

Crop Phenology Mapping using Polarimetric Parameters extracted from Sentinel-1 Images

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ABSTRACT

Accurate and high-resolution Spatio-temporal information about crop condition and phenology is a vital component for crop management and yields estimation at the local scale to regional scale. In this research, the crop phenology estimation is carried out using time-series Sentinel-1 dual-pol data. Sentinel-1 data was acquired from January 2019 to December 2020 for Chinoat city of Pakistan. Backscattering coefficients (σ_0) for VH and VV channels were computed for each acquired image. Crop calendar for the local crop of Chinoat was acquired and (σ_0) were stacked according to the cropping season of rice, maize, and wheat. The unsupervised classification was performed using the ISO-Data clustering technique. The mean of each cluster was extracted corresponding to each data of acquisition and polarimetric parameter-based phenological profiles were plotted. Hermite polynomial fitting was performed to acquire smooth phenological profiles. Extracted phenological profiles were compared with the local crop calendar and the following crops were identified: rice, maize, and wheat-based on sowing, growth, and harvesting time information. The (σ_0) in VV channel does not provide consistent results that is why it was discarded from the analysis. However, (σ_0) in VH channel provides very precise crop profiles that coincide with the cropping pattern in the crop calendar. Finally, crop phenology mapping was carried, and final crop maps are prepared. The proposed solution can provide accurate crop phenology of any crop especially in tropical countries where optical satellite data applications are limited due to cloud coverage. As proposed solution highly relies on crop calendar for crop phenology mapping, if crop calendar of given crop is unavailable precise crop phenology mapping cannot be carried out.

Keywords: Crop Phenology Mapping, Crop Pattern, ISO-Data Clustering, Unsupervised Classification.



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I. INTRODUCTION

Agriculture contributes approximately one-quarter of provincial gross domestic product (GDP) in Punjab province. The provincial share is two-third of the total national agricultural output, leading in major commodities meant for food security in the country. Mapping crop type is vital for total yield prediction which is critical for food security. Crop phenology mapping is a prerequisite for crop yield prediction, recording rotation in cropping patterns, mapping soil production, crop condition assessment, crop damage detection, and monitoring farming activities [1,2,3]. However, in-situ data-based crop type mapping is expensive, labor extensive, and destructive [4]. Remote sensing data-based crop mapping provides an alternative tool for crop inventory mapping in a non-destructive manner [5,6]. However remote sensing-based crop phenology mapping is data intensive. Satellite data is required with higher temporal resolution. Currently, an excessive amount of optical remote sensing data is being collected on daily basis which enables researchers to map crop phenology mapping precisely [7,8]. With the availability of SAR data, it has become

a powerful tool for crop monitoring due to its ability to acquire data in all-time and all-weather conditions, which is very critical for tropical countries because these countries are most covered by clouds. Due to extensive cloud coverage, the applications of optical remote sensing data are very limited in tropical regions. Furthermore, SAR signal is sensitive to dielectric constant, surface roughness and texture [9,10]. Researchers made attempts to utilize SAR data for crop condition assessment and crop area mapping [11-15]. The availability of SAR data in different modes of data acquisition, options over polarization, and its capability of acquiring data in all weather conditions make SAR data the preferred choice over optical data. The proposed solution is capable of mapping and monitoring crop phenology in all weather and all condition especially in the context of tropical countries. This research, Sentinel-1 data is being used for crop phenology mapping by utilizing backscattering coefficient σ_o and crop calendar. The main objective of this research is to map crop phenology by utilizing polarimetric parameters extracted from Sentinel-1 data in synergy with crop calendar. This paper is categorized into four sections, the current section introduces the research problem, section II describes the study area, SAR and ancillary data and methodological framework adopted in this research, section III is about results and related discussion concludes this research.

II. METHOD

A. Study Area

The study area chosen for this research is located at the bank of river Chenab in Punjab Province, Pakistan as can be seen in Figure 1. The topography of Chinoat is relatively flat with an average elevation of 179 m. Chinoat experience significant precipitation during the Monsoon, which occurs in summer from the month of June till September in most of Pakistan. The maximum and minimum temperature range from 22 °C ~ 45 °C and 10 °C ~ 30 °C respectively. The availability of water from the river Chenab and precipitation during the monsoon make Chinoat an ideal place for multiple crops including rice, maize, wheat, and cotton.

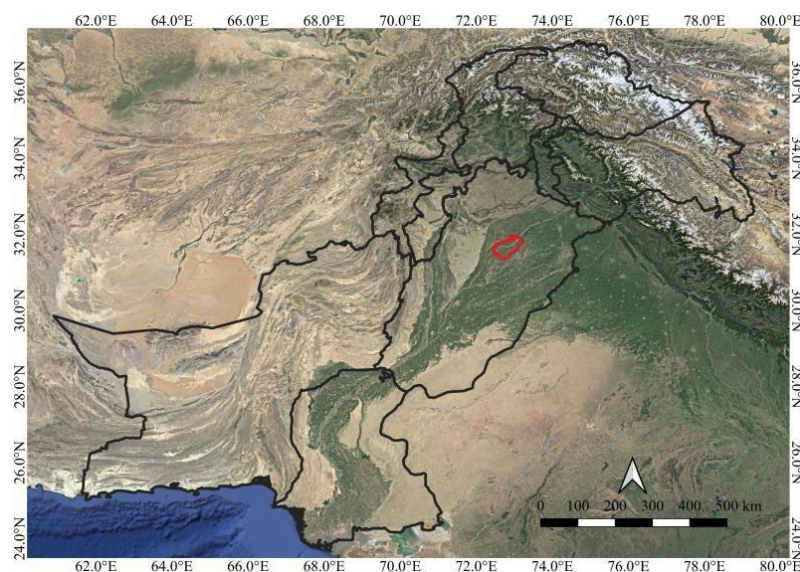


Fig. 1 Location of study area- Chinoat district, Pakistan

B. SAR and Ancillary Data

Sentinel-1 level-1 Ground Range Detected (GRD) dual-pol (VH, VV) data acquired for the year 2019 and 2020 over chosen study site. A total 71 consecutive Sentinel-1 images were acquired from Alaska Satellite Facility (<http://asf.alaska.edu>). The monthly averaged weather data (maximum temperature, minimum temperature, and precipitation) was acquired from World Weather Online (<https://www.worldweatheronline.com/>) as shown in Figure 2. The crop calendar for Chinoat was acquired from the Pakistan Bureau of Statistics (<https://www.pbs.gov.pk/>) as shown in Figure 3.

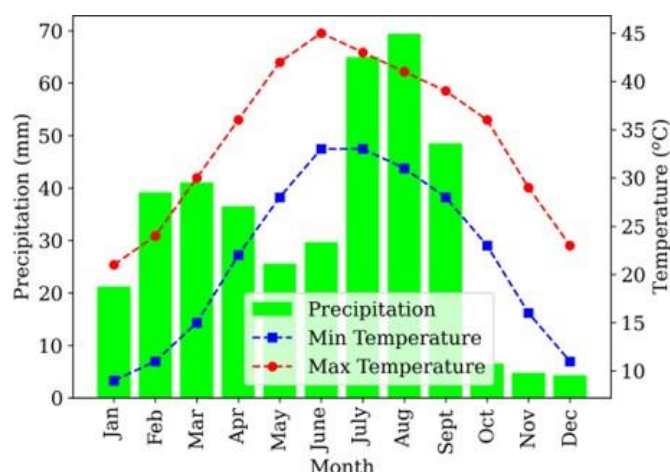


Fig. 2. The average precipitation, maximum and minimum temperature of study site

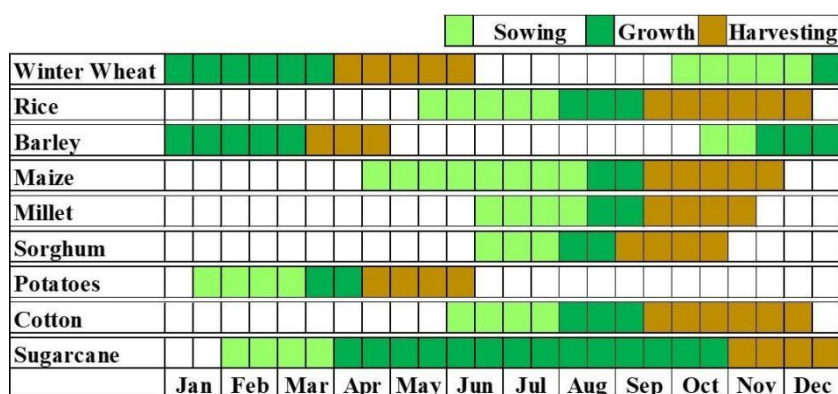


Fig. 3. Crop calendar of Punjab province, Pakistan

The crop calendar in Figure 3 shows the sowing, growth, and harvesting period recommended by the Government of Pakistan for wheat, rice, barley, maize, millet, sorghum, potatoes, cotton, and sugarcane crops respectively. However, in this research, only the rice, maize, and wheat crops calendar are utilized.

C. Methodological Framework

The acquired Sentinel-1 data were pre-processed to get σ_0 as suggested by Filipponi [16]. During Sentinel-1 data pre-processing, the first orbit file was applied which acquires precise orbit state vectors that will be used in a later stage for image range-Doppler terrain correction. As there exist radiometric artifacts at level-1 image borders which are mainly caused by azimuth and range compression; to address these artifacts border noise removal algorithm was applied. Next, σ_0 was estimated. Lee Sigma (7x7) speckle filter was applied to reduce speckles in resultant data. Next, range-Doppler terrain correction was applied to correct distortions caused by topography and to perform image geocoding. Finally, geocoded data was converted from linear to dB scale.

Using crop calendar, cropping season was extracted for rice, maize, and wheat crop. Based on cropping season, Sentinel-1 pre-processed data was stacked for each crop. For example, Sentinel-1 pre-processed data was stacked from October 2019 to June 2020 for the wheat crop. The unsupervised classification was performed on each stacked image corresponding to rice, maize, and wheat crop respectively using ISO-Data clustering algorithms. Temporal profiles corresponding to each resultant clustered image were extracted and matched with the crop calendar.

By analyzing the extracted temporal profiles (which corresponds to either crop pattern or non-agricultural land) in synergy with the crop calendar, crop mapping was performed. A detailed methodological framework adopted in this research is shown in Figure 4.

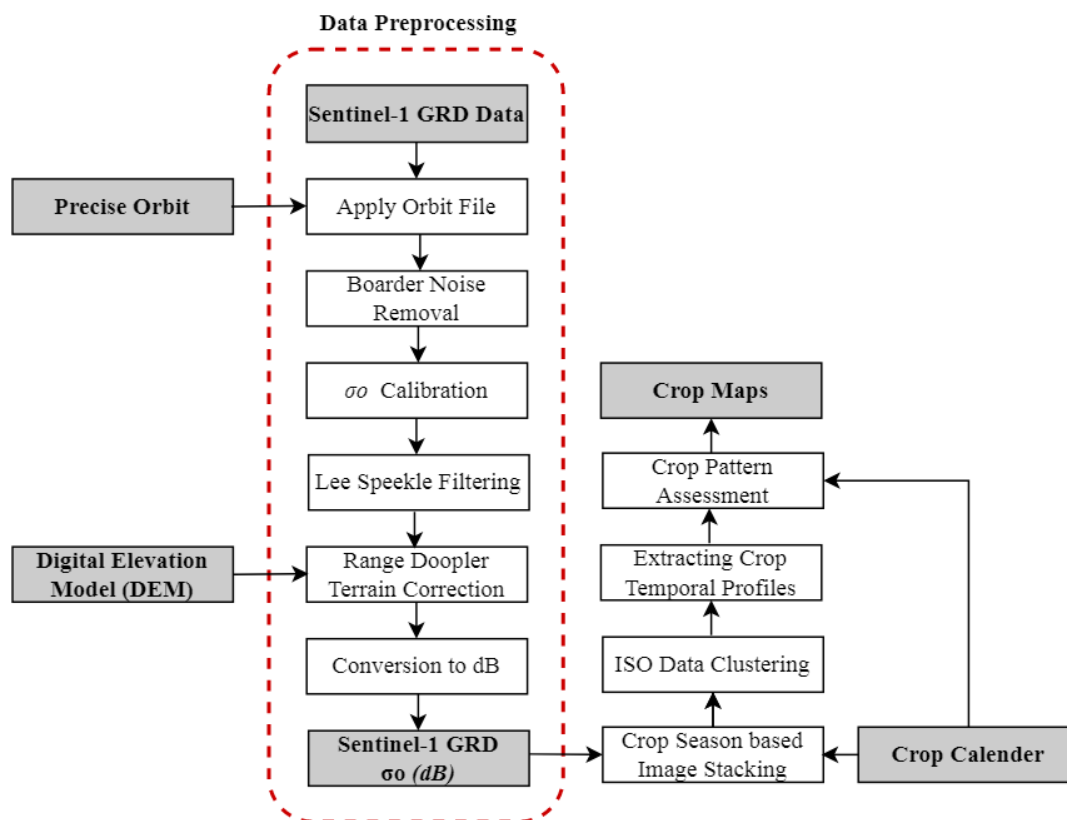


Fig. 4. Methodological framework adopted in this research.

III. RESULTS AND DISCUSSION

As discussed in the previous section, acquired data was stacked based on crop season. For convenience, we named S1, S2, and S3 to stacked images corresponding to rice, maize, and wheat seasons respectively. Where S1 is the stack of images from May~ December 2019 and 2020; S2 is the stack of images from April~ November 2019 and 2020; similarly, S3 is the stack of images from October 2019 ~ June 2020. ISO-Data clustering algorithm ($n = 5, 10, 15, 20, 25, 30, 35, 40$; where 'n' is the number of clusters) was applied to extract natural clusters existing in S1, S2 and S3. The clustering results corresponding to $n=35$ provide optimal separability among resultant clusters. Cluster signatures were extracted for S1, S2 and S3 respectively, and these signatures were analyzed in synergy with the crop calendar to identify clusters representing crops and non-crop areas.

A. Analyzing Cluster Signature in synergy with Crop Calendar

The resultant cluster profiles for S1, S2 and S3 were plotted with respect to time as shown in figure 5 (a), 5 (b) and 5 (c) respectively. Let's first consider rice crop which corresponds to S1. As can be seen from the crop calendar, the sowing time for rice crops is from mid of May to the end of July. Hence during the sowing period, agricultural land is representing by barren land; hence very small power of backscattering is expected. Similarly, the growth period of the rice crops is from August to September. During this period, the backscattering coefficient value from agricultural land is expected to increase with the growth of rice paddy. Furthermore, the harvest period for rice crops is October to mid of December, which means the backscattering coefficient value over agricultural land during the harvest period will decrease again. Hence a sinusoidal behavior is expected over the complete crop cycle. Data from both VH and VV channels were

used, however, VH channels were found to be more sensitive to crop phenology hence results produced using VH -based backscattering coefficient (σ_o) are presented below. Figure 5 (a) shows the cluster signature for rice, clusters for non-agriculture land are discarded from the analysis. As the month of May is the sowing season for rice, therefore points corresponding to May 2019 and 2020 have minimum σ_o . Similarly, the months of June and July correspond to the maturity stage hence peak of cluster signature was found over June and July (refer to Figure 5 (a)).

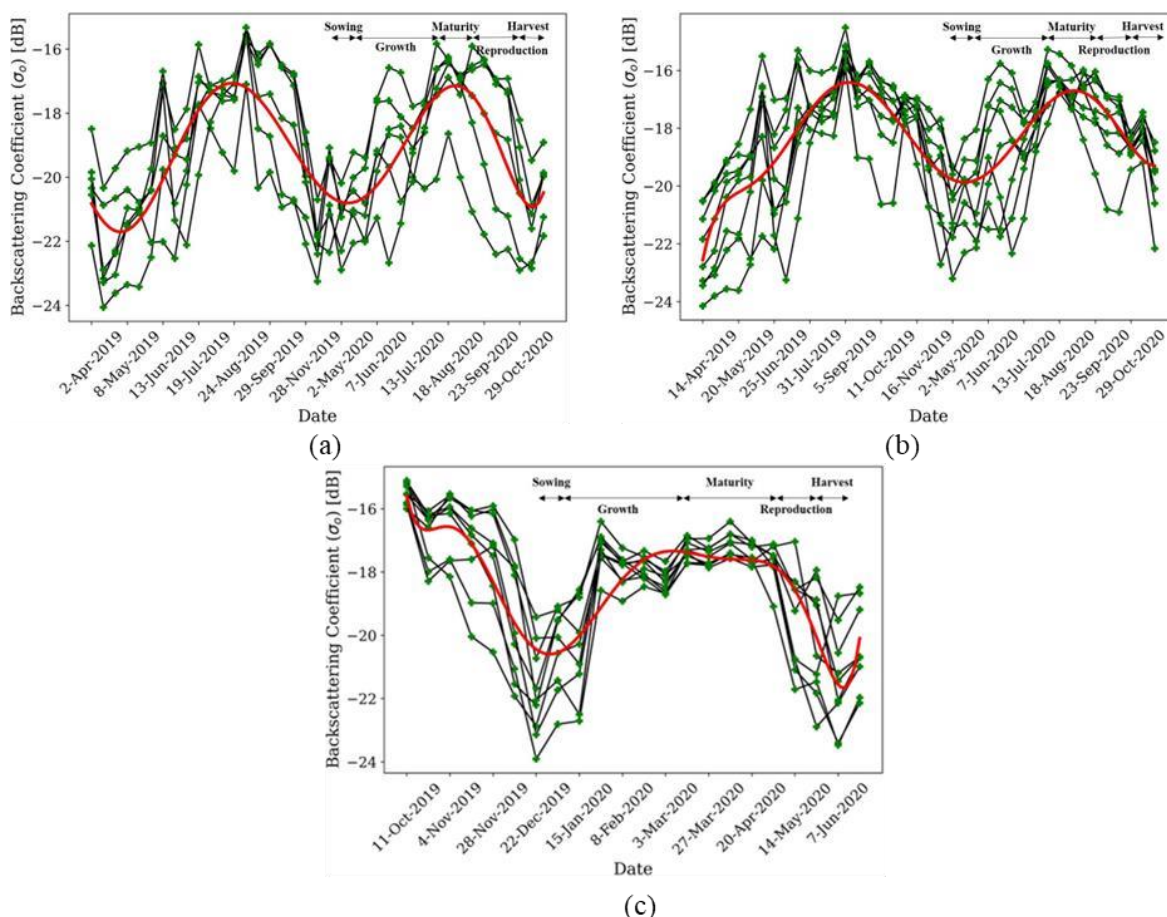


Fig. 5 – Crop phenology profiles during cropping seasons in 2019 and 2020 (a) Rice phenology profile (b) Maize phenology profile (c) Wheat phenology profile

As the harvest time for rice paddy is around October and November; it can be seen from figure 5 the cluster signature goes back to minimum value; this decrease in σ_o can be related by the absence of crop after harvest. In a similar manner, the cluster signature for maize and wheat crop can be analyzed. It can be seen from Figure 5 (b) and (c); the peak and dips exactly correspond to the sowing, maturity, and harvest stage (refer crop calendar shown in Figure 3 of maize and wheat crop respectively). As can be seen from the crop calendar; the wheat crop cropping season is from mid-October to mid-June, however in the extracted crop profile (refer Figure 5 c) the actual cropping seasons is from mid-December to mid-June. It's important to realize that cropping seasons in the crop calendar are the recommended time frame for farmers however actual cropping season may vary depending upon the local weather condition and availability of water and seeds. The red line in Figure 5 (a), (b), (c) corresponds to the hermit polynomial fitting ($n = 6$, where 'n' is the order of polynomial). Polynomial fitting was carried out to get a precise trend line over crop temporal profile. The fitted polynomial curve gives a better understanding of crop temporal profile when compared with the crop calendar.

B. Mapping Crop Phenology using Cluster Signature

Using extracted crop temporal profiles of rice, maize, and wheat crops; crop mapping was performed. Resultant crop maps for rice, maize and wheat are shown in figure 6 (a), (b) and (c) respectively. It's evident

from resultant crop maps, most of the crops are based on irrigation from the river Chenab. As can be seen from Figure 6 (a), most of the rice plantation is across the river. This can be due to the excessive need for water for rice crops. On the other hand, maize and wheat crop are evenly distributed throughout the study area. Overall, the cropping pattern coincides with the crop calendar provided by the Bureau of Statistics, Pakistan.

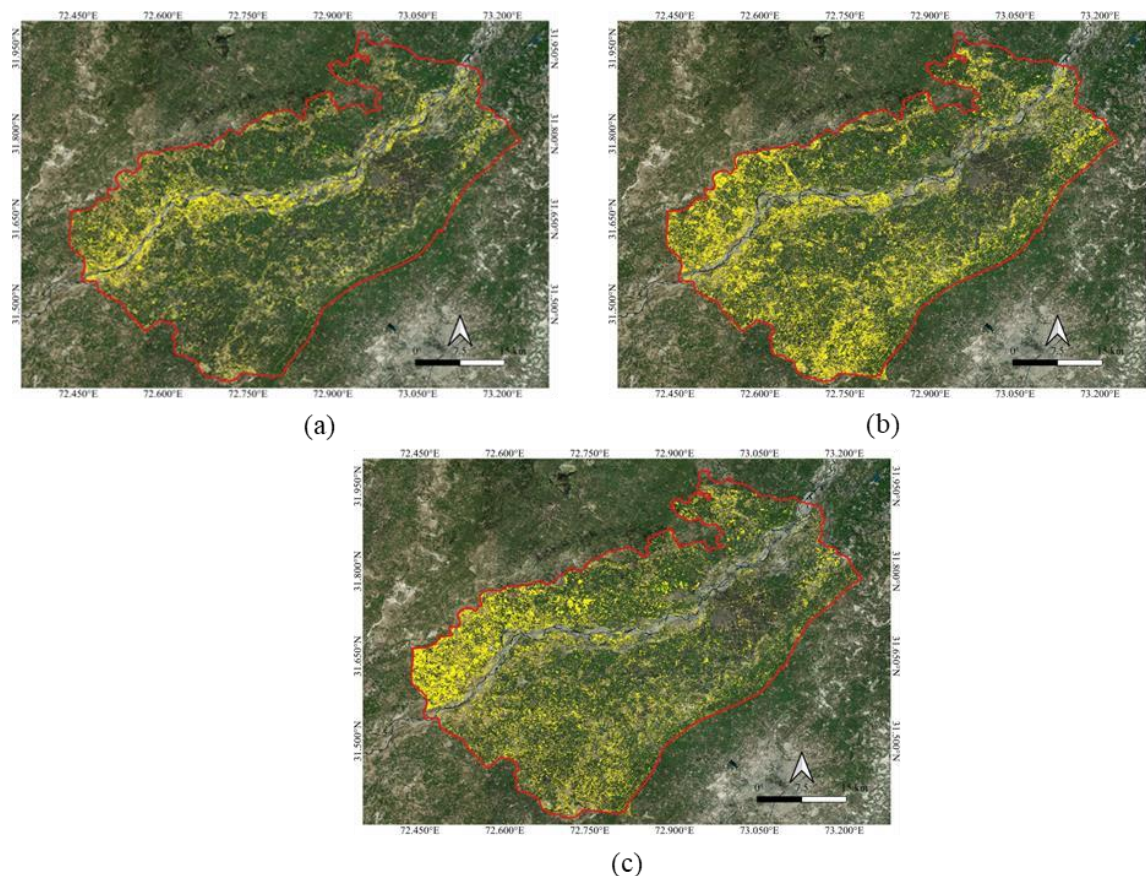


Fig 6. Crop spatial distribution in Chinoat District (a) Rice (b) Maize (c) Wheat

Wheat and Maize crop classification was found to be quite accurate when overlaid over optical data. However, in rice crop classification, roads and canals are wrongly classified as rice crops. In this research, only major crops of Chinoat city are mapped using the adopted methodological framework. Sugarcane and Cotton are also among the key crops of the Chinoat district and can be mapped by adopting the same methodological approach.

IV. CONCLUSION

In this research, crop phenology is mapped using the backscattering coefficient (σ_0) for rice, maize, and wheat crop. The information acquired from the crop calendar is successfully integrated with temporal SAR data to extract temporal crop profiles. Due to varying local conditions i.e., availability of water, seed, and fertilizer; slight variations were found among temporal profiles of the same profile over different clusters. It's further noted that the sowing period can be shifted from the one provided in the crop calendar; it can again be related to the crop rotation cycle and local conditions. As in this research Sentinel-1, dual-pol data was used. From the experiment, it was found that VH gives better results to extract crop phenology if compared to the VV channel. As ISO-Data algorithm-based unsupervised classification was used to extract naturally identically clusters from temporal lay stacked images; there exist misclassification with other land-cover if their temporal behavior is similar to the crop growth pattern as mentioned in the crop calendar. Hence to get more precise results, manual editing is required. Accuracy assessment is limited to the visual image interpretation by overlaying crop map on optical data and matching crop temporal profile with the crop sea son from crop calendar.

ACKNOWLEDGMENT

The authors would like to acknowledge the Bureau of Statistics, Pakistan for providing an updated crop calendar of Punjab province, Pakistan. The authors also would like to acknowledge ESA for providing Sentinel-1 data. All the processing was done in the python environment and mapping was performed in QGIS.

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