in pastures but very rare in artificial meadows. A further finding common to all applications was the higher spectral diversity of mown plots. This was probably due to the exposition of bare soil, which was more present at mown plots and increased the spectral diversity. The observed results are likely to be related to the functional diversity of alpine grassland, better ground truth data would be needed to make more certain conclusions.

The results that were explainable the best, the most consistent and returned highly significant differences were obtained generally when analyzing the full spectrum and NDVI of AVIRIS-NG (also NDII) and SwissImage RS. This means that high spatial- and spectral resolution both offer advantages that are worth exploitation. For certain applications, it is difficult to predict which data set is more suitable, which method of data aggregation to choose and which spectral metric will give the best results. When calculating spectral diversity metrics on plot level on the full spectrum or the NDVI of AVIRIS-NG and SwissImage RS, one can expect to observe differences in the functional diversity of grassland.

7.2 Research Questions

1) Is it possible to study the spectral diversity of agriculturally managed plots in the Lower Engadin using an object-based approach?

Significant differences between plots of different management types were observed across several datasets and data aggregation methods. This suggests that when having plot data of adequate quality available, this approach works. But as the resulting values are often contradictory, the input data needs to be specifically selected and the results additionally verified and carefully interpreted. Also is the reproducibility not certain, as the results are dependent on local conditions.

2) How can the spectral diversity of agriculturally managed plots of the Lower Engadin serve as a proxy for biodiversity measures?

It is likely and can be justified, that the spectral diversity of the agricultural managed plots of the lower Engadin related to the FD of the respective areas. Therefore, one can expect that the spectral diversity can serve as a broad proxy for certain biodiversity measures, specifically in the context of the alpine managed grassland of the Lower Engadin. Significant results can be achieved using various spectral and spatial resolutions, also correlation can be observed between different datasets. For biodiversity measures defined on a finer spatial grain (e.g., species richness), the analyzed data did not provide indicators and a relation cannot be expected.

7.3 Outlook

If I had to conduct the study again, applying the same methodology, I would invest more time in finding a way to do the cloud filtering of the AVIRIS-NG data more precisely. In addition, a minimum number of analyzed pixels would have to be set when calculating the diversity metrics for a plot to be considered.

Generally, for future applications, I would recommend working with AVIRIS-NG, because the spatial resolution is still adequate and the large spectral coverage is useful for vegetational studies. But also the SwissImage RS I can recommend, as the NIR band and the high spatial resolution offer valuable information. It would be desirable to work with a reference plot dataset that contains more specific information on biodiversity metrics than just the management types, e.g., by working on a few experimental plots. This would make the obtained values directly relatable. Conclusions about the observed relationships could be more certain if the relationships would be studied isolated. Then statements about causality, which could only be speculated about in this study, would be more reliable. Finally, more sophisticated techniques could be applied. This could be done by calculating more and more complex spectral metrics, although even then one cannot expect non-contradictory results. Also, further remote sensing datasets could be introduced. For example, one could try to work with radar data, as this would most likely also observe the diversity introduced by structures on grassland. The vegetational properties could also be represented more accurately when applying canopy reflectance models or atmospheric models.

8 Appendix A – Overviews

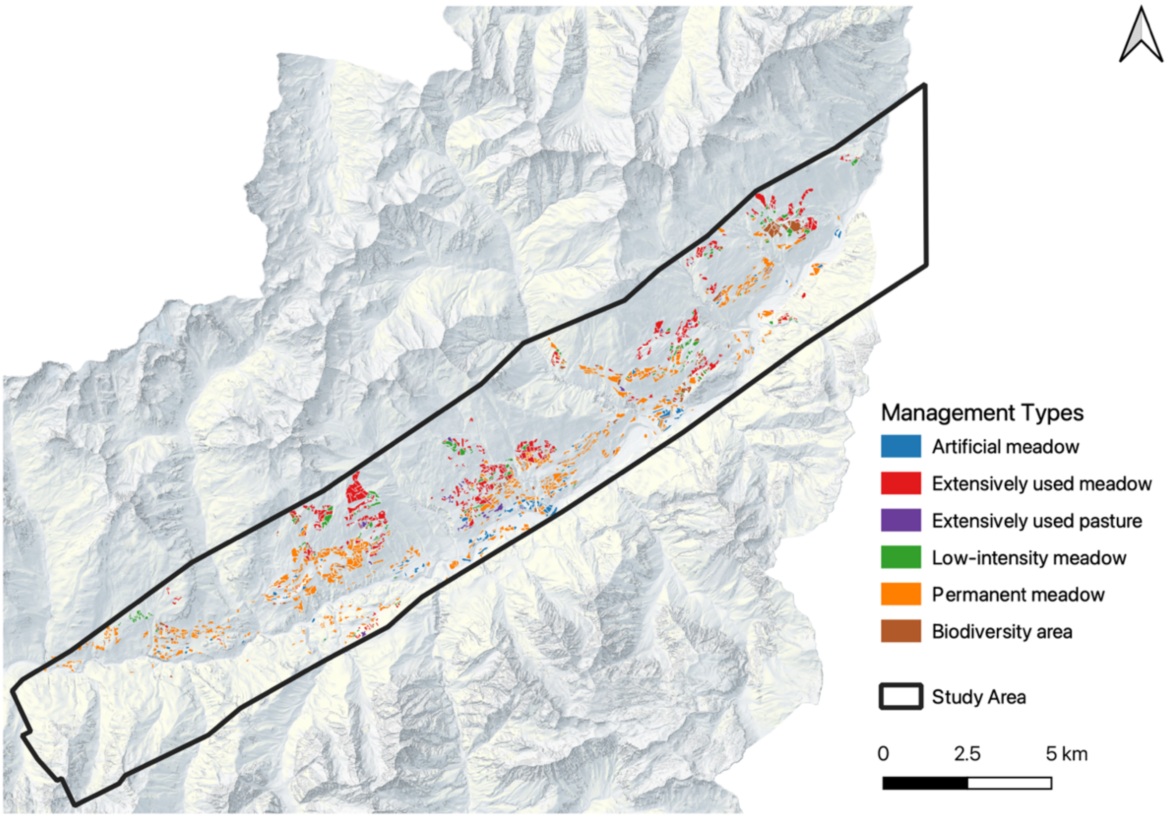

Figure 51: Plots and their respective Management Type in the Lower Engadin.

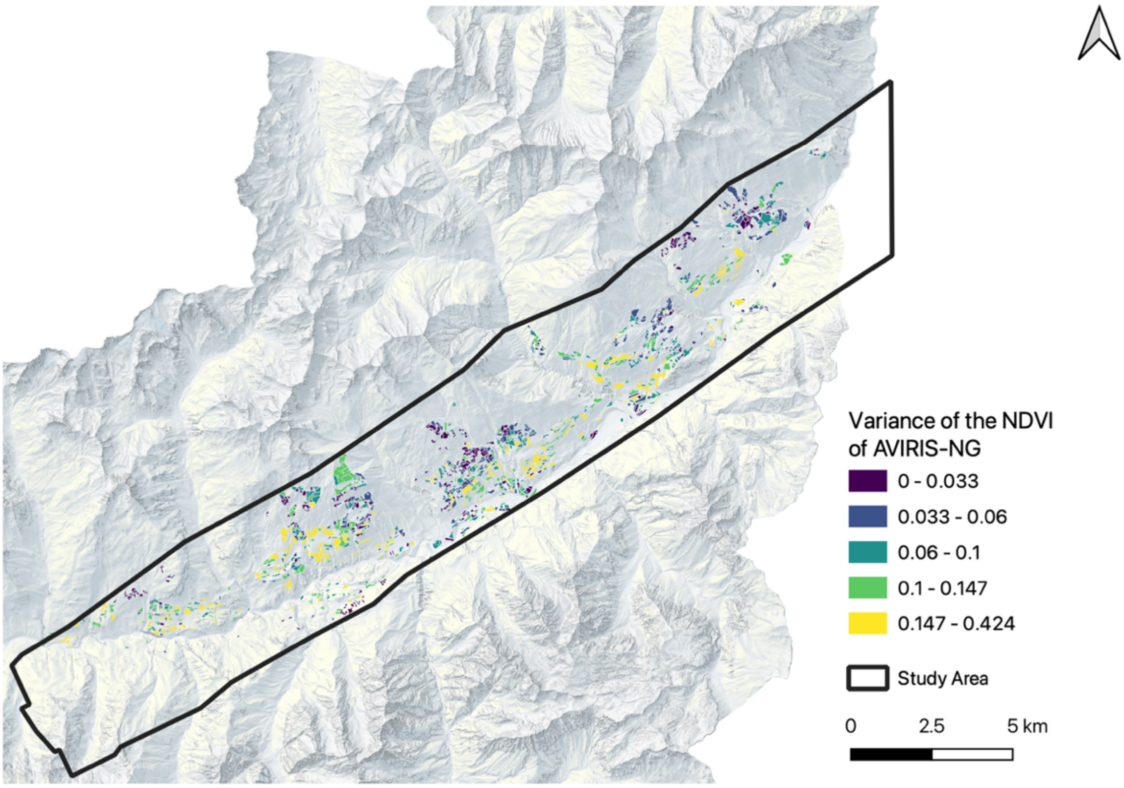

Figure 52: Example result of the spectral diversity analysis: Spatial variation of the result obtained from analyzing the Variance of the NDVI of AVIRIS-NG.

9 Appendix B – Further Results of the AVIRIS-NG Spectral Diversity Analysis

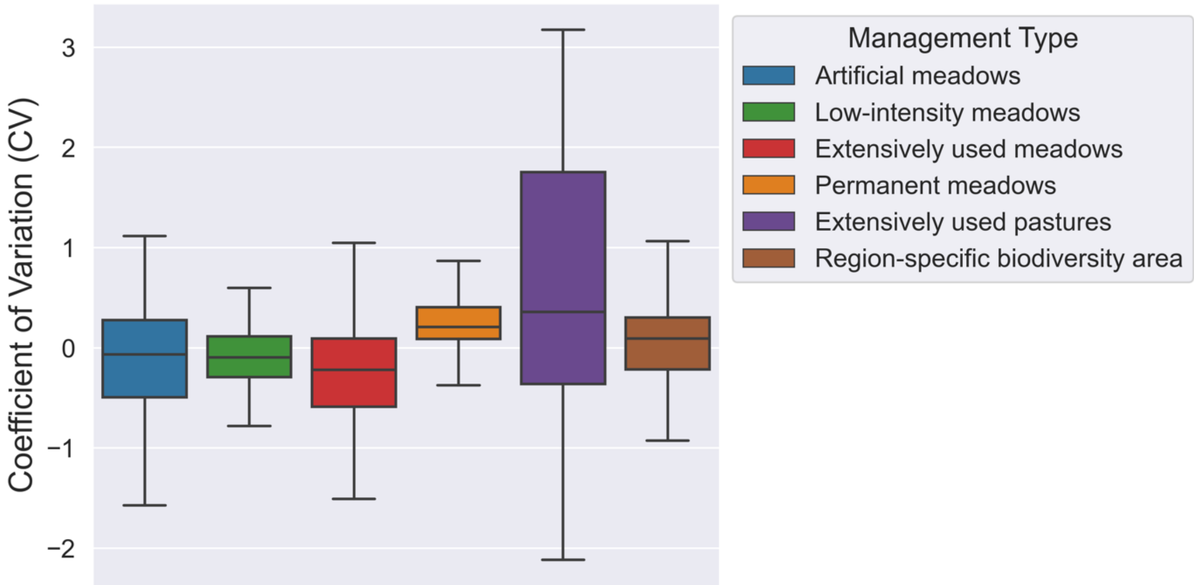

Figure 53: CV of the first three PCs of AVIRIS-NG.

Table 28: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the CV of the first three AVIRIS-NG PCs.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1.00000	0.55265	0.01415	0.00000	0.02067	0.05370
Low-intensity meadows	0.55265	1.00000	0.06313	0.00000	0.00644	0.00875
Extensively used meadows	0.01415	0.06313	1.00000	0.00000	0.00010	0.00000
Permanent meadows	0.00000	0.00000	0.00000	1.00000	0.88279	0.00867
Extensively used pastures	0.02067	0.00644	0.00010	0.88279	1.00000	0.26237
Region-specific biodiversity area	0.05370	0.00875	0.00000	0.00867	0.26237	1.00000

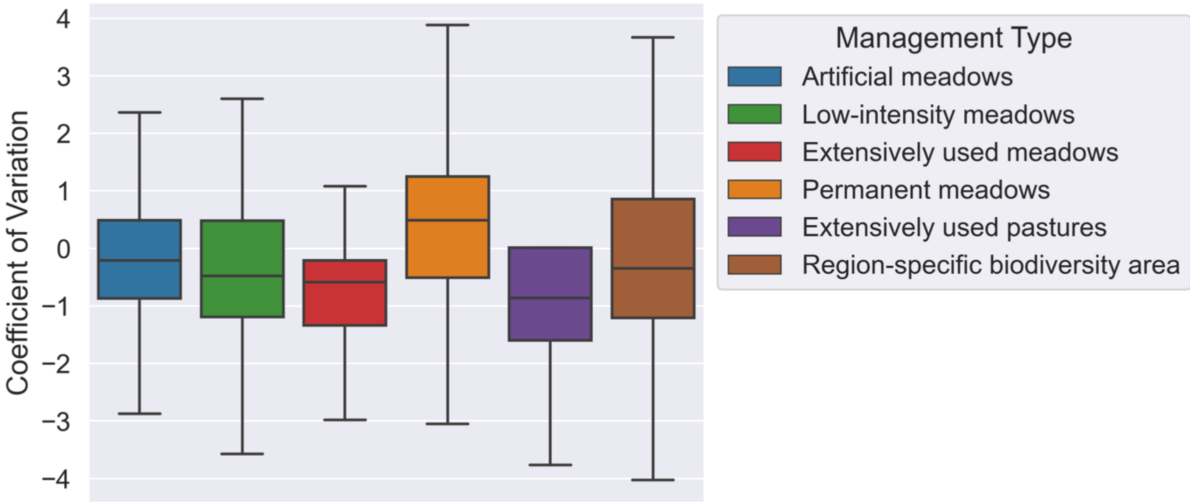

Figure 54: CV of the TGI of AVIRIS-NG

Table 29: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the CV of the TGI of AVIRIS-NG.

	Artificial meadows	**Low-intensity meadows**	**Extensively used meadows**	**Permanent meadows**	**Extensively used pastures**	**Region-specific biodiversity area**
Artificial meadows	1	0.20944	0.00164	0.00258	0.25181	0.58947
Low-intensity meadows	0.20944	1	0.0766	0	0.71052	0.46152
Extensively used meadows	0.00164	0.0766	1	0	0.57583	0.00853
Permanent meadows	0.00258	0	0	1	0.00369	0.0001
Extensively used pastures	0.25181	0.71052	0.57583	0.00369	1	0.413
Region-specific biodiversity area	0.58947	0.46152	0.00853	0.0001	0.413	1

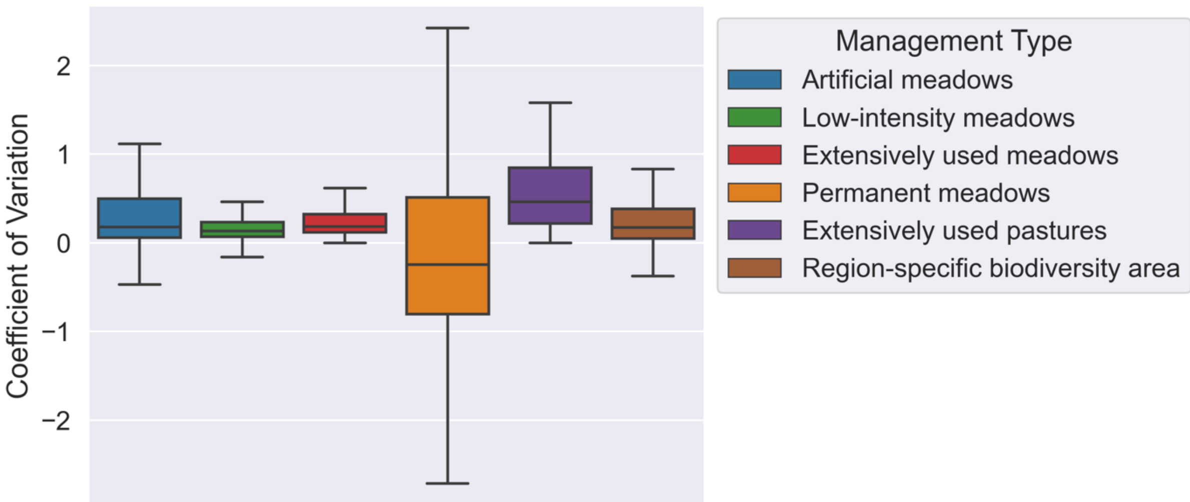

Figure 55: CV of the NDII of AVIRIS-NG.

Table 30: P-Values of the Dunn-Bonferroni post-hoc test of all management types of the CV of the NDII of AVIRIS-NG.

	Artificial meadows	Low-intensity meadows	Extensively used meadows	Permanent meadows	Extensively used pastures	Region-specific biodiversity area
Artificial meadows	1	0.08982	0.83272	0.00001	0.04627	0.26997
Low-intensity meadows	0.08982	1	0.01965	0.01302	0.00197	0.54441
Extensively used meadows	0.83272	0.01965	1	0	0.04292	0.11218
Permanent meadows	0.00001	0.01302	0	1	0	0.00125
Extensively used pastures	0.04627	0.00197	0.04292	0	1	0.00658
Region-specific biodiversity area	0.26997	0.54441	0.11218	0.00125	0.00658	1

10 Appendix C – Github Repository

The most important coding steps of this thesis are found under:
https://github.com/MaurusF/Thesis_SpectralDiversity.git

11 Appendix D – Spectral Diversity Analysis Cross-Comparissons

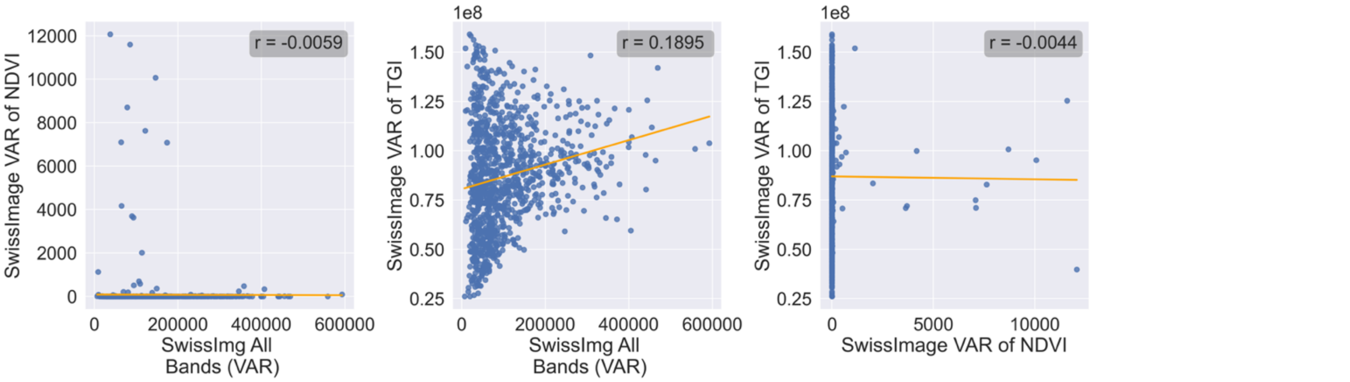

Figure 56: Pairplots of the Variance of the SwissImage RS products.

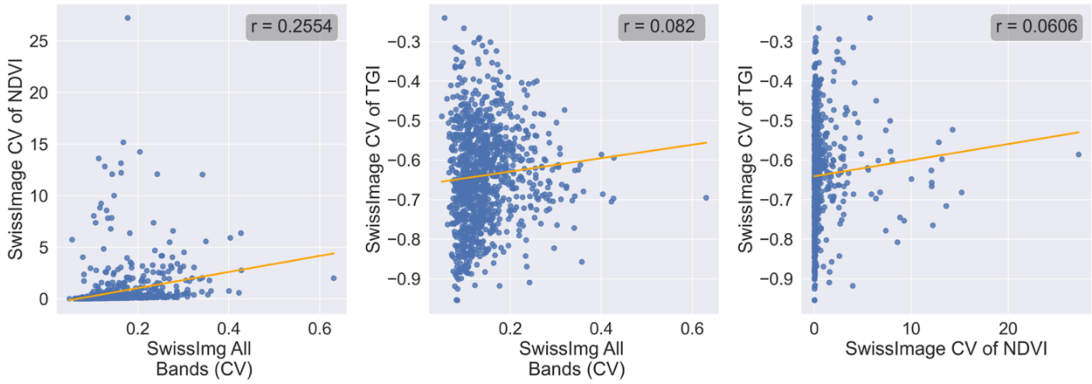

Figure 57: Pairplots of the CV of the SwissImage RS products.

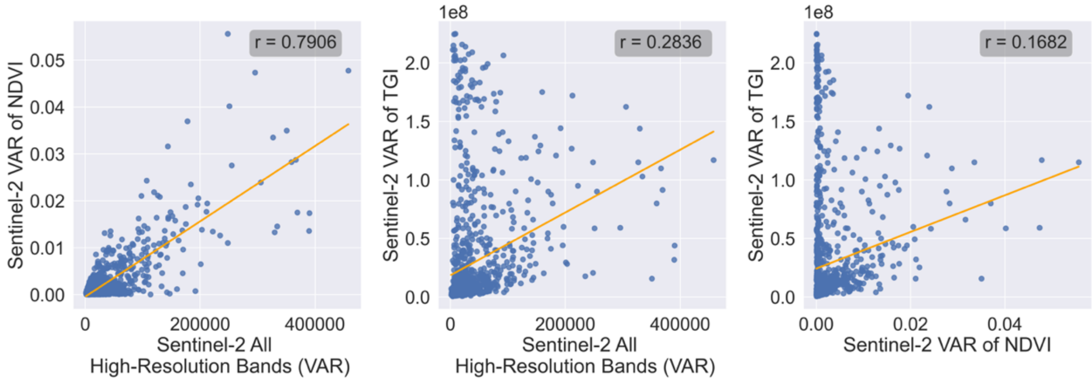

Figure 58: Pairplots of the Variance of the Sentinel-2 products.

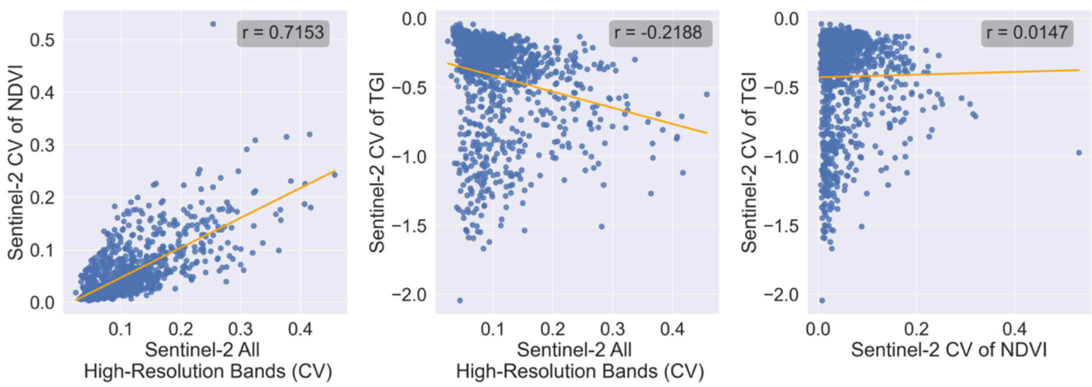

Figure 59: Pairplots of the CV of the Sentinel-2 products.

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Personal Declaration

I hereby declare that the sub- mitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

Date: 28.09.2023

Signature 

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