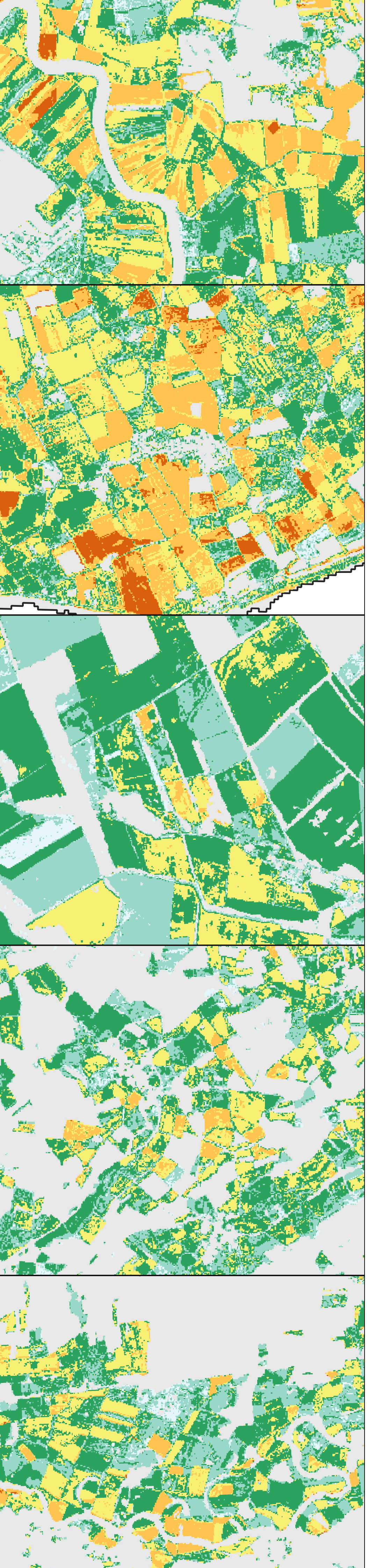

Earth Observation Time Series for Grassland Management Analyses

Development and large-scale Application of a Framework to detect Grassland Mowing Events in Germany

Dissertation zur Erlangung der Doktorwürde der Philosophischen Fakultät der Julius-Maximilians-Universität Würzburg

vorgelegt von

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Januar 2023

Julius-Maximilians-
UNIVERSITÄT
WÜRZBURG

Titelbild:
Die Abbildung zeigt die Häufigkeit der detektierten Mahden in 2020, welches ein Ergebnis der entwickelten Methode dieser Thesis darstellt und in den folgenden Kapiteln genauer erläutert wird.

Eingereicht am: 31.01.2023

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"Science progresses best when observations force us to change preconceptions."

– Vera Rubin

Acknowledgments

I would like to express my sincere gratitude to a group of people without whom this thesis would not have been possible:

To my mentor and supervisor, Prof. Dr. Claudia Kuenzer, for her constant support and guidance throughout the dissertation journey. I am especially thankful for her vital feedback, her encouragement, and her unfailing commitment to advancing my scientific development far beyond my expectations.

To my mentor at the University of Wuerzburg, Prof. Dr. Tobias Ullmann, for our valuable discussions and his helpful feedback, and to him and Prof. Dr. Barbara Sponholz for agreeing to supervise this thesis.

To my team members at DLR-DFD for the exchange of ideas, mutual support and cake breaks. In particular, I am extremely grateful for the constant encouragement, feedback and advice of my team leader, Dr. Ursula Gessner, and my office neighbor, Dr. Sarah Asam.

To all my colleagues at DLR-DFD for stimulating exchanges and their kind support. Special appreciation goes to my former and fellow PhD students – Dr. Celia Baumhoer, Dr. Mariel Dirscherl, Marius Philipp, Soner Uereyen, Aiym Orynbaikyzy, Daniela Palacios Lopez, Simone Zepp, Jonas Koehler, Thorsten Hoeser, Tuyen Ha Van, Philipp Reiners, Patrick Sogno and Patrick Kacic – for their exceptional camaraderie throughout these PhD years. Furthermore, I would like to thank Julian Zeidler for his continuous and patient IT support and Daniela Palacios Lopez for translating the summary of this thesis.

To scientific colleagues from the project and all the students who helped out during the field work. Special thanks goes to Dr. Anne Schucknecht for our fruitful discussions while cutting grass.

To my friends from university, Dorothee, Katharina and Susanne, without whom I might not even have managed to graduate. Thank you for never ceasing to believe in me.

To my entire family, for their trust in me and always encouraging me to reach my goals. I am extremely grateful to my parents for their unconditional support, to my brother and his family for constantly reminding me what is important in life, and to David for his patience and unwavering belief in me. My deepest appreciation also goes to my dearly missed grandmother, who was an incredibly open-minded and wonderful person and motivated me to stay curious.

To all my friends and flatmates, for making sure that I ate, for cheering me up, and for listening to me. I thank you all that you were there for me these past few years.

Summary

Grasslands shape many landscapes of the earth as they cover about one-third of its surface. They are home and provide livelihood for billions of people and are mainly used as source of forage for animals. However, grasslands fulfill many additional ecosystem functions next to fodder production, such as storage of carbon, water filtration, provision of habitats and cultural values. They play a role in climate change (mitigation) and in preserving biodiversity and ecosystem functions on a global scale.

The degree to what these ecosystem functions are present within grassland ecosystems is largely determined by the management. Individual management practices and the use intensity influence the species composition as well as functions, like carbon storage, while higher use intensities (e.g. high mowing frequencies) usually show a negative impact. Especially in Central European countries, like in Germany, the determining influence of grassland management on its physiognomy and ecosystem functions leads to a large variability and small-scale alternations of grassland parcels. Large-scale information on the management and use intensity of grasslands is not available. Consequently, estimations of grassland ecosystem functions are challenging which, however, would be required for large-scale assessments of the status of grassland ecosystems and optimized management plans for the future. The topic of this thesis tackles this gap by investigating the major grassland management practice in Germany, which is mowing, for multiple years, in high spatial resolution and on a national scale.

Earth Observation (EO) has the advantage of providing information of the earth's surface on multi-temporal time steps. An extensive literature review on the use of EO for grassland management and production analyses, which was part of this thesis, showed that in particular research on grasslands consisting of small parcels with a large variety of management and use intensity, like common in Central Europe, is underrepresented. Especially the launch of the Sentinel satellites in the recent past now enables the analyses of such grasslands due to their high spatial and temporal resolution. The literature review specifically on the investigation of grassland mowing events revealed that most previous studies

focused on small study areas, were exploratory, only used one sensor type and/or lacked a reference data set with a complete range of management options.

Within this thesis a novel framework to detect grassland mowing events over large areas is presented which was applied and validated for the entire area of Germany for multiple years (2018–2021). The potential of both sensor types, optical (Sentinel-2) and synthetic aperture radar (SAR) (Sentinel-1) was investigated regarding grassland mowing event detection. Eight EO parameters were investigated, namely the Enhanced Vegetation Index (EVI), the backscatter intensity and the interferometric (InSAR) temporal coherence for both available polarization modes (VV and VH), and the polarimetric (PolSAR) decomposition parameters Entropy, K0 and K1. An extensive reference data set was generated based on daily images of webcams distributed in Germany which resulted in mowing information for grasslands with the entire possible range of mowing frequencies – from one to six in Germany – and in 1475 reference mowing events for the four years of interest.

For the first time a observation-driven mowing detection approach including data from Sentinel-2 and Sentinel-1 and combining the two was developed, applied and validated on large scale. Based on a subset of the reference data (13 grassland parcels with 44 mowing events) from 2019 the EO parameters were investigated and the detection algorithm developed and parameterized. This analysis showed that a threshold-based change detection approach based on EVI captured grassland mowing events best, which only failed during periods of clouds. All SAR-based parameters showed a less consistent behavior to mowing events, with PolSAR Entropy and InSAR Coherence VH, however, revealing the highest potential among them. A second, combined approach based on EVI and a SAR-based parameter was developed and tested for PolSAR Entropy and InSAR VH. To avoid additional false positive detections during periods in which mowing events are anyhow reliably detected using optical data, the SAR-based mowing detection was only initiated during long gaps within the optical time series ($<$ 25 days). Application and validation of these approaches in a focus region revealed that only using EVI leads to the highest accuracies (F1-Score = 0.65) as combining this approach with SAR-based detection led to a strong increase in falsely detected mowing events resulting in a decrease of accuracies (EVI + PolSAR ENT F1-Score = 0.61; EVI + InSAR COH F1-Score = 0.61).

The mowing detection algorithm based on EVI was applied for the entire area of Germany for the years 2018-2021. It was revealed that the largest share of grasslands with high mowing frequencies (at least four mowing events) can be found in southern/south-eastern Germany. Extensively used grassland (mown up to two times) is distributed within the entire country with larger shares in the center and north-eastern parts of Germany. These patterns stay constant in general, but small fluctuations between the years are visible. Early mown grasslands can be found in southern/south-eastern Germany – in line with high mowing frequency areas – but also in central-western parts. The years 2019 and 2020 revealed higher accuracies based on the 1475 mowing events of the multi-annual validation data set (F1-Scores of 0.64 and 0.63), 2018 and 2021 lower ones (F1-Score of 0.52 and 0.50).

Based on this new, unprecedented data set, potential influencing factors on the mowing dynamics were investigated. Therefore, climate, topography, soil data and information on conservation schemes were related to mowing dynamics for the year 2020, which showed a high number of valid observations and detection accuracy. It was revealed that there are no strong linear relationships between the mowing frequency or the timing of the first mowing event and the investigated variables. However, it was found that for intensive grassland usage certain climatic and topographic conditions have to be fulfilled, while extensive grasslands appear on the entire spectrum of these variables. Further, higher mowing frequencies occur on soils with influence of ground water and lower mowing frequencies in protected areas. These results show the complex interplay between grassland mowing dynamics and external influences and highlight the challenges of policies aiming to protect grassland ecosystem functions and their need to be adapted to regional circumstances.

Zusammenfassung

Grünland prägt viele Landschaften der Erde, da es etwa ein Drittel der Erdoberfläche bedeckt. Es ist Heimat und Lebensgrundlage für Milliarden von Menschen und wird hauptsächlich als Futterquelle für die Viehhaltung genutzt. Neben der Futterproduktion erfüllen Grünlandflächen jedoch viele weitere Ökosystemfunktionen, wie die Speicherung von Kohlenstoff, die Wasserfilterung, die Bereitstellung von Lebensräumen, als auch kulturelle Werte. Sie spielen eine Rolle bei der Abschwächung des Klimawandels und bei der Erhaltung der biologischen Vielfalt und der Ökosystemfunktionen auf globaler Ebene.

Das Ausmaß, in dem diese Ökosystemfunktionen in Grünlandökosystemen vorhanden sind, wird weitgehend durch die Bewirtschaftung bestimmt. Einzelne Bewirtschaftungspraktiken und die Nutzungsintensität beeinflussen sowohl die Artenzusammensetzung als auch Funktionen wie die Kohlenstoffspeicherung, wobei höhere Nutzungsintensitäten (z. B. hohe Mähfrequenzen) in der Regel einen negativen Einfluss haben. Insbesondere in mitteleuropäischen Ländern wie Deutschland, führt der bestimmende Einfluss der Grünlandbewirtschaftung auf die Physiognomie und die Ökosystemfunktionen zu einer großen Variabilität und kleinräumigen Differenziertheit einzelner Grünlandflächen. Großräumige Informationen über die Bewirtschaftungs- und Nutzungsintensität von Grünland sind nicht verfügbar. Folglich sind Schätzungen der Ökosystemfunktionen von Grünland eine Herausforderung, die jedoch für großräumige Bewertungen des Zustands von Grünlandökosystemen und optimierte Bewirtschaftungspläne für die Zukunft erforderlich wären. Das Thema dieser Arbeit greift diese Lücke auf, indem es die wichtigste Grünlandbewirtschaftungsmethode in Deutschland, die Mahd, über mehrere Jahre, mit hoher räumlicher Auflösung und auf nationaler Ebene untersucht.

Die Erdbeobachtung hat den Vorteil, Informationen über die Erdoberfläche in multitemporalen Zeitschritten zu liefern. Eine umfangreiche Literaturrecherche zur Nutzung von Erdbeobachtung für Grünlandmanagement und Produktion, welche Teil dieser Arbeit war, hat gezeigt, dass insbesondere die Forschung zu kleinparzelligem Grünland mit einer großen Vielfalt an Bewirtschaftungs- und Nutzungsintensitäten, wie in Mitteleuropa gängig, unterrepräsentiert ist. Insbesondere die vor wenigen Jahren erfolgte Start

der Sentinel-Satellitenmissionen ermöglicht nun auch die Analyse solcher Grünlandflächen aufgrund der hohen räumlichen und zeitlichen Auflösung ihrer Aufnahmen. Die Literaturrecherche speziell zur Untersuchung von Mähereignissen auf Grünland ergab, dass die meisten bisherigen Studien sich auf kleine Untersuchungsgebiete konzentrierten, explorativ waren, nur einen Sensortyp verwendeten und/oder keinen Referenzdatensatz mit einer vollständigen Palette von Managementoptionen enthielten.

Im Rahmen dieser Arbeit wird eine neuartige Methodik zur Erkennung von Grünlandmahdereignissen vorgestellt, welches über mehrere Jahre (2018-2021) flächendeckend in Deutschland angewendet und validiert wurde. Beide Sensortypen – optisch (Sentinel-2) und SAR (Sentinel-1) – wurden hinsichtlich ihres Potentials zur Detektion von Grünlandmahdereignissen ausgewertet. Acht EO-Parameter wurden untersucht, nämlich der Enhanced Vegetation Index (EVI), die Rückstreuintensität und die interferometrische zeitliche Kohärenz (InSAR) für beide verfügbaren Polarimetrien (VV und VH), sowie die polarimetrischen (PolSAR) Zerlegungsparameter Entropie, K0 und K1. Ein umfangreicher Referenzdatensatz wurde auf der Basis täglicher Bilder von Webcams generiert, welche über Deutschland verteilt sind. Dieser enthält Mahdinformationen für Grünland mit dem gesamten möglichen Spektrum an Mähfrequenzen – von eins bis sechs Mahden – und 1475 Referenz-Mähereignisse für die Untersuchungsjahre.

Zum ersten Mal wurde ein Ansatz basierend auf tatsächlichen Beobachtungen zur Erkennung der Mahd entwickelt, angewandt und großflächig validiert, der Daten von Sentinel - 2 und Sentinel - 1 verwendet und beide miteinander kombiniert. Anhand eines Subset der Referenzdaten (13 Grünlandparzellen) wurden die EO-Parameter untersucht und der Algorithmus zur Mahddetektion entwickelt und parametrisiert. Die Analyse hat gezeigt, dass ein schwellenwertbasierter Ansatz zur Erkennung von Veränderungen auf der Grundlage des EVI die Ereignisse der Grünlandmahd am besten erfasst, und nur während Bewölkungsperioden Mahden nicht erfolgreich detektiert. Alle SAR-basierten Parameter zeigten ein inkonsistenteres Verhalten gegenüber Mähaktivitäten als EVI, wobei PolSAR Entropie und InSAR Kohärenz VH noch das höchste Potenzial aufwiesen. Ein zweiter, kombinierter Ansatz, der auf EVI und einem SAR Parameter basiert, wurde entwickelt und für PolSAR Entropie und InSAR VH getestet. Aufgrund vieler zusätzlicher Veränderungen, die in den Zeitreihen erkennbar sind, wurde die SAR-basierte Mahddetektion nur während langer Lücken in den optischen Zeitreihen ($<$ 25 Tage) initiiert. Die Anwendung und Validierung dieser Ansätze in einer Fokusregion ergab, dass die Verwendung des EVI-Ansatzes zu den höchsten Genauigkeiten führt (F1-Score = 0.65), da die Kombination dieses Ansatzes mit der SAR-basierten Detektion zu einem starken Anstieg der falsch erkannten Mähereignisse und damit zu einer Abnahme der Genauigkeiten führte (EVI + PolSAR ENT F1-Score=0.61; EVI + InSAR COH F1-Score = 0.61).

Der auf EVI basierende Mahddetektionsalgorithmus wurde für die gesamte Fläche Deutschlands für die Jahre 2018–2021 angewendet. Es zeigte sich, dass der größte Anteil an Grünland mit hoher Mähfrequenz (mindestens vier Mähereignisse) im Süden/Südosten Deutschlands zu finden ist. Extensiv genutztes Grünland (bis zu zweimal gemäht) ist über das gesamte Bundesgebiet verteilt, mit größeren Anteilen in der Mitte und im Nordosten Deutschlands. Diese Muster bleiben im Allgemeinen konstant, aber es sind kleine Schwankungen zwischen den Jahren erkennbar. Früh gemähtes Grünland findet sich in Süd-/Südostdeutschland - entsprechend den Gebieten mit hoher Mähfrequenz -, aber auch in Mittel- und Westdeutschland. Die Jahre 2019 und 2020 zeigen höhere Genauigkeiten (F1-Scores von 0.64 und 0.63), 2018 und 2021 niedrigere (F1-Score von 0.52 und 0.50).

Darüber hinaus wurden mögliche Einflussfaktoren auf die Mahddynamik untersucht. So wurden Klima, Topografie, Bodendaten und Informationen über Schutzmaßnahmen mit der Mahddynamik für das Jahr 2020 in Verbindung gebracht, für welches eine hohe Anzahl gültiger Beobachtungen und eine hohe Erfassungsgenauigkeit erzielt werden konnten. Es zeigte sich, dass es keine starken linearen Beziehungen zwischen der Mahdhäufigkeit oder dem Zeitpunkt der ersten Mahd und den untersuchten Variablen gibt. Es wurde jedoch festgestellt, dass für eine intensive Grünlandnutzung bestimmte klimatische und topografische Bedingungen erfüllt sein müssen, wohingegen extensive Grünlandflächen im gesamten Spektrum dieser Variablen auftreten. Außerdem treten auf Böden mit Grundwassereinfluss höhere und in Schutzgebieten niedrigere Mahdhäufigkeiten auf. Diese Ergebnisse zeigen das komplexe Zusammenspiel zwischen der Dynamik der Grünlandmahd und äußeren Einflüssen und verdeutlichen die Herausforderungen in der gezielten Erstellung von Maßnahmen zum Schutz von Grünland-Ökosystemfunktionen und die Notwendigkeit diese regional anzupassen.

Spanish Summary

Los pastizales constituyen uno de los ecosistemas más grandes del mundo, ya que cubren aproximadamente un tercio de su superficie. Son el hogar y sustento de miles de millones de personas y se utilizan principalmente como fuente de forraje para los animales. Además de esto, los pastizales juegan un papel importante en la preservación de diferentes funciones ecosistémicas a escala mundial. Por ejemplo, los pastizales contribuyen al almacenamiento de carbono y la filtración de agua, son el hábitat de numerosas especies y tienen valores culturales. De igual manera, desempeñan un papel en el cambio climático (regulación y mitigación) y participan en la conservación de la biodiversidad.

Sin embargo, el grado en el que los pastizales pueden ejecutar estas funciones ecosistémicas depende en gran medida en como estos son gestionados. En particular, las prácticas de gestión individuales y la intensidad de uso influyen tanto en la calidad de composición de los pastizales, así como en su habilitad para satisfacer importantes necesidades ecológicas. Por ejemplo, el pastoreo continuo e intensificado, suelen mostrar mayormente un impacto negativo.

Dicho esto, especialmente en los países centroeuropeos como Alemania, existe una gran variedad de manejo e intensidad de uso, que ha dado lugar a la creación de pequeñas parcelas con diferentes tipos o clases de pastizales (ej. diferente composición y estructura). Sin embargo, debido a que no se dispone de información sobre la gestión y la intensidad de uso de pastizales a gran escala (ej. a nivel de país), resulta difícil realizar estimaciones y mediciones de las funciones ecosistémicas que cada uno de los diferentes tipos de pastizales proveen. Estas estimaciones, son a su vez necesarias para evaluar el estado y composición de los pastizales, así como para optimizar los planes de gestión en el futuro. El tema de esta tesis aborda esta brecha, investigando la principal práctica de gestión de los pastizales en Alemania, que es la siega, durante varios años y a escala nacional.

Los sistemas de Observación de la Tierra (acrónimo en ingles EO) como los satélites artificiales, tienen la ventaja de proporcionar información de la superficie terrestre en pasos temporales múltiples. Sin embargo, una extensa revisión sistemática de la literatura llevada a cabo durante esta tesis, demostró que el uso de EO para la investigación, análisis y

gestión de los pastizales, principalmente aquellos que consisten de pequeñas parcelas con una gran variedad de manejo e intensidad de uso como es común en Europa Central, es en generalmente limitada. Por ejemplo, en los últimos años, debido a alta resolución espacial y temporal de los satélites “Sentinel”, ha sido posible realizar análisis detallados sobre estos tipos de pastizales. Sin embargo, una revisión de la literatura enfocada específicamente en eventos de siega, reveló investigaciones previas solo se han enfocado pequeñas áreas de estudio, han sido exploratorios, han utilizado solo un tipo de sensor satelital (óptico o radar), y/o carecen de un conjunto de datos de referencia con una gama completa de opciones de gestión.

De esta manera, dentro de esta tesis se presenta un marco novedoso para detectar eventos de siega de pastizales en grandes áreas, que se aplicó y validó para toda el área de Alemania cubriendo eventos de siga por cuatro años (2018–2021). Se investigó el potencial de ambos tipos de sensores, óptico (Sentinel-2) y SAR (Sentinel-1) en relación con la detección de eventos de siega de pastizales. Se investigaron ocho parámetros: el índice de vegetación mejorado (EVI), la intensidad de retrodispersión y la coherencia temporal interferométrica (InSAR) para los dos modos de polarización disponibles (VV y VH) y los parámetros de descomposición polarimétrica (PolSAR) Entropía, K0 y K1. Se generó un amplio conjunto de datos de referencia basado en imágenes diarias de cámaras web distribuidas por Alemania, que dio como resultado información sobre la frecuencia de eventos siega: uno a seis eventos al año en toda Alemania, obteniendo 1,475 eventos de siega de referencia durante los cuatro años de estudio.

Por primera vez se desarrolló, aplicó y validó un método de detección de siega ascendente utilizando datos de Sentinel - 2 y Sentinel - 1 y combinaba ambos. El algoritmo de detección se desarrolló y parametrizo utilizando un subconjunto de los datos de referencia (ej. 13 parcelas de pastizales con 45 eventos de siega en el 2019). Este análisis demostró que el método de detección de cambios basado en umbrales de EVI capturó mejor los eventos de siega de pastizales, que solo falló durante días o periodos nublados. Todos los parámetros basados en SAR mostraron un comportamiento menos consistente con los eventos de siega, con, sin embargo, PolSAR Entropía y InSAR Coherencia VH revelaron el mayor potencial entre ellos. De la misma manera, se desarrolló y probó un segundo método basado en la combinación de EVI y un parámetro basado en SAR para PolSAR Entropía y InSAR VH. Para evitar falsos positivos durante periodos en los que los eventos de siega se detectan de forma fiable utilizando datos ópticos, la detección de siega basada en SAR sólo se llevó acabo en periodos donde las series temporales ópticas ocurrieron con menor frecuencia inició ($<$ 25 días). La aplicación y validación de estos métodos en una región de interés reveló que el uso de EVI produce a las precisiones más altas (F1-Score = 0,65), ya que la combinación basada en SAR resulto en un alto número de falsos positivos. Dicho de otra manera, los métodos basados en SAR detectaron un mayor numero de eventos de siega incorrectamente, lo que resultó en una disminución de las precisión (EVI + PolSAR ENT 0,65). F1-Score = 0.61; EVI + InSAR COH F1-Score = 0,61).

Finalmente, el algoritmo de detección de siega basado en EVI se aplicó para toda el área de Alemania para el periodo del 2018-2021. Los resultados revelaron que la mayor parte de los pastizales con altas frecuencias de siega (al menos cuatro eventos de siega) se encuentran en el sur / sureste de Alemania. Los pastizales de uso extensivo (segados hasta dos veces al año) se distribuyen por todo el país, con una mayor proporción en el centro y el noreste de Alemania. Estos patrones se mantienen generalmente constantes, pero se aprecian pequeñas fluctuaciones de un año a otro. Las praderas segadas temprano se encuentran en el sur/sureste de Alemania, en línea con las zonas de alta frecuencia de siega, pero también en las partes centro-occidentales. Análisis efectuados para el año 2019 y 2020 revelaron mayores precisiones basadas en los 1475 eventos de siega del conjunto de datos de validación plurianual (puntuaciones F1 de 0,64 y 0,63), 2018 y 2021 menores (puntuaciones F1 de 0,52 y 0,50).

En base a este nuevo conjunto de datos que no tiene precedentes, se investigaron por primera vez los posibles factores que influyen en la dinámica de la siega en Alemania. Así, el clima, la topografía, los datos del suelo y la información sobre los planes de conservación se relacionaron con la dinámica de siega para el año 2020, lo que mostró un elevado número de observaciones válidas y una gran precisión de detección. Se puso de manifiesto que no existen relaciones lineales fuertes entre la frecuencia de siega (o el momento de la primera siega) y las variables investigadas. Sin embargo, se comprobó que para el uso intensivo de los prados deben cumplirse determinadas condiciones climáticas y topográficas, mientras que los prados extensivos aparecen en todo el espectro de estas variables. Además, las frecuencias de siega más altas se dan en suelos con influencia de aguas subterráneas y las frecuencias de siega más bajas en zonas protegidas. Estos resultados muestran la compleja interacción entre la dinámica de siega de los pastizales y las influencias externas, y resaltan los desafíos que existen para determinar o establecer políticas destinadas a proteger las funciones ecosistémicas de los pastizales y su necesidad de adaptarse a las circunstancias regionales.

French Summary

Les prairies façonnent de nombreux paysages de la planète puisqu'elles couvrent environ un tiers de sa surface. Elles constituent le foyer et le moyen de subsistance de milliards de personnes et sont principalement utilisées comme source de fourrage pour les animaux. Toutefois, outre la production de fourrage, les prairies remplissent de nombreuses autres fonctions écosystémiques, comme le stockage du carbone, la filtration de l'eau, la fourniture d'habitats et les valeurs esthétiques. Elles jouent un rôle dans le changement climatique (mitigation) et dans la préservation de la biodiversité et des fonctions écosystémiques à l'échelle mondiale.

Le degré de présence de ces fonctions écosystémiques dans les écosystèmes de prairie est largement déterminé par la gestion. Les pratiques de gestion individuelles et l'intensité d'utilisation influencent la composition des espèces ainsi que les fonctions, comme le stockage du carbone, tandis que les intensités d'utilisation élevées (par exemple, les fréquences de tonte élevées) ont généralement un impact négatif. Dans les pays d'Europe centrale, comme l'Allemagne, l'influence déterminante de la gestion des prairies sur leur physionomie et leurs fonctions écosystémiques entraîne une grande variabilité et des alternances à petite échelle de diverses prairies. Des informations sur la gestion et l'intensité d'utilisation des prairies ne sont pas disponible en grande échelle. Par conséquent, les estimations des fonctions de l'écosystème des prairies sont difficiles à réaliser, alors qu'elles seraient nécessaires pour des évaluations à grande échelle de l'état des écosystèmes des prairies et des plans de gestion optimisés pour l'avenir. Le sujet de cette thèse aborde cette lacune en étudiant la principale pratique de gestion des prairies en Allemagne, à savoir la tonte, sur plusieurs années et à l'échelle nationale.

L'observation de la terre (OT) a l'avantage de fournir des informations sur la surface de la terre sur des pas de temps multi-temporels. Un examen approfondi de la littérature sur l'utilisation de l'OT pour la gestion des prairies et les analyses de production, qui faisait partie de cette thèse, a montré qu'en particulier la recherche sur les prairies constituées de petites parcelles avec une grande variété de gestion et d'intensité d'utilisation, comme c'est le cas en Europe centrale, est sous-représentée. Le lancement des satellites Sentinel dans

un passé récent permet maintenant d'analyser de telles prairies grâce à leur haute résolution spatiale et temporelle. La revue de la littérature portant spécifiquement sur l'investigation des événements de tonte des prairies a révélé que la plupart des études précédentes se concentraient sur de petites zones d'étude, étaient exploratoires, n'utilisaient qu'un seul type de capteur et/ou manquaient d'un ensemble de données de référence avec une gamme complète d'options de gestion.

Dans le cadre de cette thèse, un nouveau cadre pour détecter les événements de tonte des prairies sur de grandes surfaces est présenté, qui a été appliqué et validé pour l'ensemble de la superficie de l'Allemagne pendant plusieurs années (2018–2021). Le potentiel des deux types de capteurs, optique (Sentinel-2) et SAR (Sentinel-1) a été étudié concernant la détection des événements de tonte des prairies. Huit paramètres OT ont été étudiés, à savoir l'indice de végétation amélioré (EVI), l'intensité de rétrodiffusion et la cohérence temporelle interférométrique (InSAR) pour les deux modes de polarisation disponibles (VV et VH) et les paramètres de décomposition polarimétrique (PolSAR) Entropie, K0 et K1. Un vaste ensemble de données de référence a été généré à partir d'images quotidiennes de webcams réparties en Allemagne, ce qui a permis d'obtenir des informations sur la tonte des prairies avec toute la gamme possible de fréquences de tonte - de une à six en Allemagne - et 1475 événements de tonte de référence pour les quatre années considérées.

Pour la première fois, une approche de détection de tonte ascendante incluant les données de Sentinel - 2 et Sentinel - 1 et combinant les deux a été développée, appliquée et validée. Sur la base d'un sous-ensemble de données de référence (13 parcelles de prairie avec 45 événements de tonte) de 2019, les paramètres d'OT ont été étudiés et l'algorithme de détection développé et paramétré. Cette analyse a montré qu'une approche de détection des changements basée sur desseuils et fondée sur les EVI capturait le mieux les événements de tonte des prairies, qui n'échouait que pendant les périodes de nuages. Tous les paramètres basés sur le SAR ont montré un comportement moins cohérent par rapport aux événements de tonte, avec le PolSAR Entropie et InSAR Cohérence VH, cependant, révélant le plus grand potentiel parmi eux. Une deuxième approche combinée basée sur EVI et un paramètre basé sur SAR a été développée et testée pour PolSAR Entropie et InSAR VH. Afin d'éviter des détections supplémentaires de faux positifs pendant les périodes où les événements de tonte sont de toute façon détectés de manière fiable à l'aide des données optiques, la détection de tonte basée sur le SAR n'a été initiée que pendant les longs intervalles de la série temporelle optique ($<$ 25 jours). L'application et la validation de ces approches dans une région ciblée ont révélé que seule l'utilisation de l'approche EVI conduit aux meilleures précisions (score F1 = 0,65), car la combinaison de cette approche avec la détection basée sur le SAR a conduit à une forte augmentation des événements de fauchage faussement détectés, entraînant une diminution des précisions (EVI + PolSAR ENT). F1-Score = 0.61; EVI + InSAR COH F1-Score = 0,61).

L'algorithme de détection de tonte basé sur EVI a été appliqué à l'ensemble de la superficie de l'Allemagne pour les années 2018-2021. Il a été révélé que la plus grande part des prairies avec des fréquences de tonte élevées (au moins quatre événements de tonte) se trouve dans le sud/sud-est de l'Allemagne. Les prairies utilisées de manière intensive (tontées jusqu'à deux fois) sont réparties sur l'ensemble du territoire, avec des parts plus importantes dans le centre et le nord-est de l'Allemagne. Ces schémas restent constants en général, mais de petites fluctuations sont visibles d'une année sur l'autre. On trouve des prairies tontées précocement dans le Sud/Sud-est de l'Allemagne, ce qui correspond aux zones où la fréquence de tonte est élevée, mais aussi dans le centre-ouest du pays. Les années 2019 et 2020 ont révélé des précisions plus élevées sur la base des 1475 événements de fauche de l'ensemble de données de validation pluriannuel (scores F1 de 0,64 et 0,63), 2018 et 2021 des précisions plus faibles (scores F1 de 0,52 et 0,50).

Sur la base de ce nouvel ensemble de données, les facteurs d'influence potentiels sur la dynamique du tonte ont été étudiés. Ainsi, le climat, la topographie, les données pédologiques et les informations sur les programmes de conservation ont été mis en relation avec la dynamique de la tonte pour l'année 2020, ce qui a montré un nombre élevé d'observations valides et une grande précision de détection. Il a été révélé qu'il n'existe pas de relations linéaires fortes entre la fréquence de tonte ou le moment de la première tonte et les variables étudiées. Cependant, il a été constaté que pour une utilisation intensive des prairies, certaines conditions climatiques et topographiques doivent être remplies, alors que les prairies extensives apparaissent sur l'ensemble du spectre de ces variables. En outre, les fréquences de tonte sont plus élevées sur les sols ayant une influence sur les eaux souterraines et plus faibles dans les zones protégées. Ces résultats montrent l'interaction complexe entre la dynamique de la tonte des prairies et les influences externes et mettent en évidence les défis des politiques visant à protéger les fonctions des écosystèmes des prairies et leur nécessité d'être adaptées aux circonstances régionales.

Table of Contents

List of Figures

List of Tables

Abbreviations and Acronyms

ANN	Artificial Neural Network
APAR	absorbed photosynthetically active radiation
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATCOR	Atmospheric Correction software
AVHRR	Advanced Very High Resolution Radiometer
CAP	Common Agricultural Policy
CASA	Carnegie-Ames-Stanford Approach
CDC	Climate Data Center
CNN	Convolutional Neural Network
COH	Coherence
CPU	Central Processing Unit
DEM	Digital Elevation Model
DNDC	Denitrification-Decomposition
DWD	Deutscher Wetterdienst - German Weather Service
ECLUE	Eddy Covariance - Light Use Efficiency
EO	Earth Observation
ENT	Entropy
EU	European Union
EVI	Enhanced Vegetation Index
FAPAR	Fraction of absorbed Photosynthetic Active Radiation
GDEM	Global Digital Elevation Model
GLO-PEM	Global Production Efficiency Model
GPP	Gross Primary Productivity
GR	Greenness and Radiation
GRD	Ground Range Detected
HH	Horizontal transmission and horizontal reception
HRL	High Resolution Layer
IPCC	Intergovernmental Panel on Climate Change
InSAR	Interferometric Synthetic Aperture Radar
IW	Interferometric Wide-swath
ORCHIDEE	Organizing Carbon and Hydrology in Dynamic Ecosystems
K	Kelvin
LAI	Leaf Area Index
LUE	Light Use Efficiency
MACCS	Multi-Temporal Atmospheric Correction and Cloud Screening software
MAJA	MACCS-ATCOR Joint Algorithm

mm	Millimeter
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Instrument
NASA	National Aeronautics and Space Administration
NIR	Near-Infrared Radiation
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NPP	Net Primary Productivity
PolSAR	Polarimetric Synthetic Aperture Radar
RGB	Red Green Blue
RON	Relative Orbit Number
SAR	Synthetic Aperture Radar
SAVI	Soil-Adjusted Vegetation Index
S1	Sentinel-1
S2	Sentinel-2
SEDAC	Socioeconomic Data and Applications Center
SLC	Single Look Complex
SPOT	Satellite Pour l'Observation de la Terre
SPOT-VGT	Satellite Pour l'Observation de la Terre - Vegetation
SRTM	Shuttle Radar Topography Mission
STICS	Simulateur multidisciplinaire pour les Cultures standard
TG	Temperature and Greenness
UTM	Universal Transverse Mercator
VPM	Vegetation Photosynthesis Model
VPRM	Vegetation Production and Respiration Model
VV	Vertical transmission and vertical reception
VH	Vertical transmission and horizontal reception
WGS	World Geodetic System

Chapter 1

Introduction

1.1 Scientific Relevance and Research Motivation

1.1.1 The Impact of Agriculture on the Living Environment

For centuries, humanity has drastically changed the planet and one of the main driving forces for changes of the terrestrial surface is agriculture. Land use-change and intensification processes have increased agricultural production rapidly on a global scale (IPBES, 2019). However, this comes at the expense of ecosystem functions which are not production-oriented, with severe consequences. On the one hand, agriculture is one of the main contributors to climate change. On the other hand, land use change and intensification processes in agriculture are the main cause for a drastic loss in global biodiversity, accompanied by a degeneration of ecosystems through a decline in regulating and cultural ecosystem services (Newbold et al., 2015; IPCC, 2019, 2021).

Despite the potential of being a carbon dioxide CO_2 sink though vegetation photosynthesis, the agricultural sector contributes to about one-quarter of global greenhouse gas emissions according to the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2019, 2021). Agriculture is the main source of methane (CH_4) and nitrous oxide (N_2O), which are the most important greenhouse gases, next to CO_2 (IPCC, 2022). In particular, livestock production is responsible for about 30–45 % of emissions of these chemical compounds (IPCC, 2019; Reay et al., 2012). Climate change is going to have existential impacts, some of which are already visible. As a result of global climate change temperatures rise and extreme events increase in their occurrence and intensity, including hot extremes, heavy precipitation events and droughts (IPCC, 2022). All ecosystem types are affected by substantial damages and partly irreversible losses of ecosystem functions which reduces food and water security (IPCC, 2022).

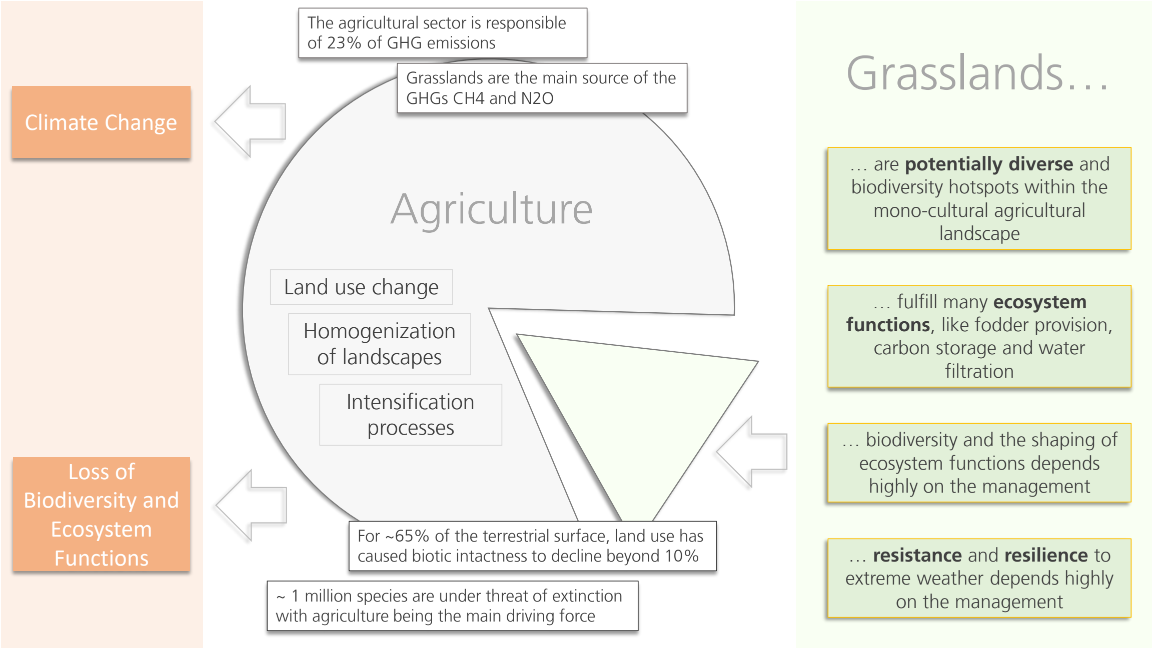

Figure 1.1: Overview of the relationship of the agricultural sector and grasslands in particular to climate change and the loss of biodiversity and ecosystem functions. Sources for statistical information: IPCC (2019); IPBES (2019)

Apart from this indirect influence of agriculture on ecosystem functions through its augmentation of climate change, agriculture also directly affects ecosystems. It is the major contributor to the global loss of biodiversity (Newbold et al., 2015). About 25 % of animal and plant species are under threat of extinction worldwide at the moment (IPBES, 2019). Species' habitats are lost due to land use change, homogenization of landscapes and intensification of agricultural management (Newbold et al., 2016). These processes usually negatively influence aspects of ecosystem functions which are not oriented towards the provision of agricultural products, e.g. the water cycle, chemical fluxes and soil processes. It was estimated that the human induced ecological footprint exceeds the rate of Earth's regeneration already since 1970 (WWF, 2022).

1.1.2 The Role of Grasslands and its Management

Grasslands play a specific role in the context of agriculture-driven global climate change and the loss of biodiversity and ecosystem functions (1.1). Firstly, the global grassland biome covers 30–40 % of the earth's surface (White et al., 2000) and about 70 % of the agricultural land globally (Suttie et al., 2005; O'Mara, 2012). Secondly, grasslands are mainly used for fodder production but have multiple other ecosystem functions (White et al., 2000; Gibon, 2005; Gibson, 2009). Compared to most other agricultural crops, grasslands are no mono-cultures. They are potentially very species-rich and can build biodiversity hotspots within the agricultural landscape (Dengler et al., 2014, 2020; Bond and Parr, 2010). Temperate grasslands contain similar numbers of vascular plant species like tropical rainforests on a certain grain size (Dengler et al., 2014). In addition, many insect, spider and breeding bird species rely on grassland habitats (Chisté et al., 2016; Jungandreas et al., 2022). Further, grassland ecosystems store carbon and play therefore a role for global carbon budget. Within grasslands, carbon is mostly stored below-ground. This soil carbon is not released when grasslands are managed non-destructively, i.e. when grazing or mowing activities do not kill the plants (Ward et al., 2016; Kühnel et al., 2019). Due to the large share of terrestrial surface covered by grasslands, the contribution of carbon storage of these ecosystems is of high importance (Conant, 2010; Dass et al., 2018). The share of global terrestrial carbon storage of grassland ecosystems is estimated to be about 34 % (White et al., 2000; Suttie et al., 2005). It is therefore comparable to forests, even though uncertainties in estimations are high (Suttie et al., 2005). Furthermore, grasslands play a role regarding water filtration and erosion control (Gibson, 2009). Grasslands fulfill also multiple cultural services as they potentially shape aesthetic and diverse landscapes, are important for tourism and provide a sense of home for many people worldwide (FAO, 2009; Hatfield and Davies, 2006; Angelsen et al., 2014).

The degree to which individual ecosystem services are fulfilled in grasslands varies strongly, especially because grassland ecosystems are highly diverse (White et al., 2000; Gibson, 2009). They occur on every continent apart Antarctica, hence, in various climates and include temperate grasslands, tropical grasslands and savannas (White et al., 2000; Gibson, 2009). In addition, the diversity is determined by various management practices and use intensity of grasslands (Socher et al., 2012; Gossner et al., 2016; Neyret et al., 2021). As presented before, grasslands are responsible for a large share of methane and nitrous oxide emissions, but the amounts highly depend on the management of the grasslands, e.g. the stocking rate (Butterbach-Bahl et al., 2011; Jarvis et al., 2011; De Vries et al., 2012). Management and use intensity of grasslands therefore directly influence how much grasslands contribute to global climate change. Regarding biodiversity and ecosystem services, large gradients occur among differently managed grasslands. Even though grasslands potentially contain high numbers of species, many grasslands show only few. Apart from specific cases, this is usually connected to higher use intensities of the grasslands (Socher et al., 2012; Hilpold et al., 2018; Neyret et al., 2021). Higher grazing pressure and more frequent mowing and fertilization events lead to a shift within grassland species composition towards more productive plant species. Less productive plant species and species with flowering cycles that do not fit to the timing of mowing events have a disadvantage and disappear. This reduces the overall number of plant species in a grassland with strong negative effects on the distribution of pollinators for which reductions are already evident (IPBES, 2019). Devastating future effects regarding a pollinator loss are anticipated. Negative effects of higher use intensity of grasslands were also found for other insect and bird species (Di Giulio et al., 2001; Chisté et al., 2016; Lengyel et al., 2016; Jungandreas et al., 2022). In addition, intensification processes of the agricultural sector are accompanied by a homogenization of landscapes which also leads to losses in biodiversity and habitats as hedges and single trees are removed, areas are flattened and moist wells are assimilated, for example (Gossner et al., 2016). Management also influences the carbon and water cycle of grassland ecosystems (Baer et al., 2002). It was found that intensive use leads to a reduction in soil carbon of grasslands (Ward et al., 2016; Kühnel et al., 2019). Grasslands normally function as water purifiers but high amounts of fertilizer applications on intensively used grasslands reduce the water quality in many grassland ecosystems (Botter et al., 2021).

Grassland management also changes the impact of climate change-related extreme weather and climate conditions, like drought events, on grassland productivity. Intensively used grasslands were found to be less resistant against drought conditions which might be related to higher functional and phenological diversity in extensively used grasslands with higher amounts of plant species (Kreyling et al., 2008; Beierkuhnlein et al., 2011; Vogel et al., 2012; Isbell et al., 2015).

1.1.3 The Need to monitor Grassland Management

Global climate change and the loss of biodiversity and ecosystem functions are on-going and accelerating processes. An increase in world population and changes in consumer behavior will put additional pressure on Earth's ecosystems in the future (Tilman and Clark, 2014). Policies and adapted management plans are needed to mitigate climate change and protect nature and its functionality (Leclère et al., 2020). The agricultural sector is a main contributor but also a potent field of action as sustainable management practices are relatively low-priced and quick to implement (IPCC, 2019). However, the development and implementation of holistic and sustainable management plans requires knowledge on the condition of ecosystems and their services. In particular in grassland ecosystems, there are uncertainties in estimates of biodiversity and ecosystem functions as well as their contribution to climate change. This is caused by the diversity of global grassland ecosystems which is amplified by varying management practices and use intensities. It is however known, that global grasslands are degrading and sustainable management techniques are required (Carbutt et al., 2017; Strömberg and Staver, 2022).

Information on grassland management is therefore needed to support the assessment and monitoring of grassland ecosystem services and the development of a holistic and sustainable management plan for grasslands in the future. In Germany, like in many parts of the world but in particular in many European countries, grassland mowing complements and partly substitutes direct grazing by animals (Schoof et al., 2020b,a). Many grasslands are regularly mown throughout the year, whereby the timing and frequency of the mowing events vary. For the ecology and ecosystem services of grasslands both, timing and frequency of mowing, plays an important role. However, there is no extensive information on grassland mowing dynamics available in Germany. In addition, mowing dynamics of years with differing climatic conditions, relationships of mowing dynamics to site conditions and incentives of farmers for intensive or extensive grassland use are poorly understood.

Remote Sensing is a valuable tool to investigate grassland vegetation dynamics beyond the scales possible through reporting farmers or field measurements. Earth observation (EO) provides repeated, area-wide, independent and open source data which can be used to develop automated algorithms to monitor processes on the Earth's surface. Satellite constellations, like the Sentinels, which acquire data of the Earth's surface with revisit times of only some days provide optimal data basis to investigate inter-annual temporal vegetation dynamics, like mowing activities on grasslands.

1.2 Research Objectives

As outlined in section 1.1, biodiversity and ecosystem services of grasslands are largely influenced by its management and use intensity, but information on grassland management, specifically mowing patterns, are missing. This information is lacking in particular on scales which are relevant for policy makers as it should be available automatically and over wide areas.

To address this, a novel framework to detect grassland mowing events in Germany based on satellite data is developed as key objective of this study. Due to small grassland parcel sizes and the small-scale heterogeneity of grasslands in Germany, in particular the high-resolution data sets of the Sentinels, Sentinel-1 and Sentinel-2, are of advantage. In addition to the spatial resolution, dense and continuous time series, which are needed to investigate short-lived grassland management activities, are available through the Sentinel fleets. Therefore, the Copernicus data archives of multiple years for the entire area of Germany are used to develop a method for and assess grassland mowing dynamics. The research objectives of this thesis are:

- **Objective 1**: An extensive literature review on the usage of EO data for grassland management and production analyses is conducted to identify spatio-temporal patterns of the investigated study sites, used sensors and applied methods, and to detect research gaps from previously conducted studies.

- **Objective 2**: A central objective of the thesis is the development of a novel framework to automatically detect grassland mowing events in Germany. The potential of Sentinel-1 and Sentinel-2 data time series for the detection of grassland mowing events is assessed in combination with a self-created reference data set.
- **Objective 3**: Based on the developed framework to detect mowing events, the method is applied to data archives of multiple years (2018–2021) to assess the multi-annual applicability and performance and compare mowing dynamics between years of varying climatic conditions.
- **Objective 4**: The linkage between mowing dynamics and potential influencing factors on grassland management and use intensity, like climatic, topographic, soil or socio-political conditions is investigated to highlight existing conditions and potential incentives of farmers for intensive or extensive grassland usage.

Several key questions need to be answered to elaborate on the overarching research objectives of the thesis. The first group of questions is about the literature review on the use of EO data for grassland management and production analyses:

Research Questions 1:

1. How extensively has grassland management and production with EO data been researched, where are research foci and research locations of previous studies?
2. Which sensor types, sensors, indices and methods are applied to investigate grassland management and production in previous studies?
3. Which research gaps exist and how are they potentially addressed?

The second group of questions refers to the development of the framework to detect grassland mowing dynamics, including the analyses of potentials and limitations of various parameters based on Sentinel-1 (S1) and Sentinel-2 (S2) imagery, the development of the detection algorithm and an accuracy assessment:

Research Questions 2:

1. What are potentials and challenges to detect grassland mowing events with optical and SAR imagery, as provided by Sentinel-2 and Sentinel-1, and how can they be exploited and overcome, respectively?
2. Which sensor and which parameter is able to detect grassland mowing events most successfully or is a combination of both the most accurate approach?
3. How reliably can mowing events be detected and what are limiting factors?

The third group of questions is related to the multi-annual application of the developed method and the investigation of mowing dynamics of four consecutive years with varying climatic conditions in Germany:

Research Questions 3:

1. How does the developed grassland mowing event detection approach perform for the entire area of Germany?
2. What are patterns of multi-annual nation-wide mowing dynamics in Germany?
3. Where are hotspots of intensively used grasslands and where are regions of extensive grassland use?

The last group of research questions is about the investigation of relationships between mowing dynamics and potential influencing factors:

Research Questions 4:

1. To what extent do climatic, topographic, soil conditions and socio-political frameworks influence mowing dynamics in Germany?
2. What do these relationships imply for management options and the status of grasslands in the future?

1.3 Thesis Outline

In the following chapters, first, the results of the extensive literature review on EO for grassland management and production are presented to give a broad overview over existing literature and research gaps in the field (chapter 2). Afterwards, background on the geography and, here, in particular grassland use and protection mechanisms in the study area is given in chapter 3. The framework of grassland mowing detection is presented in detail in chapter 4. It includes the description of data sets and methods as well as results of the mowing detection based on various input parameters and the Germany-wide and multi-annual application of the developed approach. The next chapter considers the linkage between mowing dynamics and climatic, topographic, soil conditions and protection mechanisms (chapter 5). Finally, the results of the thesis are summed up and the research questions answered in the final chapter (6).

Chapter 2

A Review on Remote Sensing of Grassland Management and Production*

This chapter presents a systematic literature review of research on using EO data to investigate grassland management and production. The usage of remote sensing in grassland biomes is underrepresented compared to other land cover types, however, numbers are growing. By reviewing previous studies, information of existing research, such as investigated study sites, used sensors, applied methods, among other aspects, was collected and assessed. The results of this review present state-of-the-art methods as well as potentials and limitations of approaches of previous work and highlight research gaps.

Studies between 1986 and the first quarter of 2020 were systematically searched and reviewed, and more recent research was included when appropriate which led to a total of more than 250 studies. The chapter starts with the definition and distribution of grasslands worldwide to give a background on this diverse land cover type (section 2.1). Afterwards, the results of the literature review are presented starting with general properties of the existing work (section 2.2.1). Next, previous research on using remote sensing to investigate grassland production traits is presented (section 2.2.2), followed by the review of studies on remote sensing for grassland management and use intensity (section 2.2.3). As it is related to one of the main objectives of this thesis, state-of-the-art approaches using remote sensing for grassland mowing detection is highlighted in the final section (2.2.4).

2.1 Background on Grassland Characteristics

Grasslands occur on every continent of the world apart from Antarctica (Reynolds and Frame, 2005; Dixon et al., 2014). Their distribution shows a large climatic gradient as

*Parts of this chapter have been published in Reinermann et al. (2020).

they exist on cold continental to tropical climates and in various elevations (Figure 2.1). A global mapping of grasslands is challenging due to the large variety in physical appearance resulting from differing species compositions of grasslands. Ramankutty et al. (2010) used Moderate Resolution Imaging Spectroradiometer (MODIS) and Satellite Pour l'Observation de la Terre - Vegetation (SPOT-VGT) data along with agricultural inventory information to map pastures (Figure 2.1). The focus of this map is on managed grasslands and it represents the situation in 2000 (Ramankutty et al., 2008). For many parts of the world, this is probably already outdated as grassland ecosystems permanently face the risk of conversion into croplands. However, other mapping approaches reveal other disadvantages, such as no focus on managed grasslands. Dixon et al. (2014) mapped the distribution of grasslands, however, focusing on different grassland ecosystem types resulting in a broader scale mapping, missing European grasslands, for instance. Grasslands with large and continuous coverage occur in North America (Great Plains), South America, Europe, Central and South Africa, southeastern and southwestern Australia and New Zealand, and Central Asia (Figure 2.1).

The diversity in grassland climatic conditions and physiognomy becomes visible when examining annual temperature and precipitation rates as well as images of various grassland sites of the world (Figure 2.1 A–F). The global distribution and diversity of grasslands result in difficulties and disagreements of the definition of grasslands. An extensive compilation of definitions can be found in Gibson (2009). Grasslands are defined to consist of grass species (Poaceae) and herbaceous vegetation, including herbs, shrubs and trees (White et al., 2000; FAO, 2009; Dixon et al., 2014). Per definition, grasslands should not exceed 25 % of shrub cover and the share of trees should remain smaller than 10 % in temperate and 40 % in tropical regions (Faber-Langendoen and Josse, 2010). Apart from visible features, grasslands are characterized by specific environmental conditions, which usually involve sufficient moisture for grass growth and external conditions that limit tree growth (Allaby, 2012). Bush and tree encroachment is usually hindered by recurrent disturbances, such as herbivory and fire (Suttie et al., 2005).

The terms used for grasslands vary and a strict separation into sub-categories is challenging. However, terms which are usually used for managed grasslands are rangelands and pastures. Rangelands are mostly associated with grazing livestock and pastures with grazed and/or mown grasslands (Allen et al., 2011). The term meadow is often applied for grasslands which are used to produce hay and silage. Terms for grasslands associated to specific geographic regions and local legal connotations include campos, cerrados, llanos, pampas, prairies, savannas and steppes (Allen et al., 2011). These consist at times not only of grasslands and form relatively specific land cover types. In particular, savannas constitute

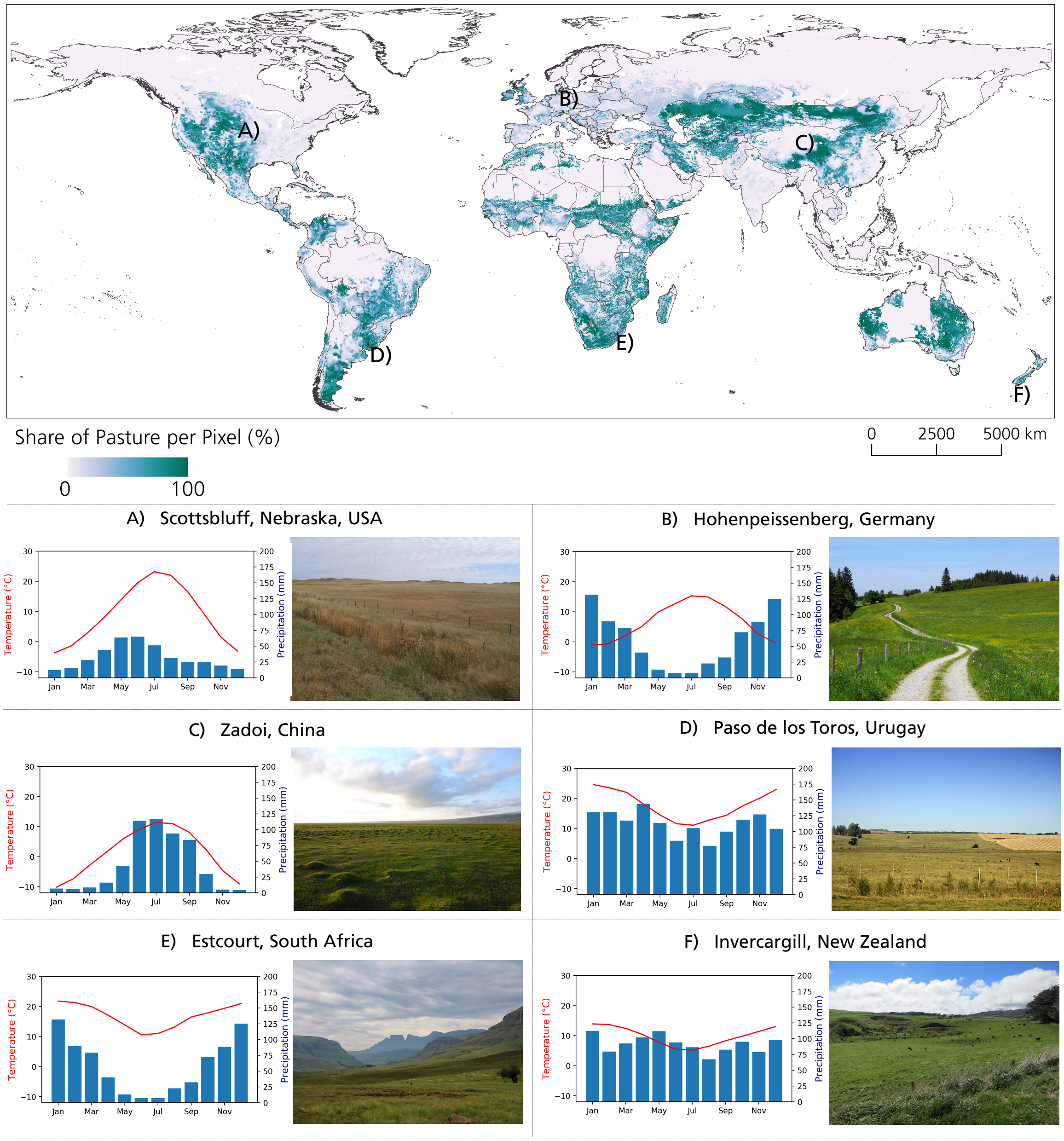

Figure 2.1: Coverage of pastures worldwide according to NASA SEDAC (Ramankutty et al., 2010) as well as climate diagrams of locations with grasslands showing mean temperature and precipitation for around 30 years between 1960 and 2000 (NOAA, 2011) (A–F). The climate diagrams are not exhaustive but highlight the diversity of climatic conditions of grassland areas. The images show grasslands close to the weather stations and were downloaded from flickr.com. The figure was adapted from Reinermann et al. (2020).

a special case. These occur in sub-tropical and tropical regions and are often a transition zone between grassland and forest (Dixon et al., 2014). Hence, savannas were excluded from this review.

Grasslands are often separated into natural and non-natural grasslands. The existence of natural – or native – grasslands is determined by natural conditions, such as climate, fire or native grazers. Non-natural, managed or cultural grasslands are characterized by human influence (Suttie et al., 2005; Dixon et al., 2014). A strict separation between those classes is, however, often not possible as humans influence most grasslands to some degree. Nonetheless, it is important to understand that there are differences regarding the degree of human impact within grassland ecosystems. For instance, some European grasslands depend completely on human action. They are annually seeded, regularly fertilized, at times irrigated, and harvested throughout the year. As a result, the ecology of these grasslands is completely altered compared to naturally occurring grasslands.

2.2 Results of the Literature Review

Grasslands gain more and more interest in research recently. This is related to the fact that grasslands are more relevant for global processes, such as climate change (mitigation) than previously anticipated (compare section 1.1.2) and provide important ecosystem functions (Figure 2.2). In addition, field sampling which is time consuming and expensive is aggravated by the diverse nature of grasslands (Nestola et al., 2016). Remote sensing provides an opportunity to continuously monitor grasslands on large scales.

Optical sensors provide information on greenness, vitality and density of vegetation. SAR sensors capture information on vegetation height, canopy structure (Hill et al., 1999; Wegmuller and Werner, 1997), soil attributes, surface roughness (McNairn and Brisco, 2004) and dielectric properties of the surface (Hill et al., 1999; McNairn and Shang, 2016).

For the literature review, the focus lied on research on grassland management and production traits using remote sensing. Fodder production is a major function of grasslands and closely related to management which, itself, is an important determining factor for grassland ecosystem services. Previous reviews on using remote sensing for grassland management and production analyses focus only on a specific aspect, such as biomass retrieval or grazing, did not provide a complete picture on the use of different sensor types or are outdated (Tucker, 1980; Tueller, 1989, 1995; Hill et al., 2004; Lu, 2006; Schellberg et al., 2008; Ali et al., 2016; Shoko et al., 2016; Wachendorf et al., 2018). All research which was found during an extensive literature search and screening through the references therein covering the topics of grassland management or production was reviewed. Only articles with a clear

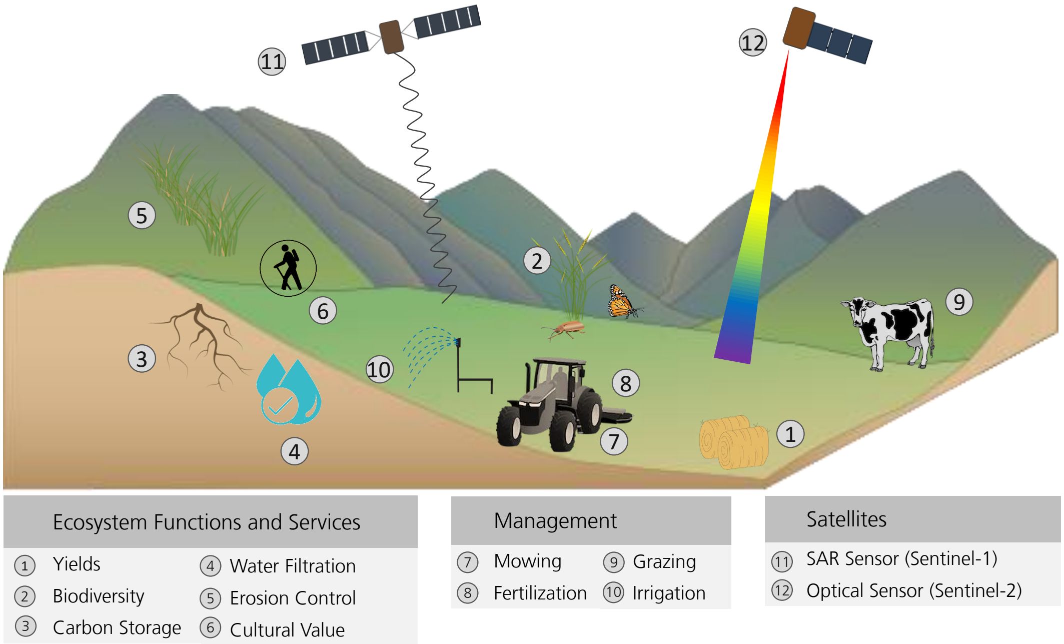

Figure 2.2: Services and functions of grassland ecosystems as well as major management activities and optical and SAR satellite sensor data retrieval. The source of the symbols is the Integration and Application Network (ian.umces.edu/media-library).

focus on grassland ecosystems and using space-borne remote sensing data were included in the review process. The search was conducted on Google Scholar and Web of Science using the search terms shown in Table 2.1. The literature search was conducted in the first quarter of 2020 leading to 253 articles. More recent publications were added when appropriate.

Table 2.1: Search strings and terms used for the literature review on research on remote sensing use for grassland management and production analyses.

Field	Search Terms
Management and Use Intensity	harvest*, cut*, mow*, irrigat*, fertiliz*, graz*, management, monitoring, "use intensity", intensity
Production Traits	biomass, production, productivity, quantity, yields
Grasslands	grassland*, pasture*, meadow*, steppe*, rangeland*
Remote Sensing	"remote sensing", "earth observation", satellite*

2.2.1 Properties of the Reviewed Studies

Around 70 % of the reviewed articles were about remote sensing of grassland production. Studies with a focus on remote sensing analyses of grassland management and use intensity made up about 18 % of the reviewed articles and approximately 12 % investigated both topics. Most of the reviewed studies were published in the International Journal of Remote Sensing (14 %), followed by the Journal of Remote Sensing (12 %), Remote Sensing of Environment (9 %) and Ecological Indicators (6 %), among other journals.

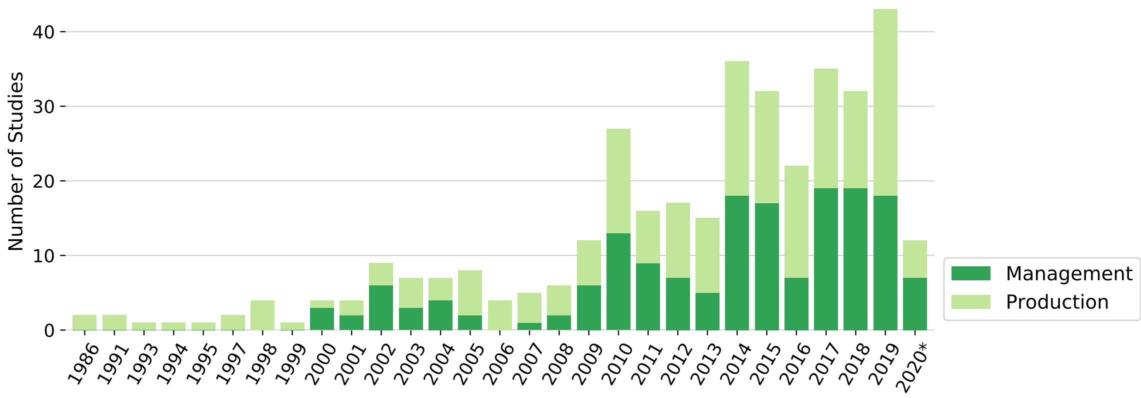

Figure 2.3: Number of studies investigating grassland management or production with satellite imagery per year resulting from the literature review. * Only studies until April 2020 were included in the review.

The number of publications per year shows an increasing trend (Figure 2.3), in particular from 2010 onwards. Investigations on grassland management and use intensity started later compared to production trait estimations, but both remained important. Studies including both topics were counted double.

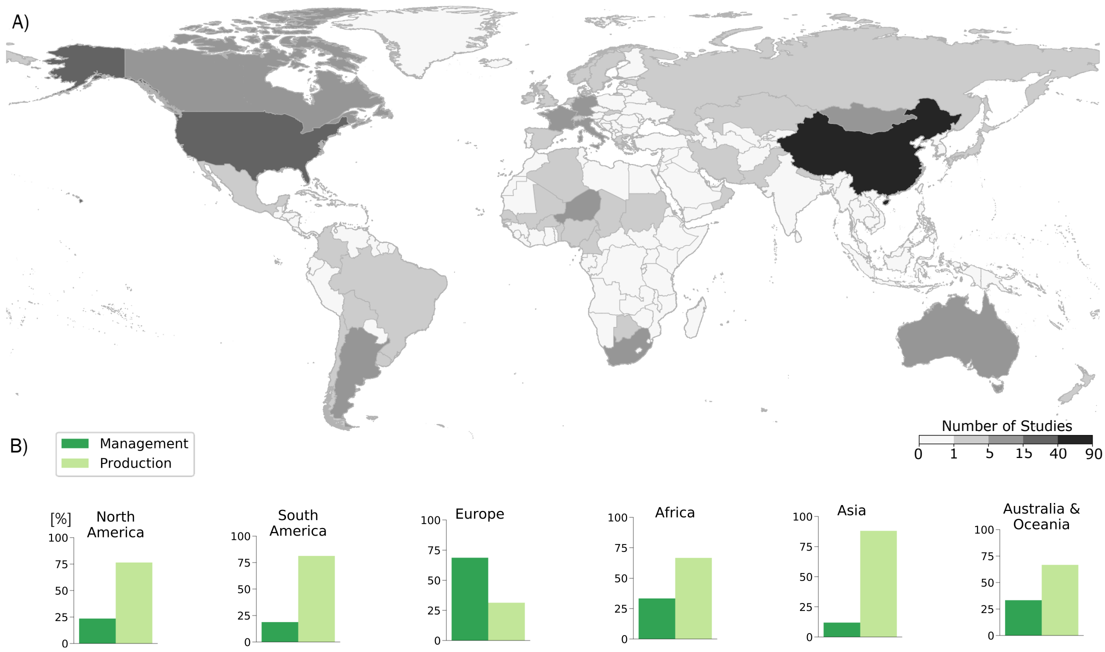

Figure 2.4: Number of studies per country and distribution of studies focusing on management or production analysis per continent resulting from the literature review.

The global frequency distribution of the locations of study sites per country is highlighted in Figure 2.4. Large-scale applications, of which two investigated entire Europe and six the entire globe, were not included in the map. Most studies were conducted in China (n=89). When comparing the locations of study sites of previous research to the distribution of grasslands worldwide (Figure 2.1) it becomes visible that some grasslands are not yet investigated at all, e.g. in southern and eastern Africa. Regarding the research topics of the reviewed literature, all continents apart from Europe show a larger share of studies focusing on grassland production traits instead of management (Figure 2.4 Barcharts).

Some grasslands have already been extensively investigated, such as the Xilingol steppe in China, others seem to be underrepresented. This does not mirror the value of the grasslands, but is probably related to practical reasons, such as a lack in financing research in this area. Hence, some grasslands of the world have been studied only rarely or not at all using remote sensing.

The temporal dimension of the reviewed literature was examined as it was investigated whether single images, multiple images or time series were used for the analyses. Which of these categories were used, while multi-temporal is defined by at least five consecutive images, and the start and end points of the investigated satellite imagery in the order of the publication dates are shown in Figure 2.5. It becomes clear that time series analyses have always played an important role, however also single images or multi-temporal data sets were frequently investigated regarding grassland production or management. A visible starting point of investigated data of many studies is around 1999 and 2000, which were the launch years of Landsat-7 and MODIS Terra.

The use of sensor systems and satellites was investigated which showed that the majority of research on remote sensing analyses of grassland production and management clearly relies on optical systems (Figure 2.6). Regarding single satellite fleets, mostly MODIS (Terra and Aqua) and Landsat data was applied, followed by Advanced Very High Resolution Radiometer (AVHRR) and SPOT-VGT (Figure 2.7). The Sentinel fleets, launched in 2014 and 2015, respectively, provide high spatial resolution images with a revisit time of a few days for most grasslands worldwide. In the future, they will play a major role in the analysis and monitoring of grassland production and management.

The clear dominance of optical sensors is related to the enhanced interpretability and understanding of optical imagery compared to SAR data accompanied by a longer history of usage. However, SAR data has already shown potential in the exploitation of grassland information. Hence, SAR data sets will most likely experience more usage for monitoring of grassland production traits and management, alongside other topics, in the future. In particular combinations of optical and SAR data sources have the potential to overcome limitations of each sensor type (e.g. cloud coverage for optical data) and, therefore, improve grassland monitoring activities.

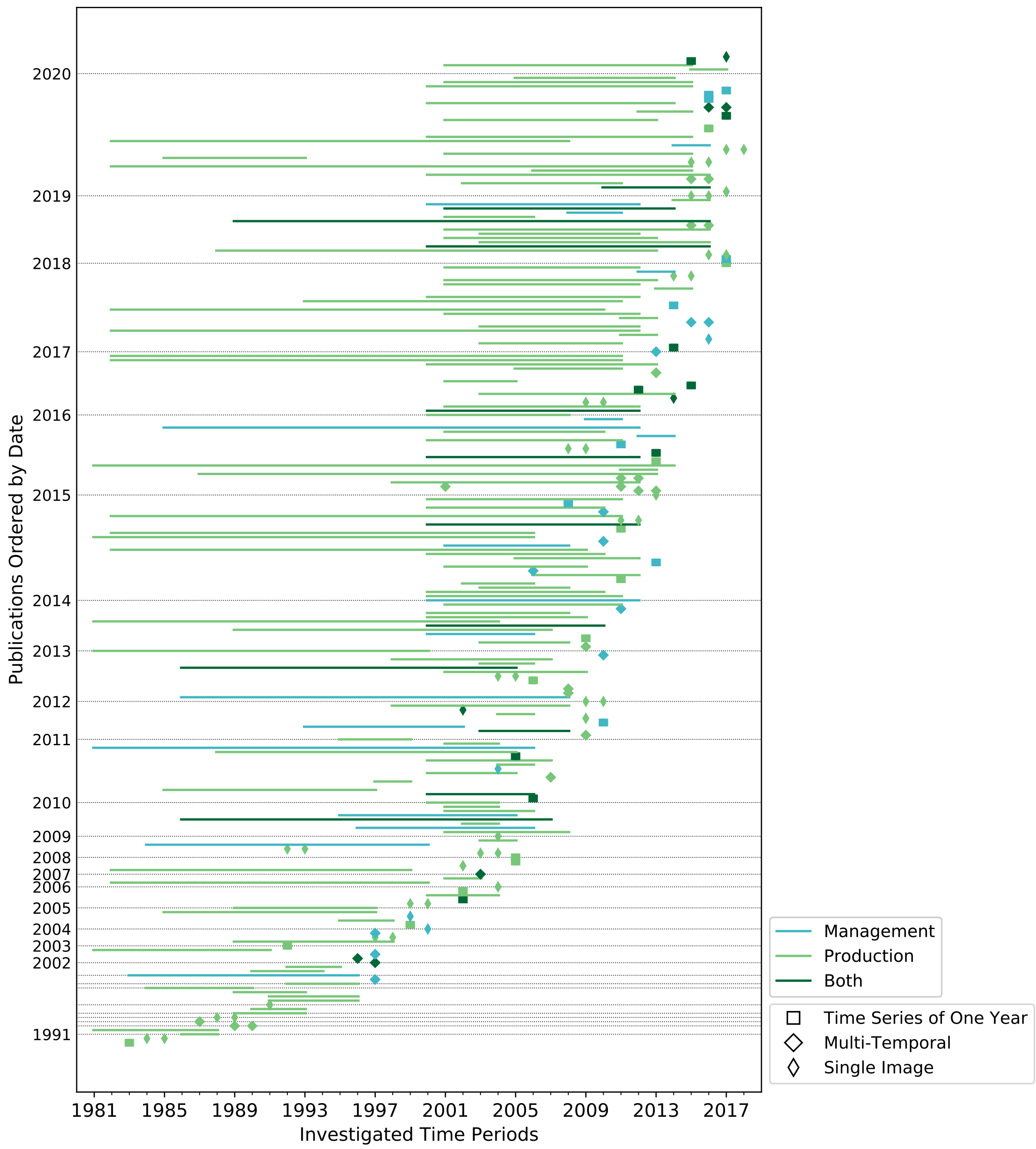

Figure 2.5: Study periods (x-axis) of the reviewed studies ordered according to their publication date (y-axis) highlighting the use of single or multiple images or time series and the investigated time frames of previous literature.

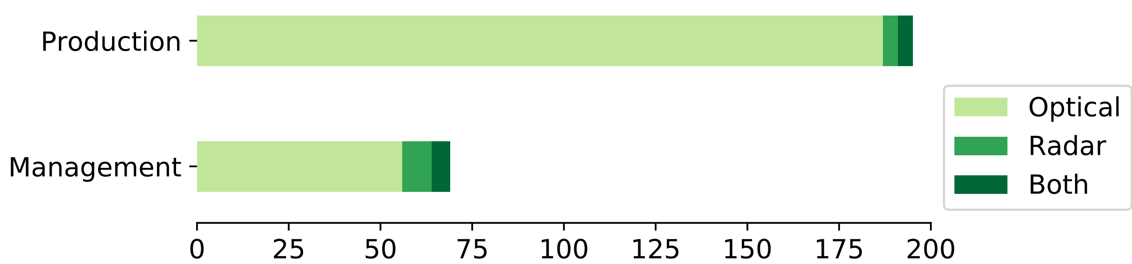

Figure 2.6: Number of studies based on optical or SAR sensors of all reviewed studies for the two topics, grassland production and management analysis.

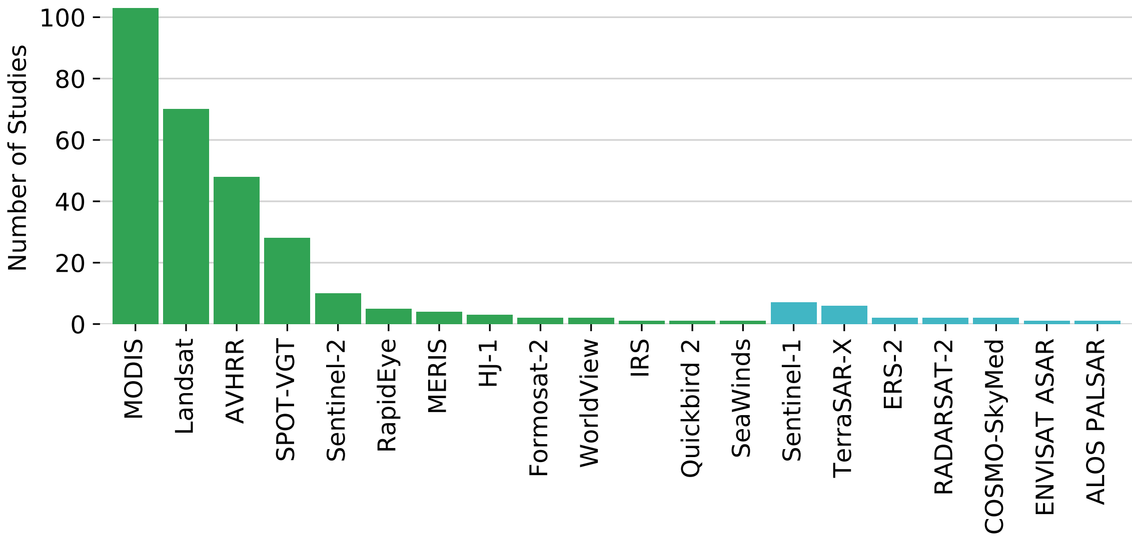

Figure 2.7: Number of studies with each sensor or sensor fleet.

2.2.2 Remote Sensing of Grassland Production

To investigate spatial and temporal patterns of grassland production, mainly vegetation indices based on optical sensors were used in previous literature (Tucker et al., 1986; Yang et al., 1998; Ricotta et al., 2003; Franklin and Molina-Freaner, 2010; Reeves and Baggett, 2014; Yin et al., 2014; Gu and Wylie, 2015; Gao et al., 2016; Qamer et al., 2016; Kath et al., 2019). Almost all of these indices are based at least partly on the near-infrared and red bands. The calculated indices, from which the normalized difference vegetation index (NDVI) was by far mostly used, were visually interpreted and spatial patterns or the temporal development of an area investigated.

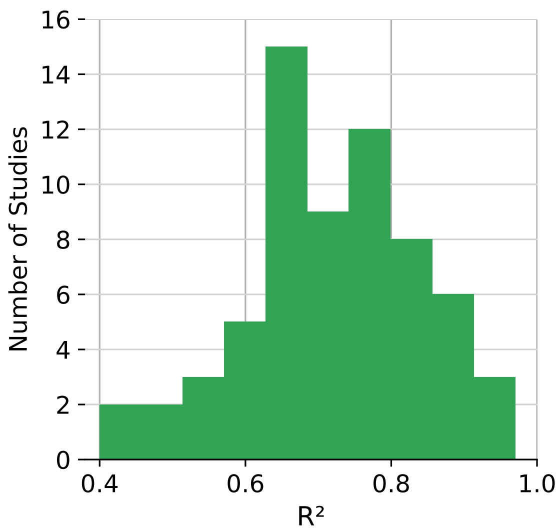

Figure 2.8: Distribution of the R^2 values of empirical models to estimate grassland biomass of previous literature.

2.2.2.1 Empirical Models for Grassland Production

Apart from using vegetation indices as direct proxies for grassland production estimation, they are often also used as input for models in combination with ground-truth data. Here, bio-physical, process-based as well as empirical models played a role and typical ground-truth data sets were eddy covariance measurements and biomass samples. The relationship of several vegetation indices to eddy covariance measurements was studied, finding that the EVI was significantly correlated during periods of high vegetation cover in a temperate grassland, the Soil-Adjusted Vegetation Index (SAVI) during low vegetation cover periods (Zhou et al., 2014). This is in accordance to another study which found that the relationship between the greenness index based on satellite imagery and eddy covariance measurements changes through time (Yan et al., 2019). However, an empirical model based on eddy covariance measurements accompanied by other bio-physical measurements and optical vegetation indices resulted in weekly grassland production estimates. The model was based on a regression tree approach and revealed the potential of grasslands to act as carbon sinks (Wylie et al., 2016).

Another common approach in previous literature was to develop an empirical model based on above-ground biomass samples and satellite data. The models which consisted of one to several spectral bands and indices were trained with a subset of the ground data and tested with the remaining part to estimate the performance of the model. More than half of the studies (approximately 62 %) using this approach included the NDVI in their models. Other often used indices were the EVI (15 %), the SAVI (9 %) and the leaf area index (LAI) (8 %).

The models to estimate grassland production were in 60 % of the reviewed studies simple linear or multiple linear regression models (Edirisinghe et al., 2011, 2012; Smith et al., 2011). Apart from that, machine learning models were applied to map grassland production based on satellite imagery and biomass samples. Here, Random Forests (Ramoelo et al., 2015; Wang et al., 2017; Magiera et al., 2017; Zeng et al., 2019), Support Vector Machines (Zhang et al., 2016), Generalized Linear Models (Baghi and Oldeland, 2019), Gaussian process regression (Yin et al., 2018), Artificial Neural Networks (Xie et al., 2009; Li et al., 2013; Ali et al., 2017a,b; Quan et al., 2017; Yang et al., 2018) and Adaptive Neuro-Fuzzy Inference Systems (Ali et al., 2017b). The accuracy of the biomass models varied with R^2 values between 0.4 and 0.97 (Figure 2.8). However, these are only partially comparable as the degree of diversity of the studied grassland varied. The highest R^2 values were reached when the grassland was pre-selected according to the cover types of studies which investigated single time steps (Marsett et al., 2006; Wehlage et al., 2016).

Empirical models usually require field data along with satellite imagery and the model performance depends on the quality of the ground data. This is a limitation for large-scale applications and continuous monitoring field data with a large diversity would be needed for which collection is cost and time intensive. Field data collection is also a source of error and inconsistencies between studies.

Next to the spatial variability of grasslands influencing the quality of empirical models and the field data collection, also the temporal variability of grassland biomass plays a role. Grasslands which are frequently mown or grazed contain various amounts of biomass throughout the year. The development of empirical relationships between satellite imagery and field samples as well as the timing of field data collection has to take this into account. On the one hand, multi-temporal grassland biomass information might reveal the timing and type of management activities, such as mowing. On the other hand, information on management of grasslands could improve biomass models and enable the challenging task of yield estimation in grassland ecosystems.

2.2.2.2 Process-based Models for Grassland Production

Another regularly used approach to estimate grassland production with remote sensing data is the application of radiative transfer models. An often used model is the RPOSAIL model which is a combination of a leaf optical properties (PROSPECT) and a canopy bi-direction reflectance (SAIL) model and is often applied to estimate bio-physical properties of vegetation (Jacquemoud et al., 2009; Quan et al., 2017). Another model which is used to estimate crop growth and is also applied in grassland ecosystems is the Simulateur multi-disciplinaire pour les Cultures standard (STICS) (Bella et al., 2004).

Many studies investigated grassland productivity which is defined as mass unit per area per time. This was usually done by applying a Light Use Efficiency (LUE) model (Monteith, 1972, 1977; Hill et al., 2004; Donald et al., 2010), from which the mostly used one among the reviewed articles was the Carnegie-Ames-Stanford Approach (CASA) model (Zhang et al., 2014; Sun et al., 2017), followed by the Vegetation Photosynthesis Model (VPM) (Yu et al., 2018). Within LUE models, productivity is estimated as a function of LUE and of absorbed photosynthetically active radiation (APAR) which is obtained from vegetation indices of optical imagery for certain vegetation types (Potter et al., 1993). Some process-based models which were used to estimate grassland productivity were the BIOME-BGC (You et al., 2019), C-Fix (Maselli et al., 2013), Denitrification-Decomposition (DNDC) model (Wang et al., 2016), Global Production Efficiency Model (GLO-PEM) (Fan et al., 2010), Temperature and Greenness (TG) model (Jia et al., 2018), Greenness and Radiation (GR) model (Jia et al., 2018), Eddy Covariance - Light Use Efficiency (ECLUE) model (Jia et al., 2018), Vegetation Production and Respiration Model (VPRM) (Jia et al., 2018) and Organizing Carbon and Hydrology in Dynamic Ecosystems (ORCHIDEE) model (Tan et al., 2010). The mode-based grassland productivity estimates were validated by comparing them with eddy covariance measurements (Wu et al., 2008; Tan et al., 2010; Wang et al., 2010; Rossini et al., 2012; He et al., 2014; Zhou et al., 2017b).

Using process-based modeling approaches has the advantage that these models are usually applicable on large scales and no field data is needed to build the model to estimate productivity. Global products of this kind are already available, such as the MODIS Net Primary Productivity (NPP) product in eight-daily or monthly temporal resolution (Running et al., 2004). It enables the analysis of global processes, such as climate change. However, these models are at times not able to depict the small-scale diversity of grassland landscapes which is potentially supported by ground data, such as eddy covariance measurements (Niu et al., 2016; Gaffney et al., 2018; Zhu et al., 2018).

2.2.3 Remote Sensing of Grassland Management and Use Intensity

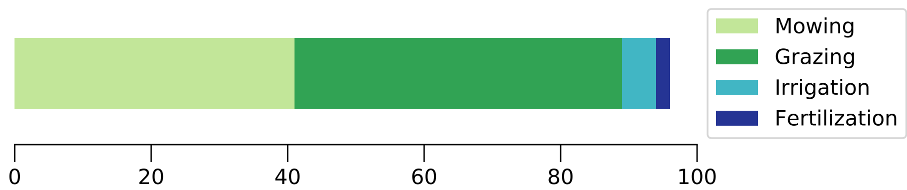

Figure 2.9: Number of studies focusing on a management type out of all reviewed research on remote sensing of grassland management.

Studies focusing on investigating grassland management and use intensity mostly explored the management activities grazing and mowing (Figure 2.9). These are common management practices for which information is potentially obtained using satellite imagery. Among the reviewed studies almost no one investigated management activities like fertilization or irrigation. On the one hand, these might be more difficult to analyze with satellite data, on the other hand, grazing and mowing are major management practices influencing the ecology of the grassland ecosystems.

The extents of the study sites of research papers on grassland management and use intensity were investigated (Figure 2.10). The approximate size of the investigated study areas were extracted from maps when not specified in the literature. The study site sizes were analyzed according to the different management options. It is shown that only a few studies analyzed areas larger than 10000 km^2 which is less than one thirtieth of the area of Germany. It highlights that satellite-based analyses of grassland management and use intensity so far were conducted on farm or regional scale mostly.

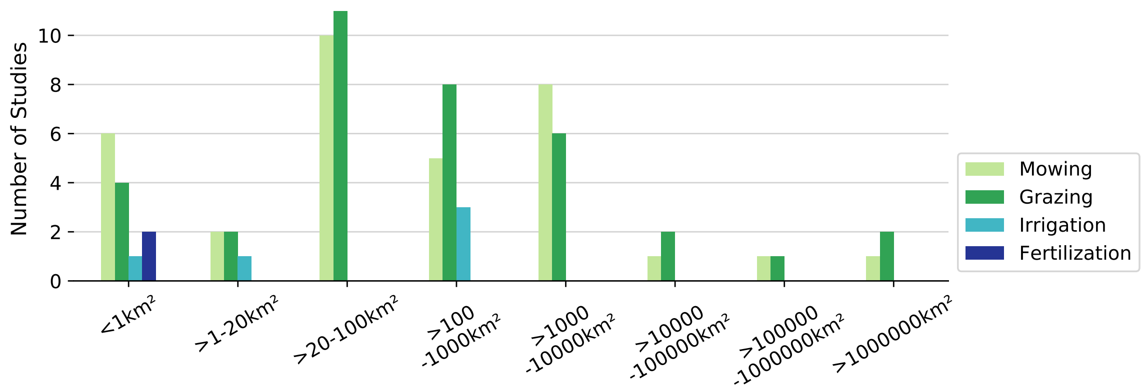

Figure 2.10: Distribution of the size of the investigated region of interest within the reviewed studies.

Concerning used indices, again the NDVI was mostly used in previous studies (46 %) to investigate grassland management and use intensity with remote sensing. Other often used indices were the LAI (12 %), reflectances of single bands (11 %), the EVI (7 %) and the fCover (5 %). Apart from that, the Fraction of absorbed Photosynthetic Active Radiation (FAPAR), Tasseled Cap components, the Normalized Difference Water Index (NDWI), the SAVI and vegetation indices based on red edge bands of S2 were used in the reviewed articles. Based on SAR, backscatter intensity data was mostly used (15 % of all studies), followed by interferometric temporal coherence (6 %). Among additional investigated SAR parameters were polarimetric decomposition parameters, such as alpha angle and entropy.

2.2.3.1 Analyses of Grassland Management Types

The literature on remote sensing of grassland management and use intensity can be divided into separate topics. One of these is the detection of grassland management types. Mostly, grasslands were classified and the three groups "grazed", "mown" and "mixed" were distinguished. An approach using time dynamic warping on Landsat-TM and Satellite Pour l'Observation de la Terre (SPOT)-4 data reached a kappa value of 83 % (Dusseux et al., 2013). In another management type detection exercise the LAI was proven to be an important model input parameter (Dusseux et al., 2012). An additional result of previous literature was that observations in spring and early summer are relevant for the detection of grassland management types (Dusseux et al., 2014b; Price et al., 2002b). In particular the delineation of the mixed class, which often leads to difficulties, is improved through cloud-free images in spring and early summer (Dusseux et al., 2014b). This is probably related to the high biomass levels and fast vegetation growth of grasslands in spring. As a consequence, the reduction of biomass through mowing or grazing leads to strong changes in the amplitude of satellite-based vegetation indices or backscatter intensity which enhance the detectability of these events.

Considering SAR data, grassland phenology was well captured by the HH/VV ratio (Dusseux et al., 2014a). However, adding backscatter information to classification models aiming at differentiating management types did not improve the results (Price et al., 2002a; Dusseux et al., 2012).

The investigation of grassland management was so far mainly focused on grazing and mowing. Other management activities, like irrigation or fertilization, have not yet been studied extensively using remote sensing. Fertilization has a large impact on the ecology of grasslands as regular application of fertilizer alters the species composition of grasslands, among other things. The irrigation of grasslands will play an increased role in future climates, in particular in regions which are assumed to experience more frequent dry spells like the Mediterranean. As a consequence, these aspects will be of increased interest in the future.

2.2.3.2 Analyses of Grazing Intensity

Another major aspect of research on remote sensing of grassland management and use intensity was the analysis of grazing intensity. Grazing intensity was defined as proxy, a vegetation index, for instance (Reeves and Baggett, 2014), or derived from estimated biomass (Long et al., 2010; Li et al., 2016). At times, satellite-based information was coupled with statistical data, e.g. livestock census data as animal per area (Roeder et al., 2008; Gomez-Gimenez et al., 2017) or field experiments (Ma et al., 2019; Xu et al., 2019).

A large majority of studies focused on the analysis of optical vegetation indices to investigate grazing intensity (Blanco et al., 2009; Li et al., 2013; Ma et al., 2019; Xu et al., 2019). In many articles, time series of vegetation indices were used to investigate trends or spatial patterns of grazing intensity (Reeves and Baggett, 2014; Li et al., 2016; Xu et al., 2016). The NDVI was found to correlate significantly with ground-truth data on grazing intensity levels (Xu et al., 2018; Ma et al., 2019). Various spatial patterns were detected, for instance, hotspot areas of grazing intensity around watering ponds (Blanco et al., 2009). The analysis of temporal dynamics of grazing intensity revealed positive as well as negative trends; for some areas, success of conservation efforts were detected (Roeder et al., 2008; Blanco et al., 2009; Xu et al., 2016).

Some studies analyzed the relationship of grazing intensity to the degradation of grassland ecosystems. Proxies of vegetation condition were correlated to indicators of grazing intensity, e.g. livestock density, or multivariate analyses including meteorological data to account for climate effects were conducted (Roeder et al., 2008; Blanco et al., 2009; Paudel and Andersen, 2010; Li et al., 2013; John et al., 2018). Mixed effects were found in that regard as stocking rate, for instance, showed significant as well as insignificant relationships to grassland degradation indicators in previous research (Roeder et al., 2008; Li et al., 2013; John et al., 2018).

Grazing is the most common management type of grasslands worldwide. Intensive grazingor overgrazing is a substantial cause for the degradation of grassland ecosystems and the loss of related ecosystem functions. This makes research on grazing intensity highly relevant. However, although remote sensing has advantages, such as the coverage of large areas, cost-efficiency and repeatability of methods, approaches to monitor degradation induced by grazing intensity are limited. The impact of grazing pressure on ecosystems is often entangled with climate effects. This interplay needs to be understood to develop effective monitoring mechanisms and prevention plans.

2.2.4 Remote Sensing of Grassland Mowing Detection

Next to the delineation of management types or the analyses of grazing intensity, the detection of mowing events plays a central role in research on remote sensing of grassland management. Several studies, which are mostly rather exploratory, used optical and SAR data on various spatial scales and temporal dimensions. One previously used methodological approach of mowing detection is the classification of cut versus uncut grasslands, for potentially multiple events during the year. Mainly SAR data sets, but also optical data or a combination of optical and SAR data were used in that regard (Halabuk et al., 2015; Siegmund et al., 2016, 2019; Taravat et al., 2019; Lobert et al., 2021; Lange et al., 2022). Halabuk et al. (2015) used vegetation indices based on MODIS with a decision tree-based classification approach resulting in a F1-Score of 0.85, however only for extensively used grasslands. An Artificial Neural Network (ANN)-based classification of SAR backscatter intensity reached an accuracy of 0.85 (F1-Score) but only for two test sites in Germany (Taravat et al., 2019). A combination of optical and SAR with data from Landsat 8, S2 and S1 was used in a Convolutional Neural Network (CNN) approach, whereas the model with the highest accuracy (F1-Score = 0.84) included the NDVI, backscatter cross-ratio and InSAR Coherence (Lobert et al., 2021). This classification approach was tested for single grassland parcels with a relatively good data coverage in Germany and still needs to be explored for a broader research area. Within a study on grassland use intensity, the mowing frequency was determined based on a CNN classification approach for the entire grassland area of Germany using S2 data resulting in an F1-Score of 0.57 (Lange et al., 2022).

Although the classification-based approaches often used multi-temporal satellite data, the temporal information, namely the signal development of mowing events over time, was not included. Several exploratory studies investigated the signals of various satellite-based indices before, during and after grassland mowing events. This involved the comparison of parameters of single images before and after mowing events, such as backscatter intensity using COSMO-SkyMed or S1 (Grant et al., 2015a; Malss et al., 2018) or InSAR coherence based on TerraSAR-X (Ali et al., 2017a), showing that changes of these parameters after mowing events are visible. The investigation of time series for various parameters, including the NDVI based on S2 (Rossi et al., 2019), Gross Primary Productivity (GPP) based on MODIS and Landsat (Skinner et al., 2011; Zhou et al., 2017a), backscatter intensity based on S1 and COSMO-SkyMed (Grant et al., 2015b,a), polarimetric decomposition parameters based on TerraSAR-X and Radarsat-2 (Voormansik et al., 2013, 2015) and interferometric temporal coherence based on COSMO-SkyMed (Zalite et al., 2014, 2015) and S2 (Tamm et al., 2016), revealed visible changes of the parameters after mowing events which were, however, varying in their amplitude and inconsistent. In previous time series-based mowing detection approaches, the temporal information was involved and mostly a change detection or other rule-based detection approach was developed. A temporal decision rule-set led to a F1-Score of 0.9 for detected mowing events which were used as input for a crop growth model (Courault et al., 2010). However, only homogeneously managed grasslands, all characterized by three mowing events per year, were included in the study. The detection of abrupt drops in a S2-based NDVI time series reached a detection rate of 77 % (accounting only for correctly detected mowing events) in a study area in Switzerland (Kolecka et al., 2018). For entire Europe, however on a coarser spatial resolution using MODIS data, mowing events were detected with a thresholding-based location of throughs (splines) (Estel et al., 2018). The detected mowing events were combined to mowing frequencies which resulted in an accuracy of 80 %. Schwieder et al. (2021) applied a rule set developed by Griffiths et al. (2020), which is based on the detection of strong minima in a Landsat 8 and S2-based EVI time series, to detect mowing events for entire Germany for the years 2017-2020. The validation of the approach relying solely on optical data resulted in F1-Scores of 0.58 to 0.67. Apart from the classification-based approach by Lobert et al. (2021), only De Vroey et al. (2022) used a combination of optical and SAR data for mowing detection so far. The thresholding approach which works on parcel level and resulted in F1-Scores of 0.64 (S2) and 0.58 (S1+S2) for a validation data set from Belgium was applied to grassland sites in Czech Republic, Italy, Netherlands, Lithuania, Romania, Spain and Belgium (De Vroey et al., 2021, 2022).

The number of studies on grassland mowing detection increased strongly within the last few years as the feasibility rose with the launch of the Sentinel satellites. A large majority of studies presented above are more exploratory and investigated the signals of various parameters related to mowing events, but only a few developed mowing detection algorithms and even less applied it to a large and heterogeneous grassland area to map grassland mowing dynamics. Without a mapping result as in De Vroey et al. (2021, 2022) for instance, the plausibility and comparability of the mowing detection results is largely reduced. Another important aspect which was often completely missing or at least very limited was the availability of an independent and complete validation data set in previous research. Many studies used a validation data set based on the visual interpretation of optical satellite data (Kolecka et al., 2018; Schwieder et al., 2021) which potentially leads to a bias of the accuracy assessment as the mowing detection algorithm as well as the creation of the validation data set are limited by the same factors (e.g. cloudy conditions). The validation data set requires information of various management options and intensity levels of grasslands, which was mostly not given in previous literature as reference information of intensively mown sites was very limited. Without a complete validation data set the quality of the accuracy assessment is largely reduced. A mowing detection approach based on optical and SAR data, applied to a large and heterogeneous grassland area in high resolution and for multiple years, and validated with an extensive validation data set – as conducted within this thesis – was still missing in the research landscape.

2.3 Summary

Research on the use of EO data to investigate grassland management strategies, use intensities and production traits was assessed to highlight patterns of previous studies and extract research gaps. All papers on these topics which were found by an extensive search within the Web of Knowledge and Google Scholar were included, leading to a comprehensive literature review of, in total, 253 papers, published between 1986 and 2020. Studies investigating grassland management and production increased within the last years, in particular since 2010. Study sites in South America and Africa are underrepresented as research from these continents cover only 5 and 4 % of the reviewed literature. As large and diverse grassland areas occur in South America and Africa, this shows that more research is needed, in particular as many people's livelihoods depend on grassland ecosystems there (Angelsen et al., 2014). Previous studies used single images, multiple images and complete time series to investigate grassland management and production traits. Data from MODIS and Landsat played a central role in the past, however, now and in the future the Sentinels gain increased importance in that regard. The vast majority of the reviewed studies used optical data and only a small share (4 %) combined optical and SAR data to investigate grassland management and production.

Compared to the other continents, grassland production traits show a small share in Europe (30 %). This is probably related to the fact that European grasslands are characterized by a strong human influence through management and small parcels. The grasslands are managed differently leading to grassland landscapes with small-scale, alternating parcels which differ in their management and use intensity and, consequently, their physiognomy and ecosystem services. A lack of knowledge on grassland management aggravates analysis of grassland production traits, for example yields, in European grasslands. Only six studies covered all grasslands worldwide and many took place on a rather local level. The research on larger extents (mostly LUE-based productivity estimations) were more generalized due to a lack of detailed spatial information. Large-scale analyses including more spatial detail, which is needed due to the diversity and small-scale heterogeneity of grasslands, are mostly lacking. In addition, many grasslands show intra-annual dynamics related to management and use strategies (like mowing or grazing events) which need to be included. Many studies lack a multi-temporal approach, which at its best includes continuous information on grassland management.

Studies focusing on grassland management and use intensity were usually conducted on small study sites as 90 % shows sites smaller 10000 km^2. Furthermore, research on remote sensing of grassland management traits lacks an automatized monitoring approach. Many studies are rather exploratory and are limited by ground-truth information about grassland management. In addition, often not all intensity levels of grasslands were included which misses to cover the diverse nature of these ecosystems in reality. More spatially detailed research on grassland management and productivity traits are needed for the development of continuous monitoring frameworks covering large extents. Lastly, combined analyses of optical and SAR data are still rare in previous literature.

Chapter 3

Study Area: Grasslands in Germany

3.1 Climate and Topography of Germany

Germany is located in the center of Europe, with coastlines to the North Sea and the Baltic Sea (Figure 3.1 A). The federal republic is covering an area of about 357 000 km^2 and consists of 16 federal states. From north to south, Germany is geomorphologically structured by the Northern Lowlands, the Central Uplands, the Pre-Alpine and Alpine regions. Highest elevations are found in the Alps with the peak “Zugspitze” (2 962 m.a.s.l), the average altitude is 370 m.a.s.l. (Figure 3.1 B) (Zöller, 2017). According to characteristics regarding topography, climate and vegetation cover, Germany can be grouped into great natural landscapes (Meynen et al., 1962), from which seven are on land (Figure 3.1 C).

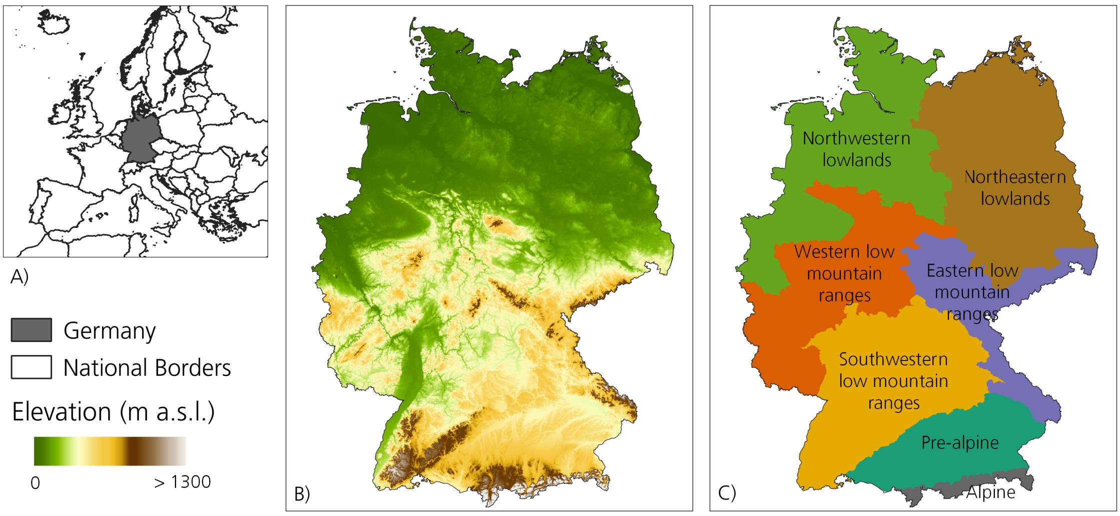

Figure 3.1: Location of Germany in Central Europe (A), altitude (B) and great natural landscapes of Germany (C).

Germany shows a humid temperate climate with warm summers (Koeppen and Geiger, 1936). It lies between the maritime west and the continental east, in the region of the westerlies. Rainfall rates remain relatively constant throughout the year with an average annual precipitation of 789 mm (Deutscher Wetterdienst, 2022b). Highest precipitation rates can be found close to or in areas with higher elevations in Germany, e.g. in the south close to the Alps, in the Black Forest and the Sauerland (with annual rainfalls exceeding 1500 mm). Areas in central and central-eastern Germany show the lowest rainfall rates (Figure 3.2 B). The average annual temperature was 8.2 °C for the reference period 1961–1990 and has risen to 9.3 °C for 1991–2020 (Deutscher Wetterdienst, 2022b). Temperatures show an annual profile with lowest temperatures in January and highest temperatures in July (Figure 3.2 C). The highest annual temperatures are reached in lower altitudes in the west of Germany, e.g. within the valley of the river Rhine (Figure 3.2 A). There is a significant increasing trend in temperature in Germany, revealing a rise of 1.6 K from 1881 to 2021 (Imbery et al., 2021). The years 2018, 2019 and 2020 were among the warmest in the recent past with temperatures of 2.1 to 2.3 K higher compared to the reference period of 1961–1990 (Imbery et al., 2021). In addition, 2018 was an unusually dry year with a precipitation rate 202.6 mm lower than the long-term average (1961–1990) (Imbery et al., 2021).

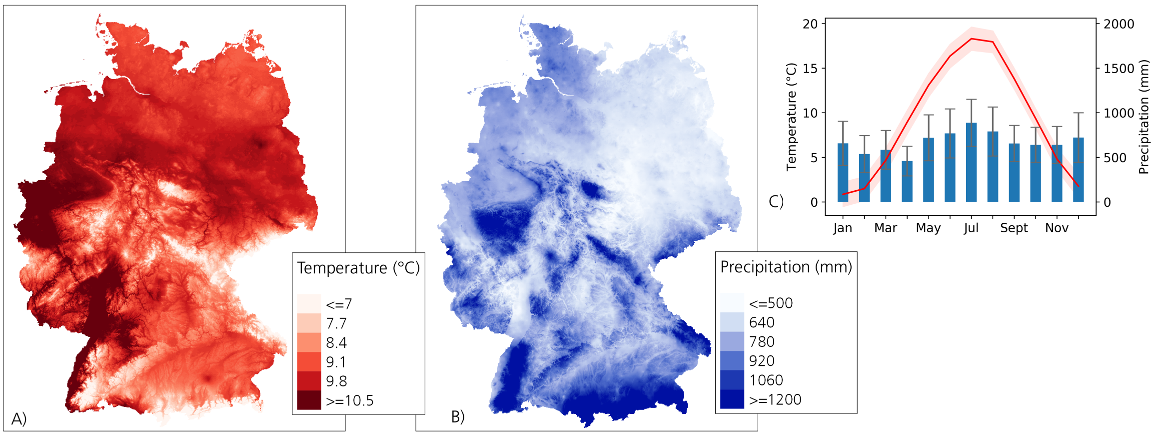

Figure 3.2: Multi-annual mean temperature (1981–2010) and mean precipitation rates (1981–2010) interpolated from station data from the German Weather Service, and monthly mean temperatures and precipitation averaged over Germany (1991–2010) derived from the Climate Data Center of the German Weather Service.

3.2 Grasslands in Germany

3.2.1 Distribution and Usage

Grasslands are a dominant land cover in many regions in Germany as they account for about one third of the agriculturally used area (Statistisches Bundesamt, 2021). In Germany, almost all grasslands are secondary grasslands, meaning that their occurrence is not natural but requires human action (Dengler et al., 2014). Without human influence, these grasslands would change into more woody ecosystems as most of the land area in Germany would be forests naturally. Common human actions preventing bush encroachment in grassland biomes are management practices, like cattle grazing and mowing (Schoof et al., 2020b,a).

In Germany, grasslands are heavily used which determines its physiognomy, fulfillment of ecosystem services and biodiversity. Grassland vegetation is harvested and provided as fodder for livestock or directly grazed. Hence, many grasslands are regularly mown during the year and at times additionally grazed (Schoof et al., 2020b,a). In addition, grasslands are usually fertilized and very rarely irrigated in Germany. The timing and frequency of management activities and, consequently, the use intensity varies from parcel to parcel. In Germany, grasslands are mown from zero to six times per year. Higher use intensities, meaning higher numbers of mowing events per year and regular fertilization, provoke a shift within the plant species community towards more productive species (Socher et al., 2012; Neyret et al., 2021). As described in section 1.1.2, this is also related to additional changes within grassland ecosystem functions. In addition, the timing of the first mowing event plays a critical role for the ecology of grasslands. In Germany, early mowing events take place already in April. As a consequence, many plant species are locally extinct as they can not reproduce. Also, next to insect and spider species, in particular breeding birds are negatively influenced by early mowing activities in Germany. Grasslands which are mown relatively early are usually also mown more often.

Grasslands are distributed throughout Germany, covering large gradients of elevations, climatic conditions and soil types (Figure 3.3 A). They often occur in regions and spots which are unfavorable for agricultural use of common crops, for instance, areas which are rather wet, or show steep slopes, high elevations or poor soils (Schoof et al., 2020b,a). Large parts of the agricultural land are used as grassland in southern and northern Germany and in some regions in central-western Germany (Figure 3.3 B). These areas also mostly overlap with the amount of cattle per area, which are highest in southern and northern Germany (Figure 3.3 C). Livestock is additionally fed with bought fodder, such as soy. Germany has the largest dairy industry in Europe and cattle farming is oriented towards the dairy industry. A large proportion of cows are dairy cows, meaning that they are mainly used to produce milk. The number of cattle per area is not necessarily related to the size of the farms as can be seen from the differences between these parameters in Germany (Figure 3.3 D). The average farm sizes in the states of the former German Democratic Republic (north-eastern part of Germany) is generally larger as combining agricultural land into larger farms was a common practice there.

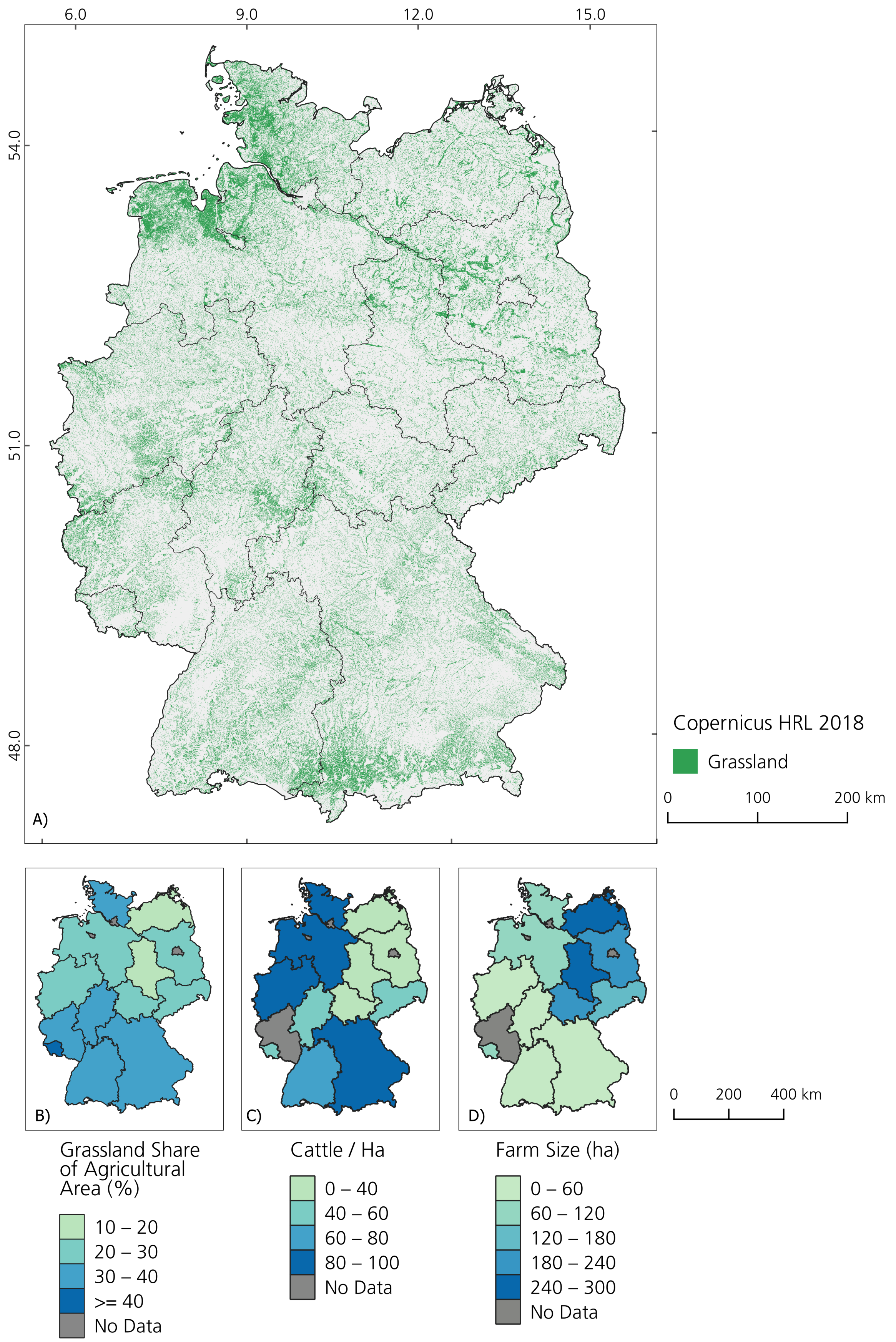

Figure 3.3: Distribution of grassland in Germany (A) according to the Copernicus High Resolution Layer 2018 (Copernicus, 2018) and information on the proportion of grassland of agricultural land (B), the number of cattle per hectare (C) and the mean farm size (D) on federal level for 2020 (Statistisches Bundesamt, 2020, 2021).

The management and use intensity of grasslands in Germany varies. As a consequence and in combination with the wide distribution, grasslands are very heterogeneous. They are characterized by small parcels with diversified use intensities and, consequently a high diversity in their physiognomy and provision of ecosystem services. The available information on the management of grassland ecosystems and their ecosystem functions is comparably limited in Germany.

3.2.2 Status and Protection Mechanisms

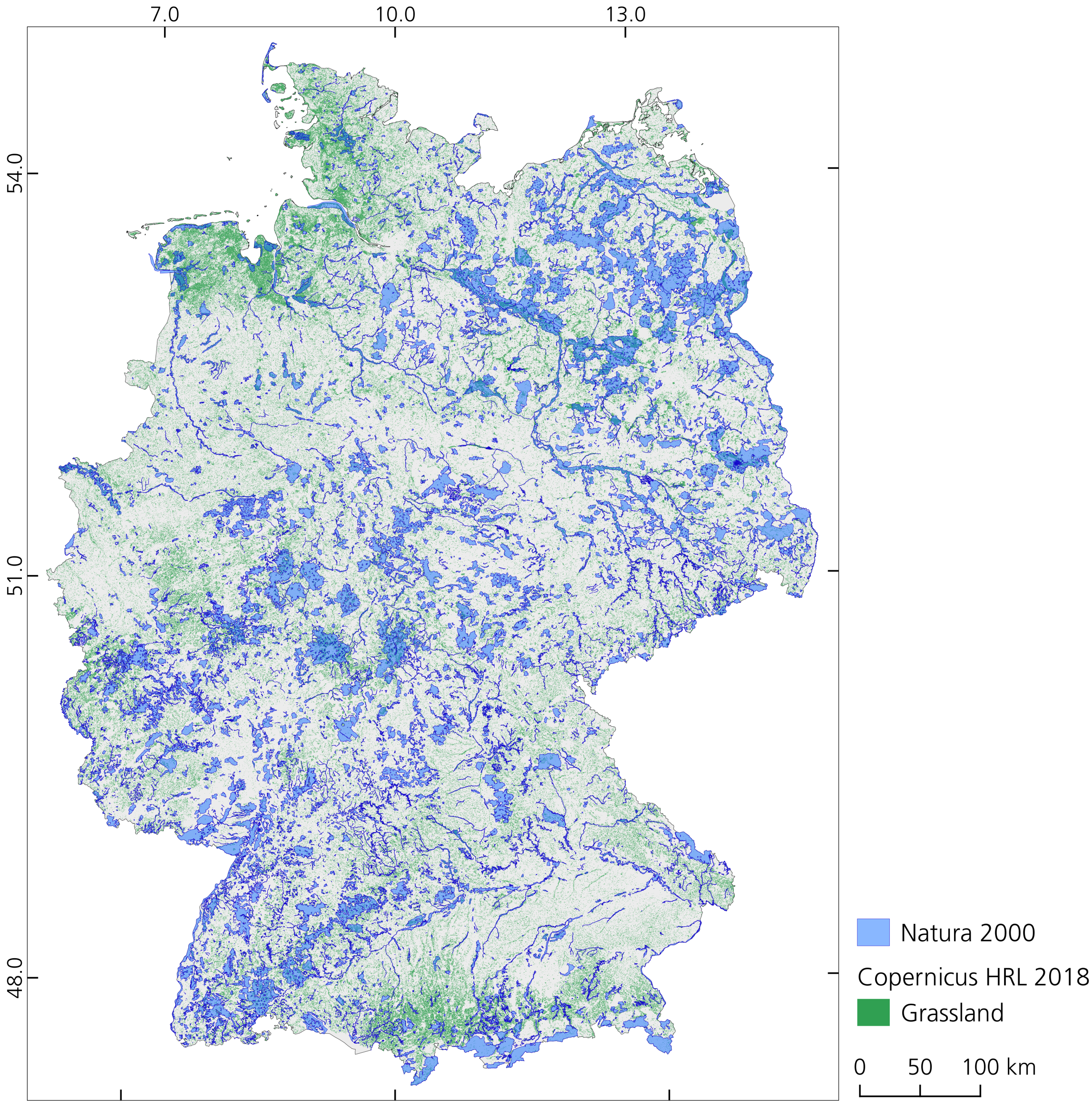

Figure 3.4: Distribution of Natura 2000 sites (Habitats Directive and Birds Directive) in Germany and occurrence of grassland according to the Copernicus High Resolution Layer 2018 (Copernicus, 2018).

Temperate grasslands are among the most species rich habitats in Europe and exceed species numbers of agricultural sites or forests by far (Dengler et al., 2014). Many vascular plant species, as well as insects, such as cicadas and butterflies, spiders and breeding birds are bound to extensively used grassland sites (Schoof et al., 2020b). A large number of grassland related species are currently endangered which mirrors the critical condition of these ecosystems. In Germany, 84 % of the grassland habitats are threatened, from which 31 % count as severely threatened to complete extinction according to the red list status classification (Finck et al., 2017; Schoof et al., 2020b). An evaluation of grassland sites according to the flora-fauna-habitat guidelines showed that more than 55 % of habitat types are in an unfavorable state and less than 10 % revealed a favorable condition, while three quarters of all grassland types additional show negative development trends (BMU, BfN, 2020). Not only special grassland habitats are endangered as also species rich lowland and mountainous hay meadows are often classified as threatened through intensification processes (mowing frequency and fertilization) in Germany (BMU, BfN, 2020).

The conservation of grassland habitats and species is defined by policies on different tiers. A general framework and guidelines for agricultural management for members of the European Union (EU) are determined within the Common Agricultural Policy (CAP) (European Commission, 2013). The CAP consists of two pillars, of which the first is about the income support of farmers and the second one is on agricultural practices, rural development and nature conservation within the agricultural landscape. The second pillar considers the agricultural environmental measures which are usually composed of compensatory payments for restrictive covenants resulting from measures in agricultural practices supporting environmental protection (Schoof et al., 2020b). The exact restrictions and requirements are defined by each member state. In Germany, this is defined through the national nature conservation law, which protects some grassland habitats (biotope protection) which are not allowed to be destroyed (Schoof et al., 2020a). In addition, grasslands are, in principal, protected against being converted into agricultural areas, in particular when the occurrence of endangered species is ascertained. The condition of grasslands within protected areas, such as Natura 2000 which is a European framework of protected areas to conserve species and habitats (Figure 3.4), is restraint to deteriorate but only if the conservation of the grassland habitat was part of the preservation goals of the protected area (Schoof et al., 2020a). Within the national law for nature conservation in Germany, also some concrete measures regarding grassland management are named which are, however, defined in detail – accompanied by the amount of compensatory payments – on federal level.

In Bavaria, the south-eastern most state of Germany, which is covered by large amounts of grassland, there are two major conservation programs (StMELF and StMUV, 2022). The first one, which is called cultural landscape program ("Kulturlandschaftsprogramm") compensates sustainable grassland management by farmers. Next to topics, such as extensive pasture management, farmers are compensated for mowing after the 15^{th} of June or the 1^{st} of July. In the second program, the contract nature conservation, regulations of protected areas, including Natura 2000 sites, for instance, are defined. Apart from financial support for turning cropland into grassland and waiving of fertilization, for example, applicants are compensated for mowing after 1^{st} of June, 15^{th} of June, and so on and for management dormancy periods (StMELF and StMUV, 2022). Lower Saxony, which is the north-western most state of Germany, is also occupied by large shares of grassland. There, several conservation programs exist, which focus on rural development, the conservation of specific habitats and species, and the compensation for difficulties arising from protection measures in protected areas (Ministerium für Umwelt, Energie und Klimaschutz, 2014). Within the first one, farmers are compensated for nature friendly practices, for example late mowing. The mowing date in that regard is defined as the phenological 25^{th} of May and is, therefore, newly calculated every year. The compensatory payment for nature friendly management practices within protected areas is a complex point awarding scheme, including mowing dates, mowing frequency and fertilization application (Ministerium für Umwelt, Energie und Klimaschutz, 2014; Schoof et al., 2020a).

The critical status of grassland habitats and severe threat of many grassland-related species shows that the applied conservation regulations are not sufficiently effective. One point of critique are the complex systems which are difficult to compare and accompanied by a large amount of bureaucracy, often exceeding the capabilities of the responsible authorities (Schoof et al., 2020b). In addition, the amount of financial aid on all levels can be considered as too low to effectively implement nature conservation schemes in agriculture (BMU, BfN, 2020). Regarding protected areas, such as Natura 2000, studies on their success in conserving habitats and species come to mixed results (BMU, BfN, 2020). Protected areas need adequate management and monitoring system, of which the latter is in general a major difficulty regarding the effective implementation of conservation plans (Schoof et al., 2020a).

Chapter 4

A Novel Framework to detect Grassland Mowing Events*

Despite their large area coverage, many aspects of grasslands are unknown. They are very diverse which is partly caused by varying management practices and use intensity. As outlined in chapter 1.1, grasslands potentially contain large numbers of plant species, accompanied by other important ecosystem services, like the provision of habitats, carbon storage, water filtration and cultural aspects. Large-scale assessment and monitoring of grassland biodiversity and ecosystem services is however highly challenging due to the diverse nature of the grassland biome and due to missing information on grassland management and use intensity, being the most determining factor. Without sufficient information on grassland biodiversity and ecosystem services and the relationship to management, the development of sustainable management plans for future climates are impossible.

In Germany, mowing is the most important grassland management activity. Most grasslands are at least also mown, apart from grazing, and the frequency and timing of mowing events largely influence the ecology of the grassland ecosystems, and therefore, its biodiversity and provision of ecosystem services (Schoof et al., 2020b,a; Socher et al., 2012; Neyret et al., 2021). Hence, the automated detection of grassland mowing events is the main objective of this thesis.

Remote sensing is a unique tool enhancing the monitoring of grassland management (2) and, therefore, enabling large-scale assessments of grassland biodiversity and ecosystem services. In particular, the Sentinel sensors – providing earth observation imagery in high spatial and temporal resolution – are of advantage in investigating grassland management as grassland parcels are rather small, in Germany. In addition, the effects of grassland management activities, like mowing, are often only visible for a short period of time (days to few

*Parts of this chapter have been published in Reinermann et al. (2022) and Reinermann et al. (2023).

weeks) which makes a revisit time of a few days highly important. Both Sentinel sensors, optical (S2) and SAR (S1) provide information which could be valuable in investigating and monitoring grassland mowing activities.

Optical imagery, and here in particular vegetation indices, have a long history in monitoring vegetation as they provide information on vegetation greenness, density and photosynthetic activity (Huete et al., 2002). Hence, multi-temporal optical data enables the depiction of temporal patterns of vegetation, like phenology. Grassland mowing leads to a change in color and density of the vegetated surface which is potentially portrayed by optical data.

Space-borne SAR data has a shorter application history compared to optical data regarding vegetation monitoring. However, SAR data was already intensively used to investigate characteristics of forest ecosystems (e.g. biomass) and, more recently, finds more and more usage in EO-based analyses of agricultural areas (Holtgrave et al., 2020). Changes of scatters, for example regarding their polarimetric, dielectric, among other physical characteristics, resulting from grassland mowing events, are potentially depicted by SAR imagery. As optical data is negatively influenced by cloudy weather conditions and SAR data alone probably won't depict grassland mowing as reliable as optical data, a combination of both sensors might enhance grassland mowing detection substantially. Hence, within this thesis the potential of optical and SAR data and the combination of both regarding grassland mowing detection is examined and an automated framework developed.

Within the following sections, first, the data sets are described which include satellite data as well as reference data used for parametrization and validation of the mowing detection approach. Secondly, the methodological approach is described in detail and afterwards the results of the automated mowing detection algorithm are presented and discussed. The chapter is finalized by a summary.

4.1 Data

Within the following sections, the input data required for the development of the grassland mowing detection algorithm is described. The satellite data, consisting of S2 and S1 imagery, is described in section 4.1.1. As the developed mowing detection algorithm is a knowledge-based approach, reference data based on which the method is developed and calibrated is needed. The reference data, including calibration and validation data, is described in section 4.1.2.

4.1.1 Satellite Data

4.1.1.1 Optical Data

S2 consists of two polar-orbiting satellites, Sentinel-2A and Sentinel-2B, with a revisit time of five days (Drusch et al., 2012). Due to overlapping orbits higher acquisition frequencies of up to every second day are possible in Germany. As a consequence, the data availability of S2 is unevenly distributed in Germany. The coverage of the S2 satellites is shown in Figure 4.1 highlighting areas covered by overlapping orbits and areas covered by only one orbit. In addition, optical data is limited to cloud-free observations which influences the availability of data.

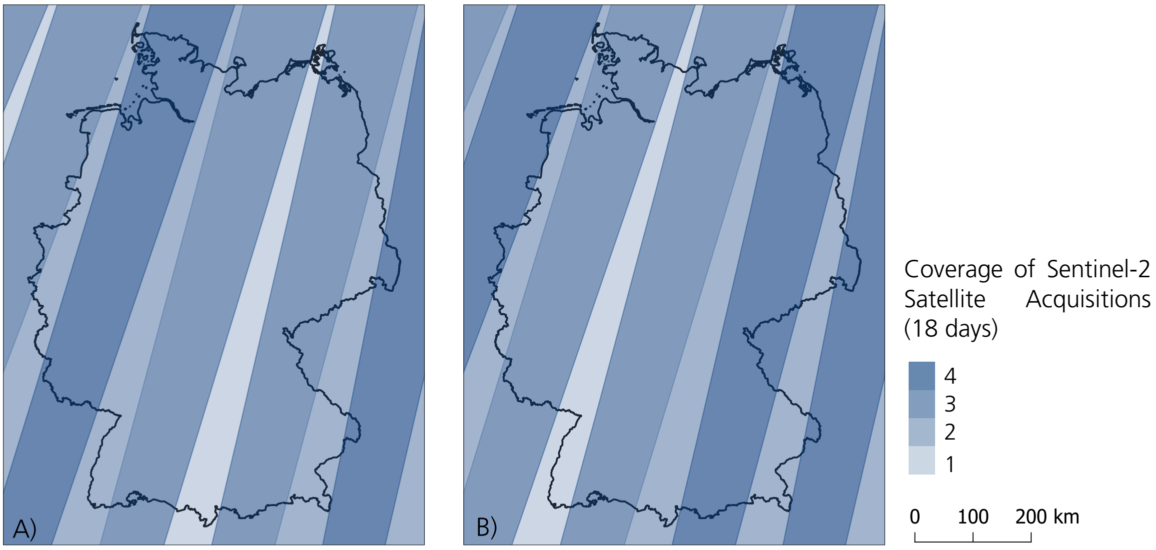

Figure 4.1: Coverage of S2A (A) and S2B (B) orbits for a period of 18 days showing the unevenly distributed data availability according to the acquisition plan.

The S2 satellites carry a passive Multispectral Instrument (MSI) recording reflected radiation from the Earth's surface within the visible to infrared range. The data is acquired in 13 spectral bands which have differing spatial resolutions from 10–60 m. The four bands with the highest spatial resolution of 10 m, which are also the most important for vegetation monitoring, are Blue (central wavelength $\approx$ 492 nm), Green (central wavelength $\approx$ 559 nm), Red (central wavelength $\approx$ 665 nm) and Near-Infrared Radiation (NIR) (central wavelength $\approx$ 833 nm).

The grassland mowing detection algorithm was developed on time series data of 2019 and then applied to the years 2018–2021 for entire Germany. Only data from the period where vegetation is active in Germany, namely March to November, was included. Hence, S2 Level 2 data from March to November of 2018–2021 for all 64 tiles covering Germany was processed for the multi-annual grassland mowing detection. This resulted in 1.6 TB

(4374 scenes) of processed data in 2018, 1.2 TB (3483 scenes) in 2019, 1.5 TB (4122 scenes) in 2020 and 1.1. TB (3191 scenes) in 2021.

4.1.1.2 SAR Data

Similar to S2, S1 consists of two polar-orbiting satellites, Sentinel-1A and Sentinel-1B, resulting in a revisit time of six days. The two satellites carry SAR sensors covering data in the microwave frequency domain at C-band, making the data acquisition independent from sunlight and cloud conditions (Torres et al., 2012). The data is acquired in interferometric wide-swath (IW) mode which consists of three sub-swaths with several bursts merged together. The SAR sensors collect data in dual polarization, with vertical emission and vertical and horizontal reception (VV, VH). For this thesis ground-range-detected GRD as well as single-look-complex SLC data is used. The GRD data is detected, multi-looked and projected to ground-range and therefore the preferred product when focusing on the intensity (amplitude). As within this thesis next to the intensity also interferometric (InSAR) and polarimetric (PolSAR) parameters are investigated, the SLC data is included as it contains the needed phase information. The feasibility of SAR data for grassland mowing detection is investigated only for a focus region and therefore S1 GRD and SLC data of RON 117 in ascending mode is processed for March to November 2019. This results in 45 GRD and 45 SLC scenes which were investigated regarding grassland mowing detection.

4.1.2 Reference Data

A ground-truth reference data set, independent from satellite imagery was used to calibrate and validate grassland mowing events. This data set was created by exploiting public webcam and self-installed camera images (RGB) for grasslands distributed in Germany and the entire time period of 2018–2021 (Figure 4.2). Cameras were installed at farm sites where close information exchange and collaboration with farmers were conducted. These sites were in the south of Munich in the Pre-alpine area of southern Bavaria, which is characterized by a large share of grasslands and a large diversity regarding grassland use intensity. These self-installed cameras were accompanied by webcams which were more widely distributed to include information of grasslands in other geographical regions in Germany. In total, 80 cameras (11 self-installed and 69 public) took images at least once per day and captured information on grassland management activities, like mowing, fertilization and grazing. In addition, many cameras covered multiple grassland parcels within their field of view. While location and field of view of the self-installed cameras was known, the location of the public webcams was determined according to all available information, which usually were coordinates of the position or at least a town or place name. The parcels viewed by the camera were then located by inspecting the recorded images along with high resolution satellite data (e.g. Google Earth). The shapes for the grassland parcels were created by hand according to this information. All recorded images were viewed and management activities, like mowing dates, were extracted.

Data from 192 grassland parcels and, in total, 1475 mowing events were generated in that regard which were used for calibration and validation. The exact numbers of grassland parcels and mowing events vary between the years (Table 4.1) as some cameras were deprecated or out of order for some time or changed their view angle. In addition, systematic recording started only in 2019, leading to a lower number of observed grassland parcels and mowing events for 2018. Only a small share ($n_{Grasslands} = 13$ and $n_{MowingEvents} = 44$) of 2019 were used for parametrization and calibration of the mowing detection approach. The remaining grasslands were used for validation (Table 4.1). For some accuracy statistics, like the F1-Score (section 4.2.2), also falsely detected events are considered. Therefore, to calculate these statistics, only cameras (and mowing events taken place there) with continuous information are used as they can provide also information on false positives. The distribution of mowing frequencies available for validation varies between the year (compare Table 4.1). 2018 shows more grassland parcels with lower mowing numbers per year, followed by 2021. 2019 and 2020 show higher numbers of more frequently mown grasslands.

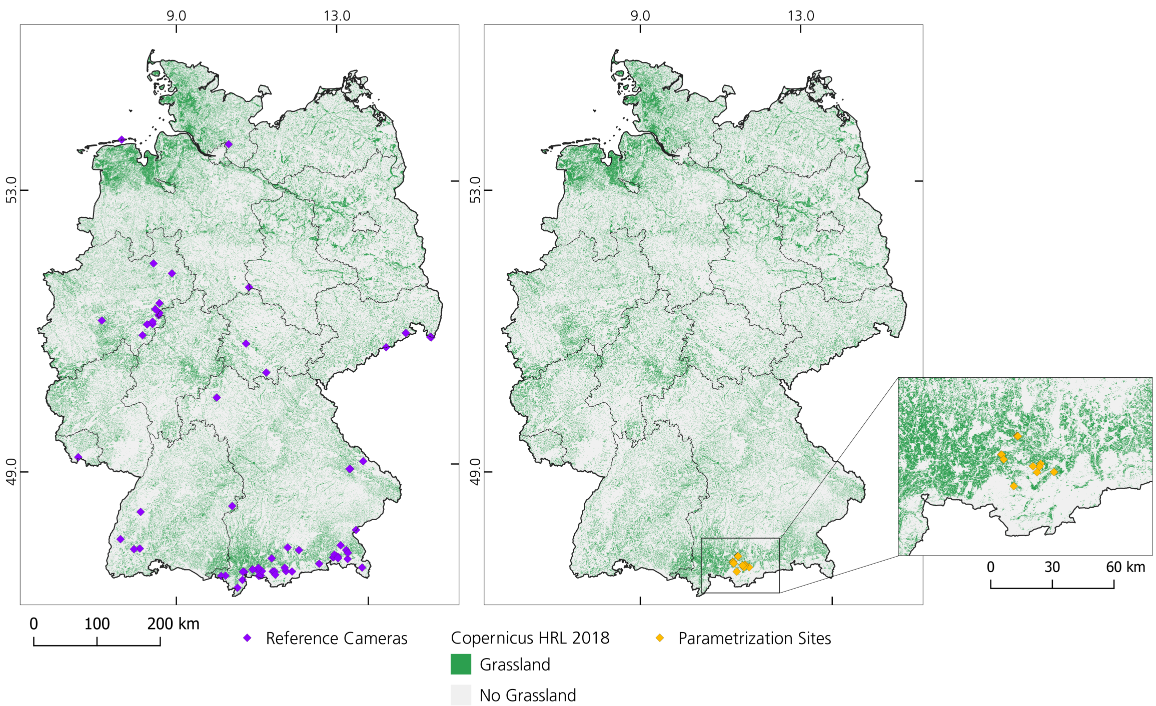

Figure 4.2: Location of webcams used for validation and cameras used for parametrization of the grassland mowing detection approach.

Table 4.1: Reference data used for parametrization and validation of the grassland mowing detection. The Zoom corresponds with the investigated focus region.

	2018	**2019** (*)	**2020**	**2021**
Number of mowing events	117	536 (491)	448	419
Number of mowing events based on continuous information	108	328 (283)	410	334
Number of grassland parcels	49	192 (179)	161	159
Grassland mown up to 1 time	34.7%	19.0%	14.3%	23.3%
Grasslands mown 2–3 times	42.9%	52.5%	57.1%	52.2%
Grasslands mown more than 4 times	22.4%	28.5%	28.6%	24.5%

* **Values in brackets refer to numbers of mowing events and grassland parcels which remain for validation and are not used for parametrization.**

The mowing detection based on S1 and the combination of S2 and S1 was tested for a focus region in southern Germany and validated with a subset of the validation data set. This subset consisted of mowing information from 66 grassland parcels with 229 mowing events, in total. The focus region corresponds with the zoom area of Figure 4.2.

As mentioned above, a small share, namely 13 grassland parcels were used to parameterize the detection algorithm (compare Figure 4.1.2). Only data from 2019 was used in that regard. To minimize over-fitting these grassland parcels were excluded completely from the validation. These parcels show a complete range of possible mowing frequencies on German grassland as they range between one and six mowing events. In addition, some of these parcels are additionally grazed. A detailed description of the 13 parcels can be found in Table 4.2.

Table 4.2: Detailed information of the 13 parametrization sites which were used to develop and calibrate the mowing detection approach.

	Name	**Coordinates (xy)**	**Number of Mowing Events**	**Grazing**
FE1	Fendt 1	5299758, 654263	4	No
FE2	Fendt 2	5299584, 654286	5	No
FE3	Fendt 3	5299584, 654286	1	Yes
FE4	Fendt 4	5299574, 654517	4	No
RB1	Rottenbuch 1	5290622, 646496	5	No
RB2	Rottenbuch 2	5290534, 646763	1	No
RB-L	Rottenbuch-L	5288210, 647705	4	No
UGAU	Unterammergau	5275185, 652597	3	Yes
MW	Murnau-West	5281987, 663910	3	No
MN	Murnau-Nord	5284733, 665111	4	No
HF	Hofheim	5286114, 665689	1	Yes
GL	Glentleiten	5282120, 672186	6	No
UF	Uffing	5284930, 661943	3	No

4.1.3 Auxiliary Data

The Copernicus HRL grassland layer from 2018 was used to mask the grassland area (Copernicus, 2018). It is a raster data set in 20 m resolution and covers all grassland types in Germany, including natural, semi-natural and agricultural grassland. The grassland layer is based on a classification with S1 and S2 data and has an overall accuracy of 89.9 %. For S1 pre-processing, the EU-DEM from Copernicus was used (Copernicus, 2016). It is a combination of Shuttle Radar Topography Mission (SRTM) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM), has a spatial resolution of 25 m and an error of +/- 7 m (Figure 3.1 B).

Phenological information from the Climate Data Center (CDC) of the German Weather Service (DWD) was used to compare them with the results of the mowing detection. Multi-annual data sets from 2018–2021 with information on the greening of grassland (DWD Climate Data Center, 2018a, 2019a, 2020a, 2021a), the first hay cut (DWD Climate Data Center, 2018b, 2019b, 2020b, 2021b) and the first silage cut (DWD Climate Data Center, 2018c, 2019c, 2020c, 2021c) were acquired and investigated further. The grid data sets are derived from a network of phenological observations in Germany and have a spatial resolution of 1 km.

In addition to that, spatial data sets were used for aggregation purposes. Country borders and spatial information on states and counties in Germany were downloaded from the GADM Service (GADM, 2019). Further, spatial data on the great natural landscapes of Germany were used. These are defined according to geographical and geomorphological properties (e.g. climate, topography) (Meynen et al., 1962) and are provided by the German Federal Agency for Nature Conservation (Figure 3.1 C).

4.2 Methodological Approach

Within the following sections the processing of the data and the development of the mowing detection algorithm are presented. This includes the pre-processing of data set, the description of the analysis of all parameters, the parametrization and validation approaches of the mowing detection (section 4.2.2).

For data processing, mostly python in version 3.6 was used. The most important modules which were applied were raterio, pandas, geopandas, numpy, scipy and matplotlib. The automated processing of the national and multi-annual high resolution satellite data time series was implemented on the in house high-performance cluster of the German Remote Sensing Data Center of the German Aerospace Center. The developed algorithm was therefore generalized and embedded into a batch script to be executable automatically on the Linux machine. Apart from the that, QGIS in version 3.8.2 was mainly used for the development of maps and inkscape 1.2 for creating schematic overviews.

4.2.1 Pre-processing

All data sets were masked with the Copernicus High Resolution Grassland Layer (HRL) of 2018 (Copernicus, 2018) based on which areas not covered by grassland were excluded. In addition, sensor-specific pre-processing followed by temporal filtering and smoothing were conducted as described in more detail in the following sections.

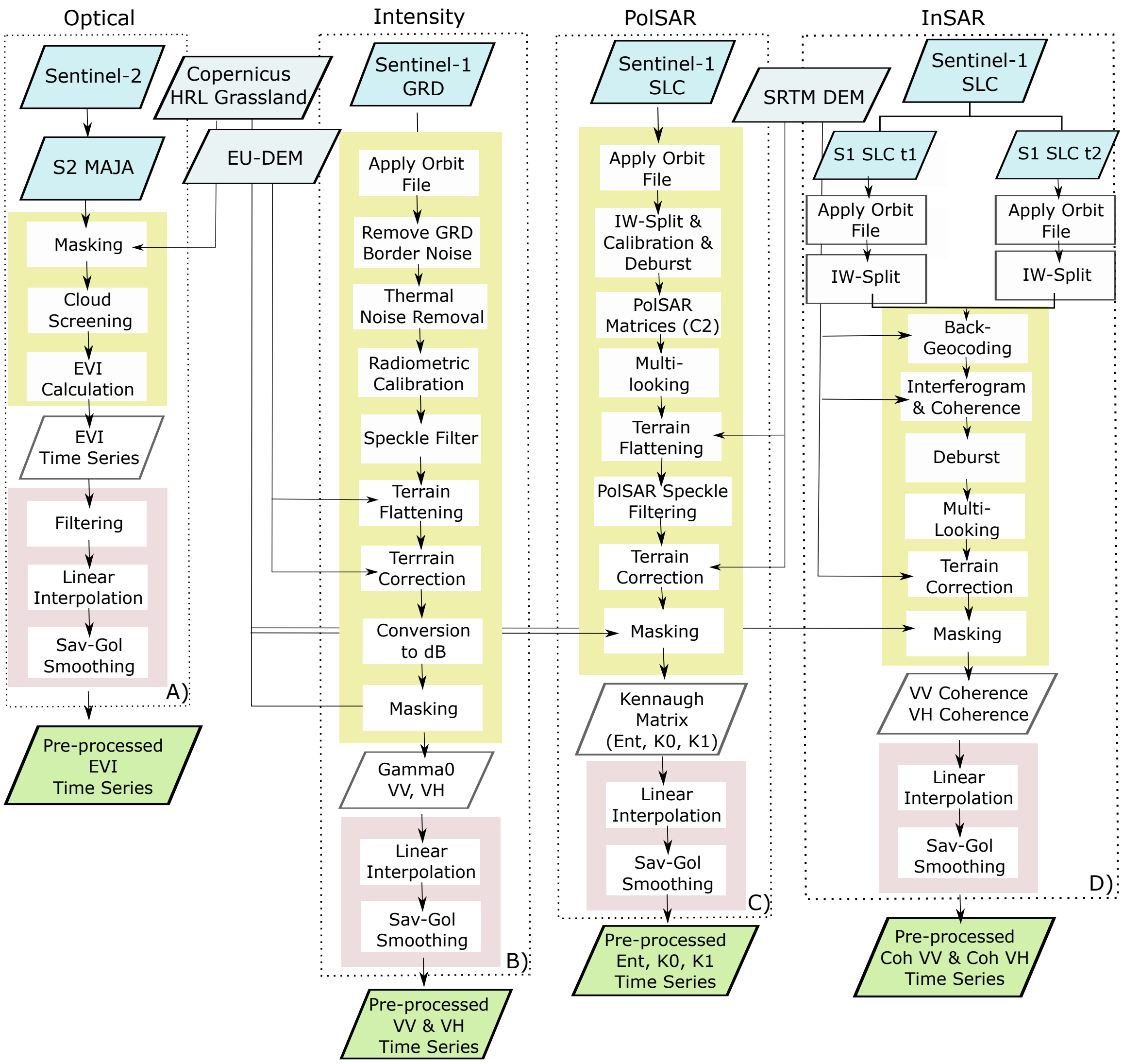

Figure 4.3: Pre-processing steps of S2 and S1 data to obtain the parameter time series investigated regarding grassland mowing detection. Adapted from the supplementary material of Reinermann et al. (2022).

4.2.1.1 Sentinel-2

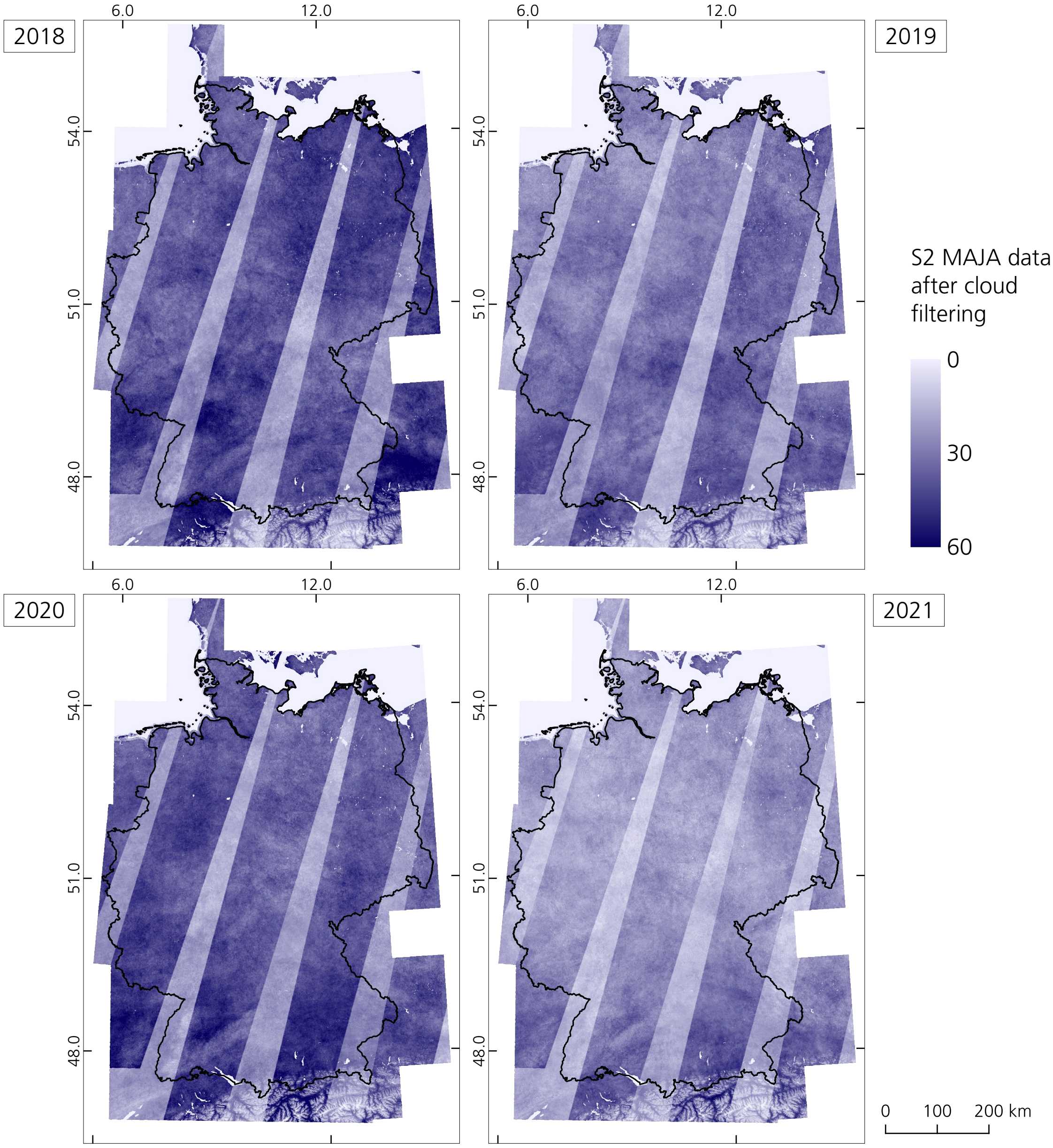

Figure 4.4: Availability of cloud-free S2 data for the years 2018–2021 after applying the MAJA pre-processing algorithm and cloud-screening.

The MACCS-ATCOR Joint Algorithm (MAJA) is a combination of an multi-temporal algorithm for atmospheric correction and cloud screening (MACCS) and an atmospheric correction software (ATCOR). S2 Level 2 data corrected with the MAJA version 3.3 was used (Hagolle et al., 2017). The data was pre-processed and pixels, which were influenced by clouds, cloud shadows or unfavorable terrain according to the algorithm, were excluded (Figure 4.4). Only clear pixels were as the influence of clouds is easily confused with mowing activities on the grassland parcel. Therefore the most strict cloud-screening was conducted to ensure that no artifacts remain within the optical data set. When the grass is mown, the dense vegetation is removed leaving grass stubble, which are often yellow or brown, accompanied by a higher fraction of visible soil compared to before the mowing. This change in the terrestrial surface properties is translated to the reflectance values of optical sensors. Vegetation indices can best capture these changes and therefore should be used to detect grassland mowing events. Vegetation indices have the advantage of reducing uncorrected influences of atmosphere, terrain and additive noise, and are therefore particularly robust and well suited for multi-temporal change analyses of vegetation. Within this thesis, the EVI was used for that purpose as it is a common and well-known vegetation index, but does not saturate as quickly as other indices over grasslands. Based on the NIR, Red and Blue bands of the S2 surface reflectance data the EVI was calculated for every scene as follows (Huete et al., 2002):

$$EVI = \frac{2.5^{*}\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + 6^{*}\mathrm{Red} - 7.5^{*}\mathrm{Blue} + 1} \tag{1}$$

As vegetated areas usually have positive EVI values, negative ones were filtered out. This should remove persistent clouds as well as unvegetated areas not masked by the HRL layer. The EVI scenes were afterwards stacked to data cubes and EVI time series were pre-processed pixel-wise. The EVI time series was linearly interpolated to daily data per pixel as the time series showed irregular spacing of observation times due to unevenly spaced data acquisition and cloud masking. Afterwards the time series was smoothed with a Savitzky-Golay filter (Savitzky and Golay, 1964) with a window length of 31 days and a polynomial fit of order two to remove small fluctuations (Figure 4.3 A).

4.2.1.2 Sentinel-1

previous studies have shown that the changes in the physical properties of the Earth's surface caused by grassland mowing activities are potentially captured by SAR data time series. Such changes of, for example, dielectric, height or polarimetric properties are acquired by the backscatter intensity and interferometric (Interferometric Synthetic Aperture Radar (InSAR)) or polarimetric (Polarimetric Synthetic Aperture Radar (PolSAR)) features which can be calculated from the S1 SAR data. To test whether the intensity (amplitude) of the SAR signal or the parameters including phase information are better suited to investigate grassland mowing dynamics, all of these parameters were investigated. The SAR intensity data in Vertical transmission and vertical reception (VV) and Vertical transmission and horizontal reception (VH) polarization is based on the S1 Ground Range Detected (GRD) data.

The S1 GRD intensity data was pre-processed by applying the orbit files, removing border noise and thermal noise and undertaking a radiometric calibration. Further, a refined Lee speckle filter with a window size of 3 x 3 was applied. The data was then further pre-processed by conducting a terrain flattening and correction using the EU-DEM (Copernicus, 2016). Afterwards, the VV and VH data sets were resampled to 10 m spatial resolution and transformed to gamma nought in logarithmic scale (dB) (Figure 4.3 B).

To obtain the PolSAR parameters, S1 Single Look Complex (SLC) data is used which was downloaded for a focus region in the south of Germany. As the S1 data is available in VV/VH polarization, the dual-polarization entropy/alpha decomposition (Cloude, 2007) was used. After applying the orbit file and calibration, the covariance matrix (C2) and the VV/VH-polarized Kennaugh matrix were calculated and the polarimetric features Entropy, Alpha, K0, K1, K5 and K6 were obtained (Schmitt et al., 2015; Ullmann et al., 2017). The features K5 and K6 which describe the real and imaginary parts of the signal are known to add only limited value to vegetation analysis and Alpha and Entropy are highly correlated (Löw et al., 2021; Schmitt et al., 2015). Therefore, to investigate grassland mowing dynamics, only the parameters Entropy, K0 and K1 are investigated further (Figure 4.3 C). Entropy ranges between zero to one and is a measure of scattering randomness (i.e., depolarization) where higher values are related to increased depolarization and vice versa (Cloude, 2007). K0 represents the total intensity of the complex signal and is defined as $K0 = |S_{VV}|^2 + |S_{VH}|^2$, and K1 shows the difference between the intensities of the complex signal and is defined as $K1 = |S_{VV}|^2 - |S_{VH}|^2$ (Schmitt et al., 2015).

Next to the PolSAR features, the interferometric coherence was calculated for VV and VH based on S1 SLC data (Ullmann et al., 2019; Voormansik et al., 2020). The interferometric coherence is a measure of decorrelation between SAR images. It is defined as the complex correlation coefficient of two SAR acquisitions s_1 and s_2 containing phase information:

$$\gamma = \frac{|\langle s_1 s_2^* \rangle|}{\sqrt{\langle s_1 s_2^* \rangle \langle s_1 s_2^* \rangle}} \tag{2}$$

The estimated coherence (γ) is a product of several types of decorrelation, including decorrelation due to signal-to-noise ratio, for example. However, the dominant factor is the temporal decorrelation which captures decorrelation due to changes in physical properties of the surface. The coherence ranges between zero and one where zero represents complete signal decorrelation and vice versa.

All S1 parameters, namely VV and VH backscatter intensity, PolSAR Entropy, K0 and K1 and InSAR Coherence VV and VH were linearly interpolated and afterwards smoothed to minimize small fluctuations. Several smoothing algorithms with varying degrees were tested in this regard resulting in a Savitzky-Golay filter with a window size of 31 days and a polynomial fit of order two (Savitzky and Golay, 1964). In addition, likewise the EVI, the SAR parameters were masked using the Copernicus HRL Grassland layer 2018 (Copernicus, 2018).

4.2.2 Mowing Detection Method Development, Parametrization and Validation

The development of the mowing detection algorithm of this thesis is a observation-based approach. The EVI and the seven S1 parameters are investigated regarding their potential to capture and detect grassland mowing activities. This is done by analyzing the center-pixel time series of the parameters for 13 grassland parcels with known management activities. These sites showed varying mowing intensities, i.e. timing and frequency of mowing events, and exhibited 44 mowing events in 2019. Time series of spatially averaged parameters of 3 x 3 pixel windows and entire parcels were observed as well. However, these were not visibly different from the center-pixel time series. in addition, an approach based on single pixel time series has the advantage of maintaining the pixel resolution. For these reasons, the investigations were focused on the center-pixel time series of the parametrization sites.

It is hypothesized that mowing activities are detectable from time series of the investigated parameters. For undisturbed vegetation, the EVI usually shows an increase in spring, with a peak in late spring or summer, followed by a gradual decrease, which portrays the natural vegetation growth cycle in Germany. As the EVI signal is highest for green, dense and active vegetation, it is assumed that a mowing event, i.e. by a removal of biomass results in a drop in the EVI time series. The remaining grass stubble with more yellow coloring and a higher share of reflectance from the soil leads to smaller EVI values. This is followed by another increase of EVI when the grassland vegetation grows back (Huete et al., 2002).

Regarding the potential to cover grassland mowing events with the S1-based parameters, the change from long, thin-leaved, overlapping vegetation to grass stubble with higher reflectance rates from the soil and a reduction in moisture are probably of highest importance. The backscatter intensities of both channels are assumed to show an increase after grassland mowing events due to these reasons (McNairn and Brisco, 2004). The behavior of the PolSAR parameters is not easily anticipated as they are underrepresented in literature about grassland dynamics. However, the removal of long vegetation with different plant species which usually shows a rather diffuse signal most probably results in a decrease of Entropy due to a reduction in randomness. Regarding the InSAR Coherence it can be assumed that more grassland vegetation leads to increased decorrelation and, therefore, to lower Coherence values, and short vegetation after mowing to higher Coherence values (Wegmuller and Werner, 1997). As the InSAR Coherence results from the comparison of two images there is also the possibility that one of the images is acquired before and the other one after the mowing event. In that case, the Coherence would be very low, as this would lead to high levels of decorrelation.

To detect the dates of grassland mowing events, changes within the time series of the investigated parameters were located. In the context of grassland mowing events a change detection approach is of advantage compared to other time series approaches, as the investigated time series are rather short (March to November) and do not show a consistent periodicity (seasonality) within and between time series. Therefore, other common time series approaches, like break point analysis for example, are not well applicable. Time series of remotely sensed parameters naturally fluctuate as acquisition properties do not stay strictly constant due to differences in atmospheric conditions or surface properties, e.g. dew, even after pre-processing. Hence, an approach was chosen to locate strong changes in time series individually for each pixel and each mowing event, to detect grassland mowing within the time serie. The detection of mowing events was defined by a thresholding approach (compare Figure 4.5). A fixed threshold leads to more control over the grassland mowing detection compared to using a time series specific (per pixel) statistic as threshold. To establish the thresholds, averaged changes in amplitude over all mowing events of each parameter were calculated and compared for the parametrization sites. In that regard, also the most suitable parameters were selected which were processed further to detect grassland mowing events.

The thresholds of the mowing detection were determined with the 13 parametrization parcels based on the accuracy achieved for the 44 mowing events of these parcels. The accuracy was determined by the percentage of correctly detected mowing events and the F1-Score which also includes the information on falsely detected mowing events (Sokolova and Lapalme, 2009):

$$F1 = \frac{\mathrm{TP}}{\mathrm{TP} + \frac{1}{2}(\mathrm{FP} + \mathrm{FN})} \tag{3}$$

The parameterized mowing detection algorithms were afterwards applied to entire grassland area of Germany and validated with an independent validation data set. The German-wide accuracy assessment was again based on the number of correctly detected mowing events and the F1-Score.

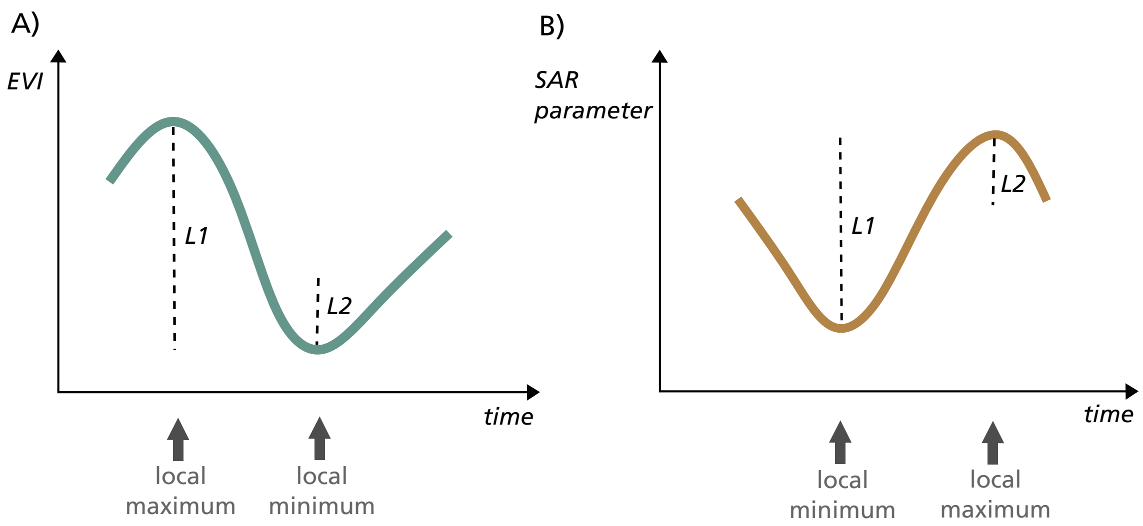

Figure 4.5: Illustration of the change detection within the time series of the parameters to locate mowing events. Local minima and maxima are located and the differences in parameter values at these positions investigated. The EVI (A) shows drops after a mowing event, therefore local minima are detected and the EVI amplitude there is compared to the EVI at the previous local maximum (indicated by L1). A Local minimum is defined by an immediate increase afterwards (indicated by L2). SAR parameters (B) usually show an increase after mowing events, therefore local maxima are located accordingly.

4.2.3 Development of a Mowing Detection Uncertainty Layer

An uncertainty layer was developed which informs on the certainty or reliability of all detected mowing events in high resolution (10 *x* 10 m). It was developed and applied for the focus region and the detected mowing events of 2019 based on S2 data. The uncertainty layer depends on an estimated uncertainty of each individual detected mowing event which has two components (compare Figure 4.6). The first component is about the availability of cloud-free S2 observations during detected mowing events. It is calculated as the time span between the last clear-sky observation before the local maximum and the first right after the local minimum of the detected mowing event (Figure 4.6 A). Smaller time spans indicate that the mowing detection relied on actual EVI acquisitions instead of interpolated data. Therefore, smaller time spans between observations right before and after detected mowing events are considered more reliably than larger time spans. The second component of the uncertainty measure is the magnitude of the change in amplitude of the EVI related to the mowing event. Hence, the gradient of the EVI is calculated as the difference between the EVI value at the local minimum and the EVI value at the local maximum, divided by the time span between the local maximum and local minimum belonging to the detected mowing event (Figure 4.6 B). Higher gradients are related stronger decreases within shorter time periods making higher gradients more reliable than smaller gradients.

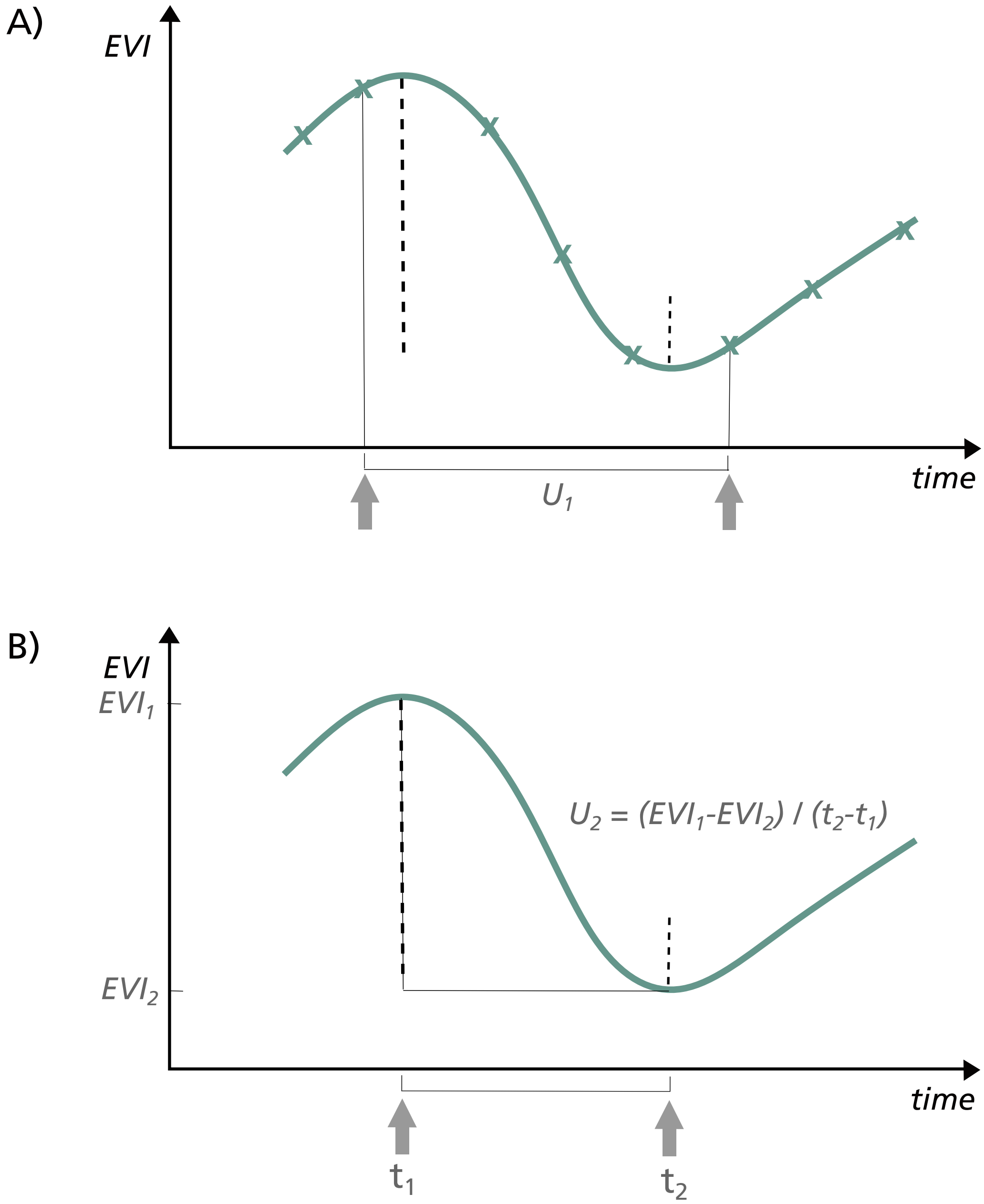

Figure 4.6: Schematic illustration of the estimation of the two uncertainty components, time span between actual EVI observations (U_1) (A) and gradient of EVI at the mowing date (U_2) (B). The uncertainty measures are calculated for each detected mowing event as illustrated, afterwards combined and averaged for all mowing events.

The first uncertainty measure component, the time spans between actual observations before and after the detected mowing event, results in values between two to 100. The second measure, the magnitude of change in amplitude of the EVI related to the mowing event, resulted in small values which is why it was multiplied by 10000 to adjust it to the value range of the first measure. As a result, the second uncertainty measure ranges between ten to 300 which is approximately three times larger than the first measure. The two uncertainty components were combined by subtracting the first component (time spans) from the second one (gradients). Due to the different value ranges between the two components, the second component (gradients) were weighted three times.

The combined uncertainty measure was afterwards z-normalized and divided by the largest value (300). The resulting uncertainty information fluctuates around zero with a value range of [-2,2]. The lower the value, the lower the uncertainty of the detected mowing event, and vice versa. The estimated uncertainty of all detected mowing events were averaged to obtain an overall uncertainty layer of detected mowing events in pixel resolution.

4.3 Results

In the following, first, the results of the investigation of all input parameters and the parameter selection for the mowing detection are presented. Second, the results of the mowing detection based on S2 only and a combined approach are shown for a focus region. Finally, the results of the application of the developed grassland mowing detection for the entire area of Germany and the years 2018–2021.

4.3.1 Investigation of Time Series and Parameter Selection

To investigate whether the parameters of interest have the potential to detect grassland mowing events and to decide based on which the mowing detection approach is developed, time series of all parameters were analyzed for 13 parametrization sites. As presented in section 4.1.2, these grassland sites show differing management properties and use intensities making them suitable for the investigation of the behavior of the parameters before, during and after mowing events. In total, the 13 parametrization sites contain 44 mowing events in 2019, which were investigated here.

The EVI shows rapid drops after mowing events, followed by instantaneous increases (Figure 4.7). The drops as well as the increases take only around two weeks, highlighting that the visible effects of mowing of the EVI time series is short-lived. The pattern of EVI decreasing after mowing is consistent among the calibration sites and mowing events. Only a few mowing events (n=6) are not followed by an EVI drop, i.e. the third mowing event of RB-L, the second mowing event of UGAU, the third event of GL, the third mowing event of MN, the third mowing event of RB1 and the fourth mowing event of FE2. In addition, there are only a few EVI drops unrelated to mowing events visible which take place during the year and not at the end of the vegetation period in October/November, i.e. HF in July/August and September, FE3 in September and UF in April.

The backscatter information (intensity) of S1 shows inconsistent temporal patterns related to mowing events for VV and VH (Figures 4.8 and 4.9). For some of the parametrization sites the anticipated increase of backscatter after a mowing event is visible, e.g. for VH the second mowing event of FE4, all three mowing events of UGAU, the first mowing events of RB1, FE1, FE3 and FE2, and for VV the first mowing events of RB-L, RB1, MN and FE3. However, the temporal signals of backscatter VV and VH fluctuate strongly and many peaks unrelated to mowing events can be depicted, e.g. for VH in MW and for VV in FE1, for example.

Similar to the backscatter information, the PolSAR parameters, Entropy, K0 and K1 show much fluctuation which sometimes seems to be related to mowing, but not in all cases (Figures 4.10, 4.11 and 4.12). K1 shows mostly drops after mowing events, Entropy and K0 show peaks. From the three parameters, Entropy shows peaks after mowing events most consistently, for example all mowing events of RB-L and RB1. However, there are many additional peaks unrelated to mowing events visible within the Entropy time series, e.g. in MW.

Comparable to the other S1-based parameters, the behavior related to mowing events of InSAR Coherence VV and VH are inconsistent (Figures 4.13 and 4.14). Both parameters show peaks after mowing events for many of the mowing events of the calibration sites, e.g. for Coherence VV all four mowing events of RB-L, all three mowing events of UF, the mowing event of HF, and for Coherence VH the first two mowing events of FE4, MN and FE1, among other examples. However, the time series show also peaks which are unrelated to mowing activities, like in RB2 for both parameters. In addition, the values range below 0.4 for most sites, which is close to the noise level of temporal coherence data.

In addition to the visual observation of time series of the investigated parameters, their values before and after all mowing events (n=44) of the parametrization sites were compared. All raw data values (Figure 4.15) as well as smoothed values (Figure 4.16) were averaged to investigate how and by how much the values change after a mowing event and to assess if the smoothing might blur some relationships. The values of six days before and six days after each mowing event were considered in that regard. The averaged EVI of

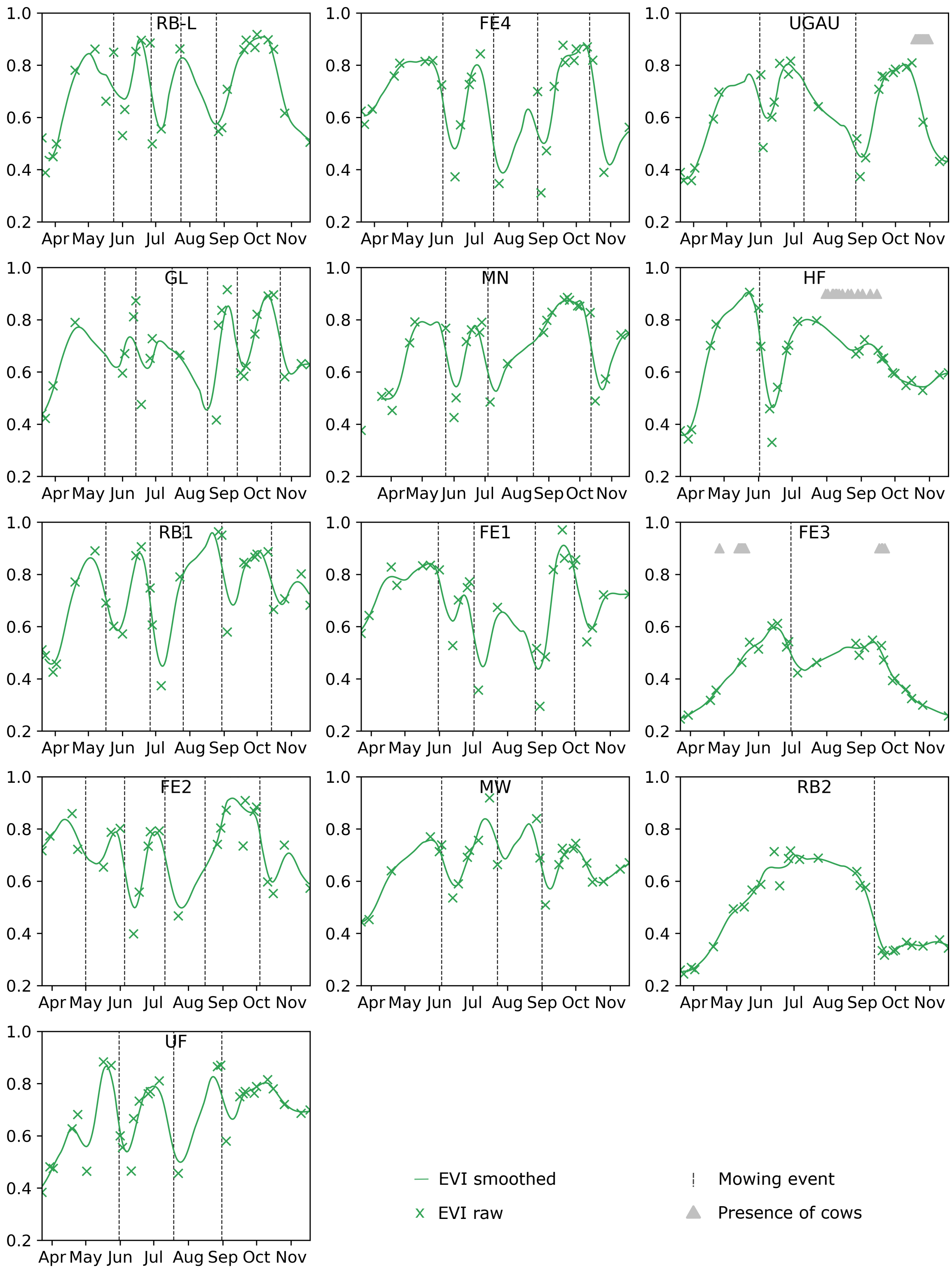

Figure 4.7: Raw and smoothed time series of EVI, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the EVI before, during and after mowing events and during the presence of cows on the sites.

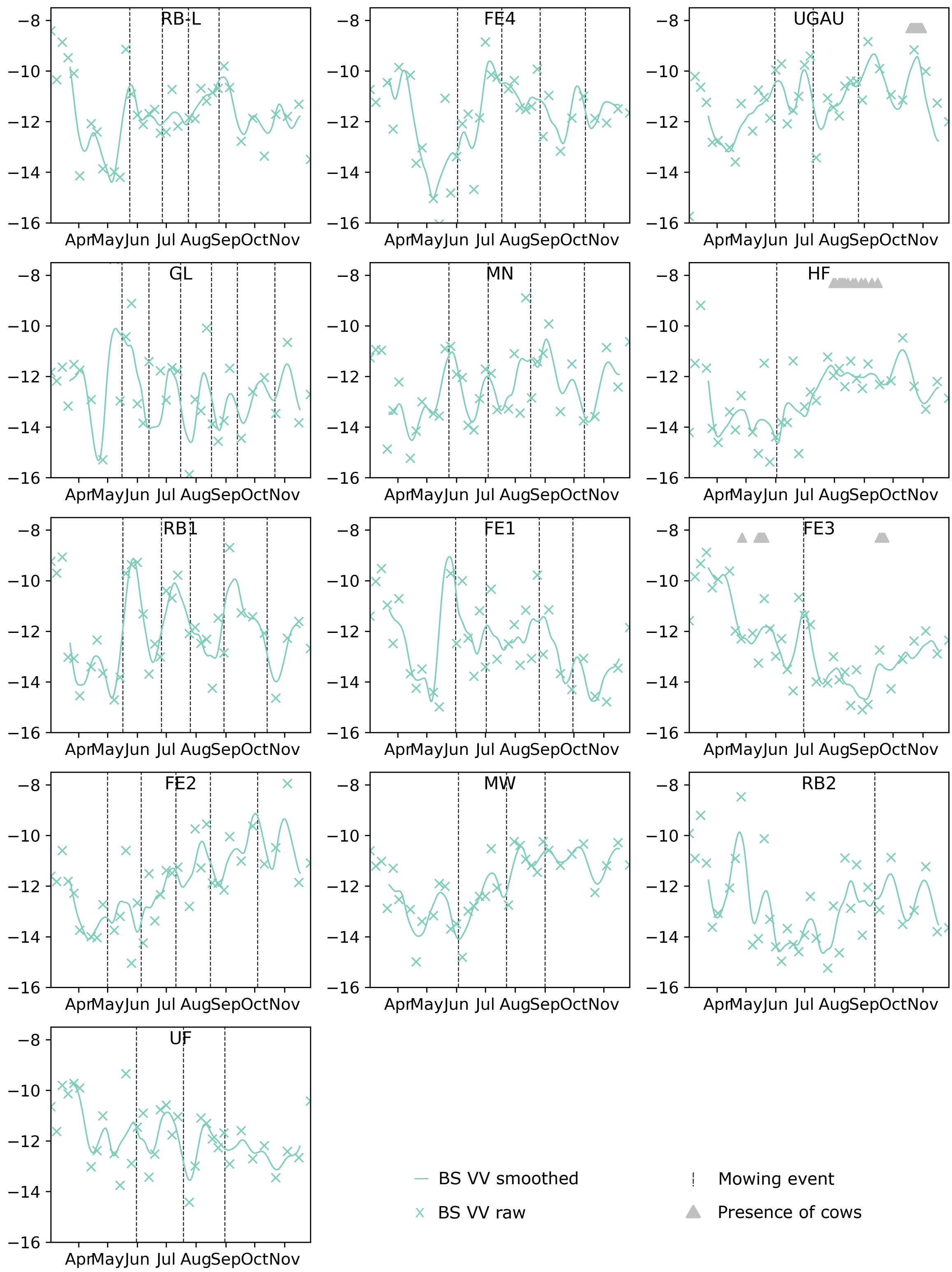

Figure 4.8: Raw and smoothed time series of Backscatter Intensity VV, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the Backscatter VV before, during and after mowing events and during the presence of cows on the sites.

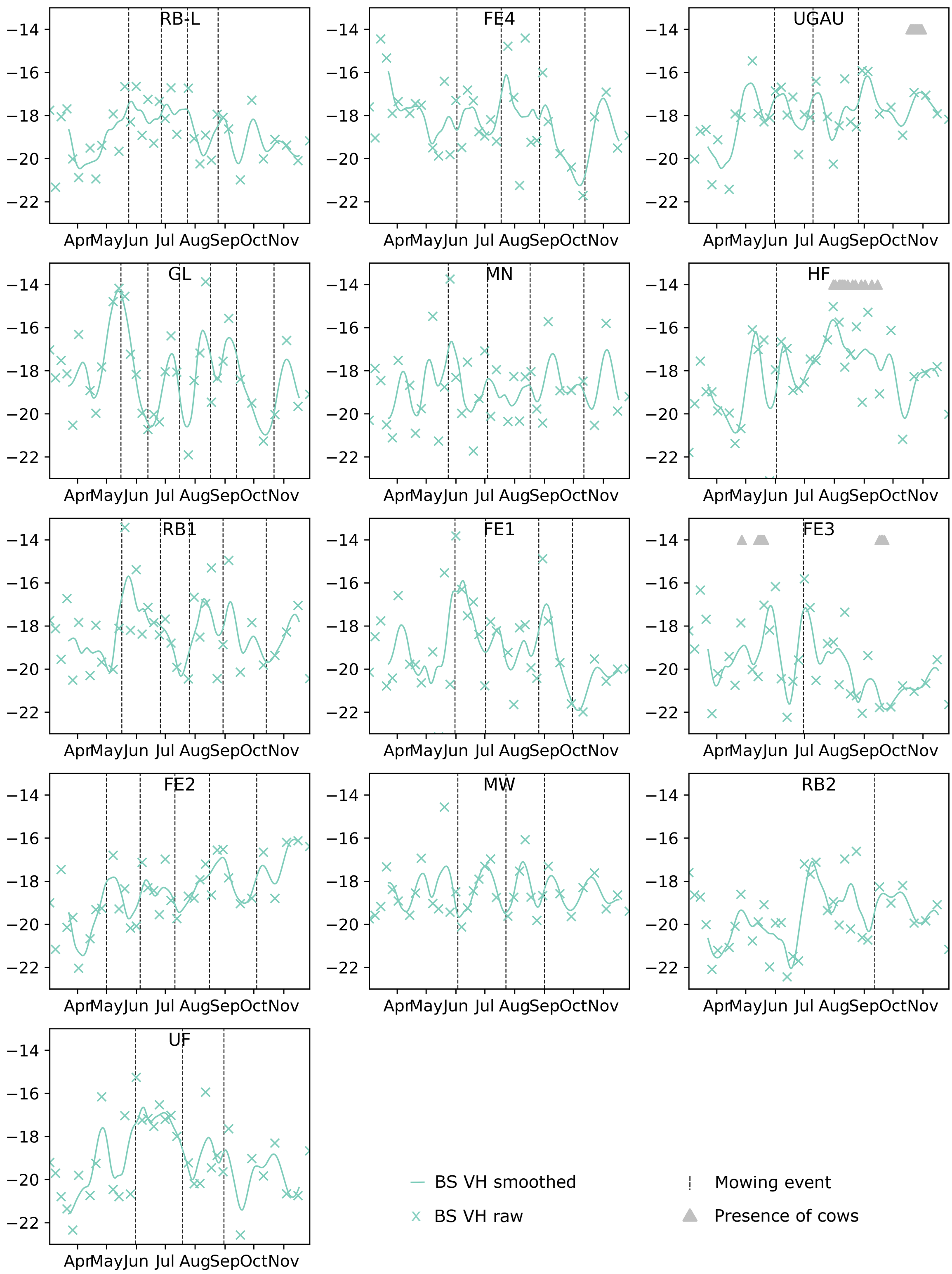

Figure 4.9: Raw and smoothed time series of Backscatter Intensity VH, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the Backscatter VH before, during and after mowing events and during the presence of cows on the sites.

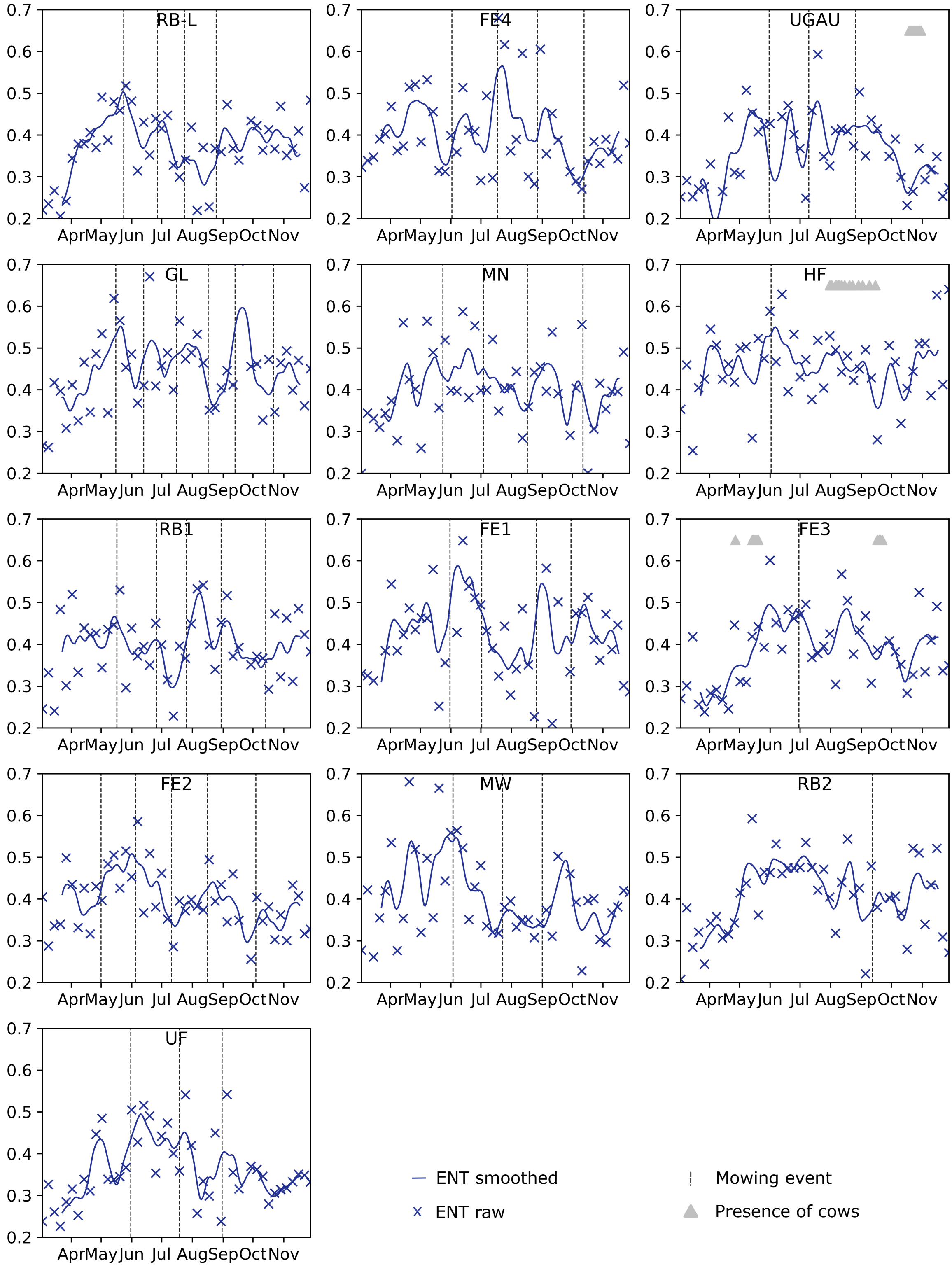

Figure 4.10: Raw and smoothed time series of PolSAR Entropy, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the Entropy before, during and after mowing events and during the presence of cows on the sites.

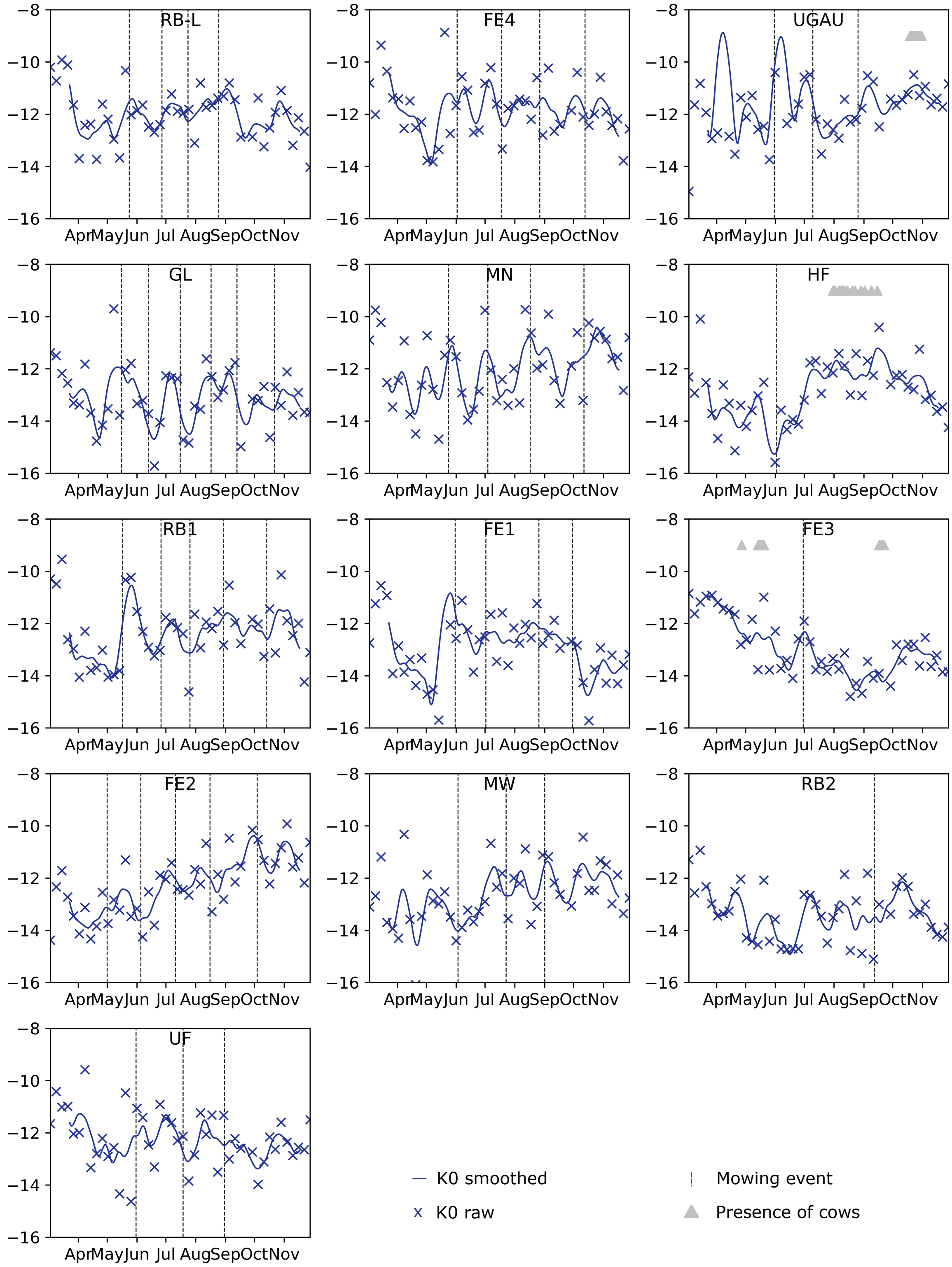

Figure 4.11: Raw and smoothed time series of PolSAR feature K0, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the K0 parameter before, during and after mowing events and during the presence of cows on the sites.

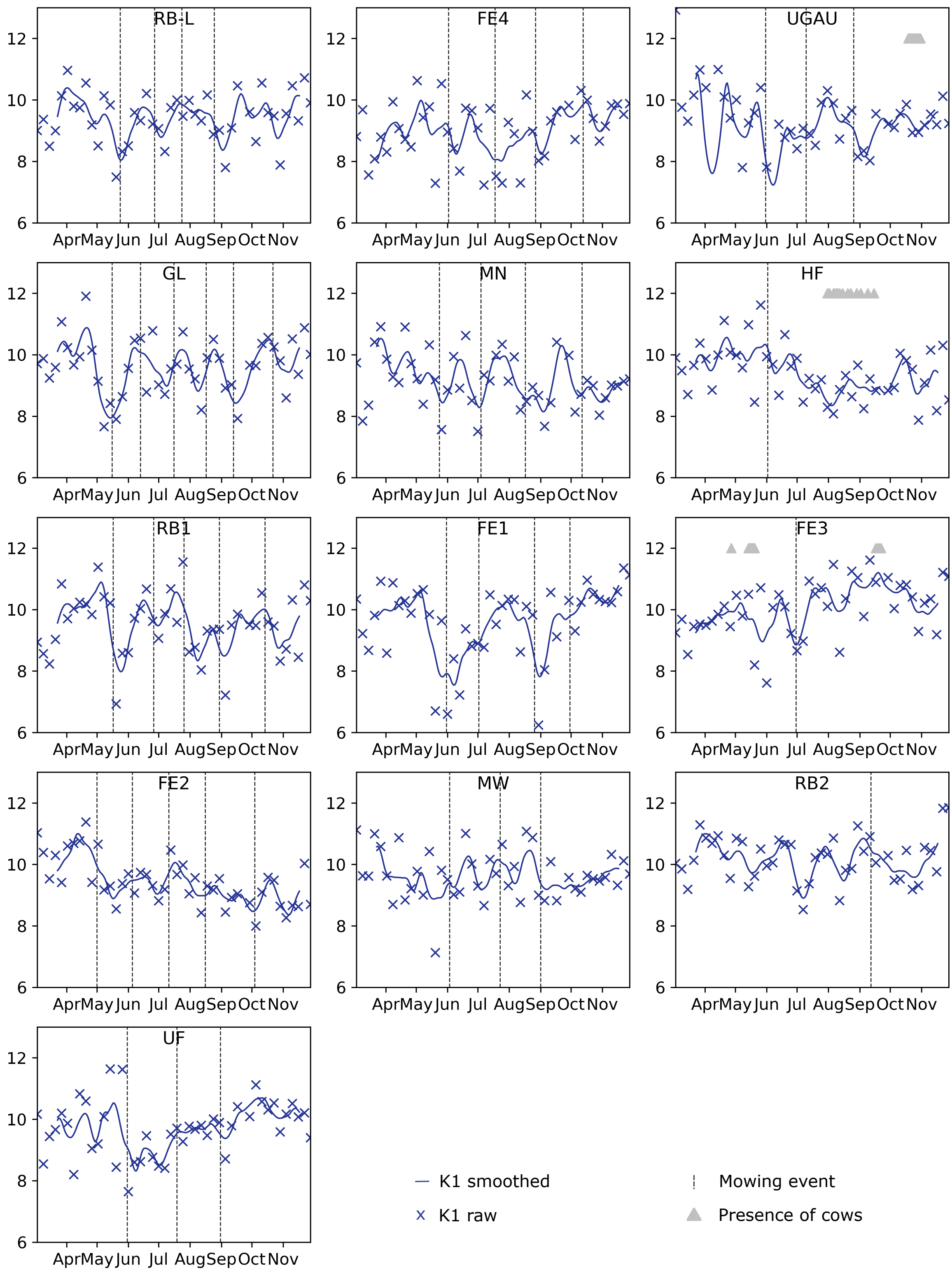

Figure 4.12: Raw and smoothed time series of PolSAR feature K1, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the K1 parameter before, during and after mowing events and during the presence of cows on the sites.

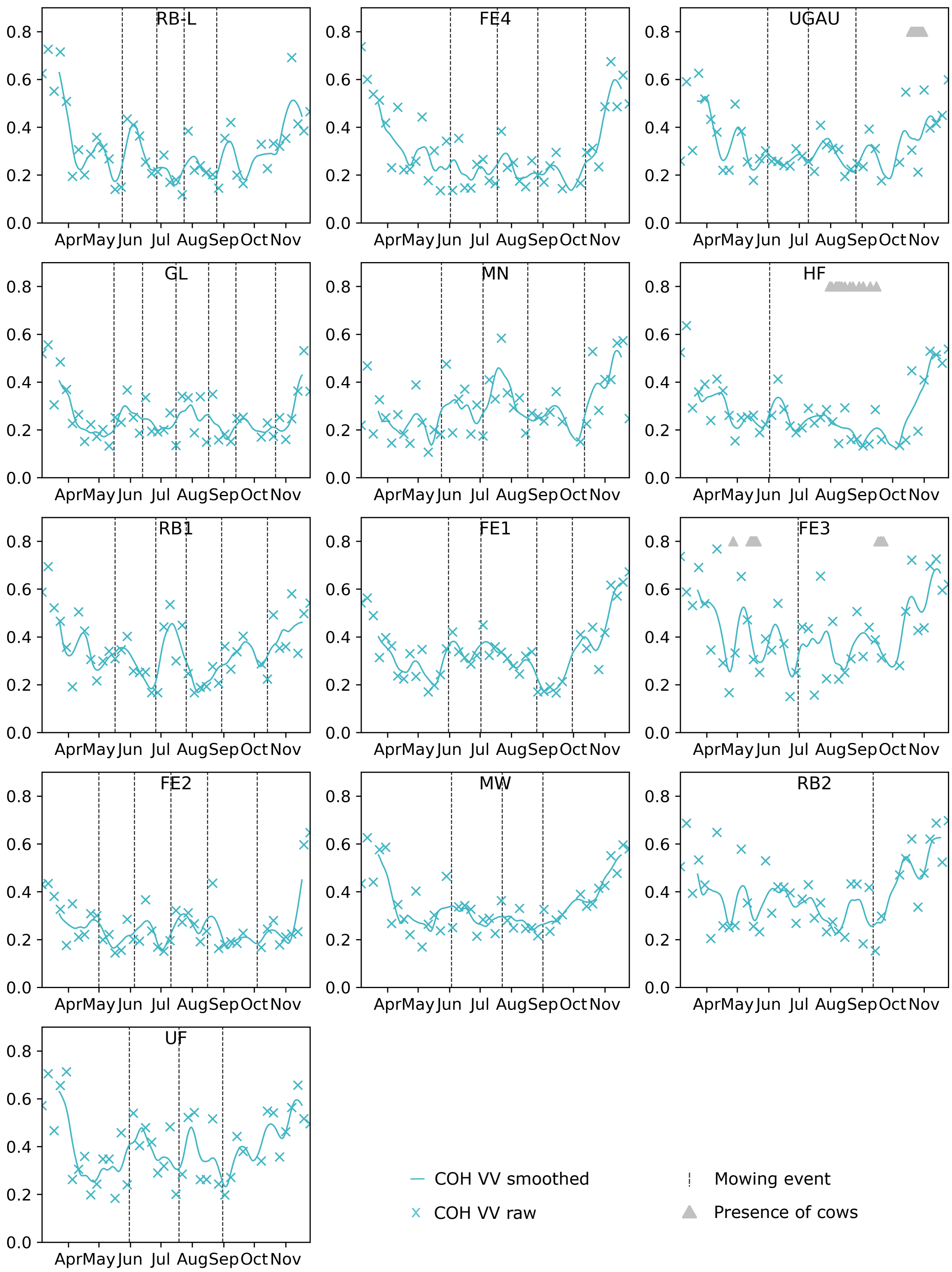

Figure 4.13: Raw and smoothed time series of InSAR Coherence VV, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the Coherence VV before, during and after mowing events and during the presence of cows on the sites.

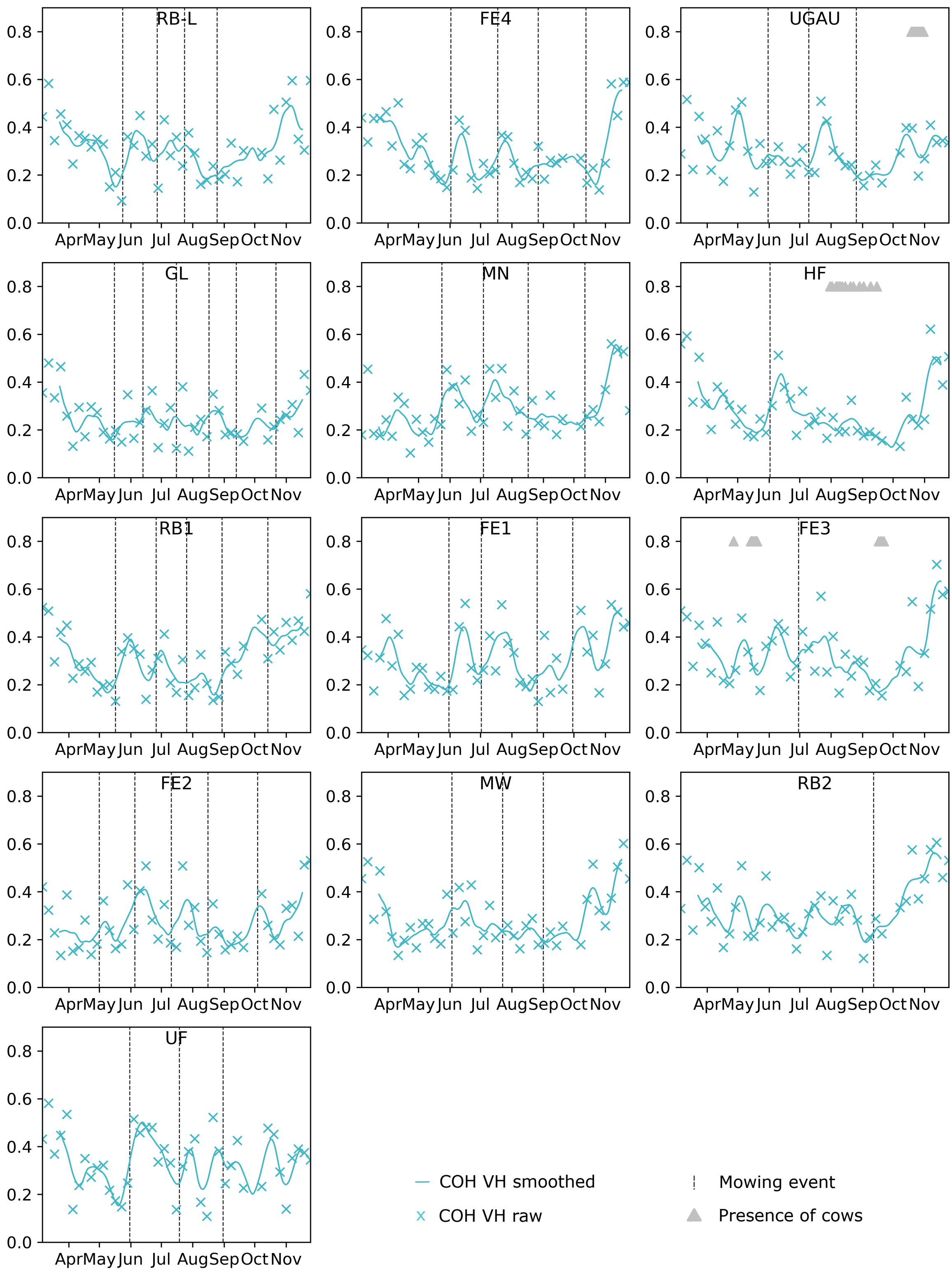

Figure 4.14: Raw and smoothed time series of InSAR Coherence VH, mowing events and the presence of cows for the calibration sites. The observation of the time series informs on the behavior of the Coherence VH before, during and after mowing events and during the presence of cows on the sites.

the raw data is based on less observations (Figure 4.15) as there are missing values due to clouds, which are gap-filled in the smoothed time series. Again, the EVI shows the most consistent pattern when comparing the values before and after mowing events. The ration of decreases to increases of all mowing events (n=44) was 39 to six (compare Table 4.3). Regarding the SAR parameters, Coherence VV shows the highest consistency with a decrease to increase ration of nine to 36, followed by Coherence VV (10/35) and Entropy (14/31) (Table 4.3). When comparing the averaged changes in amplitude among the parameters, the EVI shows the highest change (0.29 and 0.11, respectively), followed by Entropy (0.14 and 0.06, respectively) and Coherence VH (0.09 and 0.06, respectively) (Table 4.3).

The comparisons of averaged values before and after mowing events of the raw time series (Figure 4.15) show, in general, similar patterns compared to the smoothed time series (Figure 4.16). However, the smoothed parameters show weaker differences in their amplitude when comparing the values of before and after a mowing event. Even though smoothing weakens the changes in amplitude related to mowing events, it is needed to reduce fluctuations unrelated to mowing. In particular for the SAR parameters, which show much fluctuation, finding the right degree of smoothing is difficult. Several smoothing algorithms (rolling mean, Whittaker Smoother) and degrees of smoothing as well as decompositions (Empirical Mode Decomposition) and transformations (Fourier Transformation) were tested on the SAR time series with the aim to extract the signals of mowing events and separate them from noise. However, all of these tests conducted on the parametrization sites resulted in less consistent or less strong detectable changes related to mowing events compared to the applied approach using the Savitzky-Golay smoothing (compare section 4.2.1).

Overall, the examination of the parametrization sites revealed that the EVI shows the most consistent behavior and strongest change in amplitude after grassland mowing events. All S1-based parameters showed inconsistent behavior, however, Entropy and Coherence VH show increases for many of the investigated mowing events. In particular, the analyses on the parameter values before and after mowing events and observations from the time series revealed that Entropy shows one of the highest differences in amplitude and is relatively consistent. Coherence VH and Coherence VV show similar changes in amplitude, however Coherence VH a higher consistency. Hence, next to the EVI, Entropy and Coherence VH are included in the mowing detection approach for these reasons and to consider a polarimetric decomposition parameter to investigate the relevance of polarimetry as well as an InSAR parameter accounting for the temporal coherence.

Table 4.3: Averaged changes of values of six days before and six days after all mowing events used for parametrization (n=44) for all investigated parameters. All differences were normalized using the 95%-percentiles. Modified according to Reinermann et al. (2022)

	Decrease/Increase Ratio	Normalized Difference (Raw Data)	Normalized Difference (Smoothed Data)
EVI	39/6	0.29	0.11
ENT	14/31	0.14	0.06
K0	23/22	0.002	0.0009
K1	29/16	0.06	0.02
BS VV	25/20	0.03	0.008
BS VH	15/30	0.08	0.02
COH VV	10/35	0.08	0.06
COH VH	9/36	0.09	0.06

EVI = Enhanced Vegetation Index, ENT = PolSAR Entropy, K0 = PolSAR K0, K1 = PolSAR K1, BS VV = Backscatter VV, BS VH = Backscatter VH, COH VV = InSAR Coherence VV, COH VH = InSAR Coherence VH.

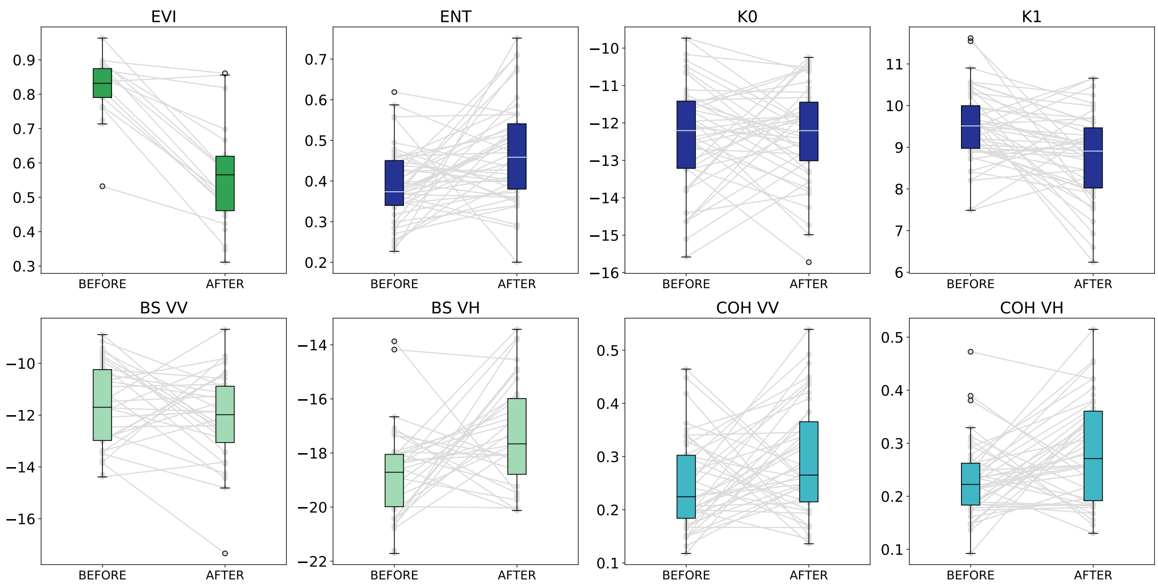

Figure 4.15: Average values for six days before and six days after all mowing events (n=44) of parametrization sites of raw time series for all investigated parameters. It shows the averaged change in amplitude of each parameter related to mowing and the change of each single mowing event as grey line.

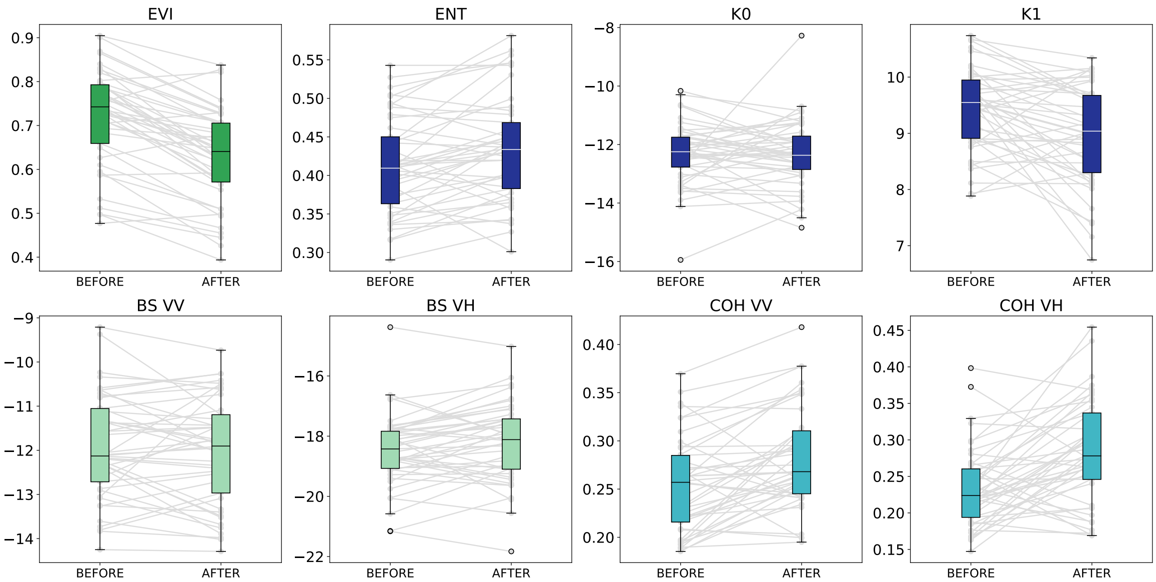

Figure 4.16: Average values for six days before and six days after all mowing events (n=44) of parametrization sites of smoothed time series for all investigated parameters. It shows the averaged change in amplitude of each parameter related to mowing and the change of each single mowing event as grey line.

4.3.2 Mowing Detection Approach and Threshold Calibration

The results from the investigation of all parameters revealed that especially the EVI captures grassland mowing events well through a consistent and distinctive decrease. Therefore, an mowing detection algorithm solely using EVI was developed. However, close examination of the parametrization time series showed that the EVI times series missed the drop related to mowing events when S2 observations were missing around the time of the mowing event due to clouds. A combined approach of S2 and S1 was therefore developed in addition, as the S1 parameters alone led to inconsistent results with many peaks/troughs within the time series unrelated to mowing activities (compare section 4.3.1).

4.3.2.1 Parametrization of Grassland Mowing Detection

4.3.2.1.1 Sentinel-2 The approach solely using the EVI time series was developed and parameterized using the 13 grassland parcels. A comparison of all mowing events of these sites revealed that the smoothed EVI drops on average by 0.07 after a mowing event took place (compare Figure 4.16). To detect mowing events, the EVI drop was located by searching for local maxima and minima within the time series and comparing the EVI values of those. Based on the information of the time series of the parametrization sites, it was defined that, in addition to the abrupt decrease in EVI, an immediate increase has to follow afterwards to detect a mowing event. This was important to prevent the false detection of natural plant senescence processes related to decreasing EVI. Based on this mowing detection approach, 77 % (34 of 44 mowing events) of the mowing events of the parametrization sites were correctly detected (compare Figure 4.17). Ten events were missed and ten falsely detected resulting in a F1-Score of 0.77. EVI decreases between 0.01 to 0.15 were tested consecutively as thresholds for a mowing event detection on the mowing events of the parametrization sites showing that for a large value range of 0.02–0.12, the accuracy of the mowing detection stays the same. Below and above these thresholds, the accuracy goes down. For further mowing detection the threshold of 0.07 was implemented as, apart from being the average EVI decrease of all mowing events, it is the center value between the thresholds which lead to the highest accuracy for the parametrization sites.

When a mowing event is detected the mowing date needs to be defined which potentially lies between the local maximum and local minimum which led to the mowing detection. it was decided to set the mowing date on the exact date between the local maximum and the local minimum to minimize the offset on average.

4.3.2.1.2 Sentinel-2 and Sentinel-1 Combined When applying the EVI-based mowing detection approach on the parametrization sites, it was revealed that most of the events missed by the EVI approach were related to unfavorable weather conditions. Eight of the ten missed mowing events were within periods of cloud cover or shortly before or after that. A second mowing detection approach was therefore defined, in which the EVI-based approach is complemented by a S1-based detection in periods of cloud gaps. The PolSAR Entropy as well as the InSAR Coherence VH were tested in that regard. Cloud gaps of at least 25 days within the optical time series were considered as critical gaps in which the S1-based information is added. In case there already is a S2-based detection (up to 10 days before or after the S1-based detection), the S1 detection is not added, but disregarded. As both, Entropy and Coherence VH, showed mostly peaks after mowing events, these are searched for within a time frame of five days before the beginning of the cloud gap and ten days afterwards. Multiple thresholds for mowing detections were tested of which an Entropy increase of 0.05 revealed the best results for the parametrization sites. Regarding the Entropy, the mowing detection within cloud gaps led to twelve additional mowing event detections for the parametrization sites, of which eight were correct (compare Figure 4.17). However, five of these additional detections were already detected by the EVI-based approach. Only three of the remaining additional S1-based detections were correct (i.e. the third events in RB1 and MN, and the fourth event in FE2) and four were falsely detected events (i.e. in UGAU, MN, FE3 and MW). Consequently, the combined approach led to a correct detection of 84.4% of mowing events of the parametrization sites and a F1-Score of 0.78.

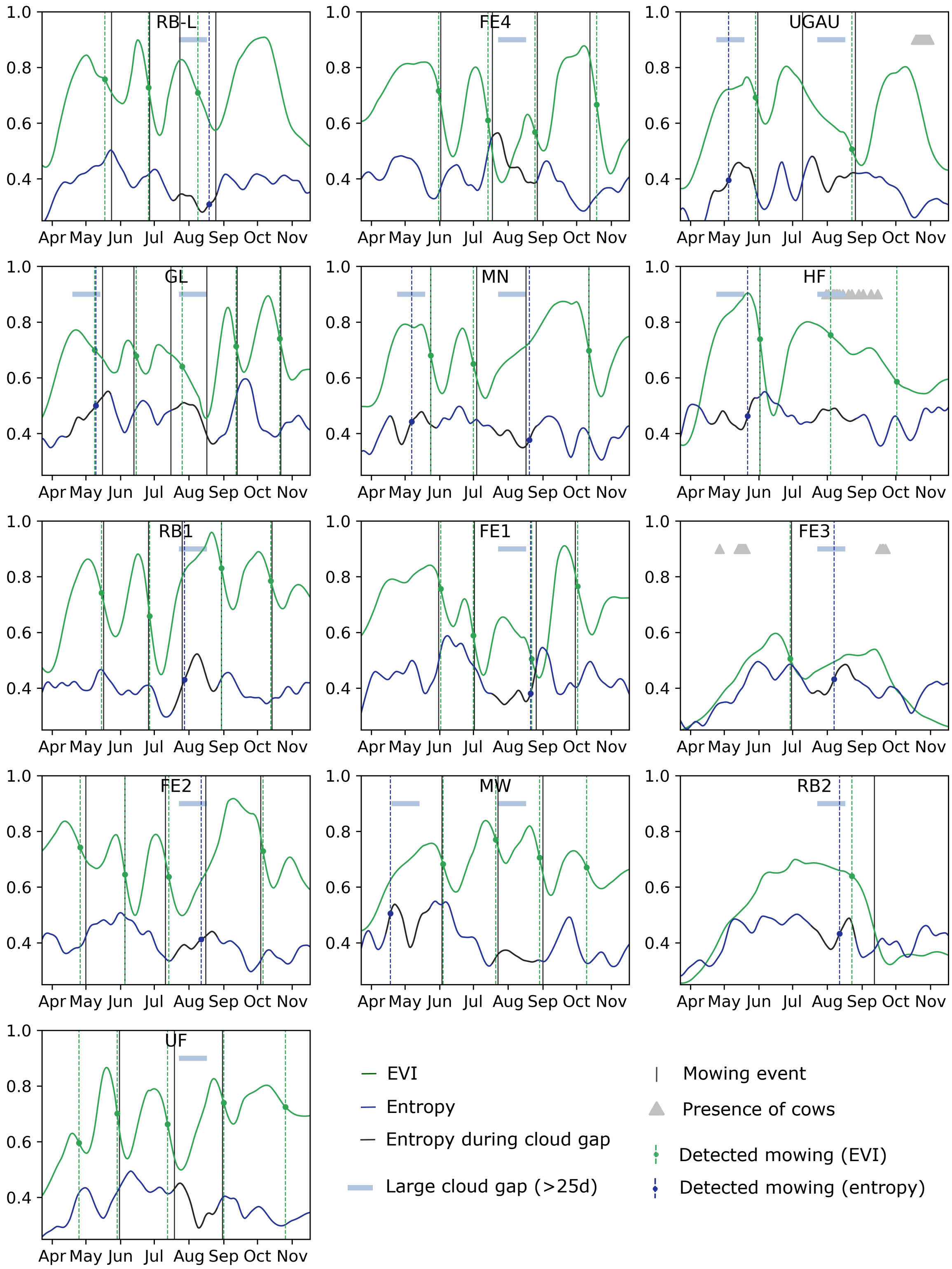

Figure 4.17: EVI (S2) and Entropy (S1) time series and their mowing detection and actual mowing events for the parametrization sites.

4.3.2.2 Results of Grassland Mowing Detection - Focus Region

The parameterized mowing detection based solely on the EVI and the combined approach were applied in a focus region and validated with an independent data set. The focus region is in southern Germany and the area contains a high share of grasslands which show the entire range of possible treatments and use intensities as they are mown from zero to six times per year and potentially additionally grazed. The validation data set of the focus region consisted of 229 mowing events on 66 grassland parcels. By applying the EVI-based approach and allowing a time difference of up to seven days between detected and actual mowing date, 148 of the 229 mowing events (64.6%) were correctly detected (compare Table 4.4). The approach combining EVI and PolSAR Entropy led to an increase in correctly detected mowing events as 169 of 229 (73.8 %) mowing events were detected. However, the number of falsely detected mowing events increased as well, from 76 to 157 false positives of the EVI-only to the combined (EVI+Entropy) approach. The combined approach of the EVI and InSAR Coherence mowing detection resulted in a similar picture as the other combined approach. The number of correctly detected mowing events increased to 72 % of the 229 mowing events, but also the number of false positives increased to 156. The overall accuracy was therefore best for the approach solely using the EVI as the F1-Scores decreased from 0.64 (EVI only) to 0.61 for both, the combination of EVI and Entropy as well as EVI and Coherence. The distributions of the actual and detected mowing frequency in the focus region show that only using the EVI leads to an underestimation and using a combination of S2 and S1 parameters to an overestimation of mowing events (Figures 4.18 and 4.19).

Table 4.4: Accuracy results of the EVI approach and the combined approaches, EVI+Entropy and EVI+Coherence, for a focus region in southern Germany.

	EVI	**EVI+ENT**	**EVI+COH**
Correctly detected	64.6%	73.8%	72%
F1-Score	0.65	0.61	0.61

EVI = Enhanced Vegetation Index, ENT = PolSAR Entropy, COH = InSAR Coherence VH.

The developed combined approach using S2 EVI and S1 Entropy was applied to detect mowing events for the entire focus region. Figure 4.20 shows the detected mowing frequency based on the algorithm only using S2 EVI and the combined EVI+ENT approach. It becomes visible that, overall, higher mowing frequencies are detected using the combined approach. The differences are more visible when examining the zooms (Figure 4.20 A and B). The border between the area covered by two orbits (east of zoom A) and the area covered by one orbit (west of zoom A) is visible using the EVI-only approach. It is still present within the EVI+ENT based mowing frequency, however in an attenuated

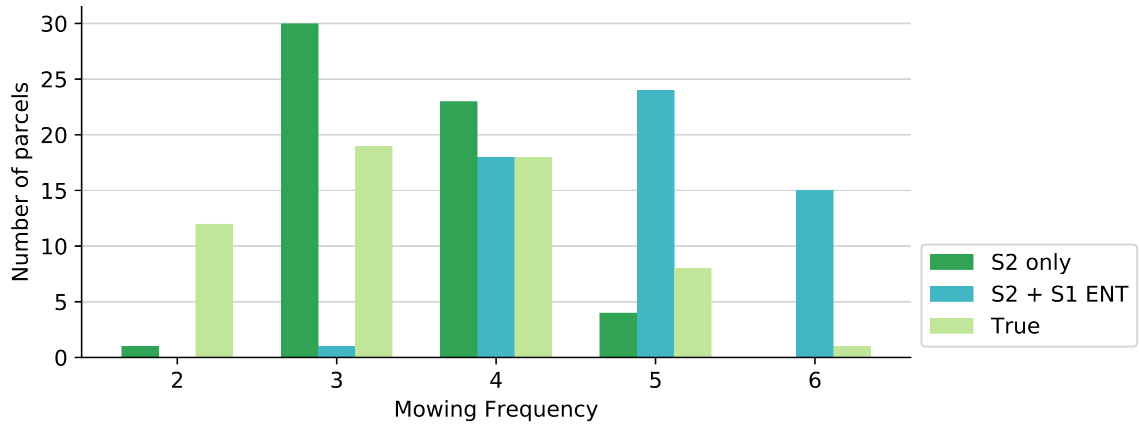

Figure 4.18: Mowing frequency of EVI and EVI+Entropy as detected with the presented approaches and the reference data of the focus region. The comparison of the detected mowing frequencies to the actual conditions shows an underestimation of the EVI and an overestimation of the combined approach.

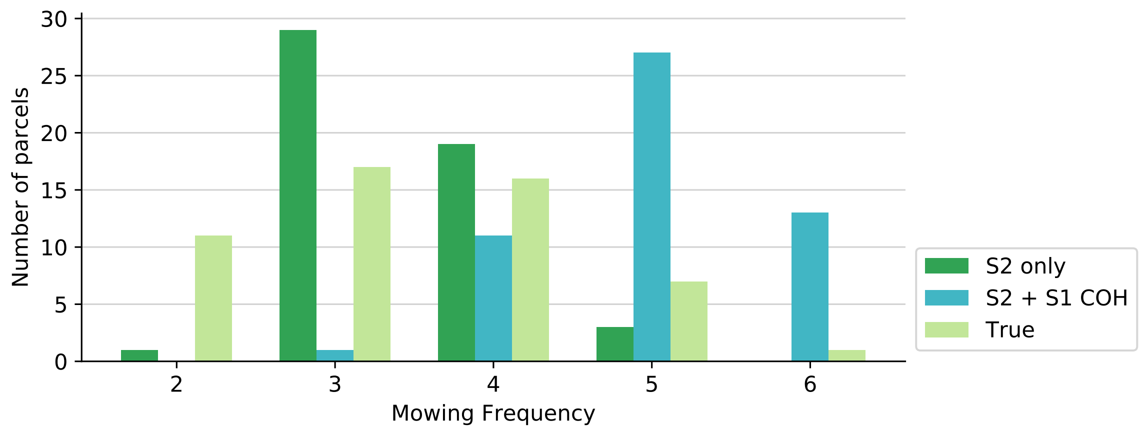

Figure 4.19: Mowing frequency of EVI and EVI+Coherence VH as detected with the presented approaches and the reference data of the focus region. The comparison of the detected mowing frequencies to the actual conditions shows an underestimation of the EVI and an overestimation of the combined approach.

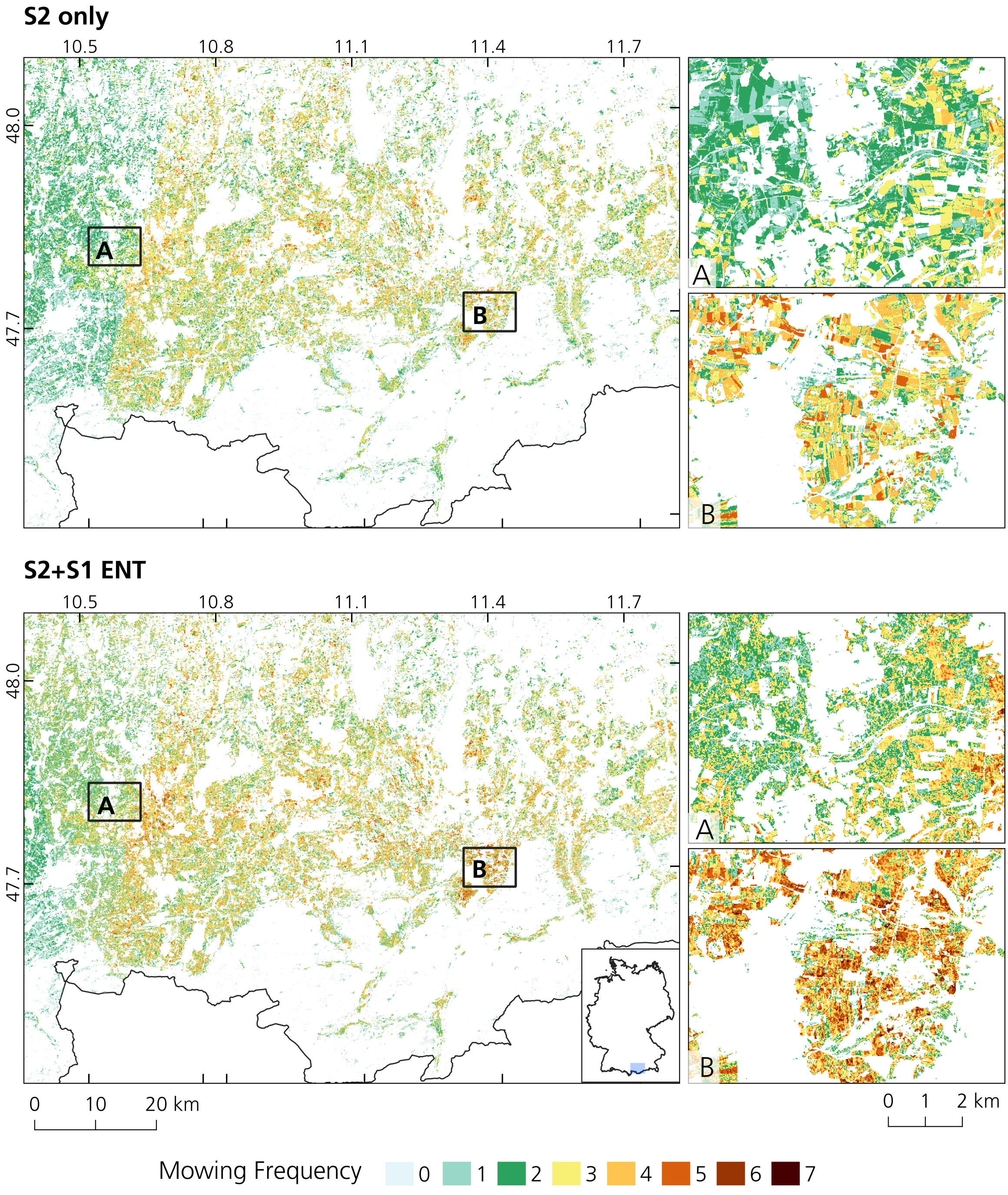

Figure 4.20: Mowing frequency detected by using the EVI-only (S2) algorithm and by using the EVI+ENT combined approach (S2+S1) for the entire focus region and two zoom regions (A and B) in 2019.

manner. Complementing the mowing detection with S1 information seems to improve the large scale mapping in that regard. However, a more detailed examination of the spatial patterns shows that the EVI-based mowing frequency reveals relatively homogeneous parcel structures, while the EVI+ENT mowing frequency pattern shows parcel borders less clearly and a higher salt and pepper effect (Figure 4.20 A and B).

It was demonstrated that complementing the mowing detection approach based on EVI with S1 information led to some improvement but, overall, could not increase the detection accuracy. The following mowing detection analyses were therefor solely based on the EVI algorithm.

4.3.3 Nation-wide, multi-annual Mowing Detection

Based on the application of the mowing event detection using S2 for entire Germany for 2018–2021 multi-annual mowing dynamics are analyzed. For that purpose, the S2-based mowing detection algorithm was transformed to be applicable for all S2 tiles covering Germany and all four years of interest (2018–2021). The S2 data of the area of Germany was in three UTM zones (UTM31, UTM32 and UTM33) which was accounted for during the processing. After the mowing detection algorithm was applied to each tile, the resulting Geotiffs were reprojected to World Geodetic System (WGS) 84 (EPSG: 4326) and all tiles were merged together. The per-tile mowing detection, which included the processing of annual time series data, was parallelized on a high performance computing environment using multiple CPUs. The finalization of the mowing detection took between half and one day for the entire area of Germany and one year.

After the detection of mowing events per year, the mowing frequency and the timing of the first mowing event were mapped and investigated for 2018–2021 on varying spatial scales to highlight temporal and spatial patterns of mowing dynamics.

4.3.3.1 Multi-annual Mowing Detection

The detected grassland mowing frequencies show a relatively stable spatial pattern among the years, where in particular regions in southern and south-eastern Germany show high numbers of more frequently (more than 3 times) mown grasslands (Figures 4.21, 4.22, 4.23 and 4.24). Higher shares of intermediate (three times) and intensive (more than 3 times) grassland use can also be found in western Germany and the north. Regions in central and eastern parts of Germany seem to be less intensively used (mown less than three times). The zooms of Figures 4.21 to 4.24 highlight the fine spatial resolution (10 m) of the mowing frequency maps and show mowing dynamics in seven differing grassland landscapes. The two northern regions (A and B) are characterized by the influence of water as they are close to the coasts and the appearance of dykes. There are extensively used grasslands in these landscapes, but a majority shows intermediate and a smaller share intensive use. The two zoom regions show higher mowing frequencies in 2020, lower mowing frequencies in 2021 and an intermediate mowing intensity in 2018 and 2019 when all four years are compared to each other. The landscape in north-eastern Germany (C) has larger parcels which is also visible from the zooms as they are all in the same scale. This is a relic from the more unified usage of agricultural area in the former Eastern German Republic. The area is in general characterized by low mowing frequencies with small proportions of grasslands with intermediate numbers of mowing frequencies. The mowing frequency stays relatively constant for the years 2018-2020 and was a little less in 2021. The landscape in the center of Germany (D) is a typical central-German low mountain range area with isolated patches of forests and grassland. The area overall shows intermediate grassland mowing intensities with grasslands with low, intermediate and (a little less) high numbers of mowing frequency. Comparable to the zoom regions A and B, the area shows higher numbers of mowing frequency in 2020, lower numbers in 2021 and intermediate mowing frequencies in 2018 and 2019. The landscape in south-eastern Germany (E) lies in the northern part of the Bavarian Forest Nature Park and contains patches of forest, grassland and agricultural areas, whereas large parts are under protection. Like the zoom area D, the area shows an intermediate mowing intensity with grasslands of lower, intermediate and (less) higher numbers of mowing frequency. Within this region, the use in 2018 was more intensive compared to 2019, 2020 and 2021 when comparing all four years. Some areas of the southern Alpine Foreland are among the most intensively used grassland areas in Germany (F, G). The southern Alpine Foreland is characterized by high precipitation rates and a high share of grasslands. Both regions (F, G) show highest mowing frequencies in 2020 and lower number of mowing in 2018 and 2021.

The aggregation to districts through averaging reveals a similar general picture for mowing dynamics in Germany (Figure 4.25). Differences between the years are visible, in particular when examining the high-resolution (10 *x* 10 m) maps (Figures 4.21 to 4.24). Grasslands in central and north-eastern regions of Germany are less often mown. This pattern stays relatively similar for the four years of interest for these areas. Regions in the north and in western/south-western Germany show intermediate mowing intensity when considering the entire area of Germany. The year 2020 shows higher mowing numbers in northern and north-western Germany. Highest mowing intensities can be found in southern/south-eastern Germany. In particular the valley of the river “Inn” appears to have a large share of grasslands with high mowing frequencies. This pattern stays relatively constant, apart from

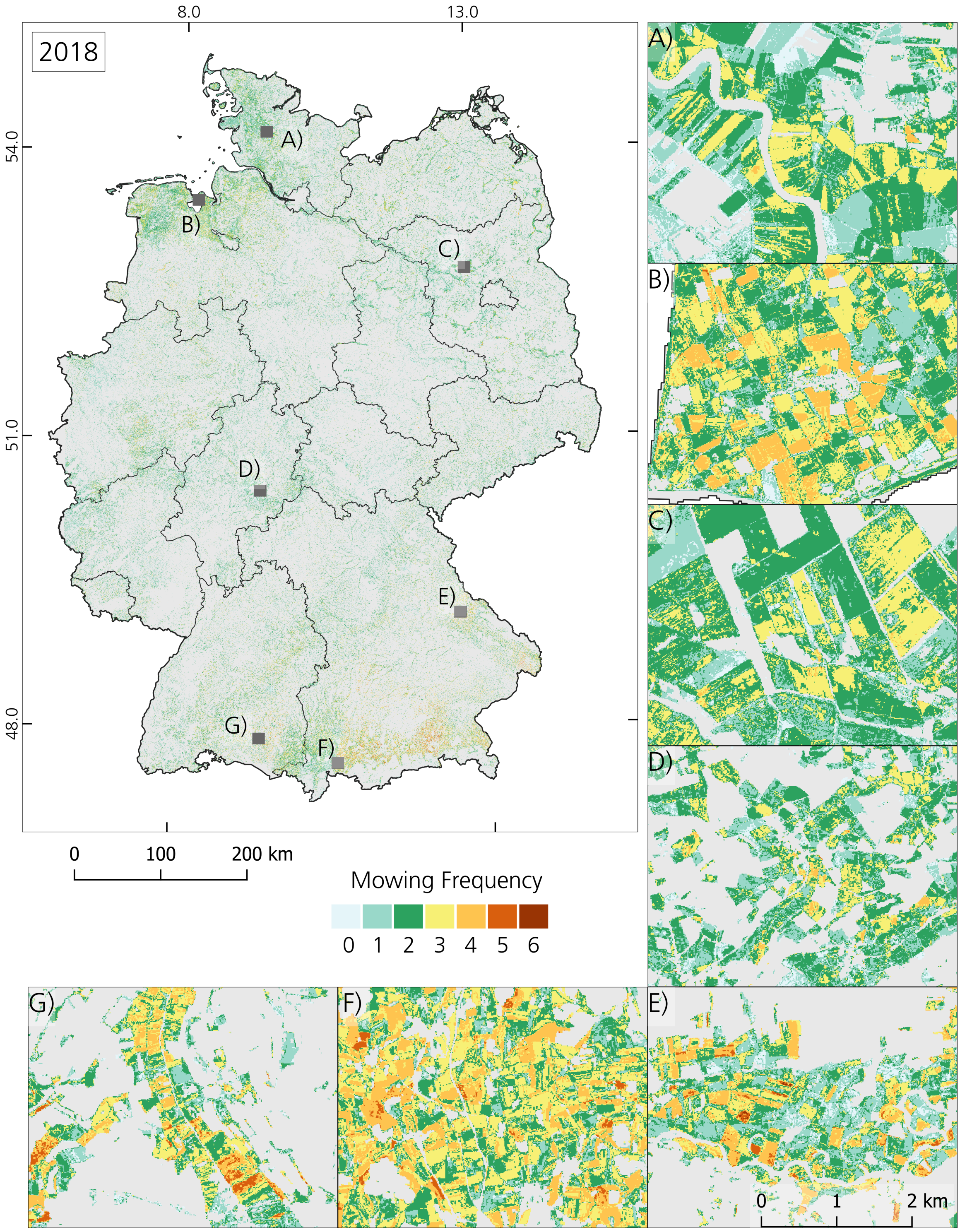

Figure 4.21: Detected mowing frequency in 2018 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

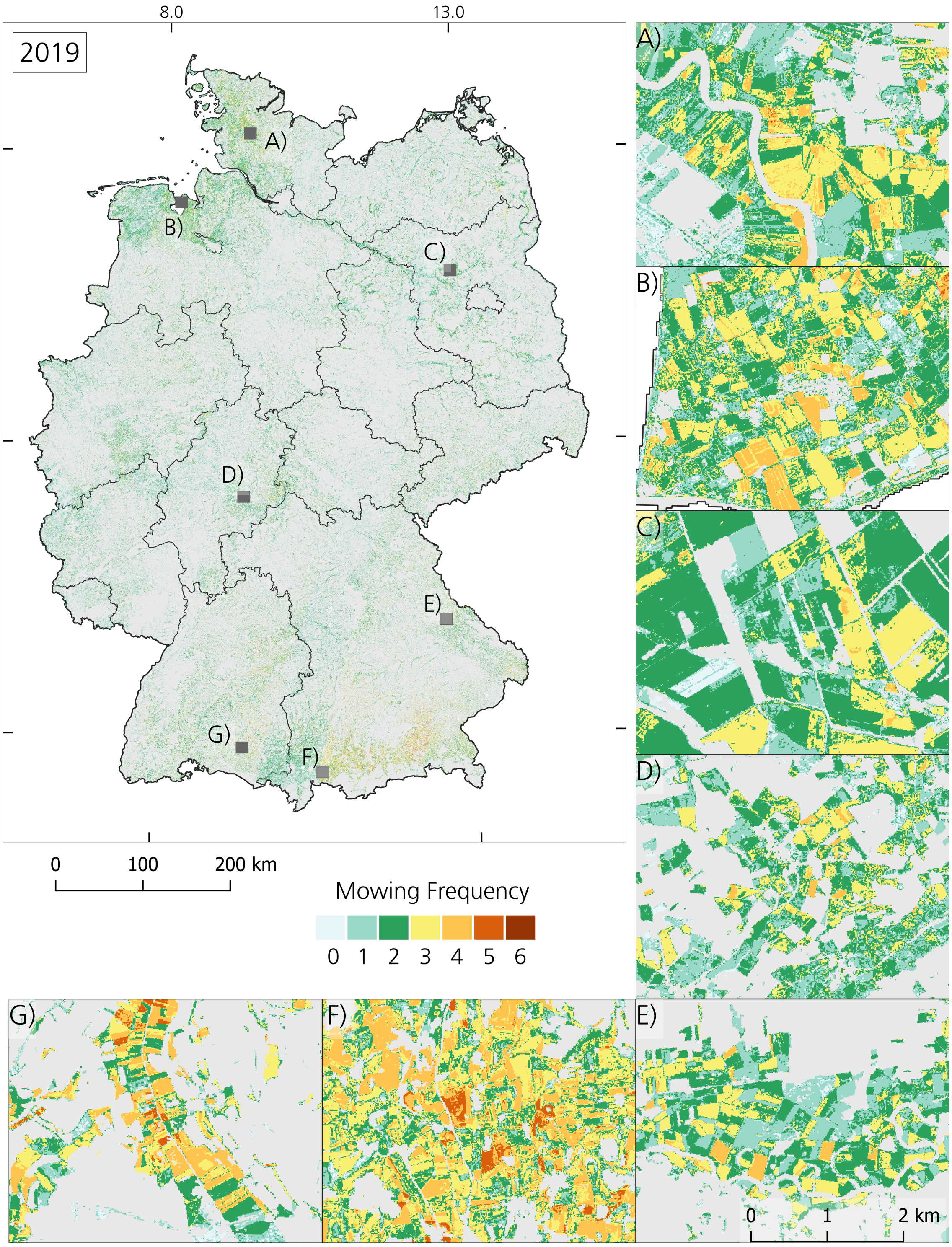

Figure 4.22: Detected mowing frequency in 2019 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

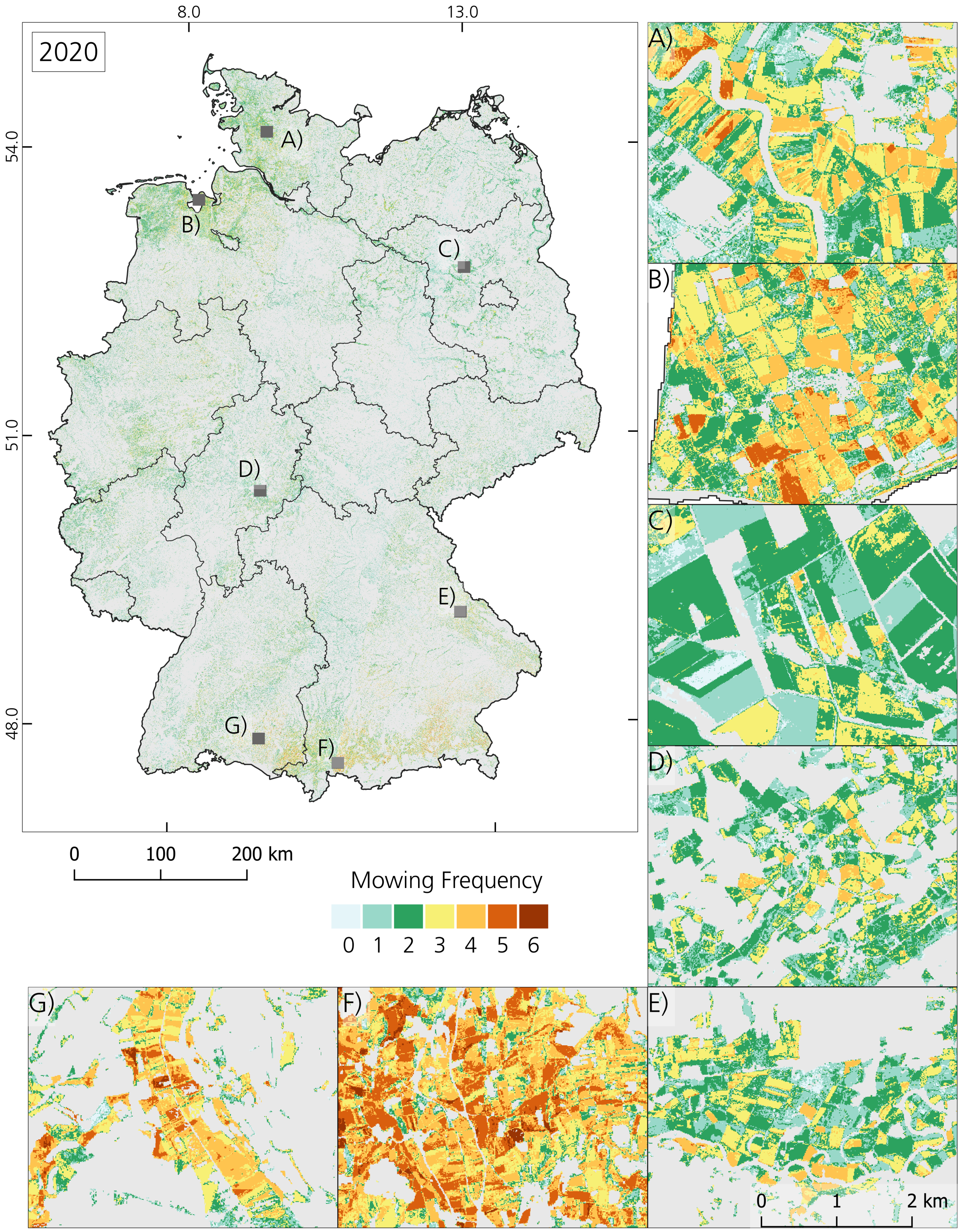

Figure 4.23: Detected mowing frequency in 2020 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

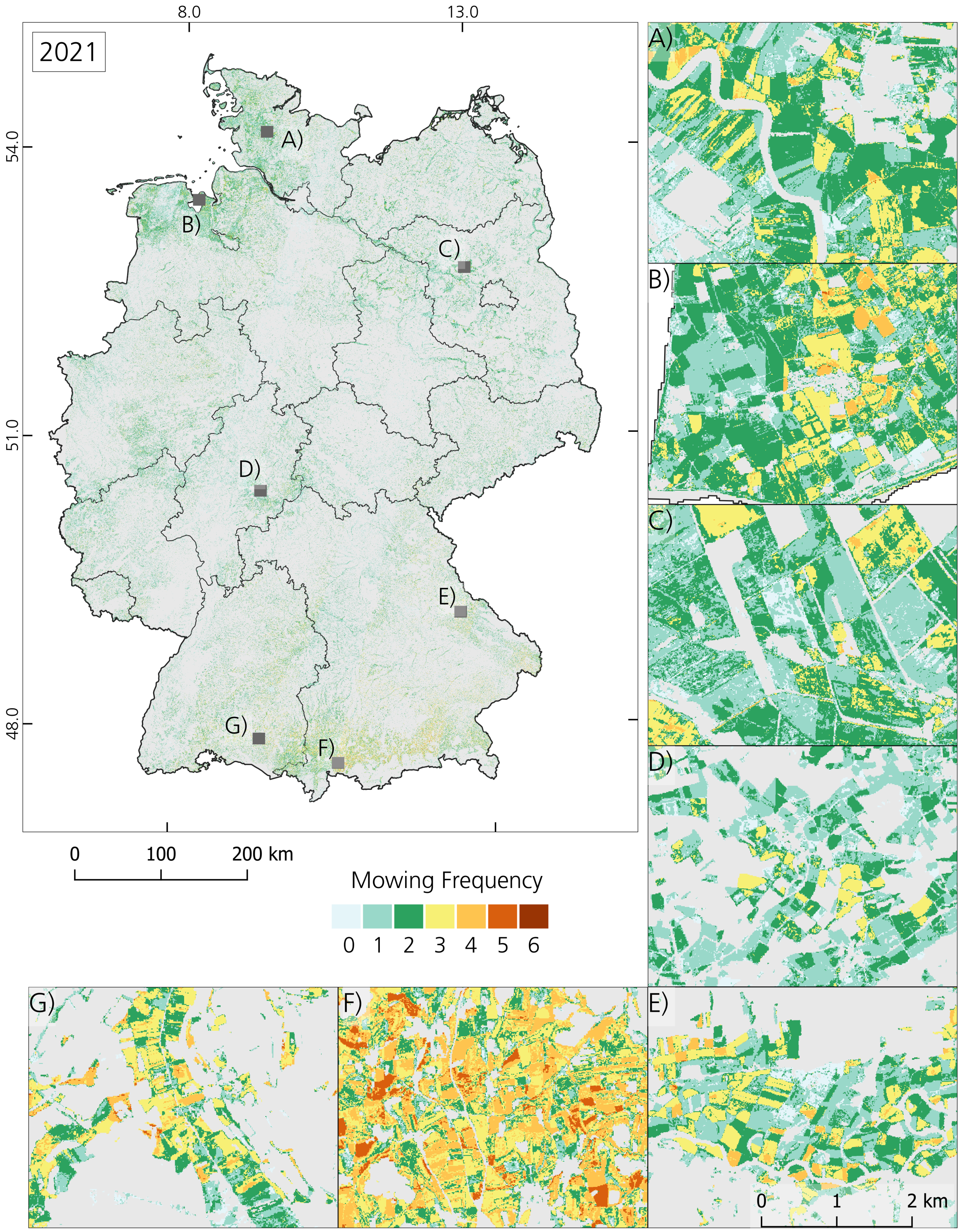

Figure 4.24: Detected mowing frequency in 2021 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

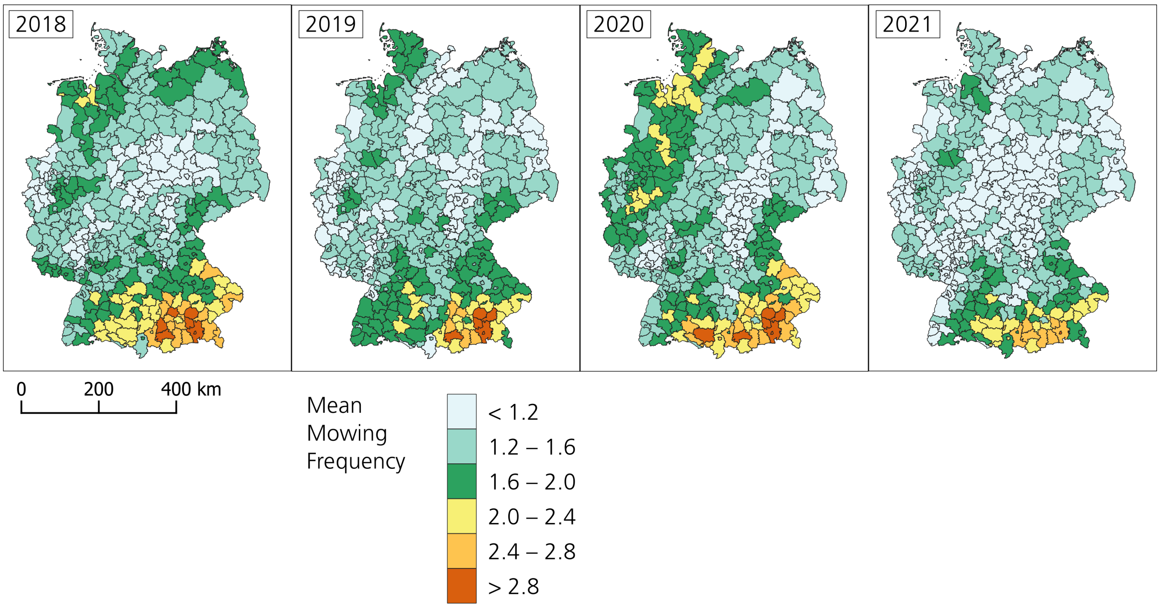

Figure 4.25: Detected mowing frequencies for 2018, 2019, 2020 and 2021 averaged per county.

2021 which shows lower numbers of mowing events, in particular in the intensively used areas.

Averaged over the entire area of Germany, the overall distribution of mowing frequencies for the entire country for all four years becomes visible (Figure 4.26). The overall share as well as the area of grasslands with the respective mowing frequency stays similar for the four years (Figure 4.26 A and B). In addition, it can be seen that most of the grassland is mown one to two times in all years. Between 10 to 17 % (depending on the year) of all grasslands in Germany are mown three times or not at all, and a minimum shows intensive mowing of four mowing events per year or more.

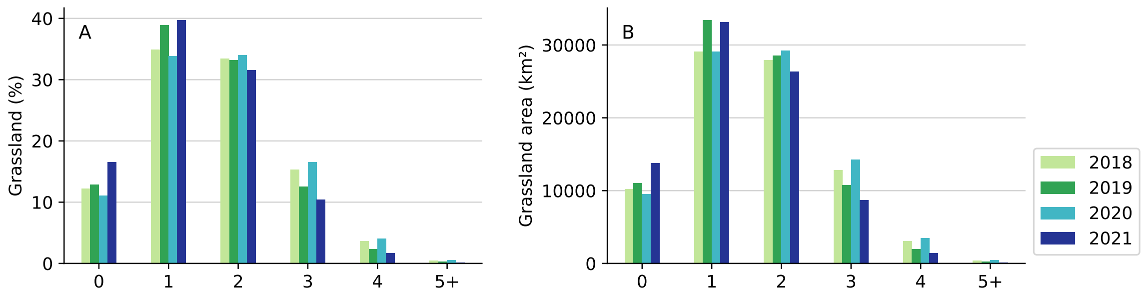

Figure 4.26: Detected mowing frequencies for 2018, 2019, 2020 and 2021 averaged over Germany. The relative share of detected mowing frequencies per grassland (A) and the absolute areas (B) are shown, which only show minimal differences when the entire grassland area of Germany is included.

As not the entire area of Germany is covered by two S2 orbits, the data availability is not evenly distributed in Germany which is amplified by varying cloud conditions. The averaged mowing frequencies of grasslands (share and total area) for regions with higher data availability is shown in Figure 4.27. Only pixels with cloud-free acquisitions of at least 20 days are included here. As the atmospheric conditions were weakest in 2021 compared to the other years, the absolute area of grassland with detected mowing frequencies is smaller (Figure 4.27 B). The detected areas are highest for 2020 followed by 2018 for all mowing frequencies. The distribution of mowing frequencies for grasslands with good data availability reveal, that overall mowing frequencies were smaller in 2018, higher in 2020 and 2021 and intermediate in 2019 (Figure 4.27 A, B).

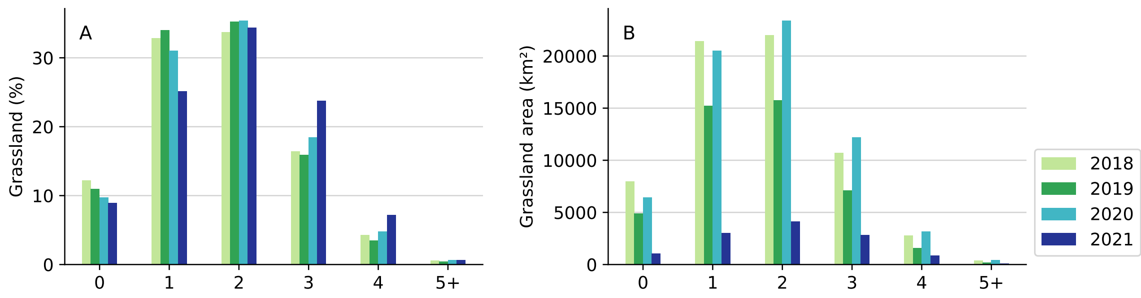

Figure 4.27: Detected mowing frequencies for 2018, 2019, 2020 and 2021 averaged only for areas with good data quality in Germany (covered by two orbits). The relative share of mowing frequencies per grassland area shown per year (A) and the absolute area of mowing frequencies zero to at least five per year (B) differ as the data availability was not equal among the years.

Another aggregation analysis was conducted using the great natural landscapes of Germany which are defined by natural geographic zones, like climatic or topographic (compare section 3.1). Figure 4.28 shows the mowing frequency for each great landscape averaged over the four years and the distribution of mowing frequencies per great landscape and year (A–G). For this aggregation only pixels with a good data availability, defined by at least 20 valid scenes per year, were included. It becomes clear that the Pre-Alpine and Alpine regions show higher mowing frequencies compared to the rest of Germany (Figure 4.28 F, G). In these two regions, grasslands which are mown three times are the largest group while in the other great landscapes, grasslands mown one or two times build the majority. In addition, the share of grasslands with high mowing intensities (mown at least four times) is higher for the south-eastern landscapes, in particular the Pre-Alpine region (Figure 4.28 F). Even though the overall picture stays the same for the four years, there is some variability visible (Figure 4.28 A–G). The Northwestern Lowlands, the Western Low Mountain Ranges and the Alpine great landscape show higher mowing frequencies in 2020 when comparing all four years (Figure 4.28 A, C, G). For the regions Northeastern Lowlands and Southwestern Low Mountain Ranges the mowing frequency stays relatively constant for

2018–2021 (Figure 4.28 B and E). The Pre-Alpine great landscape shows higher mowing frequencies in 2018 and 2020 when comparing all years (Figure 4.28 F).

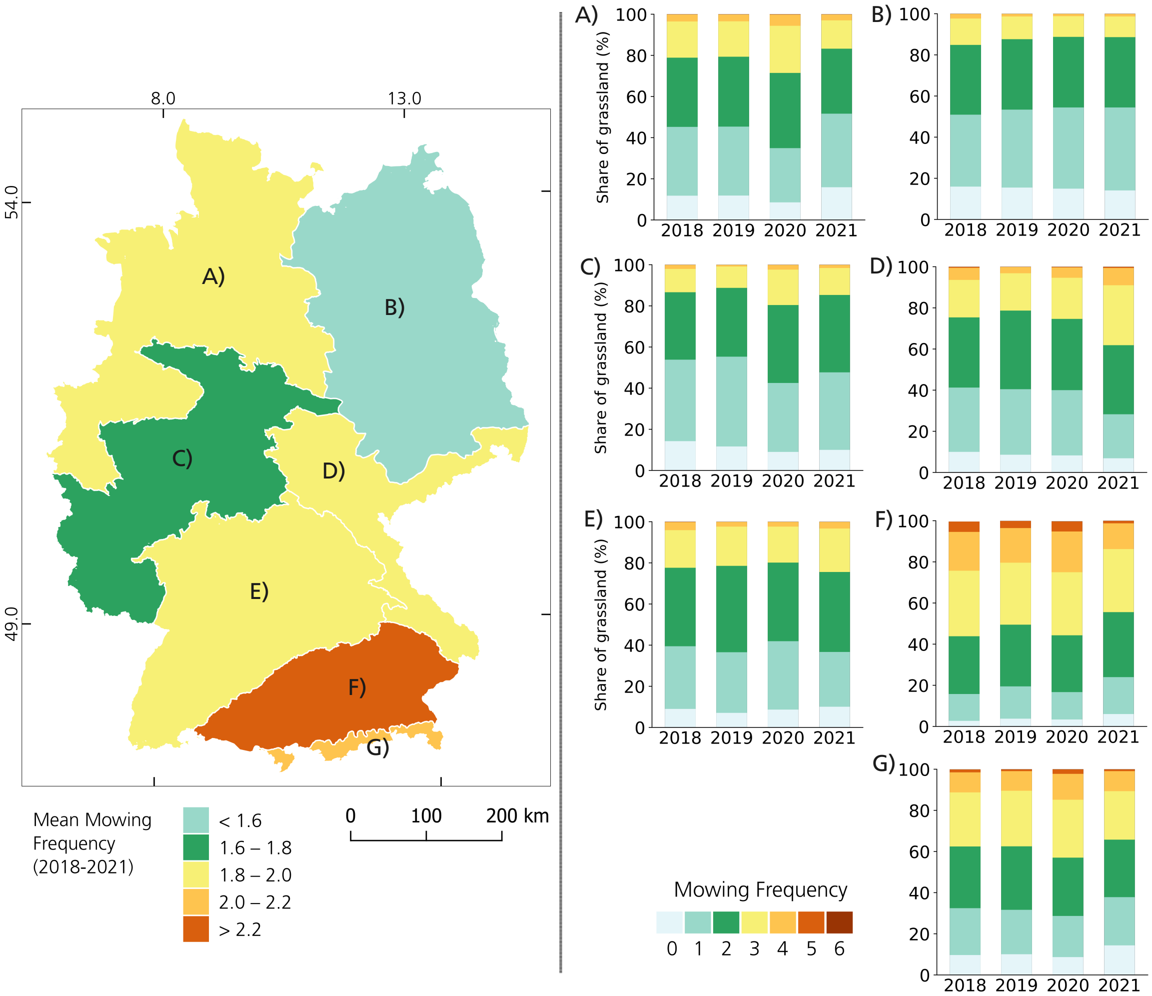

Figure 4.28: Detected mowing frequencies averaged per year and great natural landscape and distribution of mowing frequencies for each year per landscape (bar charts). Great natural landscapes A: Northwestern Lowlands, B: Northeastern Lowlands, C: Western Low Mountain Ranges, D: Eastern Low Mountain Ranges, E: Southwestern Low Mountain Ranges, F: Pre-Alpine and G: Alpine.

4.3.3.2 Timing of Mowing Events

Regarding the timing of the first mowing event, the overall picture shows that many grasslands are mown relatively early, apart from single parcels which become visible when zooming in (Figures 4.29, 4.30, 4.31 and 4.32). Areas with more grasslands with late first mowing events can be found for some years in higher elevated regions, like the Swabian Jura in the north of Zoom B in 2020 or areas in the Bavarian Forest Nature Park (Figure 4.31), south-east of Zoom E in 2021 (Figure 4.32). When comparing the four years, in particular in 2018 grasslands were mown early. On parcels level it is visible that there is a variability of the timing of the first mowing event between years (Figures 4.29 to 4.32 A–G). The northern regions (A, B, C) show later mowing events in 2020 and 2021 when compared to the other years. The regions in central and southern Germany (D, E, F and G) show early grassland mowing in particular in 2018. Overall, comparably large grassland parcels are mown earlier than smaller ones. Early mown grasslands are at times connected to each other, but this is not necessarily the case. Grassland parcels which are mown relatively late are often small and irregularly shaped. The exact timing of the first mowing event of single parcels varies between the years, but the tendency, i.e. if the parcels are mown comparably early or late, stays constant.

The results of the aggregation of the timing of first mowing event to districts highlight the variability in-between years as well as similarities and differences to the mowing frequency (4.33). Regions in southern and western Germany have higher shares of early mown grasslands than other regions. Concurrent with overall lower numbers of mowing events per year, many grasslands in central and eastern Germany are mown relatively late. In 2018, almost the entire area of Germany shows early first mowing dates. In 2019 and 2020, in particular parts in western Germany are characterized by early mown grasslands.

The distribution of the timing of the first mowing event was further investigated for the great landscapes with the highest share of grasslands (more than 15 %) in Figure 4.34. As broad areas of the violins indicate that many grasslands were mown around this date, it is revealed if there were one or more preferred dates when the first mowing event took place for each landscape and year. There are differences visible between landscapes and years. Remarkable are relatively early first mowing dates for the Western Low Mountain Ranges and the Pre-Alpine regions (Figure 4.34 B, C) and relatively late ones for the Northwestern Lowlands and the Western Low Mountain Ranges (Figure 4.34 A, B). Even later mowing dates show large shares of grassland in the Western Low Mountain Ranges and the Pre-Alpine great natural landscape in 2021 (Figure 4.34 B, C).

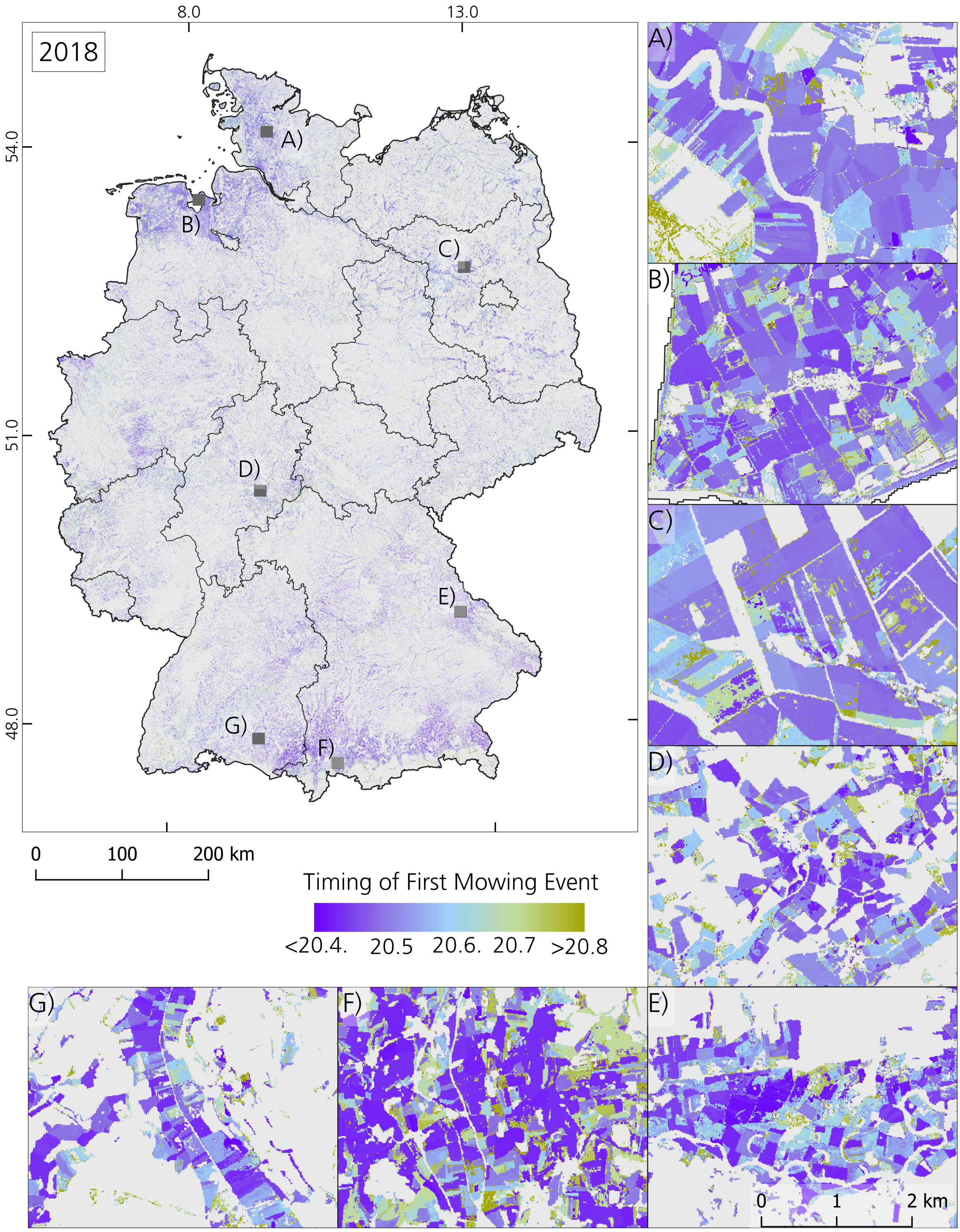

Figure 4.29: Detected date of first mowing event in 2018 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

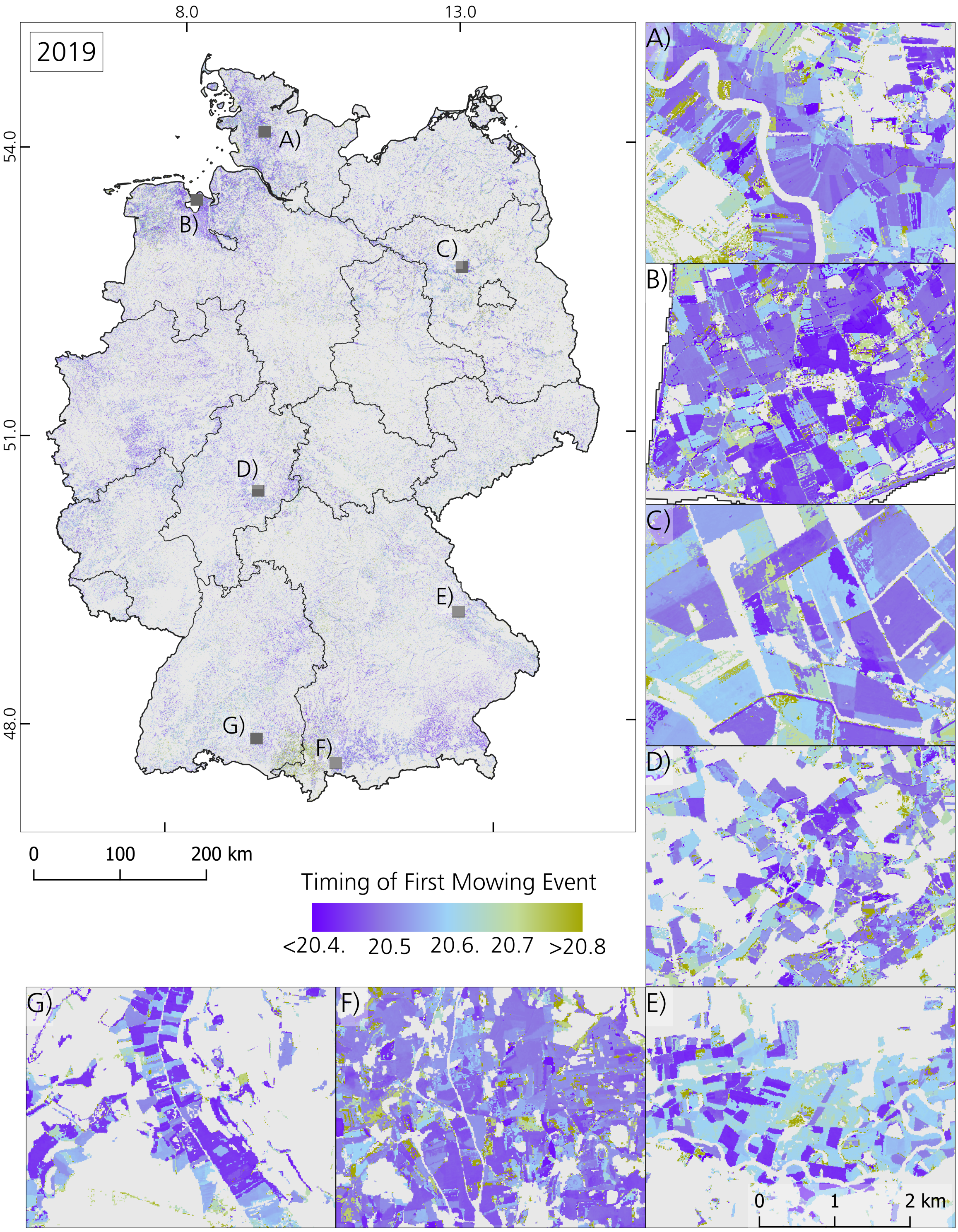

Figure 4.30: Detected date of first mowing event in 2019 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

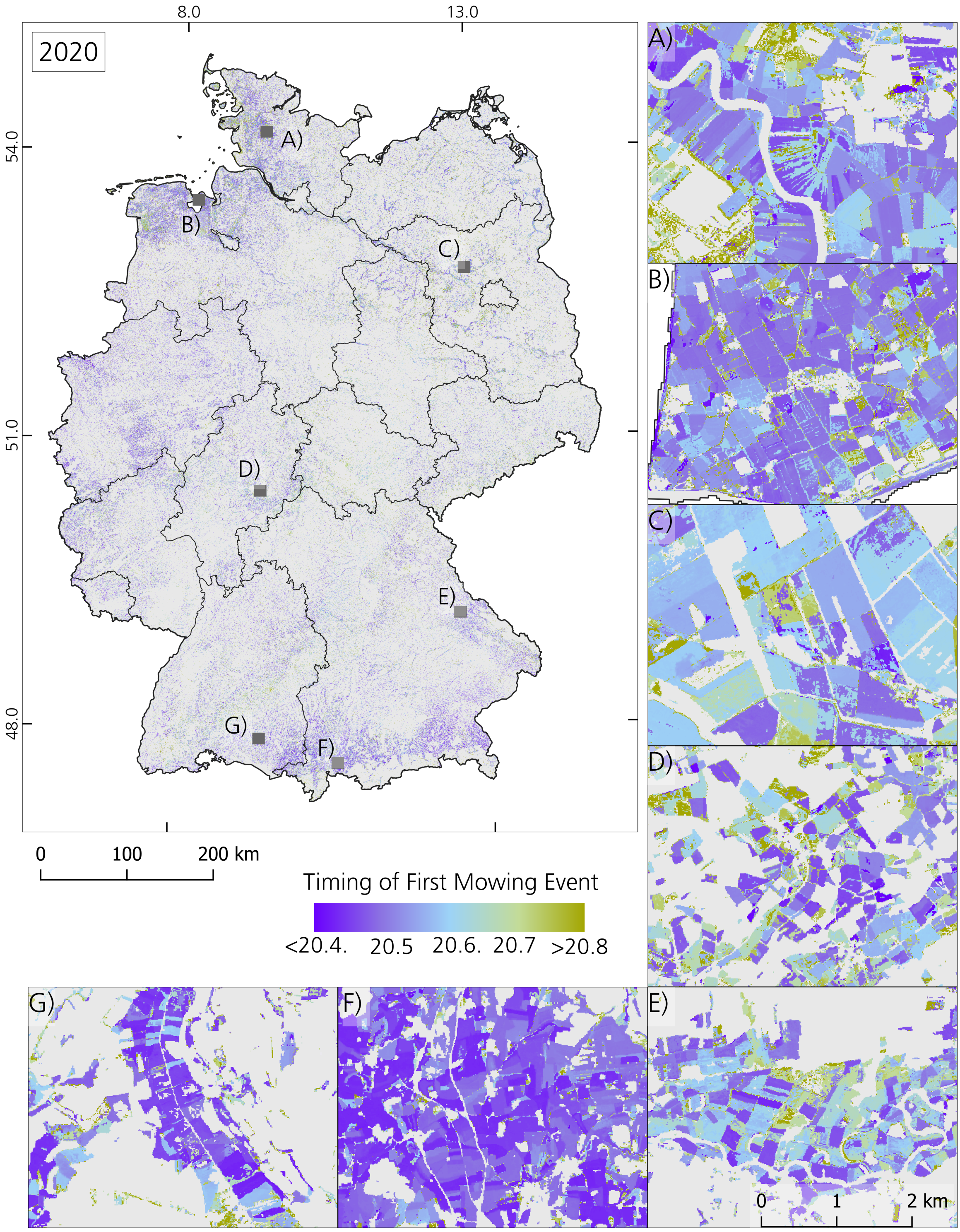

Figure 4.31: Detected date of first mowing event in 2020 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

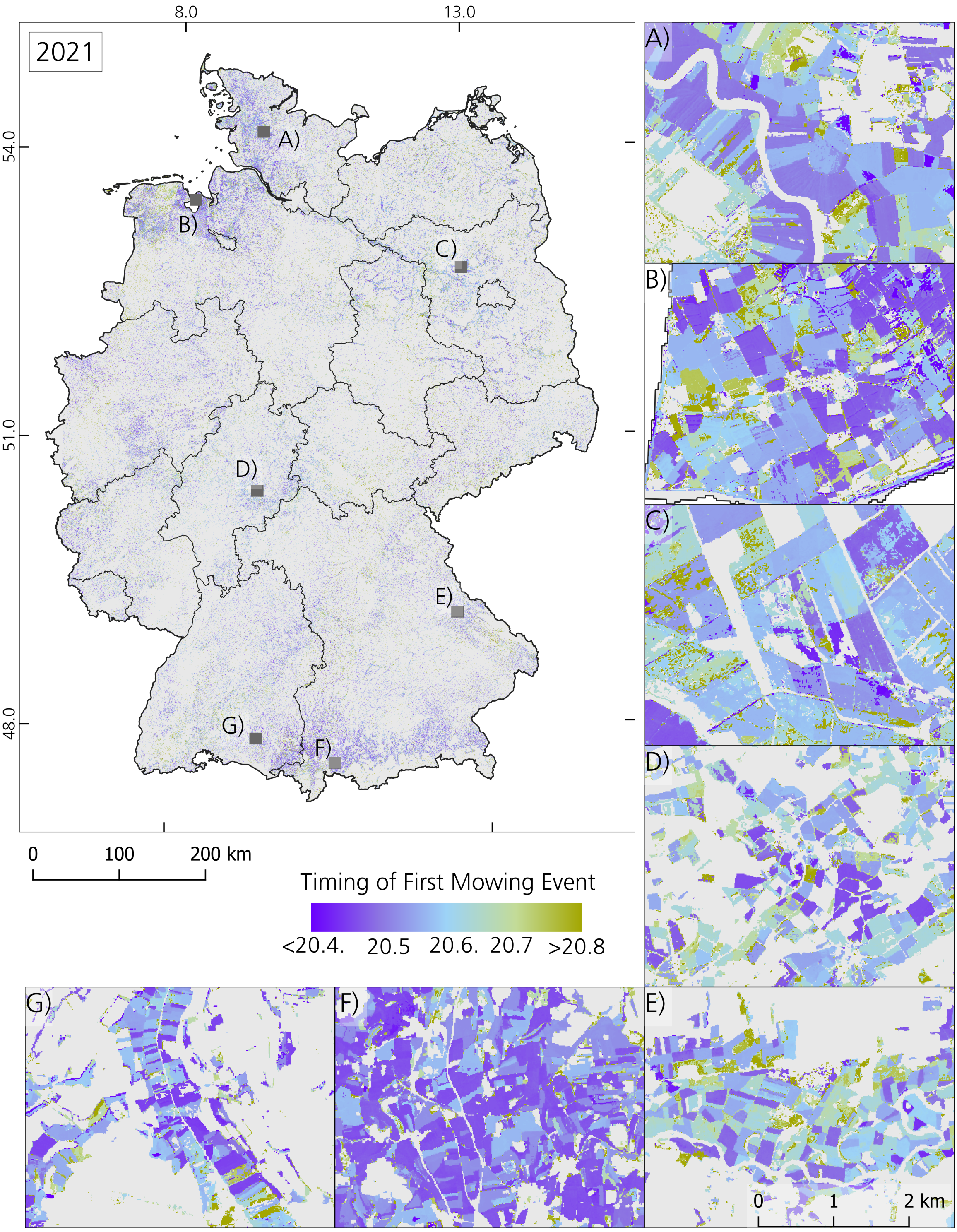

Figure 4.32: Detected date of first mowing event in 2021 based on S2 in high resolution with the zoom regions A: Schleswig Geest, B: Weser Marsh, C: North Brandenburg Plateaux and Upland, D: Vogelsberg mountain, E: Upper Bavarian Forest, F & G: Southern Alpine Foreland.

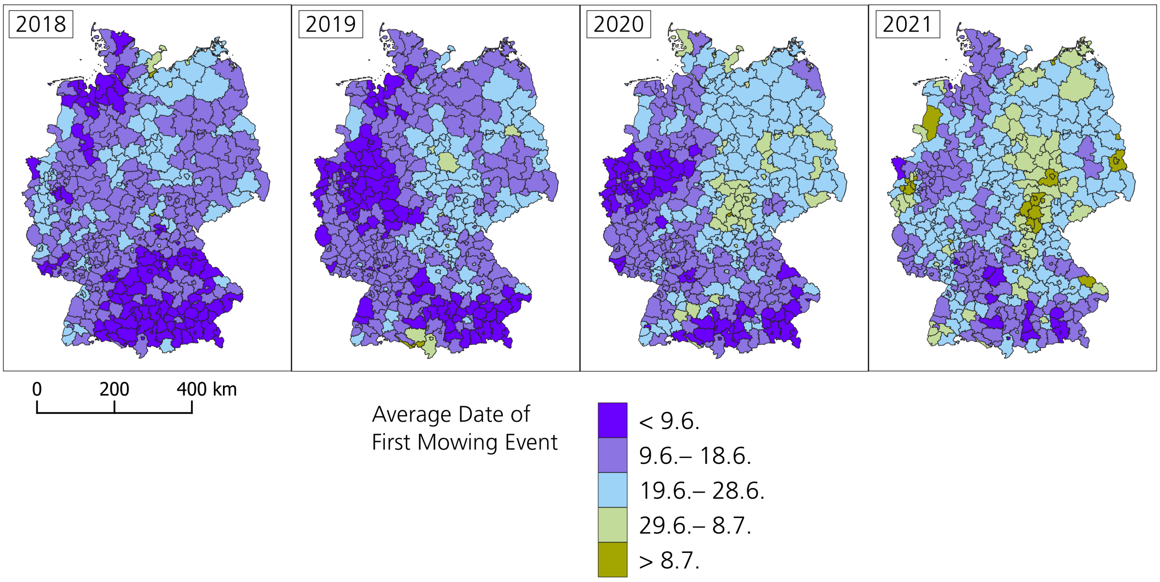

Figure 4.33: Timing of first mowing event for 2018, 2019, 2020 and 2021 averaged per county.

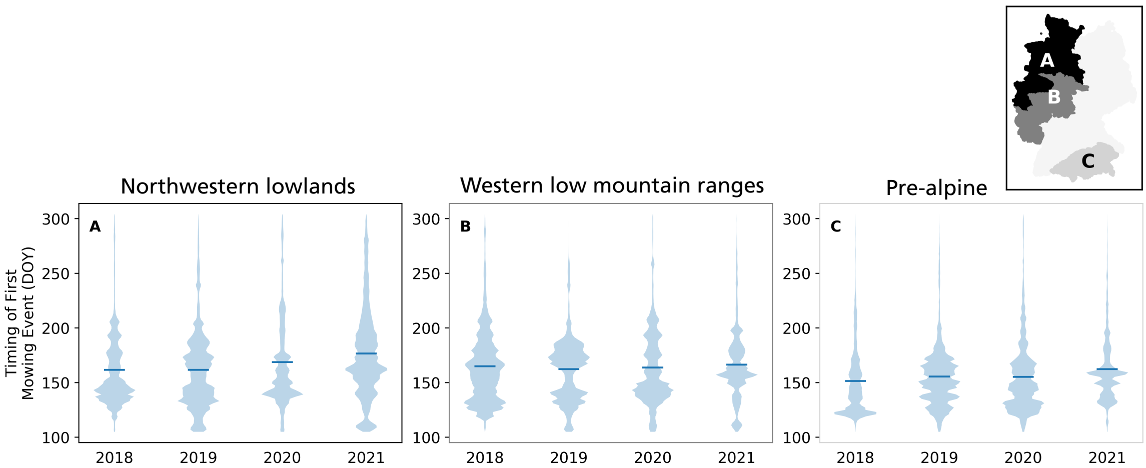

Figure 4.34: Frequency distribution of the timing of the first mowing event for three natural landscapes (A–C) in Germany for 2018–2021. The blue line indicates the mean. Adapted from (Reinermann et al., 2023).

4.3.3.3 Hotspot Regions of high Mowing Intensity

The shares of extensively as well as intensively used grasslands, grasslands with intermediate use and early mown grasslands per grassland area per district highlight hotspots of use preferences (i.e. hotspots of extensive or intensive grassland use) (Figure 4.35 A–D). All districts of Germany are characterized by a share of extensively used grassland (mown zero to one time) of at least 10 % (Figure 4.35 A). For many districts in the center and eastern parts of Germany, the proportion of extensive grassland is around 50 %. Some districts show shares of extensively used grasslands of up to 93 %. The districts which show high shares of grasslands with intermediate use (mown two to three times) (Figure 4.35 B) seem to be opposed to the ones with high shares of extensively used grassland (Figure 4.35 A). This is related to the fact that only small proportions of grasslands within districts are intensively used (Figure 4.35 C) and, therefore, the large proportion of grasslands are used extensively or show intermediate use. Shares of grasslands with intermediate mowing frequencies reach 72 % of the grassland area of a district, which can be mostly found in southern or western parts of Germany (Figure 4.35 B). Grasslands with high mowing frequencies show two hotspot regions in Germany, which are in the north-west and in the south-east of Germany (Figure 4.35 C). While only some districts in the north-western hotspot region reach shares of intensively used grasslands of up to 15 %, the south-eastern hotspot region reveals many districts with proportions of intensive grassland of more than 20 %. Districts with shares of grassland mown before first of June of at least 50 % can be found in south-eastern Germany (partly overlapping with districts characterized by high shares of intensively used grasslands), but also in western Germany (Figure 4.35 D).

4.3.3.4 Comparison with Phenology Data

The results of the multi-annual mowing detection were compared to phenology information about the greening and mowing of grasslands, based on observations (compare section 4.1.3). Surprisingly, the greening of permanent grassland in 2018 was rather late according to this data (Figure 4.36), even though the spring of 2018 was characterized by mild temperatures resulting in an early onset of vegetation activity (Reinermann et al., 2019). The observed first silage and hay cuts in 2018 were relatively early compared to 2019–2021 (Figure 4.36) which is in accordance with our findings as the detected first mowing dates in 2018 were earlier than for the other years for large parts Germany. The phenology information shows that the year 2021 was characterized by late grassland greening and late observed silage and hay cuts which is also in accordance with our findings concerning the detection of the first mowing event in 2021. The overall spatial patterns of

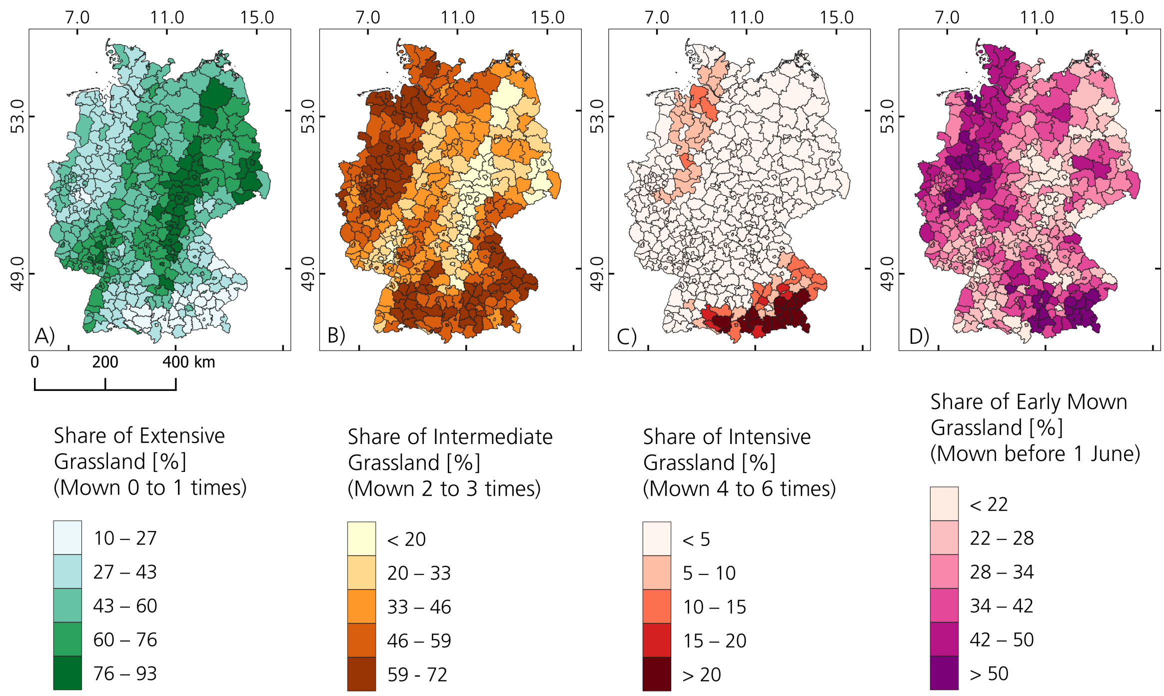

Figure 4.35: The share of extensively mown grassland (zero to one mowing event) (A), intermediately mown grassland (mown two to three times) (B), intensively mown grassland (mown four to six times) (C) and early mown grassland (before 1st of June) (D) for the year 2020, averaged per county.

areas for which rather early silage and hay cuts were observed for all years also overlap with areas for which early first mowing events were detected within this thesis.

The phenology information is a valuable source to compare the results with observation-based data and evaluate the plausibility of the overall patterns of the results. These data sets, however, lack high resolution information on sub-parcel level and cannot substitute an automated mowing event detection algorithm.

4.3.4 Estimation of Mowing Detection Uncertainty

An uncertainty layer was developed (compare section 4.2.3) which informs on the overall reliability of the detected mowing events based on S2 EVI. The uncertainty measure consists of two components, the time spans between actual observations right before and after a detected mowing event and the magnitude in change in amplitude of the EVI of a mowing event and ranges around zero. The uncertainty was estimated for the focus region for all detected mowing events of 2019 (Figure 4.37). Values below zero are related to higher uncertainties and vice versa. It is shown that at times entire parcels are characterized by higher mowing detection uncertainty levels. However, in many cases field borders or small and irregularly shapes grassland parcels show higher uncertainty. This might be related to influence of mixed pixels at field borders, for instance. The western part of the

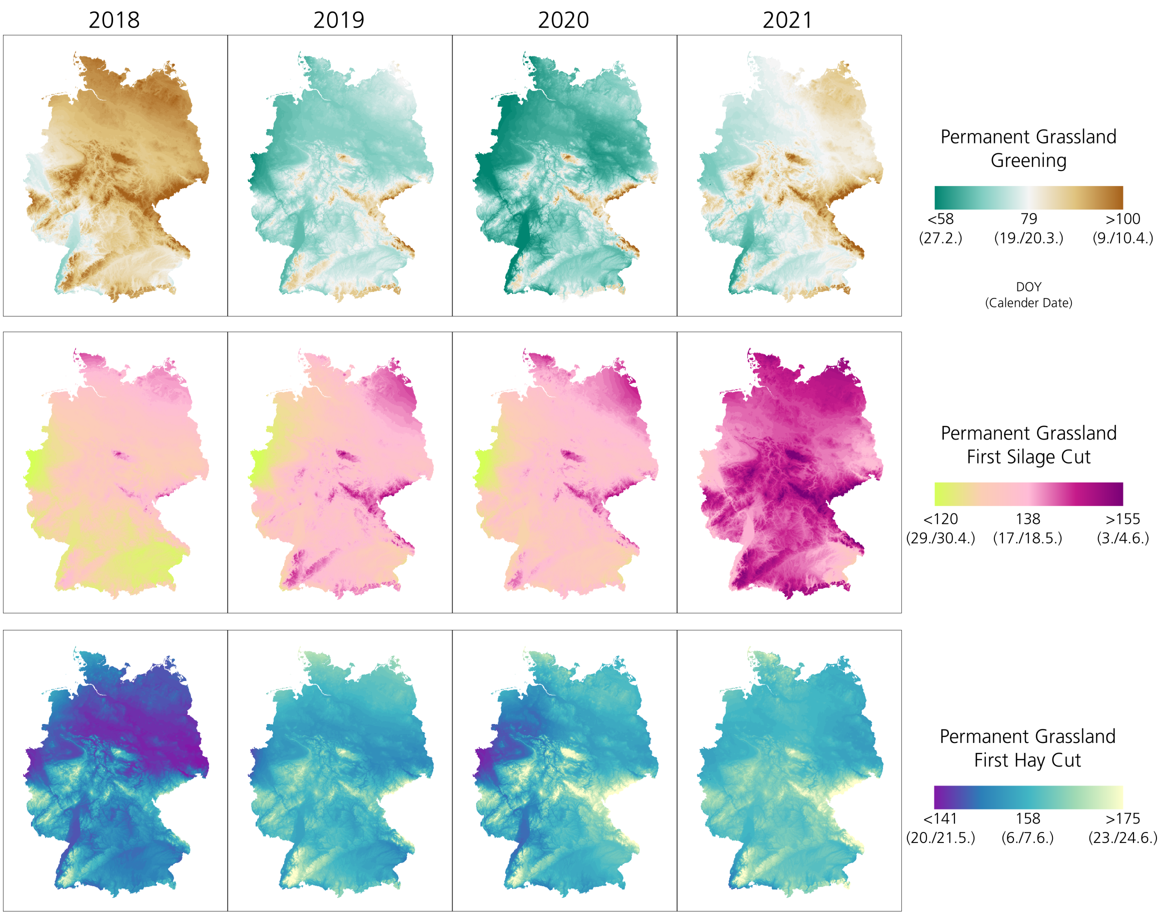

Figure 4.36: Grassland phenology information based on observations of the German Weather Service (DWD), including the greening of permanent grasslands and the first silage as well as hay cuts, for the years of interest (2019–2021).

focus region shows overall higher levels of uncertainty (Figure 4.37). The reason for that is that this area is only covered by one S2 orbit while the remaining area of the focus region is characterized by the coverage of two overlapping orbits (compare Figure 4.1) resulting in a difference in data availability (compare Figure 4.4). The lack of cloud-free S2 observations influences both uncertainty measure components leading to higher levels of uncertainty when less data is available. This pattern is also visible when examining the occurrence of large data gaps within the S2 time series (Figure 4.38). the same area which shows high levels of uncertainty is also characterized by the occurrence of large data gaps which were defined by at least 25 days without cloud-free observation. The spatial pattern of the number of large data gaps is related to the MAJA cloud detection approach.

4.3.5 Accuracy Assessment

The Germany-wide mowing detection between 2018 to 2021 was validated with an independent validation data set which consistent of 1475 mowing events on 179 grassland parcels for 2018–2021 (section 4.1.2). Allowing a time difference of up to seven days between the detected and the actual mowing date, the highest number of correctly detected mowing events was achieved in 2020 (66.3 %), followed by the results of 2019 where 63.3 % of the mowing events were correctly detected (compare Table 4.5). In 2018 and 2021, a fewer number of mowing events was correctly detected (57.4 % and 46.4 %, respectively). Within the year 2019, the highest exactness of the mowing detection (precision) was achieved. While the number of correctly detected mowing events informs on the quantity of the detection approach, the precision is a measure of the quality as it is defined as the number of correctly detected events of all detected events, i.e. informing about the share of falsely detected mowing events. The lowest precision was found in 2018. The F1-score which is a statistical accuracy metric combining the amount of correctly detected events and the precision (section 4.2.2) was highest for 2019 (0.64), closely followed by 2020 (0.63).

While the previous accuracy measures accounted for every detected or undetected mowing event individually, also the overall quality of the algorithm to predict the mowing frequency correctly (and if not, by how far) was assessed. The annual mowing frequency was correct for about one third of grassland parcels in 2020 resulting in the highest accuracy among the years regarding the mowing frequency. This result is followed by 2018, for which 28 % of grassland parcels showed the correct mowing frequency. Only one event apart from the actual mowing frequency were around one half of grassland parcels in 2019 (54 %) and 42 % in 2020. The number of days between actual and detected mowing date was smallest for 2019 and highest for 2021. The allowed time span between actual and

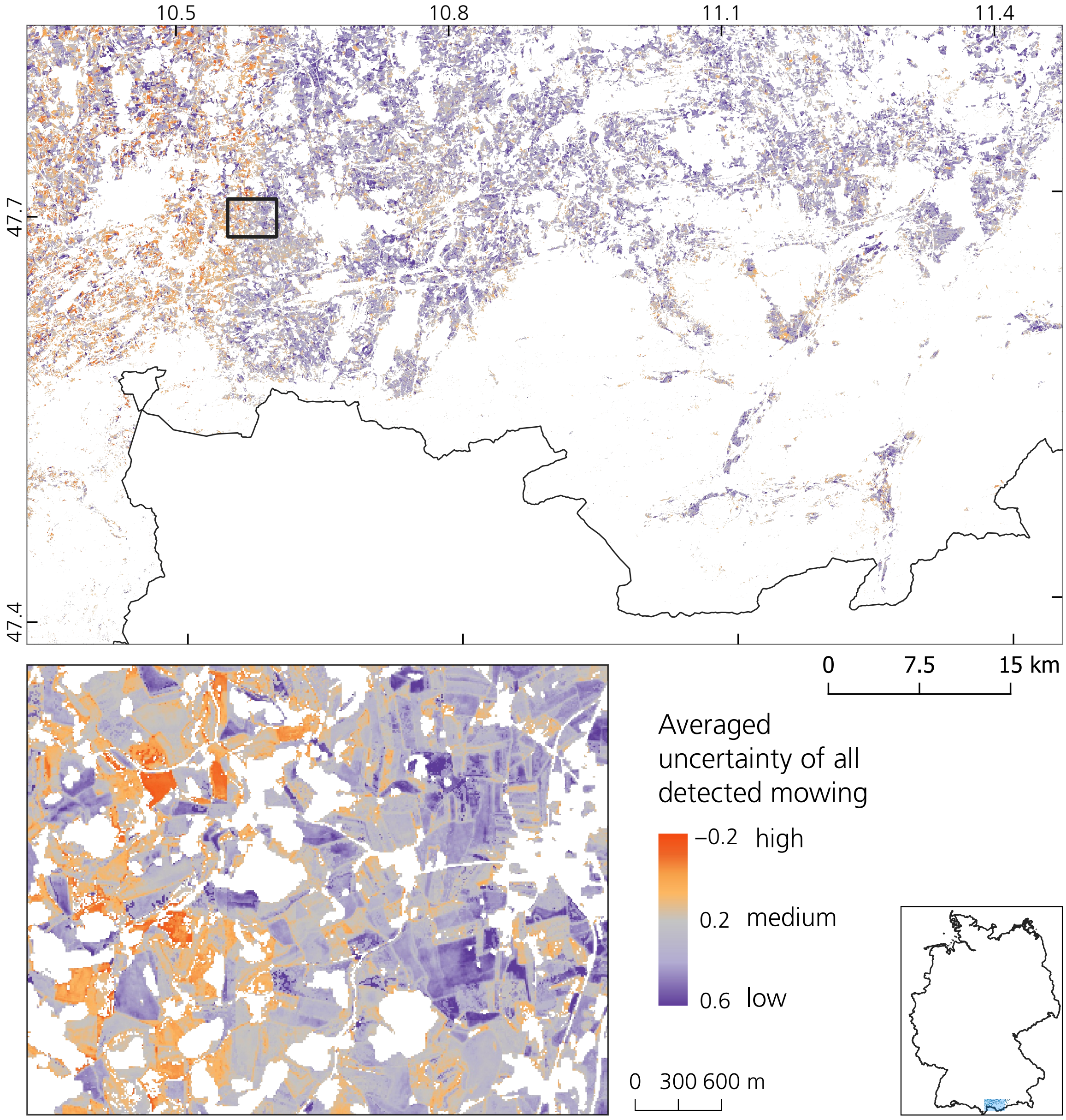

Figure 4.37: Estimated uncertainty of all detected mowing events in 2019 which was based on two components, namely the time span between actual observations before and after detected mowing events and the gradient of the EVI during a detected mowing event.

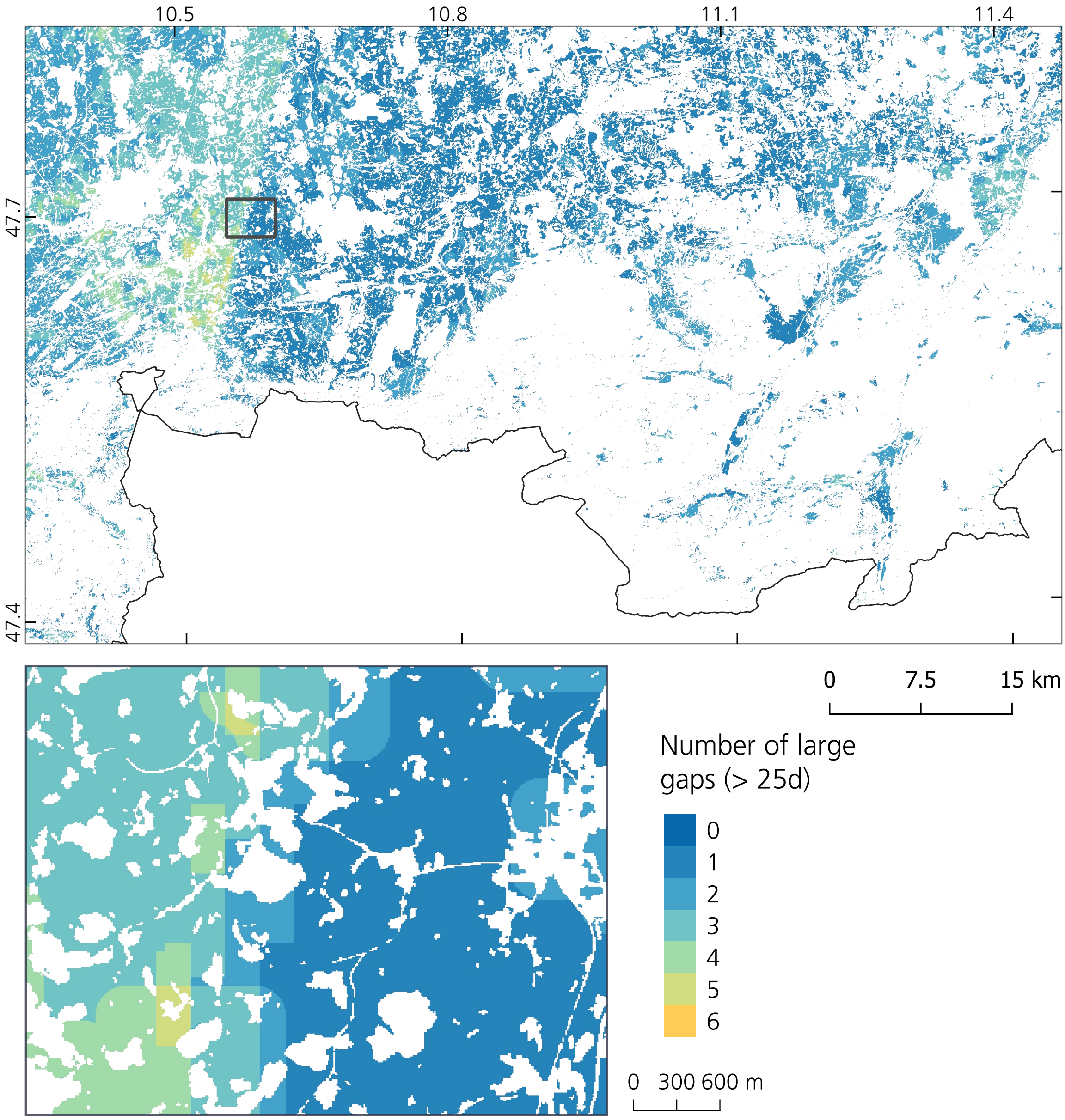

Figure 4.38: Number of large data gaps, which were defined as larger than 25 days, of the pre-processed and cloud-screened EVI time series for 2019. It informs on the distribution of the data availability of S2.

detected mowing date for a mowing date to be classified as correctly detected, has a high influence on the detection accuracy which is illustrated in Figure 4.39 for the mowing detection in 2019. For small numbers of allowed time difference betwen actual and detected mowing dates (i.e. zero to four days), the jumps in the number of detected mowing events when adding one day to the allowed time difference are high. These changes are smaller in the value range of a higher number of allowed time difference (i.e. ten to 14 days).

Table 4.5: Results of the validation of the EVI-based grassland mowing detection of Germany for 2018–2021 with the reference data set.

	2018	**2019**	**2020**	**2021**
Correctly detected mowing events	57.4%	63.3%	66.3%	46.4%
Precision	0.48	0.66	0.60	0.53
F1-Score	0.52	0.64	0.63	0.50
Share of grassland parcels with no difference in detected and true mowing frequency	28%	20%	34%	19%
Share of grassland parcels with a difference in detected and true mowing frequency of one	35%	54%	42%	33%
Average days between detected and true mowing date	2.9	2.5	2.7	3.4

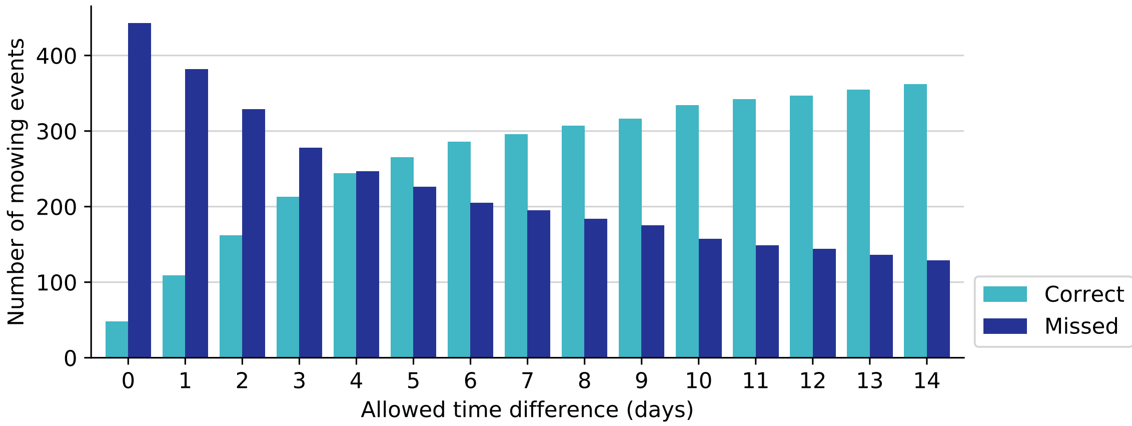

Figure 4.39: Number of correctly detected and missed mowing events with different allowed time spans between actual and detected mowing date based on S2-based mowing detection of 2019.

4.4 Discussion

4.4.1 Multi-annual Mowing Dynamics in Germany

The detection of the mowing frequency and the timing of mowing events led to plausible results. Between zero to six mowing events were detected per year for individual grasslands which is in accordance with information of the German federal agency for nature protection and the reference data set (Schoof et al., 2020b,a). Even though the mowing detection algorithm works on pixel basis, the borders of grassland parcels become visible when mapping mowing frequency or the timing of the first mowing event which indicates that the approach works successfully. However, shapes of grassland parcels are not needed for the algorithm which is an advantage over other approaches which need such information (De Vroey et al., 2021, 2022). In many cases, grasslands are used differently on sub-parcel-level which means that they are only mown or grazed partly. This leads to difficulties for approaches investigating grassland management on parcel level, but is accounted for in the pixel-wise, high-resolution approach of this thesis.

The spatial patterns of the detected mowing frequency in Germany overlaps with the results from Schwieder et al. (2021) who also found high mowing frequencies in southern/south-eastern Germany and an annual frequency range of up to six mowing events. Another study found mowing frequencies of up to three events only, even in regions in southern/south-eastern Germany (Lange et al., 2022). However, bulletins from the German federal nature protection agency and our reference data set show that grasslands are indeed mown up to six times per year in these regions (Schoof et al., 2020b,a).

The reason for the relatively large share of high mowing frequency grasslands in the south/south-eastern part of Germany might be the high precipitation rates (section 3.1). In addition, the overall share of grasslands is high in these areas as the landscapes are hilly and, therefore, not as favorable for agricultural crop cultivation. The numbers of cattle and farms focused on milk production are highest in Bavaria (south-eastern Germany), followed by Lower Saxony (north-western Germany) which is the second most intensive region regarding mowing frequency (Statistisches Bundesamt, 2020).

By comparing all four investigated years to each other, it becomes clear that the general picture of mowing intensity stays relatively constant as the regions with large shares of high mowing frequencies show these patterns for 2018–2021 as well as regions with large shares of low mowing frequencies. This is related to the fact that varying management strategies and use intensities have an impact on grassland ecosystems and shape their functionality on the long term and, therefore, presumably stay the same (compare section 1.1.2). Extensive grasslands with high numbers of species on moist sites, for example, would not produce large amounts of yields just because they are mown more often in one year (Le Clec'h et al., 2019).

However, the detailed analysis of mowing dynamics on parcel level (Figures 4.21 to 4.24 and 4.29 to 4.32 A–G) showed that there are some small variations and grasslands are not managed entirely the same every year. It can be assumed that farmers react to external changes (e.g., weather conditions), but rather in one additional or less mowing event or a shift in the timing of mowing events than a complete change, e.g. from intensive to extensive usage.

In 2018, the first mowing event was conducted earlier compared to the other years. For some regions (e.g. in the north), the mowing frequency in 2018 was lower, for other regions (e.g. in the south) it was higher. The year 2018 was extremely hot and dry (Deutscher Wetterdienst, 2020) which might have influenced the grassland mowing dynamics. The months April and May in 2018 were relatively warm which resulted in an early onset of vegetation growth in spring (Reinermann et al., 2019; Deutscher Wetterdienst, 2020). This early spring resulted in relatively early first mowing events in large parts of Germany as found in this thesis. An overall strong reduction of the mowing frequency due to hot and dry weather conditions and stressed vegetation was not found apart from local effects. This might be related to the fact that many grasslands occur in rather moist sites and are not severely affected by drought. Kowalski et al. (2022) found small drought effects in moist grassland sites in north-eastern Germany which is in accordance with these findings. Further, here, mowing dynamics are investigated in contrast to yields. It is possible that mowing activities stayed the same in 2018, but yields were reduced. Schwieder et al. (2021) found lower numbers of mowing frequency for some parts of Germany compared to other years, however also only to a small degree.

It was observed that grasslands with a higher mowing frequency also show earlier first mowing events compared to grasslands with lower numbers of mowing events per year. In addition, the timing of the first mowing event is influenced by weather conditions and the growth rate of the grassland vegetation. However, there is also a political influence on the timing of the first mowing event. As early mowing constitutes a disadvantage for man plant species and consequently for insects and spiders, as well as breeding birds, there are monetary incentives provided by the German government for farmers to conduct later mowing in spring (Dengler et al., 2014; Schoof et al., 2020a). The subsidy payments are coordinated per state and, therefore, vary, but often the first of June is the effective date according to which farmers a payed if the have not mown their grassland parcel before.

The year 2019 showed intermediate mowing intensities, 2020 the highest for large parts of Germany. 2020 presumably had favorable weather conditions for grassland growth, it was rather warm but not as dry as 2018 (Imbery et al., 2021). The year 2021 showed the smallest mowing intensity when comparing all years. In addition, the first mowing event was comparably late in 2021. The reason for these patterns is the cold spring as in particular April 2021 was very cold (Deutscher Wetterdienst, 2022a). This led to late vegetation growth onset in spring and presumably shifted the mowing activities to later dates and/or reduced the number of possible harvests.

4.4.2 Advantages and Drawbacks of Grassland Mowing Detection based on S2 and S1

4.4.2.1 Patterns of the Mowing Detection Accuracy

The developed mowing detection approach applied for the entire grassland area of Germany resulted in F1-Scores between 0.5 to 0.64 which is in a similar range compared to other studies conducting grassland mowing detection on large scales (Schwieder et al., 2021; De Vroey et al., 2021, 2022). For a majority of grasslands in Germany, the mowing frequency was either correctly detected or off only by one mowing event. Consequently, the overall grassland mowing intensity can be captured by applying the developed algorithm.

Even though the accuracy statistics were similar among previous studies and this thesis, the comparison of varying approaches for grassland mowing detection is challenging as the accuracies strongly depend on the validation data set. As there is no public information on grassland management in general, or mowing dynamics in particular, the acquisition of validation data itself is effortful. In addition, grasslands in Germany (and worldwide) show a large variety with varying mowing frequency and timing of mowing activities which should be captured by the validation data to guarantee a meaningful accuracy assessment. Here, we generated an extensive validation data set including grasslands showing the entire possible range of mowing frequencies (up until 6 per year) and a large share of intensively mown grasslands (high mowing frequencies). In addition, our approach had the advantage that the reference data was based on webcam images and was, therefore, independent from satellite images in contrast to other studies (Kolecka et al., 2018; Schwieder et al., 2021). A validation data set based on satellite imagery has the disadvantage that it is potentially biased towards cloud-free observations leading to a potentially biased accuracy assessment. During cloudy weather conditions mowing events are missed while generating a validation data set based on satellite images which biases the accuracy towards better results when these mowing events are also missed in the detection approach. Furthermore, the allowed time period between actual and detected mowing date varied between studies. The time span for which a detected mowing date is considered correct naturally influences the detection accuracy (compare Figure 4.39).

The mowing detection accuracies of this study varied between the years, with 2019 as well as 2020 showing higher and 2018 as well as 2021 lower F1-Scores. The year 2018 was exceptionally hot and dry in Germany leading to stress conditions for the vegetation (Deutscher Wetterdienst, 2020; Reinermann et al., 2019). This probably impairs the mowing detection accuracy as the mowing of dried, brown vegetation would not lead to a strong drop in the EVI signal or the drying process itself is falsely detected as mowing event. The accuracy assessment speaks for the latter case as 2018 showed the highest number of false positives among the investigated years. However, also the validation data set of 2018 was smaller compared to the other years as it consisted of about one-fourth of mowing events only, which has an influence on the accuracy. Also 2021 (F1-Score=0.50) revealed weaker accuracies compared to 2019 (F1-Score=0.64) and 2020 (F1-Score=0.63). The year 2021 was characterized by higher rates of cloud coverage which impaired the availability of dense time series which probably weakens the mowing detection success, especially as a purely S2-based approach, hence relying on cloud-free conditions, was applied in the end. The approach was designed with data from 2019 which is probably the reason for the high accuracies of this year. However, also 2020 reached accuracies almost as high as in 2019. It shows that the approach is transferable to other years with similar or better data availability without losing detection accuracy. An assessment for the future would be to test if complementing the mowing detection approach based on S2 with S1 data would lead to improvements during years with relatively high cloud coverage rates, such as 2021.

4.4.2.2 The Potential and Drawbacks of S2 to Detect Grassland Mowing Events

Previous studies already investigated vegetation indices, like the NDVI or EVI regarding their potential to capture grassland mowing events. In the past, mostly the NDVI was used for which drops of 0.2 to 0.5 of the raw time series were found after mowing events for various European grasslands (Courault et al., 2010; Kolecka et al., 2018; Griffiths et al., 2020). The EVI was used more recently as it appears to saturate not as quickly as the NDVI for grasslands which is also the reason why it was used here. Within this study, we found that the exact threshold to detect a mowing event within the optical time series is not that critical. For a range of 0.1 of EVI equivalents (from 0.2 to 0.12) of tested thresholds the accuracy of the mowing detection remained the same for the parametrization sites. The critical factor is that there is a detectable signal change within the vegetation index which is largely determined by the data availability. The results suggest that in particular optical satellite imagery showing high spatial and temporal resolution, like S2, is needed to successfully detect grassland mowing events.

The availability of optical data plays an important role for grassland mowing event detection. Approaches based on vegetation indices derived from optical data have shown to successfully detect grassland mowing events (Kolecka et al., 2018; Schwieder et al., 2021). However, the local minimum caused by a mowing event is only visible for a few days (around ten) within the time series of vegetation indices as the grassland vegetation grows back rapidly. Therefore, the availability of dense and cloud-free time series of optical data is necessary to detect all mowing events successfully. As the orbit coverage of S2 is not uniform within Germany, there are areas with image acquisitions every second and third day and areas with acquisitions every fifth to sixth day. The areas which are covered by only one orbit have a lower amount of continuously available dense data and, consequently, there might be less mowing events detected there (compare Figures 4.1 and 4.4). Including satellite data from different sources, like backscatter, interferometric coherence or polarimetric decomposition parameters of S1, did not lead to an increase in grassland mowing detection accuracy as presented here. Adding an additional optical dataset (L8) also did not reveal a substantial improvement of mowing event detection in Germany (Schwieder et al., 2021).

4.4.2.3 The Potential and Drawbacks of S1 to Detect Grassland Mowing Events

Mowing detection is best captured by the EVI time series, however, some mowing events are potentially missed by the EVI algorithm during cloudy weather conditions. In particular in areas which are not covered by two S2 orbits, there remains an underestimation of mowing activities. Within this thesis, several SAR-based parameters were tested to complement the EVI detection, consisting of backscatter intensity and InSAR Coherence in both polarization geometries each and PolSAR decomposition features Entropy, K0 and K1.

The backscatter intensities showed at times increases after mowing events which were, however, inconsistent. The literature on the potential of SAR backscatter to capture grassland mowing events is divided. Some found significant increases of the SAR backscatter signal after mowing events (Schuster et al., 2011; Grant et al., 2015a,b). However, other studies found no consistent visual or statistical relationship between the SAR backscatter signal and grassland mowing events (Zalite et al., 2015; Tamm et al., 2016) which is in line with our results. It is possible that varying moisture conditions lead to the inconsistency in the backscatter patterns as dielectric properties affect the signal. Another possibility is that the backscatter's reaction towards mowing events varies because the procedure on ground differs. Often, the grass remains on the parcel for some days after mowing to dry. In this context, the grass is at times left flat, at times put together to lines. However, comparisons of these management procedures extracted from the reference images (webcams) with the backscatter did not reveal a systematic behavior.

The InSAR Coherence parameters were also not able to completely capture grassland mowing events successfully. Actual mowing events were often followed by peaks in Coherence VV and VH, but there were many additional peaks detectable within these time series which were unrelated to mowing activities. Within other studies, the InSAR Coherence of various sensors was also often inconsistent regarding its behavior to grassland management activities (Zalite et al. (2014, 2015) for COSMO-Skymed; Ali et al. (2017b) for TerraSAR-X; Voormansik et al. (2020) for S1). In addition, the Coherence signal over grassland is very close to the noise level which makes its interpretation less reliable (Wegmuller and Werner, 1997). De Vroey et al. De Vroey et al. (2022) included the S1 Coherence into a mowing detection approach and states that it was an improvement, however, the overall accuracy was not improved as the F1-Score decreased from 0.64 to 0.58 for their research site in Belgium.

PolSAR decomposition parameters were so far only sparsely investigated regarding grassland mowing detection. Similarly to our results, previous studies – which investigated PolSAR decomposition features based on TerraSAR-X and Radarsat-2 (Voormansik et al., 2013, 2015) – found some relationships between PolSAR parameters and grassland mowing activities, e.g. an increase in Entropy after mowing events. However, these increases were not consistent and the interpretation remains challenging. One explanation is that grown grass is more up-right and therefore vertically oriented while mown grass on the grown is horizontally oriented. Following this explanation, grassland mowing activities would lead to an increase in depolarization and, therefore, Entropy. This is in accordance with our findings as an many cases, Entropy increased after mowing events. However, as the entropy time series shows additional peaks unrelated to mowing events, disentangling the reaction to mowing events from other influencing factors would be required.

4.4.2.4 The Potential and Drawbacks of the S2 and S1 combined

As the optical as well as the SAR-based parameters have their advantages and disadvantages in detecting grassland mowing events, one hypothesis of this thesis was that a combination of both might result in the best results. As the optical parameter – the EVI time series – showed a more consistent behavior and, hence, a much higher potential regarding grassland mowing detection compared to the SAR parameters, these were only considered in periods for which the EVI-based algorithm potentially fails, namely in long data gaps, within this study. However, the SAR-based detection still led to a strong increase in falsely detected mowing events resulting in overall smaller F1-Scores compared to the EVI-only approach. In a classification-based approach to detect grassland mowing events with a deep learning algorithm, Lobert et al. (2021) found best results when including the NDVI, backscatter cross-ration and InSAR Coherence. However, this was only tested for a small area which was characterized by coverage by two S2 orbits and a large-scale application still needs to be tested. As previously mentioned, De Vroey et al. De Vroey et al. (2022) combined S1 and S2 parameters to detect grassland mowing events and stated that including SAR information supported the detection, however the F1-Score decreased. Including PolSAR features, such as Entropy, in a classification approach based on EVI to detect grassland mowing events and, hereby, in particular in a deep learning model might improve detection accuracies in future studies.

4.5 Summary

An automated mowing detection algorithm was developed based on Sentinel time series data. The approach was knowledge-based as it was developed according to observations and analyses undertaken using parametrization sites. Therefore, an extensive reference data set was generated used to develop the algorithm and to validate the results. The reference data set was created by the exploitation of daily RGB images of self-installed (11) and public webcams (69) distributed in Germany. Mowing dates during the years 2018–2021 were extracted from the camera images resulting in 1475 mowing dates available for validation on 179 grassland parcels in Germany. In addition to that, mowing information of 13 grassland parcels, including all mowing intensity levels, in the south of Germany in 2019 was collected based on which the mowing detection approach was developed and parameterized. Hence, S2 and S1 parameter were investigated to analyze if the effects of grassland mowing events were visible within the time series, consisting of the EVI, the backscatter intensity VH, the backscatter intensity VV, the polarimetric decomposition parameters K0, K1 and Entropy, and the interferometric coherence VH and VV.

The EVI showed the largest and most consistent change in amplitude following a mowing event. Hence, an EVI-based mowing detection approach was developed which consisted of the location of strong decreases within the time series followed by an immediate increase. The thresholding (amplitude of decrease) for the mowing detection was conducted using the 13 parametrization sites. The EVI approach successfully detected most mowing events apart from mowing activities taking place during cloudy weather conditions. Therefore, a second mowing detection algorithm was developed in which the EVI algorithm was complemented by a S1 parameter. All S1-based parameters showed less consistent reactions towards mowing events compared to the EVI and additional fluctuations unrelated to mowing activities within their respective time series were visible when investigating the parametrization sites. Hence, in the combined approach mowing events were detected by the EVI and only during periods of long cloud gaps (> 25 d), the S1-based mowing detection is initiated. Out of the S1 parameters, the PolSAR Entropy and the InSAR Coherence VH showed the most promising results to successfully detect mowing events which is why the S1 and S2 combined detection approach was tested with Entropy and InSAR Coherence as input parameters. The S2-only and the combined (S2 and S1) approach were applied and validation in a focus region in southern Germany in 2019. The resulting mowing frequencies differed as with the combined approach more mowing events were detected than with the S2-only algorithm. The validation showed that the combined detection algorithm often overestimated the mowing frequency. The F1-Score of the EVI approach was highest (0.65) as the detection complemented with S1 led to many false positives resulting in F1-Scores of 0.61 (Entropy) and 0.61 (Coherence VH).

The S2-only approach was therefore further developed and applied to the entire grassland area of Germany and for the years 2018–2021. The application of the pixel-wise algorithm using EVI time series resulted in detected mowing dates for all four years, based on which annual grassland mowing frequencies and the timings of the first mowing event per year were extracted and analyzed in detail. The resulting maps showed that extensively mown grasslands (zero to one mowing event) occur everywhere in Germany, the highest shares of grasslands with extensive grassland use are found in central and north-eastern Germany. Hotspots of intensive grassland mowing (more than three times) are in south-eastern Germany showing most intensively used grasslands, followed by an area in northern Germany. The spatial patterns of grassland mowing frequency and the timing of the first mowing event stayed constant throughout the four investigated years. However, variability in mowing dynamics was found on small scales. The accuracy assessment of the national, multi-annual mowing detection showed higher mowing detection accuracy for 2019 (F1-Score=0.64) and 2020 (F1-Score=0.63) compared to 2018 (F1-Score=0.52) and 2021 (F1-Score=0.50). This is probably related to the extreme climatic conditions in 2018, which was an exceptionally dry and hot year in Germany and the relatively weak data availability in 2021, resulting from higher cloud cover rates. The high accuracy in 2020 shows that the EVI-based mowing detection approach is successfully transferable into different years with relatively similar weather conditions as the year 2019, for which the detection algorithm was developed.

Chapter 5

Relationships of Mowing Dynamics to external Conditions*

Agriculture, with grassland usage as a major contributor, have a huge impact on the earth's surface, on fluxes and functions of ecosystems. It plays a central role in critical global aspects, like climate change and the loss of biodiversity and ecosystem functionality (as outlined in section 1.1). However, the agricultural sector, with grassland management as important contributor, is also an important area of potential action as it is man-made and adaptations are often quickly implemented and do not require high budgets ((IPCC, 2019)). In addition, the agricultural sector is strongly affected by climate change. The increase in drought and heat extremes has an accelerated negative impact on vegetation growth in the future which requires adapted, sustainable management strategies. For the development of management plans, information on current practices are needed, e.g. how often grasslands are mown and how these are distributed in Germany, as investigated in chapter 4.3.3. However, the question on why grasslands are managed that way remains. The conditions which have to be fulfilled for rather intensive grassland management or extensive management are usually unknown. A quantification of incentives of farmers about their management practices is challenging. Information on these aspects are, however, valuable to create sustainable management strategies for future climates which conserve and protect grassland ecosystem functions.

In Germany, grasslands occur mostly in areas which are characterized by lower productivity as higher productive regions are mostly used for crop cultivation, resulting in many grasslands in areas with relatively high moisture levels, steep slopes or less qualitative soils (Bruns et al., 2000). This is the result of multiple conversions of grassland into cropland in the past and a general intensification and homogenization of landscapes in Germany (Wolff

*Parts of this chapter have been published in Reinermann et al. (2023).

et al., 2021). In general, agricultural land is usually more intensively used when the abiotic conditions are suitable, however, also socio-political conditions have a strong influence (Levers et al., 2018). The external conditions and circumstances for intensive or extensive grassland use are not known for larger spatial areas.

Hence, within this chapter of the thesis, the relationship between abiotic and socio-political conditions to mowing dynamics are compared to analyze which aspects are important and which conditions have to be fulfilled for certain grassland usage. The investigated data consists of climate data (precipitation and temperature), topographic data (elevation and slope), soil data (soil classes) and conservation schemes (Natura 2000 sites). In addition, the mowing dynamics are compared to grassland productivity and yield indicators to investigate if there is a relationship between mowing intensity and productivity or yields. In the following, first, all data sets are described (section 5.1), then the pre-processing and analysis of the data is presented in the methods section (section 5.2). Afterwards the results of the analysis are presented (section 5.3) and, finally, these are discussed and summarized (sections 5.4 and 5.5).

5.1 Data

5.1.1 Satellite Data

S2 data from Copernicus (Drusch et al., 2012), pre-processed using the MAJA algorithm (version 3.3, Hagolle et al. (2017)), were used to provide the information on mowing dynamics in Germany. All scenes between March to November 2018–2021 for the entire area of Germany were downloaded consisting of 64 S2 tiles. Within 2020, there are overall most clear sky observations available which is why this year was selected to investigate relationships of mowing dynamics to abiotic and conservation conditions (compare Figure 4.4). To investigate grassland productivity, S2 data of all four years is analyzed. S2 consists of two polar-orbiting satellites (S2A and S2B) acquiring multispectral optical imagery in 13 bands with varying spatial resolutions. The Blue, Green, Red and NIR bands, all in 10 m spatial resolution, are used further (compare section 4.1.1). Due to the orbiting geometry of both S2 satellites there are areas in Germany which are covered by two orbits and areas only covered by one orbit resulting in varying data availability.

5.1.2 Environmental and Socio-Political Data

To analyze which factors have an influence on grassland mowing dynamics and which conditions are fulfilled for rather intensive or extensive management, several data sets are investigated. The abiotic data consisted of climate, topographic and soil data for the entire area of Germany. The climate data, namely annual mean temperature and summed up rainfall rates for 2020, were acquired from the German Weather Service (DWD Climate Data Center, 2022b,a). The data sets were available as raster data in 1 km spatial resolution (Figure 5.1). They rely on station data which was interpolated for the entire area of Germany.

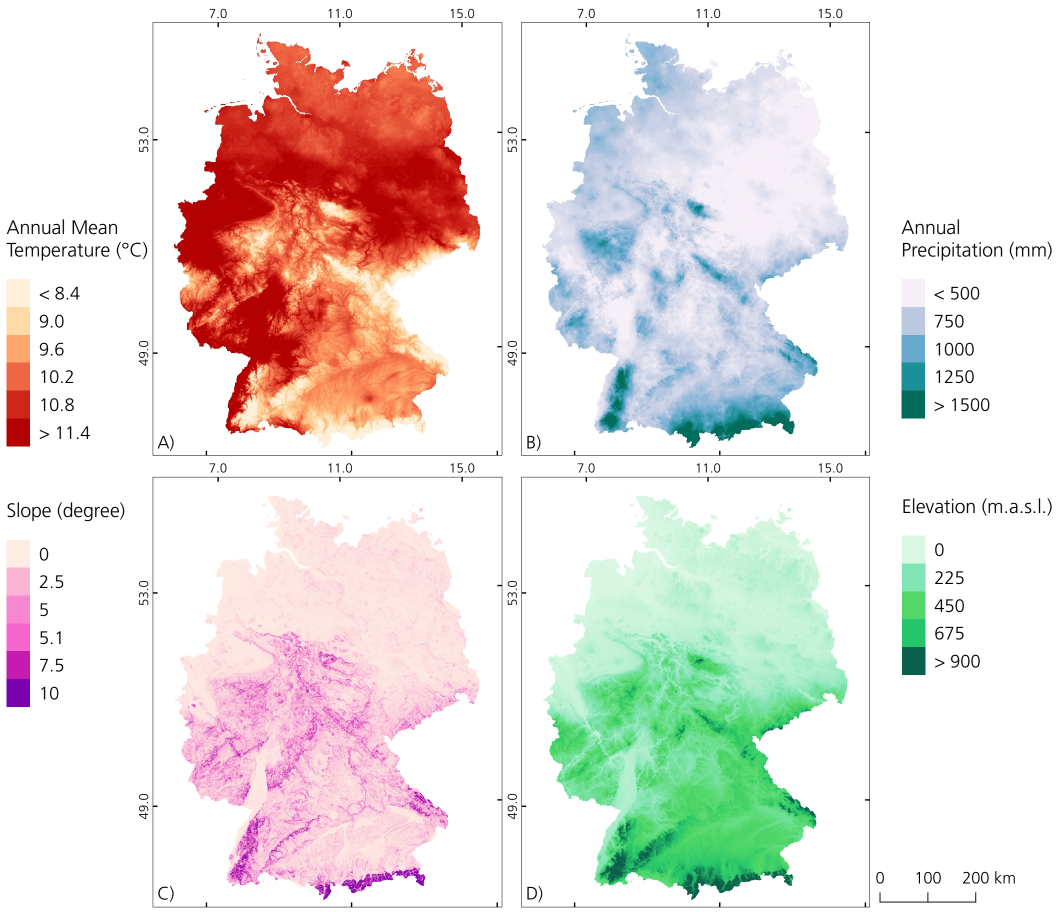

Figure 5.1: The investigated parameters for the comparison analysis between mowing frequency as well as timing of first mowing event and climate as well as topographic information for 2020: annual mean temperature, annual rainfall of 2020 and slope and elevation.

The topography information consisted of elevation and slope data which was extracted from the EU-DEM provided by Copernicus (Copernicus, 2016). The EU-DEM is a digital surface model based on SRTM and ASTER GDEM in 25 m resolution. The soil information is based on soil classes which were extracted from the compiled soil map of Germany (BUEK 250, Bundesanstalt für Geowissenschaften und Rohstoffe (BGR) (2018)).

As apart from environmental conditions also socio-political circumstances potentially influence the grassland management, information on conservation schemes are included in

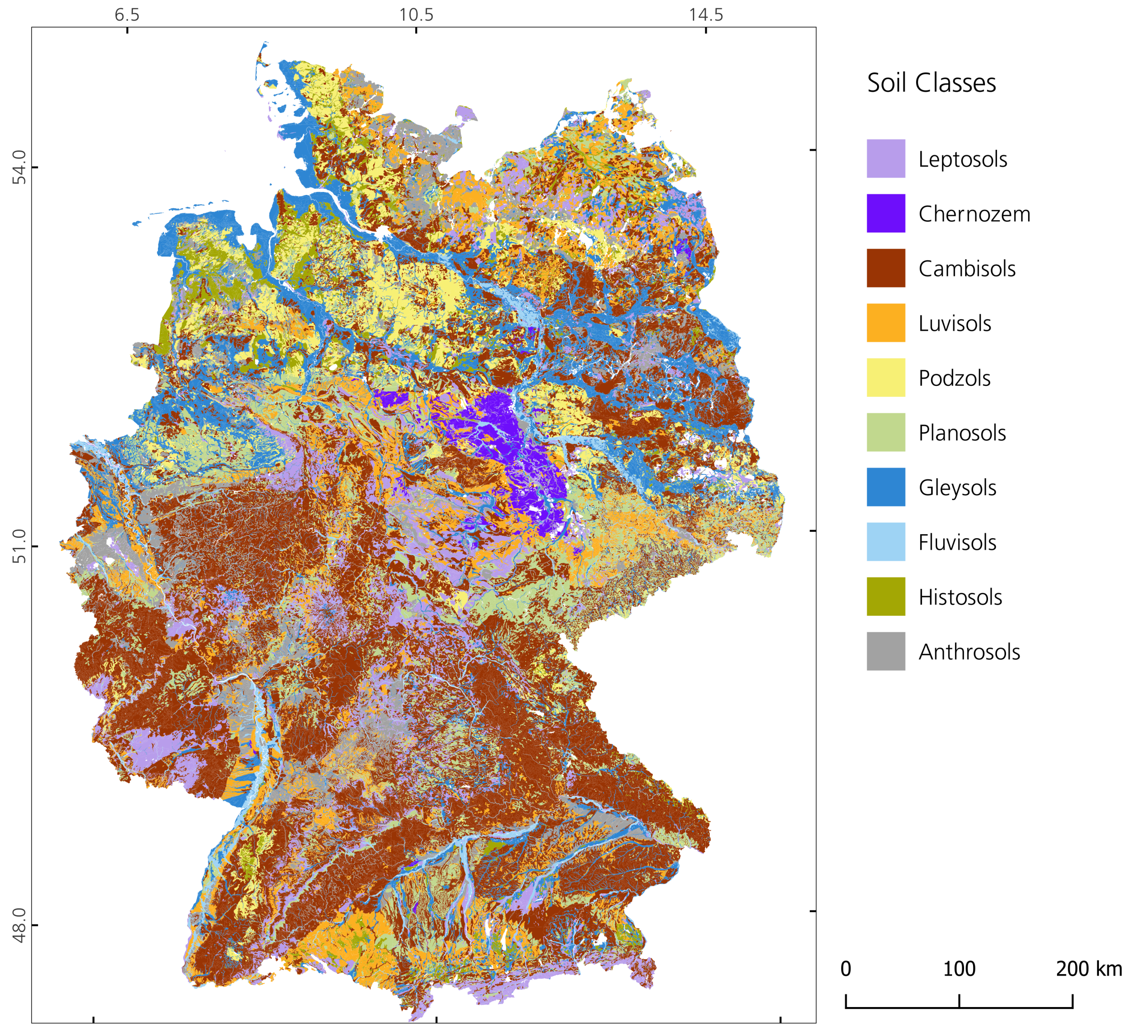

Figure 5.2: The soil classes of Germany which were compiled from the German soil map (Bundesanstalt für Geowissenschaften und Rohstoffe (BGR), 2018).

the analyses. In that regard, Natura 2000 sites provided by the European Environmental Agency (European Environmental Agency, 2021) were investigated (Figure 3.4). Natura 2000 is a network of protected areas aiming at conserving species and habitats among multiple countries. Both classes, the Habitats Directive and the Birds Directive were considered here.

In addition to that, statistical data with information on grassland yields and the number of cattle, both available per district, from the German state Bavaria were included in the analyses. The data sets were acquired from the Bavarian State Office for Statistics (Bayerisches Landesamt für Statistik, Fürth, 2022b,a). Whereas the yield information was available for the four years of interest (2018–2021), the number of cattle was only available for 2018, 2019 and 2020.

5.2 Methodological Approach

5.2.1 Pre-processing

5.2.1.1 Sentinel-2 Data

The satellite data consisting of the S2 time series was filtered using the MAJA-based cloud mask while only best quality pixels (no clouds, no cloud shadows) were retained. In addition, all areas which are not covered by grassland were excluded from the analysis. Therefore, the Copernicus High Resolution Layer of grassland of 2018 was applied (Copernicus, 2018). Afterwards the EVI was calculated with equation (1) and the EVI time series filled and smoothed as explained in section 4.2.1. This was the base data set for the productivity estimation. To investigate mowing dynamics, the EVI-based mowing detection algorithm was applied and mowing events were detected for the year 2020 for the entire grassland area of Germany as described in sections 4.3.2 and 4.3.2.2. The same procedure and thresholds as for section 4.3.3 were used resulting in a mowing detection accuracy (F1-Score) of 0.60 (compare section 4.3.5).

For the analysis of relationships between the mowing patterns and environmental and socio-political variables, the annual grassland mowing frequency and the timing of the first mowing event are used as proxies for mowing dynamics and mowing intensity. To compare the mowing frequency and the timing of the first mowing event with the climate and topography data sets, they are resampled to a spatial resolution of 1 km (average) and projected to the Gauss-Kruger Zone 3 (EPSG: 31467) coordinate system. As a consequence of averaging the mowing frequencies to a coarser resolution, the discrete values between zero to six are transformed into continuous values.

5.2.1.2 Environmental and Socio-Political Data

To harmonize the data sets, the elevation and slope layers were also re-projected to Gauss-Kruger Zone 3 (EPSG: 31467) and a spatial resolution of 1km which are the characteristics of the climate data sets. The soil classes of the compiled soil map of Germany (BUEK250) were condensed according to the World Reference Base of Soil Resources to guarantee and international comparability. The remaining soil classes which were Leptosols, Cambisols, Podzols, Gleysols, Histosols, Chernozems, Luvisols, Planosols, Fluvisols and Anthrosols (compare Figure 5.2). The Natura 2000 were subset and sites with an area smaller than 1 ha were excluded from further analysis. The statistical data sets on grassland yields consisted on information of yield information of meadows and agricultural grassland which were combined by averaging these two values. The statistics on grassland yields and the number of cattle which were in tabular format were joined to shape data of the districts in Bavaria.

5.2.2 Statistical Analysis

After pre-processing and harmonization of all data sets, they were statistically analyzed and their relationships examined. The climate and topographic data, which were raster data sets all in the same resolution and projection, were linearly correlated. Hence, the Pearson's correlation coefficient and the significance of the linear relationships were examined. As these relationships are potentially not identical for the entire area of Germany, the relationships between climate as well as topography data and mowing frequency as well as timing of first mowing event were investigated per great natural landscape. Here, only the great natural landscapes with a grassland share of more than 15% were included (compare Figure 3.1), which are the Northwestern Lowlands, the Western Low Mountain Ranges and the Pre-Alpine region. In addition, the intensively, extensively and early mown grasslands are investigated according to their distribution on the feature spaces of temperature-precipitation and elevation-slope. This reveals potential frameworks of climatic or topographic conditions related to intensive, extensive or early mowing. The soil classes data set is in vector format and covers the entire area of Germany. It is used to analyze on which soil classes most grasslands occur in general and on which most intensively or extensively mown grasslands. The Natura 2000 sites are also in vector format. This data set is used to compare the mowing frequency and timing of first mowing event of grasslands within protected areas to grasslands which are not protected.

5.2.3 Grassland Productivity Estimation

Information on grassland yields and productivity were acquired and mapped to investigate their relationship to mowing intensity. Next to the statistical data on yields and the number of cattle per district for Bavaria, a grassland productivity indicator was generated which was compared to mowing dynamics. It was based on S2 EVI time series data of 2018–2021 of the entire grassland area of Germany. The productivity indicator was defined as integral of the filtered, interpolated and smoothed EVI time series per pixel. The integral is derived by summing up the EVI values between March and November of each year. Hence, the productivity indicator is a qualitative estimate of the annual grassland productivity suitable to investigate which regions in Germany show relatively high, medium and low productivity rates.

5.3 Results

Within the following sections the results of the relationship analysis between mowing dynamics and potential influencing factors are presented. First, the relationships between climatic (temperature, precipitation) and topographic (slope, elevation) variables to mowing dynamics, namely the mowing frequency and the timing of the first mowing event, are elaborated (section 5.3.1). Then, the relationship between soil classes and the grassland mowing frequency is shown (section 5.3.2) and, finally, mowing dynamics within and outside of Natura 2000 sites are presented (section 5.3.3).

5.3.1 Relationship of Mowing Dynamics to Climate and Topography

Linear regressions between temperature, precipitation, slope as well as elevation and the mowing frequency as well as the timing of the first mowing event as response variables were investigated. The data sets of 2020 in 1 km resolution were utilized and all areas covered by grassland in Germany included. All variables showed significant relationships to the grassland mowing parameters (Table 5.1). However, the correlation coefficient Pearson's r revealed weak correlations for all parameters as 13 % of variance were not exceeded (Table 5.1). The relationship between the mowing frequency and precipitation revealed the highest correlation with a Pearson's r of 0.36. The second highest correlation was found between the mowing frequency and elevation (0.20), the third highest between the timing of the first mowing event and temperature as well as precipitation (-0.11). The correlation coefficients of the latter is negative which signals that higher temperature and precipitation rates are related to earlier mowing dates. The relationship and correlation analyses were also conducted for great natural landscapes (compare Figure 3.1 C) individually which did also not lead to higher correlations or clearer relationships.

Table 5.1: Pearson's r correlation coefficients for the linear relationship between climatic as well as topographic variables and mowing information.

	Mowing Frequency	Timing of 1st mowing event
Temperature	-0.13***	-0.11***
Precipitation	0.36***	-0.11***
Slope	-0.04***	0.03***
Elevation	0.20***	-0.05***

***=p-value < 0.001.

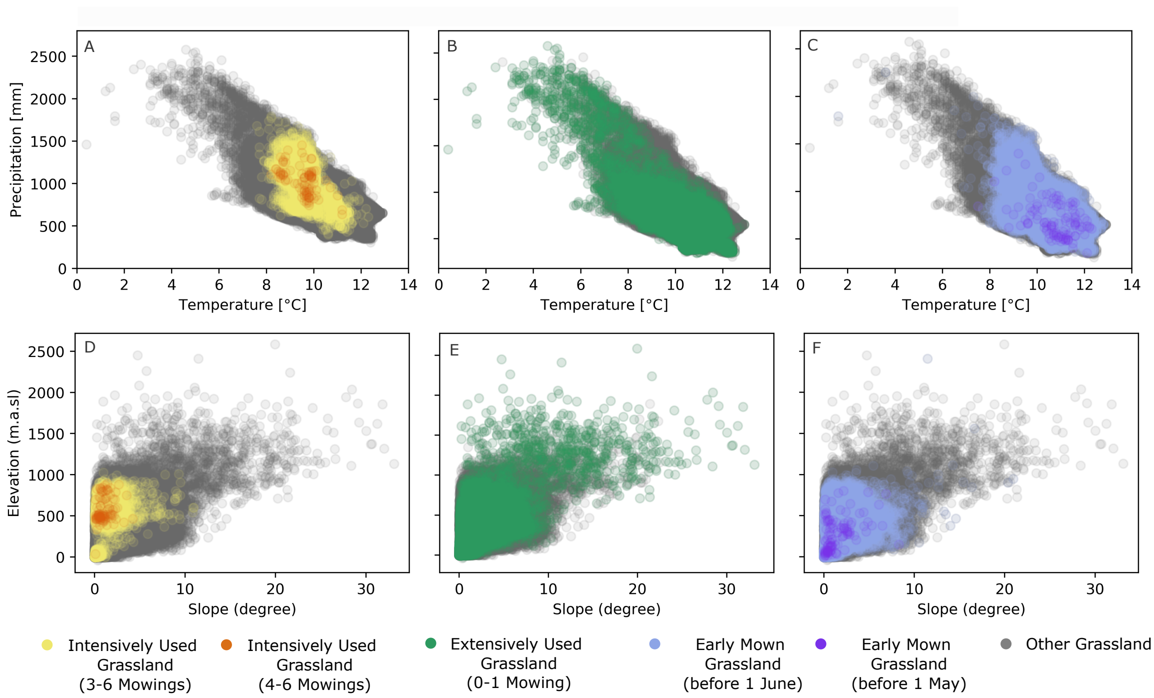

Figure 5.3: Distribution of intensively, extensively and early mown grasslands on the temperature-precipitation and the slope-elevation feature space.

The climatic and topographic conditions under which grasslands are intensively or extensively used were investigated. Therefore, the climatic and topographic ranges of grasslands were mapped and their distribution on the climatic (temperature and precipitation) and topographic (slope and elevation) feature spaces were analyzed (Figure 5.3). The climatic and topographic ranges of intensively used, extensively used and early mown grasslands were compared to all grasslands in Germany. The two investigated groups of intensively used grasslands are defined by showing at least three mowing events per year and by showing at least four mowing events per year. As the mowing frequency data set was resampled to 1 km spatial resolution (compare section 5.2) for this analysis, and higher frequencies is therefore underrepresented, grasslands at least mown three times per year were considered

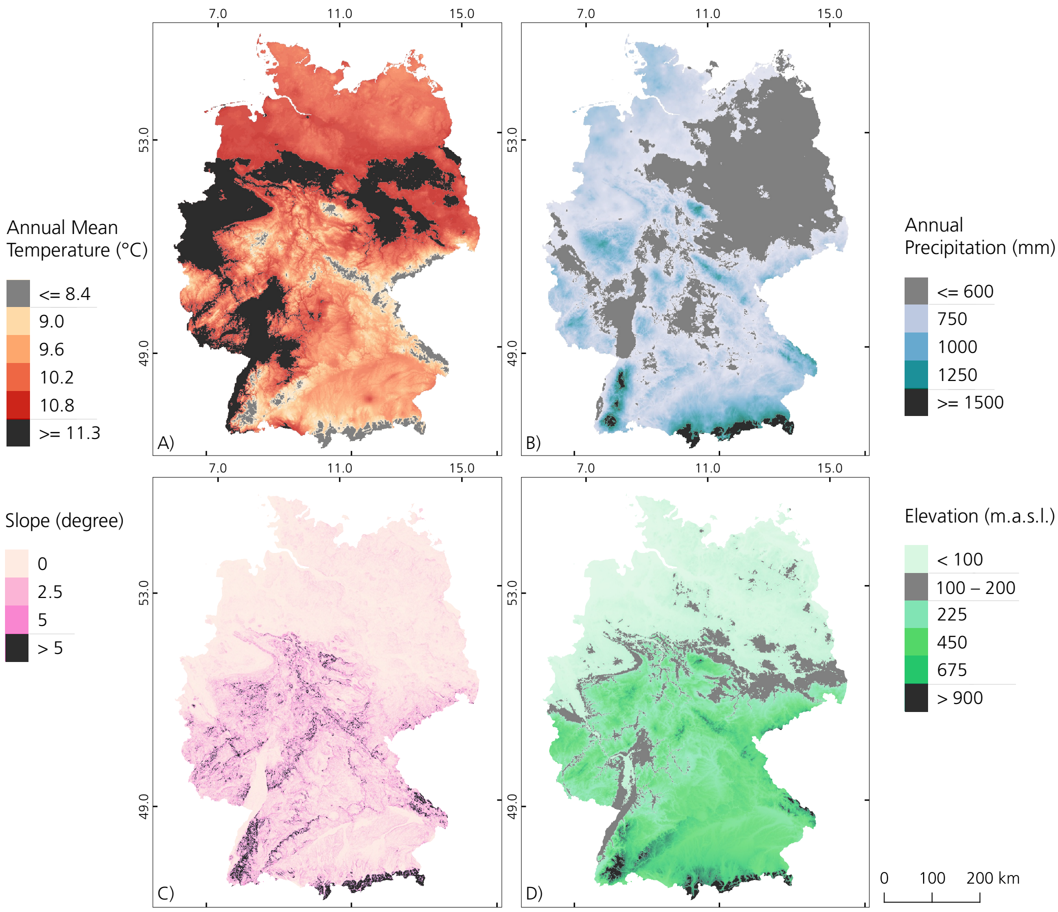

Figure 5.4: Areas which are potentially too cold, too hot, too dry, too wet, too steep or too high for intensive (mown 3 to 6 times) grasslands usage.

intensive. For extensively used grasslands the ones mown up to only once per year were included. The two groups of early mown grasslands were defined as mown before 1^{st} of June and mown before 1^{st} of May.

Grasslands mown three to six times per year occurred on a smaller climatic gradient compared to all grasslands (Figure 5.3 A). The temperatures of intensively used grasslands mown between three to six times range between approximately 8.4 to 11.2 °C and precipitation rates of 600 to 1500 mm per year. Grasslands which are even more intensively used – mown four to six times – show even smaller climatic gradients. Extensively used grasslands which are mown up to once per year, appeared on the entire climatic gradient (Figure 5.3 B).

The timing of the first mowing event shows a relatively clear boundary for grasslands mown before first of June. These areas occurred only in areas with temperatures of at least 8 °C but in the entire precipitation gradient (Figure 5.3 C). Grasslands already mown before first of May appear on an even smaller climatic gradient with temperatures of 9.5 to 12.2 °C and precipitation rates of 500 to 1000 mm, approximately.

The topographic gradients of the investigated grassland classes reveal a comparable pattern (Figure 5.3 D–F). Grasslands mown three to six times occurred on small slopes of up to 5 degrees, approximately, and elevations of up to 800 m.a.s.l. with an interrupt between 100 and 200 m.a.s.l. (Figure 5.3 D). Even more intensively used grasslands with annual mowing frequencies between four and six show smaller topographic gradients with slopes of up to 2 degrees and elevations of 400 to 850 m.a.s.l., approximately. Comparable to the climatic variable feature space, extensively used grasslands appeared on the entire topographic gradient like all grasslands (Figure 5.3 E). Grasslands mown before 1^{st} of June occurred on slopes of up to 9.5 degrees and elevations of up to 1000 m.a.s.l. The occurrence of grasslands mown before 1^{st} of May does not reveal clear borders of topographic conditions but distributes mostly on small slopes of up to 3 degrees and elevations of up to 500 m.a.s.l. (Figure 5.3 F).

The climatic and topographic gradients on which intensively used grasslands – mown three to six times – occurred are shown in Figure 5.4. It highlights the spatial extents of the ranges of temperature, precipitation, slope and elevation for intensively used grasslands. All values outside of this range were greyed out. As intensively used grasslands did not occur on the grey areas, it can be assumed that these were too cold, too hot, too dry, too wet, too steep or too high for intensive grassland use.

5.3.2 Relationship of Mowing Dynamics to Soil Classes

As first aspect, the distribution of soil classes on the entire grassland covered area in Germany was investigated. The largest group were Cambisols (33 %), followed by Histosols and Gleysols which add up to a little over one third (36 %) of the share of soil classes covered by grassland. The remaining soil classes constitute smaller proportions. Next, the distribution of grassland mowing frequencies per soil class was analyzed with the result that there is no soil class which is only covered by intensively or extensively mown grassland (Figure 5.5). However, some soil classes show overall higher mowing intensities compared to others, such as Histosols (Figure 5.5 D). Leptosols and Chernozems were mostly covered by extensively used grasslands. The overlay of mowing frequency and soil classes also shows such tendencies but no consistent patterns (Figure 5.5 A–C). In the region in northern Germany, both Gleysols and Histosols are covered by patches of rather intensively as well as extensively mown grasslands (Figure 5.5 Zoom 1 B–C). In the central German region. grasslands on Cambisols show a tendency to be mown more often than the grasslands on Leptosols (Figure 5.5 Zoom 2 B–C). In southern Germany, Luvisols and Gleysols show a large share of grasslands with high mowing frequencies, whereas Cambisols are rather extensively mown or not used as grasslands at all (Figure 5.5 Zoom 3 B–C).

Another aspect of the analyses of the relationship between mowing intensity and soil classes was the investigation of the investigation of the shares of soil classes per intensity levels of grassland. Considering the most intensively used grassland – mown between four to six times –, a large proportion of these are present on Cambisols (30 %) and Gleysols (20 %). However, these are also among the most common soil classes in Germany. This becomes also visible when focusing on extensively used grasslands – mown only up to once per year – as the largest shares of extensively used grassland occurs also on Cambisols (31 %) and Gleysols (22 %). Hence, the shares of intensively or extensively mown grasslands were investigated per soil class. This analysis showed that the share of intensively used grasslands was relatively small for all soil classes as it did not exceed 10 %. The soil classes with the largest share of intensively mown grasslands were Luvisols (9 %), followed by Histosols (7 %). The shares of extensively used grasslands are higher compared to intensively used ones over all soil classes. Chernozems show the highest share of extensively used grassland out of all grassland occuring on Chernozems (64 %). This was followed by Leptosols (49 %), Anthrosols (44 %) and Podzols (43 %). Chernozems are considered as highly productive which is why they are usually not covered by grassland but other agricultural land.

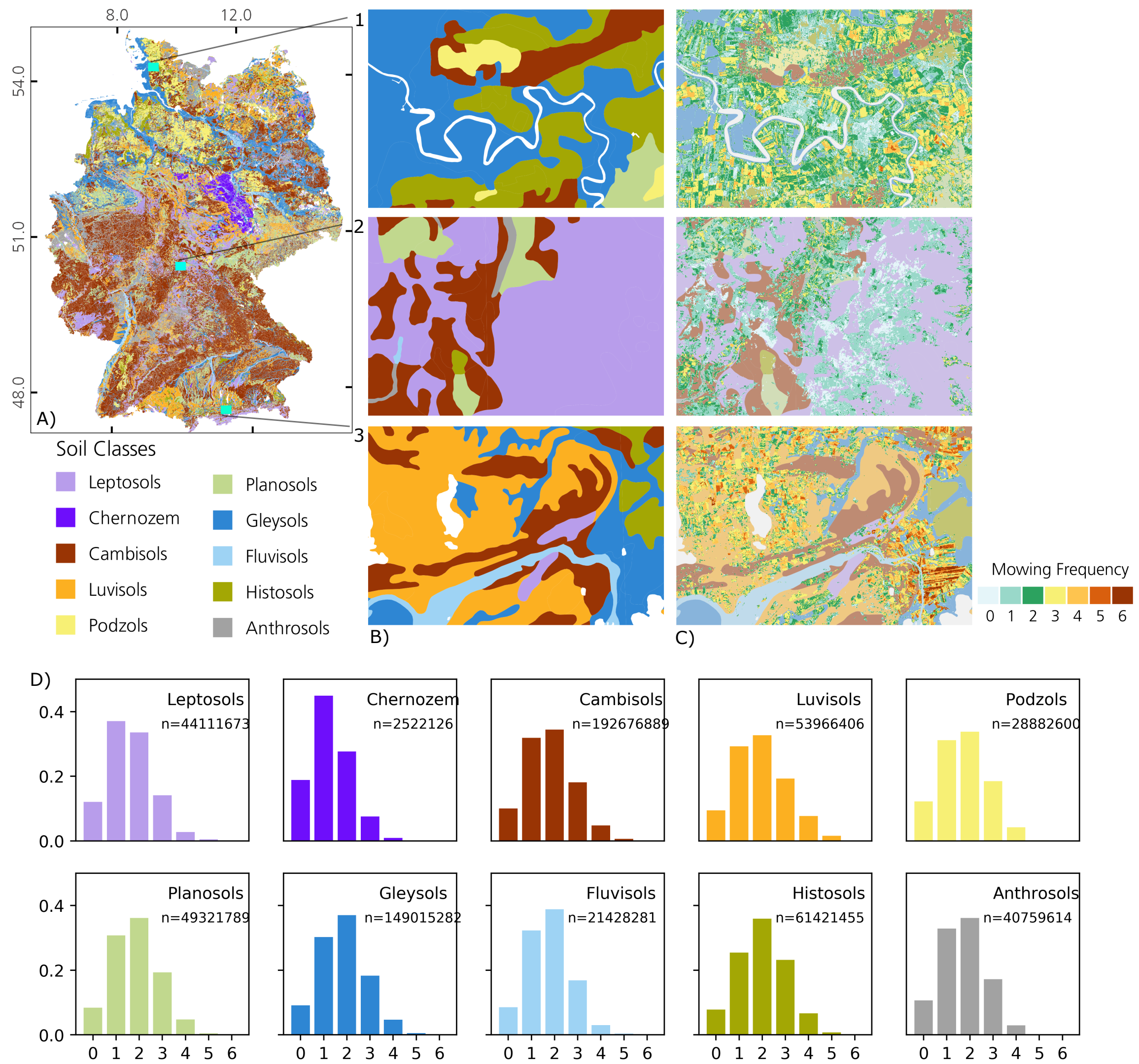

Figure 5.5: Analysis of the mowing frequency of various soil classes by comparing the soil classes of Germany (A) and zoom regions (B) with the detected mowing frequency (C) and the distribution of the mowing frequency for each soil class (D).

5.3.3 Relationship of Mowing Dynamics to Protection Mechanisms

Previous results have demonstrated that abiotic factors, e.g. temperature and precipitation rates, constitute the environmental framework for grasslands with high mowing frequencies, while extensively used grasslands were not restricted by certain environmental conditions. Hence, the relationship between mowing dynamics and protection schemes was investigated as this potentially has an influence on the use intensity (compare section 3.2). The averaged mowing frequencies per Natura 2000 site (Figure 5.6 A) and the spatial overlay of Natura 2000 sites and detected mowing frequencies (Figure 5.6 B) show that grasslands characterized by all mowing frequencies occur within Natura 2000 sites. The averaged mowing frequencies per Natura 2000 site reach values of more than two mowing events per year (Figure 5.6 A), indicating that grasslands are also intensively used even though they are within a protected area. This can also be seen when investigating the spatial mapping of mowing frequencies inside and outside of Natura 2000 sites, in particular for the region in southern Germany (Figure 5.6 B). Averaged over the entire area of Germany, there are more grasslands with smaller numbers of mowing events per year within Natura 2000 sites compared to the rest of Germany, however again also intensively mown grasslands are detectable within protected areas (Figure 5.7). Considering the timing of the first mowing event, grasslands within Natura 2000 sites are mown later for the first time compared to other grasslands (Figure 5.8). In particular the number of grasslands mown before first of June is higher for unprotected compared to protected areas. However, many grasslands within Natura 2000 sites are mown around mid of May indicated by a peak. Another peak of the timing of the first mowing event is visible after the first of June as many grasslands protected by Natura 2000 were mown then.

5.3.4 Relationship of Mowing Dynamics to Productivity and Yield

The estimated productivity indicator was based on the sum of filtered, interpolated and smoothed S2 EVI time series between March and November each year (compare section 4.2.1. The maps covering the entire area of Germany show some variability in grassland productivity on different levels (Figure 5.9). Parcel borders of grasslands are visible showing different productivity levels between ans also within single grassland parcels (Figure 5.9 A–C). There is also inter-annual variability visible as 2018 shows lower values in estimated productivity compared to the other years. The differences between the years are nit equal for all regions. The grassland region in the north shows lower productivity rates in 2018 (Figure 5.9 A), while the region in the central-north is characterized by lower estimated productivity in 2018 and 2019 (Figure 5.9 B). The pre-alpine region in the south of Germany shows relatively homogeneous patterns with smaller visible reductions in grass-

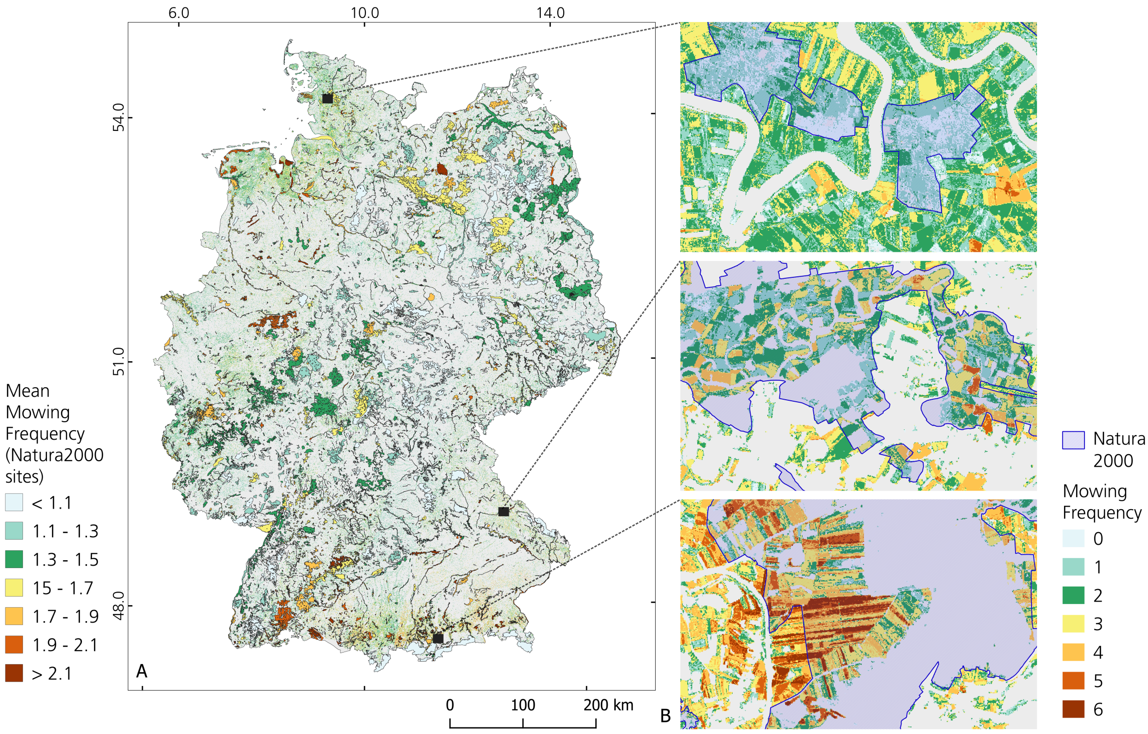

Figure 5.6: Mowing frequency averaged for protected areas (Natura 2000 sites) (A) and zooms of high resolution mowing frequency for protected and unprotected grasslands (B).

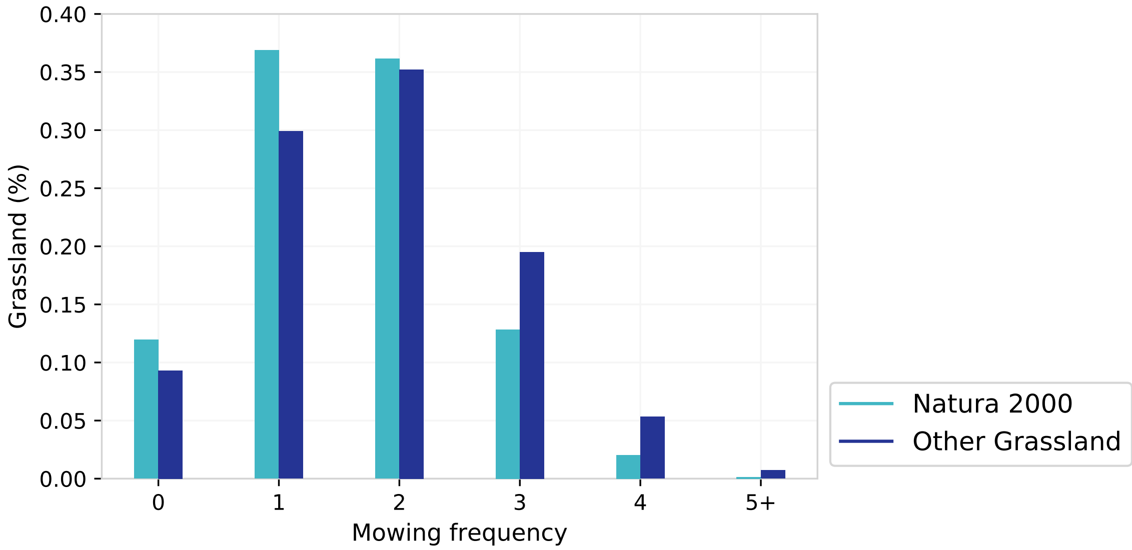

Figure 5.7: Distribution of mowing frequency of all Natura 2000 sites compared to grasslands not protected by Natura 2000 showing a lower mowing frequency for protected compared to unprotected grasslands.

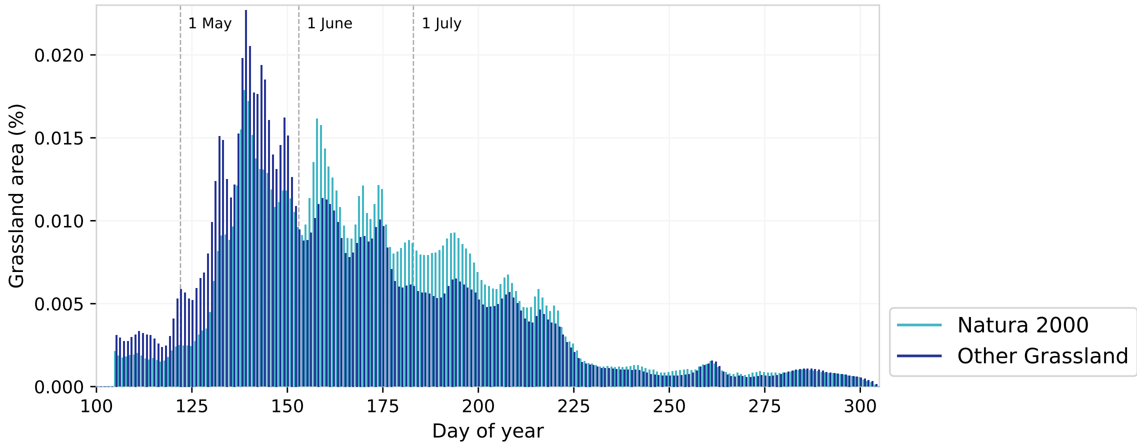

Figure 5.8: Distribution of the timing of the first mowing event of all Natura 2000 sites compared to grasslands not protected by Natura 2000.

land productivity in 2018 compared to the other regions (Figure 5.9 C). The productivity indicator averaged per district highlights the mentioned inter-annual differences as 2018 shows overall lower productivity rates (Figure 5.10). The year 2021 shows the highest estimated productivity among the investigated years. Regions with relatively high annual productivity rates coincide with regions of high mowing frequencies, such as southern/ south-eastern Germany and parts in the north (compare Figure 4.25). Lower productivity rates are present in central and north-eastern German regions which are also characterized by low numbers of annual mowing events.

Another analysis concerning grassland productivity was undertaken by investigating yield (Figure 5.11 B) and cattle statistics (Figure 5.11 C) together with the mowing frequency (Figure 5.11 A) and the estimated productivity (Figure 5.11 D) averaged to district level for the south-eastern most state of Germany, Bavaria. Bavaria shows the highest detected mowing frequency in Germany, but includes also the entire range of grassland mowing frequencies, between zero to six mowing events per year. Averaged per district leads to more than three mowing events per year at the most, occurring in some districts in southern Bavaria (Figure 5.11 A). The districts with relatively large number in mowing events only partly overlap with regions characterized by high annual grassland yield rates (Figure 5.11 B). High yields can be found in south-eastern and western districts of Bavaria. The number of cattle per district shows high numbers in south-eastern Bavaria, as well as some south-western and western districts (Figure 5.11 C). The productivity indicator shows highest values for the districts in southern Bavaria. These general patterns stay the same among the four investigated years, apart from some minor changes. In particular, the number of cattle stayed constant. The productivity measure indicates higher overall values in 2020 and 2021, which partly coincides with the yield statistics.

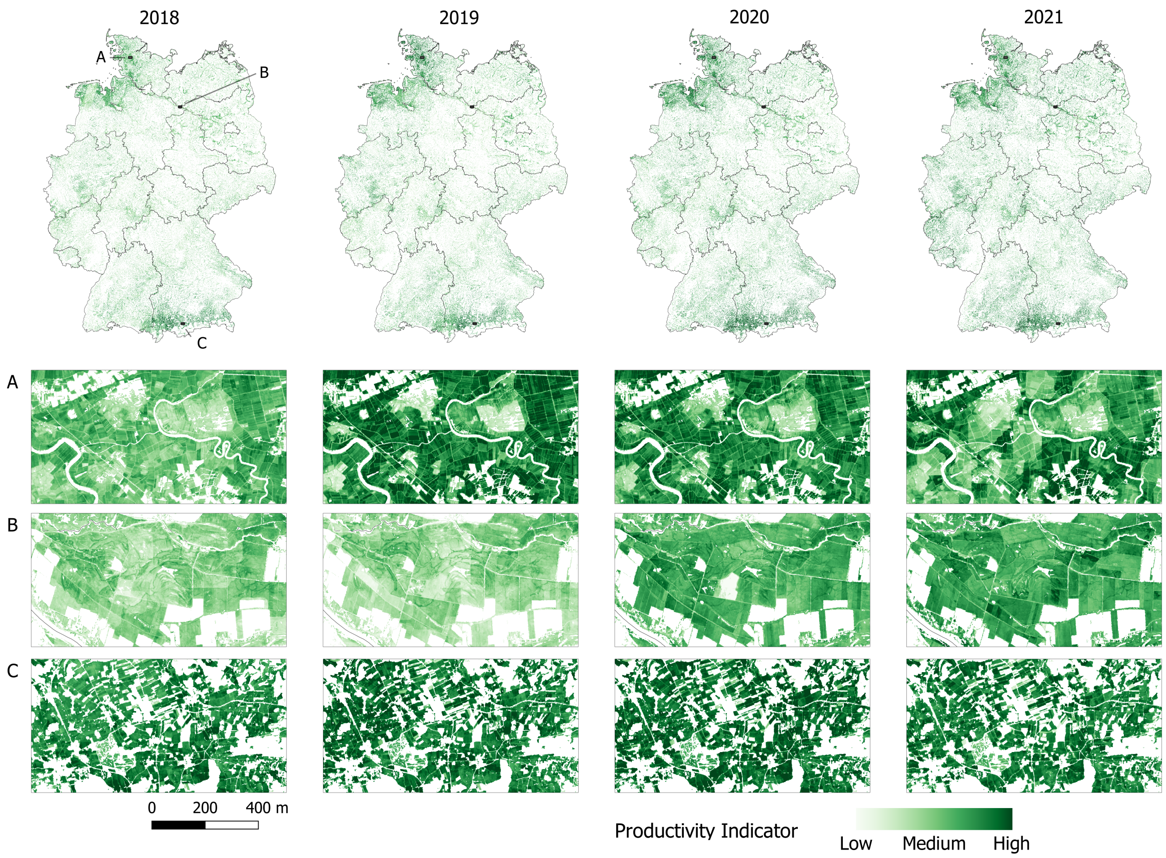

Figure 5.9: Productivity indicator which is defined as the sum of interpolated and smoothed EVI values between March and November per year for all grasslands in Germany and the four investigated years (2018–2021).

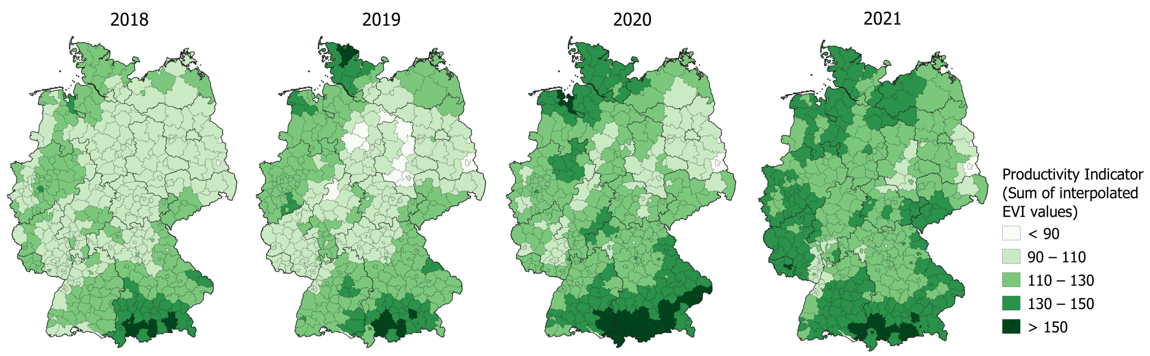

Figure 5.10: Productivity indicator which is defined as the sum of interpolated and smoothed EVI values between March and November per year for all grasslands in Germany averaged per district, for the four investigated years (2018–2021).

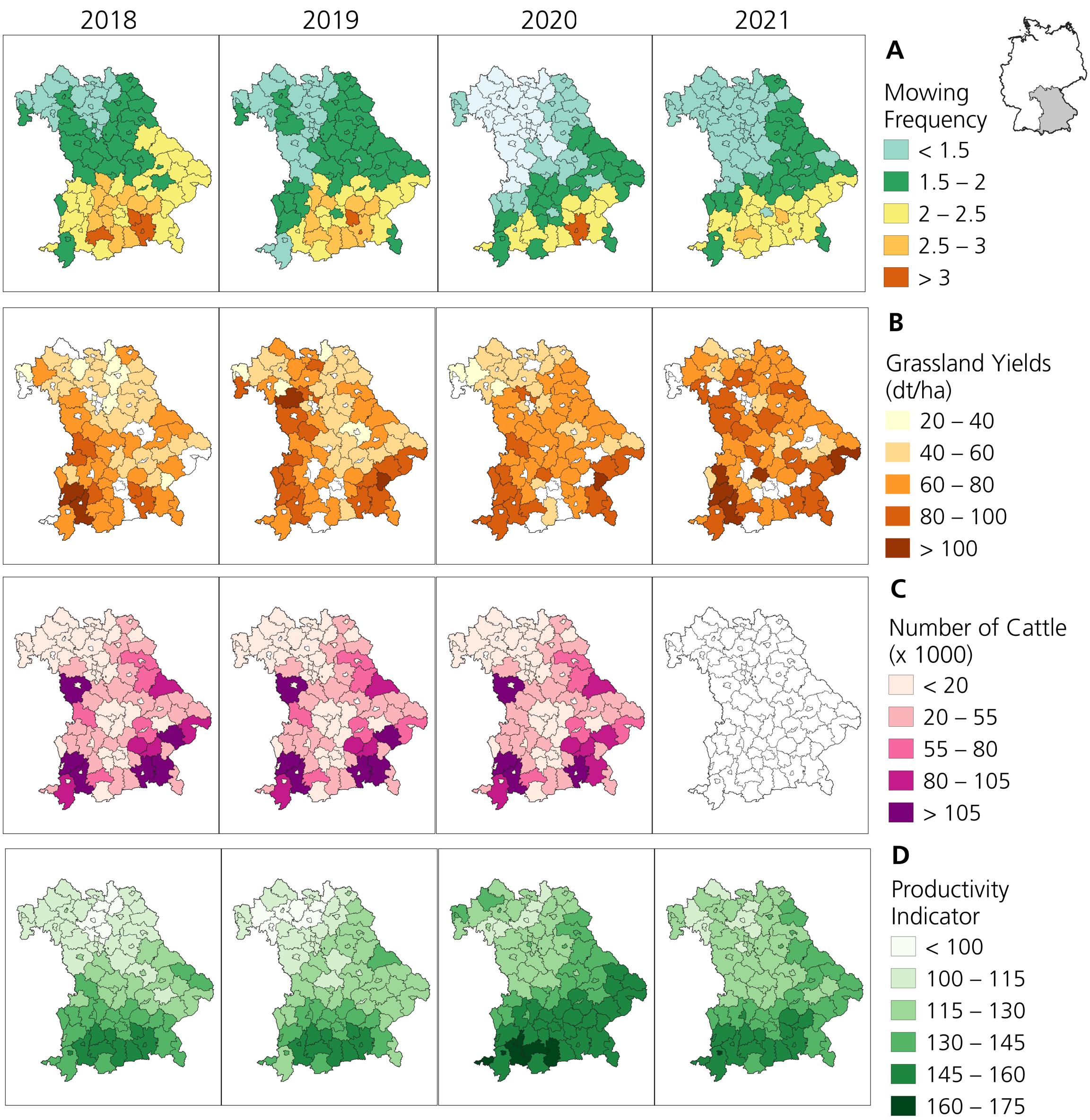

Figure 5.11: Grassland mowing frequency per district (A), statistical information on grassland yields (B), the number of cattle (C) and the estimated productivity averaged per district (D). Blank areas indicate no data availability.

5.4 Discussion

5.4.1 Relationships of Mowing Dynamics to Climate and Topography

Even though the relationships between the two parameters on mowing dynamics, namely the mowing frequency as well as the timing of the first mowing event, to all four investigated climatic and topographic variables (temperature, precipitation, slope and elevation) were significant, low correlation values revealed only small explanatory power of the variables. The significance of the relationship is influenced by the number of data points (Rouder et al., 2009) which are high when investigating satellite image data sets. The highest correlation was found between the mowing frequency and the rainfall sum of 2020 (Pearson's $r = 0.36$). However, the slope of the regression line for this relationship was almost zero. The results show that abiotic conditions, such as temperature, precipitation, slope and elevation, have an influence on mowing dynamics whereby precipitation is the most important factor. However, the relationships are probably not consistent for the entire grassland area of Germany or are more complex and intertwined. It is known that precipitation favors vegetation growth and, consequently, more intensive use, but only to a certain degree until a point of saturation is reached (Smit et al., 2008). Remote sensing studies investigating the relationship between gross or net primary productivity of grasslands and climatic variables found that precipitation is a major influencing factor (Li et al., 2013; Jia et al., 2015; Gao et al., 2016, 2017; Zhao et al., 2019), however differences for different grasslands and various time scales were revealed (Petrie et al., 2016). Primary productivity was mostly negatively correlated to temperature in previous research on grasslands in China (Mao et al., 2014; Xiong et al., 2019). The highest influence of temperature on grassland productivity was found at the beginning of the growing season (Wang et al., 2020). Future research should consider the relationships between climatic and topographic variables to mowing dynamics and conduct multi-variate analyses.

The analyses of climatic and topographic conditions for different mowing dynamics revealed existing environmental frameworks for grassland mowing intensity levels, in particular for intensively used grassland. All intensively mown grasslands occurred in a specific value range defined by temperature, precipitation, slope and elevation, indicating that the remaining area might be too cold, too hot, too dry, too wet, too steep or too elevated for intensive grassland use. Apart from direct effects, like optimal climatic conditions favoring vegetation growth and, consequently also intensive grassland use (Bernhardt-Römermann et al., 2011), these patterns can also be explained by indirect effects. For instance, the frequent usage of heavy machinery, which is needed for intensive mowing on grasslands, is limited on wet sites or steep slopes. In addition, grassland sites in high altitudes are often more difficult to reach. Another factor influencing plant growth – and, therefore, the potential to intensively use grassland – is the availability of soil organic matter which showed lower contents in grassland soils on steep slopes, for instance (Kühnel et al., 2019).

The timing of the first mowing event shows a clear visible border with grasslands mown before 1^{st} of June as these occur only in areas which show an annual mean temperature of at least 8 °C. This clear pattern is related to the influence of spring temperatures for the onset of (grassland) vegetation growth (Huang et al., 2020). It highlights the importance of temperature on grassland mowing dynamics, in particular the timing of the first mowing event, which is especially interesting as this factor can only hardly be adapted by farmers to increase plant growth to intensify the grassland use. In contrast to that, other factors determining plant growth, such as precipitation rate, nutrient availability and moisture level are potentially changed by management options like irrigation, fertilization and drainage.

5.4.2 Relationship of Mowing Dynamics to Soil Classes

The analysis of the influence of soil classes on the mowing frequency revealed no distinct pattern but tendencies. Soil classes which are characterized by constant water influence, such as Histosols and Gleysols, show the highest mowing frequency rates in Germany, indicating the importance of plant available water for grassland growth and, consequently, mowing intensity. The soil class that revealed the least intensive grassland usage were Leptosols, which are typically poorly permeable for roots. This characteristic seems unfavorable for grassland growth rates. Even though water availability plays a role for intensive grassland use, wet soils have the disadvantage (in that perspective) of hindering the frequent use of heavy machines. Therefore, it can be assumed that wet grassland sites are drained to enable intensive mowing.

In Germany, many grasslands occur on sites which are not favorable enough for crop cultivation, for example on soils with poor nutrient availability (Schoof et al., 2020b,a). From the remaining grasslands, in particular Histosols are favorable for grass growth due to their high rates in organic carbon (Eswaran et al., 1993). Spatial information on drainage and soil organic carbon contents (e.g. Zepp et al. (2021)) would be needed in future research to disentangle the influence of water availability and soil quality, such as organic carbon, on grassland mowing dynamics.

5.4.3 Relationship of Mowing Dynamics to Conservation Schemes

Abiotic conditions, including temperature, precipitation, slope, elevation and soil characteristics shape the environmental framework in particular for the potential to intensively use grasslands. The circumstances and motivation for farmers for extensive usage seem unrelated to these site conditions and are probably of a socio-political nature. Conservation schemes, in which farmers are compensated for extensive use are an important incentive. Here, the locations of Natura 2000 sites in Germany were included as these sites represent a broad framework of protected areas aiming at the conservation of vulnerable and endangered flora and fauna, and their habitats. As previously described (section 1.1.2), the frequency and timing of mowing events have a determining impact on grassland ecology. Mowing dynamics influence the species composition and provision of ecosystem functions. Extensive use (lower mowing frequency and later first mowing events) facilitates higher species numbers and a broader spectrum of ecosystem functions aside the provision of fodder (Socher et al., 2012; Neyret et al., 2021). It was therefore hypothesized that grasslands within Natura 2000 sites are more extensively used compared to the other grasslands, which was only partly confirmed. Overall, grasslands within Natura 2000 show lower mowing frequencies and later first mowing events. However, not all of the grasslands protected by Natura 2000 are extensively used as also grasslands with intermediate or evene intensive use were present. Most probably, this is related to the fact that the Natura 2000 framework aims at sustaining habitats or single endangered species. This is potentially but not necessarily coupled with extensive grassland usage. In addition, the single Natura 2000 sites are individually managed and have individual goals. The overall guidelines and restraints are defined by the countries and in Germany, by the federal states. Comparing the enforcements and its effects on national level is therefore challenging (Fischer-Hüftle and Gellermann, 2018).

5.4.4 Relationship of Mowing Dynamics to Productivity and Yield

Ideally, a productivity measure together with mowing information could inform on grassland yields. Grassland yield estimation is a challenging task, in particular in such heterogeneously and dynamically used grassland landscapes like in Germany. The developed productivity indicator applied here showed plausible patterns and variability on different scales. The drought-induces negative effects for vegetation in 2018 (Reinermann et al., 2019) become visible, for instance, when examining the productivity indicator. However, the developed productivity measure is a qualitative information which needs further refinement to be used as input for grassland yield estimations. The comparison with statistical information from the south-eastern most German state (Bavaria) showed only partly coinciding patterns, which potentially indicates that the productivity indicator is not entirely correct. However, also the statistical information is error-prone as it is the result of (often visually) estimated grassland yields of different farmers. The results underline that there is no spatially detailed, accurate information on grassland yields available in Germany. In future research, a combination of productivity estimates, e.g. estimated biomass, and mowing information potentially improves the challenging task of large-scale and high-resolution grassland yield estimation.

5.5 Summary

The relationship of grassland mowing dynamics to abiotic conditions, conservation schemes and productivity indicators were analyzed to explore, assess and illustrate the conditions and motivation of farmers for varying grassland mowing intensity. The mowing dynamics were retrieved from the application of the developed framework to detect grassland mowing events based on S2 time series (chapter ch4:framework), whereby the mowing frequency and the timing of the first mowing event in 2020 were examined here. Climatic data (temperature and precipitation) and topographic data (slope and elevation) were retrieved to examine the relationship to mowing dynamics. Mean annual temperature, annual rainfall sum of Germany of 2020 derived from the German Weather Service (DWD) and slope and elevation extracted from the Copernicus EU-DEM were used.

All four variables revealed significant relationships to the mowing frequency as well as the timing of the first mowing event, however the correlation coefficients were low. The results highlight that there is an influence of abiotic conditions on mowing dynamics but that the explanatory power is low. However, it was found that climatic and topographic conditions shape a framework for different mowing intensity levels, in particular for intensively used grassland. Grasslands mown relatively often occurred only in a certain value range of abiotic variables revealing regions which might be too cold, too hot, too dry, too wet, too steep or too elevated for intensive mowing of grasslands. These patterns are probably related to optimal growth conditions of vegetation as well as practicability and accessibility of the grassland sites. The investigation of soil classes showed that the availability of plant available water plays a role for the potential to intensively use grasslands as Histosols and Gleysols showed the highest shares of intensively mown grasslands among all soil classes in Germany. However, all grassland mowing intensity levels occur on all soil classes and a distinct pattern is not present.

The previous analyses showed that extensively used grasslands occur throughout Germany independent of abiotic conditions. The conditions for extensive grassland use are therefore probably defined by socio-political factors. To further examine this, grasslands within the conservation network Natura 2000 were compared to grasslands outside of this protection scheme as the Natura 2000 sites aim at conserving vulnerable species. As an intensifcation of grassland use usually leads to a reduction in species numbers, in particular rare ones, and alters habitats, it was hypothesized that protected grasslands are more extensively used than unprotected ones, which was only partly confirmed. The mowing frequency was lower and the timing of the first mowing event was found to be later in Natura 2000 protected grasslands compared to the other grasslands, however, also grasslands with high mowing frequencies and early mown grasslands were among the protected grasslands. This is related to the fact that the Natura 2000 sites are managed to sustain habitats and species which is potentially also fulfilled with more intensive mowing and not necessarily with extensive use.

The analyses of the influence of abiotic and socio-political conditions on mowing dynamics reveal the characteristics of various factors in shaping environmental frameworks and incentives for varying use intensity levels. However, the motivation of the grassland management is also influenced by personal factors, such as tradition and education, which are difficult to measure and incorporate. Many of the investigated abiotic conditions are potentially altered to improve plant growth and enable intensive grassland use, for example by irrigation, fertilization and drainage, which highlights the importance of protection schemes to guarantee the conservation of a large variety in grasslands and accompanying species.

In addition to that, spatial and temporal patterns of grassland productivity and yield were investigated to assess the relationship of mowing dynamics to grassland fodder production which is the major provisioning ecosystem service of grasslands. The examined productivity indicator was based on the integral of the filtered, interpolated and smoothed EVI time series per pixel. It showed small scale variability of grassland productivity within and between parcels and between the investigated years. Even though plausible results were achieved, the indicator is qualitative and not equatable with yield. Information on annual grassland yields is not available on high spatial resolution and no monitoring systems exist yet. A combination of a productivity indicator with mowing information would provide a valuable information in the research of grassland yields which is still challenging due to the diverse and dynamic grassland use in areas like in Germany.

Chapter 6

Synthesis and Outlook

6.1 Summary and Conclusive Findings

The following chapter gives an overview over the thesis, whereby first, the importance of the topic and the research gap are shortly summarized, then, the objectives and research questions of the study are discussed and finally, a brief outlook to future research is presented.

Grasslands cover about one-third of the Earth's surface and provide livelihoods for billions of people as they are used for fodder production for animals. As outlined in section 1.1, they fulfill many additional ecosystem services, including carbon storage, water filtration, provision of habitats and cultural values. Hence, grasslands play an important global role in climate change mitigation and preservation of biodiversity and ecosystem functions. Which ecosystem services are provided and to what degree is largely depending on the management and use intensity of the grasslands (section 1.1.2). In Germany, like in many other central European countries, grassland management and use intensity show a wide range resulting in alternating grassland parcels with diverging physiognomy and ecosystem functions. There is no public information on the management and use intensity available in Germany which aggravates the assessment of the condition and status of provision of ecosystem services of the grasslands. The management activity with the largest impact – after conversion to cropland – is mowing, which is conducted up to six times per year. The timing and frequency of mowing events influence the species composition and consequently, the carbon storage potential, the fodder quality and the habitat quality, among other things. This dissertation addresses the lack of information about grassland mowing activities in Germany. The major objective of this thesis was the development, nation-wide application and validation of an algorithm to detect grassland mowing events in Germany. Grasslands are widely distributed in Germany; however, they are usually composed of small parcels with alternating management. Therefore, satellite data time series, in particular the high-resolution Sentinel sensors, are needed to provide and analyze large-scale and continuous data sets used for the detection and analyses of grassland mowing events. Based on the exploitation of this satellite data achieve, a novel framework was developed to, for the first time, operationally monitor grassland mowing dynamics for the entire grassland area of Germany.

Around this core element of the thesis, more objectives were defined, of which the first was to conduct an extensive literature review on the use of satellite imagery to investigate grassland management and production. The research questions related to the first objective were the following:

Research Questions 1:

1. How extensively has grassland management and production with EO data been researched, where are research foci and research locations of previous studies?
2. Which sensor types, sensors, indices and methods are applied to investigate grassland management and production in previous studies?
3. Which research gaps exist and how are they potentially addressed?

To answer these questions and approach the first objective, research on the topics of EO data usage to analyze grassland management and production was searched, assessed and evaluated. All papers covering these topics found through an extensive literature search (details explained in chapter 2) were included leading to a review of 253 studies, in total. All studies were assessed and patterns of investigated study areas, used data, methods and results were extracted and research gaps highlighted.

A large majority of studies can be found in China (35 %), which is probably related to the fact that the great value of grassland there has been recognized. An underrepresentation of studies was found for grasslands in South America and Africa (5 and 4 % of all studies). These continents contain large and diverse grassland areas, which highlights the need to study these ecosystems further in the future. In particular, as many livelihoods depend on grassland ecosystems in regions in South America and Africa. In a global comparison and for most continents, there were more studies investigating grassland production traits (82 %) than grassland management and use intensity (30 %), some studies investigated both. Only in Europe, the number of studies investigating grassland management exceeded the one on production (by more than double). This is probably related to the diversity of grasslands in Europe which are characterized by small, alternating grassland parcels with different physiognomy and ecosystem services. This diversity which is a result of varying management strategies and use intensities of the farmers aggravates the estimation of grassland productivity traits.

The literature review showed that the large majority of studies focused on optical data to investigate grassland management and production traits (94 %) and only 4 % combined optical and SAR sensor types. The focus often was on the analysis of vegetation indices, in particular the NDVI. Regarding the temporal resolution, single images, multi-temporal imagery and time series were used. In the past, mostly Landsat and MODIS played important roles for grassland management and use intensity analyses as imagery based on these satellites make up about one half of the reviewed literature. In the recent past, the Sentinels gained more and more importance due to their high spatial and temporal resolution.

Most studies investigated small study areas, in particular when investigating grassland management. Almost all studies in this context investigated grasslands on an area of up to 10000 km^2, which is about the size of Crete. Often, the diversity of grassland, e.g. regarding mowing intensity in European regions, were not covered. Spatially detailed analyses of grassland production are often hindered by the lack of information on grassland management which itself is usually unknown. As some grasslands show high intra-annual variability (i.e. through mowing or grazing activities), integrating continuous, temporal information on grassland management would improve production estimations of grasslands, like yields, also on larger scales.

Many of the studies focusing on the analysis of grassland management strategies or use intensities were exploratory, were conducted on only a very small research area or for a limited range of possible use intensities. Larger scale applications were usually based solely on optical data or aggravated by the lack of an extensive reference data set to validate their approach.

The second objective of this thesis is about the central aim of the thesis which was the development of a novel framework to automatically detect grassland mowing events in Germany. The aim was to included both sensor types, S1 and S2, in the analysis regarding their potential to capture grassland mowing events and within an automated mowing event detection algorithm. The research questions of the second objective are presented in the following.

Research Questions 2:

1. What are potentials and challenges to detect grassland mowing events with optical and SAR imagery, as provided by Sentinel-2 and Sentinel-1, and how can they be exploited and overcome, respectively?

2. Which sensor and which parameter is able to detect grassland mowing events most successfully or is a combination of both the most accurate approach?

3. How reliably can mowing events be detected and what are limiting factors?

To approach these questions, parameters of S2 and S1 were analyzed regarding their potential to capture grassland mowing events and based on this, a framework to automatically detect grassland mowing events was developed. Based on 13 differently used parametrization sites, the temporal signal of eight parameters were investigated and their reaction to mowing events on these sites were analyzed and compared to each other. The time series of the EVI based on S2 showed consistent drops after mowing events, followed by immediate increases. There were no additional drops independent of mowing activities observable apart from the decrease of the EVI in autumn which is related to the natural remission of vegetation growth and photosynthesis in this climate. In a few cases, mowing events were not captured by the EVI time series as no decrease was observable. This was usually related to periods of cloud conditions resulting in data gaps. In can be concluded that the EVI captures grassland mowing event well, however, potentially misses some events during cloudy weather conditions. A mowing detection approach was developed which located strong EVI decreases (local minima), followed by an increase (instead of a plateau). The threshold for the mowing event detection was calibration with the parametrization sites and resulted in an EVI change of 0.07.

Regarding S1, several parameters were investigated, consisting of the backscatter intensity of VH and VV, the polarimetric decomposition (PolSAR) parameters Entropy, K0 and K1, and the interferometric temporal (InSAR) Coherence of VH and VV. All of these parameters showed inconsistent behavior towards grassland mowing events as their time series were characterized by many fluctuations even after smoothing, with increases or decreases unrelated to mowing events. It became clear that a S1 parameter alone could not successfully be used for an automated detection of grassland mowing events. Among all investigated S1-based parameters, the PolSAR Entropy and the InSAR Coherence VH showed the most potential to capture grassland mowing events as increases after mowing events were mostly present and additional increases unrelated to mowing were not as frequent as for other parameters. As the EVI-based mowing detection algorithm potentially misses mowing events within periods of data gaps, a second mowing detection approach was developed which combined S2 and S1 to detect mowing events. Mowing events were detected like in the EVI-only approach, however, within S2 gaps of at least 25 days the S1-based parameter is checked for strong increases within a time period of 5 days before until 10 days after the gap to detect mowing events. The PolSAR Entropy and the InSAR Coherence VH were both calibrated in that regard using the parametrization sites and their performance for the combined mowing detection approach tested.

The EVI-only and the combined approaches were applied and validated in a focus region in southern Germany with a large share of grasslands, including all levels of mowing intensity from zero to six events per year. It showed the high potential of the EVI time series for mowing detection with 64.6 % of correctly detected mowing events and an F1-Score of 0.65. The combined approach using the EVI accompanied with the PolSAR Entropy and the InSAR Coherence VH led to an increase in correctly detected mowing events to 73.8 and 72.0 %, respectively. However, also the number of falsely detected mowing events rose which resulted in a reduced accuracy with F1-Scores of 0.61 for EVI+Entropy and 0.61 for EVI+Coherence. Hence, it could be revealed that the potential of SAR parameters for grassland mowing detection is limited. Most probably varying moisture conditions or changing practices when grasslands are mown – e.g. at times grass is left on parcels to dry – influence the reaction of the SAR parameters to mowing events and aggravate an automatic detection approach.

The most successful approach, which was the detection algorithm based on the EVI, was then applied to the entire area of Germany and validated with an extensive reference data set for the years 2018–2021. The reference data was collected from touristic webcams distributed in Germany which acquired daily RGB images of landscapes covering one to multiple grasslands. In total, information of around 179 differently managed grasslands were available for validation resulting in 1475 reference mowing events for 2018–2021. The accuracy assessment revealed similar results like the focus region with a F1-Score of 0.64 for 2019. The mowing detection in 2020 was almost as accurate with a F1-Score of 0.60, however a larger number of correctly detected mowing events (66.3 %). The years 2018 and 2021 reveal lower accuracies with F1-Scores of 0.48 and 0.53. The results show the algorithm developed with data from 2019 and in a local region is transferable with constant accuracy to the entire area of Germany and other years with similar weather conditions and data availability like 2019. The year 2018 was exceptionally hot and dry which has negatively influenced the detection capability of mowing events and, in 2021, the availability of cloud-free data was lower compared to the other years.

The third objective of the thesis was related to the analysis of the detected mowing dynamics in Germany for the years 2018–2021 with the following research questions.

Research Questions 3:

1. How does the developed grassland mowing event detection approach perform for the entire area of Germany?
2. What are patterns of multi-annual nation-wide mowing dynamics in Germany?
3. Where are hotspots of intensively used grasslands and where are regions of extensive grassland use?

This objective was approached by the application of the developed mowing detection algorithm to all grassland areas of Germany for the years 2018–2021. Based on the detected mowing events, annual mowing frequencies and the timing of the first mowing event of each year were mapped and analyzed. The maps show mowing dynamics in high spatial resolution of 10 m which potentially also captures patterns within parcels.

The investigation of mowing frequencies in Germany showed that a high share of intensively mown grasslands can be found in the south/south-eastern parts of Germany (mown more than three times). Central and central-northern parts of Germany show high shares of extensively mown grasslands (mown up to two times). Early mown grasslands can be found in southern/south-eastern Germany – comparable to areas with high mowing frequencies –, but also in western/north-western parts of the country. The southern Pre-Alpine region of Germany is the one with the highest precipitation rates which might be the reason for large shares of high mowing frequency grasslands. In addition, the overall proportion of grassland is high which is also translated into the highest numbers of cattle in the south-eastern state of Bavaria. Western/North-western Germany is characterized by higher temperatures and mild winters which is probably the reason for comparably early first mowing events.

Considering the entire grassland area of Germany, 11–16 % are mown not at all, 33–40 % one time, 31–33 % two times, 10–16 % three times and 4–5 % at least four times, depending on the year.

The mowing dynamics between the years stay relatively constant, however some variability was visible on smaller scales. It is revealed that farmers overall maintain the management practices apart from small deviations of one additional or less mowing event. Farmers probably react to external influences, for example weather conditions. The year 2020 showed overall higher mowing frequencies, probably a reaction to the overall warm temperatures of this year. In 2018, some areas revealed lower mowing frequencies which were probably related to the high temperatures and dry weather conditions of this year. However, mowing frequencies were not reduced for all grasslands of Germany in 2018. In 2018, the first mowing event took place earlier compared to the other years which was probably the result of an early spring in that year. In 2021, the timing of the first mowing events was late for many regions. This year was characterized by a very cold April and late start of vegetation growth in spring.

The final objective was about the relationship of mowing dynamics to potential influencing factors, namely climatic, topographic, soil and protection conditions. The following research questions were approached in that regard.

Research Questions 4:

1. To what extent do climatic, topographic, soil conditions and socio-political frameworks influence mowing dynamics in Germany?
2. What do these relationships imply for management options and the status of grasslands in the future?

Data sets of abiotic conditions and conservation schemes were acquired and related to the detected mowing dynamics to analyze which conditions are usually fulfilled for intensive and which for extensive grassland use. In that regard, data sets of 2020 were used as this year showed a high mowing detection accuracy and good optical satellite data availability. The climatic data consisted of annual mean temperature and annual precipitation sum in 1 km spatial resolution. The topographic data, consisting of slope and elevation, and the mowing information were resampled to the projection and resolution of the climatic data to make the raster data sets comparable. The mowing frequency and the timing of the first mowing event were averaged from 10 m to 1 km, resulting in continuous values also for the mowing frequency. The soil classes were assimilated to match the World Reference Base to make them internationally comparable. The Natura 2000 sites were used as proxy for the presence of conservation schemes and were filtered to maintain only sites larger 1 ha.

The comparison of climatic as well as topographic data with the mowing dynamics revealed that there were significant relationships between all four variables and the mowing frequency as well as the timing of the first mowing event. The correlation coefficients were, however, small as the Pearson's r was almost always smaller 0.3. Solely the relationship between precipitation and mowing frequency revealed a higher correlation with a Pearson's r of 0.36. This already indicates a relative importance of precipitation for mowing frequency.

To analyze the conditions which are related to intensive or extensive grassland use, the climatic and topographic gradients of intensively used grasslands (mown three to six times or four to six times), extensively used grasslands (mown up to one time), and early mown grasslands (mown before 1^{st} of May or 1^{st} of June) were depicted. This revealed that intensively used grasslands in Germany occur on a smaller climatic and topographic gradient compared to all grasslands, revealing that a framework of conditions have to be fulfilled for intensive grassland use. Extensively used grasslands were shown to cover the entire climatic and topographic gradients like all German grasslands. Grasslands mown before 1^{st} of June occurred only at annual temperatures of at least 8 °C.

A comparison of mowing frequencies of different soil classes showed that there are no strict boundaries of mowing intensity levels between them. However, there were tendencies visible that soil classes with influence of ground water are more intensively used compared to others, highlighting the importance of the availability of water for intensive grassland use. Grassland within Natura 2000 sites showed lower numbers of mowing frequency and were later mown compared to the grasslands outside of Natura 2000 sites. However, also protected grasslands are at times intensively managed and show mowing frequencies of up to six events per year. This is related to the fact that the Natura 2000 ecosystems are managed to maintain their habitats and species which might be achieved with rather intensive management for some cases. The results highlight that climatic and topographic conditions build a framework for intensive grassland use, and extensive use is not coupled to abiotic conditions. The reason for this is that many abiotic conditions which would naturally result in extensive use, like high water levels or reduced nutrient availability, can be circumvented by farmers through drainage and fertilization, for example. The results underline the importance of protection mechanisms for grassland ecosystems to maintain the diversity also in future climates.

6.2 Outlook for Future Research

The monitoring of grassland management plays an increasingly important role in the future. The use of many grasslands in Germany is intensified continuously. In addition, grasslands are permanently at risk of being converted into cropland. Hence, the number of grasslands with a large variety in ecosystem services and biodiversity is decreasing in Germany. Furthermore, actions within the agricultural sector are required regarding the mitigation of climate change and the conservation of species and ecosystem functions. Sustainable and holistic management plans require continuous and comprehensive information on use and state of the ecosystems, with mowing dynamics being of central importance for grasslands.

For future research, further development and improvements to the monitoring framework are possible. One aspect for which a more detailed refinement is useful concerns the unevenly distributed optical satellite imagery resulting from unequal coverage of S2 orbits in Germany. Complementing the S2-based detection with S1 data was shown to not solve this issue – as presented within this thesis – as the mowing detection accuracy could not be improved. Adding other sources of optical data did also not result in an improvement of grassland mowing detection analyses. However, tackling remaining artifacts resulting from unevenly distributed S2 data in post-processing is a promising future approach, e.g. by revising the mowing detection in areas characterized by less data availability by an empirically trained model based on information of areas with more data availability. In addition, the aspect of grazing is potentially approached in future research. Grazing events are often confused with mowing events, however, grazing has a different impact on grassland ecology compared to mowing. While investigating mowing dynamics, some recurring patterns related to grazing became visible within the time series of satellite imagery which could be useful to investigate grazing (intensity) on grasslands. One example is a large spatial variability of vegetation index values on grassland parcels.

The framework to monitor grassland mowing dynamics developed within this thesis is going to be applied for the entire grassland area of Germany within future years. Results from the analyses conducted here have shown that the approach is transferable to other years. However, for years with a relatively low data availability, the approach could be potentially adjusted to improve the results. In addition to the temporal extension, the mowing detection algorithm could also be applied to other temperate grasslands which occur outside of Germany and are regularly mown, including Northern, Central and Eastern European grasslands.

Another aspect of future research is the integration of spatial mowing date information into models, e.g. to estimate carbon and nitrogen fluxes in grassland ecosystems. Another field of application is the biodiversity estimation of grassland ecosystems, for which the mowing intensity is a valuable additional explaining variable for the analyses. Co-operations in that regard are already ongoing and are further maintained in the future. Lastly, mowing dates are a valuable input feature for the estimation of grassland yields which is a research focus in the future. Due to the large variety of grasslands and the large diversity in the timing and types of management actions, the estimation of grassland yields is challenging. Spatial information of grassland yields is not available in Germany and combining models to estimate grassland biomass with mowing information potentially enables successful grassland yield estimations in the near future.

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