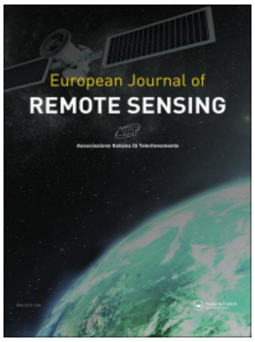

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Integrating Landsat, Sentinel-2 and Sentinel-1 time series for mapping intermediate crops

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ABSTRACT

Intermediate crops are grown between main crops to protect soils and nutrients when fields would otherwise be bare. Despite being an essential constituent of cropping systems, spatial information on intermediate crops is scarce. Here, we propose a classification algorithm that combines field data, satellite imagery from multiple optical sensors and synthetic-aperture radar (SAR) data to map intermediate crops across Brandenburg, Germany. We trained random forest models using different sets of input features, including spectral-temporal metrics from optical data, metrics derived from SAR data and information on the scheduled main crop. The best classification was based on a combination of all input features and achieved an overall accuracy of 92.9%. Intermediate crops were overestimated, which can be partly attributed to misclassification of volunteers and weeds as intermediate crops. The overestimation was mitigated by aggregating results to the field level. Our results highlight the need for good optical data coverage during autumn and winter to accurately map intermediate crops while demonstrating the ability of SAR data to enhance classification accuracy. Overall, our study shows the potential of remote sensing methods to capture the characteristics of intermediate crops and derive spatially explicit data for monitoring sustainable agricultural practices.

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Cover crops; catch crops; agriculture monitoring; land cover classification; random forest; spectral-temporal metrics

Introduction

Current agricultural landscapes are dominated by simplified cropping systems that evolved from agricultural intensification. These systems are characterised by fewer species in rotations, enabling farmers to focus on the economically most important crops and enhancing agricultural productivity (Hufnagel et al., 2020). However, they rely on intensive management practices and external inputs that may cause nutrient leaching (Bowles et al., 2018), soil erosion (Montgomery, 2007), climate-relevant greenhouse gas emissions (Bowles et al., 2018; Smith et al., 2008) and a decline in biodiversity (Tscharntke et al., 2012). On the contrary, more diverse cropping systems are likely to maintain productivity and resilience while reducing adverse impacts on the environment (Renard & Tilman, 2019; Rosa-Schleich et al., 2019). Crop diversification therefore holds significant potential for addressing environmental challenges and has become an increasingly discussed topic in science and policy to enhance agricultural sustainability.

The integration of Intermediate Crops (ICs) into rotations is one important diversification strategy that especially targets soil health. ICs are annual plants that are grown during fallow periods in summer or during winter, but not for the purpose of producing any marketable products (Eurostat, 2023). Being commonly known as cover, catch or break crops, the term ’intermediate crops’ addresses them as an umbrella term. It reflects their function in the system and the terms used in most languages in Europe, other than English. Generally, ICs may be used as fodder or for biogas production, but their primary function depends on the condition of the respective field. While the numerous environmental benefits of ICs are recognised through targeted agricultural policies, spatial information on IC cultivation is scarce. In this study, we evaluate the potential of integrating various remote sensing data for mapping ICs in north-eastern Germany. We aim to address challenges such as data gaps during winter by combining data from different sensors and to map ICs as comprehensively as possible by using field data. The field data were collected in a campaign tailored to the classification problem, particularly addressing crop types that could be confused with ICs due to similar growing patterns, and that are not included in official campaigns. This allows us to cover a broad range of ICs (regarding different growing periods, species compositions and functions)

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reflecting real-world agricultural practices across the study area. As a consequence, the study does not focus on mapping specific IC types but rather aims to represent the diversity of crops cultivated as ICs.

A great variety of species can be cultivated as ICs, either in mixtures or as sole crops. ICs can also be grown simultaneously with agronomic crops, i.e. as an undersown crop that remains on the field after the main crop was harvested. Ensuring a more continuous plant cover on agricultural soils, ICs help to control soil erosion ("cover crops"; Langdale et al. (1991)) and prevent nutrient leaching (Thapa et al., 2018). Certain ICs are specifically grown to enhance soil fertility ("fertility-building crops"), either through fixing atmospheric nitrogen in root-colonising bacteria and providing it to the succeeding crop (Dabney et al., 2011) or through leaving above- and belowground residues that increase soil organic matter in the long term (Poeplau & Don, 2015). Some ICs even improve the physical conditions in the soil through strong, deep-growing roots that may alleviate soil compaction ("conditioning crops"; Chen and Weil (2010)). Deep rooting ICs tap nitrogen reservoirs that have accumulated below the root zone of the main crops and bring this nitrogen back to the soil surface for later re-use by the main crops in the rotation ("catch crops"; Thorup-Kristensen et al. (2020)). ICs may have phytosanitary effects and break the cycle of soil-borne pests or diseases ("break crops"; Kirkegaard et al. (2008)) or suppress weeds through vigorous growth ("smother crops"; Liebman and Davis (2000)). Furthermore, ICs provide late flowering and contribute to more diverse habitats supporting soil organisms, birds and insects (Blanco-Canqui et al., 2015).

In the European Union (EU), the cultivation of ICs has been financially supported since the 2013 reform of the Common Agricultural Policy (CAP). Until the beginning of 2023, ICs were partly eligible for subsidies related to two of the three greening measures – crop diversification and ecological focus areas (Regulation 1307/2013). With the 2021 CAP reform, ICs have become an integral component of the ruleset contributing to good agricultural and environmental conditions (GAECs), and therefore to conditionality (Regulation 2021/2115). ICs cultivated with the intention of receiving direct payments would thus be reported by farmers and included in the Integrated Administration and Control System (IACS) of the EU (Regulation 2021/2116). The IACS provides information for almost every field in Europe, detailing the main crop grown during the reporting period (May) of each year and whether an IC eligible for subsidies is cultivated. This self-reporting by farmers is, however, also the weakness of the data, as it is neither complete, nor completely reliable. It requires independent on-site controls to validate the farmers' reports. Notably, the system does not fully capture the complexity of cultivated ICs, as some farmers do not apply for subsidy payments and not all ICs qualified for subsidies under greening measures in certain member states, e.g. Germany (DirektZahlDurchfV, 2014, § 31).

Spatial information on the cultivation of ICs thus remains scarce and incomplete, although it is of critical importance for assessing the efficacy of policy measures and environmental implications. For such assessments, mechanistic (i.e. process-based) agro-ecosystem models are often used, as they provide a relatively simple, quick and low-cost method to investigate the impact of climate or management changes on productivity and environment (Nendel et al., 2014). Such models simulate yields, nitrate leaching, carbon storage and greenhouse gas emissions in response to weather, site conditions and management. Applying them at larger scales requires spatial data to inform the models, and simulations that specifically require information on ICs could benefit from a more detailed monitoring of crop rotation patterns (Faye et al., 2023; Kollas et al., 2015; Nendel et al., 2023).

Providing information from satellite remote sensing is the main method to approach this objective, as it can efficiently capture the dynamics of agricultural land cover over time and space (Bégué et al., 2018). A large amount of freely available satellite data from the Landsat and Copernicus programmes allows to disentangle phenological characteristics of individual crops. In addressing these complexities, machine learning models have emerged as pivotal tools in remote sensing applications for agricultural monitoring. These models are particularly effective for tasks such as the classification of crop types and land cover (Blickensdörfer et al., 2022). Ensemble learning techniques, such as Random Forests (RF), have gained prominence due to their ability to handle high-dimensional datasets, including spectral-temporal metrics derived from optical and radar imagery. RF models are robust against overfitting and can effectively manage heterogeneous input feature splits (Belgiu & Drăguţ, 2016), making them well suited for complex datasets like those used in this study. By leveraging these capabilities, machine learning enables the integration of multi-sensor data to capture the subtle phenological differences and compositional variability of ICs, ultimately enhancing classification accuracy and adaptability to real-world conditions. While this has enabled the production of high-quality crop type maps (Blickensdörfer et al., 2022; d'Andrimont et al., 2021; Griffiths et al., 2019; Johnson, 2019), the current methods focus on the detection of one crop during the growing season, which is usually the main crop. The need for separation of crop types in greater detail is often emphasised but has been addressed by comparatively few remote sensing studies (Bégué et al., 2018). Mapping approaches of ICs are particularly aggravated by data gaps in optical data due to cloudy winter months during the growing season and a lack of reliable reference data (Fendrich et al., 2023; Najem et al., 2024; Schulz et al., 2021). Missing information and an uneven distribution of data during the growing season highlight the need to integrate data from different satellite sensors and test compositing techniques (Gao et al., 2020, Najem et al., 2024). Furthermore, the similarity of ICs to some main crops, their highly variable seeding times and differing species compositions challenge a distinction of ICs from other cultivated crop types.

Here, we aim to address these gaps by mapping ICs using Spectral-Temporal Metrics (STMs) derived from combined optical and Synthetic-Aperture Radar (SAR) satellite imagery, and incorporating ground-truth data from the field. STMs have been widely used in land-cover mapping and are often preferred to e.g. best-pixel composites or single observations from optical sensors as they provide reliable information for periods of low data coverage (Frantz et al., 2023; Müller et al., 2015; Pflugmacher et al., 2019). By summarising the spectral distribution and temporal variability of a pixel over a specified period, STMs capture important phenological information. Furthermore, integration of SAR data, which unlike optical images are not affected by atmospheric conditions can be beneficial, considering data gaps during the main growth period of ICs (Jennewein et al., 2022; Meroni et al., 2021). This motivates the following research questions:

- How do STMs of combined optical satellite imagery of high spatial resolution (10–30 m) and SAR-based metrics account for the spectral-temporal characteristics of ICs?
- How does the integration of different input features, including optical metrics, SAR metrics, and main crop information, impact the classification accuracy of intermediate crops?
- To what extent do the obtained results align with official agricultural statistics and may contribute to long-term monitoring of agricultural systems?

The paper is structured as follows: Section 2 introduces the study area, Section 3 describes the data and preprocessing steps, Section 4 outlines the methods used for classification, Section 5 presents the results, and Section 6 discusses the findings and concludes the study.

Study area

The study area is located in north-eastern Germany and comprises the federal states of Berlin and Brandenburg (Figure 1). Its area of approximately 30000 km^2 is predominantly covered with agricultural land (~44%), of which 84% is arable land (MLUK, 2021b). Brandenburg is characterised by a warm temperate climate with annual precipitation totals averaging 558 mm and a mean annual air temperature of 9.2 °C (DWD, 2019). With increasing continental influence, the southern and south-eastern regions of Brandenburg experience a slightly warmer and drier climate. Soils within the study area evolved from quaternary loose sediments (MLUK, 2020) and are comprised of sandy to sandy-loamy substrates that vary in their suitability for agricultural use (Hanff & Lau, 2021; Wolff et al., 2021). Sandy soils in the outwash plains and meltwater valleys provide low water retention capacity and soil fertility. They are mostly used as grassland or non-agricultural land. Instead, sandy-loamy soils found on plateaus of young and old moraines (e.g. Uckermark, Fläming Heath) are more fertile and better suited for crop cultivation. Other intensively used cropland sites are situated on drained floodplain soils along rivers (e.g. Oderbruch).

Phenological stages of commonly grown main crops in the study area were obtained from regular field observations reported by the German Meteorological Service (Deutscher Wetterdienst, DWD; Figure 2). Different spring and winter crops are grown, with silage maize, winter rye and winter wheat occupying most of the area (Amt für Statistik Berlin-Brandenburg, 2021). Certain crop types, e.g. sugar beet, are grown less frequently as they require very good soil qualities. For some crops, phenological data were unavailable, e.g. for potatoes, which show highly variable sowing (March – May) and harvesting (June – October) dates.

To ensure good growing opportunities, ICs should be sown right after harvesting the main crop and no later than by the end of September (Schmidt & Gläser, 2014). Accordingly, two main cultivation windows for ICs can be identified. If grown after an early-harvested main crop (e.g. winter barley, early potatoes), ICs may be sown from the beginning of July. Fast-growing ICs may then be ploughed before a succeeding winter crop, whereas slow-growing ICs remain on the field until next year's spring crop is sown. The latter are referred to as winter ICs and are most common. They can either serve as forage if winter-hardy or leave frostbitten crop residues in spring. We will consider June 2021 to March 2022 to map different ICs.

Data

Optical satellite data

The growing seasons of ICs require the use of potentially cloudy and noisy winter imagery. We therefore combined different optical satellite data acquired between 1 June 2021 and 31 March 2022. Our analysis was based on Landsat 7 (Enhanced Thematic Mapper Plus, ETM+), Landsat 8 (Operational Land Imager/Thermal Infrared Sensor, OLI/TIRS), Landsat 9 (Operational Land Imager-2/Thermal Infrared Sensor-2, OLI-2/TIRS-2) and Sentinel-2A/B (Multispectral Instrument, MSI) scenes with a maximum cloud cover of 70%. The different sensor swaths overlap laterally, resulting in shorter revisit intervals and higher observation numbers

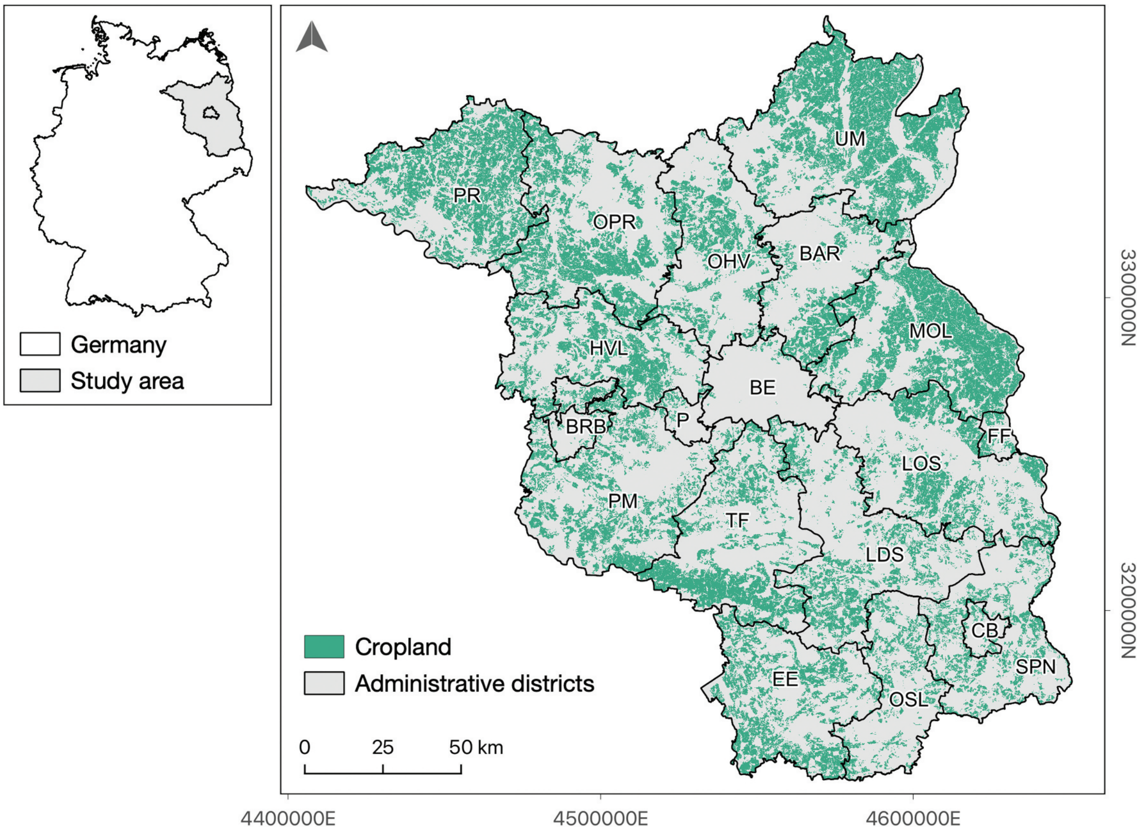

Figure 1. Cropland in Brandenburg and Berlin, Germany (cadastral data ©MLUK, dl-de/by-2–0). BAR: Barnim; BE: Berlin; BRB: Brandenburg an der Havel; CB: Cottbus; EE: Elbe-Elster; FF: Frankfurt (Oder); HVL: Havelland; LDS: Dahme-Spreewald; LOS: Oder-Spree; MOL: Märkisch-Oderland; OHV: Oberhavel; OPR: Ostprignitz-Ruppin; OSL: Oberspreewald-Lausitz; P: Potsdam; PM: Potsdam-Mittelmark; PR: Prignitz; SPN: Spree-Neiße; TF: Teltow-Fläming; UM: Uckermark (©GeoBasis-DE/BKG (2022), dl-de/by-2–0).

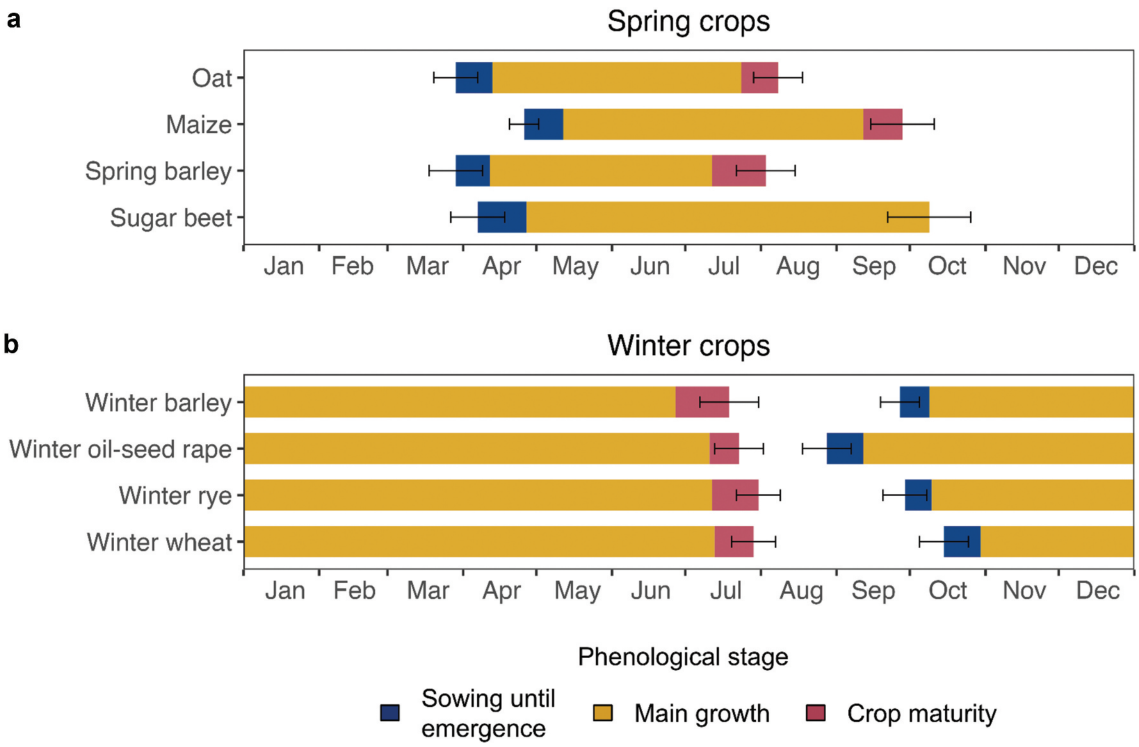

Figure 2. Average vegetation periods of common main crops in Brandenburg based on phenological data from 2019–2021 (DWD Climate Data Center CDC, 2021, 2022). The error bars display standard deviations for the observed sowing and harvesting dates. (a): Phenology stages of commonly grown spring crops. (b): Phenology stages of commonly grown winter crops.

(Li & Roy, 2017). This allows to generate denser time series which are beneficial for remote sensing applications that require reconstructing the phenological behaviour of plants, specifically agricultural land cover mapping. As of 1 January 2022, Landsat 7 imagery was excluded from the analysis due to its official replacement by Landsat 9 which offers improved radiometric and geometric quality. Satellite imagery was obtained and processed using the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE). FORCE provides cloud masking, radiometric correction and higher-level processing modules in a data cube structure (Frantz, 2019). All accessed satellite data were quality masked to exclude clouds, cloud shadows, snow, no data and saturated or sub-zero reflectance. The native Landsat (30 m) and Sentinel-2 (20 m) bands were resampled to obtain a spatial resolution of 10 m, while the 10 m native Sentinel-2 bands remained unchanged. Instead of using the raw bands, we selected five vegetation indices for our analysis – namely Soil-adjusted vegetation index (SAVI), Normalised difference tillage index (NDTI) and Tasseled Cap Brightness, Wetness and Greenness (Table 1).

Sentinel-1 Ground Range Detected (Interferometric Wide swath mode (IW), Processing level 1 high-resolution products) data were integrated in the study. To ensure optimal quality and consistency, the SAR data underwent several pre-processing and filtering processes. Initially, Sentinel-1 observations were filtered based on their acquisition mode – either descending or ascending – and their relative orbit. Additionally, data with extreme incidence angles, which often result in significant noise, were masked. We further pre-processed the data using a Gamma Map Filter (Lopes et al., 1990) with 5 × 5 kernel size to reduce speckle noise. The cross-polarisation ratio (VH/VV) was computed from the pre-processed data to augment our optical data time series.

Field data

A field campaign focusing on the detection of ICs was conducted throughout different agricultural landscapes in Brandenburg. Field data were collected from late August 2021 until April 2022, with the majority of records reported at the end of September and in November 2021. A total of 759 fields were reported, of which 509 were covered with ICs. The documented variables include the observed crop species according to Table 2, corresponding coordinates, date and additional comments, e.g. on vegetation density and suitability for subsequent analysis. The crop species were explicitly noted to keep track of which IC types and non-IC crop types were sufficiently covered by the field campaign. The samples were then assigned to their corresponding target class for classification (cf. Table 2). The target class "other crop types" refers to non-ICs observed in the study area during the campaign. This includes fallow land, fodder or

Table 1. List of indices used in the study.

Index	Name	Formula	Reference
SAVI	Soil-adjusted vegetation index	$SAVI = ((NIR - RED)/(NIR + RED + L)) * (1 + L)$	Huete (1988)
NDTI	Normalised difference tillage index	$NDTI = (SWIR1 - SWIR2)/(SWIR1 + SWIR2)$	van Deventer et al. (1997)
TCB	Tasseled cap brightness	$TCB = 0.2043 * BLUE + 0.4158 * GREEN + 0.5524 * RED + 0.5741 * NIR + 0.3124 * SWIR1 + 0.2303 * SWIR2$	Crist (1985)
TCG	Tasseled cap greenness	$TCG = -0.1603 * BLUE - 0.2819 * GREEN - 0.4934 * RED + 0.7940 * NIR - 0.0002 * SWIR1 - 0.1446 * SWIR2$	Crist (1985)
TCW	Tasseled cap wetness	$TCW = 0.0315 * BLUE + 0.2021 * GREEN + 0.3102 * RED + 0.1594 * NIR - 0.6806 * SWIR1 - 0.6109 * SWIR2$	Crist (1985)

Table 2. Observed crop types and their corresponding training and validation sample sizes obtained after initial cleaning of the field data and balancing of the training dataset.

Target class	Crop type	Training sample size	Validation sample size
Other crop type	Fallow land	5	1
	Fodder or sugar beet (*Beta vulgaris* ssp. *vulgaris*)	6	1
	Oil-seed rape (*Brassica napus*)	104	40
	Vegetables	4	0
	Volunteer oil-seed rape (*Brassica napus*)	6	1
	Volunteer cereals	59	12
	Weeds	18	5
	Winter cereals	70	20
Intermediate crop	Lucerne (*Medicago sativa*)	15	8
	Black oat (*Avena strigosa*)	7	2
	Buckwheat (*Fagopyrum esculentum*)	3	1
	Clover (*Trifolium incarnatum, Trifolium pratense, Trifolium resupinatum, Trifolium repens*)	4	1
	Lupine (*Lupinus* spp.)	5	1
	Oil radish (*Raphanus sativus* var. *oleiformis*)	6	1
	Pea (*Pisum sativum*)	5	1
	Phacelia (*Phacelia tanacetifolia*)	18	8
	Ramtil (*Guizotia abyssinica*)	2	0
	Rye (*Secale cereale*)	5	1
	Ryegrass (*Lolium perenne*)	2	0
	Seed mixture with legumes	133	75
	Seed mixture without legumes	76	41
	Serradella (*Ornithopus sativus*)	1	0
	Sunflower (*Helianthus annuus*)	4	1
	Turnip rape (*Brassica rapa*)	8	2
	White mustard (*Sinapis alba*)	36	15
	Other sole crops (*Cannabis spec., Helianthus tuberosus, Sisymbrium spec., Sorghum spec.*)	5	0

sugar beet, oil-seed rape, vegetables, volunteer crops, weeds, and winter cereals. These categories encompass a mix of unmanaged vegetation, residual crops from previous harvest, or main crops that were still or already present in the fields. The target class "intermediate crops" refers to crops that were identified as ICs based on their time of observation and development stage. It is comprised of various sole crops, seed mixtures and potential perennial species. At most sites, pictures were taken to allow retrospective data interpretation. During the mapping process, particular attention was drawn to (i) maintaining a certain distance between fields of the same crop type to avoid spatial autocorrelation, (ii) capturing rarely observed crop species, and (iii) ensuring a good representation of within-class variability.

Training and validation sample

After a data cleaning procedure that minimised sampling near headlands, which tend to be unrepresentative due to compaction and external inputs (Sunoj et al., 2021). (Appendix A), and avoided mixed pixels along field boundaries, a final selection of 734 fields was retained for analysis. As the information on ICs captured by IACS data was considered too incomplete for validation purposes, we split the field points into training and validation samples. Classes with limited representation in the field data were included in the training dataset as they reflect the real-world complexity and diversity of ICs present in the study area. Not considering these crop types for training would have oversimplified the classification task and reduced the ecological validity of the models. However, the small amount of field samples of certain crop types (e.g. ryegrass) did not allow to include them for both training and validation. Consequently, IC types that were represented poorly in the field data were not used for validation since their underrepresentation limited their reliability for assessing model performance on false positives or false negatives. Otherwise, validation samples were manually selected in proportion to their total count in Table 2 without choosing points that had been relocated during the data cleaning, e.g. due to buffer strips or heterogeneous parcels. All remaining points formed the training set which was initially affected by class imbalance. We therefore adjusted the training data by duplicating samples from the class "other crop type" whenever a minimum distance of 300 m to the neighbouring training point of the same field could be maintained (cf. Figure B1). This duplication ensured better balance in the training dataset by addressing class imbalance while maintaining spatial distinctness to avoid introducing spatial autocorrelation. Figure 3 illustrates the spatial distribution of the selected samples indicating the respective target class and their use for training or validation.

Methods

Spectral-temporal metrics and data availability

We defined four different aggregation periods for the computation of seasonal STMs, covering the complete growing season of ICs. The periods were selected with regard to the data availability of optical satellite data (Figure 4) and the expected phenology of crop types in the study area (Table 3).

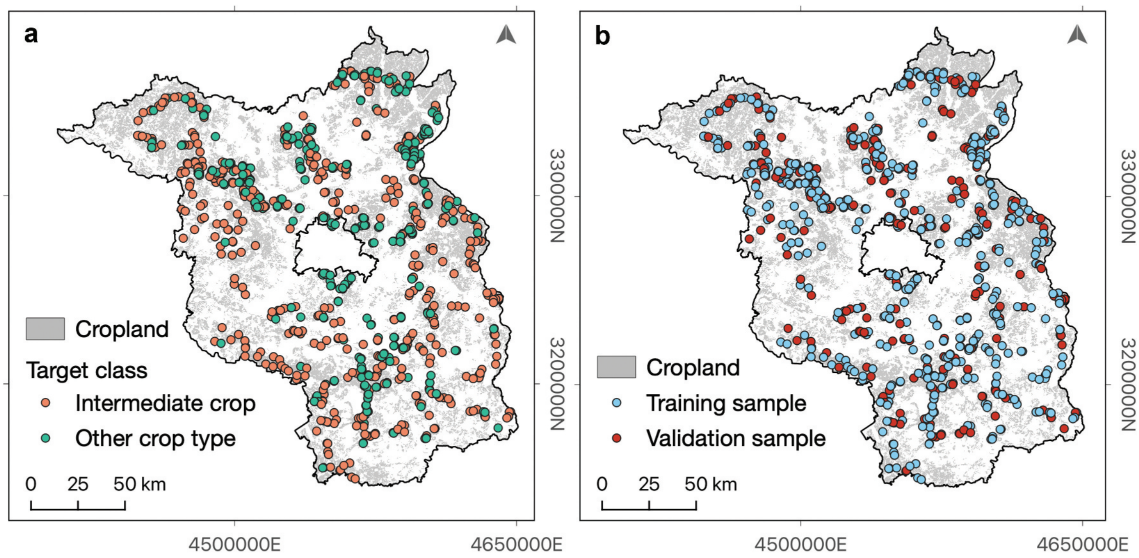

Figure 3. Spatial distribution of ground-truth data gathered in the field (cadastral data ©MLUK, dl-de/by-2–0). (a): Target classes. (b): Training and validation samples.

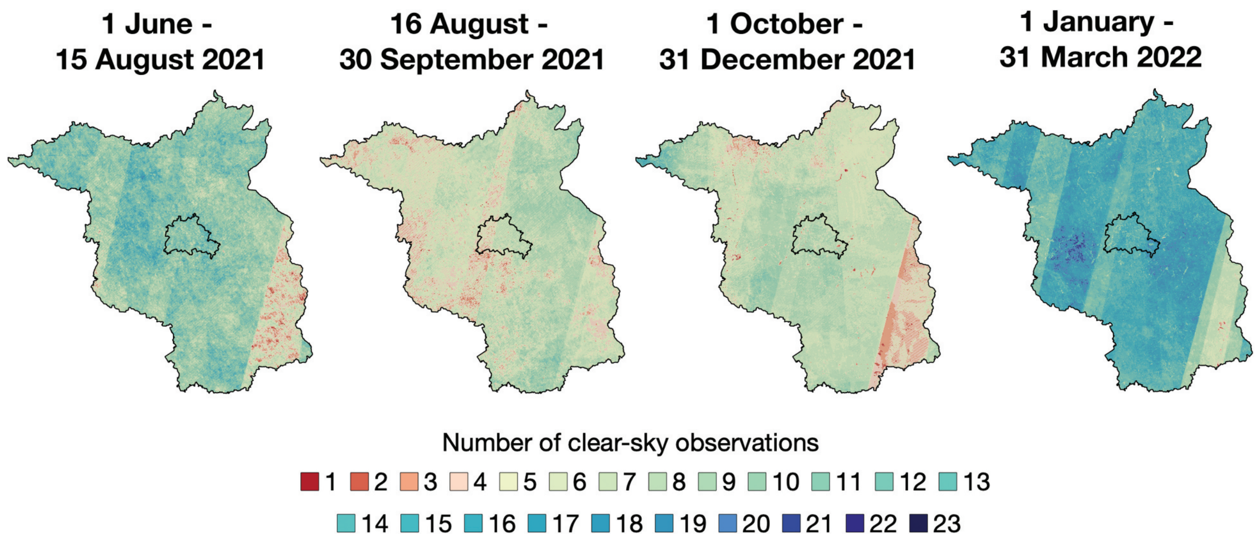

Figure 4. Clear-sky observation counts for each aggregated period (1 June – 15 August 2021: T1; 16 August – 30 September 2021: T2; 1 October – 31 December 2021: T3; 1 January – 31 March 2022: T4).

Table 3. Anticipated crop development within the selected aggregation periods.

No.	Aggregation period	DOY	Expected phenology
T1	1 June 2021–15 August 2021	152–227	Harvest of main crops Sowing and emergence of early ICs
T2	16 August 2021–30 September 2021	228–273	High biomass of early grown ICs Growth of weeds and volunteers Sowing and emergence of winter ICs Sowing of winter main crops
T3	1 October 2021–31 December 2021	274–365	Harvest of remaining main crops (maize, sugar beet) Fast development of ICs Slow development of other crop types
T4	1 January 2022–31 March 2022	001–090	Winter dormancy of main crops and winter-hardy ICs with continuing growth in spring Frost damages of most ICs

The number of valid observations per pixel, referred to as clear-sky observations (CSOs), varied strongly across the defined periods and across the study area, depending on orbit overlaps and cloudiness. During summer, it was possible to select shorter aggregation periods with average numbers of observations yielding 9.7 for T1 and 6.2 for T2. T3 and T4 include winter months and therefore cover longer time spans to ensure continuous data coverage. Nevertheless, a large part of the study area depicted less than five CSOs per pixel between 1 October 2021 and 31 December 2021, due to missing orbit overlap, the sensor failure of Landsat 7 and a higher incidence of clouds during autumn and winter. The obtained data densities for this period (T3, average CSOs = 6.5) provide a more typical representation of the winter condition, compared to the second winter period (T4, 1 January 2022–31 March 2022) which depicts an unusually high number of 14.3 CSOs on average due to exceptional cloud scarcity. Given the limited number of cloud-free observations, particularly during the winter months, compositing was employed to ensure sufficient spatial and temporal coverage under suboptimal conditions. By focusing on STMs that summarise phenological trends over these defined periods, we mitigated the potential impact of using observations from different dates and reduced the influence of short-term variability.

STMs were computed from each index or band (NDTI, SAVI, TCB, TCG, TCW, VV, VH, VH/VV). For optical data, minimum (MIN), maximum (MAX), range (RNG), median (Q50), standard deviation (STD) and interquartile range (IQR) values were derived for each period – adding up to 120 features. A reduced number of features was produced for the Sentinel-1 bands including MAX, MEAN, Q50 and STD metrics.

Classification models

In this study, the RF ensemble learning method (Breiman, 2001) was chosen for classification due to its robustness against overfitting and capability to handle high-dimensional data typical of remote sensing. It has been widely used in classification tasks using remotely sensed data (Blickensdörfer et al., 2022; Pelletier et al., 2016; Sherrie; Wang et al., 2019).

Several scenarios were tested based on time steps, optical and SAR data input (Table 4) to evaluate the relative importance of different input features. The models furthermore considered information on the scheduled main crop in 2021 as declared in the IACS (MLUK, 2021a) as input (cf. Figure B1). Each model was based on 500 decision trees, and the square root of the total number of features was randomly sampled at each split (Belgiu & Drăguţ, 2016). The models were applied to produce a binary crop type map across actively managed cropland sites in the study area (MLUK, 2021b). Post-classification, the minimum mapping unit (MMU) of the obtained maps was changed from a single pixel to the IACS polygon level. To achieve this, a frequency analysis of all pixel classes within a given parcel was performed. The most frequent class was then assigned to the corresponding field, and the aggregated maps were masked to match the cropland areas that were used for prediction. Following the classification, feature importance was extracted based on the mean decrease in Gini impurity. This metric evaluates the contribution of each feature to reducing classification uncertainty by assessing its role in splitting decision nodes across the trees in the RF model. Feature importance was calculated for all input variables, including STMs derived from optical and SAR data, to determine the most significant drivers for distinguishing ICs from other crop types.

Accuracy assessment

We performed a statistical accuracy assessment by comparing the validation data to the different map classifications at pixel and field level. The resulting confusion matrices were used to calculate common coefficients, including Overall Accuracy (OA), Producer's Accuracy (PA) and User's Accuracy (UA).

We used the map with highest OA to estimate the area of each target class and compared it to agronomic statistics. Official information on agricultural areas including ICs was obtained from agricultural structure surveys conducted in 2010, 2016 and 2020 (Destatis, 2011, 2017, 2021). In contrast to our study, perennial crops – which by definition are no ICs – were specifically excluded from the surveys. We therefore subsequently excluded lucerne and clover fields that were reported as main crops in the 2021 IACS data from the area assessment. Thereby we improved the comparability to the survey results while not changing the map design.

Table 4. Classification models. Each model was based on a different set of input features including spectral-temporal metrics from optical data, spectral-temporal metrics from SAR data or both. All models additionally included information about the cultivated main crop in 2021.

Model	Input features	Number of features
Optical	5 vegetation indices × 4 time periods × 6 metrics + main crop	121
SAR	3 bands × 3 time periods (T2–T4) × 4 metrics + main crop	37
Combined	5 vegetation indices × 4 time periods × 6 metrics + 3 bands × 3 time periods (T2–T4) × 4 metrics + main crop	157

Table 5. Validation results for the obtained maps. For classifications at pixel level, we compared the validation sample to the class assigned to the pixel containing the validation sample. For field level, we compared the validation sample to the most frequent class within each corresponding field.

		Producer's accuracy in %		User's accuracy in %	
Classification	Overall accuracy in %	Intermediate crop	Other crop type	Intermediate crop	Other crop type
Optical, pixel level	85.36	94.97	66.25	84.83	86.89
Optical, field level	92.47	96.23	85.00	92.73	91.90
SAR, pixel level	78.48	93.04	49.37	78.61	78.00
SAR, field level	83.68	93.08	65.00	84.09	82.54
Combined, pixel level	90.30	96.20	78.48	89.94	91.18
Combined, field level	92.89	96.23	86.25	93.30	92.00

Results

Model comparison

The fitted models achieved different accuracies for distinguishing ICs grown between summer 2021 and spring 2022 from other crop types in the region (see Table 5). Overall accuracies ranged from 78.5% to 92.9%, depending on the different input features used and the chosen MMU.

While optical data alone yielded high classification accuracies, the independent use of SAR data led to less accurate results. Highest accuracies were attained for the combined use of optical and SAR data, indicating that SAR data can effectively improve the classification. Moreover, aggregation to field level consistently improved OA and class-wise accuracies across all models. This particularly reduced the omission error of other crop types by the *Optical* and *SAR* models. The improvement in accuracy, however, was less pronounced for the *Combined* model, suggesting that the model provides more robust estimates of the target classes. Despite the overall enhancement, aggregation to field level occasionally introduced artefacts, e.g. if the declared IACS field boundaries differed from the actual cropping pattern. The applied majority vote would then result in an under- or overestimation of the IC area of the respective field.

In general, features from T3 and T4 were found to have the largest impact on all classifiers (Figure 5). In the *Optical* model, features from T2 proved to be valuable inputs when providing information on low or high biomass levels (e.g. TCG-MIN/MAX, SAVI-MIN/MAX), while T1 features were least informative. Most optical indices – except for TCB – demonstrated high importance with a particular relevance of their MIN, MAX and Q50 values. These trends were also reflected in the *Combined* model where feature importances of optical input variables were usually higher than importances of SAR metrics. Nevertheless, the highest-scoring SAR metrics (VV/VH from T3) had a significant impact on the *Combined* model's performance. In contrast, SAR data from T1 introduced noise leading to a decrease in accuracy by over 3% and were excluded from the final models. Compared to the satellite data, the inclusion of the cultivated main crop in 2021 as input feature provided limited value and resulted in moderate feature importances across all models.

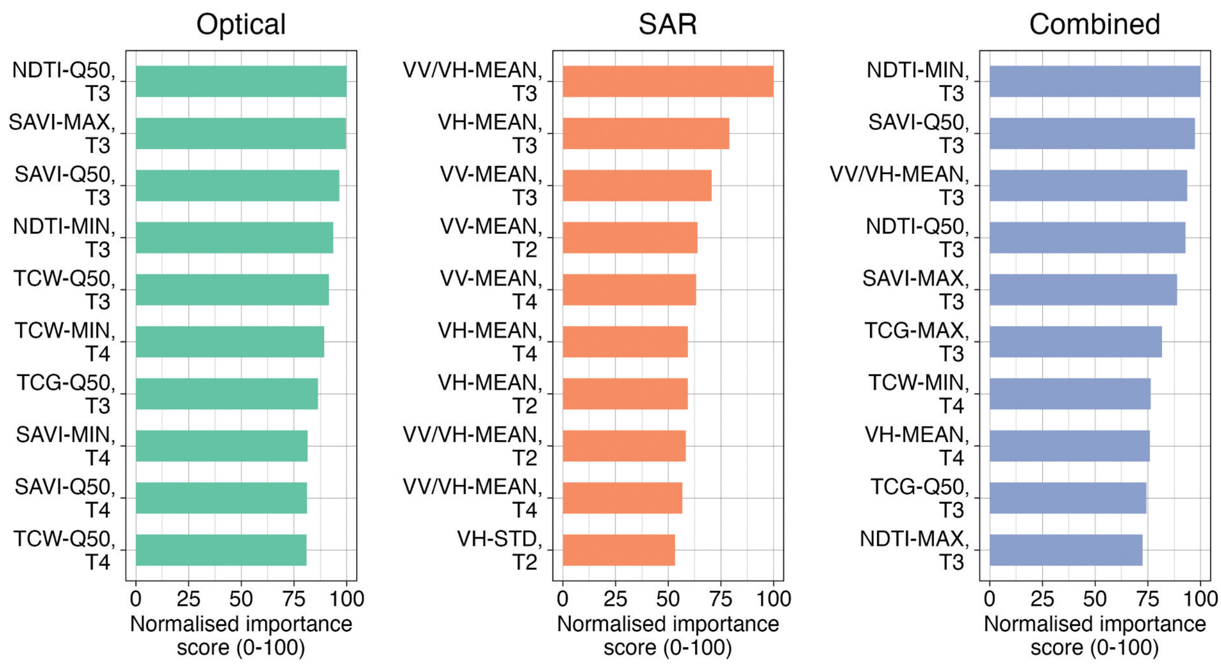

Figure 5. Normalised feature importance of the fitted models. Shown are the ten most important variables of each tested input set. The features are labelled by their index or band, statistical metric and aggregation period.

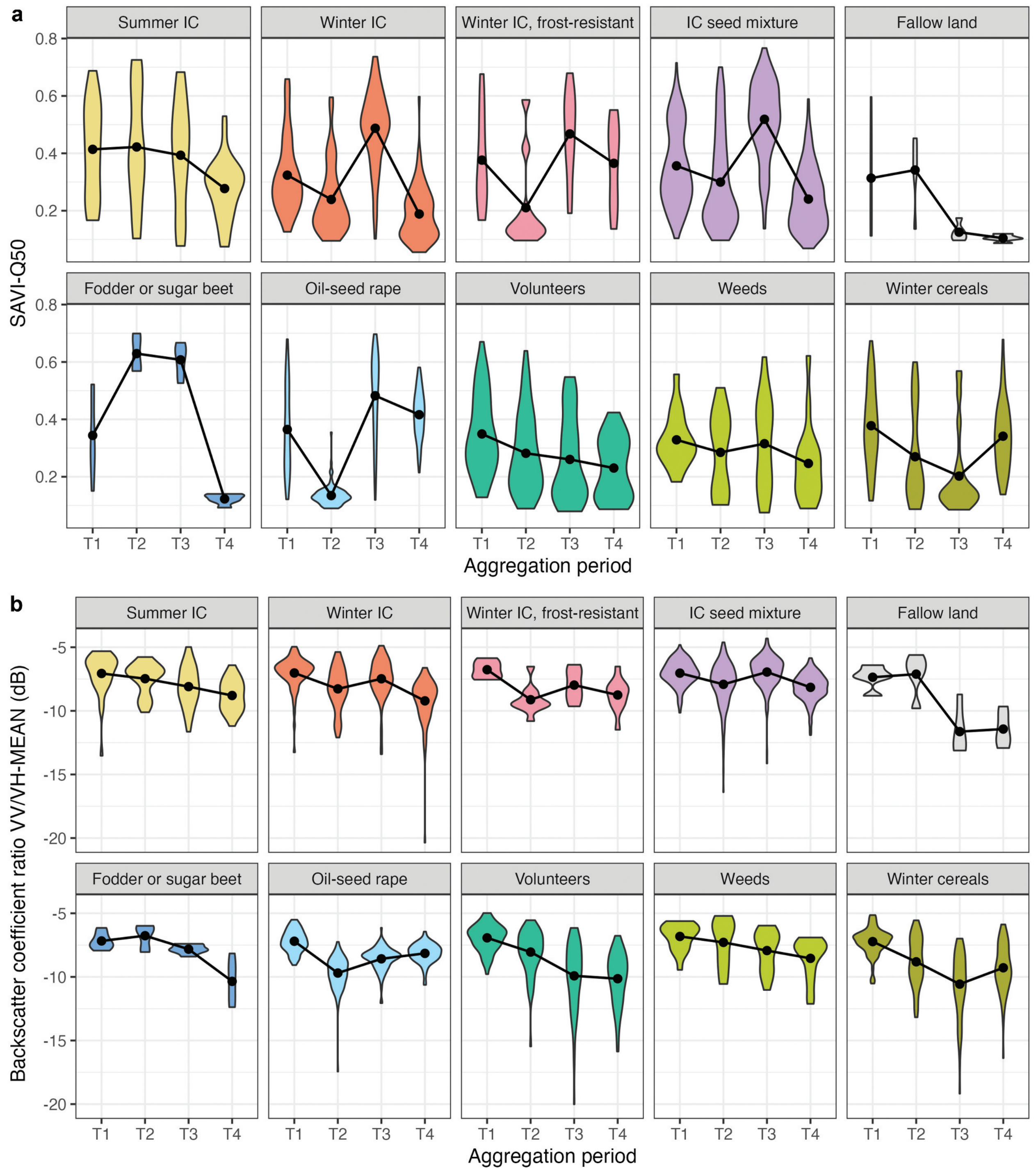

Figure 6. Temporal profiles for observed crop groups, considering training samples only. The black lines represent average phenological trends over the aggregation periods used to calculate the spectral-temporal metrics, the violins display underlying value distributions. (a): Optical metric (median of the soil-adjusted vegetation index: SAVI-Q50). (b): SAR metric (average cross-polarisation ratio: VV/VH-MEAN).

Representation of phenological patterns

The STMs used in this study were computed for periods that specifically aim to capture the anticipated phenology of ICs in the study area. In an exemplary way, SAVI-Q50 and VV/VH-MEAN profiles were examined to assess the actual representation of phenological patterns (Figure 6). For this purpose, some of the crop types reported in the field were grouped to facilitate visualisation. The grouping was chosen as a compromise between interpretability and detail, allowing to identify potential sources of misclassification that would otherwise be masked by the great heterogeneity within the two target classes.

Optical and SAR metrics often displayed similar patterns and were able to detect phenological differences between groups (Figure 6). The largest differences were observed for T2, T3 and T4, corresponding to the feature importance results (Figure 5). ICs were mostly characterised by peak vegetation signals in T3 followed by a significant decline in T4. Since this decrease is related to ploughing events or severe frost damage, it appeared rather moderate for frost-resistant winter ICs (Figure 6a). The SAVI-Q50 values of frost-resistant winter ICs thus resembled those of oil-seed rape which also develops a high leaf mass before winter and is marginally affected by frost. However, SAR metrics might resolve this potential source of confusion as they showed distinct VV/VH-MEAN values for oil-seed rape in the last period (Figure 6b). ICs sown late in the year, e.g. after silage maize, developed very little aboveground biomass in T3 with an increasing growth in T4 (Appendix C Figure C1). Consequently, their temporal profiles differed strongly from most winter ICs, making them susceptible to misclassification with winter cereals. Apart from that, the general patterns of winter cereals, fallows and sugar beet clearly differed from that of ICs. Summer ICs, volunteers and weeds were characterised by similar trajectories with high standard deviations across the illustrated metrics. Although summer ICs are typically grown earlier in the year and peak in T2, their average temporal profile was flattened due to the potentially large amount of lucerne and clover samples being cultivated as perennial crops. Weeds and volunteers, on the other hand, are not grown on purpose and can develop very differently on each field. Their individual samples may show a unique pattern or resemble any other reported crop type.

Summarising, the varying development of unmanaged crops (i.e. weeds or volunteers) as well as the incorporation of different main crops – each following a distinct phenology – add to a significant heterogeneity of the target class "other crop types". Conversely, most IC species and mixtures follow distinct patterns with minor differences depending on their sowing date, frost resistance and growth period. The considered metrics suggest a potential confusion between ICs and oil-seed rape, winter wheat, volunteers and weeds.

Best model and comparison to official statistics

In this section, we focus on the classification of the *Combined* model aggregated to field level which yielded the highest overall and class-wise accuracies. The model was based on STMs from optical and SAR data, as well as on auxiliary information about the cultivated main crop in 2021. ICs were mapped on all field sizes ranging from fine-scale structures to very large parcels, sometimes forming clusters across neighbouring fields. The map displays regional management differences with significantly less IC plots on very fertile soils, e.g. in the Uckermark (Figure 7a). Higher shares of ICs were present in areas with low (Figure 7c) to medium (Figure 7b) soil qualities.

According to the confusion matrix (Table 6), the majority map achieved an OA of 92.9%. The best class-wise accuracies were attained for ICs with both high

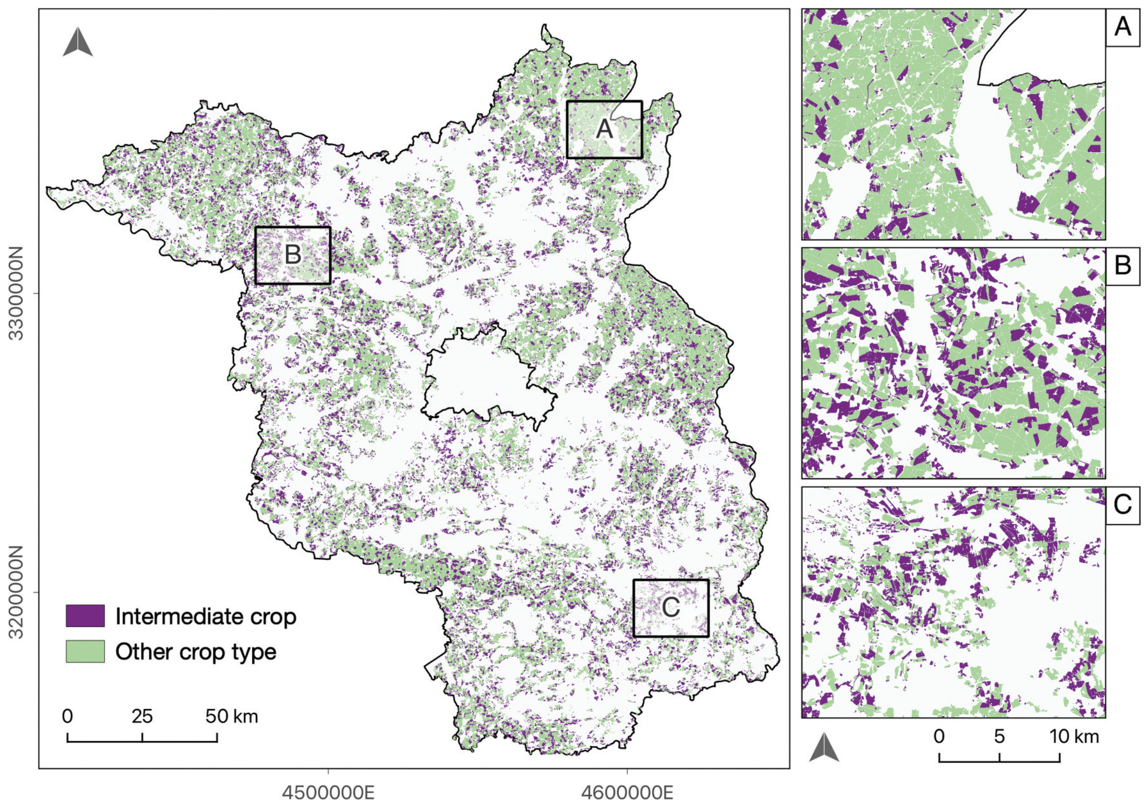

Figure 7. Binary crop type classification of the study area based on the *Combined* model aggregated to field level. The three detailed views are characterised by decreasing soil qualities from a to c.

Table 6. Confusion matrix of the *Combined* classification at field level.

		Reference		
		Intermediate crop	Other crop type	Sum
Prediction	Intermediate crop	153	11	164
	Other crop type	6	69	75
Sum		159	80	239

UA (93.3%) and PA (96.2%). Other crop types were mapped with a comparable UA (92.0%), but lower PA (86.3%). This suggests an overestimation of ICs mainly arising from other crop types being mistaken for ICs. Among the misclassified validation samples, weeds and volunteer grain were most prominent. Additionally, sugar beet and winter cereals introduced confusion with ICs. Vice versa, seed mixtures were partially mapped as other crop types, as were lucerne, white mustard, sunflower and turnip rape.

The overestimation of ICs was also reflected in the obtained area proportion which yielded 32.4% of all cropland. A subsequent exclusion of lucerne and clover fields that were declared as main crops in the IACS reduced the area proportion of ICs to 28.9%. Comparison data from agricultural structure surveys are reported every four to 6 years by the German Federal Statistical Office and were therefore not available for the growing season of interest. Data from previous years reported significantly lower area proportions of ICs with an increasing trend over the last decade (13.2% in 2009/10; 16.2% in 2015/16; 17.9% in 2019/20). Following these records, a realistic area proportion of ICs would amount to approximately 20%. The reported area proportions are statistical estimates based on a sample of 1300 farms in Brandenburg indicating whether an IC was grown between two main crops from June to May of the following year. Both subsidised ICs as well as ICs that were not cultivated in relation to greening measures of the EU were detected.

Discussion

Overcoming challenges of mapping ICs

Despite the challenges of mapping ICs, we were able to capture most phenological differences between ICs and other crop types with the chosen methodology. The derived STMs resembled the anticipated phenological development of crops over time, suggesting that the spectral information was summarised in a meaningful way. Our results confirm the particular importance of autumn and winter months for identifying ICs which has been reported in previous studies using SAR data (Fendrich et al., 2023; Najem et al., 2024) or optical satellite data (Schulz et al., 2021). While optical data densities during winter are critical for IC detection, a combination of data from multiple optical sensors can help overcome this challenge (Lewińska, Frantz, et al., 2024). The higher probability of missing or low-quality pixels due to clouds during the growing season of ICs additionally justifies the use of STMs. We improved the only existing approach for mapping ICs from optical satellite data (Schulz et al., 2021) we are aware of by implementing more optical-based metrics and by SAR-based input features. Direct comparison to accuracies from other studies is difficult, though, given the wide range of training and validation data used. A consistent definition of ICs across Europe, as proposed by Fendrich et al. (2023), and a publicly available reference dataset are required to improve validation of single studies and comparability between studies. Still, several findings of our study compare well to previous research. In line with Schulz et al. (2021), similar phenological characteristics occur in different IC profiles, indicating that a differentiation of IC species composition is not yet feasible. Moreover, our models encountered problems in detecting weakly developed ICs as found by Najem et al. (2024), especially when grown after silage maize. Beyond that, the use of our own field data enabled the identification of other potential sources of misclassification and allowed for a wide representation of various ICs in the derived map. As a result, our map provides a spatial overview of the cultivation of ICs at field level, no matter if the IC was reported in the IACS data (i.e. registered for subsidies) or not. We hence provide the first comprehensive wall-to-wall mapping of ICs for the study area. The conducted field campaign further allowed to include volunteers and weeds which are neither reported in the IACS nor in official ground-truth campaigns (e.g. Land Use – Land Cover Area Frame Survey (LUCAS)), nor in agricultural structure surveys as used by Fendrich et al. (2023). Unmanaged crops can serve as a bridge for pests and diseases and have a different agronomic and ecological value than ICs. A clear distinction between ICs and volunteers or weeds is therefore necessary, but remains challenging given their considerable spectral-temporal similarities.

Impact of remote sensing-based input features on IC mapping

Based on the results presented, we strongly recommend the incorporation of multiple optical sensors allowing for better data coverage, since optical metrics of the winter periods (T3, T4) were most important for model performance. The primary reason for T3 (October – December) and T4 (January – March) being most important is that those phases capture critical growth stages of winter ICs and highlight their seasonal variations in contrast to other crop types. Accurate and continuous data during those periods are therefore essential for reliable model performance. NDTI and SAVI were among the most important variables because they provide crucial insights into the vegetation and soil conditions during the winter periods. NDTI is effective in detecting tillage activities and is sensitive to changes in moisture (Quemada et al., 2018), which are key during the post-harvest of main crops and pre-planting phases of ICs. SAVI, on the other hand, adjusts for soil brightness and enhances vegetation signal detection, particularly useful in periods with sparse vegetation cover.

The varying observation density of optical data, however, compromises the robustness of complex distributional metrics (i.e. STD, IQR) across time and space (Lewińska, Ernst, et al., 2024). This questions the reliability of these STMs and might contribute to their low impact on the classifiers. A sensitivity analysis could be performed to better understand the minimum requirements in terms of optical data coverage for mapping ICs. For this purpose, the number of available observations could be artificially reduced step by step while evaluating feature importance and accuracies. Additional use of SAR metrics enhanced classification accuracies as well as robustness and should be favoured over a purely optical classification. Besides reducing misclassification of other crop types, the incorporation of SAR data minimises the effect of varying optical data densities in time and space which may be particularly relevant in years and study areas that yield less CSOs.

Features from T1 (June – Mid-August) yielded low variable importances and SAR metrics from that period were excluded from analysis because they added more confusion. Considering the peak vegetation period could still be valuable for the models since it captures information on the development of the main crops, including harvest, and on early sown ICs. Depending on the availability of optical data in different world regions, it might be useful to modify T1 to either cover a shorter period focusing on maturity and harvest of the main crops (in our case e.g. July – Mid-August), or a longer period covering a major part of the growing season (e.g. April – Mid-August). This adjustment could help to determine the relevance of the first period for future analyses and whether a refined version of T1 is more appropriate.

Limitations

This study encountered several limitations, particularly related to the crop types considered, the overestimation of ICs, and the validation process, all of which are closely tied to the field data collection methodology.

The training data mainly cover winter ICs due to the relatively late start of the conducted field campaign. Each field was only visited once during the campaign which is related to several limitations. First, the field data do not include information on the period over which a crop was grown (e.g. annual or perennial cultivation of lucerne). Second, crops that can be grown as IC based on the timing of tillage (e.g. green rye) were not detected. Third, we may not know if a summer IC was grown before late-sown winter crops, such as winter wheat, were reported. And last, information on the proper development of the crop (e.g. whether farmers decided to break the crop due to winterkill or diseases) was not available. Some of these issues were addressed by closely examining the time series during the data cleaning process, i.e. by excluding field samples that displayed unexpected temporal profiles. However, interpreting individual profiles is highly subjective and does not completely resolve the limitations of the field data.

The overestimation of ICs throughout the study area is partly due to classifying potential perennial species as ICs, particularly in areas with a high percentage of forage crops. On average, the overestimation of ICs could be significantly reduced by excluding lucerne and clover fields from the area assessment. Applying this logic to the map post-classification would reveal that exceptionally high IC shares, as observed in Figure 7c, are unrealistic and result from training perennial crops as ICs. Thus, training perennial crops as other crop types would have been more appropriate and could be achieved by incorporating multitemporal field data that provide additional information (e.g. on cultivation periods, crop development and crop management). Such information would further advance the understanding of other classification errors, especially originating from volunteers and weeds.

Moreover, aggregating the map from the pixel level to the IACS field level assumes spatially consistent management over time (Appendix B cf. Figure B1). If farmers cultivate only parts of a field with ICs, this aggregation leads to misclassification and misrepresentation of the cultivated area. Nevertheless, the accuracy assessment indicates that a greater MMU compensates for mixed pixel effects and intra-field heterogeneity.

Another limitation of the analysis was the lack of independent validation data. For this reason, we split the field data into a training and validation dataset which reduced the number of samples available for building the models. Determining a validation point for each observed crop type was not always possible, and in some cases only a few validation samples were derived. This lack of validation samples substantially limits our ability to assess whether a crop type was correctly assigned to its target class. For example, frost-resistant winter ICs could poorly be validated, with some crop types in this group being completely misclassified (e.g. turnip rape) and others lacking validation samples (e.g. ryegrass). Additionally, frost-resistant winter ICs showed very similar temporal profiles to oil-seed rape but were trained with fewer samples. Therefore, if a field displays comparable patterns, the models are more likely to predict oil-seed rape. Balancing between crop groups with similar spectral-temporal characteristics, rather than between the two very heterogeneous target classes, could facilitate more plausible predictions and accurate validation.

While our approach does not provide species-specific information, the map provides essential information for modelling soil organic carbon, water and nitrogen carry-over, as well as soil erosion risks. For these purposes, the exact IC species is less important than the overall presence of an IC, as the additional carbon input (soil organic carbon modelling) or the water and nutrient uptake (water and nitrogen carry-over) and degree of soil coverage (soil erosion) varies little among winter ICs. The specific IC species would be important, though, for modelling pest and disease survival (Donatelli et al., 2017), nitrogen fixation by legumes (Liu et al., 2011), and allelopathic effects (An et al., 2003; Dubey & Hussain, 2000; Martins, 2006).

Our study enhances the understanding of patterns from remote sensing for IC mapping and identifies remaining challenges which are important to address in future studies. The IC mapping approach demonstrated here can be applied to agricultural systems similar to our study area. For transferability to other regions, it will be essential to consider local agricultural practices, climatic conditions and satellite data observation densities to make necessary adjustments to the temporal aggregation periods (Pham et al., 2024). The transferability of the approach also relies on adequate ground-truth data for model training and validation, which can be difficult to obtain in data-scarce regions. To address these challenges, future applications could adopt flexible aggregation methods and explore the use of publicly available regional databases or crowd-sourced agricultural data to improve model generalisability.

A significant source of misclassification in our study arose from volunteers and weeds which were often mistaken for ICs. Addressing this issue is critical for improving the reliability of IC mapping and depends on the availability of appropriate training and validation data. The detection of soil tillage prior to the cultivation of ICs, as opposed to volunteers, is one potential solution to enhance discrimination between unmanaged crops and ICs. For this purpose, complete time series or different aggregation periods for SAR data and suitable optical indices, such as NDTI, could improve detection capabilities of soil tillage. Future research should address opportunities to promote the detection of different crop type groups (i.e. summer ICs, winter ICs, frost-resistant winter ICs) or species-specific classification. This could involve exploring grouping strategies for IC types with similar spectral and temporal characteristics to enhance classification accuracy and reduce misclassification risks. Considering the spectral-temporal similarities of IC species, integration of additional datasets, such as hyperspectral and thermal data might be beneficial (Barnes et al., 2021; Wang et al., 2023). Detailed narrowband hyperspectral data (such as EnMAP or PRISMA) could significantly improve the accuracy of identifying and distinguishing between various plant species. The incorporation of logics based on detailed and multi-annual crop type information (e.g. Blickensdörfer et al. (2022)) could contribute to achieving this objective, e.g. by assuming a higher probability of oil radish in crop rotations with potatoes. Moving forward, it is essential to incorporate additional datasets and test our methods on data from different years and near-real-time scenarios (e.g. Gao et al. (2020, 2023)) to validate the robustness and generalisability of our findings.

Conclusions

Mapping ICs using remote sensing methods presents several challenges related to the diversity of IC species, their spectral and phenological similarity to main crops and varying growing periods. Additionally, the primary growing season for ICs in temperate regions is during autumn and winter, a period marked by frequent cloud cover, limiting the availability and quality of optical remote sensing data.

Despite these challenges, our study demonstrates an effective approach to map ICs by integrating Landsat, Sentinel-2 and Sentinel-1 data. Optical satellite data provided crucial variables for the classification, such as vegetation indices during the key growing stages of ICs. On the other hand, the integration of Sentinel-1 data was particularly important, enhancing the accuracy of the classification by compensating for the limitations of optical data during periods of high cloud cover. Temporal aggregation informed by knowledge of growing seasons emphasised phenological differences between ICs and main crops. Based on a combination of optical metrics, SAR-based metrics and additional information from IACS data, the best classification achieved an overall accuracy of 92.9%, highlighting the value of integrating different remote sensing data sources for IC mapping. The resulting map not only offers valuable spatially explicit information which is crucial for reporting and monitoring sustainable agricultural practices but also provides input for simulation models that generate further information on agricultural production, related emissions and environmental impacts.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, G.G., upon request.

References

Amt für Statistik Berlin-Brandenburg. (2021). *Bodennutzung der landwirtschaftlichen Betriebe im Land Brandenburg 2021*. https://download.statistik-berlin-brandenburg.de/998ab5045064dac6/63ca932b2223/SB_C01-02-00_2021j01_BB.pdf

An, M., Liu, D. L., Johnson, I. R., & Lovett, J. V. (2003). Mathematical modelling of allelopathy: II. The dynamics of allelochemicals from living plants in the environment. *Ecological Modelling*, *161*(1), 53–66. https://doi.org/10.1016/S0304-3800(02)00289-2

Barnes, M. L., Yoder, L., & Khodaee, M. (2021). Detecting Winter cover crops and crop residues in the Midwest US using machine learning classification of thermal and optical imagery. *Remote Sensing*, *13*(10), 1998. https://doi.org/10.3390/rs13101998

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., De Abelleyra, D., Ferraz, P. D., Lebourgeois, R., Lelong, V., Simões, M., & Verón, S. R. (2018). Remote sensing and cropping practices: A review. *Remote Sensing*, *10*(1), 99. https://doi.org/10.3390/rs10010099

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry & Remote Sensing*, *114*, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Blanco-Canqui, H., Shaver, T. M., Lindquist, J. L., Shapiro, C. A., Elmore, R. W., Francis, C. A., & Hergert, G. W. (2015). Cover crops and ecosystem services: Insights from studies in temperate soils. *Agronomy Journal*, *107*(6), 2449–2474. https://doi.org/10.2134/agronj15.0086

Blickensdörfer, L., Schwieder, M., Pflugmacher, D., Nendel, C., Erasmi, S., & Hostert, P. (2022). Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany. *Remote Sensing of Environment*, *269*, 112831. https://doi.org/10.1016/j.rse.2021.112831

Bowles, T. M., Atallah, S. S., Campbell, E. E., Gaudin, A. C. M., Wieder, W. R., & Grandy, A. S. (2018). Addressing agricultural nitrogen losses in a changing climate. *Nature Sustainability*, *1*(8), 399–408. https://doi.org/10.1038/s41893-018-0106-0

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Chen, G., & Weil, R. R. (2010). Penetration of cover crop roots through compacted soils. *Plant and Soil*, *331*(1), 31–43. https://doi.org/10.1007/s11104-009-0223-7

Crist, E. P. (1985). A TM tasseled cap equivalent transformation for reflectance factor data. *Remote Sensing of Environment*, *17*(3), 301–306. https://doi.org/10.1016/0034-4257(85)90102-6

Dabney, S. M., Delgado, J. A., Meisinger, J. J., Schomberg, H., Liebig, M. A., Kaspar, T., Mitchell, J., & Reeves, W. (2011). Using cover crops and cropping systems for nitrogen management. In J.A. Delgado & R.F. Follett (Eds.), *Advances in nitrogen management for water quality* (pp. 230–281). Soil and Water Conservation Society.

d'Andrimont, R., Verhegghen, A., Lemoine, G., Kempeneers, P., Meroni, M., & van der Velde, M. (2021). From parcel to continental scale - a first European crop type map based on Sentinel-1 and LUCAS Copernicus in-situ observations. *Remote Sensing of Environment*, *266*, 112708. https://doi.org/10.1016/j.rse.2021.112708

Destatis. (2011). *Land- und Forstwirtschaft, Fischerei - Bodennutzung der Betriebe (Struktur der Bodennutzung) - 2010*. https://www.statistischebibliothek.de/mir/servlets/MCRFileNodeServlet/DEHeft_derivate_00004300/2030312107004.pdf

Destatis. (2017). *Land- und Forstwirtschaft, Fischerei - Bodennutzung der Betriebe (Struktur der Bodennutzung) - 2016*. https://www.statistischebibliothek.de/mir/servlets/MCRFileNodeServlet/DEHeft_derivate_00033419/2030312167004_ergaenzt05022018.pdf

Destatis. (2021). *Land- und Forstwirtschaft, Fischerei - Bodennutzung der Betriebe (Struktur der Bodennutzung) - 2020*. https://www.statistischebibliothek.de/mir/servlets/MCRFileNodeServlet/DEHeft_derivate_00064306/2030212207004.pdf

DirektZahlDurchfV. (2014). *Verordnung zur Durchführung der Direktzahlungen an inhaber landwirtschaftlicher Betriebe im Rahmen von Stützungsregelungen der Gemeinsamen Agrarpolitik (Direktzahlungen-Durchführungsverordnung - DirektZahlDurchfV) § 31 Flächen mit Zwischenfruchtanbau oder Gründecke (Artikel 46 absatz 2 Buchstabe i der Verordnung (EU) Nr. 1307/2013)*. https://www.gesetze-im-internet.de/direktzahldurchfv/__31.html

Donatelli, M., Magarey, R. D., Bregaglio, S., Willocquet, L., Whish, J. P. M., & Savary, S. (2017). Modelling the impacts of pests and diseases on agricultural systems. *Agricultural Systems*, *155*, 213–224. https://doi.org/10.1016/j.agsy.2017.01.019

Dubey, B., & Hussain, J. (2000). A model for the allelopathic effect on two competing species. *Ecological Modelling*, *129*(2), 195–207. https://doi.org/10.1016/S0304-3800(00)00228-3

DWD. (2019). *Klimareport Brandenburg*. Deutscher Wetterdienst. https://www.dwd.de/DE/leistungen/klimareport_bb/klimareport_bb_2019_download.html

DWD Climate Data Center. (2021). *Phenological observations of crops from sowing to harvest (annual reporters, historical)* (Version v007) [Dataset].

DWD Climate Data Center. (2022, March 17). *Phenological observations of crops from sowing to harvest (annual reporters, recent)* (Version) [Dataset].

Eurostat. (2023, August 10). *Glossary: Soil cover*. Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Soil_cover

Faye, B., Webber, H., Gaiser, T., Müller, C., Zhang, Y., Stella, T., Latka, C., Reckling, M., Heckelei, T., Helming, K., & Ewert, F. (2023). Climate change impacts on European arable crop yields: Sensitivity to assumptions about rotations and residue management. *The European Journal of Agronomy*, *142*, 126670. https://doi.org/10.1016/j.eja.2022.126670

Fendrich, A. N., Matthews, F., Van Eynde, E., Carozzi, M., Li, Z., d'Andrimont, R., Lugato, E., Martin, P., Ciais, P., & Panagos, P. (2023). From regional to parcel scale: A high-resolution map of cover crops across Europe combining satellite data with statistical surveys. *Science of the Total Environment*, *873*, 162300. https://doi.org/10.1016/j.scitotenv.2023.162300

Frantz, D. (2019). FORCE—Landsat + Sentinel-2 analysis ready data and beyond. *Remote Sensing*, *11*(9), 1124. https://doi.org/10.3390/rs11091124

Frantz, D., Rufin, P., Janz, A., Ernst, S., Pflugmacher, D., Schug, F., & Hostert, P. (2023). Understanding the robustness of spectral-temporal metrics across the global Landsat archive from 1984 to 2019 - a quantitative evaluation. *Remote Sensing of Environment*, *298*, 113823. https://doi.org/10.1016/j.rse.2023.113823

Gao, F., Anderson, M. C., & Hively, W. D. (2020). Detecting cover crop end-of-season using VENμS and Sentinel-2 satellite imagery. *Remote Sensing*, *12*(21), 3524. https://doi.org/10.3390/rs12213524

Gao, F., Jennewein, J., Hively, W. D., Soroka, A., Thieme, A., Bradley, D., Keppler, J., Mirsky, S., & Akumaga, U. (2023). Near real-time detection of winter cover crop termination using harmonized Landsat and Sentinel-2 (HLS) to support ecosystem assessment. *Science of Remote Sensing*, *7*, 100073. https://doi.org/10.1016/j.srs.2022.100073

Griffiths, P., Nendel, C., & Hostert, P. (2019). Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping. *Remote Sensing of Environment*, *220*, 135–151. https://doi.org/10.1016/j.rse.2018.10.031

Hanff, H., & Lau, H. (2021). *Datensammlung für die betriebswirtschaftliche Bewertung landwirtschaftlicher Produktionsverfahren im Land Brandenburg*. Ministerium für Landwirtschaft, Umwelt und Klimaschutz. https://lelf.brandenburg.de/sixcms/media.php/9/Datensammlung-2021-web.pdf

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, *25*(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X

Hufnagel, J., Reckling, M., & Ewert, F. (2020). Diverse approaches to crop diversification in agricultural research. A review. *Agronomy for Sustainable Development*, *40*(2), 14. https://doi.org/10.1007/s13593-020-00617-4

Jennewein, J. S., Lamb, B. T., Hively, W. D., Thieme, A., Thapa, R., Goldsmith, A., & Mirsky, S. B. (2022). Integration of satellite-based optical and synthetic aperture radar imagery to estimate Winter cover crop performance in cereal grasses. *Remote Sensing*, *14*(9). https://doi.org/10.3390/rs14092077

Johnson, D. M. (2019). Using the Landsat archive to map crop cover history across the United States. *Remote Sensing of Environment*, *232*, 111286. https://doi.org/10.1016/j.rse.2019.111286

Kirkegaard, J., Christen, O., Krupinsky, J., & Layzell, D. (2008). Break crop benefits in temperate wheat production. *Field Crops Research*, *107*(3), 185–195. https://doi.org/10.1016/j.fcr.2008.02.010

Kollas, C., Kersebaum, K. C., Nendel, C., Manevski, K., Müller, C., Palosuo, T., Armas-Herrera, C. M., Beaudoin, N., Bindi, M., Charfeddine, M., Conradt, T., Constantin, J., Eitzinger, J., Ewert, F., Ferrise, R., Gaiser, T., Cortazar-Atauri, I. G. D., Giglio, L. & Wu, L. (2015). Crop rotation modelling-A European model intercomparison. *The European Journal of Agronomy*, *70*, 98–111. https://doi.org/10.1016/j.eja.2015.06.007

Langdale, G. W., Blevins, R. L., Karlen, D. L., McCool, D. K., Nearing, M. A., Skidmore, E. L., Thomas, A. W., Tyler, D. D., & Williams, J. R. (1991). Cover crop effects on soil erosion by wind and water. In W.L. Hargrove (Ed.), *Cover crops for clean water* (pp. 15–22). Soil and Water Conservation Society.

Lewińska, K. E., Ernst, S., Frantz, D., Leser, U., & Hostert, P. (2024). Global overview of usable Landsat and Sentinel-2 data for 1982-2023. *Preprints*, 2024021169. https://doi.org/10.20944/preprints202402.1169.v1

Lewińska, K. E., Frantz, D., Leser, U., & Hostert, P. (2024). Usable observations over Europe: Evaluation of compositing windows for Landsat and Sentinel-2 time series. *European Journal of Remote Sensing*, *57*(1), 2372855. https://doi.org/10.1080/22797254.2024.2372855

Li, J., & Roy, D. (2017). A global analysis of Sentinel-2A, Sentinel-2B and Landsat-8 data revisit intervals and implications for terrestrial monitoring. *Remote Sensing*, *9*(9), 902. https://doi.org/10.3390/rs9090902

Liebman, M., & Davis, A. S. (2000). Integration of soil, crop and weed management in low-external-input farming systems. *Weed Research*, *40*(1), 27–47. https://doi.org/10.1046/j.1365-3180.2000.00164.x

Liu, W., Baddeley, J., & Watson, C. (2011). Models of biological nitrogen fixation of legumes. A review. *Agronomy for Sustainable Development*, *31*(1), 155–172. https://doi.org/10.1051/agro/2010008

Lopes, A., Nezry, E., Touzi, R., & Laur, H. (1990). Maximum a posteriori speckle filtering and first order texture models in SAR images. In *10th Annual International Symposium on Geoscience and Remote Sensing* (pp. 2409–2412). https://doi.org/10.1109/IGARSS.1990.689026

Martins, M. L. (2006). Exact solution for the An-Liu-Johnson-Lovett model related to the dynamics of allelochemicals in the environment. *Ecological Modelling*, *193*(3), 809–814. https://doi.org/10.1016/j.ecolmodel.2005.09.012

Meroni, M., d'Andrimont, R., Vrieling, A., Fasbender, D., Lemoine, G., Rembold, F., Seguini, L., & Verhegghen, A. (2021). Comparing land surface phenology of major European crops as derived from SAR and multispectral data of Sentinel-1 and -2. *Remote Sensing of Environment*, *253*, 112232. https://doi.org/10.1016/j.rse.2020.112232

MLUK. (2020). *Steckbriefe Brandenburger Böden*. https://mluk.brandenburg.de/mluk/de/ueber-uns/oeffentlichkeitsarbeit/veroeffentlichungen/detail/~01-07-2011-steckbriefe-brandenburger-boeden

MLUK. (2021a). *Daten aus dem Agrarförderantrag - Agrarantragsdaten* [Dataset]. https://geobroker.geobasis-bb.de/gbss.php?MODE=GetProductInformation&PRODUCTID=996f8fd1-c662-4975-b680-3b611fcb5d1f

MLUK. (2021b). *Digitales Feldblock Kataster* [Dataset]. https://geobroker.geobasis-bb.de/gbss.php?MODE=GetProductInformation&PRODUCTID=9e95f21f-4ecf-4682-9a44-e5f7609f6fa0

Montgomery, D. R. (2007). Soil erosion and agricultural sustainability. *Proceedings of the National Academy of Sciences*, *104*(33), 13268–13272. https://doi.org/10.1073/pnas.0611508104

Müller, H., Rufin, P., Griffiths, P., Barros Siqueira, A. J., & Hostert, P. (2015). Mining dense Landsat time series for separating cropland and pasture in a heterogeneous Brazilian savanna landscape. *Remote Sensing of Environment*, *156*, 490–499. https://doi.org/10.1016/j.rse.2014.10.014

Najem, S., Baghdadi, N., Bazzi, H., Lalande, N., & Bouchet, L. (2024). Detection and mapping of cover crops using Sentinel-1 SAR remote sensing data. *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing*, *17*, 1446–1461. https://doi.org/10.1109/JSTARS.2023.3337989

Nendel, C., Kersebaum, W., & Mirschel, K. (2014). Testing farm management options as climate change adaptation strategies using the MONICA model. *The European Journal of Agronomy*, *52*, 47–56. https://doi.org/10.1016/j.eja.2012.09.005

Nendel, C., Reckling, M., Debaeke, P., Schulz, S., Berg-Mohnicke, M., Constantin, J., Fronzek, S., Hoffmann, M., Jakšić, S., Kersebaum, K.-C., Klimek-Kopyra, A., Raynal, H., Schoving, C., Stella, T., & Battisti, R. (2023). Future area expansion outweighs increasing drought risk for soybean in Europe. *Global Change Biology*, *29*(5), 1340–1358. https://doi.org/10.1111/gcb.16562

Pelletier, C., Valero, S., Inglada, J., Champion, N., & Dedieu, G. (2016). Assessing the robustness of random forests to map land cover with high resolution satellite image time series over large areas. *Remote Sensing of Environment*, *187*, 156–168. https://doi.org/10.1016/j.rse.2016.10.010

Pflugmacher, D., Rabe, A., Peters, M., & Hostert, P. (2019). Mapping pan-European land cover using Landsat spectral-temporal metrics and the European LUCAS survey. *Remote Sensing of Environment*, *221*, 583–595. https://doi.org/10.1016/j.rse.2018.12.001

Pham, V. D., Thiel, F., Frantz, D., Okujeni, A., Schug, F., & van der Linden, S. (2024). Learning the variations in annual spectral-temporal metrics to enhance the transferability of regression models for land cover fraction monitoring. *Remote Sensing of Environment*, *308*, 114206. https://doi.org/10.1016/j.rse.2024.114206

Poeplau, C., & Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops - a meta-analysis. *Agriculture, Ecosystems & Environment*, *200*, 33–41. https://doi.org/10.1016/j.agee.2014.10.024

Quemada, M., Hively, W. D., Daughtry, C. S. T., Lamb, B. T., & Shermeyer, J. (2018). Improved crop residue cover estimates obtained by coupling spectral indices for residue and moisture. *Remote Sensing of Environment*, *206*, 33–44. https://doi.org/10.1016/j.rse.2017.12.012

Regulation. (2013). *Regulation (EU) No 1307/2013 of the European parliament and of the council of 17 December 2013 establishing rules for direct payments to farmers under support schemes within the framework of the common agricultural policy and repealing council regulation (EC) No 637/2008 and council regulation (EC) No 73/2009*. https://data.europa.eu/eli/reg/2013/1307/oj/eng

Regulation. (2021). *Regulation (EU) 2021/2116 of the European parliament and of the council of 2 December 2021 on the financing, management and monitoring of the common agricultural policy and repealing regulation (EU) No 1306/2013*. https://data.europa.eu/eli/reg/2021/2116/oj/eng

Regulation (2021/2115). *Regulation (EU) 2021/2115 of the European parliament and of the council of 2 December 2021 establishing rules on support for strategic plans to be drawn up by member states under the common agricultural policy (CAP strategic plans) and financed by the European agricultural guarantee fund (EAGF) and by the European agricultural fund for rural development (EAFRD) and repealing regulations (EU) No 1305/2013 and (EU) No 1307/2013* (Original work published 1905). https://data.europa.eu/eli/reg/2021/2115/oj/eng

Renard, D., & Tilman, D. (2019). National food production stabilized by crop diversity. *Nature*, *571*(7764), 257–260. https://doi.org/10.1038/s41586-019-1316-y

Rosa-Schleich, J., Loos, J., Mußhoff, O., & Tscharntke, T. (2019). Ecological-economic trade-offs of diversified farming systems - a review. *Ecological Economics*, *160*, 251–263. https://doi.org/10.1016/j.ecolecon.2019.03.002

Schmidt, A., & Gläser, H. (2014). *Anbau von Zwischenfrüchten - Auswertung der Versuchsanlagen 2013/14 in Sachsen*. Landesamt für Umwelt, Landwirtschaft und Geologie. https://slub.qucosa.de/api/qucosa%3A4624/attachment/ATT-0/

Schulz, C., Holtgrave, A.-K., & Kleinschmit, B. (2021). Large-scale winter catch crop monitoring with Sentinel-2 time series and machine learning-an alternative to on-site controls? *Computers and Electronics in Agriculture*, *186*, 106173. https://doi.org/10.1016/j.compag.2021.106173

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., Wattenbach, M., & Smith, J. (2008). Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1492), 789–813. https://doi.org/10.1098/rstb.2007.2184

Sunoj, S., Kharel, D., Kharel, T., Cho, J., Czymmek, K. J., & Ketterings, Q. M. (2021). Impact of headland area on whole field and farm corn silage and grain yield. *Agronomy Journal*, *113*(1), 147–158. https://doi.org/10.1002/agj2.20489

Thapa, R., Mirsky, S. B., & Tully, K. L. (2018). Cover crops reduce nitrate leaching in agroecosystems: A global meta-analysis. *Journal of Environmental Quality*, *47*(6), 1400–1411. https://doi.org/10.2134/jeq2018.03.0107

Thorup-Kristensen, K., Halberg, N., Nicolaisen, M., Olesen, J. E., Crews, T. E., Hinsinger, P., Kirkegaard, J., Pierret, A., & Dresbøll, D. B. (2020). Digging deeper for agricultural resources, the value of deep rooting. *Trends in Plant Science*, *25*(4), 406–417. https://doi.org/10.1016/j.tplants.2019.12.007

Tscharntke, T., Tylianakis, J. M., Rand, T. A., Didham, R. K., Fahrig, L., Batáry, P., Bengtsson, J., Clough, Y., Crist, T. O., Dormann, C. F., Ewers, R. M., Fründ, J., Holt, R. D., Holzschuh, A., Klein, A. M., Kleijn, D., Kremen, C., Landis, D. A. & Westphal, C. (2012). Landscape moderation of biodiversity patterns and processes - eight hypotheses. *Biological Reviews*, *87*(3), 661–685. https://doi.org/10.1111/j.1469-185X.2011.00216.x van Deventer, A. P., Ward, A. D., Gowda, P. H., & Lyon, J. G. (1997). Using thematic mapper data to identify contrasting soil plains and tillage practices. *Photogrammetric Engineering & Remote Sensing*, *63*(1), 87–93.

Wang, S., Azzari, G., & Lobell, D. B. (2019). Crop type mapping without field-level labels: Random forest transfer and unsupervised clustering techniques. *Remote Sensing of Environment*, *222*, 303–317. https://doi.org/10.1016/j.rse.2018.12.026

Wang, S., Guan, K., Zhang, C., Jiang, C., Zhou, Q., Li, K., Qin, Z., Ainsworth, E. A., He, J., Wu, J., Schaefer, D., Gentry, L. E., Margenot, A. J., & Herzberger, L. (2023). Airborne hyperspectral imaging of cover crops through radiative transfer process-guided machine learning. *Remote Sensing of Environment*, *285*, 113386. https://doi.org/10.1016/j.rse.2022.113386

Wolff, S., Hüttel, S., Nendel, C., & Lakes, T. (2021). Agricultural landscapes in Brandenburg, Germany: An analysis of characteristics and spatial patterns. *International Journal of Environmental Research*, *15*(3), 487–507. https://doi.org/10.1007/s41742-021-00328-y