

Scaling Remote Sensing Data for Sustainable Grassland Conservation and Management

Dissertation

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*"When speaking of facts, tangible matters,
I do indeed strive to express myself precisely and at length."*
(Emiel Regis Rohellec Terzieff-Godefroy)

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Abstract

Among Earth's major biomes, grasslands are particularly affected by global change phenomena, including land use change, intensification, and climate change. In Europe, these ecosystems continue to degrade despite policies promoting sustainable management. A central limitation of such policies is the lack of fit-for-purpose monitoring. Established *in situ* monitoring methods are constrained by limited scalability and high costs. Remote sensing offers scalable alternatives, yet its integration into grassland monitoring faces methodological challenges. These include difficulties in achieving fine-scale assessments, assessing extensive areas when grasslands are characterized by legal frameworks, and when remote sensing models lack explainability.

This thesis addresses these challenges by developing scalable remote sensing approaches for monitoring sustainable grassland conservation and management, using case studies from Schleswig-Holstein, Germany. First, it presents a novel remote sensing approach for mapping grassland indicator plant species. Leveraging the distinct spectral pattern of magenta-colored vegetation, the newly developed Magenta Vegetation Index enabled analysis to derive spatially comprehensive plant counts of magenta-colored species in a high nature value grassland with mapping performance comparable to conventional field surveys. Second, the thesis establishes a change detection framework for monitoring the population development of magenta-flowered indicator species through repeated drone surveys. This approach identifies both areas in need of interventions and conservation success, demonstrating the value of drone-based monitoring for data-driven conservation planning. Third, to support large-scale monitoring of high nature value grasslands, this thesis leverages time series analysis of Harmonized Landsat Sentinel-2 data. Machine learning models trained on ecologically grounded grassland categorization produce annual, spatially comprehensive high nature value grassland maps. These maps identified previously unmapped high nature value grasslands and may guide future field surveys. Finally, the thesis enhances model explainability by adapting SHapley Additive exPlanation values, providing insights into cross-model decision-making patterns and key temporal-spectral predictors. This advancement lowers key barriers for a broader adoption of remote sensing in grassland monitoring.

Findings of this thesis emphasize the transformative potential of integrating drone and satellite remote sensing for monitoring sustainable grassland conservation and management. Drones enable fine-scale assessments, while satellites support extensive coverage timely. Enhanced model explainability builds confidence for remote sensing analysis. This thesis advocates for the integration of remote sensing and field data through interdisciplinary collaboration, contributing to more effective grassland stewardship in an era of rapid environmental change.

Kurzfassung

Unter den großen Biomen der Erde ist Grünland überproportional von globalen Umweltveränderungen betroffen, darunter Landnutzungsänderungen, -intensivierung und Klimawandel. In Europa schreitet die Degradierung dieser Ökosysteme trotz politischer Maßnahmen zur Förderung eines nachhaltigen Managements weiter voran. Eine zentrale Schwäche dieser Maßnahmen sind unzureichende Monitoringsysteme. *In situ* Monitoring ist begrenzt skalierbar und mit hohen Kosten verbunden. Fernerkundung bietet skalierbare Alternativen, stößt jedoch auf Herausforderungen bei der Integration in bestehendes Grünlandmonitoring. Zu diesen Herausforderungen zählen Monitoring kleinskaliger Zielvariablen, Erfassung großflächiger Gebiete unter Berücksichtigung rechtlicher Grünland-Typisierung und die mangelnde Interpretierbarkeit von Fernerkundungsmodellen.

Diese Dissertation widmet sich diesen Herausforderungen durch die Entwicklung skalierbarer Fernerkundungsmethoden für das Monitoring eines nachhaltigen Grünlandmanagements und -schutzes, am Beispiel von Schleswig-Holstein, Deutschland. Zuerst wird ein neuer Fernerkundungsansatz zur Kartierung von Grünlandindikatorarten vorgestellt. Mithilfe des charakteristischen spektralen Signatur magenta-farbender Vegetation ermöglicht der neu entwickelte Magenta Vegetation Index die flächendeckende Zählung von Individuen magenta-farbender Pflanzenarten in hochwertigen Grünlandflächen. Die Genauigkeit ist mit konventionellen *in situ* Zählungen vergleichbar. Zweitens etabliert die Arbeit ein Monitoringverfahren zur Überwachung der Populationsentwicklung von magenta-farbenden Indikatorarten mittels wiederholter Drohnenbefliegungen. Dieses Verfahren dokumentiert sowohl Populationsgebiete mit Handlungsbedarf als auch erfolgreiche Naturschutzmaßnahmen und unterstreicht damit den Nutzen drohnengestützter Monitoringverfahren für eine datenbasierte Naturschutzplanung. Drittens wird zur Unterstützung eines großflächigen Monitorings von hochwertigem Grünland eine Zeitreihenanalyse harmonisierter Landsat-Sentinel-2 Daten durchgeführt. Modelle des maschinellen Lernens, die auf ökologisch fundierten Grünlandtypisierungen trainiert wurden, erzeugen flächendeckende Karten von hochwertigem Grünland mit einer jährlichen Auflösung. Diese Karten identifizieren bislang nicht erfasste hochwertige Grünlandflächen und können zukünftige Monitoringaktivitäten gezielt unterstützen. Abschließend verbessert die Dissertation die Interpretierbarkeit von Fernerkundungsmodellen durch eine angepasste Form von SHapley Additive exPlanations Analysen. Dies liefert Einblicke in modellübergreifende Entscheidungsprozesse und einflussreiche zeitlich-spektrale Prädiktoren und trägt zur Überwindung von Hürden für eine breitere Anwendung von Fernerkundung im Grünlandmonitoring bei.

Die Ergebnisse dieser Arbeit betonen das transformative Potenzial der Kombination aus drohnen- und satellitengestützter Fernerkundung für das Monitoring eines nachhaltigen Grünlandmanagements. Drohnen ermöglichen feinskalige Analysen, während Satelliten eine zeitliche, großflächige Abdeckung sicherstellen. Eine verbesserte Interpretierbarkeit von Fernerkundungsmodellen schafft Vertrauen für eine operationelle Anwendung. Diese Dissertation plädiert für die Integration von Fernerkundung und *in situ* Monitoring durch interdisziplinäre Zusammenarbeit und leistet so einen Beitrag zu einem nachhaltigen Grünlandmanagement im Zeitalter fortschreitender Umweltveränderungen.

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List of Abbreviations

ARVI	Atmospherically Resistant Vegetation Index
ATSAVI	Adjusted Transformed Soil-adjusted Vegetation Index
AVHRR	Advanced Very High Resolution Radiometer
B	Blue
BAP	Best-Available-Pixel
BWDRVI	Blue-wide Dynamic Range Vegetation Index
CAP	Common Agricultural Policy
CHIME	Copernicus Hyperspectral Imaging Mission
CHT	Composite Habitat Type
CRI	Chlorophyll Red-Edge Index
CVI	Chlorophyll Vegetation Index
DM	<i>Dactylorhiza majalis</i>
DOY	Day of Year
EBI	Enhanced Bloom Index
EnMAP	Environmental Mapping and Analysis Program
EPSG	European Petroleum Survey Group Geodesy
ES	Ecosystem Service
ESA	European Space Agency
EU	European Union
EUNIS	European Nature Information System
EVI	Enhanced Vegetation Index
FFH	Flora Fauna Habitat Directive
FIS	Feature Impact Score
FN	False Negative
FP	False Positive
G	Green

GARI	Green Atmospherically Resistant Vegetation Index
GBNDVI	Green-Blue Normalized Difference Vegetation Index
GPS	Global Positioning System
GNDVI	Green Normalized Difference Vegetation Index
GRNDVI	Green-Red Normalized Difference Vegetation Index
GRVI	Green-Red Vegetation Index
HLS	Harmonized Landsat Sentinel-2
HNV	High-Nature Value
HOT	Haze-Optimized Transformation
LIME	Local Interpretable Model-Agnostic Explanations
L8	Landsat 8
MASD	Mean Absolute Spectral Dynamic
MaVI	Magenta Vegetation Index
MODIS	Moderate-Resolution Imaging Spectroradiometer
MSI	Multispectral Instrument
MTCI	MERIS Terrestrial Chlorophyll Index
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near-Infrared
NN	Neural Network
OLI	Operational Land Imager
PA	Producer Accuracy
PRISMA	PRecursore IperSpettrale della Missione Applicativa
R	Red
RDVI	Renormalized Difference Vegetation Index
RF	Random Forest
RMSE	Root-Mean-Square-Error
RS	Remote Sensing
RSPC	Remote Sensing Plant Count
SAVI	Soil-adjusted Vegetation Index
SARVI	Soil and Atmospherically Resistant Vegetation Index
SHAP	SHapley Additive exPlanations

SIPI	Structure Insensitive Pigment Index
SH	Schleswig-Holstein
SMOTE	Synthetic Minority Oversampling Technique
SNR	Signal-to-Noise Ratio
S2	Sentinel-2
TP	True Positive
TSAVI	Transformed Soil-adjusted Vegetation Index
UA	User Accuracy
UAV	Unmanned Aerial Vehicle
UN	United Nations
VIS	Visible
VI	Vegetation Index
WDRVI	Wide Dynamic Range Vegetation Index
XGBoost	eXtreme Gradient Boosting

Chapter 1

Introduction

Since the mid-20th century, the biosphere has undergone transformations at an unprecedented scale in human history (Millennium Ecosystem Assessment, 2005). Among terrestrial biomes, grasslands have been particularly vulnerable to these shifts, experiencing disproportionate impacts from global change phenomena (Gibson, 2009; Bardgett et al., 2021). These phenomena arise from the growing demand for natural resources and energy from a human population that has doubled, a global economy that has quadrupled, and global trade that has expanded tenfold in the past 50 years (IPBES, 2019). While these developments have contributed to human prosperity, scientific evidence accumulated ever since, that they have been achieved unsustainably and at escalating costs (Meadows et al., 1974; Conca and Dabelko, 2018). Humanity's ongoing exploitation of nature interferes with the climate system, degrades ecosystem services (ES), and increases the risk of irreversible changes, with benefits and burdens unevenly distributed across regions and generations (IPBES, 2018b; Calvin et al., 2023). The consequences become increasingly evident, with six of nine planetary boundaries already exceeded (Richardson et al., 2023), underscoring the urgent need for sustainable land management and broader transformative changes in how we live (Newbold et al., 2016).

Grasslands, covering a significant portion of the Earth terrestrial surface, are a potent field of action. These ecosystems share history with the emergence of agricultural practices, as their fertile soils and open landscapes have made them prime targets for cultivation, grazing, and land conversion (Ellis, 2021). Historically, extensive grassland management maintained a balance between ecological integrity and human use. However, this balance has been disrupted. Agricultural intensification, alongside urban and infrastructure development, are accelerating transformations that threaten the resilience of grassland ecosystems (Shipley et al., 2024), while climate change is projected to become an increasingly significant driver of ecological change (IPBES, 2019).

European grasslands serve as a clear example of these ongoing transformations. Grasslands shape the agricultural landscape of Europe (Isselstein et al., 2005) and serve a critical role as biodiversity hotspots for a variety of endangered flora (Hobohm and Bruchmann, 2009) and fauna (Veen et al., 2009). Despite their ecological importance, their extent and quality continue to decline (Bengtsson et al., 2019). In response, the European Union (EU) has introduced various policy instruments to promote sustainable grassland management and protect high nature value (HNV) sites. However, the effectiveness of these policies often falls short of their intended objectives. While incentives for sustainable grassland management exist, the same policies also permit intensive land use forms, which, being easier to implement, are often favored in agricultural practice (Pe'er et al., 2020). At the same time, conservation policies frequently lack robust enforcement mechanisms, resulting in inconsistent implementation and protection among member states (Kati et al., 2015). Multiple policy revisions have attempted to address these shortcomings, yet fundamental gaps remain. A critical gap is the lack of a robust and scalable monitoring framework for grassland management (Sot-CoBD, 2020). Such a framework is essential for generating the insights needed to facilitate adaptive management and evidence-based policymaking (Perino et al., 2022).

Traditionally, *in situ* methods have been the primary approach for obtaining ecological insights. However, the accelerating pace of environmental change and accumulating policy requirements make grassland monitoring increasingly complex, exposing limitations of existing methodologies. These constraints include high labor demands, significant costs, and challenges related to spatial and temporal scalability (Moersberger et al., 2024). Remote sensing (RS) has emerged as a powerful complementary tool, offering alternatives for assessing biodiversity, detecting land-use changes, and monitoring conservation efforts across multiple scales (Wang et al., 2022b). Recent advances in RS technology, such as hyperspatial drone imagery and data harmonization across satellite missions, have significantly improved RS's ability to monitor grassland ecosystems.

Despite these advancements, the operational adoption of RS remains limited. While institutional reluctance among monitoring actors remains a significant barrier (Vanden Borre et al., 2011b; Ustin and Middleton, 2021), methodological challenges at the interface of RS and *in situ* monitoring continue to hinder its full integration. One major challenge is achieving fine-scale assessments of HNV grasslands, where habitat quality is often inferred from indicator plant species. Conventional *in situ* methods rely on extrapolation from small sample plots, whereas drone-based species mapping has the potential to provide exhaustive population assessments. However, this application remains underdeveloped, particularly in its ability to assess population dynamics and evaluate conservation success over time. At

broader spatial scales, RS integrated with machine learning has improved grassland assessments, yet these advancements have not fully translated into more efficient field mapping strategies. A major challenge arises when legal frameworks, rather than ecological distinctions, characterize monitoring target variables, making them difficult to distinguish through RS. In such cases, RS can provide proxy information to support field mapping, but this requires analytical approaches adapted to specific monitoring programs and regional contexts. Closing this gap demands both methodological advancements in RS and adjustments in monitoring requirements, yet this alignment is rarely pursued, leading to the premature dismissal of RS as ineffective. Another major challenge is the "black-box" nature of advanced RS models, which often lack interpretability. This opacity complicates validation against ecological reference data and limits the integration of model reasoning into decision-making processes, further hindering the adoption of RS in monitoring grasslands.

This thesis engages with these research gaps by investigating scalable RS approaches for monitoring sustainable grassland conservation and management. In doing so, it contributes to the growing body of knowledge at the interface of *in situ* and RS-based monitoring, lowering key barriers and advancing the integration of both methods. By enhancing the capacity for a holistic assessment across spatial and temporal scales, this research supports more effective grassland stewardship in an era of rapid environmental change.

1.1 Research Objectives

The overarching goal of this thesis is to extend RS applications in monitoring grassland conservation and management. Special emphasis is placed on addressing *in situ* scaling issues through RS — specifically, assessing small target variables at scale and extensive areas timely — while enhancing modelling explainability to facilitate broader operational adoption of RS technologies. To achieve this, the following research objectives are defined in this thesis.

Research Objectives

1. Develop RS methods for mapping indicator plant species in HNV grasslands using hyperspatial drone data
2. Establish a framework to assess indicator plant population development through repeated drone surveys to assess conservation efforts
3. Leverage RS time series analysis to improve the monitoring of HNV grasslands over extensive areas
4. Enhance the explainability of RS models in grassland monitoring to facilitate broader adoption

These objectives are addressed through three distinct studies, each investigating specific research questions aligned with one or more objectives. The first study Gröschler and Oppelt (2022): "*Using Drones to Monitor Broad-Leaved Orchids (*Dactylorhiza majalis*) in High-Nature-Value Grassland*" focuses on RS-based monitoring of small target variables relevant to grassland conservation, emphasizing spatial scaling and model explainability. It contributes to research objectives 1 and 4. The second study Gröschler et al. (2023): "*Monitoring the Population Development of Indicator Plants in High Nature Value Grassland Using Machine Learning and Drone Data*" extends RS-based monitoring of small grassland target variables to the temporal domain, contributing to objective 2. The third study Gröschler et al. (2024): "*Data-Driven Identification of High-Nature Value Grasslands Using Harmonized Landsat Sentinel-2 Time Series Data*" emphasizes the temporal domain of large-scale grassland monitoring by integrating RS techniques with explainable machine learning, contributing to objectives 3 and 4.

1.2 Thesis Outline

This thesis is organized into eight chapters. Chapter 1 establishes the relevance and motivation for this research, outlining the overarching goal and research objectives. Chapter 2 presents a comprehensive literature review, situating the study within the broader context of contemporary grassland research. Chapter 3 provides an overview of the area under investigation and elaborates key themes from the literature review in the context of this specific region. Chapters 4, 5, and 6 present the primary research findings of this thesis and correspond to the peer-reviewed articles Gröschler and Oppelt (2022) (published in *Drones*; DOI: 10.3390/drones6070174), Gröschler et al. (2023) (published in *Drones*; DOI: 10.3390/drones7100644), and

Gröschler et al. (2024) (published in *Remote Sensing Applications: Society and Environment*; DOI: 10.1016/j.rsase.2024.101427), respectively. Chapter 7 synthesizes the key findings from Chapters 4 to 6, critically evaluating them in relation to the research objectives. Finally, Chapter 8 identifies unresolved challenges for future research that need to be addressed to advance RS applications in monitoring grassland conservation and management.

Chapter 2

Literature review

2.1 A primer on grasslands

Grasslands cover approximately 40% of the Earth's terrestrial surface (Blair et al., 2014), occurring on every continent except Antarctica (see Figure 2.1). These ecosystems provide essential provisioning, regulating, and cultural ES, contributing significantly to the existence and well-being of humans (Kumar, 2012). Approximately 800 million people rely directly on grasslands for their livelihoods (White et al., 2000), while nearly all individuals benefit from grassland-derived products in daily life (Blair et al., 2014).

Accounting for roughly 70% of agricultural landscapes, grasslands play a crucial role in global food security (O'Mara, 2012). Despite their structural simplicity, they can be biodiversity hotspots (Habel et al., 2013), locally supporting more vascular plant species than tropical rainforests (Wilson et al., 2012), while serving as habitats to endangered fauna (Köhler et al., 2016). Beyond their ecological significance, grasslands contribute to climate regulation. They store substantial amounts of carbon below-ground, primarily in root biomass and soil organic carbon, which remains stable under non-destructive management (Scurlock and Hall, 1998). Estimates suggest that grasslands contribute up to 34% of global carbon storage (White et al., 2000), with their role projected to increase regionally under future climate conditions (Dass et al., 2018). Their extensive root systems also stabilize soils, mitigating erosion, while enhancing water quality through filtration (Hönigová et al., 2012). The global economic value of grassland ES is estimated at \$20.8 trillion annually, translating to approximately \$4,000–\$5,500 per hectare (Liu et al., 2022a), further underscoring their environmental and economic significance.

Grasslands likely originated around 70 million years ago, evolving in un-forested, seasonally dry regions across temperate, subtropical, and tropical climates (Petermann and Buzhdygan, 2021). A significant expansion occurred approximately 30 million years ago, driven by atmospheric CO₂ de-

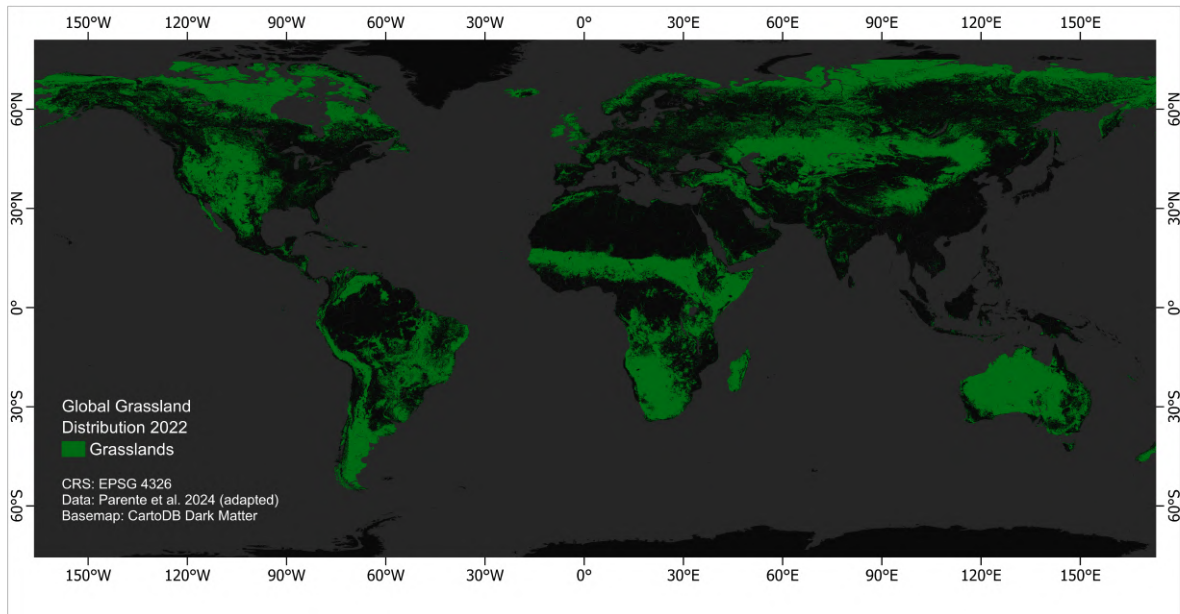


Figure 2.1: Global grassland distribution 2022 derived from Parente et al. (2024b). The mapped grasslands include any land cover type, which contains at least 30% of dry or wet low vegetation, dominated by grasses and forbs (less than 3 meters) and (a) a maximum of 50% tree canopy cover (greater than 5 meters), (b) a maximum of 70% of other woody vegetation (scrubs and open shrubland), and (c) a maximum of 50% active cropland cover in mosaic landscapes of cropland and other vegetation. Original land cover classes were aggregated and the dataset resampled for illustrative purposes.

cline and climatic change, leading to the evolution and global expansion of C_4 grasses at the expense of C_3 grasses¹ (Gibson, 2009). Natural disturbances such as regular wildfires and large herbivore grazing further facilitated their expansion in the Miocene (Strömberg, 2011). Evidence suggest that early *Homo* and modern *Homo Sapiens* may have arisen in African grassland environments about 2 million and 160,000 years ago, respectively (Stringer, 2003; Strömberg and Staver, 2022). However, systematic anthropogenic influence on grassland development only began around 12,000 years ago with the advent of Neolithic husbandry, when early civilizations domesticated wild grasses and initiated agricultural practices (Ellis, 2021).

The long-term interplay of natural and anthropogenic factors has resulted in a variety of grassland ecosystems, leading to diverse definitions in the scientific literature. Broadly, grasslands are characterized as open landscapes dominated by graminoid or graminoid-like vegetation, with little to no tree

¹ C_3 and C_4 grasses refer to different photosynthetic pathways, named for the number of carbon atoms in the first stable molecule formed during carbon fixation (Ehleringer and Cerling, 2002).

or shrub cover (Blair et al., 2014). Depending on the biogeographical context and climate conditions, grasslands appear in regional variations such as African savannas, North American prairies, Eurasian steppes or South American pampas (Suttie et al., 2005). Site-specific biotic and abiotic factors, including fauna, soil type, pH levels, and nutrient availability, further contribute to ecological diversification (Blair et al., 2014). Grasslands are often further distinguished based on the level of human influence (see Figure 2.2). Natural grasslands are primarily shaped by climatic conditions and natural disturbances — mainly wildfires and grazing — that prevent their transition into forests or deserts (Buisson et al., 2022). Semi-natural grasslands originate from deforestation or modified natural or intensively managed grasslands (Bardgett et al., 2021) and require low-intensity human intervention that mimics natural disturbance regimes (Petermann and Buzhdygan, 2021). In contrast, intensively managed grasslands are subjected to high levels of agricultural modification, including artificial inputs such as fertilizers and irrigation, to maximize productivity, particularly for forage production (Shipley et al., 2024).



Figure 2.2: Illustrations of grasslands under varying human influence: (a) Natural grassland in the Ötztal Alps, Austria, above the treeline; (b) Semi-natural grassland in Mecklenburg-Western Pomerania, Germany, with low-intensity grazing; (c) Intensively managed grassland on the North Sea coast in Schleswig-Holstein, Germany, affected by both intensive grazing and mowing. Sources: Kim-Cedric Gröschler

2.2 Grasslands under pressure

Despite their ecological and economic significance, grasslands face widespread degradation², affecting up to 49% of their global area (Gang et al., 2014). Degradation is driven by a combination of land-use changes, environmental pressures, and evolving management practices. Historically, agricultural expansion has been the primary cause (Blair et al., 2014). In North America, for example, up to 99% of native prairies have been converted to agricultural land (Petermann and Buzhdygan, 2021), with similar trends observed in South American (Modernel et al., 2016) and African grasslands (Carbutt and Kirkman, 2022; Nzunda, 2022).

Grassland degradation is exacerbated by multiple global change phenomena. Agricultural intensification leads to homogenization of grassland flora, degrading the ecological value of managed grasslands (Gossner et al., 2016). Atmospheric deposition of nitrogen and phosphorus alters nutrient dynamics of natural and semi-natural grasslands, leading to shifts in species composition and declines in biodiversity (Shipley et al., 2024). In regions with high livestock densities, overgrazing compacts soil, accelerates erosion, diminishes soil fertility and water retention capacity (Buisson et al., 2022). In arid climates, these processes contribute to desertification, leading to further land degradation (Zhao et al., 2023). Contrasting intensification, the abandonment of grasslands leads to woody plant encroachment, which alters the ecosystem's structure (Wehn et al., 2017), reducing light availability and, therefore, species richness (Schrautzer and Jensen, 2004). The suppression of wildfires further promotes these structural shifts (Strömberg and Staver, 2022). Furthermore, the spread of invasive species — driven by land use and climate change — displaces native grassland flora, resulting in shifts in species composition and ecosystem instability (Blair et al., 2014).

Beyond agri-environmental impacts, urban expansion and infrastructure development impose further pressures on grasslands. The permanent sealing of grasslands for construction fragments habitats, which disrupts ecosystem connectivity, reduces resilience, and diminishes the effectiveness of ES (Bardgett et al., 2021). About 37% of the global grassland area are affected by fragmentation (Petermann and Buzhdygan, 2021), while projections indicate further increases in the near future (IPBES, 2018b).

Grassland degradation is both a contributor to and a consequence of climate change. The degradation of these ecosystems significantly increases soil CO₂ emissions, amplifying global warming (Abdalla et al., 2018). Meanwhile, climate change-related factors — including rising temperatures, al-

²Although there is no universally accepted definition of grassland degradation, the term is generally associated with declines in grassland area, quality, productivity, economic potential, ecosystem services, recovery capacity and biodiversity, making it a critical issue in grassland management and conservation.

tered precipitation patterns, and more frequent extreme weather events — intensify degradation processes (Blair et al., 2014). Additionally, climate mitigation measures, such as afforestation, are often implemented at the expense of existing grasslands, leading to unintended ecological trade-offs (Lyons et al., 2023).

The economic impacts of grassland degradation are substantial. For example, reduced livestock carrying capacity in degraded grasslands resulted in an estimated global economic loss of \$6.8 billion between 2001 and 2011 (Nkonya et al., 2016). The loss of regulating services, such as carbon sequestration, water retention, and erosion control, likely causes even greater financial consequences. Some estimates suggest their value is, on average, four times higher than provisioning services (Liu et al., 2022a). However, due to the absence of standardized market valuation, these losses remain difficult to quantify (Richter et al., 2021). Grassland degradation disproportionately affects rural populations, particularly in developing regions, where livelihoods depend on these ecosystems (Bedunah and Angerer, 2012). The loss of productive grasslands exacerbates food insecurity and the economic situation, making sustainable management critical for both ecological and human resilience.

2.3 Grasslands in Europe

European grasslands too are undergoing widespread degradation. Semi-natural grasslands have historically been the predominant land cover in Europe's agricultural landscape (Isselstein et al., 2005). These grasslands serve a crucial role for biodiversity, supporting about 18% of Europe's endemic vascular plant species (Hobohm and Bruchmann, 2009), along with numerous other taxa, including two-thirds of European butterfly species (Veen et al., 2009). Originating in the Middle Ages (Speier, 1996), European grasslands were traditionally managed in accordance with the natural fertility of individual sites (Shipley et al., 2024), creating a heterogeneous mosaic of open, small parcelled, often species rich habitats³. However, over the past century, up to 90% of Europe's semi-natural grasslands have been lost (Cousins et al., 2015). This development can be traced back to profound changes in agricultural practices. In Western Europe, post-World War II agricultural intensification was largely driven by subsidies under the EU's Common Agricultural Policy (CAP) (MacDonald et al., 2000), which priori-

³Historical management practices contributed to the emergence of HNV grasslands, likely not through intentional conservation efforts, but as a byproduct of limited agricultural techniques and the lack of mineral fertilizers (MELUND, 2021). Thus, the remnants of ancient species-rich grasslands today reflect a historical coincidence rather than a deliberate strategy for grassland conservation.

tized crop production and increased livestock densities to ensure food security, often at the expense of grassland biodiversity (Kachler et al., 2023). In contrast, in Central and Eastern Europe, the collapse of socialist regimes in the 1990s dismantled state-owned agricultural cooperatives, leading to widespread land privatization. As land ownership was transferred back to financially struggling former owners, large-scale land abandonment became prevalent, particularly in areas where maintaining traditional management was no longer economically viable (Török et al., 2011).

While these historical drivers persist, modern economic and policy forces have further reshaped Europe's grassland landscapes (Kuemmerle et al., 2016). The expansion of the EU and its common market continuously intensifies agricultural operations across Europe, with livestock feed production increasing by more than 50% over the past 30 years (IPBES, 2018a) and fertilizer use rising sharply (Foley et al., 2011). Agriculture has become increasingly concentrated in highly productive regions, where market incentives and subsidy structures drive efficiency, while marginal lands face abandonment, leading to biodiversity loss and ecosystem degradation (Queiroz et al., 2014). As of 2007, permanent and temporary grasslands still accounted for approximately 39% of the utilized agricultural area in Europe, but their extent continues to decline (Huyghe et al., 2014). Unfertilized, semi-natural grasslands are now nearly absent in Western and Central Europe (WallisDeVries et al., 2002), with few remaining areas existing as small, fragmented patches within crop-dominated landscapes.

Overall, grasslands rank among the poorest conservation statuses of ecosystems within the EU (EEA, 2010), with restoration efforts becoming increasingly necessary for their survival (Helsen et al., 2012). Consequently, ecologists lobby for sustainable grassland management and restoration of natural and semi-natural grasslands within conservation strategies and agri-environmental schemes (Isselstein et al., 2005). These efforts are reflected in complex array of EU policies, like the CAP, the Flora-Fauna-Habitats (FFH) Directives and their derivatives, as well as complementary member-state policies at local to national scales. Several key topics emerge from the interaction of these policies, including agricultural practices, biodiversity conservation, energy and afforestation strategies, and the evolving focus on sustainable grassland management (Haensel et al., 2023).

As the EU's primary agricultural policy instrument, the CAP plays a pivotal role in shaping grassland management (EU, 2012). Since its inception in 1962, the CAP has undergone multiple reforms aimed at addressing agricultural challenges beyond production, including environmental sustainability. The 2013 CAP reform, for example, introduced greening measures, linking direct payments to specific sustainable management practices. These included maintaining permanent grasslands, promoting crop diversification, and establishing Ecological Focus Areas, all of which directly or indi-

rectly affect grassland management. However, these measures have faced widespread criticism regarding their effectiveness. For instance, the permanent grassland measure permits up to a 5% reduction in grassland area, undermining its ability to prevent biodiversity loss (Pe'er et al., 2019). Moreover, this requirement applies only to designated areas, which, aside from existing NATURA 2000 sites, are determined at the discretion of individual member states (Burrascano et al., 2016).

Another major limitation of the CAP is its focus on maintaining grassland extent rather than improving management quality, meaning that even intensively managed grasslands remain eligible for subsidies (Pe'er et al., 2014). The uniformity of CAP regulations across diverse agricultural landscapes has also led to unintended environmental losses, as they fail to account for regional differences in ecological conditions and management needs (Babai et al., 2021). The 2023 CAP reform sought to address some of these shortcomings through the introduction of ecoschemes, which offer voluntary financial incentives for farmers who implement measurable environmental improvements. However, ecologists criticize that the new strategy once again falls short of achieving meaningful environmental transformation. A joint NGO assessment found that only 19% of ecoschemes were likely to deliver tangible environmental benefits, while many others required substantial improvements to be effective (Midler et al., 2023). Additionally, less demanding, lower-cost schemes often outcompete more effective but resource-intensive options, reducing the overall impact of the policy (Nyssens et al., 2021).

Beyond the CAP, biodiversity conservation in the EU is primarily regulated by the Habitats Directive (92/443/EEC) (EU, 1992), which has protected around 14% of grassland areas as Natural Habitat Types of Community Interest. Many of these grasslands are included in the NATURA 2000 network. However, the effectiveness of NATURA 2000 varies across member states due to differences in conservation priorities, enforcement capacity, and financial support (Kati et al., 2015). Many designated sites lack effective management plans, limiting their ability to prevent biodiversity decline. In alignment with the Habitats Directive, the EU Biodiversity Strategy 2020 set ambitious targets to increase the area of biodiversity-rich landscapes under CAP-supported management (EU, 2011). However, these goals were only partially met, with CAP reforms proving insufficient in reversing biodiversity loss (Pe'er et al., 2014). To address these shortcomings, the Biodiversity Strategy 2030 proposes the legal protection of at least 30% of EU land area, including grassland habitats. However, researchers remain skeptical about the feasibility and effectiveness of enforcement, given persistent gaps in funding, oversight, and environmental monitoring (Rinaldi, 2021; Shipley et al., 2024).

Grassland restoration efforts are also gaining momentum in EU policies, particularly in the broader context of international conventions such as the Kunming-Montreal Global Biodiversity Framework, the United Nations (UN) Sustainable Development Goals or the UN Decade on Ecosystem Restoration. The recently enacted EU Nature Restoration Law (EU, 2022), for example, underscores the prioritization of restoring biodiversity- and carbon-relevant ecosystems, such as extensively managed grasslands, emphasizing their role in climate resilience and habitat protection. Nevertheless, the CAP continues to present a conflict of interest. While CAP supports grassland restoration in certain areas, it simultaneously promotes afforestation and bioenergy production, potentially resulting in the conversion of grassland habitats into forested or bioenergy landscapes (Burrascano et al., 2016). This misalignment between conservation and agricultural incentives complicates restoration efforts, reducing the effectiveness of EU biodiversity policies.

2.4 Grassland management

Translating conflicting policy objectives into effective grassland management presents a significant challenge. Managing grassland generally involves the removal of above-ground biomass as a critical ecological disturbance. The type, frequency, and intensity of biomass removal are thus fundamental variables shaping grassland dynamics with significant implications for either conservation or agricultural applications (Tälle et al., 2016). In Europe, this is traditionally achieved by mowing or grazing.

Mowing removes biomass uniformly at set times, making the timing of each mow a key factor in maintaining diverse species composition (Lepš, 2014). Low frequency and late-season mowing assists flowering plants to build a seed bank, though it may decrease forage quality due to lower palatability and nutrient content of mature grasses compared to young regrowth (Ignatavičius et al., 2013). In contrast, frequent and early-season mowing promotes higher-quality forage by favoring young, nutrient-rich regrowth but reduces plant species diversity by preventing certain species from completing their life cycle (Zechmeister et al., 2003). Heterogeneous inter-annual mowing regimes might enhance plant biodiversity by preventing the dominance of plant species adjusted to certain mowing times (Johansen et al., 2019). However, in production-focused systems, farmers often prioritize high-yielding grasses to optimize harvest and adjust their mow timing accordingly (Plantureux et al., 2005). Additionally, the height of the mow cut influences regrowth dynamics, with lower cuts resulting in greater biomass removal but potentially compromising the regenerative capacity of grasslands (Ignatavičius et al., 2013).

Grazing presents a more heterogeneous approach to biomass removal, with its ecological effects influenced by livestock species, stocking rate, and the duration of regrowth periods between grazing cycles. Documented effects of grazing include biomass consumption, trampling, nutrient cycling, and diverse mechanisms of seed dispersal (Wellstein et al., 2007). Dietary preferences among livestock and adaptive grazing schemes further increase complexity at microhabitat scales, fostering conditions favorable for diverse taxa (Rook and Tallowin, 2003; Schrautzer et al., 2016). However, intensive grazing produces short, dense swards that deplete seed resources, degrade forage quality, and reduce habitat suitability for invertebrates (Morris, 2000). Intensively managed grasslands may be subject to additional management practices, including organic and mineral fertilization, pesticides, anthelmintics, or melioration practices like water drainage or ploughing (Planteux et al., 2005).

Restoring degraded grasslands requires targeted management strategies aimed at enhancing biodiversity, ecosystem services, and habitat structures across multiple scales. Restoration efforts typically seek to reestablish a predefined reference condition that defines the desired ecological characteristics of a restored site. These reference conditions are often based on historical ecosystem states. However, determining which historical state serves as the ideal benchmark remains a conceptual and methodological challenge (Waldén, 2018). The shifting baseline syndrome, in which each generation perceives a progressively degraded state as the norm, complicates the selection of appropriate reference ecosystems, as does the reliance on outdated or incomplete monitoring data (Papworth et al., 2009). While historical conditions can offer valuable guidance, fully recreating past ecosystems is rarely feasible (or rather possible), as restoration processes may take centuries or even millennia to rebuild species richness, restore soil processes, and reestablish complex ecological interactions (Buisson et al., 2022). Moreover, environmental changes and socio-economic transformations impose additional constraints, making it increasingly difficult to replicate historical conditions within contemporary ecological and land-use contexts (Balázs, 2018).

Grassland restoration's success is heavily influenced by the initial degradation level and specific site conditions (Waldén et al., 2017). High levels of residual soil fertility and ongoing nutrient availability often limit improvements in biodiversity (Isselstein et al., 2005), making direct interventions, such as topsoil removal or mowing without fertilization, necessary (Schrautzer et al., 2009). Natural regeneration can be effective when degraded sites are located near intact habitats (Petermann and Buzhdygan, 2021), as they benefit from seed dispersal and recolonization. However, its effectiveness depends on habitat connectivity (Jakobsson et al., 2016) and often favors highly competitive species at the expense of rarer, stress-adapted plants, limiting

overall biodiversity recovery (Carboni et al., 2015). The introduction of native species through seed sowing can accelerate the return of target species, but its success is often constrained by the limited availability of high-quality seeds (Tölgyesi et al., 2022). An alternative approach is hay transfer, where seed-rich hay from biodiverse donor sites is used to rebuild species-rich seed banks while suppressing invasive weeds (Valkó et al., 2022). However, the success of hay transfer is highly dependent on the quality and quantity of the hay and the method of application. In abandoned sites, mechanical removal of shrubs and woody plants may be necessary to restore the open habitat conditions required by grassland species (Blair et al., 2014).

As restoration measures are typically carried out as projects with limited funds and time frame (Borgström et al., 2016; Pe'er et al., 2021), longterm restoration success ultimately depends on post-restoration management (Tölgyesi et al., 2022). Extensive grassland management practices are often cited as the best methods for maintaining restored grasslands, balancing ecological integrity and human use (Goret et al., 2021). However, in modern predominantly productivistic agriculture, these management practices are rarely profitable for farmers without subsidies, particularly when competing in a global market with less stringent agri-environmental regulations (Waldén and Lindborg, 2018). EU payments designed to promote sustainable grassland management, on the other hand, allow for a broad range of use intensity and simpler land use alternatives (Pe'er et al. (2019), see also Section 2.3). Restoration success, therefore, depend on securing willing participants who recognize the long-term benefits of sustainable grassland management despite short-term economic trade-offs.

However, several barriers hinder participation, as highlighted by Waldén and Lindborg (2018) or Bethge and Lakner (2023). Bureaucratic complexity often discourages engagement, as application processes for agri-environmental schemes can be costly and time-consuming. Many farmers lack adequate advisory support, with inconsistencies in policy guidance creating uncertainty about best management practices. Variability in enforcement further exacerbates the issue, as regional differences in subsidy conditions lead to unpredictability in compliance requirements. Additionally, farm succession issues present a major challenge, as many traditional grassland managers struggle to find successors, threatening the continuity of sustainable land use. Non-profit conservation organizations partly bridge this gap, as they are insulated from market pressures and can prioritize sustainable grassland management. However, their capacity remains limited, as they rely on external funding, grants, and volunteer participation. The scientific community urges to address these issues to consolidate already limited grassland restoration success long-term (Mahy et al., 2024), proposing major changes to the previously discussed conglomerate of environmental policies. These changes include increasing transparency, accountability and participation

through an evidence-based, result-oriented, stakeholder-inclusive policy design, while offering simple, expert-supported grassland management solutions at different scales (Pe'er et al., 2022).

2.5 Monitoring grasslands

A fundamental pillar to support these proposals is fit-for-purpose monitoring. Environmental monitoring involves the systematic collection and analysis of ecosystem data to assess changes over time (Lovett et al., 2007). It plays a crucial role in evaluating policy performance, enabling comparisons between actual outcomes and intended objectives (Perino et al., 2022), while generating valuable scientific insights that inform future policy reforms (Habel et al., 2013). In Europe, grassland monitoring is typically integrated into broader habitat, land-use, or agricultural assessments, forming part of the policies discussed in Section 2.3. These programs examine grassland characteristics and the factors shaping their development across multiple ecological scales, ranging from individual fields to Pan-European mapping initiatives (EEA and MNHN, 2014).

The complexity of ecological processes in grasslands necessitates a critical consideration of scale in monitoring program design and interpretation. Many of these processes are inherently scale-dependent, therefore, the perception of target variables varies with spatial extent and observational resolution (Field et al., 2009). Sampling size, method, and frequency directly influence detected patterns, shaping analytical outcomes and policy recommendations. Moreover, ecological processes rarely operate within a single scale but emerge from multi-scale interactions, necessitating an integrative approach (Thompson et al., 2018). Wu and Li (2009) identify six key scales in environmental monitoring: observation, modeling, operational, geographic, policy, and cartographic. The observation scale determines parameter granularity, influencing the detection of fine-scale patterns, while the modeling scale must align with the observation scale to enable accurate extrapolations. Operational scale reflects the spatial extent of ecological processes, such as species dispersal and habitat connectivity, whereas geographic scale dictates study coverage and data requirements. Policy scale governs conservation strategies at administrative levels and cartographic scale influences data visualization for decision-making.

The interactions between spatial and temporal scales is particularly relevant in environmental monitoring. Large-scale ecological processes unfold over extended timeframes, whereas localized biodiversity changes can occur within much shorter periods (Anderson, 2018). Furthermore, small-scale interactions often drive regional trends, creating feedback loops that must be accounted for in monitoring frameworks (Anderson, 2018). For instance,

grassland fragmentation at the local level contributes to biodiversity loss at broader landscape scales, while climate change reshapes species distributions at regional and global levels. Recognizing scale thresholds is also essential, as ecological processes tend to remain stable within a given range but may shift abruptly when dominant environmental drivers change (Wu and Li, 2009). Lastly, scale effects — where biodiversity metrics vary with measurement scale — pose a significant challenge. For example, species richness estimates can fluctuate dramatically depending on sampling resolution, potentially leading to inconsistencies in biodiversity assessments.

Regardless of scale, *in situ* methods form the primary approach for data collection in most European monitoring programs, such as in Sweden's National Inventory of Landscapes (Esseen, 2007), the Swiss Biodiversity Monitoring (Montgomery et al., 2014), and the Biotope Mapping Programs in Germany and the Czech Republic (EEA and MNHN, 2014). These programs typically assess target variables associated with management practices discussed in Section 2.4, including grassland type, land use, sward height, biomass, forage quality, phenology, productivity, species composition, landscape elements, and soil processes (Ali et al., 2016).

However, contemporary monitoring efforts face several challenges. The European monitoring landscape comprises numerous schemes, programs, agencies, and infrastructures (Liquete et al., 2024). Its actors often have overlapping geographic responsibilities, but lack coordination, with few actively seeking synergies despite sharing similar mandates. Additionally, new European and national directives continually increase the workload for monitoring actors (Jedicke et al., 2024). Subject reviews and expert workshops have identified key issues, including insufficient funding, personnel shortages, limited training opportunities, lack of transparency, data accessibility challenges, inconsistent reporting standards, technological inertia⁴ and methodological inconsistencies both between and within monitoring programs (European Court of Auditors, 2017; Pe'er et al., 2021; Moersberger et al., 2024).

Considering methodological issues, *in situ* monitoring suffers from a target-dependent trade-off between the area covered and the level of detail achieved. While *in situ* methods can provide detailed information on a small scale, they are time- and labor-intensive, inherently leading to scaling issues. Addressing these issues often compromises precision, comprehensiveness or the monitoring interval (Wijesingha, 2020). For example, Schoof et al. (2020) report infrequent and long monitoring intervals between 10 and 20 years and an incomprehensive dataset — both in terms of spatial coverage and the characterization of the target variable — for the German Biotope Mapping, in which grasslands are a major part of. Another issue presents the reliability

⁴Here, technological inertia refers to the resistance of those responsible for monitoring to adopt new technologies due to investments in the status quo, even when benefits exist.

of *in situ* data acquisition methods. While some *in situ* monitoring variables are approximated via calibrated measurement devices, others rely on simple expert judgement (European Environment Agency et al., 2015), often omitting quantitative uncertainty estimations, while making these variables subject to observer (Gotfryd and Hansell, 1985) or sampling bias (Hughes et al., 2021).

Overall, methodological and structural limitations hinder conventional monitoring to meet the diverse needs of grassland stakeholders who require comprehensive and timely data to guide decision-making processes (Morsberger et al., 2024). These insights are neither new nor exclusive to grassland monitoring. Indeed, they have been discussed for decades now in one form or another (e.g. Piechocki and Bundesamt für Naturschutz (2021); Jedicke et al. (2024)). This ongoing mismatch underscores the need for methodological advancements. In response to these challenges, the scientific community has proposed recommendations for developing fit-for-purpose monitoring systems that better align with contemporary policy and conservation needs. A recent contribution to this effort is the "*Proposal for an EU Biodiversity Observation Coordination Centre*" (Liquete et al., 2024), which outlines key strategies for improving environmental monitoring across Europe. Key points from the report include the following:

- Unify monitoring efforts by adopting a coordinated European-wide observation network and integrate data and metadata at national and EU levels
- Harmonize and enhance data gathering and sharing, with an emphasis on filling already identified monitoring gaps
- Overcome technological inertia and leverage novel and underutilized technologies to increase monitoring efficiency
- Increase funding and ensure a long-term perspective for monitoring programs, alongside cross-country and cross-sectoral coordination of resources
- Expand human resources, enhance support for citizen science, and encourage active stakeholder participation in the monitoring process

2.6 Remote sensing in grassland monitoring

RS offers a powerful toolkit that aligns with these recommendations. RS encompasses all techniques for obtaining information about the Earth's surface by measuring and interpreting its reflected or emitted electromagnetic radiation (Campbell and Wynne, 2011). The scientific literature frequently highlights its advantages including extensive spatial coverage, frequent data acquisition, data consistency, cost-effectiveness, scalability, non-invasiveness, and the ability to assess inaccessible areas (Nagendra et al., 2013; Wachen-dorf et al., 2018; Jongman et al., 2019). These advantages, combined with modern digital processing techniques, make RS particularly suitable for analyzing grasslands at scales unachievable by *in situ* methods alone. The increasing automation of RS data processing further enhances its utility, improving transparency, reproducibility, and efficiency in grassland monitoring.

2.6.1 Remote sensing principles

The effectiveness of RS originates from its unique approach to data acquisition. RS sensors measure electromagnetic radiation in specific intervals, i.e. bands, ranging from a few bands in multispectral or radar systems to hundreds in hyperspectral systems. Hereby, a distinction is made between passive, i.e. optical, RS, measuring natural radiation (e.g. solar), and active RS, measuring sensor-emitted radiation (e.g. Synthetic Aperture Radar (SAR)). Central to RS analysis is the concept of distinct spectral signatures of objects, which result from their wavelength-dependent reflection, emittance, and absorption properties (Campbell and Wynne, 2011). These signatures can be exploited to distinguish between objects or extract information about their physical, chemical, and structural properties.

For vegetation, several plant characteristics contribute to a distinct spectral response, as summarized by Campbell and Wynne (2011) and Cavender-Bares et al. (2022). Chlorophyll strongly absorbs visible light (400 – 700 nm) for photosynthesis, particularly in the blue and red wavelengths, resulting in a phenomenon referred to as the "Green Peak". In the near-infrared (NIR, 700 – 1400 nm) range, leaf reflectance is primarily influenced by the spongy mesophyll tissue. The cuticle and epidermis are largely transparent to NIR radiation to minimize heat absorption, resulting in significant internal scattering within the mesophyll and, consequently, high NIR reflectance. The transition from red to NIR reflectance, known as the "Red Edge", is characterized by an exceptionally sharp increase and serves as a key indicator of vegetation health and stress. Beyond the visible and NIR regions, plant water content significantly influences absorption in the shortwave infrared (SWIR, 1400 – 2500 nm) range. Water molecules exhibit distinct absorption features at 1450 and 1950 nm, while additional rotation-vibration interactions

cause a general increase in absorption from 1400 nm onward. This results in a characteristic decline in reflectance beyond the NIR plateau. Structural properties of leaves, including cellular composition and surface morphology, further impact scattering in the NIR and SWIR regions, affecting overall reflectance patterns.

Plant species have evolved distinct biochemical compositions and anatomical structures to optimize survival and growth under varying environmental conditions (Cavender-Bares et al., 2022). Canopy structure, influenced by growth strategies in response to climate and ecological disturbances, further modifies spectral reflectance. Variability among individual plants, populations, and evolutionary lineages reflects genetic and environmental differences, which are readily expressed in above-ground physiology, biochemistry, and structure (Cavender-Bares et al., 2022). Spectral reflectance measurements at the leaf and canopy levels can, in theory, capture these variations, enabling the assessment of vegetation properties on multiple scales. Practically, however, this poses several challenges. Spectral differentiation capabilities depend on sensor resolutions. A measured signal can only approximate the “true” spectral response, therefore important details might be lost, for example, to sensor noise. Additionally, grasslands are a combination of different species in different mixtures contributing unpredictably to the spectral signal at different scales (Schmidt et al., 2014). Consequently, many grassland types exhibit highly similar spectral signatures, increasing complexity in RS-based grassland monitoring (Rocchini et al., 2013). Addressing these issues strongly depend on the type of RS data (see Section 2.6.3) and methodology (see Section 2.6.4) employed.

2.6.2 Sensor platforms

Another notable benefit of RS is the variety of sensor platforms available. These platforms differ in altitude, mobility, operational scope, and length of use history, facilitating data acquisition across scales (see Table 2.1). For instance, satellite-mounted sensors have been in use for over 50 years⁵ (Wulder et al., 2019), providing global spatial and synoptic data at regular intervals, with resolutions ranging from tens of centimeters to several hundred meters. Conversely, drones serve as highly mobile and cost-effective sensor platforms, enabling on-demand data acquisition at unprecedented spatial resolutions on the field scale. While various drone types have been utilized for environmental applications since the 1990s, their popularity surged in the 2010s (Nowak et al., 2018) due to the convergence of key technologies, such as sensor miniaturization or battery performance. Higher-altitude airborne platforms, such as planes and helicopters, were once the primary sources of

⁵Although prior earth observation satellites existed, it was the Landsat program in 1972 that laid the foundation for modern RS of environment.

optical RS data, but their usage has declined with the advent of high-resolution satellite data (Mondello et al., 2011). Nevertheless, these platforms still play a crucial role in bridging intermediate spatial scales in RS analysis and serve as platforms for specialized sensors like Light Detection and Ranging (LiDAR).

Table 2.1: Overview typical sensor-platform configurations with main operational parameters, adapted from Toth and Józków (2016). Abbreviations: MS = Multispectral, HS = Hyperspectral, LiDAR = Light Detection and Ranging, SAR = Synthetic Aperture Radar

Parameter	Satellite	Airborne	Drone
Maneuverability	no/limited	moderate	high
Scale	global	regional	local
Sensor diversity	MS/HS/LiDAR/SAR	MS/HS/LiDAR/SAR	MS/HS/LiDAR/SAR
FOV	narrow	narrow to wide	narrow to wide
Repeat rate	days	hours	minutes
Spatial resolution	0.3 – 300 m	0.05 – 0.25 m	<0.01 – 0.05 cm
Spatial accuracy	1 – 3 m	0.05 – 0.1 m	0.01 – 0.25 m
Deployability	difficult	complex	easy
Observability	vertical/oblique	vertical/oblique	vertical/oblique/360°
Operational risk	moderate	high	low
Cost	very high ⁶	high	low

2.6.3 Remote sensing applications

Exploiting the variety of RS data, the scientific community has successfully employed RS techniques in grassland research, as documented by recent subject reviews (Reinermann et al., 2020; Soubry et al., 2021; Lyu et al., 2022; Masenyama et al., 2022; Wang et al., 2022b; Bangira et al., 2023; Lyu et al., 2024). Among RS data, optical data dominates grassland applications due to its interpretability and extensive historical datasets (Reinermann et al., 2020). Multispectral satellite imagery forms the foundation of RS-based grassland assessments and has been instrumental in global (Parente et al., 2024a) and continent-scale (EEA, 2020) mapping efforts. It enables evaluations of key characteristics at scale, including above-ground biomass (Kumar and Mutanga, 2017), vegetation health (Guo et al., 2005), grassland typology (Huber et al., 2023), and management practices such as mowing (Griffiths et al., 2020) and grazing (Numata et al., 2007). Commonly used

⁶Initiated by the democratization of Landsat data in 2008, the user costs for non-commercial satellite data is actually very low.

sensors include the Advanced Very High Resolution Radiometer (AVHRR), Moderate-Resolution Imaging Spectroradiometer (MODIS), Sentinel-2 (S2), as well as the Landsat and PlanetScope fleets.

Despite the advantages of multispectral satellite data, spatial and temporal resolution trade-offs pose challenges in monitoring time-dependent grassland variables. Sensors like MODIS provide frequent observations but at coarse spatial resolutions, making them unsuitable for assessments of small-parcelled European grasslands. Conversely, higher-resolution sensors have longer acquisition intervals, which, coupled with frequent cloud cover, leads to data gaps. While these challenges affect all satellite sensors, the increasing availability of multispectral missions offers potential solutions. Multi-satellite constellations carrying the same sensor, such as the twin S2 satellites, partially address this issue. PlanetScope's deployment of over 130 microsattellites takes this approach to the extreme, collecting global daily nadir imagery at high spatial resolution. However, intercalibration challenges affect data consistency (Frazier and Hemingway, 2021). Efforts to harmonize PlanetScope with S2 (e.g., Gašparović et al. (2018)) show promise, though their operational effectiveness remains under evaluation. Another approach is the fusion of large swath satellites, as demonstrated by the Harmonized Landsat-Sentinel-2 (HLS) dataset developed by National Aeronautics and Space Administration (NASA) and United States Geological Survey (Claverie et al., 2018), which achieves a revisit rate of 2–3 days at minimal additional cost.

Complementing satellite data, UAV-mounted sensors like the MicaSense Altum (MicaSense, 2020) and Parrot SEQUOIA (Parrot, 2017) enable hyperspatial analysis of multispectral imagery. In addition to previously discussed applications for multispectral data, this data acquisition method allows for sward height estimation (Forsmo et al., 2018), stocking rate monitoring (Ji et al., 2023), and detailed plot structure analysis (Cunliffe et al., 2016). Another application is plant species assessments. While airborne hyperspectral data has traditionally been used for this purpose, multispectral UAV imagery has recently gained traction as an alternative. Studies indicate that hyperspatial data can, to some extent, compensate for the limited spectral resolution in such assessments (e.g. Sulik and Long (2015); Horton et al. (2017); Carl et al. (2017)). A critical requirement for this approach is a distinct spectral response of the target plant species during the flowering period. However, the practical application of this principle remains underutilized. Most existing approaches have been developed within agricultural contexts, where flowering plants are evenly spaced, sufficiently separated, or surrounded by relatively homogeneous vegetation. Furthermore, applications have mostly been limited to flowering plants of agricultural relevance, such as rapeseed (*Brassica napus*). This constraint limits the direct transfer of such methods to complex grassland ecosystems, particularly HNV grass-

lands, which exhibit intricate structural and species diversity.

Despite the advantages of multispectral RS data, its spectral resolution ultimately limits the detection of subtle vegetation differences. Hyperspectral sensors, such as Hyperion, PROBA-1 CHRIS, and EnMAP, address this limitation by capturing near-continuous spectral information. These sensors enable detailed plant community-level assessments (Psomas et al., 2011), plant trait retrieval (Schucknecht et al., 2023), nutrient status evaluation (Singh et al., 2017), and degradation analysis (Lyu et al., 2020). UAV-based hyperspectral sensors, such as the Resonon Pika XC2 (Resonon, 2024) and HySpex Mjolnir (HySpex, 2024), extend these capabilities to site-specific, high-resolution applications, including chlorophyll content estimation (Zhang et al., 2023), grass quality assessment (Oliveira et al., 2019), crude protein quantification (Qi et al., 2025), and species-level composition analysis (Zhang et al., 2022).

However, hyperspectral RS poses several challenges, including band correlation, spectral mixing, and noise-related measurement degradation due to atmospheric effects (Bioucas-Dias et al., 2013). The high dimensionality of hyperspectral data necessitates dimensionality reduction techniques to mitigate information redundancy (Maxwell et al., 2018) and improve computational efficiency. Additionally, the computational demands of hyperspectral analysis require specialized expertise, software, and high-performance computing resources, impeding large-scale operational deployment. Another major limitation is cost. Hyperspectral sensors are significantly more expensive than their multispectral counterparts, restricting data acquisition frequency and accessibility for routine monitoring.

Beyond optical RS, SAR provides an alternative for overcoming atmospheric challenges, particularly cloud cover. SAR platforms, including TerraSAR-X and Sentinel-1, penetrate cloud obstructions and offer diverse acquisition modes through varying polarizations, incidence angles, and orbital directions. By analyzing backscatter signals, interferometry, or polarimetry, SAR enables the assessment of grassland height (Zhang and Ren, 2023), leaf area index (Crabbe et al., 2019), soil characteristics (El Hajj et al., 2016), surface roughness (Ullmann and Stauch, 2020), and dielectric properties (Hill et al., 1999). SAR also facilitates the detection of time-sensitive management practices, such as mowing events (Taravat et al., 2019). Recent advancements in SAR miniaturization enable UAV deployment, opening new possibilities such as scalable below-ground tomography (Góes et al., 2021). This technology holds significant potential for extending RS applications to below-ground biomass and carbon sequestration estimates, as well as monitoring root structures and soil porosity. Preliminary studies (e.g., Oré et al. (2023)) have demonstrated its capabilities for vegetation monitoring; however, its specific applications in grassland ecosystems remain unexplored to date.

Despite its strengths, SAR has notable limitations in grassland research (Ali et al., 2016). A major challenge lies in distinguishing vegetation-related backscatter from signals influenced by soil moisture and acquisition conditions. Weather factors, such as strong precipitation and wind, introduce further uncertainty. Additionally, SAR imagery is inherently affected by speckle noise, necessitating filtering techniques that may reduce spatial resolution. Extensive ground-based validation is often required to ensure accurate data interpretation, increasing implementation complexity and costs.

To address these limitations, some studies have integrated optical and SAR data, leveraging their complementary strengths. This approach has often been applied to detect time-sensitive management practices, such as mowing events (Reinermann et al., 2020). However, results remain mixed. While some studies report improved modeling performance (Lobert et al., 2021; De Vroey et al., 2022), others find no added value or even a decline in predictive performance (Reinermann et al., 2022). Optical RS performs well for known study sites and timeframes, whereas SAR data enhances transferability (Holtgrave et al., 2023). Challenges such as false-positive mowing detections (Reinermann et al., 2022) can be mitigated by integrating ancillary data, such as weather conditions (Dujakovic et al., 2025).

2.6.4 Methods of remote sensing

RS data and grassland variables exhibit complex interactions, necessitating diverse analytical methodologies to extract meaningful insights. Conventionally, pixels serve as the basic spatial entity, corresponding to a specific (yet arbitrary (Fisher, 1997)) area on the earth surface. Alternatively, Geographic Object-Based Image Analysis (GEOBIA) aggregates neighboring pixels into semantically meaningful objects, such as species patches (Lu and He, 2017) or shrubs (Hellesen and Matikainen, 2013), aiming to enhance explainability. Regardless of spatial representation, RS analysis generally follows two main approaches: (1) classification, which assigns objects to predefined categories, and (2) regression, which predicts continuous-valued attributes. A fundamental descriptor for both approaches, and a method of RS analysis itself, are vegetation indices (VIs). VIs are calculated as ratios of two or more sensor bands, highlighting specific patterns within a spectral response known to serve as proxy for biophysical parameters (Song et al., 2013). Numerous VIs exist, ranging from general-purpose indices to highly specialized formulations. Xue and Su (2017) provides a comprehensive overview on this regard. Some VIs, however, stand out due to their extensive usage, including the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973), the Enhanced Vegetation Index (EVI) (Huete, 1997), and the Soil-Adjusted Vegetation Index (SAVI) (Baret and Guyot, 1991). Each index offers distinct advantages, mitigating atmospheric, soil background, or structural effects.

Traditional statistical methods have long played an essential role in RS analysis, particularly in early land cover classification, predictive modeling, and trend analysis. Various techniques have been developed in these domains. Some of which remain integral to RS processing pipelines due to their robustness and explainability (Campbell and Wynne, 2011). For instance, Maximum Likelihood Classification has been widely used as a parametric approach that assigns pixels to land cover classes based on probability distributions. Linear regression models have been applied to estimate environmental parameters such as biomass accumulation and soil moisture levels. Bayesian methods introduce probabilistic reasoning, enhancing classification robustness by quantifying uncertainty.

Statistical approaches, however, struggle with high-dimensional, nonlinear relationships, which are more the norm than the exception in RS analysis. This issue has driven the adoption of more advanced machine learning approaches for RS analysis, in particular for complex applications such as grassland type classification or monitoring of grassland phenology. Algorithms such as Random Forest (RF) (Breiman, 2001), Support Vector Machines (Mammone et al., 2009) and eXtreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016), for example, have demonstrated superior performance in high-dimensional feature spaces. Recent advancements have introduced time-aware machine learning models, such as HIVE-COTE (Middlehurst et al., 2021), Proximity Forest (Lucas et al., 2019), and Rocket (Dempster et al., 2020), which explicitly incorporate temporal dependencies. Unlike conventional machine learning models that treat sequential observations as unordered descriptors, these approaches preserve temporal structure, potentially improving predictions for dynamic grassland monitoring tasks, such as mowing detections. However, their theoretical advantages require further empirical validation to determine whether their emphasis on temporal dependencies translates into performance gains (Dhariyal et al., 2023).

Deep learning represents a specialized branch of machine learning with significant implications for RS. Unlike traditional machine learning, which often relies on manual feature engineering, deep learning automates feature extraction from raw data. Convolutional Neural Networks (NN) (Kattenborn et al., 2021) have achieved high accuracy in image segmentation and land cover classification, while Recurrent NN (Lakhal et al., 2018) and Long Short-Term Memory (Russwurm and Korner, 2017) models have proven effective in analyzing time-series data, such as seasonal vegetation dynamics. More recent advances include Generative Adversarial Networks (Jozdani et al., 2022) for enhancing the spatial resolution of satellite imagery and Transformer models (Aleissae et al., 2023) for capturing long-range dependencies within spectral data.

Although machine learning techniques generally outperform traditional statistical methods, their increased predictive accuracy often comes at the expense of explainability. Deep learning models, in particular, employ hierarchical feature representations that obscure the underlying decision-making processes. This opacity has raised concerns regarding the reliability of machine learning models — an issue that has already gained prominence in fields such as healthcare or finance (Linardatos et al., 2021) and is becoming increasingly relevant in RS applications. Consequently, model explainability methods were developed. In the context of RS-based grassland assessment, explainability methods serve multiple purposes including the following:

- Validating model reasoning against ecological processes
- Utilize model reasoning to optimizing field campaigns for reference data collection
- Feature selection in high-dimensional datasets
- Assessing the effectiveness of analytical components independently
- Building trust with stakeholders unfamiliar with RS methodologies

Early explainability approaches generally calculated some form of feature importance. However, those approaches were largely limited to semi-explainable machine learning models like RF, which consist of inherently explainable decision trees. While these methods offer a broad indication of relative feature relevance within the training data, they are generally sensitive to feature order and high cardinality variables, limiting their robustness and transferability (Louppe, 2015). Over the past decade, methodological advancements have led to more sophisticated model-agnostic explainability techniques. A major milestone was Local Interpretable Model-Agnostic Explanations (LIME) (Ribeiro et al., 2016). LIME generates explanations for individual predictions by creating perturbed samples around an instance and fitting an interpretable model to approximate the black-box model's behavior locally. It highlights the most influential features for a specific prediction, making complex models more transparent. However, LIME suffers from high sensitivity to initial parameterization, resulting in potential instability (Garreau and von Luxburg, 2020).

SHapley Additive exPlanation (SHAP) values provide a more stable alternative for interpreting model outputs by distributing a model's predictions among its input features based on cooperative game theory principles (Lundberg and Lee, 2017). SHAP quantifies each feature's contribution by systematically comparing predictions with and without a given feature across all possible subsets. This dual capability provides both local explainability, i.e.

the individual contribution of features for each prediction instance, and global explainability i.e. the average contribution of feature across all instances. SHAP holds significant potential for RS analysis, where highly complex feature spaces already exhibit black-box characteristics, and machine learning models can help uncover obscure patterns. By enhancing model explainability, SHAP provides new perspectives on data insights. Although some researchers in the RS community have begun exploring SHAP's capabilities (e.g. Vega García and Aznarte (2020); Zhou et al. (2022b); Kawauchi and Fuse (2022); Huang et al. (2022); Lange et al. (2022a)), its broader implementation in the RS field remains limited. In particular, its application in grassland monitoring is still in its early stages, highlighting the need for further investigation into its adaptability and effectiveness in this niche domain.

Chapter 3

Area under investigation

The study area for this thesis is Schleswig-Holstein (SH), the northernmost federal state of Germany (see Figure 3.1). SH serves as a representative example for the contemporary grassland situation in Europe, as it features a diverse agricultural landscape, extensive grassland coverage, and faces pressures that are widely shared across Western and Central Europe. As a German federal state, SH is subject to both EU and national policies that shape grassland management. Consequently, grassland monitoring in SH aligns with EU reporting obligations and encounters challenges similar to those experienced by other member states.

3.1 Geographical and environmental characteristics of Schleswig-Holstein

SH is located on the Jutland Peninsula and forms part of the northwestern lowlands of Germany (Meynen and Schmithüsen, 1953). It belongs to both the Atlantic and Continental Biogeographic regions of Europe (EEA, 2002). Covering approximately 15,800 km² (Statistik Nord, 2022), SH accounts for around 4.5% of Germany's total landmass. The state's landscape is shaped by past glacial activity during the Saalian and Weichselian ice ages, resulting in a predominantly flat terrain with localized rolling hills (Böse et al., 2022). SH comprises of three natural regions (LLUR, 2019). The Western Marshlands extend the North Sea coast and consist of fertile, reclaimed marshlands protected from tidal inundation by dykes. The Geest is a transition zone between the marshlands and the uplands, characterized by nutrient-poor sandy soils, interspersed with small rivers and streams. The Eastern Uplands feature a more undulating landscape shaped by glacial processes, featuring diverse soils and numerous lakes.

SH is situated within the West Wind Zone, where its climate is primarily influenced by low-pressure systems from the North Atlantic, resulting in

29.1. Geographical and environmental characteristics of Schleswig-Holstein

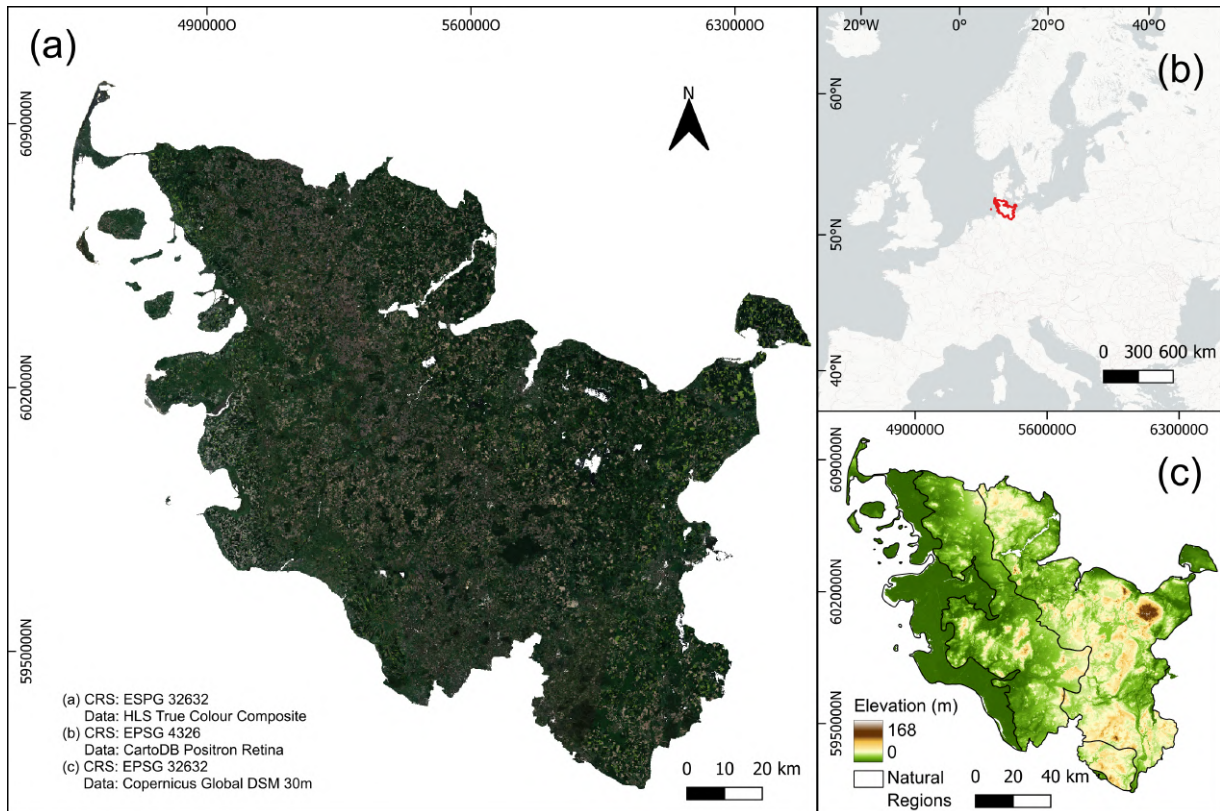


Figure 3.1: (a) Overview HLS true color composite study area; (b) Location study area in Europe; (c) Elevation study area and division by natural regions

generally unstable weather conditions throughout the year. The region experiences a temperate oceanic climate (Cfb in the Köppen-Geiger climate classification; Beck et al. (2018)), with moderate temperatures and relatively consistent precipitation. The average annual temperature for 1991 – 2020 is 9.3 °C, reflecting an increase of 0.7 °C compared to the 1961 – 1990 reference period (DWD, 2023). This rise in mean temperature has led to an extension of the vegetation period by 24 days (MELUND, 2021). Due to its coastal location, SH experiences high average annual wind speeds (geostrophic wind: 10.4 m/s) and frequent storms, ranging from 39 storm days per year in the Eastern Uplands to 105 along the North Sea coast (DWD, 2023). Overcast conditions are prevalent, particularly in winter, contributing to relatively low annual sunshine duration (1657 hours; DWD (2023)). A notable climatic gradient runs from northwest to southeast. The northwest, under stronger maritime influence, has milder temperatures and higher annual precipitation (800 – 900 mm), whereas the southeast exhibits more continental characteristics with cooler, drier conditions and annual precipitation ranging from 550 to 700 mm (LLUR, 2021).

3.2 Grasslands in Schleswig-Holstein

The environmental characteristics of SH have historically fostered diverse grassland ecosystems. However, since 1950, approximately 1,640 km² of grasslands have been lost, representing a 34% decline of the total area (Leuschner et al., 2014; MELUND, 2021). This decline aligns with broader European trends discussed in Section 2.3 but is also shaped by regional factors, including the transition from pasture-based to stall-based livestock management, the expansion of energy crop cultivation, extensive drainage, and land consolidation during the 1960s and 1970s (LLUR, 2020; MELUND, 2021). As of 2018, grasslands covered about 30% of SH's land area (approximately 4,900 km², CLMS (2018)), with 3,156 km² classified as permanent grassland (Statistik Nord, 2025). However, most of these areas are intensively managed, primarily for fodder production, favoring high-yield, non-flowering grasses with limited ecological value. Common management practices include early mowing (starting as early as April), frequent mowing cycles, grazing, fertilization, and pesticide application. Consequently, only 8.6% of SH's agricultural land (as of 2017) qualifies as HNV farmland (MELUND, 2019).

The conservation status of HNV grassland ecosystems in SH is critical. Both the most recent regional biotope map (also referred to as the regional habitat map in this thesis) and the 2019 FFH report highlight widespread deterioration. Nearly all Annex I-listed grassland habitats of the EU Habitats Directive are in unfavorable conditions, experiencing plant species loss of up to 66% (LLUR, 2020). A comparative analysis of the 1978 biotope map and recent surveys illustrates a substantial expansion of anthropogenic land use forms at the expense of semi-natural habitats, including species-rich grasslands, heathlands, dry and nutrient-poor grasslands, and fens (Lütt et al., 2022).

Grassland management in SH is governed by a complex regulatory framework encompassing European, federal, and state levels. EU legislation (discussed in Section 2.3) forms the legal basis for most national and state regulations governing grassland management. At the national level, the Federal Nature Conservation Act (BNatSchG, 2009) protects specific grassland habitats under biotope conservation regulations, prohibiting their destruction and limiting conversion for agricultural purposes (Schoof et al., 2020). Within NATURA 2000 sites and other designated conservation areas, further deterioration is legally limited, provided it conflicts with site-specific conservation objective. Additional federal regulations influencing grassland management include the Fertilization Ordinance (DüV, 2017), the Federal Soil Protection Act (BBodSchG, 1995), and the Federal Water Resources Act (WHG, 2009), among others.

At the state level, grassland management in SH is primarily governed by regional implementations of federal legislation, such as the State Nature Conservation Act (LNatSchG, 2010). Additionally, the state has enacted the Dauergrünlanderhaltungsgesetz (DGLG, 2013), a permanent grassland conservation law that restricts plowing (except for maintenance) and land conversion to maintain biodiversity and soil quality. A central pillar of SH's grassland conservation strategy is its agri-environmental and climate measures, co-financed through the CAP. These programs incentivize sustainable land management by providing financial support to farmers who comply with environmental standards. Key restrictions include bans on plowing, total herbicide application, increasing water drainage, and excessive soil disturbance, with grassland renewal permitted only if it does not damage the existing turf layer. Grassland conservation in SH operates under contractual nature conservation agreements between farmers and the state, directing funding to NATURA 2000 sites, nature reserves, and Annex IV-protected habitats. Restoration strategies vary according to grassland type, protection status, and baseline conditions but typically involve enhancing habitat suitability for target species, reducing management intensity, lowering nutrient input, and actively reintroducing native species (Lütt, 2009; Dolnik et al., 2020). Grassland monitoring in SH aligns with EU and national regulatory frameworks. Key monitoring programs include the six-yearly FFH area assessments, periodic biotope mapping, and federal HNV farmland monitoring conducted on a four-year cycle.

The EU Biodiversity Strategy 2030 has further integrated these efforts into SH's regional biodiversity initiatives (MELUND, 2021). This strategy establishes targets to curb biodiversity loss, including protecting 30% of terrestrial and marine areas (one third under strict conservation), substantial restoration of degraded and carbon-rich ecosystems, and aiming for favorable conditions for 30% of habitats and species previously in unfavorable conditions. These objectives translate into targeted grassland management and restoration measures, including reducing pesticides, preserving field margins, restoring biotopes, and reversing drainage practices. Conservation efforts promote extensive livestock farming, limit veterinary pharmaceutical use, re-wet low-intensity permanent grassland and support segetal flora restoration through partnerships with organic farms and landscape initiatives. These measures are coupled with compensations for farmers adhering to grassland management that contributes to biodiversity, climate, and environmental protection.

Chapter 4

Using drones to monitor broad-leaved orchids (*Dactylorhiza majalis*) in high nature value grassland

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Abstract

Dactylorhiza majalis is a threatened indicator species for the habitat quality of nutrient-poor grassland sites. Environmentalists utilize the species to validate the success of conservation efforts. Conventionally, plant surveys are field campaigns where the plant numbers are estimated and their spatial distribution is either approximated by GPS or labor-intensively measured by differential GPS. In this study, we propose a monitoring approach using multispectral drone-based data with a very high spatial resolution (~ 3 cm). We developed the Magenta Vegetation Index to enhance the spectral response of *Dactylorhiza majalis* in the drone data. We integrated the Magenta Vegetation Index in a Random Forest classification routine among other vegetation indices and analyzed feature impact on model decision-making using SHAP. We applied an image object-level median filter to the classification result to account for image artifacts. Finally, we aggregated the filtered result to individuals per square meter using an overlaying vector grid. The SHAP analysis showed that Magenta Vegetation Index had the highest impact on model decision-making. The Random Forest model could reliably classify

Dactylorhiza majalis in the drone data (F1 score: 0.99). We validated the drone-derived plant count using field mappings and achieved good results with an RMSE of 12 individuals per square meter, which is within the error margin stated by experts for a conventional plant survey. In addition to abundance, we revealed the comprehensive spatial distribution of the plants. The results indicate that drone surveys are a suitable alternative to conventional monitoring because they can aid in evaluating conservation efforts and optimizing site-specific management.

Keywords: biodiversity conservation; indicator species; remote sensing; western marsh orchid; random forest; vegetation index; high-resolution imagery

4.1 Introduction

Dactylorhiza majalis (DM) or broad-leaved marsh orchid is an indicator species for the habitat quality of nutrient-poor grassland sites. The species is widespread across Europe, and a significant portion of the population grows in Germany (Dullau et al., 2019b; Lohr et al., 2020). However, DM used to be far more common in Germany's grasslands in the 1950s. Conservationists have reported a strong decline in the national population for at least the past 20 years (Gregor and Saurwein, 2010; Messlinger et al., 2018; Dullau et al., 2019b). Due to the severe decline, the federal agency of nature conservation and all state agencies of nature conservation in Germany list DM on the Red List of species threatened with extinction (Lohr et al., 2020). Furthermore, central European countries have reported a similar decline in DM population, e.g., the Czech Republic (Wotavová et al., 2004) or Switzerland (Reinhard et al., 1991). Likewise, they list the species in their national or regional lists of species threatened with extinction.

The causes of decline are generally agreed upon; intensification of agriculture, water drainage, scrub encroachment due to habitat abandonment, and forestation negatively impact the habitat conditions (Wotavová et al., 2004; Gregor and Saurwein, 2010; Messlinger et al., 2018; Dullau et al., 2019b; Lohr et al., 2020). Conservationists have tried counteracting the population decline by restoring the species' original habitat conditions, but the success of the conservation measures remains to be seen. To support the conservation measures, regular monitoring of the population development is required. Conventional mapping approaches assess the population size in labor-intensive field campaigns where plants are counted manually (Gregor and Saurwein, 2010) or the population size is estimated by extrapolation from small samples (Messlinger et al., 2018). These approaches, however, become infeasible and increasingly error-prone with increasing size and in-

accessibility of the study site. The aforementioned problems may additionally limit the surveyor's ability to accurately describe the spatial distribution of orchids during monitoring, which is valuable insight into whether conservation measures are successful.

Remote sensing techniques, however, can cope with these scaling problems (Pettorelli et al., 2014). Moreover, previous studies reported promising results in detecting spectrally distinguishable flowers using remote sensing techniques. For example, the authors of Horton et al. (2017) applied a threshold image segmentation on multispectral imagery to detect peach blossoms. The authors of Fang et al. (2016) developed a support vector machine classification-based approach to estimate vegetation fraction and flower fraction in oilseed rape from multispectral imagery. The authors of Abdel-Rahman et al. (2015) demonstrated how to combine hyperspectral data and a Random Forest (RF) classification to gain knowledge on the flower cycle and spatial abundance of flowering plants in the context of a bee health study. During flowering between the beginning of May and mid-July, DM also builds an inflorescence with magenta-colored flowers. This spectrally prominent feature may be a basis for remote-sensing-based monitoring.

Some studies used satellite (Hassan et al., 2015; Sulik and Long, 2015) or airborne data (Abdel-Rahman et al., 2015; Landmann et al., 2015) to identify flowers; the majority, however, utilized drone imagery (Horton et al., 2017; Fang et al., 2016; Carl et al., 2017; Roosjen et al., 2016; Severtson et al., 2016; Valente et al., 2020), since drones can provide data with a very high spatial resolution. This kind of data allows identifying small vegetation structures such as flowers or flower heads (Carl et al., 2017). There is, however, a lack of vegetation indices to detect magenta-colored flowers. To identify DM, we focused on the unique spectral response of the flower color which interferes with the concept of conventional vegetation indices. Multiple studies observed decreased values of indices such as the normalized difference vegetation index (NDVI) or the enhanced vegetation index (EVI) when colored flowers were prominently present in remote sensing data (Sulik and Long, 2015; Shen et al., 2009, 2010; Verma et al., 2002). The flower colors increase the reflectance in the red wavelengths, which in return decreases the value of all near-infrared (NIR)/red ratio-based vegetation indices. Over the last decade, multiple studies incorporated this characteristic to detect flowers (Horton et al., 2017; Fang et al., 2016); moreover, some studies designed new indices to detect specific flower colors (Sulik and Long, 2015; Chen et al., 2019). We, therefore, propose a new vegetation index called the magenta vegetation index (MaVI) that enhances the spectral characteristics of magenta-colored flowers. However, a magenta flower color is not a unique characteristic among flowering plants. Although the index was developed for DM, it is reasonable to assume that the MaVI can also be used for species

with similar flower color, e.g., *Lythrum salicaria* or *Dactylorhiza incarnata*. On the one hand, this implies a certain flexibility and multiple uses of the MaVI. On the other hand, a potential cooccurrence of flowers with similar color may lead to ambiguous results. For this study, however, local conservationists confirmed that DM was the only magenta-colored plant species in the study site during the drone flight.

Given the need to regularly monitor DM while the resources for nature conservation are limited and the lack of a specialized remote sensing toolbox, we present a drone-based monitoring approach that aims to fill this gap. With this approach, we aim to estimate the population size and assess the spatial abundance of DM using multispectral, very-high-spatial-resolution drone data (3.4 cm pixel size). We acquired the data during the flowering phase of DM to map individual inflorescences. In this paper, we provide the methodological framework and evaluate our approach in comparison to conventional in-situ monitoring. The specific objectives of this case study were to (1) determine highly predictive features to identify DM, (2) evaluate the predictive performance of the MaVI, (3) quantify the accuracy of a drone-based plant count in comparison to conventional DM monitoring, and (4) demonstrate a practical way to bridge the gap between remote sensing and ecological applications.

4.2 Materials and Methods

4.2.1 Study Site

We conducted this study in the Lehmkuhlen reservoir (Figure 4.1), an alkaline, nutrient-poor fen in the uplands of Schleswig-Holstein (SH), Germany, which reported the biggest statewide DM population (Seer and Schrautzer, 2014). As a part of the uplands of SH, the Lehmkuhlen reservoir was formed during the Weichselian ice age (Schrautzer and Trepel, 2014). At that time, the area originated as a lake but transitioned into a fen over time. Since the 1950s, parts of the Lehmkuhlen reservoir transformed into a forest fen. With an area of 0.29 km², it is a small but species-rich area, where 60 plant species threatened with extinction including DM are reported (Seer and Schrautzer, 2014; Schrautzer and Trepel, 2014). The Lehmkuhlen reservoir, therefore, is protected by the European habitat directive due to the occurrence of alkaline fens (NATURA 2000 code: FFH 7230) and transition mires (NATURA 2000 code: FFH 7140) (MELUND, 2016). Due to the ecological importance of the area, conservation measures are conducted to preserve the rare habitat conditions (MELUND, 2016). In 2011, parts of the forest were removed to increase the development potential of endangered plant species. To prevent scrub encroachment in the open fen and retain favor-



Figure 4.1: (a) Overview of the Lehmkuhlen reservoir; (b) location of the study area in Germany; (c) photograph illustrating the abundance of *Dactylorhiza majalis* during drone flight; (d) close-up picture of a *Dactylorhiza majalis* inflorescence.

able conditions for competitively weak plant species, conservationists mow the area once a year.

4.2.2 Data (Pre-)Processing and Analysis

Figure 4.2 illustrates the methodological workflow of this study, which is divided into data acquisition, preprocessing, processing, aggregation, and validation. Data acquisition includes drone flight and field mapping. The preprocessing covers exploratory data analysis, subsequent feature engineering, and the creation of a reference dataset for model training and validation. During processing, we trained an RF classifier and evaluated feature importance and interactions; we further removed redundant or non-predictive features from the training dataset, retrained the model with the best-performing set of features, and applied the retrained classifier to the drone dataset before we assessed the accuracy of the classification results. In the following aggregation, we polygonized classified pixel clusters (i.e., pixels of the same

class in direct proximity) to vector image objects and applied an object-level filtering approach to remove invalid pixels from the subsequent inflorescence count. We assessed the accuracy of the remote-sensing-derived plant count by comparison with our field mapping results. In a final step, the resulting inflorescences were summed up to individuals per square meter in a Universal Transverse Mercator coordinate system.

4.2.3 Drone Data

Aerial images were taken during the flowering phase of DM on 6 July 2021, using a Wingtra One drone (Wingtra AG, 2021). The weather during the flight was calm and consistently overcast. The overcast weather ensured a stable source of illumination during flight, thereby limiting the spectral variability between different images. The drone was equipped with a MicaSense Altum multispectral camera with spectral bands in the blue, green, red, red-edge, and near-infrared regions (refer to (MicaSense, Inc., 2020) for band designation). The camera had a focal length of 8 mm and a field of view of $48^\circ \times 37^\circ$. Each band captured data with 3.2 megapixels resulting in an image size of 2046×1544 pixels. The mean flight altitude was 150 m. Flight planning and configuration were conducted using the proprietary mission control software WingtraPilot. The raw image data were processed to surface reflectance with the Pix4D mapper software version 4.6.4 by the commissioned company. In total, 3695 images were processed to a single orthomosaic with a spatial resolution of 3.4 cm.

4.2.4 In Situ Data

On the day of the drone flight, we conducted in situ measurements to collect validation data for the remote sensing plant count. The in situ plant counts followed an established methodology in ecology (Dullau et al., 2019b; Tremp, 2005), i.e., we used a 1 m^2 frame, placed it randomly in the study site, and counted all plants of the target species within the square twice. We then took a top-down photo for reference and defined the center location of the square using a Global Positioning System (GPS) device (Garmin fenix 5). In total, we performed 10 in situ plant counts at the study site. Additionally, we measured the inflorescence diameter of some randomly selected plants to approximate the average spatial coverage of a DM inflorescence. This measure was used for comparison with the spatial resolution of the drone data. The measurements showed that the average inflorescence diameter of DM was approximately equal to or slightly smaller than the spatial resolution of the drone dataset.

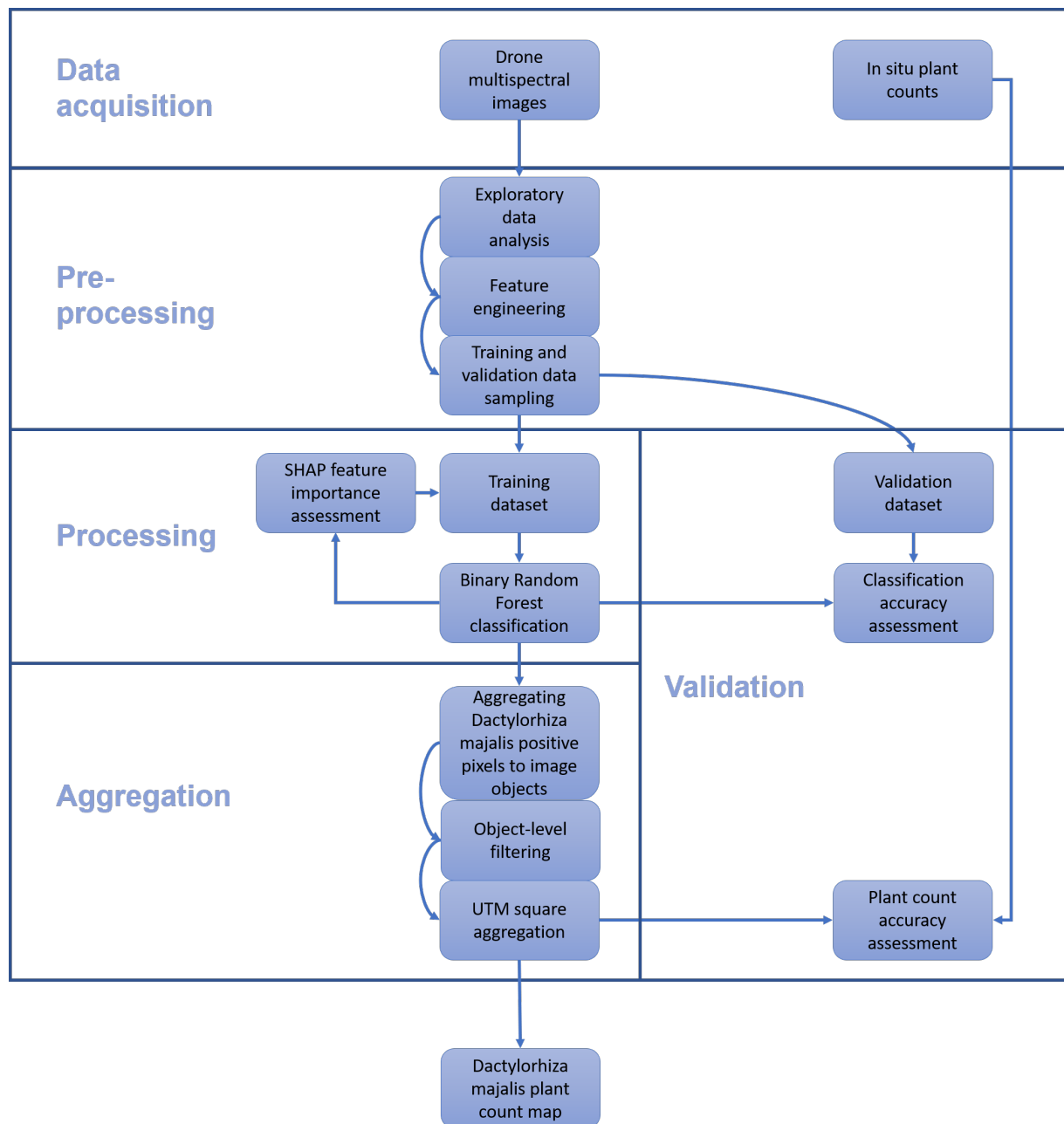


Figure 4.2: Methodological workflow of this study: from data acquisition to mapping result.

4.2.5 Labeling a Reference Dataset for Model Training and Validation

To identify DM, we created a reference dataset containing a DM-positive and a DM-negative class by applying a split sampling strategy. For the DM-positive class, we selected 2000 pixels on the basis of a visual inspection of the drone data. For the DM-negative class, we applied a pseudo-random sampling approach recommended by Maxwell et al. (2018). We undersampled the DM negative class since it made up the majority of the pixels. We used the QGIS “random points in extent” function to randomly select 2000 points in the study site and subsequently sample the underlying pixel values. We manually labeled these pixels by visual interpretation and removed all DM-positive pixels. The missing pixels were iteratively replaced by new randomly selected pixels until all pixels belonged to the DM-negative class. In summary, the reference dataset was balanced and consisted of 4000 pixels (2000 pixels for each class). Subsequently, we split the reference dataset into a training and holdout dataset for model training and independent evaluation (refer to Section 2.7).

Within the scope of image classification, a pixel can hold different values, i.e., features. In this study, the list of features included the spectral reflectances of the available drone bands and a series of vegetation indices we calculated for the subsequent analysis (see Table 4.1). All vegetation indices incorporated in the subsequent RF classification routine except for the MaVI are listed in Table 4.1. We describe the ideas and implementation of the MaVI in detail in the next section.

4.2.6 Magenta Vegetation Index—Main Ideas and Practical Implementation

We analyzed the spectral signatures of different land-cover types in the Lehmkuhlen reservoir to identify spectral characteristics of magenta-colored vegetation (Figure 4.3). We found that magenta-colored flowers tended to have relatively high reflectance values in the blue and red bands, while green vegetation showed the characteristic green peak. We identified the highest potential to differentiate magenta-colored vegetation, soil and water in the NIR. The reflectance spectra of the shallow and muddy water puddles remained approximately constant between 3% and 4% over the entire spectrum. Vegetation showed a sharp increase in reflectance from the red to NIR, while the reflectance curve of bare soil steadily increased with increasing wavelength.

Table 4.1: Vegetation indices considered for this study's RF classification. Abbreviations: B = blue band; G = green band; R = red band; NIR = near-infrared band.

Vegetation Index	Formula	Reference
Atmospherically resistant vegetation index (ARVI)	$ARVI = \frac{NIR - R - y(R - B)}{NIR + R - y(R - B)}$ $y = 1$	(Kaufman and Tanre, 1992)
Adjusted transformed soil-adjusted vegetation index (ATSAVI)	$ATSAVI = a \frac{NIR - a \times R - b}{a \times NIR + R - a \times b + X(1 + a^2)}$ $a = 1.22, X = 0.08, b = 0.03$	(Baret and Guyot, 1991)
Blue-wide dynamic range vegetation index (BWDRVI)	$BWDRVI = \frac{0.1NIR - B}{0.1NIR + B}$	(Hancock and Dougherty, 2007)
Chlorophyll vegetation index (CVI)	$CVI = NIR \frac{R}{G^2}$	(Vincini et al., 2008)
Enhanced bloom index (EBI)	$EBI = \frac{R + G + B}{\frac{G}{B} \times (R - B + \varepsilon)}$ $\varepsilon = 1$	(Chen et al., 2019)
Enhanced vegetation index (EVI)	$EVI = 2.5 \frac{NIR - R}{(NIR + 6R - 7.5B) + 1}$	(Huete et al., 1999)
Green atmospherically resistant vegetation index (GARI)	$GARI = \frac{NIR - (G - (B - R))}{NIR - (G + (B - R))}$	(Gitelson et al., 1996)
Green-blue normalized difference vegetation index (GBNDVI)	$GBNDVI = \frac{NIR - (G + B)}{NIR + (G + B)}$	(Wang et al., 2007)
Green-red normalized difference vegetation index (GRNDVI)	$GRNDVI = \frac{NIR - (G + R)}{NIR + (G + R)}$	(Wang et al., 2007)
Green-red vegetation index (GRVI)	$GRVI = \frac{G - R}{G + R}$	(Motohka et al., 2010)
Normalized difference vegetation index (NDVI)	$NDVI = \frac{NIR - R}{NIR + R}$	(Rouse et al., 1973)
Renormalized difference vegetation index (RDVI)	$RDVI = \frac{NIR - R}{(NIR + R)^2}$	(Roujean and Breon, 1995)
Soil and atmospherically resistant vegetation index (SARVI)	$SARVI = (1 + L) \frac{NIR - (R - y \times (B - R))}{NIR + (R - y \times (B - R)) + L}$ $L = 0.5, y = 1$	(Baret and Guyot, 1991)
Soil-adjusted vegetation index (SAVI)	$SAVI = \frac{NIR - R}{NIR + R + L} \text{ times } (1 + L)$ $L = 0.5$	(Baret and Guyot, 1991)
Transformed soil-adjusted vegetation index (TSAVI)	$TSAVI = \frac{s(NIR - s \times R - a)}{a \times NIR + R - a \times s + X \times (1 + s^2)}$ $s = 0.33, a = 0.5, X = 1.5$	(Baret and Guyot, 1991)
Wide dynamic range vegetation index (WDRVI)	$WDRVI = \frac{0.1NIR - R}{0.1NIR + R}$	(Gitelson, 2004)

We, therefore, propose the Magenta Vegetation Index (MaVI) as follows:

$$\text{MaVI} = \frac{B + R - G}{B + G + R} \times \left(1 - \frac{B + G + R}{\text{NIR}} \times \left(\frac{\text{NIR}}{R} \times \text{NIR}\right)\right) \quad (4.1)$$

where B, G, R, and NIR are the spectral bands of the sensor in the blue, green, red, and NIR regions of the electromagnetic spectrum. The idea of the index is based on the portion of magenta (defined as the sum of the reflectance values of the blue and red bands) in the visible (VIS) bands. By subtracting the reflectance in the green band from the magenta value, the first term forces pixels with a pronounced green peak to be negative. The spectral response of soil and water surfaces, however, might result in similar positive index values as magenta flowers since the ratios of VIS bands are comparable. To increase the separability, we introduced two scaling factors. By subtracting the VIS/NIR ratio from 1, MaVI values of water surfaces become negative. Bare soil and magenta-colored flowers are both scaled down by the first scaling factor, but the scaling effect is more pronounced for soil surfaces since its VIS/NIR ratio results in higher values compared to the magenta flowers. The second scaling factor highlights the red edge of vegetation scaled by its NIR reflectance.

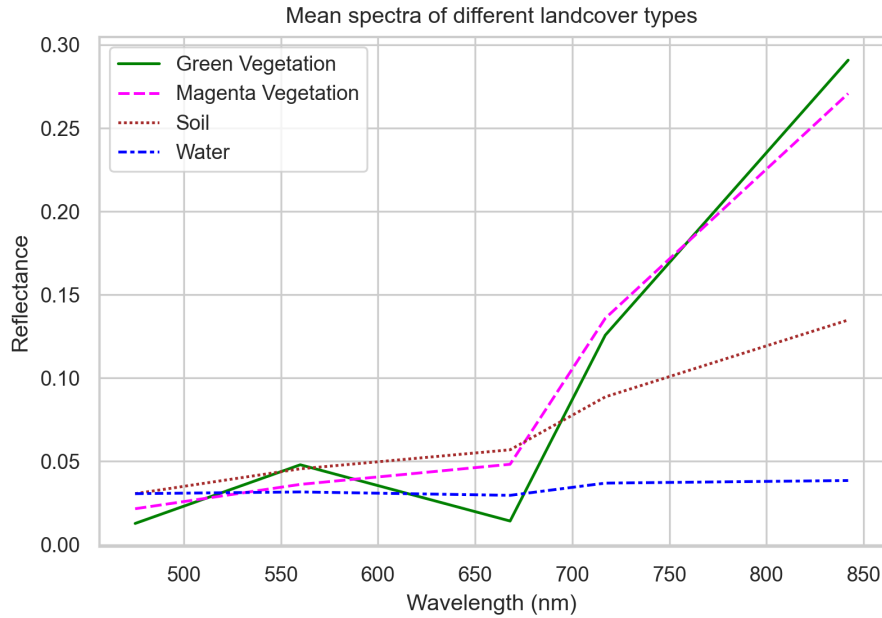


Figure 4.3: Mean spectra of different land-cover types from the drone dataset.

4.2.7 Random Forest Classification

RF is an ensemble classifier proposed by Breiman (2001) that combines the prediction of multiple decision trees via a majority vote to a single class assignment. For this study, we utilized scikit learn's implementation of an RF classifier (Pedregosa et al., 2012). We partly adopted the suggested set of parameters for an RF model by Belgiu and Drăguț (2016). We set the number of decision trees in the forest ($n = 500$) and the maximum number of features to consider when splitting a node to the square root of the total number of features available ($\max_{\text{all}} \approx 5$; $\max_{\text{selected}} \approx 3$). To prevent overfitting and reduce computational time, we set the maximum depth of a decision tree to 5 as a model constraint. For model training, we randomly split the reference dataset into a training (50%) and holdout dataset (50%), applied a fivefold cross-validation scheme on the training dataset, and performed the accuracy assessment on the validation dataset using accuracy metrics derived from a confusion matrix such as precision, recall, and F1-score. We further performed a qualitative validation by visually comparing the classification results and the original drone dataset.

4.2.8 Feature Selection and Model Interpretation

In this study, we employed the concept of SHAP (Shapley additive explanations) values to fairly quantify the contribution of a feature to model predictions (Lundberg and Lee, 2017). Using SHAP, we assessed the predictive capabilities of the given features to classify magenta-colored flowers (i.e., DM). The concept behind SHAP originated from Lloyd Shapley's work on game theory (Shapley, 1953) to assess the contribution of individual players, i.e., the dataset features, to a cooperative game, i.e., the model prediction. For the classification of each pixel (i.e., the model prediction), the marginal contribution of a feature (i.e., the SHAP value) is calculated by the weighted average of changes in model predictions for all possible feature permutations of a given dataset. We utilized the TreeExplainer (Lundberg et al., 2020) of the SHAP Python package to estimate the SHAP values of our model predictions. The model "payout" was the probability that a pixel was assigned to the DM-positive class. Using the classification test dataset, we created a SHAP beeswarm plot to visualize the global feature importance and to relate the importance ranking to the distribution of a feature. Based on this analysis we removed non-predictive features from the training data and retrained the RF model with the reduced dataset. After retraining, the model underwent a final classification accuracy assessment as described in the previous section. With the differences in accuracy measures before and after feature selection, we assessed the effect of the feature selection on the quality of the classification. Additionally, we created a change detection raster to quantita-

tively derive and visualize the changes in pixel class assignments due to the feature selection.

4.2.9 Remote Sensing Plant Count Methodology

The goal of our study was to develop a remote-sensing-based DM mapping with results comparable to conventional field mappings, i.e., the number of plants per unit area. For this, we used a zonal statistics utility of pixel count per unit area, i.e., 1 m^2 . To define the areal ratio between a DM inflorescence and a single image pixel, we assumed that one classified DM positive pixel represented one DM inflorescence (see Section 2.4).

We designed two separate zonal statistic aggregations: one for assessing the accuracy of the remote sensing plant count and another as a proposal for a remote sensing product for practical DM monitoring. For assessing the remote sensing plant count accuracy, we created a square buffer with a side length of 1 m around each GPS-logged in situ plant count (subsequently named the reference squares). We then counted all pixels classified as DM-positive in different counting settings, which we applied to optimize the remote sensing plant count against the in situ plant counts. The baseline setting simply counted all DM-positive pixels in each reference square. In all other counting settings, we applied a three-step filter approach with alternating thresholds before the remote sensing plant count. The filter approach was structured as follows:

1. Polygonize DM positive pixel clusters (i.e., neighboring pixels) to vector image objects;
2. Calculate a filter threshold for each image object on the basis of the most descriptive feature of the image classification;
3. Remove all pixels below the threshold from the remote sensing plant count.

We tested different filter thresholds by calculating object-level percentiles in 10% steps starting at the 10% percentile and ending at the 90% percentile. Additionally, we tested the object-level mean as a filter. The quality of the remote sensing plant counts was determined by calculating the root-mean-square error (RMSE) between the remote sensing plant counts and the in situ plant counts. The best counting setting was defined by the smallest error value.

For practical DM monitoring, we applied a spatial aggregation approach. Contrary to the randomly chosen reference squares of our field campaign, we created a Universal Transverse Mercator polygon grid (EPSG: 32632) overlaying the study site, with the size of each grid cell being 1 m^2 . The plant

counting process remained the same as for the best remote sensing plant count counting setting.

4.3 Results

4.3.1 Ambiguity in the Drone Dataset

Difficulties arose during image interpretation as identifying the DM-positive class was shown to be ambiguous in some cases (Figure 4.4). Although, in theory, the inflorescence area of the target species is equal to or smaller than the spatial resolution of the drone dataset, in practice, multiple neighboring pixels may appear magenta-colored. Several factors may be responsible for this phenomenon:

- Mixed pixel phenomena, due to (1) a DM individual located at the common boundary of multiple pixels, (2) multiple DM individuals in direct proximity and partly occupy multiple neighboring pixels, or (3) DM individuals which did not grow perfectly straight and, therefore, appeared in neighboring pixels;
- Adjacency effects, i.e., the magenta flowers spectrally superimpose the neighboring pixels;
- Motion blur caused by camera movement during exposure;
- Keystone effect of the camera, which may cause a slight cross-track displacement.

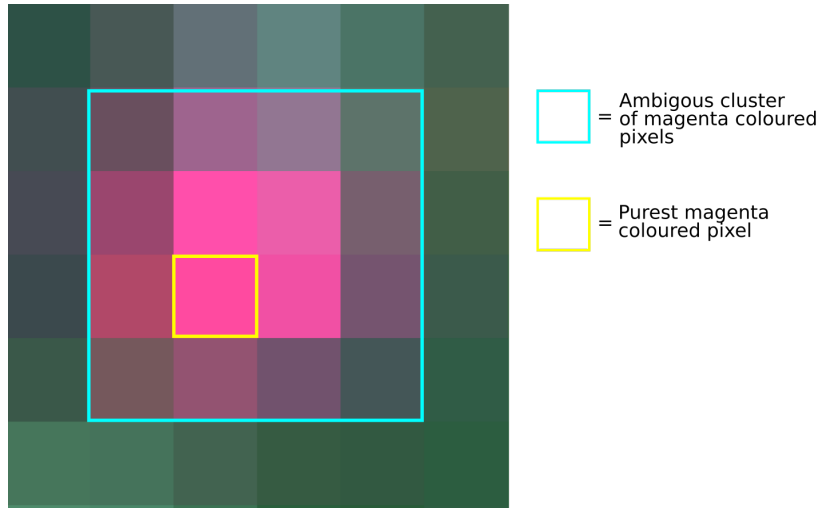


Figure 4.4: True color band combination illustrating the ambiguity problem. A common case in the dataset, where we could not unambiguously identify the most likely pixel representing a *Dactylohriza majalis* individual.

Since we had no details about the camera calibration and were missing flight details of the drone survey, an in-depth discussion about potential influence factors seemed to be of limited use. We, therefore, decided to cope with the present data quality, which may lead to misclassification (Guo et al., 2012; Stehman, 2009). To minimize the number of false-positive labeled pixels in the reference data, we only used the purest magenta-colored pixel of a pixel cluster (i.e., the pixel with the highest surface reflectance in the blue and red bands). We assumed that these pixels most likely represented a DM individual. In contrast to the effect on false-positive labeling, the ambiguity problem is a minor advantage for avoiding false-negative labeling in the reference data. A pixel cluster clearly indicates the presence of magenta-colored vegetation; in contrast to pixel-based classifications, false negative labeling, therefore, is unlikely. For the DM-positive class, the reference dataset represented a characteristic value range of the data features, and some ambiguous pixels would most likely fall within these characteristic value ranges since pixels affected by the ambiguity problem still represented the underlying band relationship of magenta-colored vegetation.

4.3.2 Classification Results before Feature Selection

The accuracy assessment of the classification before the feature selection resulted in very high accuracy scores on the holdout dataset. We can report a precision score of 0.99, a recall score of 0.99, and an F1-score of 0.99. The accuracy scores suggest a nearly perfect differentiation of DM-positive and DM-negative classes. However, the high accuracy scores may be in-

flated due to this study's sampling design. The sampling design for creating a labeled reference dataset, from which we derived the holdout dataset, was partially probabilistic and partially systematic, which may have inflated accuracy scores due to sample selection bias (Stehman, 2009; Waldner, 2020). Moreover, the methodological drawback might harm the generalization potential of the accuracy assessment, since the holdout dataset does not necessarily represent the distribution of the underlying population (Waldner, 2020). A coping strategy for the latter would have been to add more labeled pixels to the reference dataset. However, we avoided implementing this strategy since the ambiguity problem limited our labeling capabilities. Additionally, adding more reference data would not have solved the sample selection bias problem, but may have even worsened it. For the quality assessment, however, we suggest that the limitations of the accuracy assessment played a minor role.

Due to the limitations of the quantitative accuracy assessment, the qualitative accuracy assessment became more important. The visual comparison suggested a noticeably good performance of the RF model (Figure 4.5). Other than some rare outliers, magenta-colored pixels were reliably assigned to the DM-positive class. However, the results show that the classifier suffered from the ambiguity problem. Although the model was able to correctly assign the negative DM class to edge pixels of ambiguous pixels clusters, the class assignment appeared to be inconsistent.

In addition to the abovementioned restrictions, we identified leafless tree branches as a source of systematic false assignments of the DM-positive class. Spectra of tree branches showed similar reflectance curves to DM spectra with an almost constant reflectance level in the VIS; the reflectance in the NIR showed a similar steep increase in DM spectra. The high spectral similarities explain the misclassification.

4.3.3 Feature Selection and Predictive Performance of the MaVI

The feature with the highest impact was the MaVI (Figure 4.6). For the RF model, the highest MaVI values corresponded to an increased probability of assigning the DM-positive class to a pixel. Furthermore, the small variation around 0 demonstrates the high impact of the MaVI for almost all model predictions. The MaVI's high position in the feature importance ranking and the consistently high impact on model predictions support our hypothesis on the MaVI's capabilities to detect magenta-colored vegetation.

In addition to the MaVI, all features up to rank 7 showed an observable impact on the RF model to increase its predictive power (index abbreviations are listed in 4.1), i.e., CVI, the red band, the NIR band, the red-edge band, the GARI, and the SAVI. High reflectances in the NIR, red-edge, and

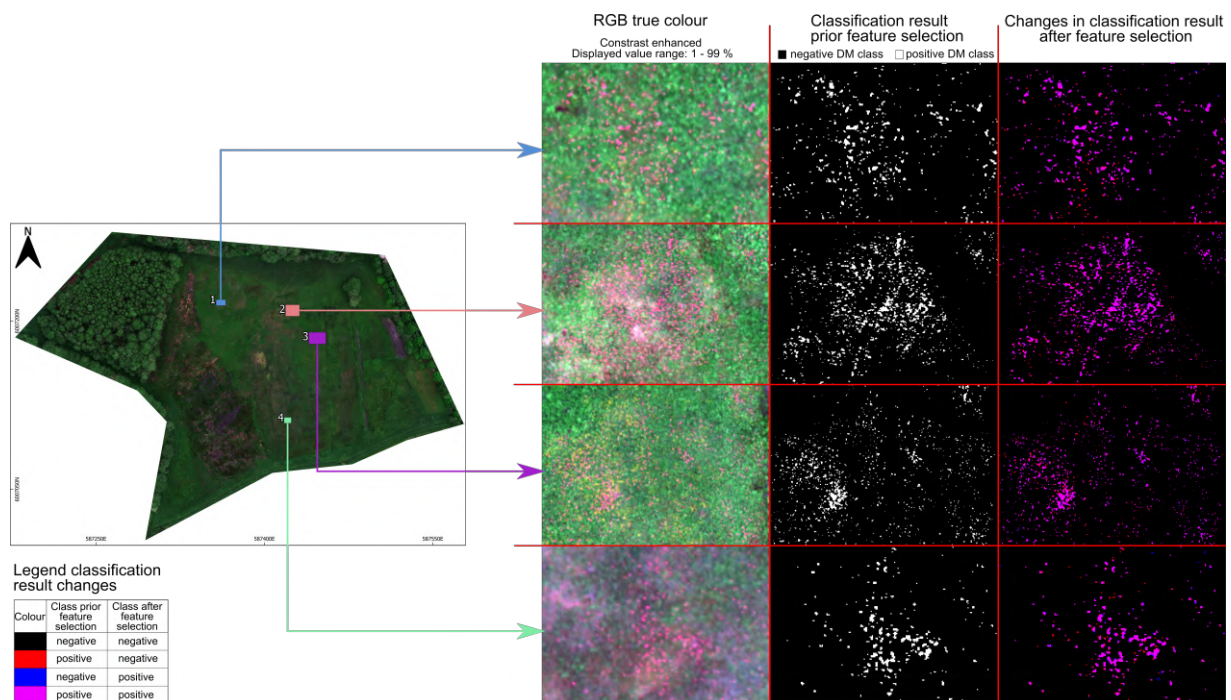


Figure 4.5: Comparison between the true color image and the RF classification results before and after feature selection. The figure illustrates the reliable performance of the classifier to identify magenta-colored vegetation. The figure additionally illustrates the change in classification results due to the SHAP value feature selection.

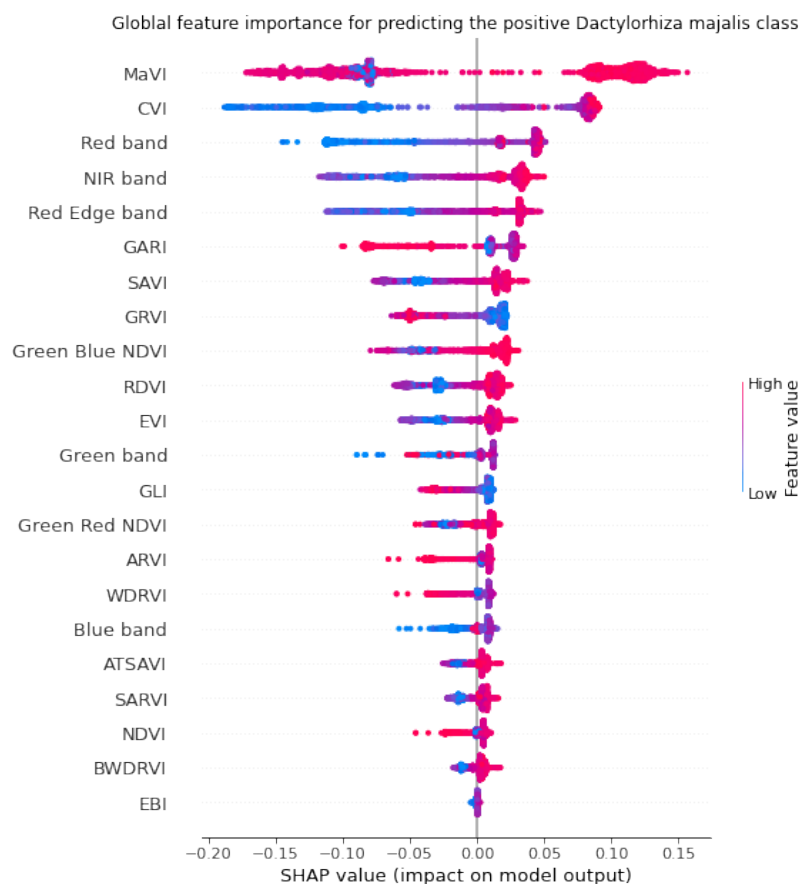


Figure 4.6: Overall feature importance for predicting the *Dactylorhiza majalis*-positive class. Note that the MaVI value range is skewed toward high negative values, whereas the continuous color scale of the beeswarm plot also colors negative high impact values in a shade of red. Index abbreviations are listed in Table 4.1.

red bands were associated with a higher magenta- and green-colored vegetation since the spectra showed the largest differences between the two land-cover types in this wavelength region. Vegetation indices such as the CVI and the GARI integrated the green and red bands. The CVI highlights the redness of a pixel, whereas the GARI highlights the greenness. Each, therefore, highlights the band relationship in the opposite extreme; higher CVI values and lower GARI values were often associated with an increase in prediction probability toward the DM-positive class. The SAVI increased the probability of a DM-positive class assignment in association with higher index values. We deduce that the model utilized the SAVI mainly for distinguishing between vegetated and non-vegetated pixels since a description of the green and red band relationship for distinguishing between magenta- and green-colored vegetation is missing in the index formula.

On the basis of our analysis of the beeswarm plot, we decided to reduce the model training dataset to the features with an observable impact on increasing the probability of predicting the DM-positive class. In summary, the reduced training dataset consisted of the following features: MaVI, CVI, the red band, the NIR band, the red-edge band, the GARI and the SAVI.

4.3.4 Classification Result after Feature Selection

The accuracy assessment of the classification after feature selection still resulted in very high accuracy scores on the test dataset. We calculated a precision score of 0.99, a recall score of 0.99, and an F1-score of 0.99. Since the accuracy scores were identical for both classifications results, i.e., before and after feature selection, the former interpretation and discussion of the metrics are generally applicable to the latter classification accuracy scores. On the basis of the identical accuracy scores, we further deduce that the feature selection based on SHAP values was successful and that we correctly removed features with low predictive capabilities. To extrapolate the differences in class assignment to the entire drone dataset, we created a change detection raster that compares both classification results. By removing all features of low predictive power, the classification result for the entire dataset changed by a diminutive portion of 0.0002% of the total number of pixels (~ 73 million). The low percentage changes in the classification results of the entire drone dataset confirm that the dropped features had a negligible impact on the class assignment of the RF model. We, therefore, propose that the interpretation and discussion of the former qualitative classification result assessment are generally applicable to the classification result of the entire dataset. A visual inspection of regions with class changes (Figure 4.5) revealed a slight improvement for ambiguous pixel clusters; some edge pixels of clusters were now assigned to the DM-negative class. It has to be noted, however, that the new class assignment was not consistent, and the

ambiguity problem persisted for most of the medium- to large-sized clusters of the DM-positive class.

4.3.5 Remote Sensing Plant Count Accuracy Assessment

The remote sensing plant count accuracy assessment is summarized in Tables 4.2 and 4.3. Counting all DM-positive pixels in the reference squares resulted in the highest error of all count settings (RMSE: 42 individuals per square meter). In nine out of 10 reference squares, the number of DM individuals was severely overestimated compared to the in situ plant count, with a mean relative overestimation of 76%. In the remaining reference square, the in situ plant count was underestimated by 17% by the baseline setting. We identified the ambiguity problem as the main cause of overestimation by comparing the classification result and the underlying drone dataset in the corresponding reference squares. Counting the pixels in a unit area is a direct aggregation of the classification results and, therefore, inherits the inflated number of DM-positive pixels in pixel clusters.

Table 4.2: Remote sensing plant count after applying different filter settings to the classification result.

<i>In situ</i>	Without filter	≥ 10% Per-centile	≥ 20% Per-centile	≥ 30% Per-centile	≥ 40% Per-centile	≥ 50% Per-centile	≥ 60% Per-centile	≥ 70% Per-centile	≥ 80% Per-centile	≥ 90% Per-centile	Mean filter
67	104	91	82	73	61	53	44	31	24	15	48
35	63	50	44	39	34	31	23	17	13	11	29
54	88	72	66	59	54	47	37	31	24	17	49
57	66	56	50	46	40	38	29	23	19	13	32
34	74	62	57	51	44	39	32	25	21	14	34
22	42	36	34	30	26	22	20	14	12	8	22
13	11	9	8	7	6	6	5	4	3	2	6
62	87	71	66	59	51	45	38	28	24	17	47
66	156	141	129	115	98	85	69	55	36	22	86
69	126	114	406	96	85	77	65	55	40	24	76

The overestimation outweighed the underestimation in terms of both the number of cases and the magnitude, and it accounted for the majority of the high error values of the baseline setting. We, therefore, applied an object-level threshold-based filter before counting to improve the error metric. We received the highest improvement by applying a median filter with an RMSE of 12 individuals per square meter, which is within the error margin stated by experts for a conventional plant survey. A similar error metric was achieved by an object-level mean filter with an RMSE of 13 individuals.

Table 4.3: Remote sensing plant count error metrics of different filter settings in comparison to the in situ plant counts.

Count setting	RMSE
Without filter	42
$\geq 10\%$ percentile	31
$\geq 20\%$ percentile	26
$\geq 30\%$ percentile	19
$\geq 40\%$ percentile	14
$\geq 50\%$ percentile	12
$\geq 60\%$ percentile	16
$\geq 70\%$ percentile	23
$\geq 80\%$ percentile	29
$\geq 90\%$ percentile	37
Mean filter	13

4.3.6 Assessing the Spatial Distribution and Abundance of *Dactylorhiza majalis*

In the open fen west of the linear trench, DM is widespread (Figure 4.7). We observed a north–south gradient of the DM population in terms of both spatial distribution and plant abundance. In the northern region of the open fen, DM formed large connected clusters with remote sensing plant counts ranging from five to over 100 DM individuals per square meter, whereas a remote sensing plant count per square meter lower than 50 predominated. However, multiple DM hotspots (remote sensing plant count per square meter >50) were present in the northern area of the open fen, noticeably forming adjacent clusters. In this part, we derived a maximum number of 164 DM individuals per square meter. In the southern part of the open fen, the size of connected DM clusters and the magnitude of DM individuals per square meter decreased. DM clusters were more sparsely spread than in the northern region. The remote sensing plant count ranged from five to 60 individuals, whereas the lower remote sensing plant count numbers predominated. The upper end of the remote sensing plant count range only occurred in a single square.

East of the beforementioned trench, only a single DM cluster with a remote sensing plant count ranging between five and 30 individuals per square meter existed. In the area which was subject to the forest fen removal in 2011, four squares above the lower display threshold existed. Two of these squares showed calibration targets for the drone during flight. For

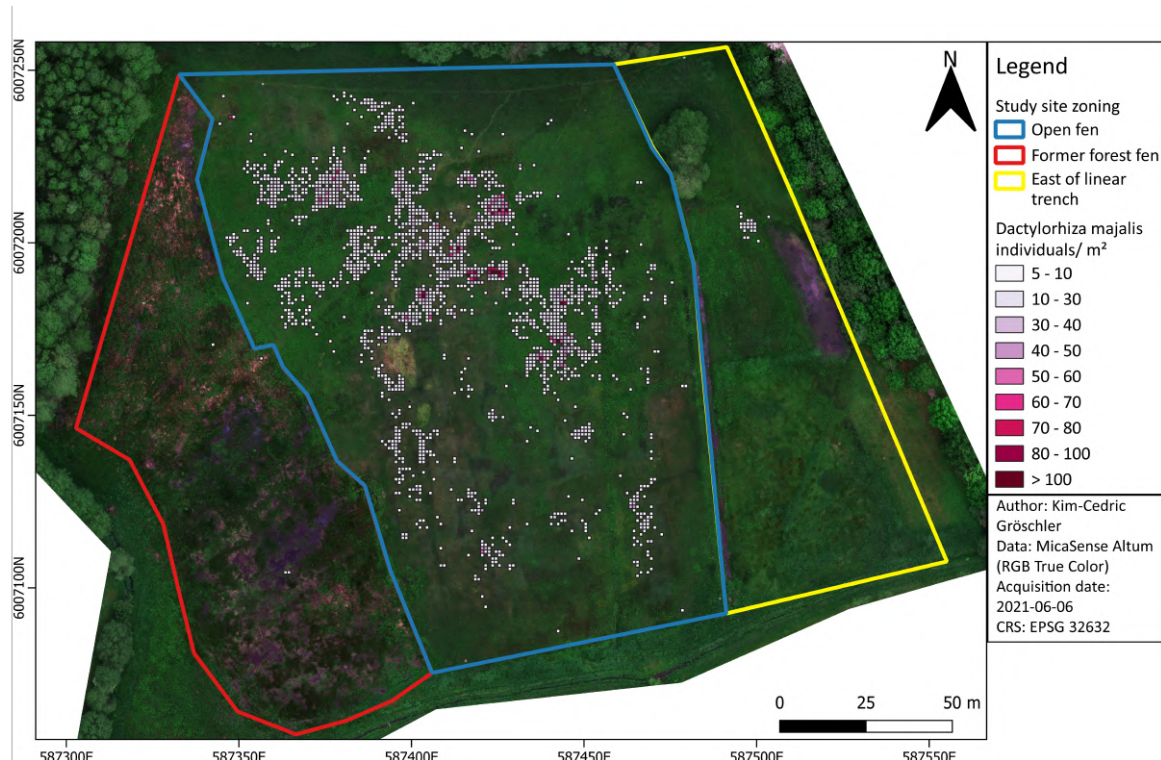


Figure 4.7: Aggregated *Dactylorhiza majalis* individuals per square meter based on the median filtered remote sensing plant count.

the remaining two squares, we were unable to derive a reliable explanation. From a visual inspection, the drone data indicated no DM pixels in the area. Considering the direct neighborhood of the squares, this observation is supported by the fact that the area was surrounded by water puddles and the squares were located at a considerable distance from the boundary of the former forest fen and the open fen. In particular, the latter indicated the absence of DM. The literature suggests that the majority of the DM diaspore is spread in direct proximity to its source, and that DM growth depends on the presence of mycorrhiza fungi in the soil (Dullau et al., 2019b), which limits the speed and distance of population spread. The MaVI, however, showed comparatively high index values, which may have been caused by leafless tree branches in these squares. However, since we are lacking in situ data for these specific locations, we are unable to exclude the possibility (although unlikely from an ecological perspective) that the DM population advanced toward the former forest fen area.

4.3.7 Relevance to Nature Conservation and Management

The study presented an approach to map DM abundance as an effective way of communicating results from a remote sensing-based analysis to a conservationist audience. Using drone data, conservationists can evaluate the success of conservation measures by introducing a comprehensive spatial perspective to a snapshot of the population development of DM. By aggregating plant individuals to a referenced grid, we paid special attention to assure reproducibility and extensibility of the presented approach. Therefore, the resulting map can be regarded as an initial state for long-term monitoring. By conducting the same analysis in subsequent years, an objective and spatially precise development of the DM population in our study site is possible.

In addition to the methodological advantages presented, using drones for plant surveys brings another benefit for nature conservation, i.e., it is possible to avoid plant damage caused by trampling. The surveyor only needs to enter the habitat to lay out or remove the calibration targets for the drone flight, which are generally located at the edges of an area of interest.

4.3.8 Conclusion

In this study, we developed and examined a drone-based approach to estimate the spatial distribution and abundance of DM in the Lehmkuhlen reservoir using very-high-spatial-resolution drone data. The results emphasize that our approach could produce valuable data on the status of a DM population during its flowering phase by highlighting the unique spectral response of magenta-colored vegetation. We integrated the spectral characteristics in our newly developed MaVI. A SHAP feature importance analysis of a RF model demonstrated the strong performance of MaVI in identifying DM. In addition to MaVI, the most suitable features were the NIR/red and the green/red band combinations. We, therefore, recommend integrating the MaVI, the CVI, and the GARI to reliably classify the presence of DM. However, in this study, transferring the classification result to a remote sensing plant count given the available data was limited due to the presence of image artefacts which we summarized under the term ambiguity problem. We tried to cope with the ambiguity problem by optimizing the remote sensing plant count against in situ plant counts via the application of a post-classification median filter on an image object level to reduce the RMSE. The error metrics indicated a noticeable improvement, while a visual inspection of the filtered classification results revealed that the ambiguity problem persisted. Consequently, the ability of this approach to accurately estimate plant counts is limited by its underlying assumption that one pixel indicates one plant individual. Nevertheless, our approach can supplement monitoring programs with

information on plant count with acceptable accuracy to address data scarcity. Additionally, our approach can extend the DM monitoring by assessing the spatial distribution of a plant population, representing a step forward from simple plant counts to indicate the success of conservation measures.

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Chapter 5

Monitoring the population development of indicator plants in high nature value grassland using machine learning and drone data

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Abstract

The temporal monitoring of indicator plant species in high nature value grassland is crucial for nature conservation. However, traditional monitoring approaches are resource-intensive, straining limited funds and personnel. In this study, we demonstrate the capabilities of a repeated drone-based plant count for monitoring the population development of an indicator plant species (*Dactylorhiza majalis* (DM)) to address such challenges. We utilized multispectral very high-spatial-resolution drone data from two consecutive flowering seasons for exploiting a Random Forest- and a Neural Network-based remote sensing plant count (RSPC) approach. In comparison to *in situ* data, Random Forest-based RSPC achieved a better performance than Neural Network-based RSPC. We observed an R^2 of 0.8 and 0.63 and a RMSE of 8.5 and 11.4 DM individuals/m², respectively. The accuracies indicate a comparable performance to conventional plant count surveys. In

a change detection setup, we assessed the population development of DM and observed an overall decline in DM individuals in the study site. Regions with an increasing DM count were small and the increase relatively low in magnitude. Additionally, we documented the success of a manual seed transfer of DM to a previously uninhabited area within our study site. We conclude that repeated drone surveys are indeed suitable to monitor the population development of indicator plant species with a spectrally prominent flower color. They provide a unique spatio-temporal perspective to aid practical nature conservation and document conservation efforts.

Keywords: remote sensing; UAV; conservation; random forest; neural networks; deep learning; high-resolution imagery; indicator species

5.1 Introduction

High nature value grasslands are ecologically diverse and play a vital role in the conservation of endangered plant (Hobohm and Bruchmann, 2009; Kuhn et al., 2021) and animal species (Öckinger and Smith, 2006; Loos et al., 2021). Nevertheless, many European high nature value grasslands are threatened by human activities (Bakker and Berendse, 1999; Habel et al., 2013) and/or climate change (Hopkins and Del Prado, 2007; Van Oijen et al., 2018). Recognizing the severity of the situation, the European Union (EU) has devised legal instruments and long-term conservation strategies, such as the Habitat Directive (EU, 1992), Bird Directive (EU, 2009) and the NATURA 2000 network. Their goal is to protect, conserve, and restore ecosystems across the EU. The EU member states translated these overarching goals to site-specific conservation objectives, necessitating regular monitoring to assess the progress towards these goals. A prevalent approach involves recurring monitoring of indicator species (Török et al., 2021) that serve as proxies for habitat integrity (Carignan and Villard, 2002). They are generally associated with specific environmental conditions, wherefore a change in the population of such species indicates changing habitat conditions.

Plant species from the family *Orchidaceae* serve as valuable indicator species for a variety of habitats due to their diversity, high habitat specificity and sensitivity to environmental changes (Swarts and Dixon, 2009; Phillips et al., 2020). *Dactylorhiza majalis* (DM), also known as broad-leaved marsh orchid, particularly stands out as an indicator species for wet and nutrient-poor grassland habitats in Central Europe (Janečková et al., 2006). The species has experienced a notable decline over the past two decades (Dulau et al., 2019b; Lohr et al., 2020), which has prompted several Central European countries, such as Germany (Maksin et al., 2018), the Czech Re-

public (Wotavová et al., 2004) and Switzerland (Reinhard et al., 1991), to categorize DM as an endangered species. The widespread decline is attributed to habitat changes due to the intensification of agriculture, drainage, and the abandonment of land use, as well as afforestation (Dullau et al., 2019b). To counteract further population decline, conservationists implement site-specific conservation measures to retain or restore favorable habitat conditions, such as late mowing in mid-July (after the flowering phase) or scrub removal. However, the effectiveness of these efforts remains unclear, for which reason the spatially accurate monitoring of DM becomes a necessity.

Traditionally, expert monitoring programs involve repeated labor-intensive field campaigns with manual plant counting (Gregor and Saurwein, 2010) or population size estimation based on limited samples (Messlinger et al., 2018). However, these approaches have methodological limitations. With the increasing size and inaccessibility of the study site, data acquisition becomes impractical and less accurate. In the last decades, some expert monitoring programs were supplemented by volunteer workforce (e.g., Pescott et al. (2019)). And although studies reported positive results (Hunter and Rollins, 2010; Albergoni et al., 2016; McKinley et al., 2017), such monitoring program designs introduce additional dependencies for successful data acquisition, i.e., the willingness of a sufficiently large volunteer group to participate. Additionally, the effect of non-expert acquired data on the result quality often remains unquantified (Conrad and Tischew, 2011).

RS techniques offer a solution to cope with the scaling problems inherent to traditional mapping approaches (Pettorelli et al., 2014). Several studies have shown that spectrally prominent flower colors can be used to identify key plant species (Horton et al., 2017; Fang et al., 2016; Abdel-Rahman et al., 2015; Sulik and Long, 2015; Landmann et al., 2015; Carl et al., 2017; Severtson et al., 2016; Gröschler and Oppelt, 2022). This identification is possible because these flower colors generally show distinct spectral responses compared to green vegetation (Shen et al., 2009, 2010). In the last few decades, satellite Earth Observation investigations have consistently highlighted the potential of machine learning techniques for image classification. However, the history of machine learning for drone-based image classification is relatively recent, dating back to the early 2000s (Nowak et al., 2018). This domain has seen rapid development and advancement since, as a result of the convergence of critical technologies such as drone hardware and machine learning algorithms. Recent investigations have reported promising results in counting plant individuals with drone-based RS data using different image analysis techniques, such as Random Forest (RF) classification (Gröschler and Oppelt, 2022) and deep learning approaches (Oh et al., 2020; Valente et al., 2020).

In one of our previous studies, we proposed an RS-based alternative for monitoring plant species with a spectrally prominent magenta-colored flower, using DM as our target species (Gröschler and Oppelt, 2022). However, our previous analysis only looked at the DM population for a single point in time. In this study, we extended the RS-based DM monitoring by the temporal dimension using a new drone dataset acquired in the consecutive flowering season. By leveraging the temporal dimension and paying special attention to data and processing consistency, we assessed the DM population development (loss or gain) in a spatially comprehensive manner. Additionally, we investigated the optimization potential of our previous approach. We compared the performance of a Neural Network (NN) classifier to RF, which was previously proposed in Gröschler and Oppelt (2022). In summary, our study's goals are as follows:

1. Show the potential of an RS-based analysis to assess the population development of an indicator species with a spectrally prominent flower.
2. Improve the understanding of RSPC, based on drone data, in comparison to an *in situ* plant count field survey.
3. Extend the RSPC methodology proposed by Gröschler and Oppelt (2022) by the temporal dimension and investigate its optimization potentials.

5.2 Materials

5.2.1 Study Site

We acquired the data for this study in the Lehmkuhlen reservoir (Figure 5.1), Schleswig-Holstein, Germany, where conservationists reported the largest statewide DM population (Seer and Schrautzer, 2014). The Lehmkuhlen reservoir is an alkaline, nutrient-poor fen which developed during the Weichselian ice age (Schrautzer and Trepel, 2014). Over an area of 0.29 km², conservationists reported 60 endangered plant species (including DM) in the study site (Schrautzer and Trepel, 2014). Due to its ecological importance, it is protected by the European Habitat Directive (NATURA 2000 codes: FFH 7230 — alkaline fens and FFH 7140 — transition mires) and managed by conservationists to retain favorable habitat conditions.

5.2.2 Drone Data

We conducted drone flights during two consecutive flowering seasons of DM on 6 June 2021 and 31 May 2022. During these periods, local conservationists verified that no other plant species with magenta-colored flowers

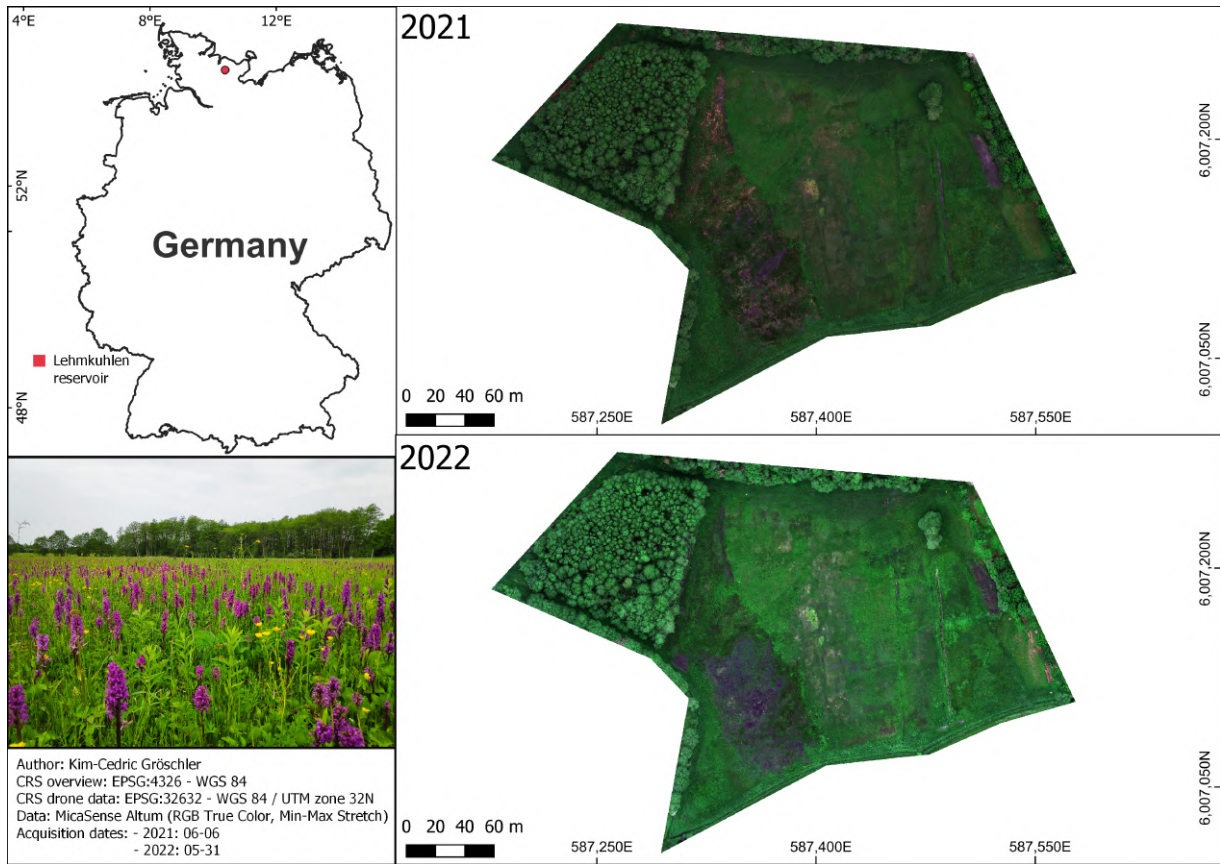


Figure 5.1: Overview of the study site during the investigation years 2021 and 2022. The photograph illustrates the abundance of *Dactylorhiza majalis* during data acquisition.

blossomed in our study site. The commissioned company used a Wingtra One drone equipped with a MicaSense Altum sensor for both acquisition campaigns. The sensor captured multispectral data with bands in the blue, green, red, red-edge, and near-infrared regions of the electromagnetic spectrum (band designations are given in Table 5.1).

The sensor had a focal length of 8 mm and a field of view of $48^\circ \times 37^\circ$ across-track and along-track, respectively. It captured data with a 3.2 megapixels resolution. A single image was composed of 2046×1544 pixels. With a mean flight altitude of approximately 150 m for both flights, we achieved a pixel size of 3.4 cm (2021) and 4 cm (2022), respectively. Additional flight parameters from each flight quality report are listed in Table 5.2 for reference.

The acquired drone data were geometrically corrected, converted to surface reflectance and combined to a single image mosaic using the Pix4Dmapper photogrammetry software (version 4.6.4). The weather during all flights was consistently overcast, wherefore the source of illumination

Table 5.1: MicaSense Altum optical band designations (MicaSense, 2020).

Band Name	Center Wavelength (nm)	Bandwidth (nm)
Blue	475	32
Green	560	27
Red	668	16
Red-Edge	717	12
Near infrared	842	57

Table 5.2: Comparison flight characteristics and parameterization from drone flight quality reports. Abbreviations: RMSE = Root-Mean-Square-Error.

Parameter	Drone Flight 2021	Drone Flight 2022
Area covered (km ²)	0.259	0.258
Median keypoints per image	10,000	15,233
Image count (calibrated)	3695 (3255)	3525 (3076)
Image matching quality check	Passed — median of 4019.56 matches per calibrated image	Passed — median of 5630.11 matches per calibrated image
Georeferencing	6 Ground Control Points mean RMSE = 0.015 m	6 Ground Control Points mean RMSE = 0.027 m

was considerably stable. Since wind speeds during the flights were low, we assumed a negligible impact on the data acquisition. In Gröschler and Oppelt (2022), we reported image artifacts that might have influenced the RSPC. We summarized these artifacts under the term "ambiguity problem" and assumed that they might have been caused by the following factors:

- Mixed pixels resulting from the positioning of one or more DM individuals relative to pixel centers.
- Adjacency effects, where magenta-colored flowers spectrally superimpose neighboring pixels.
- Motion blur caused by camera movement during exposure.
- Keystone effect of the camera, which may cause a slight cross-track displacement.

The 2021 dataset suffered severely from the ambiguity problem (refer to Gröschler and Oppelt (2022) for more details). Therefore, to cope with the

image artifacts, the commissioned company slightly increased the pixel size of the sensor in 2022 to improve the signal-to-noise ratio (SNR). However, the ambiguity problem still occurred in the image dataset, although to a much lesser extent. To address this issue in both datasets, we applied a post-classification filter to select the purest magenta-colored pixels within an image object (see Section 5.3.2).

5.2.3 Modelling Reference Data

We derived our reference dataset from the drone data as point geometries, which were labeled the DM-positive or DM-negative class. Due to the relative scarcity of the DM-positive class, we split our reference data sampling strategy to ensure a balanced number of DM reference points. We acquired the reference points for the DM-positive class through visual interpretation of the true-color and color-infrared composites of the drone datasets. To systematically derive reference points for the DM-negative class, we employed the pseudo-randomized sampling approach described in Gröschler and Opelt (2022). In summary, we iteratively sampled random points from the study site. We checked the correct class affiliation by visual interpretation. Points belonging to the DM-positive class were replaced by new randomly sampled DM-negative points. Consequently, we created a reference dataset that consisted of 2500 labeled points per class.

For modeling, we divided the reference dataset by applying a stratified random split. We used $\frac{2}{3}$ of the reference data for model training and $\frac{1}{3}$ for model validation. The point geometry locations were then used to sample pixel values from a selection of image features for each classifier (see Section 5.3.1).

5.2.4 RSPC Validation Data

To validate the RSPC, we collected *in situ* data coinciding with the drone flights by applying the acquisition technique described in Gröschler and Opelt (2022). We employed a 1 m² square frame, which we positioned randomly within the study site. Within this frame, we counted all DM individuals and logged the spatial position with a Garmin fenix 5 (precision 2–3 m according to the manufacturer). To improve spatial precision, we operated the device in a combined GPS and Galileo mode and took at least five valid point measurements per square frame. We additionally cross validated the spatial position and *in situ* DM count with a continuous track of our position during data acquisition (using the same device) and geolocated top-down photographs of each square frame (taken with a Samsung Galaxy S21 FE). After manual quality control, we took the average spatial position of the remaining points as the position of a reference square.

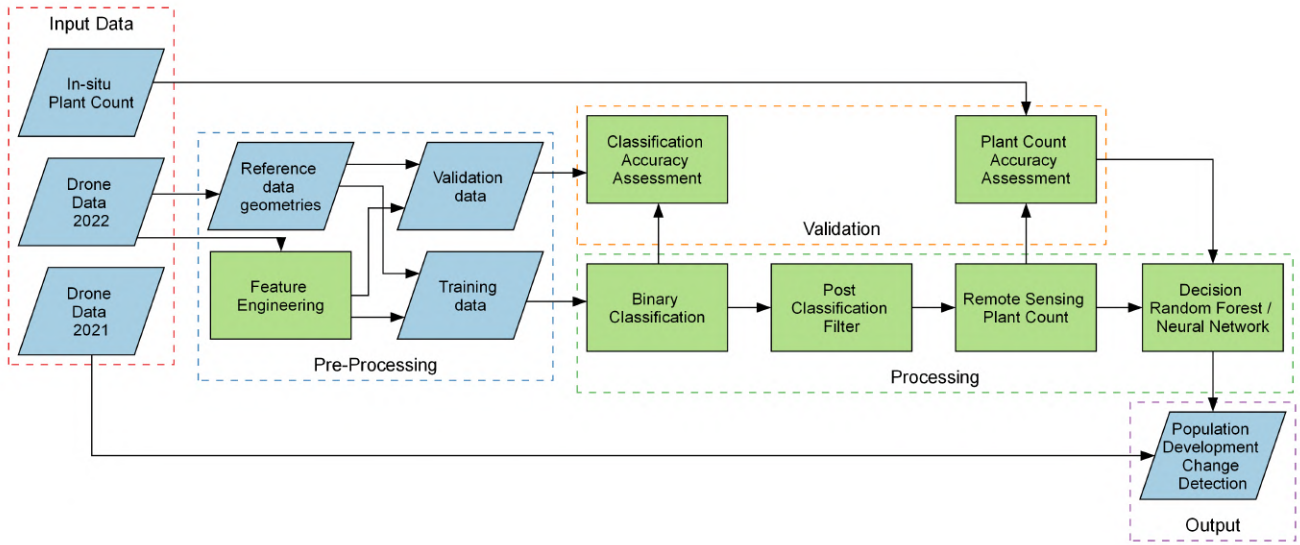


Figure 5.2: Conceptual illustration of this study's workflow — from input data to change detection map. Blue-colored parallelograms represent data, green-colored rectangles represent processing steps.

5.3 Methods

The following sections describe the processes and techniques employed to address this study's research questions. Additionally, we illustrate sequential processing steps and connections between various components of the research process in Figure 5.2.

5.3.1 Model Training, Classification, and Validation

In this investigation, we applied two different approaches (RF and NN) to identify DM individuals. The RF classifier is an ensemble machine learning algorithm that combines the results of multiple decision trees to a single class assignment (Breiman, 2001). Each tree is constructed by drawing a random subset of the training data and features with replacement. RF does not require feature scaling (normalization or standardization) because it relies on decision trees that split data based on feature thresholds. We used the RF implementation of scikit-learn (Pedregosa et al., 2012) and adopted the suggested set of hyperparameters by Belgiu and Drăguț (2016), which are summarized in Table 5.3. We did not perform additional hyperparameter tuning, as the literature suggests these settings to be a sensible default RF model parameterization in the context of RS data. Furthermore, the same setting for an RF model showed promising results in Gröschler and Oppelt (2022).

Table 5.3: RF parameters modified for this study. The other parameters are scikit-learn's default values.

Parameter	Value
Number of trees	500
Max tree depth	5
Max number of features for node split	3

For RF, we adopted the selection of image features from Gröschler and Oppelt (2022), as they showed a considerable impact on the model's ability to differentiate between the DM-positive and the DM-negative class. The feature selection consisted of the red, red-edge and near-infrared band of the sensor and four additional vegetation indices that we derived from the drone data. The vegetation indices are listed in Table 5.4.

Table 5.4: Vegetation index selection to differentiate between the DM-positive and DM-negative class. Abbreviations: B = blue band; G = green band; R = red band; NIR = near-infrared band.

Vegetation Index	Formula	Source
Chlorophyll Vegetation Index (CVI)	$NIR \times \frac{R}{G^2}$	Vincini et al. (2008)
Magenta Vegetation Index (MaVI)	$\frac{B+R-G}{B+R+G} \times (1 - \frac{B+G+R}{NIR}) \times (\frac{NIR}{R} + NIR)$	Gröschler and Oppelt (2022)
Green		
Atmospherically Resistant Vegetation Index (GARI)	$\frac{NIR-(G-(B-R))}{NIR-(G+(B-R))}$	Gitelson et al. (1996)
Soil Adjusted Vegetation Index (SAVI)	$\frac{NIR-R}{NIR+R+L} \times (1 + L); L = 0.5$	Baret and Guyot (1991)

We employed a densely connected NN with double hidden layer. The network was trained using only the spectral bands. The same training-validation split as RF was utilized in the case of the NN. We employed the trained network for the predictions (presence or absence of DM) with the prediction data, which did not participate while training and validating the NN.

We validated the classification qualitatively and quantitatively. For the latter, we used the validation data with the F1 score, which is defined as

$$F1 = \frac{2 \times (\text{precision} \times \text{recall})}{\text{precision} + \text{recall}} \quad (5.1)$$

where precision is defined as the ratio of true positive class assignments and the sum of true positive and false positive class assignments. Recall is defined as the ratio of true positive class assignments and the sum of true positive and false negative class assignments.

For the qualitative accuracy assessment, we visually assessed the performance of each model for their ability to detect the DM-positive class and how well the model coped with the ambiguity problem and potential systematic misclassifications.

5.3.2 Monitoring the DM Population Development

Monitoring the population development of DM requires a reproducible and spatially explicit count of plant individuals. To achieve this, we employed the RSPC methodology, as described in Gröschler and Oppelt (2022), in two consecutive flowering seasons. In summary, we applied the following processing steps to the RF and NN classification results separately:

1. Polygonize neighboring DM-positive pixels into image objects.
2. Calculate a filter threshold based on the image object-level median value of the MaVI.
3. Assign the DM-negative class to all pixels within an image object below the object median filter threshold.

We then aggregated the remaining DM-positive pixels on a predefined reference grid, where one grid cell had a size of 1 m². The aggregation is based on the assumption that one DM-positive pixel corresponds to one DM individual. To assess the accuracy of the RF- and NN-based RSPC, we compared each filtered result with the *in situ* data described in Section 2.4. We applied a squared buffer (1 m side length) to the GPS-logged point of each reference square. We then used the resulting polygon to sample pixels classified as DM-positive. The agreement between the RSPC results and the *in situ* data is illustrated in scatterplots and quantified using the R² metric. The deviation of the RSPC and the *in situ* plant count is quantified by the Root-Mean-Square-Error (RMSE) metric. Both metrics are described in the following equations:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5.2)$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(y_i - \hat{y}_i)^2}{n}} \quad (5.3)$$

where y_i is the RSPC, $\hat{y}_i$ is the *in situ* plant count, $\bar{y}_i$ is the average plant count, and n is the number of reference squares. When applied to a single year, RSPC documents the distribution of a DM population in a comprehensive spatial manner. Multi-year RSPCs allow conservationists to monitor the population development of DM. In this study, we illustrate the population development using a change detection map. Since we used the same reference grid for both the years, we reported the net gain and loss of DM individuals per unit area. The change in a grid cell is defined as follows:

$$\Delta DM = RSPC_t - RSPC_{t-1} \quad (5.4)$$

where ΔDM is the change of DM individuals between two years. $RSPC_t$ corresponds to the latest RSPC in 2022 and $RSPC_{t-1}$ to RSPC of the year 2021.

5.4 Results and Discussion

5.4.1 Accuracy Assessment of Classification Methods

The predictive accuracy of both classifiers on the validation data is very high (see Tables 5 and 6). We observed an F1-score of 0.99 for both RF and NN-based approach. The accuracy metrics indicated an apparent nearly perfect capability of both model types to differentiate between the DM-positive and the DM-negative class. For RF, the high F1-score confirmed the capability of the feature selection derived from Gröschler and Oppelt (2022) to identify magenta-colored vegetation. For NN, the high F1-score indicated that the classifier was able to learn important feature relationships from a simpler feature set (only the spectral bands).

Table 5.5: The confusion matrix shows the predictive performance of the NN classifier on the validation dataset of the 2022 drone flight.

	NN DM-Positive	NN DM-negative
Validation DM-positive	820	5
Validation DM-negative	8	817

Table 5.6: The confusion matrix shows the predictive performance of the RF classifier on the validation dataset of the 2022 drone flight.

	RF DM-positive	RF DM-negative
Validation DM-positive	819	6
Validation DM-negative	7	818

However, it is important to note that the model accuracies might have been influenced by certain methodological limitations in this study's reference data sampling process. The sampling process is non-probabilistic for the DM-positive class and only partially probabilistic for the DM-negative class (Stehman, 2009; Waldner, 2020). Furthermore, the limited size of the validation data might have led to inflated accuracy scores. One potential strategy to address these limitations could have been to augment the validation dataset by sampling new reference points. For our study, however, this was unfeasible since the ambiguity problem limited our ability to confidently identify additional DM-positive points without introducing image artifacts to the reference data.

The qualitative accuracy assessment revealed noticeable quality differences between the RF and NN classification results, which are illustrated in Figure 3. The NN was able to identify slightly more true-positive DM pixels than the RF classifier. However, the share of false-positive DM pixels was much higher using the NN. The majority of false positive class assignments for both classifiers can be attributed to the ambiguity problem. The NN classifier was far less able to cope with the sensor artifacts (see Figure 3d,e). We attribute this limitation to the sensitivity of the NN to the specific architectures used to arrange the computational units (Wang et al., 2017). Domain-specific insights have been observed to play a crucial role in the organization of the underlying computational units architecture, which consequently influences the final prediction performance of a NN. We noticed a rare but systematic failure of the RF classifier to distinguish magenta-colored vegetation and woody vegetation (tree branches), which might be explained by their similar spectral response (Gröschler and Oppelt, 2022), as we observed particularly in the blue, green, and red band. Depending on the influence of the ambiguity problem on a pixel, a partial overlap in the feature space in the red-edge and NIR bands may also exist, which further reduces class separability. The misconception was more severely present in the NN results. A possible explanation for the increased confusion might have been the simpler set of input features (i.e., the image bands) compared to the RF model. The NN additionally had a severe problem distinguishing magenta-colored vegetation and bare soil or shadow surfaces.

The NN can be further optimized to extract a better performance by fine-tuning the hyperparameters (epochs, number of neurons, connection dropouts, etc.). In order to avoid information redundancy, we only used the spectral bands as training features. Considering the complexity of the NN (densely connected double layer) we used for this study, we assumed that the network was capable of self-learning the additional feature representations contributed by the vegetation indices. We ensured that the network was not over-trained to specifically fit the given data (for merely obtaining a higher performance) but rather considered the generalization of the predictions. Moreover, it is important to note that the success of NNs is not universal across all domains. This is particularly true for learning problems without any special structure or under somewhat limited data conditions. Under such circumstances, NNs do not perform better than traditional machine learning methods, such as RF (Wang et al., 2017). Unlike the robust performance of RF, irrespective of the data domain, arising as a result of their randomized ensemble approach, NNs are highly prone to overfitting. The use of a generic layered architecture of the computation units may not achieve favorable outcomes. On the contrary, RFs have built-in mechanisms to combat overfitting. By constructing an ensemble of decision trees and aggregating their predictions, they tend to generalize well to unseen data without extensive hyperparameter tuning.

Unlike several Earth Observation investigations promising the ultimate performance with NNs, we observed and reported (with RF) a more realistic scenario reported by fundamental machine learning investigations (Wang et al., 2017). However, it's not universally true that RF outperforms NN or vice versa. RF might appear superior in some scenarios. It tends to perform well with relatively small- to medium-sized datasets. NNs are more sensitive to data quality. If the dataset is small or lacks diversity, NNs may be affected by noise and, consequently, struggle to generalize well. In general, RF can handle noisy data and is less sensitive to outliers. Due to their decision tree structure, RF provides better interpretability as compared to deep NNs, which are often treated as "black box" models and are difficult to train effectively under limited data conditions. On the contrary, NNs can outperform RF when non-linear feature relationships inherent to the classification problem are too complex to be captured by an RF model, provided a training dataset of sufficiently large size and high quality is available. From a computational perspective, NNs may also be preferred over RF when scalability becomes an issue. NNs can be accelerated and distributed across multiple graphics or tensor processing units, allowing them to scale efficiently to handle massive datasets and complex architectures. Training an RF model can also be parallelized to some extent but may not scale as effectively for certain tasks.

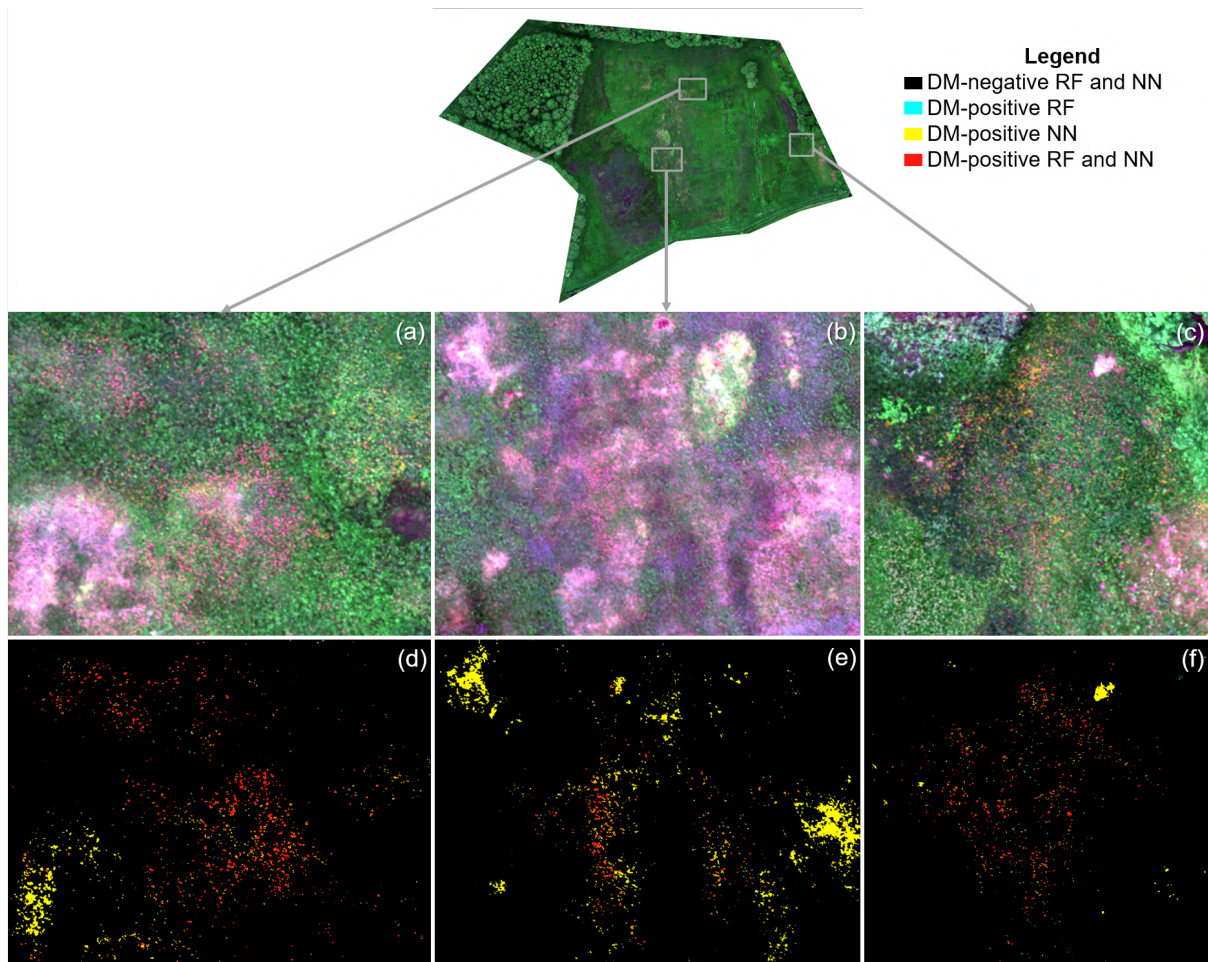


Figure 5.3: Comparison of RF and NN classification result (2022). Subfigures (a–c) are contrast enhanced RGB true color reference images of subfigures (d–f). Subfigures (d–f) illustrate the pixel level agreement of the RF and NN classifiers, respectively.

5.4.2 Done-Based Plant Count Accuracy

The RF-based RSPC showed good agreement with the *in situ* plant count. We observed an R^2 of 0.8 and a RMSE of 8.5 DM individuals/m² between the two methods. The NN-based RSPC showed reasonable agreement with the *in situ* data, with an R^2 of 0.63 and a RMSE of 11.4 DM individuals/m². Figure 5.4 illustrates that both RSPCs tended to overestimate the plant counts, with the NN-based RSPC showing a relatively pronounced overestimation. This phenomenon is associated with the characteristics of the NN classification results. The NN classifier confused woody vegetation, bare soil, and shadowed surfaces for the DM-positive class. The RSPC filter reduced these systematic misclassifications, but in the end, they persisted to a certain extent and inflated the NN-based RSPC. This was particularly evident in

the reference squares where the *in situ* plant count was 0. In two of these squares, the majority of the area is covered by bare soil, which the NN classifiers confused for the DM-positive class.

Underestimation rarely occurred in both RSPCs but was slightly more noticeable in the RF-based RSPC. Both RSPCs considerably underestimated the reference squares associated with very high *in situ* plant counts (>70 DM individuals/m²), which may be the result of the RSPC filter. A high number of DM individuals in one reference square will most likely lead to few large DM image objects. In large DM image objects, the RSPC filter drops DM-positive pixels more greedily as compared to smaller DM image objects and, therefore, tends to lose some valid DM positive pixels. The increased pixel size in 2022 addressed the issue of image artifacts by enhancing the SNR (Chen et al., 2000), which consequently played a role in improving the detection performance of DMs. The performance increased from a RMSE of 12 DM individuals/m² (Gröschler and Oppelt, 2022) to 8.5 DM individuals/m². The RSPC accuracy assessment may be subject to uncertainties related to the spatial inaccuracies of the GPS devices used to locate the reference squares. We paid special attention to maximize the logging precision and reliability via cross validation of multiple logging methods and devices. However, we have no quantified measurement available on the performance improvement relative to the device precision reported by the manufacturer when operated in normal GPS mode.

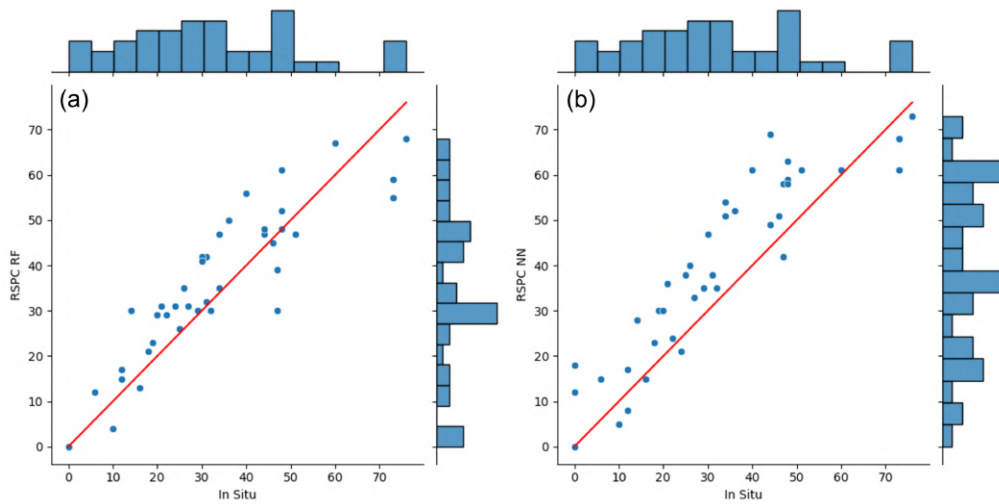


Figure 5.4: Comparison of RSPC in the RF (a) and NN (b) results in the *in situ* data. The scatterplots show the agreement between RSPC and *in situ* plant counts. The red lines show theoretical lines of perfect agreement for orientation. The histograms show the frequency distribution of each plant count method individually.

5.4.3 DM Population Development in the Lehmkuhlen Reservoir

The classification and RSPC accuracy assessment indicated that the RF-based approach performed better than the NN-based approach. We, therefore, decided to assess the population development using only the RF-based results.

In 2022, our analysis indicated an overall decrease in DM individuals compared to the survey conducted in 2021 (see Figure 5.5). On average, we calculated a loss of 62% of DM individuals per unit area, with a maximum loss for a single grid cell of 24 DM individuals. The loss covered most of the area and was especially distinct in the northern part of the study site, which we identified as a DM hotspot in Gröschler and Oppelt (2022). For this area, we were hardly able to report any grid cells with an increasing DM count. In the southern part of the study site, there were also fewer DM individuals; however, the decrease was less pronounced. Additionally, we reported multiple smaller spots with a net gain of DM individuals, with a maximum gain of 15 DM individuals for a single grid cell. In the eastern part, just south of the small pond, we identified a notable increase, which corroborates with a seed material transfer conducted by conservationists. To expand the DM habitat, they transferred grass and DM cuttings from the hotspot area to this part of the reservoir, as it showed favorable growing conditions but lacked DM individuals for natural seed transfer. Our results confirmed that the seed material transfer was successful in 2022 and that the DM habitat could be expanded eastward.

The overall loss of DM individuals in 2022 could be explained by natural fluctuations in the DM population. However, the change detection might also have some inherent uncertainties. The loss might be amplified in grid cells containing a substantial number of DM individuals in 2021 due to the increased severity of the ambiguity problem during that year. Therefore, the count of DM-positive pixels in 2021 was higher than the number of DM-positive pixels in 2022. Since we applied the RSPC filter separately to the two datasets, its influence on the plant counts might differ, which in turn might influence the change detection. We expect this factor to have a greater influence on the plant loss than on the gain. Another source of uncertainty arose from the different spatial resolution of both drone datasets. The 2022 dataset had a slightly larger pixel size at 4 cm, as opposed to the 3.4 cm pixel size in the 2021 dataset. Therefore, the number of available pixels per grid cell was lower in 2022. Consequently, this might have led to a slightly decreased count of DM individuals in 2022 relative to 2021. However, we argue that this factor might have had a negligible impact on grid cells of low to medium RSPC results. For high RSPC grid cells, this might have led to a minor loss overestimation or a minor gain underestimation. Undetected DM individuals

in one of the years might have also influenced the DM change calculation. But we expect this factor to be less important since the RF-based detection worked quite reliably.

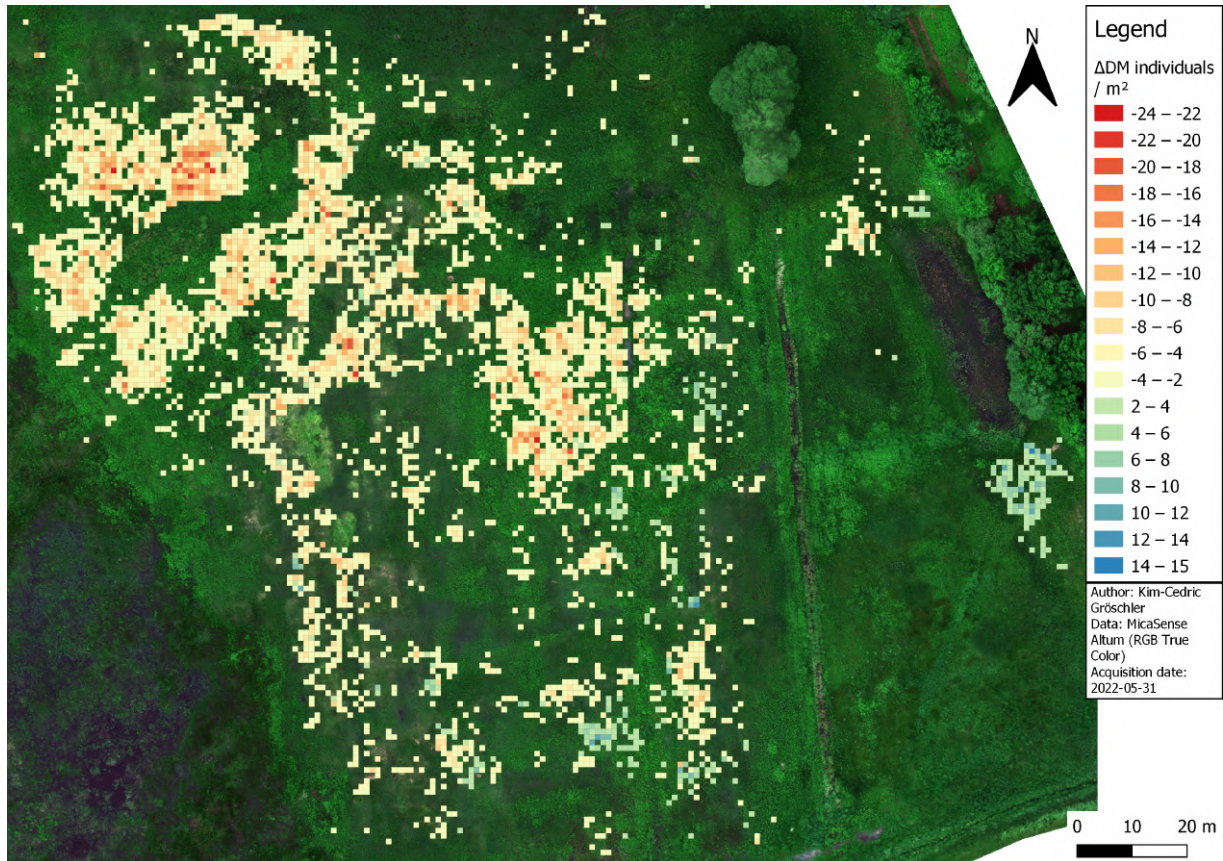


Figure 5.5: Population development of *Dactylorhiza majalis* in the Lehmkuhlen reservoir. The map shows the net change of plants per unit area as detected during the flowering seasons of 2021 and 2022, respectively.

5.4.4 Implications for Practical Nature Conservation

In this study, we presented an RS-based alternative to monitor the DM population development and visualizations that communicate effectively to a conservationist audience. The approach supplements conventional plant survey methods in a spatio-temporal manner, which is rarely available due to the limited monetary and personnel resources in the field of nature conservation. Furthermore, it has the potential to reduce the reliance of plant count surveys on the workforce of (non-expert) volunteers. Our approach is not only reproducible but also easily scalable, enabling the consistent and objective monitoring of DM populations over time. It allows conservationists to identify

areas with a declining DM population and implement targeted interventions to sustain the species. Additionally, the success of conservation measures can be visualized and documented. Since our approach exploits the spectral response corresponding to the flower color, conservationists expressed its possible applicability to monitor the population development of other plant species, such as *Dactylorhiza incarnata* or *Lythrum salicaria*.

Drone-based data acquisition provides additional benefits for practical nature conservation. Traditional ground-based surveys are time-consuming and labor-intensive, while drones allow coverage of larger territories efficiently, reducing fieldwork time and costs. Limited monetary resources can, therefore, be allocated more effectively, e.g., to ensure a longer duration of a monitoring program. The proposed method also prevents plant damage due to trampling, as the drone pilot's need to access the area of interest is generally limited to the margins of the study site to manage calibration targets. This poses a minimal disturbance to the habitat compared to traditional field campaigns.

5.4.5 Conclusion

In summary, we showed the capabilities of an RS-based approach to monitor the population development of DM within a high nature value grassland site. Leveraging very high-spatial-resolution drone imagery, we observed the net change of DM individuals over two consecutive flowering seasons using a spatially consistent reference grid.

Our study revealed an overall decrease in the DM population in the Lehmkuhlen reservoir during 2022 compared to the baseline conditions of 2021. The results indicated that only a limited number of grid cells exhibited an increase in DM individuals. The magnitude of this gain was typically less pronounced as compared to the magnitude of the observed losses. We validated the positive outcome of a DM seed transfer event conducted by the conservationists. Our results provide spatio-temporal information for conservationists that could either be only attainable with significant resources or lack the comprehensive spatial scale. Monitoring over two consecutive flowering seasons highlighted the positive outcomes of targeted conservation measures. Future research programs will benefit from the proposed methodology for long-term monitoring and reveal the temporal development trend of the indicator species. The proposed methodology can be modified and extended to other indicator plant species as well as geographical locations.

We tested the ability of two classifiers (RF and NN) with different levels of complexity to provide a data basis for the RSPC. The results showed that the RF-based RSPC produced better results than the NN-based RSPC (R^2 of 0.8 vs 0.63, respectively, in comparison to *in situ* data). We identified sys-

tematic misclassifications of bare soil and shadow surfaces with magenta-colored vegetation as the main limiting factor for NN. With a RMSE of 8.5 DM individuals/m², the performance of the RF-based RSPC was comparable to traditional plant-mapping approaches.

Our study underlines the efficacy of employing drone data and machine learning techniques for ecological assessments. By unveiling the nuances in the DM population trends and migration successes, we demonstrate that drone-based surveys can indeed supplement conservation efforts and reduce data scarcity.

Acknowledgments

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Chapter 6

Data-driven identification of high nature value grasslands using Harmonized Landsat Sentinel-2 time series data

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Abstract

Europe's high-nature value (HNV) grasslands have significantly declined in recent decades. European conservation strategies are mainly confined to protected areas, and many national initiatives aiming for comprehensive coverage suffer from long and irregular monitoring intervals. Addressing this, we propose a data-driven approach to derive information about the location, extent and HNV status of grasslands to improve the efficiency of large-scale field mappings. Serving as a representative example of European and national grassland monitoring, we utilize the regional habitat map of Schleswig-Holstein, Germany, in conjunction with Harmonized Landsat Sentinel-2 time series data to train XGBoost models for the period of 2017-2022. Our models achieved high classification performance, distinguishing eight grassland classes with average F1-scores of 0.89 before and 0.86 after feature selection. We examined model decision-making patterns using an adapted version of SHapley Additive exPlanation values, finding that start-of-sea-

son, end-of-season, Red-Edge, and spectral change features significantly impacted predictions. We produced annual HNV grassland maps and, by aggregating yearly results, derived a robust estimate of the HNV status in our study area. Applying our HNV estimate to an independent dataset comprising 2363 km² of grassland plots with unknown HNV status, we identified 84 km² as HNV, highlighting the significance of our result. Overall, our study demonstrates how integrating remote sensing data enhances the efficiency and comprehensiveness of large-scale mapping initiatives.

Keywords: Grassland; Conservation; Harmonized Landsat Sentinel-2; XG-Boost; SHAP; NATURA 2000; Time Series

6.1 Introduction

Grasslands are ecosystems of global importance. In Europe, estimates suggest that grasslands make up around 17.4% (Huber et al., 2023) to 22% (Bengtsson et al., 2019; Tarantino et al., 2023) of the terrestrial area. These grasslands provide a wide range of essential ecosystem services such as climate regulation, biodiversity preservation or fodder production (Liu et al., 2022b). Despite their importance, they are among the most endangered ecosystems in Europe (Tarantino et al., 2023; Shipley et al., 2024), threatened by agricultural intensification, abandonment, woody encroachment, overgrazing, land-use change, and climate change (Li et al., 2022; Martens et al., 2022; Tarantino et al., 2023; Zhang et al., 2024). Natural hazards, such as fire, drought, invasive species and insect damage (Wang et al., 2022a) pose additional risks. In response to these challenges, the European Union (EU) has developed legal tools and long-term conservation strategies, including the Habitats Directive (EU, 1992) and the Bird Directive (EU, 2009), along with the NATURA 2000 network. Conservation of permanent grasslands is also a major goal of the EU's Common Agricultural Policy (CAP) (EU, 2023). Restoring degraded grasslands is essential to enhance ecosystem services, especially in Central European countries where high biodiversity grasslands have transformed into species-poor ecosystems (Schils et al., 2020; Török et al., 2021; Schils et al., 2022; Martens et al., 2022; Pazúr et al., 2024). Restoration measures include reducing land use intensity through practices like mowing without fertilization or low-intensity grazing (Rosenthal et al., 2012; Köhler et al., 2016; Schrautzer et al., 2016; Elias et al., 2018) and direct techniques such as hay transfer or seeding (Valkó et al., 2022; Sommer et al., 2023; Huang and Hou, 2024).

Effective conservation requires a consistent and frequent monitoring system to evaluate the success of protection measures and compliance with subsidy guidelines Perino et al. (2022). EU member states are required to regularly

report to the European Commission about the status of grassland in their territory (Haensel et al., 2023). Individual states may also follow national conservation strategies for grassland, often in alignment with the EU monitoring obligations. Up to date, field mappings predominantly contribute to the data collected for these reports. Typically, they attain a high level of detail on a small scale, but are costly, labor-intensive, frequently subject to assessor influence and sensitive concerning the acquisition time (Lopes et al., 2017; Raab et al., 2018; Weber et al., 2018; Wang et al., 2022a; Moersberger et al., 2024). Consequently, large monitoring areas lead to scaling issues, such as long and/or irregular monitoring intervals resulting in out-of-sync and potentially outdated information (Schoof et al., 2020). Additionally, monitoring results are often incomplete because comprehensive a priori information on the location of areas of interest is required for complete coverage. Such information is rarely, if ever, available in nature conservation practice (Gaston et al., 2008), due to limited financial and human resources (Louette et al., 2011).

Generally, those responsible for monitoring across Europe deal with these limitations using a non-randomized sample-based monitoring design (EEA and MNHN, 2014), such as in Germany, Denmark, Hungary, Lithuania, Sweden or Finland (Ellwanger et al., 2018). This design introduces a bias towards sites of known conservation value (Iojă et al., 2010), potentially overlooking new or low-conservation-value sites. RS technology has shown promise in tackling these spatio-temporal scaling challenges. Systematic reviews highlight RS's effectiveness in assessing grassland characteristics, including development, management, use intensity, and production traits (e.g. Taravat et al. (2019); Reiner mann et al. (2020); Soubry et al. (2021); Wang et al. (2022a); Lange et al. (2022b)). Multiple studies also demonstrated the potential of RS to discriminate different grassland types using various sensors and modelling techniques (e.g. Tarantino et al. (2021); Masenyama et al. (2022); Huber et al. (2023); Sun et al. (2024)). However, RS often faces challenges in grassland monitoring due to limited compatibility between monitoring targets and the capabilities of RS in detecting them (Burchard-Levine et al., 2022; Cavender-Bares et al., 2022). These challenges become evident in most national offshoots of the NATURA 2000 monitoring (Vanden Borre et al., 2011a), where grasslands are classified through vegetation relevés, species lists or other difficult-to-detect ecological characteristics. Nevertheless, RS has significant potential to provide novel and essential information for grassland monitoring.

In this study, we address the fundamental challenge of spatio-temporal scaling in existing large-scale grassland monitoring programs, currently exhibiting limited compatibility with RS. Our primary objective is to utilize RS techniques to derive a priori information on the location, extent and high-nature value (HNV) status of grasslands, enhancing field mapping efficiency.

We focus our research on grassland monitoring in Schleswig-Holstein (SH), Germany, a region that serves as a representative example for NATURA 2000 and national grassland monitoring initiatives. We implemented a data-driven approach, leveraging dense multi-year time-series data from the Harmonized Landsat Sentinel-2 (HLS) project (Claverie et al., 2018) with XGBoost models (Chen and Guestrin, 2016) to identify HNV grasslands in line with regional grassland habitat type definitions that guide these monitoring programs. HLS data offers a favorable combination of relevant sensor resolutions. Its key advantage is the improved data acquisition rate for interoperable spectral bands at a Landsat-level spatial resolution, which neither the Landsat nor Sentinel-2 fleets can individually provide. This makes HLS data particularly suited for analysing target variables with limited separability in the spectral domain, such as grasslands.

We chose XGBoost for its high predictive performance across sensors (Schütt et al., ults). Several studies have demonstrated that XGBoost outperforms well established algorithms like Random Forest (Shao et al., 2024), Support Vector Machines (Yu et al., 2021) or Spectral Angle Mapper (Zhou et al., 2022b) in RS applications. As computational costs increasingly emerge as a major constraint in RS time-series analysis, the need for efficiency and scalability has become important. XGBoost addresses these challenges through its suite of features tailored for big data environments. These include its gradient boosting framework, parallelized execution capabilities, advanced tree-pruning techniques, and optimized software implementation. Additionally, XGBoost's tree-based architecture facilitates efficient analysis of model decision-making patterns, enhancing transparency and reliability. To interpret these patterns, we utilized an adapted version of SHapley Additive exPlanation (SHAP) values (Lundberg and Lee, 2017; Lundberg et al., 2020), providing insights into factors influencing HNV grassland identification. Illustrating practical implications of our work, we apply our approach to an independent dataset of permanent grassland sites within our study area. Most sites have not been evaluated for conservation relevance, underscoring the importance of our research in supporting future conservation efforts.

6.2 Materials

6.2.1 Study Area

We conducted our study in SH (see Figure 6.1), Germany's northernmost federal state. The study area experiences a suboceanic climate, with an average annual precipitation of 800 to 900 mm in the northwest and 550 to 700 mm in the southeast (LLUR, 2021). SH features a distinctive geomorphology

shaped by the Saalian and Weichselian Ice Ages. The topography includes hilly eastern uplands and flat western marshlands, primarily endowed with nutrient-rich loamy soils. In contrast, the central Geest region is characterized by nutrient-poor sandy soils (LLUR, 2019). These diverse soil types, combined with high precipitation, have historically fostered the development of various HNV grassland types adapted to high groundwater tables and/or low nutrient availability (Dierßen, 1988; LLUR, 2015). In recent decades, however, these HNV grasslands have faced significant pressures, resulting in landscapes dominated by species-poor grasslands lacking HNV characteristics (Martens et al., 2024). In response, SH initiated a special conservation program, which aims to increase biodiversity and thus the proportion of HNV habitats (MELUND, 2021). The relevance of this program underlines the suitability of SH as our study area.

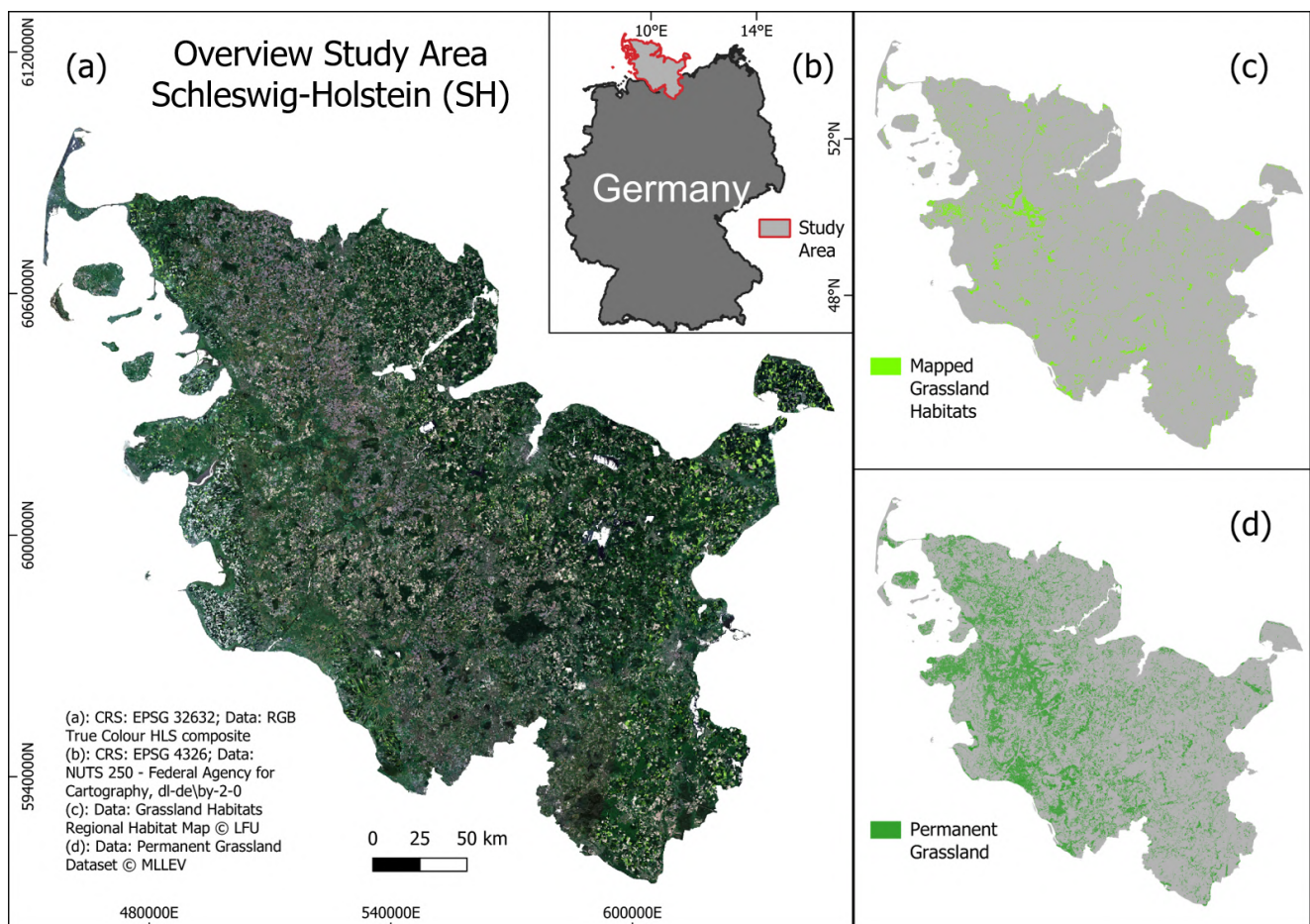


Figure 6.1: (a) Overview study area SH; (b) location study area in Germany; (c) regional grassland habitat map provided by the State Agency of Environment SH; (d) permanent grassland map provided by the State Ministry of Agriculture, Rural Areas, European Affairs and Consumer Protection SH

6.2.2 Harmonized Landsat Sentinel-2 Data

This study utilizes data from the HLS project (version 2.0) by NASA and collaborators (Masek et al., 2021b,a), which we accessed via NASA Earthdata Search platform (ESDIS et al., 2019). Data acquired by Landsat 8 OLI and Sentinel-2 MSI sensors undergo a harmonization process covering atmospheric correction, cloud masking, spatial co-registration, common gridding, view angle normalization and spectral bandpass adjustment. The virtual constellation results in a temporal resolution of two to three days at a pixel size of 30 x 30 m. For analysis, we used all spectral bands designated for terrestrial applications (see Table 6.1). We considered all HLS data available for the study area in the period between 2017 and 2022, which resulted in a total of 7270 scenes.

Table 6.1: Designations of Landsat 8 and Sentinel-2 bands considered in this study.

Band name	OLI band number	MSI band number	Wavelength range (micrometers)
Blue	2	2	0.45 - 0.51
Green	3	3	0.53 - 0.59
Red	4	4	0.64 - 0.67
Red-Edge 1	-	5	0.69 - 0.71
Red-Edge 2	-	6	0.73 - 0.75
Red-Edge 3	-	7	0.77 - 0.79
NIR	5	8A	0.85 - 0.88
SWIR 1	6	11	1.57 - 1.65
SWIR 2	7	12	2.11 - 2.29

6.2.3 Regional Habitat Data

Utilizing the official habitat map of SH as reference data, we define HNV and non-HNV grassland based on legal protection categories of the European Habitats Directive and Section 30 of the Federal Nature Conservation Act (LFU, 2022). On a scale of 1:5000, the habitat map provides *in-situ* information on the type, location and extent of a substantial portion of the state-wide grassland inventory relevant to nature conservation at a parcel level. We conducted additional field mappings between 2019 and 2022 to complement the reference data. To ensure methodological consistency, we followed the same mapping instructions used to conduct the field mapping

for the habitat map. For our study, we considered all mapped grassland areas (approximately 868 km²) and their associated types from the habitat map for model building and validation.

6.2.4 Permanent Grassland Data

According to EU regulations, permanent grassland is defined as land used to grow grasses or other herbaceous forage that is excluded from crop rotation for at least five years (EU, 2013). All EU member states report information on the type, location and size of agricultural parcels to the European Commission on an annual basis as part of the CAP monitoring (EU, 2021). For our study, we utilized the SH subset of this data (MLLEV, 2023). The dataset distinguishes between arable land, permanent grassland, permanent crops and miscellaneous agricultural land. We reduced the dataset to the permanent grassland category and used the polygon geometries as aggregation units for further analysis. In total, the permanent grassland covers an area of 3205 km².

6.3 Methods

To derive a priori grassland information on a data-driven basis, the employed machine learning models require quantitative data inputs, which we prepared as annual HLS time-series datacubes for the period 2017-2022. The methodology described below applies to each datacube individually, unless otherwise stated. Figure 6.2 schematically illustrates the processing workflow from input data to HNV assessment. Information on the software we developed and the associated software environment used for data processing, analysis, and visualization is provided in A.1.

6.3.1 In-situ Data Processing

Grassland types in the regional habitat map are based on ecological parameters traditionally assessed *in-situ*. Consequently, they have limited compatibility with RS-based analysis. To address this, we implemented a preprocessing protocol. First, we aggregated similar grassland habitat types into composite habitat types (CHT) using expert knowledge on land use intensity, differences in phenology, habitat wetness, nutrient status and floristic composition (see Table 6.2 and Appendix B.2). We then addressed issues of mapping quality and polygon geometry. Some sites may be associated with more than one habitat type, as field data were collected at the parcel level. The reference data also included grassland sites significantly smaller than the spatial resolution of the HLS data. Unfavorably shaped polygons

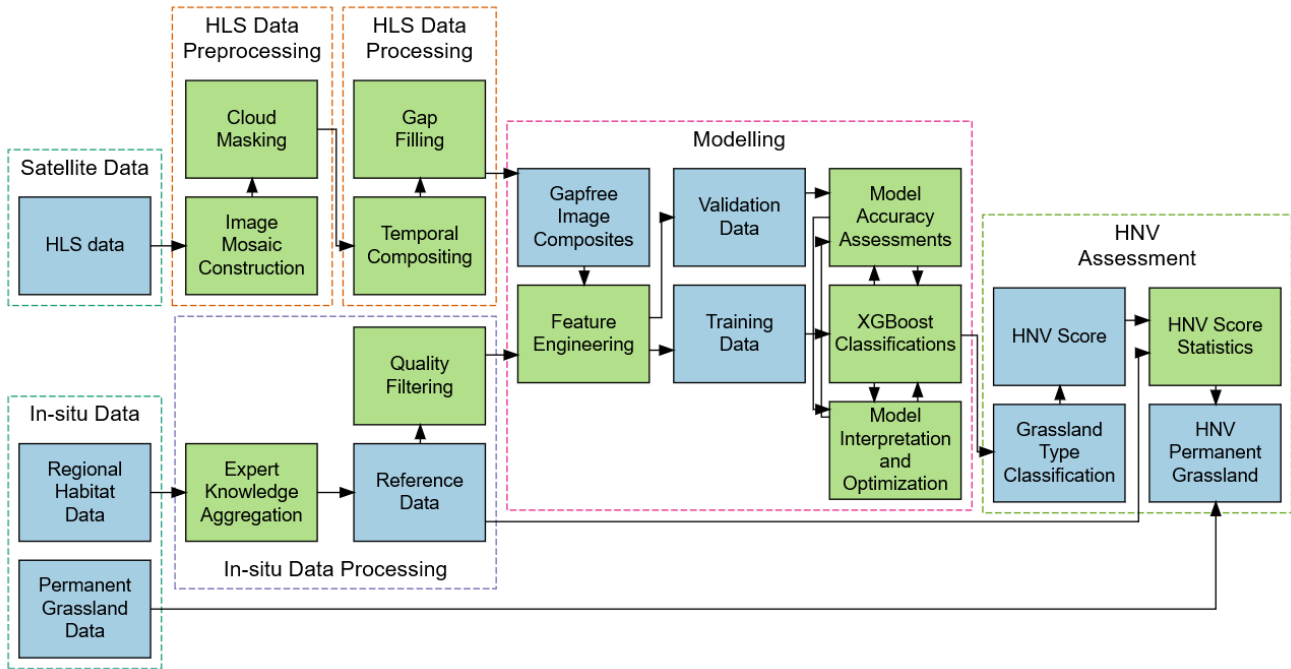


Figure 6.2: Conceptual illustration of this study's workflow – from raw data to HNV assessment of permanent grassland areas. Blue and green colored rectangles represent data and processing steps, respectively.

(i.e. extreme width-to-height ratio) pose an additional problem as they intersect one or more pixels but are not guaranteed to fully cover a single pixel (e.g. grassland on a dike), potentially enhancing mixed pixel problems. To mitigate this, we applied the following filters to the reference data:

1. Negative buffering of each polygon by one pixel (i.e. -30 meters)
2. Remove polygons associated with more than one habitat type
3. Remove polygons with known field mapping quality issues
4. Remove small polygons that do not meet the spatial resolution of HLS data
5. Remove unfavorably shaped polygons

The first filter excluded pixels at the boundaries of each polygon from subsequent analysis to reduce mixed pixel problems. The second and third filters ensured that only "pure" polygons were used for model building and validation. The fourth filter excluded polygons with an area $< 8100 \text{ m}^2$ after buffering to ensure sufficient size for further analysis. To account for polygon

shape, the fifth filter excluded polygons with a squareness threshold >1.7 , where we define squareness as follows:

$$squareness = \frac{Perimeter_{Polygon}}{4 * \sqrt{Area_{Polygon}}} \quad (6.1)$$

We employed the metric as a proxy for the with-to-height ratio of a polygon of arbitrary shape. For the fourth and fifth filters, we derived sensible thresholds by analyzing the polygon area and squareness value distribution, respectively, using a histogram coupled with a visual assessment in a geographic information system environment. After preprocessing, we split the remaining reference data using a 50/50 split, assigning approximately 24 km² of polygon geometries each to a training and validation dataset. These polygon geometries were subsequently utilized to sample pixel values from the feature space described in Section 6.3.5. For splitting, we adopted sampling best practices from the scientific literature, employing a seed-based, randomized, sampling approach without replacement (Stehman, 2009; Ramezan et al., 2019). Additionally, our sampling was stratified, ensuring that the class distribution in the training and validation sets mirrors the reference dataset to account for class imbalance.

Table 6.2: Key functional traits of Composite Habitat Types.

CHT	Start-of-Season (month)	Litter Coverage	Biomass	Chlorophyll	Land Use Intensity
Reed	5-6	High	High	Low	Low
Mesotrophic fen meadow	5-6	Low	Low	Low	Low
Dry species-rich grassland	4-5	None	Low	Low	Low
Abandoned wet meadow	5-6	High	High	Low	Low
Wet meadows	4-5	None	Medium	Medium	Medium
Wet pastures	3-4	None	High	High	High
Farmland	3-4	None	High	High	High
Moist mesic grassland	4-5	None	Medium - High	Medium - High	Medium - High

6.3.2 HLS Data Preprocessing

The study area is covered by nine tiles of the HLS dataset. Tiles with the same acquisition date and sensor were merged into an image mosaic. We then clipped the image mosaic to the administrative land boundaries of SH using vector data provided by the Federal Agency for Cartography and Geodesy (BKG, 2023). The image mosaics underwent pixel-based quality control by removing pixels with quality issues from further processing. To achieve this, we generated an invalid pixel mask based on Fmask (Qiu et al., 2019), filtering out pixels flagged as cloud, adjacent to clouds, cloud shadow, and high aerosol. To further minimize the likelihood of overlooking invalid pixels, we applied spectral tests to each mosaic, following the methodology recommended by Griffiths et al. (2019). We masked out all pixels for each band according to the following criteria:

- VIS reflectance $>20\%$ and NIR reflectance $<\text{SWIR reflectance}$
- A Haze-Optimized Transformation (HOT) value >0

The HOT is a band transformation of a sensor's blue and red reflectance band, that highlights haze and thin clouds (Zhang et al., 2002). We calculated the HOT according to Zhu and Woodcock (2012):

$$HOT = Band_{Blue} - 0.5 * Band_{Red} - 0.08 \quad (6.2)$$

6.3.3 Temporal Compositing

The masking of invalid pixels led to randomly distributed gaps in the HLS data. To increase the likelihood of spatially continuous cloud-free imagery, we aggregated preprocessed HLS data into predefined time intervals to create temporal composites. For this, we defined two composition periods, accounting for varying temporal resolutions of HLS data. This approach aimed to find a balance between data availability and precision, crucial for monitoring phenomena like plant phenology. We found a 10-day composition period to be suitable for all bands benefiting from the increased temporal resolution of HLS. However, for the Red-Edge bands of Sentinel-2, we extended the composition period to 16 days to cover three potential sensor overpasses. To generate temporal composites, we implemented a modified version of the best-available-pixel (BAP) algorithm proposed by Griffiths et al. (2013). The BAP algorithm is a parametric scoring function that identifies the best available pixel within a given period based on a maximum quality score. It calculates the weighted cumulative sum of a set of quality scores divided by the sum of their weights. We adopted the set of pixel quality scoring functions outlined by Griffiths et al. (2019), which include:

1. A logistic score based on the Euclidean distance of a pixel to cloud or cloud shadow, below a minimum distance threshold
2. A logistic score based on a pixel's HOT value
3. A Gaussian score based on the acquisition date to prioritize data close to the central date of a given time period
4. A linear score based on the percentage of cloud-free pixels in the area of interest

The first three scoring functions mirror the definitions in Griffiths et al. (2019). Our BAP implementation slightly modified the definition of the fourth scoring function. We calculated the cloud-free pixel percentage in the land area, excluding cloud coverage over water surfaces. As Griffiths et al. (2019) suggest, we assigned the highest weights (i.e. 1) to the first two scoring functions, addressing omission errors in cloud masks. However, based on initial tests that demonstrated improved results during heavily cloud-prone composition periods, we adjusted the weights of the third and fourth scoring functions from 0.25 to 0.5 and from 0.5 to 0.25, respectively.

6.3.4 Gap Filling

SH is a coastal state that often faces significant cloud cover, particularly during the winter months. As a result, the 10- and 16-day HLS composites still exhibited substantial data gaps. To fill these gaps, we employed a band-wise linear interpolation along the time axis. However, this method has limitations when no valid initial or last pixel values are available, particularly at the margins of the time series. Since this was the case for most winter composition periods, we pruned the annual sets of observations to eliminate persistent data gaps. For the 10-day composition period, a time frame of day of year (DOY) 60 to DOY 320 reliably eliminated winter data gaps. Similarly, we retained an annual set of observations spanning from DOY 60 to DOY 284 for the 16-day composition period.

6.3.5 Feature Engineering

We calculated several band indices using all bands of the gap-filled 10-day and 16-day composites (see Table 6.3). With our index selection, we aim to represent vegetation traits and development for model building, while reducing the computational payload for subsequent processing. The Enhanced Vegetation Index (EVI) and Green Normalized Difference Vegetation Index (GNDVI) are both measures of green biomass, canopy greenness and phenology (Chaves et al., 2020; Maleki et al., 2020). The Structure Insensitive

Pigment Index (SIPI) correlates with the ratio of carotenoids and chlorophyll content and functions as an indicator of plant physiology and phenology (Penuelas et al., 1995; Fusaro et al., 2019). The Normalized Difference Water Index (NDWI) indicates the Vegetation water status (Ferrant et al., 2017). The MERIS Terrestrial Chlorophyll Index (MTCI) and the Chlorophyll Red-Edge Index (CRI) are proxies for canopy chlorophyll content, canopy phenology and vegetation senescence based on the Red-Edge part of the spectrum (Maleki et al., 2020).

Table 6.3: Vegetation indices derived from HLS data. Refer to Table 6.1 for band designations.

Index Name	Formula	Reference
Enhanced Vegetation Index (EVI)	$\frac{2.5 * (Band_{NIR} - Band_{Red})}{(Band_{NIR} + 6 * Band_{Blue} - 7.5 * Band_{Blue}) + 1}$	Huete (1997)
Green Normalized Difference Vegetation Index (GNDVI)	$\frac{Band_{NIR} - Band_{Green}}{Band_{NIR} + Band_{Green}}$	Gitelson et al. (1996)
Structure Insensitive Pigment Index (SIPI)	$\frac{Band_{NIR} - Band_{Blue}}{Band_{NIR} - Band_{Red}}$	Penuelas et al. (1995)
Normalized Difference Water Index (NDWI 1)	$\frac{Band_{NIR} - Band_{SWIR1}}{Band_{NIR} + Band_{SWIR1}}$	Dash and Curran (2004)
Normalized Difference Water Index (NDWI 2)	$\frac{Band_{NIR} - Band_{SWIR2}}{Band_{NIR} + Band_{SWIR2}}$	Gao (1996)
MERIS Terrestrial Chlorophyll Index (MTCI)	$\frac{Band_{Red-Edge2} - Band_{Red-Edge1}}{Band_{Red-Edge1} - Band_{Red}}$	Dash and Curran (2004)
Chlorophyll Red-Edge Index (CRI)	$\frac{Band_{Red-Edge3}}{Band_{Red-Edge1}} - 1$	Gitelson et al. (2006)
Mean Absolute Spectral Dynamic (MASD)	$\frac{1}{m-1} \sum_{t=1}^{m-1} \left(\frac{1}{n} \sum_{i=Band}^n p_i^t - p_i^{t+1} \right)$	Franke et al. (2012)

Spectral indices typically describe the spectral signal for a specific time. Training a classifier with a sequential set of observations of the same in-

dex introduces the temporal domain to the feature space. However, rapid changes in the temporal domain (e.g. mowing of a grassland site) are only indirectly emphasized. To address this, we calculated the Mean Absolute Spectral Dynamic Index (MASD) to measure the magnitude of spectral change in time (Franke et al., 2012). Using all 10-day band composites, we detected changes between consecutive observations. Initially, a datacube comprised 182 predictor variables, which we subsequently narrowed down through a feature selection process (see Section 6.3.6 for details).

6.3.6 Identifying HNV Grasslands

To identify HNV grasslands, we employed a two-layered hierarchical classification scheme. The scheme consisted of a modelling layer and an HNV assessment layer.

Modelling

The modelling layer covered all processing steps to classify an annual HLS dataset according to the CHT aggregation. For classification, we trained one XGBoost model per datacube. XGBoost is a powerful ensemble learning algorithm that combines the predictions of multiple decision trees to create a robust classification model. By employing a gradient boosting framework while optimizing a Softmax loss function, it constructs decision trees by correcting errors from predecessors to iteratively improve model performance. Initially, we trained the XGBoost models with the complete feature space of a datacube. However, the impact of the Hughes phenomenon (Maxwell et al., 2018) emerged as a potential concern, given the rarity of certain classes in the reference data relative to the size of the feature space. To address this, we implemented a feature selection routine to reduce redundant information and minimize computational costs. This routine leverages SHAP values, a widely-used method for interpreting the decision-making processes of black-box models (Das and Rad, 2020; Linardatos et al., 2021). Originating from Shapley (1953)'s work on game theory, SHAP values quantify the contribution of each feature to model predictions by calculating the weighted average of prediction changes across all possible feature permutations within a dataset. Previous studies demonstrated the applicability of SHAP values for feature selection in an RS (Ghahremanloo et al., 2021; Zhou et al., 2022a; Huang et al., 2022; Gröschler and Oppelt, 2022) and environmental context (Effrosynidis and Arampatzis, 2021). Our feature selection routine consisted of the following steps:

1. Train a XGBoost model using the complete feature space
2. Calculate SHAP values using the trained model and the validation data

3. Aggregate the class-based local SHAP values into global mean absolute SHAP values and iteratively follow these steps:
 - (a) Train a new XGBoost model using the n most important features
 - (b) Make predictions on the validation data and record the F1-score
 - (c) Increment n by 1 until n covers the full feature space
4. Plot F1-scores against the feature count and identify the appropriate threshold

We defined the F1-score as:

$$F1 = \frac{2 \times (UA \times PA)}{UA + PA} \quad (6.3)$$

where UA and PA are the user (UA) and producer accuracy (PA), which are defined as:

$$UA = \frac{TP}{TP + FP} \quad (6.4)$$

$$PA = \frac{TP}{TP + FN} \quad (6.5)$$

where TP and FP are true and false positive class assignments, respectively, and FN are false negative class assignments. We considered a feature count threshold to be reached when the change in F1-score levelled off around zero between consecutive iterations.

In addition to feature selection, we employed SHAP to examine model decision-making processes. We trained several independent models using a standardized set of features (see Section 6.3.5) to predict the same target variables (i.e. CHT) over consecutive years. Consistent patterns in SHAP values across our models may indicate a connection between a feature and the target variable within a comparable feature space. We summarized the SHAP analysis from all models using the following routine:

1. Compute the mean absolute SHAP values for each class in every model
2. Rank features in descending order based on their SHAP values
3. Calculate the feature impact score (FIS) for each class
4. Aggregate FIS over the time series by calculating the mean FIS

The FIS is an exponential decay function that is defined as follows:

$$FIS_{CHT} = e^{-0.06 * R_{CHT}} \quad (6.6)$$

where FIS_{CHT} represents the FIS of a feature for a CHT, and R_{CHT} is the rank of a feature in the SHAP ranking of that CHT. The FIS assigns high weights to higher-ranked features and exponentially decreases weights for lower-ranked features, reflecting their diminishing impact on model decision-making. Given the class-wise mean FIS values, we split each feature into its spectral and temporal components. These components were used for global and class-wise aggregation. To ensure comparability, we resampled the 10- and 16-day composition periods to a common monthly scale, affiliating periods overlapping two months with the middle date's month. We then calculated the global mean FIS over all CHTs and illustrated the global and class-wise FIS aggregations in separate Sankey plots for the spectral and temporal components of each feature. Using the filtered feature spaces, we trained a new set of models, for which we determined a sensible set of hyperparameters using a randomized search cross-validation over a pre-defined hyperparameter space. We then assessed the models' prediction performances on the validation data, presented as a confusion matrix (aggregated over all datacubes) and derived accuracy scores, such as UA, PA and F1-score. For classification, we chose a fuzzy model output, i.e. the probability of a pixel belonging to a particular CHT. We favor this output type, as it allows for soft overlaps of categorical classes (Feilhauer et al., 2021) and supports more flexible aggregation methods.

HNV Assessment

The ensemble of independent classification results was the input for the HNV assessment layer. Based on the HNV status of each CHT, we aggregated the output from the previous layer to a continuous HNV score, which is defined as follows:

$$HNV_{score} = \frac{1}{year_{max} - year_{min}} \sum_{year_{min}}^{year_{max}} \sum_{i=1}^n P(CHT_i) \quad (6.7)$$

where $year_{min}$ and $year_{max}$ are the first and last year of our time series, respectively and $P(CHT_{i \in \{1, \dots, n\}})$ is the probability of a pixel belonging to an HNV CHT. Given the HNV score raster, we calculated the plot-wise median HNV score for the grassland polygon geometries in the regional habitat map. We checked the plot-wise median HNV score distribution for significant differences between HNV and non-HNV grassland sites by conducting a Kruskal-Wallis test (Kruskal and Wallis, 1952). Additionally, we visually assessed the plot-wise median HNV score distribution in a boxenplot (Hofmann

et al., 2017) to derive a sensible threshold for final HNV grassland identification in the permanent grassland dataset. The threshold was applied to the plot-wise median HNV score of the polygon geometries of the permanent grassland dataset.

6.4 Results and Discussion

6.4.1 Accuracy Assessment before Feature Selection

Accuracy Assessment indicated good predictive performance of all models for most classes on the validation data (see Table 6.4) We achieved an average F1-score of 0.89, with PA ranging between 0.63 (mesotrophic fen meadows) and 0.99 (farmland) and UA ranging between 0.87 (abandoned wet meadows) and 0.97 (moist mesic grassland). The confusion matrix revealed misclassification patterns characteristic of data-driven analyses. Model predictions showed a bias towards the majority classes, farmland and abandoned wet meadows, likely due to the class imbalance in the reference data. While the literature suggests different coping strategies, such as resampling imbalanced training data or synthetic data generation (e.g. SMOTE (Chawla et al., 2002)), the high similarity among CHTs from an ecological and remote sensing perspective may limit the effectiveness of such approaches. Misclassification predominantly occurred between CHTs with similar wetness or land use intensity and resulting vegetation structure. Reeds, for instance, might be similar in wetness and low land use intensity resulting in high vegetation structure comparable to abandoned wet meadows. Similarly, dry species-rich grassland or wet pastures might overlap with farmland in terms of land use intensity, leading at least temporarily to a low vegetation structure. Notably, all models struggled with correctly classifying mesotrophic fen meadows. We mainly attribute these misclassifications to the scarcity of the CHT in the reference data, reflecting the exceptional rarity of these habitat types in the study area.

Modelling uncertainties might also be related to the reference data. Typically collected through sampling-based field surveys conducted by ecologists, this data encounters various challenges in accurately defining plant communities and assessing survey thoroughness. Factors such as the multitude of surveyors, operator bias, taxonomic inflation, and taxonomic uncertainty contribute to the overall uncertainty associated with field data (Rocchini et al., 2013). Additionally, the habitat map in our study area was derived from a predefined environment, incorporating information from previous mappings conducted under the EU Habitats Directive and regional activities documenting HNV grassland. New recordings were made only where HNV grassland occurred in areas with high land use intensity. Methodologically, it is im-

portant to note the limitations of categorizing vegetation types abruptly, particularly at the species level, as vegetation groups often undergo gradual transitions due to environmental gradients and self-organization. Another issue with the habitat map is the potential mismatch with the RS data over time. The habitat map is static, based on field campaigns conducted at a single point between 2015 and 2020, with occasional updates. In contrast, HLS data was continuously acquired between 2017 and 2022. While some habitat types are relatively stable, changes in habitat composition that are reflected in the RS data but not in the habitat map cannot be ignored.

Table 6.4: Cumulative confusion matrix and accuracy scores for classification results before feature selection. The confusion matrix shows the cumulative prediction performance of all models. Producer's Accuracy (PA), User's accuracy (UA) and F1-score are derived from the cumulative confusion matrix.

Reference data	Model predictions								Total	PA
	Reed	Mesotrophic fen meadow	Dry species-rich grassland	Abandoned wet meadow	Wet meadow	Wet pasture	Farmland	Moist mesic grassland		
Reed	12667	20	19	748	35	21	77	15	13602	0.93
Mesotrophic fen meadow	178	1023	11	327	15	14	60	4	1632	0.63
Dry species-rich grassland	22	3	11562	74	19	28	1473	1	13182	0.88
Abandoned wet meadow	538	16	39	19243	223	163	744	40	21006	0.92
Wet meadow	68	4	18	738	7008	132	593	16	8577	0.82
Wet pasture	30	16	33	444	104	12168	1788	27	14610	0.83
Farmland	28	3	342	325	87	180	64767	10	65742	0.99
Moist mesic grassland	18	3	11	242	52	99	229	3111	3765	0.83
Total	13549	1088	12035	22141	7543	12805	69731	3224	F1 = 0.89	
UA	0.94	0.94	0.96	0.87	0.93	0.95	0.93	0.97		

6.4.2 Model Interpretation

Figure 6.3 visualizes the relationship between CHTs and the underlying spectral and temporal components over the time series features. Globally, the most significant spectral feature components were MTCI and MASD, playing approximately equal roles in class differentiation, indicating consistent predictive power across all models. EVI and GNDVI followed with slightly lesser but notable impacts, while NDWI 2, NDWI 1 and SIPI had the least impact. The MTCI demonstrated a consistently high impact across all CHTs, particularly for reeds and abandoned wet meadows, which are characterized by a late start-of-the season, low chlorophyll contents throughout the season and high litter coverages (Table 6.2). Despite limited availability due to a 16-

day composition period and reduced annual observations, the MTCI's high impact underscores the value of incorporating Red-Edge information in RS-based vegetation analysis. MASD significantly impacted the prediction of wet pastures and mesotrophic fen meadows by highlighting characteristic patterns of spectral change. Mesotrophic fen meadows are typically associated with low land use and consequently lower spectral change during the vegetation period. Wet pastures, in contrast, are subject to recurring anthropogenic interventions in the vegetation period, showing high MASD values during periods when spectral change differed most from other CHTs (Table 6.2). EVI and GNDVI, which measure the sharp increase from visible to near-infrared reflectance in vegetated areas, had noticeable impacts on most classes, except wet pastures. Intensively used pastures maintain relatively constant high chlorophyll contents during the season due to grazing-induced permanent renewal of vegetation, explaining the minimal impact. GNDVI also had minimal impact on reed predictions. Considering all spectral feature components, Red-Edge-based indices (MTCI and the CRI) had exceptionally high impacts on dry species-rich grasslands, probably due to low biomass production and low chlorophyll content after a long-term decrease of fertilizers. CRI also affected reed predictions but had limited impact elsewhere. Similarly, NDWI 2 and NDWI 1 significantly impacted reed and dry species-rich grassland predictions. Lastly, SIPI generally had a negligible effect on CHT differentiation.

On a global level, features derived from data acquired during March had the highest impact on model decision-making, followed by November, September and April, which had approximately equal impacts. The summer months, along with October and May, had a lesser impact on model predictions. During summer, most grassland types are at their seasonal peak in terms of vitality and greenness during this period. From a model perspective, the start and end of a vegetation season had the most impact on CHT differentiation. These periods coincide with critical phenological stages, such as a late start of plant growth and initial high litter coverages, which provide important information about vegetation presence, composition, and vigor. This leads to prominent changes in the spectral response and the structure of grassland sites. Consequently, different CHTs exhibit more similar characteristics in the feature space during summer, reducing the model's ability to differentiate classes.

Based on our interpretation of six independent XGBoost models, we recommend using the MTCI, MASD and EVI for grassland type differentiation in the spectral domain. These indices showed a stable relationship with the target variables regardless of the acquisition year. We particularly emphasize the importance of Red-Edge-based information on model-decision making. In the temporal domain, the beginning (March and April) and end (November and September) of the vegetation season had the highest impact

on model decision-making. Thus, engineering features from data acquired during these months should be prioritized in a data-driven analysis of dense RS-based time series. While our analysis of patterns in the SHAP rankings across multiple models is more robust than a single model analysis, transferability constraints may apply. Insights derived for feature selection in sparse RS-based time series might have high uncertainty, as SHAP analysis depends on the feature space. Similarly, the applicability of our feature recommendations might not improve classification quality when using other machine learning models or model parameterization, as SHAP analysis is model-dependent. However, we argue that our high-level insights might be transferable to other study areas, such as the northern German plain, since the HLS data archive is globally available and the CHT aggregation follows general ecological descriptors.

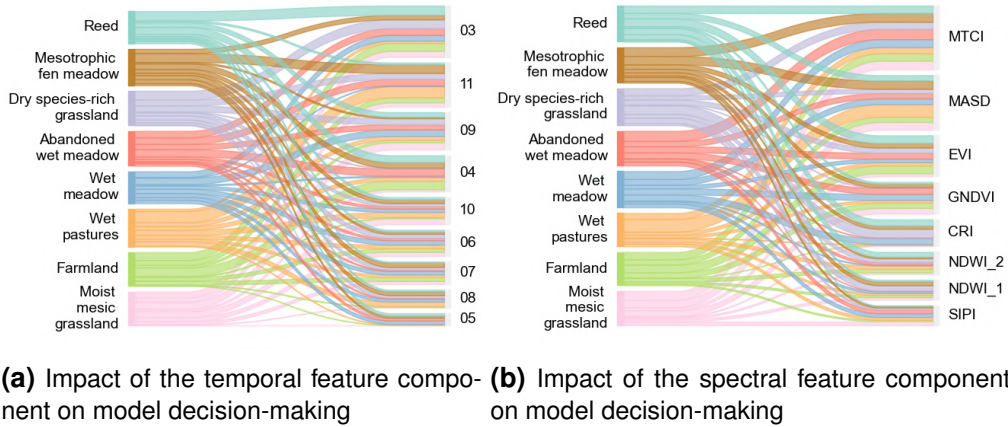


Figure 6.3: Relative feature component importance on model decision-making. Line thickness relates to the class-wise mean FIS. Feature components are listed in descending order of global mean IS. Temporal feature components are aggregated into monthly intervals. Monthly intervals are encoded numerically (i.e. 03=March, 04=April, etc.)

6.4.3 Accuracy Assessment after Feature Selection

Our feature selection protocol indicated that the gradients of the F1-score curves stabilized around zero between 30 and 40 input features, with F1-scores ranging between 0.85 and 0.87 (see Figure 6.4). Consequently, we determined a feature count threshold of 35 appropriate for all models. Compared to the F1-score derived from the aggregated confusion matrix before feature selection (see Figure 6.4), we achieved 95-97% of the initial model accuracy using just 19% of the full feature space. We argue that the heavily reduced computational costs and improved model simplicity outweighed

the slight loss in F1-scores (between 0.02 and 0.04) resulting from excluding 147 features from model training.

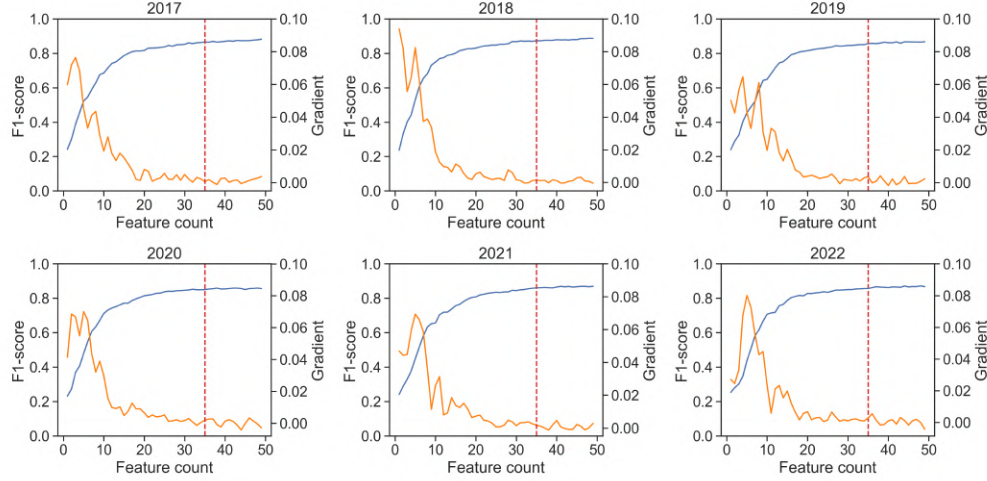


Figure 6.4: F1-scores of XGBoost models trained with n most important features while predicting the validation data. The blue line shows the F1-scores, the orange line shows the gradient of the F1-score curve concerning the feature count, respectively. The red dashed line indicates the feature count threshold chosen for each model. Feature count is limited to 50 features to simplify illustration.

Accuracy assessment after feature selection indicated a minor loss in accuracy (see Table 6.5). The models achieved an average F1-score of 0.86, PAs ranging between 0.57 (mesotrophic fen meadow) and 0.98 (farmland) and UAs ranging between 0.84 (abandoned wet meadow) and 0.95 (dry species-rich grassland). Although the patterns of misclassification in the confusion matrix after feature selection were slightly more pronounced, they remained similar to those before feature selection. Therefore, the discussion in Section 6.4.1 is generally applicable to classification results after feature selection.

6.4.4 HNV Grasslands Identification

Kruskal-Wallis test of the plot-wise median HNV score indicated significant differences between HNV and non-HNV areas in the habitat map (p -value < 0.05). A comparison of the plot-wise median HNV score distribution of both groups confirmed this observation (see Figure 6.5). The HNV score distribution shows a minor overlap of mapped HNV plots with low HNV score and vice versa. This overlap might be due to uncertainties in the underlying CHT classifications or the temporal mismatch between the habitat map and RS data (see Section 6.4.1), potentially indicating grassland site development. Based on the HNV score distribution of grassland plots in the habitat map,

Table 6.5: Cumulative confusion matrix and accuracy scores for classification results after feature selection. The confusion matrix shows the cumulative prediction performance of all models. Producer's Accuracy (PA), User's accuracy (UA) and F1-score are derived from the cumulative confusion matrix.

Reference data	Model predictions								Total	PA
	Reed	Mesotrophic fen meadow	Dry species-rich grassland	Abandoned wet meadow	Wet meadow	Wet pasture	Farmland	Moist mesic grassland		
Reed	12541	14	21	865	44	25	81	11	13602	0.92
Mesotrophic fen meadow	193	937	17	378	20	28	51	8	1632	0.57
Dry species-rich grassland	23	3	11309	96	14	53	1682	2	13182	0.85
Abandoned wet meadow	619	35	47	18717	354	232	930	72	21006	0.89
Wet meadow	76	14	19	881	6585	190	781	31	8577	0.76
Wet pasture	36	5	49	495	122	11653	2215	35	14610	0.79
Farmland	36	8	478	457	108	311	64335	9	65742	0.98
Moist mesic grassland	14	4	18	315	55	109	297	2953	3765	0.78
Total	13538	1020	11958	22204	7302	12601	70372	3121	F1 = 0.86	
UA	0.93	0.92	0.95	0.84	0.90	0.93	0.92	0.93		

we chose a threshold of 0.6 for plots in the permanent grassland dataset to be considered HNV and potentially relevant for nature conservation.

Figures 6.6 and 6.7 show the RS-based HNV grassland identification result in the permanent grassland dataset. Our approach classified about 8% (about 249 km²) of the permanent grassland in our study area as HNV (see Figure 6.8). Non-HNV permanent grassland accounted for the remaining 92% (about 2956 km²). About 66% (166 km²) of the HNV and 23% (677 km²) of the non-HNV permanent grassland areas were assessed by the habitat map. For the previously unmapped permanent grassland areas (approx. 2363 km²) we could make a new estimate of the potential importance for nature conservation. Of the unmapped area, we identified approx. 84 km² of permanent grassland area that, from an RS perspective, corresponds to the definition of grassland relevant to nature conservation in the regional habitat map.

6.4.5 Implications for Practical Nature Conservation

Due to the dramatic decline of biodiversity in European cultural landscapes during the last decades (Wesche et al., 2012), there is general agreement on the need for instruments to evaluate short-term changes in habitat quality, especially for grassland ecosystems. Fortunately, the European Habitat Directive obliges EU member states to conduct regular monitoring and to

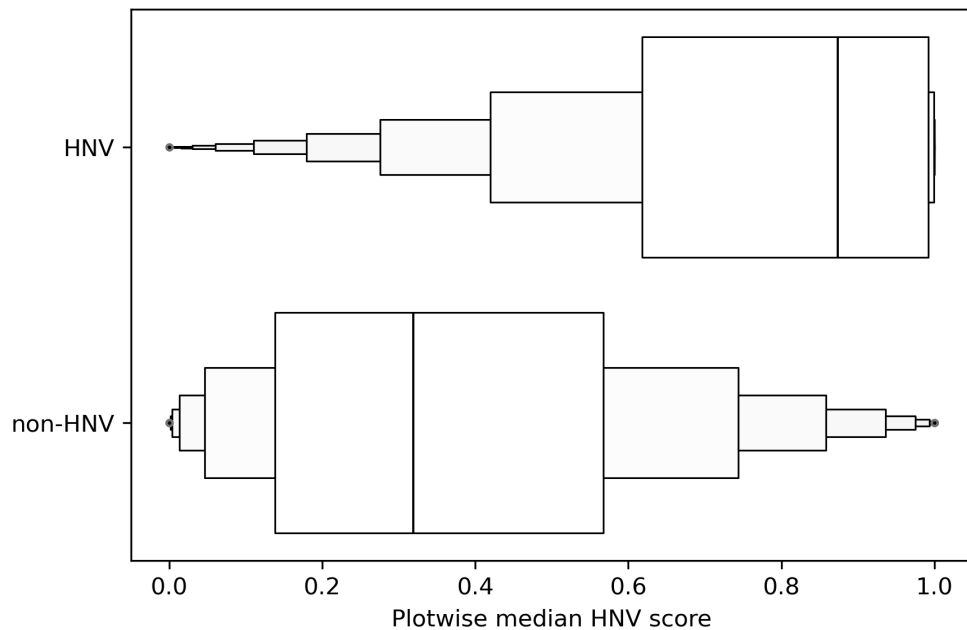


Figure 6.5: Median HNV score value distribution of HNV and non-HNV grasslands in the habitat map.

report every six years on the status of protected habitats and species and their potential for development. However, this commitment refers only to highly endangered sites, which usually occupy limited areas (Habel et al., 2013; Seer and Schrautzer, 2014; Schils et al., 2022). At regional and national levels, there is often a more detailed assessment of habitat quality, as for example in the German Nature Conservation Act or the Czech Nature and Landscape Protection Act. Consequently, besides the Europe-wide threatened habitats, the list of nationally protected biotopes now includes grassland ecosystems (e.g. Finck et al. (2017) for Germany). Area-wide monitoring activities only partially address this rapid development, due to long mapping intervals. For instance, one mapping interval in the Czech Republic requires 12 years (Ellwanger et al., 2018), whereas the preceded biotope mapping of our study area was conducted 30 years ago.

Given the spatial and temporal limitations of existing mapping initiatives, incorporating RS information offers a valuable opportunity for structured and sustainable monitoring of future grassland development. Our data-driven approach ensures high scalability and provides a robust framework for distinguishing between HNV and non-HNV grasslands, offering critical insights into the short-term development of these ecosystems. Our workflow addresses temporal scaling issues by providing an annual estimate of the HNV status of grasslands, enabling practitioners to detect significant changes over consecutive years and prioritize field mapping efforts accordingly. Addition-

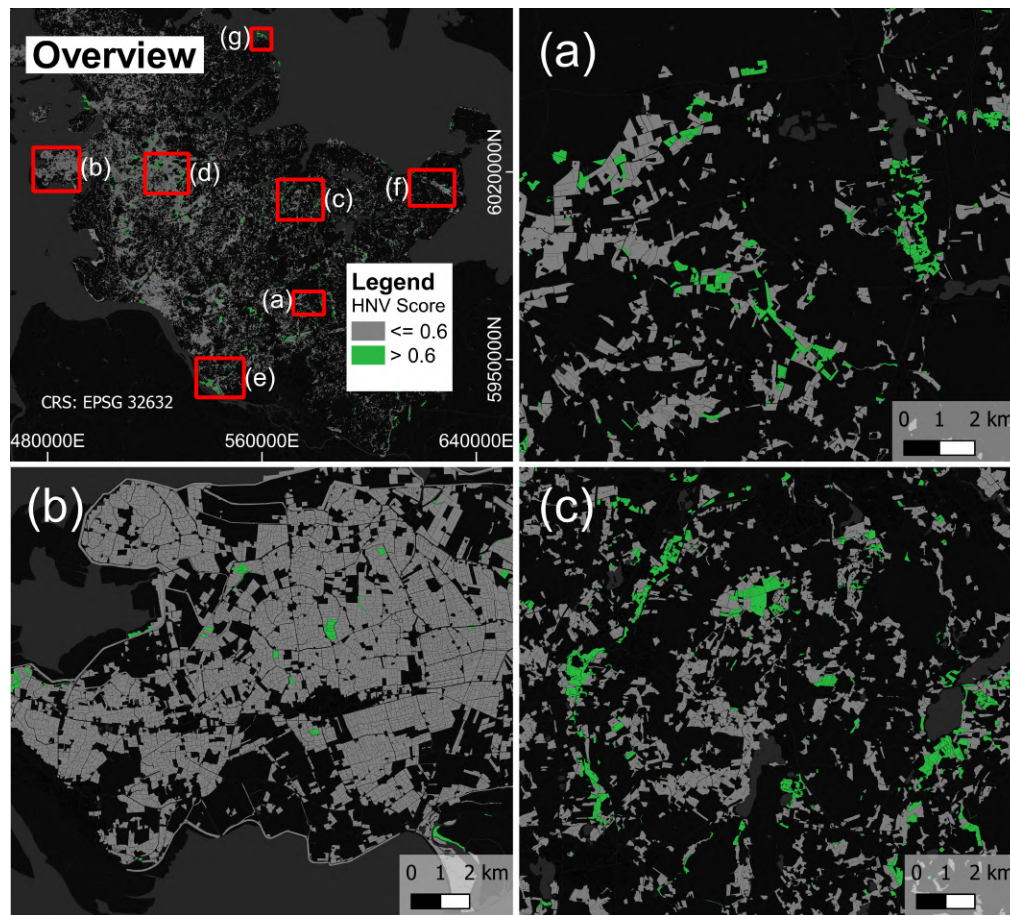


Figure 6.6: Exemplary illustration of RS-based HNV identification in the permanent grassland dataset using an HNV score threshold of 0.6. Overview shows the geographic location of subfigures (a)-(g) (see also figure 6.7). Subfigures show hotspot regions of permanent grassland or areas of relevance for nature conservation. (a): Barker Heide, (b): Eiderstedt, (c): Eidertal.

ally, it tackles spatial scaling issues by identifying HNV grasslands outside existing test environments that may align with monitoring targets. The results of our study demonstrate high methodological transfer potential to the national scale and, through comparison with the EUNIS habitat classification, to other European countries. The RS data used in this study are freely available from NASA. The high degree of automation in generating HNV grassland maps results in comparatively low costs, mainly processing hardware and time, thus addressing resource limitations in nature conservation. While RS-based monitoring cannot replace the expert knowledge of on-ground ecologists, it can significantly enhance the efficiency of their work.

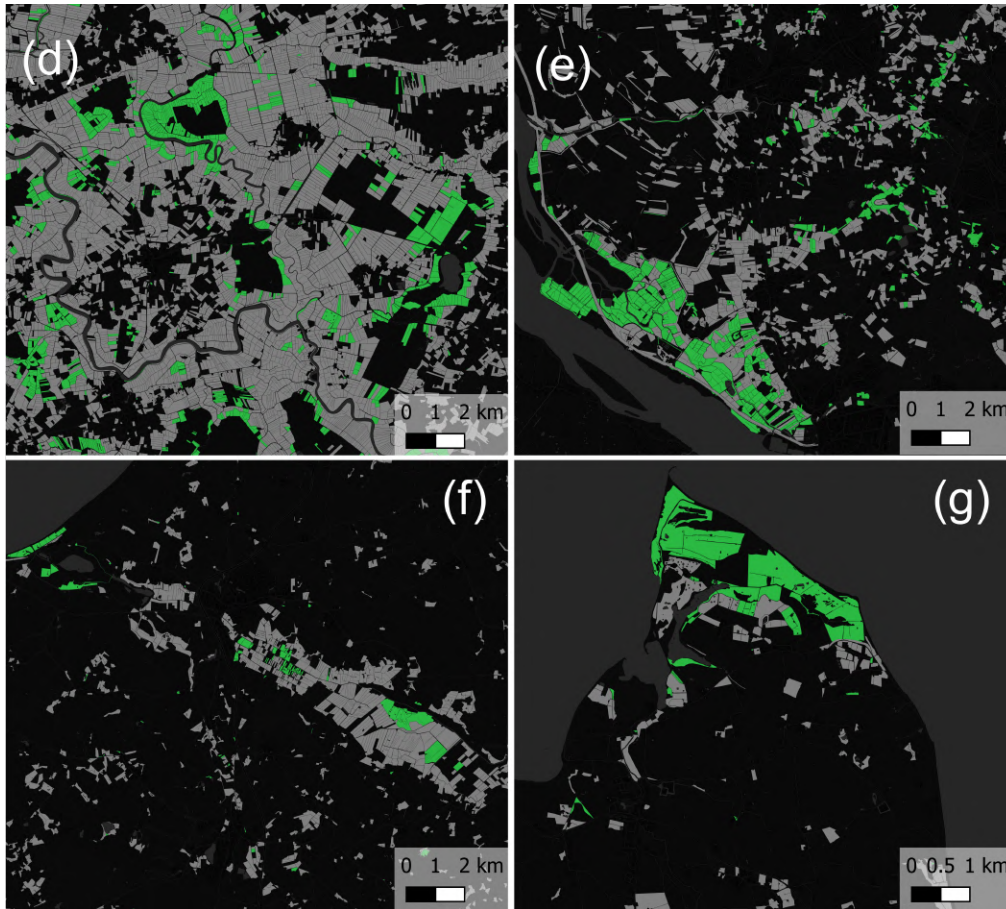


Figure 6.7: Continuation exemplary illustration of RS-based HNV identification in the permanent grassland dataset using a HNV score threshold of 0.6 (see also figure 6.6). (d): Eider-Treene-Sorge Depression, (e): Inland Elbe with Elbe foreland, (f): Oldenburger Bruch, (g): Geltinger Birk

6.4.6 Conclusion

Comprehensive a priori information on areas of interest is crucial for prioritizing mapping efforts and efficiently allocating financial and human resources in large-scale mapping initiatives. In this study, we tested a data-driven approach to derive such information from HLS time series data. Our results demonstrated that RS-based identification of HNV grassland is feasible. By aligning grassland monitoring targets with current RS capabilities using interdisciplinary expert knowledge and leveraging XGBoost, we achieved good classification performance, with F1 scores of 0.89 before and 0.86 after feature selection. Misclassification showed patterns typical for data-driven RS analysis, i.e. slightly overestimating the occurrence of majority classes and notably underestimating the minority class in the validation dataset. Analysis of the decision-making process of all XGBoost models deepened our under-

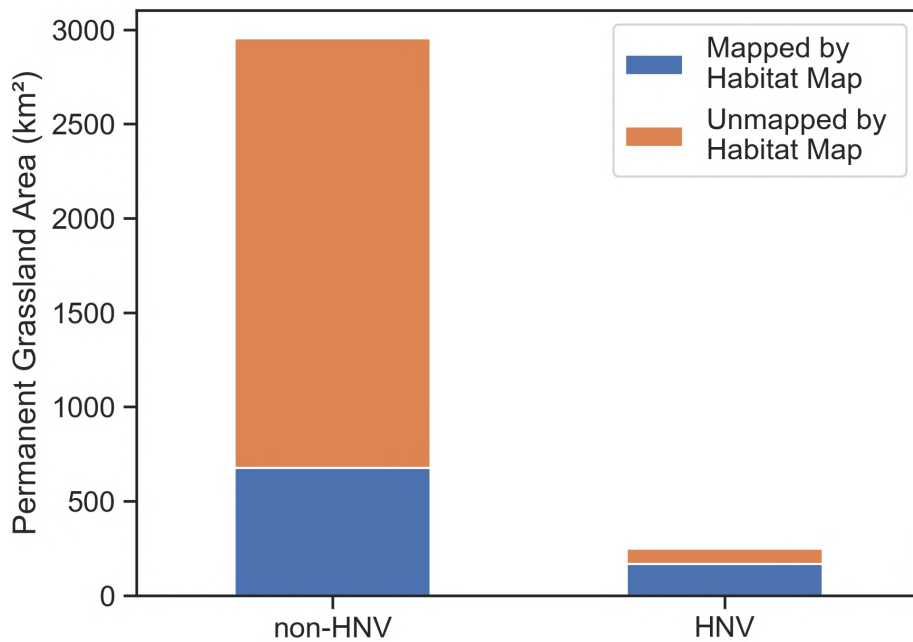


Figure 6.8: Permanent grassland areas classified as HNV or non-HNV, split by their presence in the habitat map.

standing of critical phenological periods and spectral features for grassland class differentiation. In the temporal domain, RS data acquired at the start or end of the vegetation season had the highest impact on model prediction, while in the spectral domain, Red-Edge information and spectral change influenced model predictions the most. Application of this approach to an independent dataset, comprising 2363 km² of grassland plots with previously unknown HNV status, revealed that 84 km² were classified as HNV, highlighting the significance of our results to increase the efficiency of field mapping efforts.

The results of this study may be further optimized. HLS data provides increased temporal resolution suitable for defining comparatively narrow compositional intervals at the cost of decreased spatial resolution. In complex landscapes with predominantly small HNV grassland plots, such as our study site, the importance of high spatial resolution might outweigh the benefits of increased temporal resolution. Integrating more spectral information from hyperspectral sensors in time series analysis, such as PRISMA or the recently launched EnMAP, may further enhance class separability.

Our study highlights the potential of integrating RS-based analysis into existing grassland monitoring frameworks. Although RS alone cannot achieve the

required level of detail for comprehensive reporting with current data and processing techniques, we successfully addressed spatial and temporal scaling issues of *in-situ* grassland mapping efforts. By fostering closer collaboration between RS and vegetation experts, grassland monitoring efficiency can be significantly enhanced.

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Chapter 7

Synthesis

As outlined in Chapter 1, grassland ecosystems are particularly vulnerable to global change due to their widespread distribution and dependence on regular, low-intensity disturbances. However, in much of the developed world, natural disturbance regimes have been largely eliminated, while modern agricultural practices prioritize productivity and profit over ecological integrity.

As Chapter 2 highlights, European grasslands are particularly affected by these trends, ranking among the most threatened ecosystems in the EU. The decline in grassland quality and extent is driven primarily by management intensification, land conversion, and abandonment. While policy instruments were designed to promote sustainable grassland management, they have largely fallen short of their objectives. Although recent reforms aim to address these shortcomings, ecologists consider their impact insufficient. This underscores the need for further policy adjustments, integrating expert-supported, scalable grassland management solutions while ensuring practical implementation across scales. A fundamental pillar in achieving this transformational change is a monitoring system that is fit for purpose. However, current operational frameworks rely predominantly on *in situ* methods, which lack the spatial and temporal coverage needed for a comprehensive assessment of management practices. RS offers a promising opportunity to bridge this gap, enabling regular, standardized observations across scales. Yet, its potential remains underutilized due to challenges in achieving fine-scale grassland assessments, alignment with operational monitoring needs, and integration into existing workflows. Overcoming these limitations requires an integrated approach that combines *in situ* and RS methods to ensure more comprehensive and actionable monitoring.

Building on this need, the overarching goal of this thesis is to advance RS applications in grassland management by lowering key adoption barriers and enhancing operational integration. A particular focus was set on overcoming *in situ* scaling challenges through RS — both for assessing small-

scale target variables that pose inherent scaling challenges and for monitoring large-scale variables requiring extensive spatial coverage in a timely manner. Additionally, improving model interpretability is emphasized to facilitate the broader operational adoption of RS technologies. This goal was achieved through four research objectives across three distinct studies, itemized in Section 1.1.

As Chapter 3 outlines, all studies in this thesis were conducted in the grasslands of SH, Germany, a region that serves as a representative example for the contemporary grassland situation in Europe. With its diverse agricultural landscape, extensive grassland coverage, and conflicting policies shaping management, SH provides an ideal setting for evaluating monitoring approaches across spatial and temporal scales. This synthesis integrates the main achievements of the research presented in this thesis, emphasizing methodological advancements, key contributions, and broader implications for RS in monitoring grassland management.

7.1 Main achievements

7.1.1 A novel remote sensing approach for mapping indicator plant species

Research objective 1: Develop RS methods for mapping indicator plant species in HNV grasslands using hyperspatial drone data

Chapter 4 introduces a novel RS approach for mapping indicator plant species with magenta-colored flowers in HNV grasslands. The approach demonstrates strong performance, aligning with the error margins reported by conservationists conducting long-term *in situ* plant monitoring. The DM population in the Lehmkuhlen reservoir served as a case study for method development.

At the core of this approach is a machine learning workflow that integrates hyperspatial, multispectral drone data with two novel processing steps developed in this thesis: (1) the MaVI and (2) a filter-based RS plant count. The MaVI enhances the spectral signature of magenta-colored vegetation, substantially improving differentiation from surrounding land cover. The effectiveness of MaVI is supported by high classification accuracy achieved with the employed RF model and further validated using SHAP analysis, which confirms its strong and consistent impact on model decision-making.

The filter-based RS plant count mirrors *in situ* plant counting methods while addressing image artifacts, referred to as the “ambiguity problem” in the corresponding study. The filter applies an image object-based approach, refining spatially adjacent magenta-vegetation-classified pixel clus-

ters to retain only intra-object regions with the strongest magenta vegetation reflectance signal, as expressed through MaVI. Special consideration was given to account for potential neighborhood relationships among magenta-colored plant individuals. Rather than functioning as a simple threshold filter, the approach allows for the retention of neighboring magenta vegetation pixels, when they are likely to represent distinct plant individuals. Validation against independent field surveys conducted across two consecutive flowering seasons demonstrated notable improvements in agreement between RS and *in situ* plant counts attributed to this processing step, therefore confirming its effectiveness.

Beyond its methodological contributions, this approach offers practical advantages for monitoring grassland conservation. Unlike traditional *in situ* plant counts, it is non-invasive. The approach, therefore, minimizes the risk of trampling the target plant species. Furthermore, it provides a spatially comprehensive assessment of indicator species populations, in contrast to field-based approaches, which are often restricted to small plots, rely on extrapolation, or require extensive personnel resources. Another advantage is its use of multispectral rather than hyperspectral imagery for RS plant species applications, thus reducing data acquisition costs and processing complexity. This accessibility makes the approach particularly suitable for conservationists working under funding constraints or with limited RS expertise, aligning with key recommendations for a wider RS adoption in environmental monitoring proposed by Vanden Borre et al. (2011a).

Unlike many RS studies that primarily focused on plant counts in agricultural applications (e.g. Thorp and Dierig (2011), Sulik and Long (2015), Horton et al. (2017) and Chen et al. (2019)), this approach was specifically developed for and tested in HNV grasslands. These ecosystems present distinct challenges for RS due to their structural complexity and species heterogeneity. While previous research has used multispectral data for plant species applications, it has primarily focused on detecting the absence of typical green vegetation characteristics, as seen in studies by Verma et al. (2002), Shen et al. (2010) and Xiao (2014). This thesis takes a different approach by leveraging the distinct spectral response of flowering structures, offering more targeted means for RS plant species applications. Some notable studies by Sulik and Long (2015), Horton et al. (2017) and Chen et al. (2019) and, Shao et al. (2023) have also utilized flower color for RS analysis, but the approach developed in this thesis uniquely addresses the research gap for magenta-colored vegetation.

Despite its advantages, this method is not a direct substitute for hyperspectral data. Although increased spatial resolution can partly compensate for lower spectral resolution, species differentiation remains challenging. Additionally, the reliance on the spectrally prominent magenta flower color necessitates that the flower size is sufficiently large relative to the spatial reso-

lution of the RS data. This limitation coincides with findings from the sensor ground sampling distance degradation experiments conducted by Gallmann et al. (2022). Adjusting flight parameters, such as reducing flight altitude, or employing higher resolution sensors, may address this constraint to some extent. However, flower size and positioning within pixels present additional challenges. Variations in pixel coverage due to positional geometry, such as individual plants spanning multiple pixels, can result in false-positive detections and thus inflate plant counts. Capturing drone data during low wind conditions can partially mitigate these issues, but optimal data acquisition remains difficult, as heavier flower heads frequently bend, altering their orientation relative to the sensor. Consequently, interpreting results in terms of magenta-colored vegetation pixel density per unit area rather than absolute plant counts may provide a more accurate representation of this analysis results.

Nevertheless, this approach offers a new perspective on indicator plant assessment. Its extensive spatial coverage, semi-automated yet accessible processing framework, and accuracy comparable to *in situ* methods establish a scalable foundation for indicator plant monitoring, addressing data scarcity while reducing reliance on personnel resources. Recent research has further demonstrated the potential for extending this approach. Ahmed et al. (2024) successfully integrated multispectral drone imagery with computer vision techniques to identify wild orchid species. A key component of their analysis was the MaVI. They demonstrated its applicability to other orchid species characterized by magenta-colored flowers, including *Dactylorhiza fuchsii*, *Dactylorhiza maculata*, *Anacamptis pyramidalis*, *Gymnadenia borealis*, and *Epipactis atrorubens*. Their study also confirmed applicability to other HNV grassland sites, such as Middleham Quarry and Weetslade Country Park in Great Britain.

Overall, the approach developed in this thesis advances RS applications in monitoring grassland management, aligning with the research objective stated above, while contributing to the overarching goal of this thesis. Specifically, it addresses the challenge of assessing small-scale target variables at scale with an emphasis on the spatial dimension.

7.1.2 Monitoring indicator plant population development and conservation outcomes with remote sensing

Research objective 2: Establish a framework to assess indicator plant population development through repeated drone surveys to assess conservation efforts

Chapter 5 extends the approach presented in Chapter 4 to the temporal domain, demonstrating its scalability for repeated monitoring of indicator plant species. While single-year RS plant counts provide detailed spatial distribution data, multi-year applications enable systematic assessments of population trends and conservation outcomes. This new temporal perspective is critical, as conventional monitoring approaches often struggle with scalability over time. Previous mitigation strategies, such as incorporating citizen science, have helped bridge data gaps but introduced unquantified uncertainties and reliance on voluntary participation (Conrad and Hilchey, 2011). This thesis addresses these limitations by presenting a semi-automated, RS-based alternative.

Gröschler et al. (2023) replicated the drone survey conducted by Gröschler and Oppelt (2022) during the subsequent flowering season at the same study site using identical equipment. The previously developed machine learning workflow was applied to the new dataset, and both datasets were analyzed within a change detection framework to assess DM population development. Plant individuals per unit area served as the shared metric across datasets, with classification results aggregated using a standardized grid to ensure spatial comparability. This structure enabled the calculation of plant gains or losses per unit area, mirroring methodologies established for *in situ* surveys of plant population development.

The analysis revealed a substantial decline in DM between consecutive flowering seasons, particularly within previously identified hotspots, though the decline extended across the broader study area. While a two-year change detection does not establish a long-term trend — especially given the species' natural interannual population fluctuations — the findings warrant closer monitoring of DM populations in the Lehmkuhlen reservoir as broader declines in Central European DM populations have been reported by Wotavová et al. (2004), Wegener (2011) and Dullau et al. (2019a). Unlike these previous studies, the presented approach provides a spatially explicit, high-resolution assessment of population changes, demonstrating the potential of RS for plant population monitoring. Moreover, the ability to pinpoint areas requiring timely conservation interventions aligns closely with the criteria for effective indicator species monitoring as outlined, for example, by Dullau et al. (2019b).

A particularly noteworthy finding was the emergence of new clusters of DM in previously uninhabited areas, confirming the success of seed material transfer. This direct assessment underscores the value of RS in evaluating conservation measures. *In situ* methods, such as GPS-referenced photography, are often insufficient for detecting such expansions due to the potential for oversight or the lack of baseline reference data. RS provides comprehensive, non-invasive spatial coverage, reducing the likelihood of missing new occurrences and improving the reliability of conservation assessments.

Ensuring methodological consistency across time necessitated a critical evaluation of potential sources of error propagation. Insights from Gröschler and Oppelt (2022) indicated image quality as the primary factor affecting transferability. Two methodological adjustments were explored to address this issue: (1) modifications in spatial resolution during data acquisition and (2) the use of an alternative machine learning classifier during processing.

Prior research by Chen et al. (2000) has suggested that a slightly coarser spatial resolution can improve SNR, therefore, enhancing image quality. Accordingly, the drone flight parameters were adjusted to increase the spatial resolution from 3.0 to 3.4 cm per pixel. While the newly acquired dataset exhibited fewer image artifacts than the previous one, evidence was insufficient to attribute this improvement solely to the resolution adjustments. Environmental factors such as different lighting conditions or lower wind speeds resulting in stabler flight may have also played a role. The trade-off between resolution and image quality is well recognized in drone applications (e.g. Seifert et al. (2019)), yet its implications for indicator plant population monitoring remain underexplored. This thesis contributes to the discussion by demonstrating how spatial resolution differences between datasets can introduce inconsistencies in the correspondence between pixels and target objects, potentially affecting change detection results.

To mitigate image quality issues during processing, a NN was evaluated alongside the previously used RF classifier. This thesis found that the RF classifier outperformed NN models for the given dataset. The RF model demonstrated greater robustness to image artifacts, required less tuning, and provided more accurate population estimates. In contrast, the NN model, despite identifying slightly more true positives, exhibited a significantly higher false-positive rate and was more sensitive to image artifacts. These findings challenge the prevailing trend indicated by recent subject reviews (e.g. Christin et al. (2019); Borowiec et al. (2022); Pichler and Hartig (2023)) to adopt deep learning methods indiscriminately in RS research. Instead, they underscore the importance of selecting models based on dataset characteristics, computational feasibility, and application-specific requirements, aligning with findings from Southworth et al. (2024). More broadly, this thesis highlights that increased model complexity does not necessarily improve ecological monitoring performance, particularly when training data is limited or input variables are noisy.

By integrating spatial and temporal dimensions, this approach provides conservationists with critical population development data that would otherwise require substantial resources to obtain or lack spatial comprehensiveness. Its increased methodological efficiency offers potential cost savings, allowing for a more sustainable allocation of conservation funds toward long-term monitoring initiatives. The approach advances RS applications in monitoring grassland management by enabling scalable assessments of small-

scale target variables, with an emphasis on the temporal dimension. The findings directly support the above-mentioned research objective while aligning with the overarching goal of this thesis. Specifically, they demonstrate how RS-based monitoring can enhance long-term indicator plant population assessments and support data-driven conservation decisions.

7.1.3 Annual, spatially comprehensive mappings of high nature value grasslands using remote sensing

Research objective 3: Leverage RS time series analysis to improve the monitoring of HNV grasslands over extensive areas

Chapter 6 presents a scalable, data-driven RS approach for mapping the location, extent, and HNV status of grasslands in SH. Traditional monitoring programs are limited by incomplete spatial coverage and infrequent data updates, failing to capture the dynamic nature of grassland conservation under global environmental change. The proposed methodology bridges these gaps by integrating high temporal resolution satellite time-series data with machine learning, enhancing both the spatial and temporal efficiency of management assessments.

A key contribution of this approach is a refined grassland classification scheme for RS applications, enabling the differentiation of eight grassland types. For conservationists to adopt RS techniques, analysis results must align with their monitoring guidelines, such as the biotope map used for HNV grassland monitoring in SH. However, the biotope map is partly shaped by legislative requirements rather than ecological criteria, limiting its utility for RS analysis. To address this, a classification scheme was co-developed by RS experts and regional grassland ecologists to enhance its compatibility with RS-based assessments. Despite these refinements, spectral similarities among grassland types required expanding the feature space beyond spectral characteristics. Consequently, dense, gap-free HLS time-series datacubes were integrated with fine-tuned XGBoost models, enabling the generation of annual grassland type maps from 2017 to 2022 with high classification accuracy.

While these classifications serve as intermediate results, they offer valuable short-term, landscape-scale insights into grassland management, surpassing the spatial coverage and six-year update cycle of existing FFH monitoring, as well as the infrequent decade-long cycle of the regional biotope map. Similar benefits have been observed in previous studies leveraging RS time-series data for FFH grassland differentiation (Raab et al., 2018; Tarantino et al., 2021; Pesaresi et al., 2022). However, model accuracy assessments revealed systematic misclassification patterns typical of data-

driven RS analyzes. To improve prediction robustness, a novel HNV score was developed, aggregating fuzzy model outputs into a multi-year mean probability estimate of a grassland's HNV status. This probabilistic approach enhances classification confidence by reinforcing consistent predictions across independent models while also identifying areas of uncertainty. The continuous probability scale offers flexibility for application-specific confidence thresholds, as demonstrated in Gröschler et al. (2024). Statistical validation confirmed significant differences in HNV scores between HNV and non-HNV grasslands in the regional biotope map. However, some overlap between categories suggests classification uncertainties or temporal mismatches between reference and RS data, potentially reflecting grassland development over time. Despite these uncertainties, results indicate that the HNV score is a suitable metric for identifying HNV grasslands and can serve as a decision-support tool for large-scale grassland mapping efforts and conservation planning.

To evaluate the broader applicability of the approach, a case study analyzed an independent dataset, comprising 3,205 km² of permanent grasslands, of which 2,363 km² had an unknown HNV status. The analysis identified approximately 84 km² of potentially conservation-relevant grasslands not included in the regional biotope map. These findings align with regional grassland development trends reported by authorities (e.g. MELUND (2021); Lütt et al. (2022)), which indicate that most grasslands in SH are of low nature value. Notably, the permanent grassland dataset originates from an agricultural context, making the identification of HNV grasslands within these areas particularly significant. Conversely, these findings raise concerns about the comprehensiveness of SH's biotope map, which is widely considered by authorities to provide a comprehensive inventory of conservation-relevant grasslands. Similar gaps were identified in Germany's national biotope mapping by Schoof et al. (2020), which aggregates biotope maps from all federal states, indicating that the findings of this thesis may have broader implications for other German states.

The ability to generate annual grassland type maps and multi-year HNV probability predictions from RS data represents a significant advancement in grassland monitoring. The annual update cycle helps address data gaps left by irregular field-based assessments. Since intra-annual reflectance patterns serve as independent feature spaces, inter-annual spectral variations due to environmental factors can largely be neglected as sources of prediction bias. Unlike FFH monitoring or biotope mapping, this approach extends assessments beyond designated conservation sites. By integrating freely available HLS data with an automated processing framework, it minimizes costs, with primary expenses limited to data processing and computational resources. This methodology supports regional legislative reporting and conservation planning while optimizing *in situ* survey efforts. Addition-

ally, it holds potential for application in other regional and national grassland monitoring programs and, through alignment with the EUNIS habitat classification, broader implementation across the North European Plain. The focus on method transferability addresses key barriers to RS adoption for conservation monitoring identified by Vanden Borre et al. (2017). However, regional adaptation of the classification scheme is necessary to ensure applicability beyond SH, as target variable characterization differ across regions.

Despite these advancements, certain limitations must be acknowledged. Defining HNV grasslands remains inherently challenging, as valuation criteria vary across disciplines and administrative frameworks. Differences exist not only between agricultural and conservation perspectives but also within conservation itself, depending on ecological function, species composition, and management objectives. From a technical standpoint, reliance on HLS data offers a desirable two to three day temporal resolution at the expense of S2's 10 m to 20 m spatial resolution. This potentially affects classification performance in heterogeneous landscapes with small grassland patches, such as those in Europe. In fact, evidence from this thesis aligns with other studies (e.g. Griffiths et al. (2020)), suggesting that high spatial resolution may be more critical for grassland differentiation than the temporal improvement gains over the revisit cycle of S2 alone. This finding gains further relevance in the light of recent uncertainties regarding NASA's ability to sustain its current level of earth observation services, as reports indicate significant budget cuts in the short term (American Astronomical Society, 2025). While it remains unclear how the HLS project will be affected, its potential discontinuation would represent a considerable setback for earth observation science. However, for the specific task of HNV grassland identification, the S2 constellation alone may provide a sufficient alternative for long-term monitoring. Moreover, recent geopolitical developments highlight the advantages of a Europe-centered RS strategy to ensure long-term stability of EU conservation monitoring by reducing reliance on United States-based satellite programs.

Overall, the proposed approach demonstrates the feasibility and scalability of RS-based HNV grassland mapping, significantly enhancing the information available to optimize *in situ* mapping efforts. Comprehensive prior knowledge of areas of interest is crucial for prioritizing mapping efforts and efficiently allocating financial and human resources in large-scale initiatives. Its capacity to support structured, data-driven decision-making aligns with Lique et al. (2024)'s recommendations for improving environmental monitoring across Europe, reinforcing the role of RS in biodiversity monitoring and sustainable land management. The presented approach advances RS applications in monitoring grassland management, addressing the above-mentioned research objective while aligning with the overarching goal of this thesis. Specifically, it demonstrates the scaling of RS data to assess large-

scale target variables timely.

7.1.4 Explainability enhancements of machine learning models tailored for grassland monitoring

Research objective 4: Enhance the explainability of RS models in grassland monitoring to facilitate broader adoption

As demonstrated throughout this thesis, a persistent challenge in applying RS to ecological monitoring has been the opacity of machine learning models, which complicates interpretation and limits confidence in their predictions. To address this, Chapters 4 and 6 emphasize enhancing model explainability through different forms of SHAP-based analyses.

A key aspect of this thesis is the application of SHAP values to quantify feature impact in RS-based classification, providing a more robust alternative to conventional feature importance analyses. SHAP beeswarm plots facilitated the removal of non-predictive descriptors, refining the feature space and improving model efficiency without compromising classification accuracy. While conventional methods can also achieve feature selection, SHAP overcomes key limitations such as sensitivity to feature order and cardinality, making the process more systematic and reliable. In Gröschler and Oppelt (2022), SHAP analysis identified the MaVI as the most impactful feature in a RF classification model for distinguishing magenta-colored vegetation. While the implications of this finding have been synthesized in Section 7.1.1, it is worth emphasizing SHAP's role in strengthening the evidence base. By offering a novel data-driven perspective on feature-target relationships, SHAP provides a clearer, more interpretable assessment of the role of flower color in RS analysis.

A similar methodology was employed in Gröschler et al. (2024), to address the Hughes phenomenon in high-dimensional spectral time series. By iteratively refining feature spaces based on SHAP insights, the employed models became significantly more efficient with minimal loss in classification performance. This study also extended the conventional use of SHAP by introducing a novel extension: the FIS. FIS serves as a shared metric for cross-model pattern analysis, systematically ranking the impact of spectral and temporal feature components over time and across classification classes. FIS analysis revealed that start-of-season, end-of-season, and Red-Edge spectral features consistently had the highest impact across models, emphasizing the importance of phenological transitions and spectral change metrics in grassland classification. While these findings align with prior studies using conventional methods of model explainability or domain knowledge (e.g., Schmidt et al. (2014) and Masemola et al. (2020)), the model explain-

ability framework introduced here offers a new perspective, allowing a more granular analysis of individual feature components. This level of detail surpasses what is achievable through existing model explainability methods.

The advancements in model explainability in this thesis have broader ecological applications. SHAP can be adapted to various ecological and environmental applications, including habitat suitability and land use intensity modelling, while FIS extends its utility to RS time series requiring sub-feature-level explainability. As a model-agnostic technique, SHAP is compatible with various machine learning algorithms, making it a powerful tool for environmental research. Unlike simpler approaches like permutation importance, SHAP captures feature interactions, further enhancing model transparency.

Nevertheless, certain limitations must be acknowledged. The computation of exact SHAP values requires evaluating all possible feature subsets, which is infeasible for high-dimensional datasets — a common challenge in RS analysis. Approximation techniques help mitigate this issue, but for large datasets and deep learning models, SHAP computations can still be prohibitively expensive. Additionally, while SHAP provides numerical impact scores, translating these into actionable ecological insights requires domain expertise, as SHAP values do not imply causality in the feature-target variable relationship. As FIS is a SHAP derivative, it directly inherits those drawbacks, while adding another layer of complexity. Implementation complexity also remains a barrier. Although tools such as the SHAP Python package facilitate computation, effectively applying SHAP to grassland monitoring still demands expertise in both computer science and ecology. These challenges underscore the necessity of interdisciplinary collaboration at the interface of RS and grassland ecology.

In conclusion, this achievement advances the integration of explainable machine learning into RS-based grassland monitoring by improving the explainability of black-box models. By incorporating SHAP analysis at both species- and landscape-scale assessments, RS-based conservation evaluations become more transparent, reliable, and widely applicable. By using the FIS, cross-model feature impact pattern analysis becomes possible. The methodological framework presented here addresses key challenges in feature selection and model explainability, ultimately contributing to lowering barriers in RS adoption. It therefore addresses the above-mentioned research objective while contributing to the overarching goal of this thesis.

Chapter 8

Conclusions and future challenges

This thesis presents a series of methodological advancements for scaling RS data for monitoring sustainable grassland conservation and management. The proposed methods effectively address *in situ* scaling issues through RS — specifically, assessing small target variables at scale and extensive areas timely — while enhancing modelling explainability to facilitate broader operational adoption of RS technologies. However, several avenues for further research remain, offering opportunities to refine, extend, and adapt these methodologies.

To address spatial scaling issues of small-scale target variables, this thesis introduced the MaVI and a RS-based plant count method. MaVI demonstrated strong potential for detecting magenta-colored vegetation, suggesting its suitability as a simple yet effective tool for grassland conservation. However, its full potential remains to be explored. While previous studies have demonstrated its effectiveness for certain magenta-flowering orchid species, future research should assess its applicability to similarly colored, conservation-relevant species, such as *Centaurea jacea* and *Vicia cracca*, as well as to invasive species like *Rosa rugosa*. Additionally, MaVI's formulation allows for adaptation to other secondary-colored flowering structures with minimal modifications. Future research could extend this approach to cyan-colored species (e.g., *Centaurea cyanus*) and yellow-colored species (e.g., *Hypericum perforatum* and *Hypochaeris radicata*), broadening the applicability of multispectral drone-based monitoring for grassland conservation. Investigating transitional color variations, such as the magenta-to-cyan gradient in *Echium vulgare*, could further refine the boundaries of secondary color VIs.

The proposed RS-based plant count approach achieved accuracies comparable to those reported for *in situ* plant censuses. Further refinements could enhance the method's accuracy, particularly by addressing the corre-

spondence between pixels and individual plants. As image quality was the primary factor affecting this correspondence, future research should systematically explore a wider range of flight parameter adjustments beyond those tested in this thesis. Additionally, shifting from a pixel-based to an object-based approach could enhance plant detection accuracy and enable multi-species plant censuses among magenta-colored vegetation using multispectral data, as object-based analysis introduces flower shape to the feature space. If the previously discussed secondary color VIs prove effective, the multi-species plant census for magenta-colored plants could be extended to other secondary-colored species, mitigating limitations related to the presence of specific flowering plants during drone flights. However, the feasibility of multi-species plant census based on flower color and shape should be critically evaluated against hyperspectral methods, which remain the standard for RS-based plant species applications.

To enhance temporal monitoring of small target variables, this thesis developed a semi-automated RS-based approach, utilizing MaVI and RS plant counts for assessing the population development of magenta-colored flowering species. This approach successfully documented conservation successes from a novel perspective while also pinpointing areas that may require timely intervention to sustain indicator plant species. Thus, it may serve as a valuable tool for communicating conservation outcomes and supporting data-driven decision-making in ecological management. Future research opportunities arise from the previously discussed potential refinements to the underlying methodology. Additionally, extending this approach to long-term monitoring would allow for the establishment of spatially comprehensive population trends. Combining those trends with ancillary habitat monitoring, such as logging groundwater level or nutrient availability, would facilitate a more holistic assessment of conservation success and possibly enable population projections. Furthermore, integrating multi-species plant census with ecological domain knowledge could provide deeper insights into species interactions and habitat dependencies, ultimately enhancing biodiversity monitoring and conservation management strategies.

To facilitate timely and extensive grassland monitoring, this thesis proposed an RS-based approach for mapping the location, extent, and HNV status of grasslands in SH on an annual basis. These favorable characteristics address critical monitoring gaps resulting from the long intervals and irregularities inherent in large-scale *in situ* grassland surveys. As such, it provides a data-driven information source to inform conservation planning and optimize large-scale field mapping efforts.

In the SH case study, the approach identified potentially conservation-relevant grasslands that were unknown to the regional biotope map. While its prediction quality has been thoroughly analyzed through comparisons with the biotope map and independent *in situ* surveys, further post-hoc validation

in the newly identified HNV sites would strengthen prediction confidence. Future research should also focus on minimizing misclassification errors in the underlying grassland type classification. This is particularly important for rare grassland types, which often occur in small, fragmented patches and are thus underrepresented in model training data while exhibiting spectral similarities with more common grassland types. Preliminary analyses using established techniques to address class imbalances in model training yielded unsatisfactory results, even when leveraging temporal spectral trajectories. This highlights the need for alternative methods to improve classification accuracy.

One potential solution is to utilize hyperspectral over multispectral data. While hyperspectral RS has been extensively studied across various scales, sensors, and carrier platforms, knowledge gaps remain regarding grassland time-series applications. In theory, hyperspectral time-series data offer maximum RS information, potentially enhancing grassland type differentiation. However, before advocating for its widespread adoption, future research must critically evaluate its performance gains relative to the increased computational complexity and data processing demands. Moreover, the limited availability of hyperspectral satellite sensors presents additional challenges. The temporal resolution achieved in this thesis would be impossible to replicate using hyperspectral data due to restricted orbital coverage. EnMAP, with its 27-day revisit cycle and 4-day off-nadir target revisit capability, represents the most viable option. However, frequent cloud cover in the study area further complicates data acquisition, while off-nadir observations introduce additional processing challenges. This issue will likely be addressed in the mid-term with the launch of additional hyperspectral sensors like CHIME (Copernicus Hyperspectral Imaging Mission for the Environment) in the 2020s. However, data access will likely be initially restricted to priority users, therefore, method and data transfer to practical nature conservation remains unlikely in the near-future. To maximize the utility of hyperspectral time-series data for large-scale grassland monitoring, future research should, therefore, explore strategies for optimizing acquisition timing and mitigating data availability constraints.

To facilitate the operational adoption of RS technologies, this thesis demonstrated the applicability of SHAP in RS-based grassland monitoring and introduced an extension for cross-model decision pattern analysis in multi-class time series classification problems. SHAP proved to be more robust than conventional feature importance analysis, while the FIS extension enabled cross-model comparability and a feature component-level interpretation of model decisions. Thus, these methods effectively address different model explainability challenges, and their integration into RS-based ecological monitoring may help lower key barriers to the broader adoption of RS technologies for sustainable grassland management.

While SHAP is gradually gaining traction in RS analysis as an alternative to conventional feature importance methods, its potential in grassland monitoring remains underutilized. This thesis demonstrated its applicability in machine learning-based analyses for flower color detection and grassland differentiation, yet there are numerous other areas where SHAP could prove valuable. Future research should particularly assess its effectiveness in time-sensitive classification tasks, such as mowing event detection, to further elucidate feature-target variable relationships in RS applications. Additionally, SHAP could be leveraged for analyzing complex ecological variables, such as grassland degradation, where the data-driven characterization of the target variable is not well-defined prior to analysis. In such cases, an independent, model-centric approach could provide novel ecological insights.

FIS analysis requires further investigation to assess its transferability to other target variables. Given the wide range of potential applications in RS-based grassland monitoring, one particularly relevant extension — building on this thesis — would be its use in analyzing transitional color variations in RS plant species applications across seasons, leveraging the secondary color VIs discussed earlier. By applying FIS in this context, researchers could refine the understanding of vegetation spectral responses over time, ultimately enhancing the monitoring and modeling of indicator plant species in grassland ecosystems.

Finally, this thesis contributed to bridging the gap between *in situ* and RS-based grassland assessments, addressing key barriers and advancing methodological integration. The findings emphasize the transformative potential of drone- and satellite-based RS for monitoring sustainable grassland conservation and management. Additionally, the research highlights critical challenges related to data accessibility, methodological transparency, and long-term sustainability, providing a long list of opportunities for research to come. The future of grassland monitoring lies in the synergetic integration of *in situ* surveys and remotely sensed indicators — each leveraging the strengths of the other while compensating for their respective limitations to enable a more holistic assessment. By fostering interdisciplinary collaboration between RS experts and ecologists, this thesis advocates for more effective grassland stewardship in an era of rapid environmental change.

Appendices

A.1 Software Environment

Data processing, analysis, and visualization for this study were predominantly conducted in a Python 3.10 environment. The associated software developed for this study, as well as a complete list of packages and dependencies is available in the following GitHub repository: <https://github.com/KimCedricGroeschler/RS-based-HNV-Grassland-Identification>. Data processing and visualization tasks were partially conducted using QGIS Version 3.22 (QGIS Development Team, 2009) and Graphviz (Ellson et al., 2002).

B.2 Reference Grassland Categorization

Aggregation of regional biotope types to CHT with associated EUNIS habitat types and German Red List Codes.

CHT	Regional Biotope Code	EUNIS Habitat Type	German Red List Code	Phytosociological Units
reeds	NRa	C 3.2	38.02	PHR-01 A
	NRb	A 2.5	08.02	PHR-02 A
	NRc	C 3.28, D 5.2	38.04	PHR
	NRg	C 3.2	38.05	PHR-01 A
	NRs	C 3.2.1/2/3	38.01/2/3	PHR-01 A
	Nry	C 3.2	38.07	PHR
	NSs	D 5.2	37.02	PHR-04 B
mesotrophic fen meadows	NSy	-	-	PHR
	NSa	D 2.2	35.01.01.01	SCH-02 D
	NSb	D 4.1	35.01.02.01	SCH-01 A
	GNa	D 2.2	35.01.01.01	SCH-03 B
	GNb	D 4.1	35.01.02.01	SCH-02 D (MOL-05 A)
dry species-rich grasslands	GNp	E 3.5	35.02.01	MOL-05 A
	TRb	E 1.1	34.01.01.02	COR-01 A/B
	TRh	E 1.1	34.01	COR
	TRm	E 1.2	34.02	GER
	TRj	E 1.7	34.06.02.01	NAR
	TRn	E 1.7	34.06.01.01	NAR
	TRs	E 1.1	34.04	COR
	TRy	E 1.1	34.04	COR
abandoned wet meadows	GWt	-	-	COR
	NSc	D 5.2	37.01.02	MOL-05
	NRr	C 3.26	38.06	MOL-05
	NSr	E 3.4	35.02.03.03	MOL-08
	NSj	E 3.4	35.02.03	MOL-05 B
	GNm	-	-	MOL-05
	GNr	E 3.4	35.02.03.03	MOL-05
wet meadows	GNh	E 3.4	35.02.03.03	MOL-05 B
	GFb	E 3.4	35.02.02	MOL-05 D
	GFc	E 3.4	35.02.03.01	MOL-05 B
wet pastures	GFr	E 3.4	35.02.03.02	MOL-05
	GYn	E 3.4	35.02.05.02	MOL-10 A
moist mesic grassland	GFf	E 3.4	35.02.05.01	MOL-10 A
	NSf	D 5.3	35.02.06.01	MOL-01
	GWf	E 2.2	34.07.01	MOL-01
farmland	GYf	E 2.6	35.02.06.01	MOL-01
	GAe	E 2.6	34.08.02	MOL-01
	GAy	E 2.6	34.08.01	MOL-01
	GYy	E 2.6	35.02.06.01	MOL-01

CHTs with characteristic phytosociological units, a short geobotanical characterization and key plant species.

CHT	Vegetation	Characterization
reeds	species of Phragmitetea and FFH 7140	tall helophyte bed, mesotrophic
	<i>Bolboschoenus maritimus</i> (D)	halophile <i>Bolboschoenus</i> bed
	<i>Cladium mariscus</i> (D), species of FFH 7210	riparian <i>Cladium mariscus</i> bed
	<i>Glyceria maxima</i> (D), species of Phragmitetea	<i>Glyceria maxima</i> bed
	<i>Phragmites australis</i> (D), <i>Typha</i> ssp. (D), <i>Schoenopl.</i> ssp. (D)	<i>Phragmites</i> , <i>Typha</i> , <i>Schoenoplectus</i> bed
	species of Phragmitetea	other beds
	<i>Carex</i> ssp. (D), species of Phragmitetea	Tall-sedge bed
mesotrophic fen meadows	species of Phragmitetea	other swamp
	species of FFH 7140, <i>Caricion lasiocarpae</i>	poor fen
	species of FFH 7230, <i>Caricion davallianae</i>	alkaline, calcareous small-sedge fen
	>10% cov. sedges/rushes, species of FFH 7140	poor fen
	>10% cov. sedges/rushes, species of FFH 7230	alkaline, calcareous small-sedge fen
dry species-rich grasslands	<i>Molinia caerulea</i> (D), Arten des FFH 6410	moist or wet oligotrophic grassland
	species of FFH 6120	Dry grassland with <i>Koeleria glauca</i>
	species of dry grassland, >25% tall herbs	Dry grassland with tall herbs
	species of FFH 6210	semi-dry calcareous grassland
	species of FFH 6230	moist <i>Nardus stricta</i> swards
	species of FFH 6230	dry <i>Nardus stricta</i> swards
	>25% cov. <i>Koelerio-Corynepherea</i> , <50% total coverage	open rocky grassland
	>25% cov. <i>Koelerio-Corynepherea</i> , >50% total coverage	rocky grassland
	indicative species of drought regularly, max. 25% coverage	dry species-rich mesic grassland
abandoned wet meadows	<i>Calamagrostis canescens</i> (D), species of <i>Molinietalia/Scheuchzerio-Caricetea</i>	<i>Calamagrostis canescens</i> fen
	<i>Phalaris arundinacea</i> (D), species of <i>Molinietalia</i>	<i>Phalaris arundinacea</i> bed
	<i>Filipendula ulmaria</i> (D), species of <i>Molinietalia</i>	<i>Filipendula ulmaria</i> bed
	<i>Scirpus sylvaticus</i> (D), species of <i>Molinietalia</i>	<i>Scirpus sylvaticus</i> bed
	<i>Carex nigra</i> (D), species of <i>Molinietalia</i>	moderately eutrophic wet grassland
	sedges/rushes (D), species of <i>Calthion</i>	eutrophic wet grassland, abandoned
	sedges/rushes (D), 10-25% coverage tall herbs	eutrophic wet grassland, abandoned
wet meadows	species of FFH 6440, <i>Cnidion</i>	subcontinental riverine meadows
	species of <i>Calthion</i>	moist or wet eutrophic hay meadow
	8 valuable grassland species, species of <i>Molinietalia</i>	other species-rich wet grassland
wet pastures	species of <i>Lolio-Potentillion</i> (D)	moist or wet eutrophic pasture, species-poor
	species of <i>Lolio-Potentillion</i> (D), 4 valuable grassland species	moist or wet eutrophic pasture, species-rich
moist mesic grassland	<i>Juncus effusus</i> (D)	moist grassland with <i>Juncus effusus</i>
	indicative species of moisture regularly, max. 25% coverage	species-rich moist mesic grassland
	species of <i>Cynosurion</i> , indicative species of moisture	species-poor moist mesic grassland
farmland	species of <i>Molinio-Arrhenatheretea</i>	seeded grassland
	species of <i>Molinio-Arrhenatheretea</i>	species-poor grassland
	mostly <i>Holcus lanatus</i> (D)	moderately species-rich grassland

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Declaration of Authorship

Hiermit erkläre ich an Eides statt, dass ich die vorliegende Dissertation, abgesehen von der Beratung durch meine Betreuer*innen, nach Inhalt und Form selbstständig verfasst und keine weiteren Quellen und Hilfsmittel als die hier angegebenen verwendet habe. Die Dissertation lag weder ganz noch in Teilen an anderer Stelle im Rahmen eines Prüfungsverfahrens vor. Als kumulative Dissertation sind Kapitel 4 bis 6 in peer-reviewten Fachzeitschriften veröffentlicht. Dies ist am Anfang des jeweiligen Kapitels vermerkt. Ich erkläre, dass die vorliegende Dissertation unter Einhaltung der Regeln guter wissenschaftlicher Praxis der Deutschen Forschungsgemeinschaft entstanden ist. Ich versichere, dass mir kein akademischer Grad entzogen wurde.

Kiel, den 04.07.2025