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Crop type classification in smallholder agriculture of central and South Asia using Sentinel-1/2 data fusion

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ABSTRACT

Accurate crop monitoring in smallholder-dominated regions is challenging due to fragmented fields, high crop diversity, and often limited ground truth data. This study presents a systematic and transferable framework for crop-type classification in smallholder systems by jointly evaluating multi-sensor data fusion, temporal feature aggregation, feature selection, and model applicability. This study evaluates crop-type classification accuracy across smallholder agricultural landscapes in Central and South Asia (Kazakhstan, Tajikistan, Pakistan), leveraging Sentinel-1 radar and Sentinel-2 optical data separately and combined. Employing Random Forest models, we systematically compare temporal aggregation approaches (monthly, bi-monthly, quarterly) and evaluate the impact of feature selection on model performance. Across all study regions, combined Sentinel-1 and Sentinel-2 data achieved overall classification accuracies of approximately 80–96%, with substantial performance gains relative to single-sensor models, particularly in regions where individual sensors showed limited discrimination capability. Depending on region and sensor, accuracy improvements ranged from a few percentage points to more pronounced gains, reflecting strong benefits of data fusion in heterogeneous smallholder systems. Finer temporal aggregation schemes, including monthly aggregation, yielded additional accuracy gains of approximately 1–3 percentage points compared to coarser aggregations, while feature selection further improved model performance by roughly 2–5 percentage points. Sentinel-1 proved particularly effective for structurally distinct crops such as cotton, while Sentinel-2 substantially improved classification of more diverse crop classes. Application of the Area of Applicability concept enabled spatially explicit identification of well-supported and extrapolated predictions, providing a quantitative basis for uncertainty assessment and future sampling strategies. Together, these results demonstrate the value of an integrated and transferable methodological framework for robust crop-type classification in smallholder agricultural systems using freely available Sentinel data.

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1. Introduction

Agricultural monitoring is critical for addressing climate change, biodiversity loss, population growth, and rising demand for agricultural products (Ortiz et al., 2021). It supports food security and sustainable practices by enabling timely interventions and informed decision-making (Samberg et al., 2016; Fritz et al., 2015). Crop type information is a key input for advisory services, forming the basis for targeted recommendations to farmers. This need is especially pronounced in Pakistan, Tajikistan, and parts of Kazakhstan, where agriculture is central to the economy and largely smallholder-based (Hayward and Hofman, 2022; Naqvi, 2013; Petrick and Pomfret, 2016). However, statistics in these regions are often spatially coarse or unreliable, limiting resource management and extension support (Kebede et al., 2024)

Remote sensing provides high-resolution, timely data on land use, crop distribution, and farming practices (Rao et al., 2021). Most crop type mapping studies address large-scale commercial agriculture, while research on smallholder systems remains limited. Existing studies (Lambert et al., 2018; Rao et al., 2021; Rufin et al., 2024) are geographically or thematically narrow, raising questions of transferability. Unlike commercial farming, which attracts private investment (Rufin et al., 2025), smallholder systems require robust mapping tools based on freely available data such as Sentinel-1 and Sentinel-2. Advancing crop classification in these contexts therefore depends less on site-specific optimization and more on the development and systematic evaluation of transferable methodological frameworks.

At the global and regional scale, several satellite-based land cover products are now widely available, including Dynamic World (Brown et al., 2022), ESA WorldCover (Zanaga et al., 2021), or GlobCover (e.g. Arino et al., 2012), which provide consistent and regularly updated information on land cover and, in some cases, basic cropland classes. These products play an important role in large-scale land monitoring and environmental assessments. However, their thematic resolution with respect to crop-type differentiation is limited, particularly in smallholder-dominated agricultural landscapes characterized by small fields, heterogeneous cropping patterns, and pronounced temporal dynamics.

Small and heterogeneous fields in smallholder systems pose challenges for crop type mapping. Sentinel-1 and Sentinel-2 are valuable due to their complementary datasets (Drusch et al., 2012; Blickensdörfer et al., 2022; Eisfelder et al., 2024; Orynbaikyzy et al., 2020). Integrating both sensors improve classification compared to single-sensor use, as shown for tropical crops by e.g. Trivedi et al. (2023). Yet it remains unclear whether such approaches are transferable to other cropping conditions such as in temperate and subtropical regions of Central and South Asia. Moreover, many existing studies focus on specific crops, seasons, or regions, limiting a systematic understanding of how sensor fusion performs across contrasting agro-ecological settings.

Our study addresses this gap by evaluating Sentinel-1 and Sentinel-2 data fusion in smallholder systems of Kazakhstan, Tajikistan, and Pakistan, where agro-climatic conditions, cropping patterns, and field structures are highly diverse (Alff, 2023; Zakirova et al., 2025; Zuberi et al., 2024). While improvements through sensor data fusion are documented in large-scale systems, their effectiveness under smallholder conditions has not been systematically assessed. Prior studies in Germany and India also showed gains (Blickensdörfer et al., 2022; Rao et al., 2021), but were restricted to single regions or crops and sometimes relied on commercial imagery. The scalability of Sentinel-1 and Sentinel-2 fusion for smallholder agriculture in Central and South Asia therefore remains uncertain (Orynbaikyzy et al., 2020). In this study, the selected regions are used as representative test cases to assess the robustness and transferability of a generic crop classification framework across diverse smallholder systems.

Beyond data fusion, crop monitoring faces challenges from cloud cover, revisit gaps, and missing data. Temporal aggregation helps generate consistent time series that capture crop phenology (Griffiths et al., 2019). Different schemes — seasonal, monthly, or denser — can strongly influence classification results (Rufin et al., 2019; Asam et al., 2022; Blickensdörfer et al., 2022). However, the performance of these approaches remains underexplored in smallholder systems (Orynbaikyzy et al., 2019). A systematic comparison of temporal aggregation strategies is therefore required to identify robust feature representations that balance phenological detail and data availability.

In addition, the choice of machine learning methods influences crop classification outcomes. Random Forest is widely used for Sentinel-based mapping because of its ability to handle nonlinear relationships and high-dimensional datasets (Belgiu and Drăguţ, 2016; Asam et al., 2022). While some studies reported no clear benefit of feature selection (Orynbaikyzy et al., 2020), evidence from other applications suggests it can improve accuracy and reduce redundancy (Meyer et al., 2018). This is particularly relevant for smallholder systems, where limited ground truth data (Rufin et al., 2024) make computational efficiency and interpretability crucial. In that regard, addressing uncertainty is equally important. The recently developed concept of the Area of Applicability provides a transparent way to identify where model predictions are supported by training data and where they involve extrapolation (Meyer and Pebesma, 2021). Yet, its usefulness for crop-type mapping in smallholder systems has not been systematically tested. Evaluating the Area of Applicability in this context is therefore essential to guide field sampling and communicate uncertainties.

Against this background, this study systematically evaluates crop-type classification in smallholder agricultural landscapes across Kazakhstan, Tajikistan, and Pakistan using Sentinel-1 radar and Sentinel-2 optical data. This study provides new scientific insights by demonstrating how the combined effects of multi-sensor data fusion, temporal aggregation strategies, and feature selection jointly influence classification performance and robustness in smallholder systems, an aspect that has rarely been assessed in an integrated and comparative manner. Specifically, we (i) assess the improvement in classification accuracy from integrating Sentinel-1 and Sentinel-2, (ii) identify optimal temporal aggregation intervals to capture crop phenology, (iii) evaluate the role of feature selection in optimizing Random Forest models, and (iv) explore the use of the Area of Applicability concept to guide sampling and communicate uncertainties. By explicitly linking methodological choices to performance, transferability, and model applicability, this work advances the understanding of how scalable crop-type mapping approaches can be designed for heterogeneous smallholder agricultural landscapes. In addition, we consider socioeconomic and historical contexts to interpret remote sensing outputs in practice. Together, these steps provide a framework for advancing scalable crop mapping in smallholder systems.

2. Materials and methods

To assess the potential of Sentinel-1 and Sentinel-2 data for crop type classification, we compared models with different temporal aggregation schemes. In this study, we use the term data fusion to denote feature-level fusion, in which Sentinel-1 radar–derived and Sentinel-2 optical–derived features are combined within a single classification model. The contrasting agro-ecological conditions across the three sites allow systematic evaluation of model performance at different crop growth stages. An overview of the workflow is shown in Fig. 1.

2.1. *Study areas*

We selected three case study districts: Panfilov (Kazakhstan), Jaloliddin Balkhi (Tajikistan), and Multan (Pakistan) (Fig. 2). All areas are dominated by irrigated, smallholder-based agriculture with fragmented fields. Their farming systems reflect different legacies, including post-Soviet restructuring in Kazakhstan and Tajikistan (Hofman and Visser, 2021; Petrick, 2021) and Green Revolution policies in Pakistan (Niazi, 2004).

The sites represent key agro-climatic zones of Central and South Asia according to the Köppen–Geiger classification: continental semi-arid steppe (BSk) in Kazakhstan and Tajikistan, and hot desert (BWh) in Pakistan (Kottek et al., 2006). Climatic differences shape cropping calendars: Kazakhstan has a short growing season due to cold winters, Tajikistan allows winter sowing, while Pakistan supports two annual cycles with e.g. wheat and potatoes in winter and cotton and rice in summer. Farm sizes are typically 3–10 ha in Kazakhstan and Tajikistan and less than 2 ha for the majority of farmers in Pakistan (Alff, 2023; Zuberi et al., 2024; Zakirova et al., 2025).

2.2. *Field data*

Crop type information was collected in Panfilov, Kazakhstan (June 2022), Jaloliddin Balkhi, Tajikistan (May 2022), and Multan, Pakistan (October 2022) (Table 1). At each site, 300 random sampling points were generated within cropland areas from WorldCover (2020) v100 (Zanaga et al., 2021), restricted to roads from OpenStreetMap (OpenStreetMap contributors, 2024) using 100 m buffers (Kazakhstan, Tajikistan) and 50 m (Pakistan). Some locations were excluded due to inaccessibility (42, 49, and 5 points, respectively), and in Pakistan an additional 33 were removed because crops had already been harvested. Minor crop types were merged into broader classes (Table 1). Field boundaries were then digitized using Sentinel-2 false-colour and high-resolution Google Earth/Bing imagery.

2.3. *Remote sensing data*

2.3.1. *Sentinel-1 data pre-processing*

Sentinel-1 data were processed in Google Earth Engine (Gorelick et al., 2017) following the Analysis-Ready Data framework of Mullissa et al. (2021). We used all 2022 acquisitions (VV and VH polarizations), selecting orbit direction by availability — ascending for Kazakhstan and Pakistan, descending for Tajikistan (Chakhar et al., 2021). Pre-processing included border noise correction, multi-temporal Lee filtering (15×15 kernel, stacks of 10; Lee, 1980), and radiometric terrain normalization via the volume-flattening approach (Vollrath et al., 2020) with the SRTM DEM (Farr et al., 2007). Outputs were converted to decibels (dB). We did not include backscatter ratios (e.g., VH/VV) since prior studies found no added benefit beyond VV and VH (Chakhar et al., 2021).

2.3.2. *Sentinel-2 data pre-processing*

A Sentinel-2 Level-2A surface reflectance time series (January–December 2022) was generated in Google Earth Engine (Gorelick et al., 2017). Images with >25% cloud cover were excluded, and cloud/shadow pixels were gap-filled by linear interpolation within a

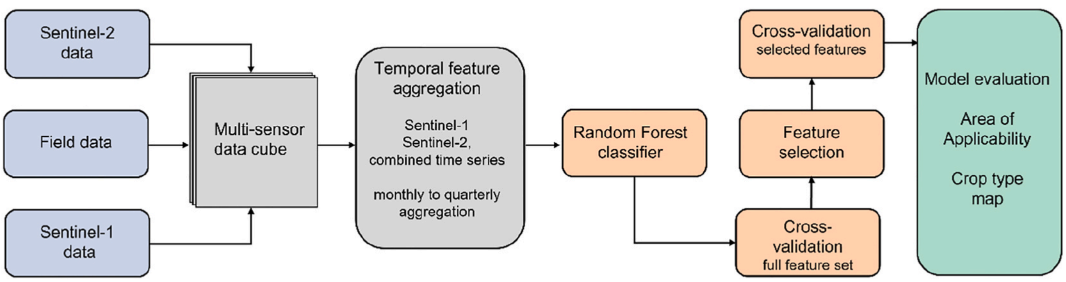

Fig. 1. Methodological workflow applied to each study site. Input data (blue) include Sentinel-1, Sentinel-2, and field observations. Data processing and classification are performed using temporal feature aggregation and Random Forest modelling with cross-validation (orange). Outputs (green) comprise crop-type maps, accuracy assessment, and Area of Applicability.

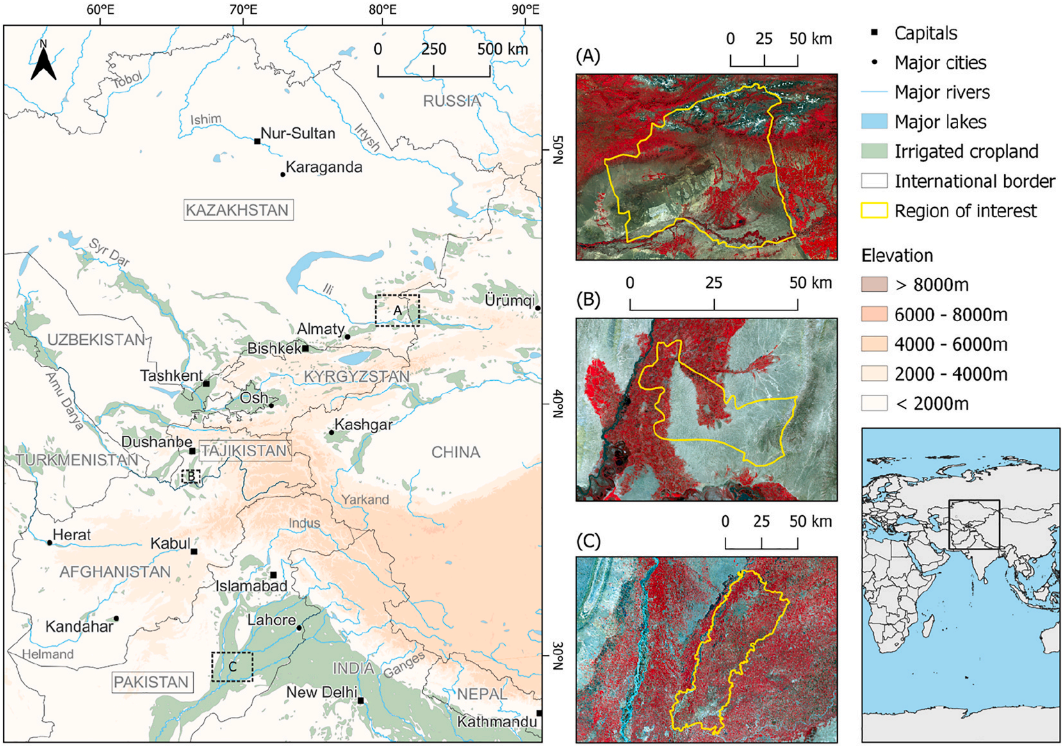

Fig. 2. Study areas in Central and South Asia: Panfilov district, Kazakhstan (a), Jaloliddin Balkhi district, Tajikistan (b), and Multan district, Pakistan (c). Background shows Sentinel-2 false-colour imagery (bands 8, 4, 3) from summer 2022. Administrative and physical layers were taken from Natural Earth (https://www.naturalearthdata.com/).

Table 1
Collected ground truth crop field data for the three case study areas.

Crop type	Kazakhstan (Panfilov)	Tajikistan (Jaloliddin Balkhi)	Pakistan (Multan)
Maize	156	25	63
Wheat	17	52	–
Cotton	–	100	90
Fodder (Alfalfa, Grassland)	71	32	–
Rice	–	–	44
Sorghum	–	–	21
Sugarcane	–	–	21
Fallow	14	23	–
Other crops	–	18 (Watermelon, Pumpkin, Vegetables)	23 (Spinach, Millet, Chilli pepper, Carrots, Okra, Horseradish, Cauliflower, Cabbage, Grass)
Total Samples	258	250	262

30-day window (Gandhi, 2024). Only 10 m and 20 m bands relevant for crop mapping were used: blue (B2), green (B3), red (B4), NIR (B8), red edge (B5–7), narrow NIR (B8A), and SWIR (B11, B12), with 20 m bands resampled to 10 m (Zhang et al., 2019). In addition, four vegetation indices were calculated (Blickensdörfer et al., 2022): NDVI (Tucker, 1979), NDWI (Gumma et al., 2020), EVI (Huete et al., 1997), and SAVI (Huete, 1988).

$$NDVI = \frac{B8 - B4}{B8 + B4} \quad \text{Eq. 1}$$

$$NDWI = \frac{B8A - B11}{B8A + B11} \quad \text{Eq. 2}$$

$$EVI = 2.5 \times \frac{(B8 - B4)}{(B8 + 6.0 \times B4 - 7.5 \times B2 + 1.0)} \quad \text{Eq. 3}$$

$$SAVI = \frac{(B8 - B4)}{(B8 + B4 + 0.5)} \times (1 + 0.5) \quad \text{Eq. 4}$$

These indices were selected because they represent widely used transformations of Sentinel- 2 spectral bands that capture complementary vegetation properties, including canopy greenness (NDVI), vegetation moisture conditions (NDWI), improved sensitivity in high biomass regions (EVI), and reduced soil background influence (SAVI). This limited set of indices was included to provide interpretable summary variables of key spectral relationships relevant for crop monitoring, while acknowledging that alternative indices could also be suitable depending on regional conditions.

2.3.3. Temporal aggregation of remote sensing data

We applied monthly, bi-monthly, and quarterly temporal aggregations to capture crop phenology while balancing data availability and computational effort. Monthly intervals provide detailed temporal resolution, bi-monthly a compromise, and quarterly a practical option under cloud cover or limited data (Rufin et al., 2019). Aggregations were conducted for 2022 (January–December in Kazakhstan and Tajikistan; March–October *kharif* season in Pakistan). For each interval, five metrics (mean, standard deviation, coefficient of variation, 10th and 90th percentiles) were calculated per spectral band, vegetation index, and radar band, producing 120–960 features depending on site (Table 2). Median values were extracted from these data cubes using field boundaries buffered inward by 5 m to reduce mixed-pixel effects (Lambert et al., 2018).

2.4. Classification, feature selection and validation

Crop type classification was performed with the Random Forest algorithm (Breiman, 2001) implemented in the R package *ranger* (version 0.16.0, Wright and Ziegler, 2017) with the package *caret,* using 500 trees and the square-root rule for variable selection (Belgiu and Drăguţ, 2016). Three datasets were tested — Sentinel-2, Sentinel-1, and their combination — across the temporal aggregation schemes in Table 2. Random Forest was selected due to its proven robustness in crop-type classification tasks using Sentinel time series, particularly under conditions of limited and imbalanced training data. Previous studies have demonstrated that Random Forest provides competitive performance in crop-type classification tasks across diverse agricultural settings, while being less demanding in terms of training data volume and model complexity (e.g. Asam et al., 2022; Orynbaikyzy et al., 2019, 2020)

To assess the effect of feature selection, we applied Forward Feature Selection (*CAST* package in R; Meyer et al., 2024), which iteratively adds predictors only if they improve accuracy. Final crop maps for each region were based on the optimal subset of predictors. Model performance was evaluated using repeated five-fold cross-validation (1000 runs). Alongside overall accuracy, we report F1-scores to capture class-specific precision and recall (Congalton, 1991). Although the number of field samples per site is limited and crop class distributions are imbalanced (Table 1), repeated cross-validation was applied to reduce sensitivity to individual training–validation splits. Nevertheless, dominant crop classes may exert a stronger influence on overall accuracy estimates, which should be considered when interpreting model performance. Due to dataset limitations (Table 1), area-adjusted accuracy (Olofsson et al., 2014) was not considered.

In addition, feature importance within the selected feature set was quantified using permutation-based importance metrics, expressed as the mean decrease in Overall Accuracy. This method measures the decrease in classification accuracy resulting from randomly permuting individual predictor variables, providing insight into each feature's contribution to classification performance (Peña and Brenning, 2015; Ruβ and Brenning, 2010). Analysing feature importance facilitates interpretation of model results and supports identification of critical predictors for distinguishing land cover and crop types (Blickensdörfer et al., 2022; Orynbaikyzy et al., 2020), and has been applied in Sentinel-1/2-based mapping studies to interpret the relative contribution of SAR and optical

Table 2
Classification models based on Sentinel-1, Sentinel-2, and combined feature sets across different temporal aggregation windows, showing the number of derived metrics per country.

ID	Kazakhstan/Tajikistan	Temporal windows	Spectral-based: Sentinel-2 (S2)		Radar-based: Sentinel-1 (S1)	Combined: S2+S1
			10 Bands	4 Vegetation indices	2 bands	
			five descriptive metrics			
V12	Monthly	12	840		120	960
V6	Bi-monthly	6	720		60	480
V4	Quarterly	4	280		40	320
	Pakistan					
V8	Monthly	8	560		80	640
V4	Bi-monthly	4	280		40	320
V2	Quarterly	2	140		20	160

predictors using mean decrease in accuracy (e.g., Bartold et al., 2024).

Spatial reliability of predictions was assessed using the Area of Applicability metric in *CAST* (Meyer and Pebesma, 2021). This method compares prediction data to training data in feature space using Mahalanobis distance. Predictions within the similarity threshold are considered reliable, while values beyond it indicate extrapolation. The resulting maps highlight where models are well supported by field data and where additional sampling would be necessary (Ludwig et al., 2023; Schumacher et al., 2024). Presenting these maps alongside crop classifications increases transparency and helps end-users interpret uncertainties.

3. Results

3.1. Accuracy assessment for different feature sets

We compared classification accuracies using Sentinel-1, Sentinel-2, and combined datasets across Kazakhstan, Tajikistan, and Pakistan (Fig. 3, Table 3). Sentinel-1 alone consistently yielded the lowest accuracies, particularly in Pakistan (79.8% overall accuracy with all features, 84.7% after feature selection). Sentinel-2 performed better, reaching 96.3% in Tajikistan after feature selection. The combination of Sentinel-1 and Sentinel-2 generally achieved the highest accuracies, for example 94.7% in Kazakhstan with bi-monthly aggregation. The respective confusion matrices are included in the supplementary material (Supplement 1).

Temporal aggregation influenced results: monthly data provided the most detailed phenological information, while bi-monthly performed comparably in Kazakhstan and Tajikistan (Fig. 3). In Pakistan, finer temporal resolution was clearly beneficial. Feature selection consistently improved results by removing redundant predictors, though the gain was smaller for combined datasets than for single-sensor inputs.

Given the minor differences between monthly and bi-monthly results in Tajikistan, subsequent analyses were based on monthly aggregation for consistency across sites.

3.2. Crop type specific accuracies

Crop-specific F1-scores differed across study areas (Tables 4–6). High accuracies were achieved for major crops, while smaller or spectrally mixed classes were more challenging.

In Kazakhstan, maize was mapped with very high accuracy (>97%), while fodder also performed well. Wheat and especially fallow land were difficult to classify, though accuracies improved when combining Sentinel-1 and Sentinel-2.

In Tajikistan, cotton, wheat, and fodder reached F1-scores above 95% with combined datasets. Maize was classified more reliably with Sentinel-2 alone, while fallow and “other crops” also benefited from optical input.

In Pakistan, cotton, maize, and rice showed robust performance (>85% with combined data), sugarcane was moderately well classified, and sorghum remained challenging despite improvements when integrating radar and optical features.

3.3. Feature importance

The Random Forest permutation-based feature importance analysis revealed distinct patterns across the three study areas, emphasizing the differential contribution of spectral and SAR-derived variables to classification accuracy (Fig. 4). Overall, vegetation indices demonstrated consistently high importance across countries, particularly in Kazakhstan and Tajikistan, whereas SAR-based

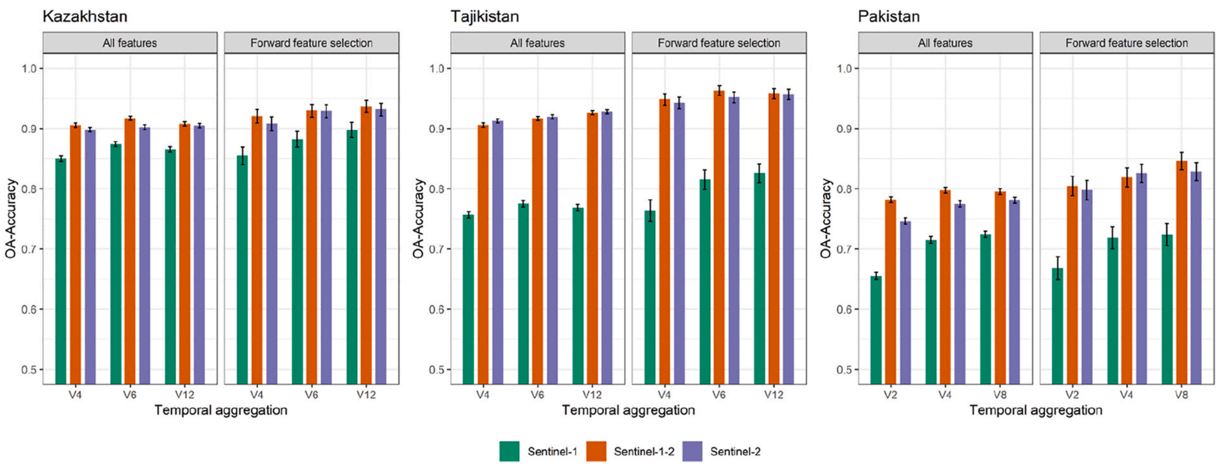

Fig. 3. Overall accuracy of Sentinel-1, Sentinel-2, and combined datasets with and without Forward Feature Selection, across temporal aggregation windows. Temporal aggregations V2–V12 are described in Table 2. Error bars indicate the range of classification accuracy values across repeated cross-validation runs.

Table 3
Overall accuracy (OA) of crop type classification with upper and lower bounds from cross-validation. "All" = all features, "FFS" = Forward Feature Selection, "S1" = Sentinel-1, "S2" = Sentinel-2. Temporal aggregations V2–V12 are described in Table 2.

Country	OA		OA lower bound 95% CI		OA upper bound 95% CI		Sensor		Temporal aggregation	
	All	FFS	All	FFS	All	FFS	All	FFS	All	FFS
Kazakhstan	91.7	93.7	91.4	92.7	92.1	94.7	S1+S2	S1+S2	V6	V12
Tajikistan	94.1	96.3	93.8	95.5	94.4	97.1	S2	S1+S2	V12	V6
Pakistan	79.8	84.7	79.3	83.1	80.3	86.1	S1+S2	S1+S2	V4	V8

Table 4
F1-scores (%) for crop type classification in Kazakhstan using monthly aggregated data after Forward Feature Selection, based on Sentinel-1, Sentinel-2, and combined datasets.

Class	F1-score (%)		
	Sentinel-1	Sentinel-2	Sentinel-1+ Sentinel-2
Maize	97.1	97.7	98.6
Fodder	85.8	89.7	91.6
Wheat	68.9	77.4	83.3
Fallow	8.6	67.0	69.0

Table 5
F1-scores (%) for crop type classification in Tajikistan using monthly aggregated data after Forward Feature Selection, based on Sentinel-1, Sentinel-2, and combined datasets.

Class	F1-score (%)		
	Sentinel-1	Sentinel-2	Sentinel-1+ Sentinel-2
Cotton	94.0	97.6	96.5
Wheat	80.4	94.9	95.8
Fodder	76.2	94.6	96.4
Maize	75.2	96.5	92.1
Fallow	70.8	92.2	93.7
Other	76.1	94.8	92.8

Table 6
F1-scores (%) for crop type classification in Pakistan using monthly aggregated data after Forward Feature Selection, based on Sentinel-1, Sentinel-2, and combined datasets.

Class	F1-score (%)		
	Sentinel-1	Sentinel-2	Sentinel-1+ Sentinel-2
Cotton	87.8	91.6	91.4
Maize	76.0	84.6	87.3
Rice	78.2	88.7	89.9
Sorghum	42.3	63.6	70.8
Sugarcane	73.3	86.1	83.2
Other	36.7	60.7	60.5

variables (VV and VH backscatter) showed greater relevance in Pakistan.

In Kazakhstan, NDVI-related metrics dominated the feature importance rankings, particularly the percentile values (e.g., NDVI_p10_p5). Red spectral bands and SAR variables (e.g., VV_p90_p9) also contributed substantially to classification accuracy. Temporal aggregation of feature importance highlighted peaks during phenologically active periods, such as the start and middle of the growing season (Fig. 4). This corresponds to critical phases in crop growth where NDVI and red-edge indices effectively capture vegetation dynamics, aligning with temporal NDVI and SAR backscatter profiles.

In Tajikistan, SAVI and blue spectral bands exhibited the highest feature importance, particularly during the mid and late growing season (Fig. 4). Furthermore, NDVI and VV backscatter showed consistent importance throughout the growing season, particularly during critical phenological transitions (e.g., flowering and senescence). The temporal radar and spectral profiles confirm these patterns, illustrating distinct trajectories for major crops like wheat, maize, and fodder.

For Pakistan, green and NIR spectral bands (e.g., green_p10_p8, nir1_p10_p8) ranked highest in feature importance, followed by selected SAR features such as VH_p10_p7 and VV_p10_p7 (Fig. 4). Vegetation indices, in contrast, played a more limited role compared to the other regions. Temporal patterns demonstrated peaks in feature importance during the late growing season (November and

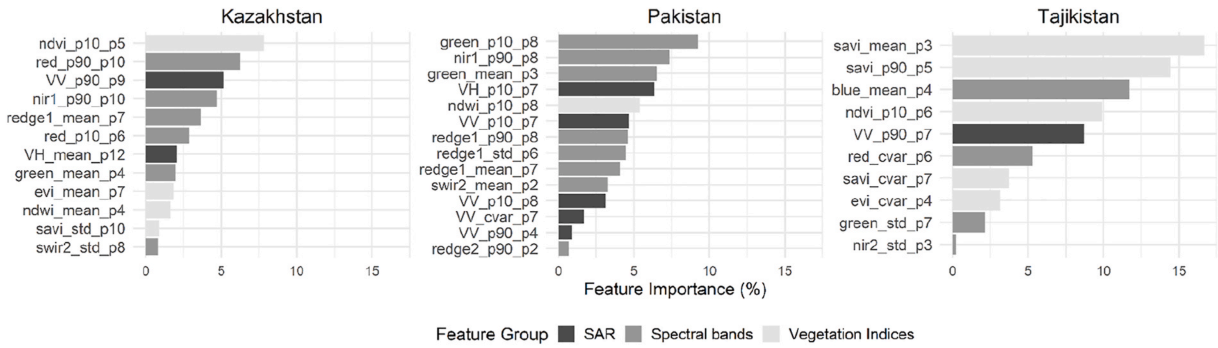

Fig. 4. Permutation-based feature importance was calculated for the final model following Forward Feature Selection, expressed as the mean decrease in Overall Accuracy. The suffixes p1–p12 correspond to the temporal window of aggregation. For Kazakhstan and Tajikistan, these suffixes represent the actual calendar months (January to December). In contrast, for Pakistan, p1 refers to March and p8 to October.

December), coinciding with the harvest phase.

3.4. Crop type maps and Area of Applicability

The crop type maps show the distribution of major crops in each study area, while the Area of Applicability indicates where predictions are well supported by training data and where uncertainty is higher (Figs. 5–10). Together, these outputs provide insights into cropping patterns as well as spatial variation in model reliability.

In Kazakhstan's Panfilov district (Fig. 5), maize (39%) and fodder crops (49%) dominate, reflecting the region's reliance on both cash crops and livestock production. Wheat (5%) and fallow land (7%) occur in smaller, scattered patches, mainly in the south. Misclassifications were most common in wetland areas in the southwest, where non-crop vegetation was misclassified as fodder.

The corresponding Area of Applicability map (Fig. 6) shows high reliability in central and northern parts of the district where sampling density was greater, while southern and southwestern margins display lower reliability due to limited field data and environmental dissimilarity.

In Tajikistan's Jaloliddin Balkhi district (Fig. 7), cotton (38%) and wheat (30%) are the main crops, followed by fodder (16%),

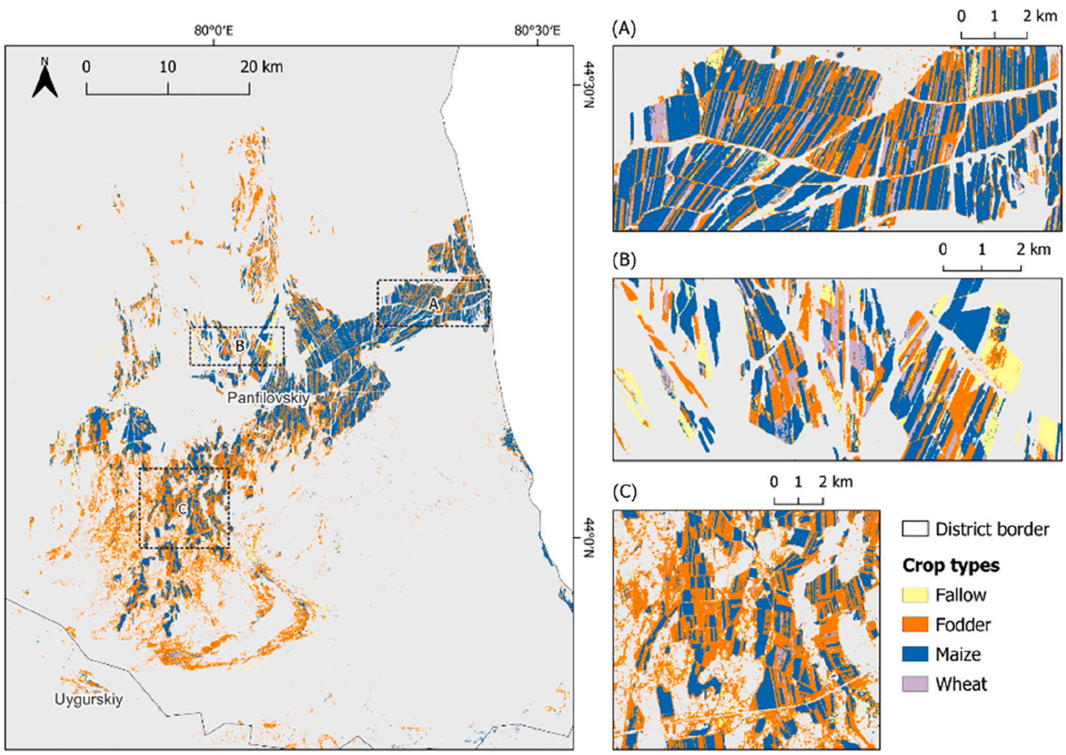

Fig. 5. Crop-type classification in Panfilov District, Kazakhstan (10 m, 2022).

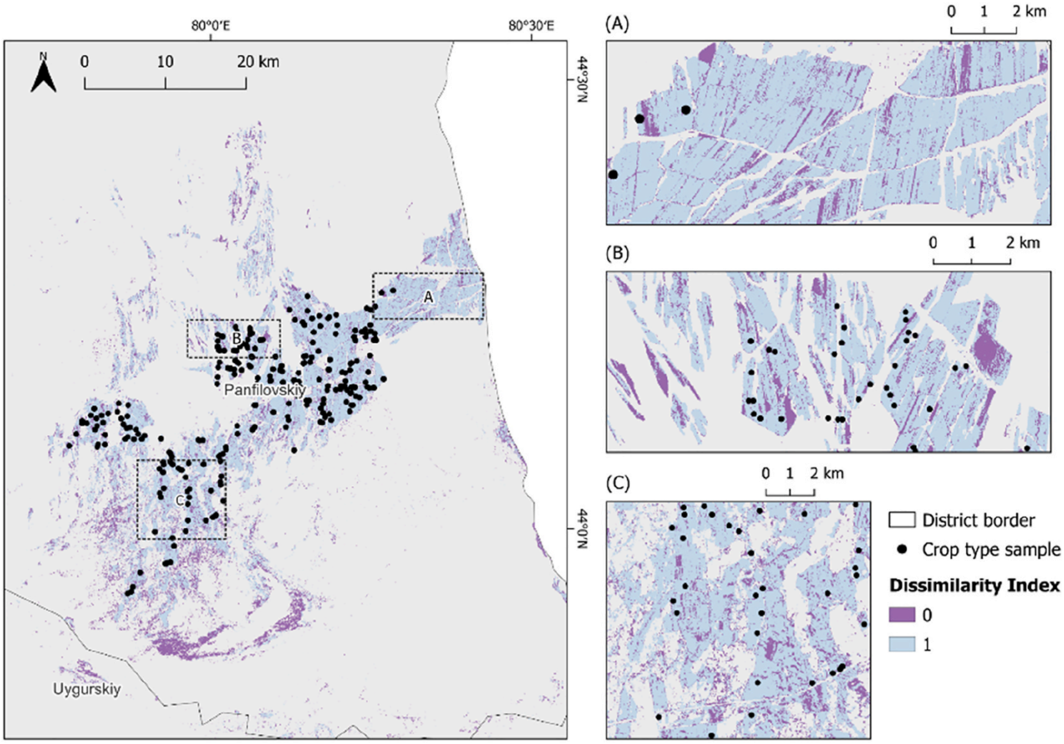

Fig. 6. Area of Applicability for crop classification in Panfilov District, Kazakhstan. Light blue indicates reliable predictions supported by field data, while purple marks lower reliability.

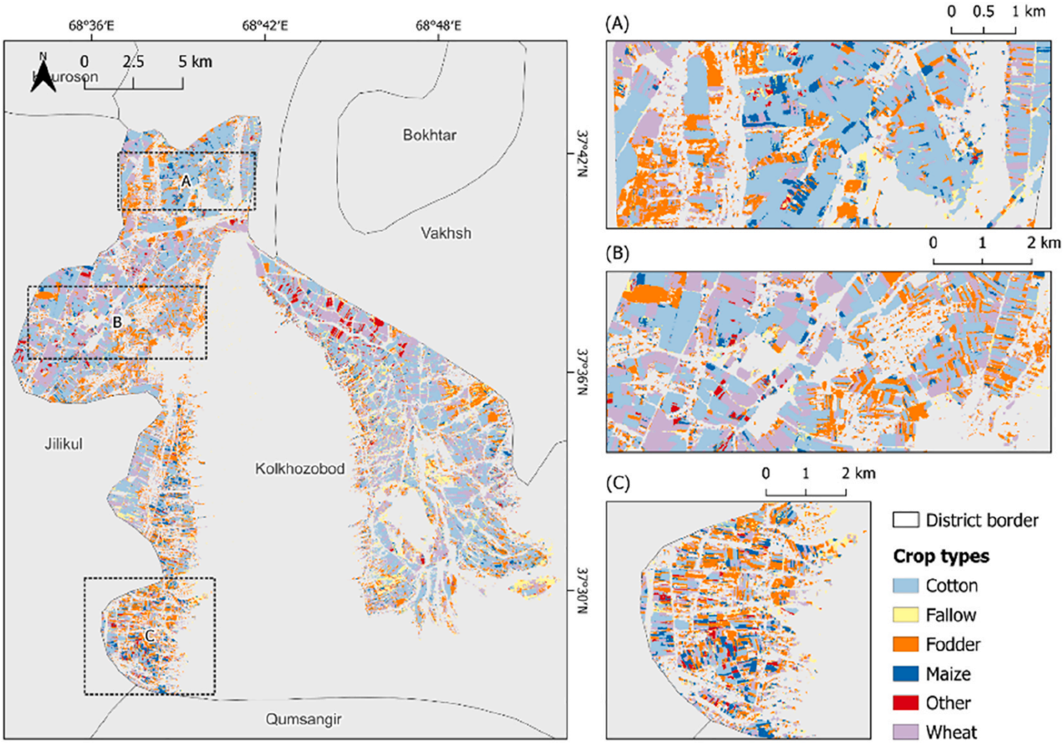

Fig. 7. Crop-type classification in Jaloliddin Balkhi District, Tajikistan (10 m, 2022).

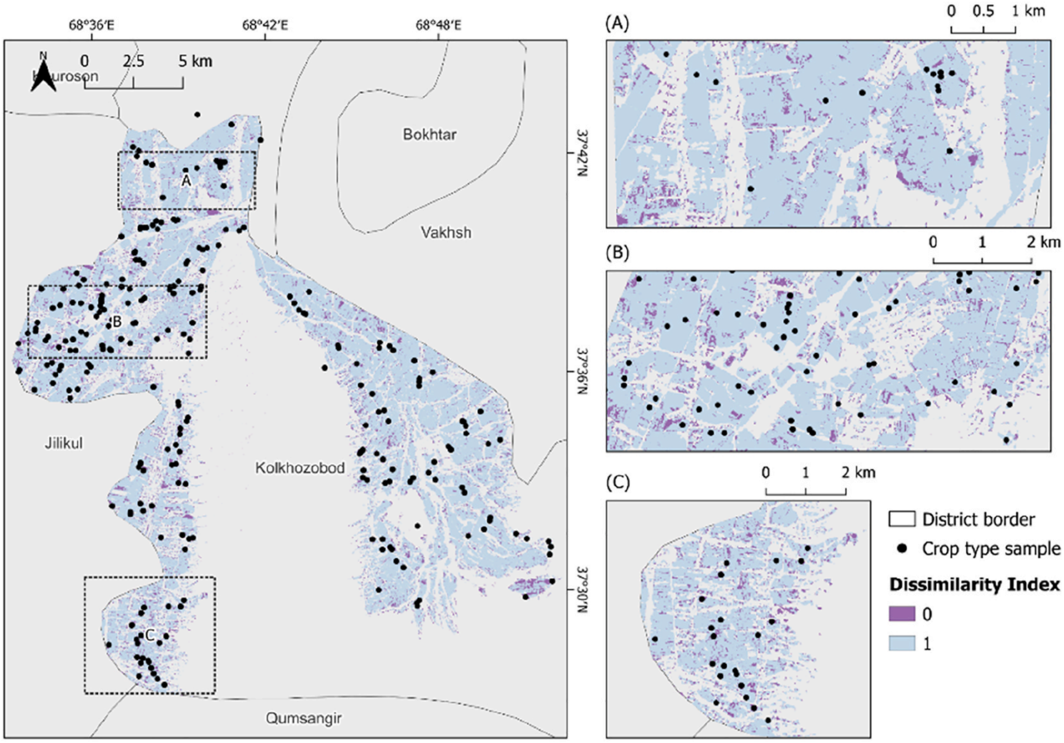

Fig. 8. Area of Applicability for crop classification in Jaloliddin Balkhi District, Tajikistan. Light blue indicates reliable predictions supported by field data, while purple marks lower reliability.

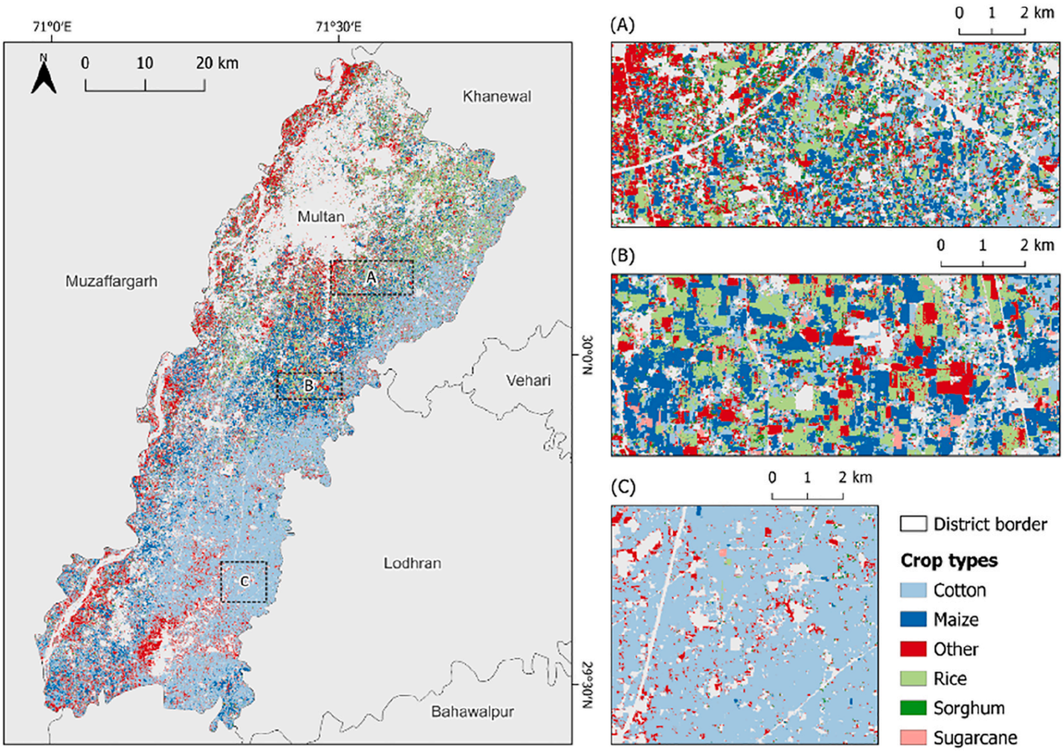

Fig. 9. Crop-type classification in Multan District, Pakistan (10 m, 2022).

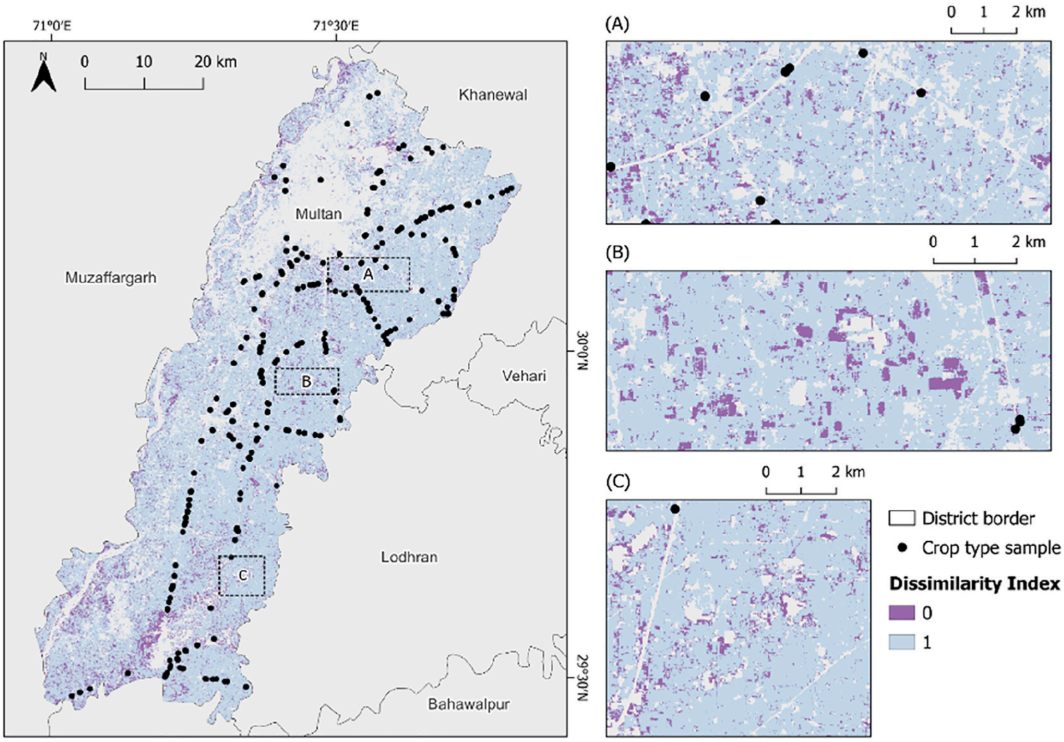

Fig. 10. Area of Applicability for crop classification in Multan District, Pakistan. Light blue indicates reliable predictions supported by field data, while purple marks lower reliability.

fallow (8%), maize (6%), and a small share of other crops (3%). Cotton dominates the central and northern regions, while wheat is concentrated in central and eastern areas. Fodder, fallow, and maize occur in more fragmented mosaics, particularly in the south, which is characterized by a heterogeneous mixture of different crops.

The Area of Applicability map for Tajikistan (Fig. 8) indicates overall good representativeness of the training data, as low dissimilarity values are distributed across the entire district. Model reliability is highest in cotton- and wheat-dominated regions where field observations are dense, while slightly lower reliability occurs in the more heterogeneous southern parts, where crop patterns are fragmented and less represented in the training data.

In Pakistan's Multan district (Fig. 9), cotton dominates (47%), followed by maize (17%), rice (8%), sorghum (6%), sugarcane (4%), and other crops (18%). Cotton is concentrated in the central and southern parts of the district, while the north exhibits more complex mosaics of maize, rice, and minor crops, contrasting with more homogeneous cotton fields elsewhere.

The Area of Applicability map for Pakistan (Fig. 10) shows high reliability across the central and southern parts of Multan district, where extensive field sampling coincides with large, homogeneous cotton fields. In contrast, higher dissimilarity values extend from north to south in the western part, where fewer reference samples were available. Localized pockets of higher dissimilarity are visible in the south.

4. Discussion

4.1. Accuracy assessment for different temporal feature sets

This study focused on crop-type classification with Random Forest models because of their robustness, interpretability, and wide use in agricultural remote sensing (Belgiu and Drăguţ, 2016). Our findings demonstrate clear performance gains from integrating Sentinel-1 and Sentinel-2 within this framework, while the transferability to other machine learning or deep learning methods warrants further study.

The accuracy assessment highlights the strong potential of data fusion for crop type mapping across the three regions. Overall accuracies ranged from 80% to 96% (Table 3), comparing favourably with earlier work that often reported around 75–80% accuracy in more homogeneous large-scale agricultural settings (Blickensdörfer et al., 2022; Orynbaikyzy et al., 2020). A structured overview of key characteristics and reported accuracies from selected crop-type mapping studies (e.g., number of classes, temporal coverage, sensor inputs, validation design, and performance metrics) is provided in the supplementary material (Supplement 2, Table S2.1). While these studies covered regions ranging from county-scale (e.g., Brandenburg) to the national scale (Germany), our case study areas are considerably smaller and marked by fine-grained field mosaics and high crop diversity. These outcomes are particularly notable given the fragmented fields, crop diversity, and limited ground-truth data characteristic of smallholder systems. Comparable findings were reported for Ethiopia, where Sentinel-1 alone produced low accuracies but improved markedly when combined with Sentinel-2 (Eisfelder et al., 2024).

Although our study employed rigorous repeated cross-validation, the chosen 5-fold scheme still implies that accuracy estimates remain partition-dependent, and they can be sensitive to how the limited field samples (Table 1) are assigned to folds. Increasing the number of folds is not necessarily advantageous under small sample sizes, because smaller test folds can reduce the stability of class-wise accuracy estimates when class counts are low (Wong, 2015). However, the relatively small number of field samples per crop type remains a limitation. This may inflate accuracies for dominant crops while reducing robustness for minor ones (Schulthess et al., 2023). Future work should therefore aim at larger and more balanced training datasets to strengthen reliability. In addition, imbalanced class distributions can bias overall accuracy estimates toward dominant crop types, which should be considered when interpreting the high overall accuracies reported here. Area-adjusted accuracy assessment (Olofsson et al., 2014) would provide a valuable complementary perspective but requires reliable reference area information for each crop class, which was not available for the study regions.

Temporal aggregation proved to be another decisive factor. Monthly data generally achieved the highest accuracies by capturing crop phenology in detail. This performance advantage can be attributed to the ability of finer temporal resolution to represent key phenological transitions, such as crop emergence, canopy development, flowering, and senescence, which are critical for distinguishing crop types. In Kazakhstan and Tajikistan, bi-monthly intervals performed comparably, suggesting that intermediate resolutions may suffice in regions with regular cropping cycles (Ibrahim et al., 2021). In contrast, the highly diverse smallholder systems in Pakistan clearly benefited from finer temporal resolution, underlining the value of high-frequency observations during complex growing seasons (Rufin et al., 2019). Crops with pronounced and temporally distinct growth stages, including cotton, maize, and rice, particularly benefit from monthly aggregation, as their spectral and structural signatures change rapidly during key periods of the growing season. These region-specific differences in optimal temporal resolution also have important implications for model transferability across contrasting phenological regimes.

Variations in climate, cropping calendars, and crop development rates can lead to systematic shifts in phenological phases, which affect the temporal signatures captured by satellite-based feature sets when models are applied across large and climatically diverse areas. Previous work has demonstrated that neglecting region-specific phenological timing can reduce the robustness of satellite-based crop monitoring and yield prediction across contrasting agro-climatic contexts (e.g. Luo et al., 2022; Maleki et al., 2025). For example, transferring models to diverse regions is challenging due to phenological differences in crop growth stages between training and target areas, leading to poor performance where crop compositions and phenology differ largely (Luo et al., 2022; Maleki et al., 2025). In this study, temporally aggregated features reduce sensitivity to individual acquisition dates and partially mitigate phenological misalignment; however, the observed regional differences in optimal aggregation schemes indicate that transferability might be conditional rather than universal.

4.2. Crop type specific accuracies

Our results underscore the complementary roles of Sentinel-1 and Sentinel-2 in crop type mapping. Sentinel-1 alone achieved high accuracies for key crops, including maize in Kazakhstan (97%), cotton in Tajikistan (94%) and Pakistan (88%), and wheat in Tajikistan (80%). Cotton, a vital cash crop for smallholders in Pakistan and Tajikistan (Zakirova et al., 2025; Zuberi et al., 2024), has been widely studied with remote sensing. For instance, Huang et al. (2025) reported F1-scores of 90–93% for cotton in Xinjiang using Sentinel-2, while Kang et al. (2023) reached 90–95% with combined Sentinel-1 and Sentinel-2. These values, obtained under more controlled conditions, are comparable to our results in smallholder settings.

Other crops also showed robust performance above 70%, including fodder in Kazakhstan (86%) and rice in Pakistan (78%), reflecting the strength of radar data in capturing structural and phenological characteristics. In Multan, sugarcane reached an F1-score of 86% with Sentinel-2, somewhat lower than the 94–99% reported by Muqaddas et al. (2024) for the same region, likely due to different methodological approaches.

Integrating Sentinel-2 spectral data substantially improved classification of heterogeneous classes. Sorghum in Pakistan increased from 42% with Sentinel-1 alone to 71% with combined data, and fallow land in Kazakhstan rose from 9% to 69%. These cases illustrate that radar data are essential for mixed or spectrally ambiguous classes, confirming that radar and optical inputs are complementary rather than interchangeable (Blickensdörfer et al., 2022; Chakhar et al., 2021).

4.3. Feature selection and importance

Unlike previous studies (e.g. Asam et al., 2022; Blickensdörfer et al., 2022; Chakhar et al., 2021), which generally did not employ explicit feature selection strategies, our study systematically evaluated the effectiveness of feature selection. Incorporating a feature selection process consistently enhanced model performance across the three case study regions. While Orynbaikyzy et al. (2020) successfully employed a group-wise forward feature selection method to identify smaller yet effective subsets of features, our findings particularly emphasize the practical value of such approaches in smallholder farming contexts, where ground truth data availability is often limited. Incorporating feature selection has demonstrated advantages, including enhanced computational efficiency, improved model interpretability, and robust classification performance using a reduced set of more relevant features (Meyer et al., 2018). This observation aligns with similar findings across various classification (e.g. Gao et al., 2024; Georganos et al., 2018) using the Random Forest algorithm.

The feature importance analysis using permutation-based methods revealed distinct patterns across the three study regions of

Kazakhstan, Tajikistan, and Pakistan. These differences indicate that the relative importance of predictors is strongly shaped by site-specific phenological development and by regional differences in spectral and SAR sensitivity. In this regard, our findings are consistent with comparative crop growth monitoring studies from Joint Experiment for Crop Assessment and Monitoring (JECAM) benchmark sites, which have shown that the relevance of specific spectral variables, phenological periods, and radar polarizations varies between agricultural regions (e.g. Gurdak et al., 2021). Optical data and derived vegetation indices consistently emerged as the most important variables across all three areas. SAR features, while valuable, generally exhibited lower importance scores than optical variables. Nonetheless, SAR and optical data showed a clear complementary relationship, consistent with prior research (Blickensdörfer et al., 2022; Orynbaikyzy et al., 2020). Taken together, these results emphasize that transferable crop classification frameworks should not be interpreted as requiring identical predictor importance across regions, but rather as robust methodological approaches that can accommodate region-specific phenological and sensor-response patterns.

4.4. Area of Applicability

The Area of Applicability maps indicate where predictions are supported by training data. In Kazakhstan, low reliability was concentrated in the southern and southwestern Panfilov District, where the applied crop mask (Zanaga et al., 2021) misclassified wetlands as cropland. The Area of Applicability captured these uncertainties, confirming reliable predictions only in adequately represented areas (Ludwig et al., 2023; Meyer and Pebesma, 2021). In Tajikistan's Jaloliddin Balkhi District, only small patches showed poor representation, while the sampling strategy captured most crop-type variability. In Pakistan's Multan District, by contrast, larger areas of low reliability occurred in western zones. Here, limited spatial coverage of field sampling — caused by logistical constraints and time restrictions — meant that the full variance of cropping systems could not be captured as effectively as in the other case study areas. These results highlight the need for more representative sampling and improved regional crop masks to capture small-scale heterogeneity. Consequently, the Area of Applicability approach serves as an effective tool to guide targeted field data collection in the future and transparently communicate uncertainties associated with remote-sensing-based crop-type mapping. However, it specifically addresses the spatial representativeness of the training data and does not quantify class-specific classification uncertainty, which could be explored through complementary uncertainty metrics in future studies. Nevertheless, presenting crop-type maps alongside Area of Applicability information is recommended to clearly communicate uncertainties to non-specialist end users, potentially enhancing user acceptance and practical application of the resulting maps.

4.5. Contextualizing crop type maps

Taking into account the socioeconomic and political context helps to explain the crop type mapping results for all three case studies and adds another layer of validation to our findings. The crop type map for the Panfilov District in Kazakhstan shows persistent maize monoculture rooted in the Soviet Virgin Lands Campaign (Petrick et al., 2013) and reinforced by modernization-oriented policies (Alff, 2023; Petrick and Pomfret, 2016). These policies established single-crop supply chains and processing industries, exemplified by Panfilov's maize sector, which constrain diversification (Alff et al., 2023). Fodder cultivation has expanded since the collapse of the Soviet Union due to rising livestock ownership, with demand further boosted by the 2021 drought (Kerven et al., 2021).

In Tajikistan's Jaloliddin Balkhi District, a different pattern emerges. Here, crop type mapping contrasts with the informal cotton quota requiring 60% of arable land to be under cotton (Zakirova et al., 2023a). The 2022 distribution reflects recent geopolitical and pandemic disruptions, which encouraged diversification toward food crops (Zakirova et al., 2023b).

In Pakistan's Multan District, cotton cultivation has followed yet another trajectory. It declined by about 50% between 2010 and 2021 (Government of Punjab, 2011, 2022) due to poor seed quality, pest resistance, extreme weather, and mismanagement of genetically modified cotton. After temporary recovery in 2021, improved seeds and support prices convinced many farmers to return to cotton in 2022, as reflected in Fig. 9.

Taken together, the three cases demonstrate how different historical legacies, policy frameworks, and external shocks shape cropping outcomes. Interpreting remote sensing-derived crop maps therefore requires attention to socioeconomic and political context. Agricultural policies, market dynamics, and broader crises strongly influence observed patterns and must be considered when applying remote sensing products for decision-making and policy.

5. Conclusions

This study addressed a critical gap by evaluating Sentinel-1 and Sentinel-2 data fusion in smallholder agricultural landscapes in Kazakhstan, Tajikistan, and Pakistan. By comparing radar, optical, and combined datasets under different temporal aggregations, we showed that data fusion substantially improves classification accuracy. Sentinel-1 alone proved effective for crops such as cotton, while monthly aggregation was most suitable for capturing phenological patterns in diverse smallholder systems.

The Area of Applicability metric further highlighted where predictions are well supported and where additional sampling is needed, making it a useful tool for guiding field campaigns and communicating uncertainties. Our results also emphasize that high-quality and balanced ground-truth data remain essential for robust crop mapping. Integrating local socioeconomic and historical contexts is equally important to interpret and apply remote-sensing outputs in practice.

Future work should explore the value of freely available higher-resolution datasets, or combined Landsat–Sentinel-2 time series for further improving crop classification in fragmented smallholder settings (Rufin et al., 2025). However, given that monthly aggregation already captures key phenological stages, the added benefit of higher-frequency observations should be carefully assessed also with regard to the spatial resolution of the data. The impacts of incorporating high-frequency Sentinel-1 time series rather than monthly composites remain to be assessed (Blickensdörfer et al., 2022). Extending the JECAM network (Bontemps et al., 2015) with additional benchmark sites in Central and South Asia would improve the representativeness of smallholder systems and strengthen cross-site evaluation of crop-type mapping approaches.

CRediT authorship contribution statement

Christoph Raab: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Viet Duc Nguyen:** Writing – review & editing, Writing – original draft, Visualization, Data curation, Conceptualization. **Brian Barrett:** Writing – review & editing, Writing – original draft, Methodology. **Aksana Zakirova:** Writing – review & editing, Writing – original draft. **Mehwish Zuberi:** Writing – review & editing, Writing – original draft. **Henryk Alff:** Writing – review & editing, Writing – original draft, Conceptualization. **Michael Spies:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author Christoph Raab used ChatGPT in order to improve the clarity and coherence of the manuscript, proofread and enhance the language of the text, summarize relevant literature, structure and organize content more effectively. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Declaration of competing interest

The authors report there are no competing interests to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2026.102007.

Data availability

Data will be made available on request.

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