

Crop type mapping in Central and South Asia using Sentinel-1 and Sentinel-2 remote sensing data



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1. Introduction

Crop type information derived from satellite remote sensing are of pivotal importance for quantifying **crop growth** and **health status**. However, such spatial information are not readily available for countries in **Central and South Asia**, where **smallholder farmers** play a dominant role in agricultural practice. These, however, are regions, particularly vulnerable to **climate change related food insecurities**.

Thus, the aim of this study was to investigate **possibilities** and **limitations** of a combined use of multi-spectral **Sentinel-2** and radar **Sentinel-1** data for **crop type mapping**.

2. Study site

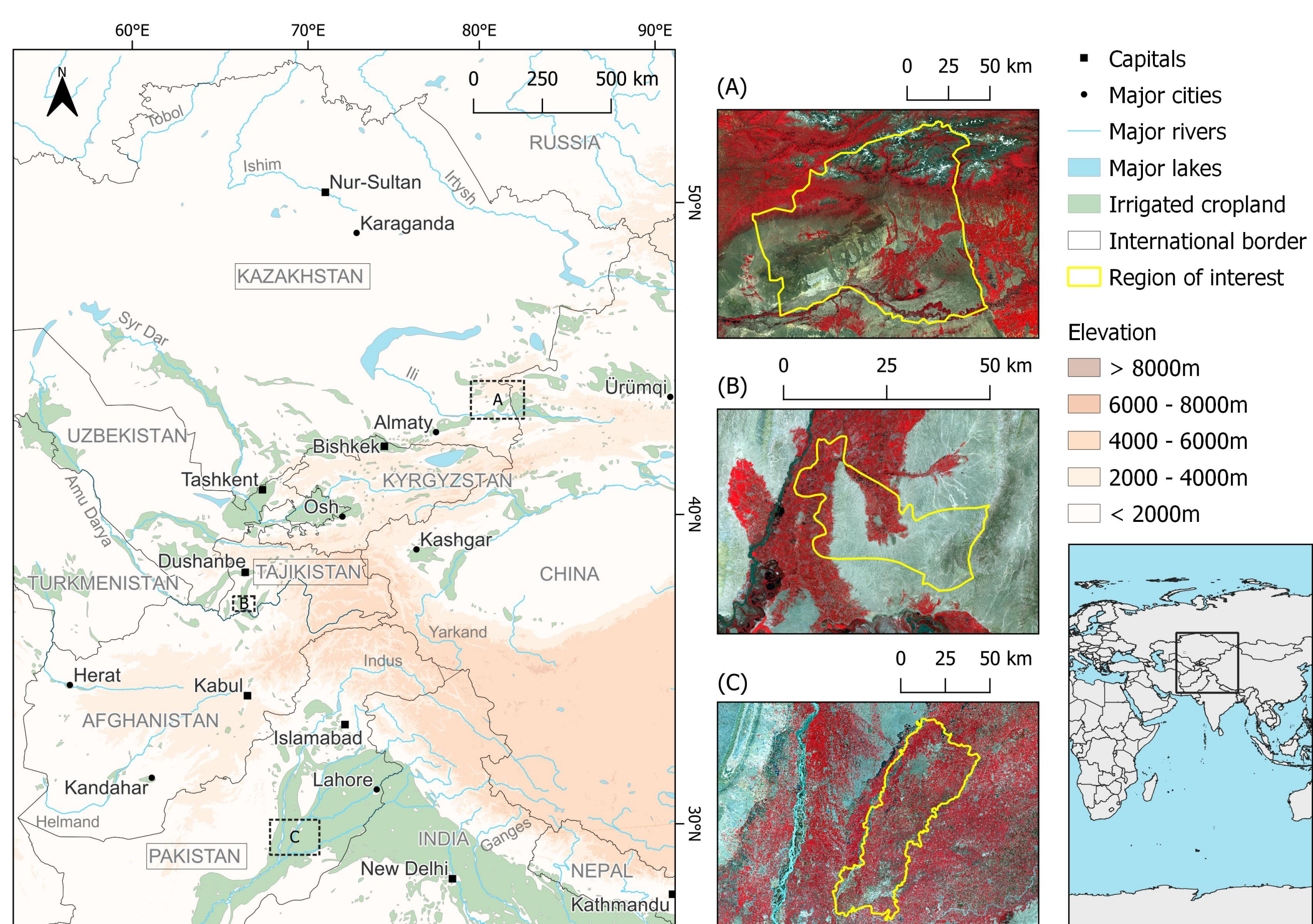


Figure 1: Overview of the study regions.

As study areas, two regions in **Central Asia** – A) Panfilov District in **Kazakhstan**, B) Jaloliddin Balkhi District in **Tajikistan** – and one in South Asia – C) Multan District in **Pakistan** – were selected (Figure 1). All three case studies are dominated by smallholder farmers, whereas **cotton** plays an important role as a cash crop in the studied regions of **Pakistan** and **Tajikistan**.

3. Materials & Methods

- **Field data** were collected in Jaloliddin Balkhi District in **Mai** 2022, in Panfilov District in June 2022 and Multan District in October 2022.
- Based on **roadside collection** approach for training data (Waldner et al., 2019).
- The **WorldCover 2020 v100** (Zanaga et al., 2021) product was used to limit the randomised sampling.
- A collection of Sentinel-2 and Sentinel-1 satellite data was used along with the **random forest classification** algorithm in the **Google Earth Engine** (Gorelick et al., 2017).
- Three different **temporal aggregation intervals** (Rufin et al., 2019).
- We evaluated the performance of **single Sentinel-2 and Sentinel-1** along with a **combined multi-spectral and radar dataset**.
- We used **cross-validation** and **area adjusted accuracy assessment** (Olofsson et al., 2014) implemented in R, respectively.

4. Results

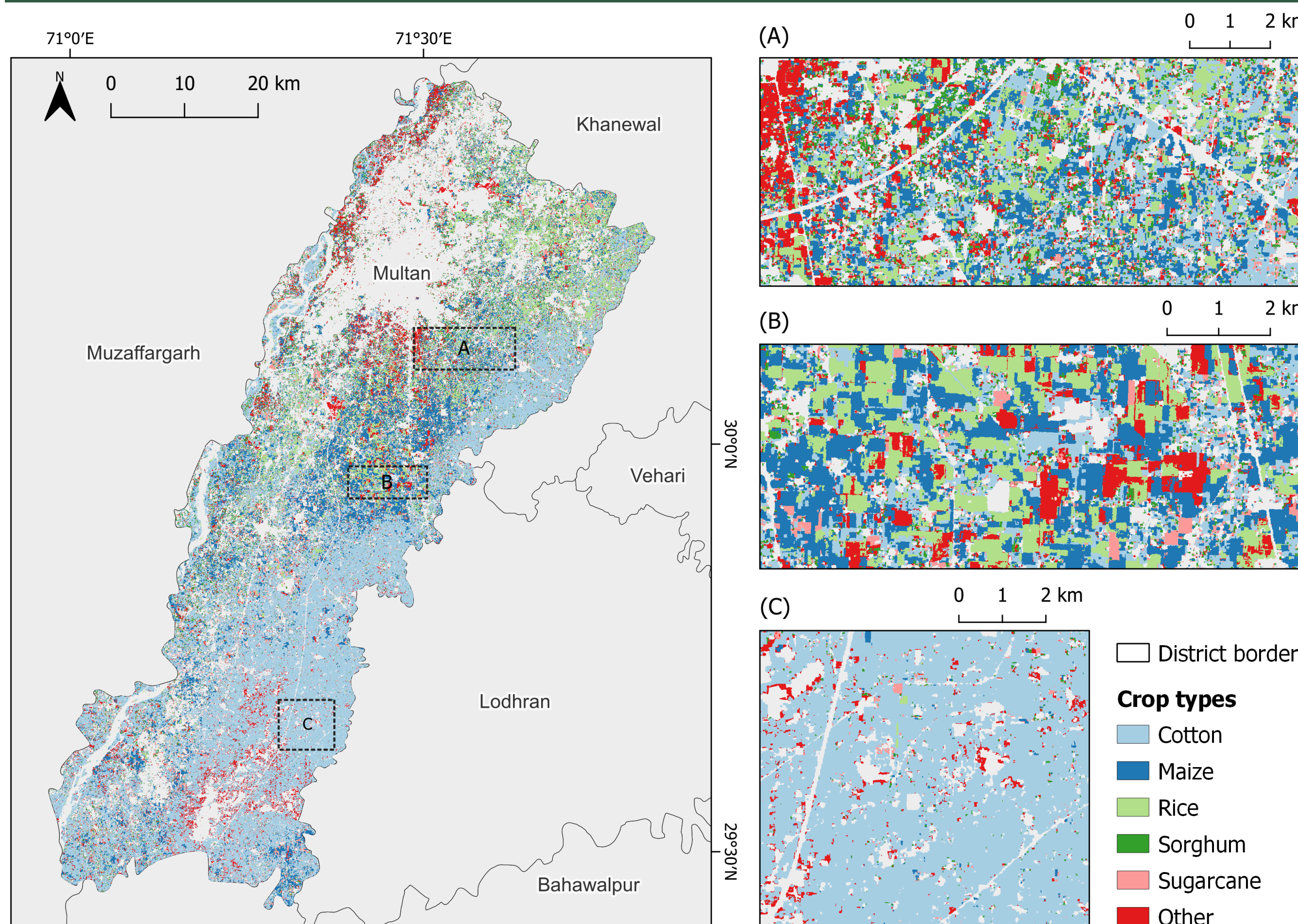


Figure 1: Preliminary results for Multan District in Pakistan.

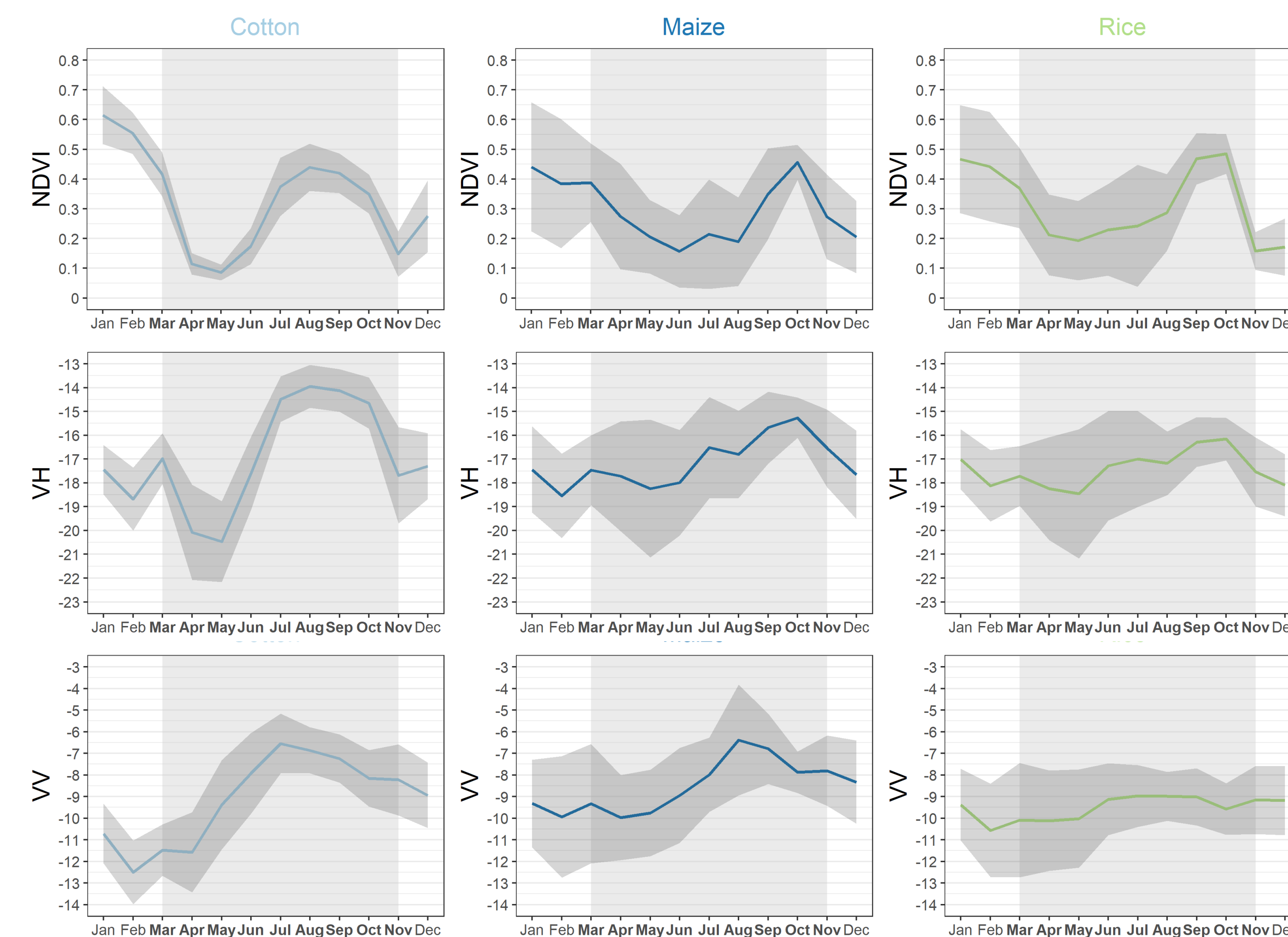


Figure 1: Temporal curves for selected crops in Pakistan. Kharif season is shaded in grey.

Sentinel-2 + Sentinel-1:

80 % Overall Accuracy, monthly aggregation

80 % OA S-2 + S-1

Sentinel-2 only:

79 % Overall Accuracy, monthly aggregation

79 % OA S-2

Sentinel-1 only:

72 % Overall Accuracy, monthly aggregation

72 % OA S-1

Table 1: Result of the area adjusted accuracy assessment for Multan District in Pakistan, using combined Sentinel-2 and Sentinel-1 data with monthly aggregation.

	km ²	km ² ±	PA	PA±	UA	UA±
cotton	1206.28	106.16	100.00	0.00	93.94	8.27
Maize	306.74	97.81	87.31	21.86	72.41	16.56
Rice	220.42	25.00	94.21	10.68	100.00	0.00
sorghum	183.99	128.68	65.34	28.81	66.67	65.33
sugarcane	132.71	49.16	100.00	0.00	77.78	28.81
other	391.13	152.71	58.47	22.83	100.00	0.00

5. Discussion & Conclusion

Preliminary results for Pakistan showed the **high potential for a combined Sentinel-2 and Sentinel-1 crop type mapping** in the context of **smallholder farming** systems. Following research activities will expand the analysis to the case studies in Tajikistan and Kazakhstan.

Project background and funding

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