Crop Classification and Crop Acreage Estimation Using Geospatial Technology in the Upper Gangetic Plains of Uttarakhand, India

ABSTRACT

Timely and accurate crop mapping plays an important role in food security, economic and environmental policies. Crop maps are also utilized for agro-environmental assessments and crop water usage monitoring. As a result, accurate and timely crop classification is essential for agricultural management and monitoring. Because it provides periodic large-scale observations of ground objects, satellite remote sensing has been regarded as an advanced tool to characterize crop types and their distributions on a regional scale. High-resolution, multispectral images of October 13, 2021, December 7, 2021 and March 6, 2022 of sentinel-2 satellite released by the European Space Agency (ESA) have been used for classification. Ground truth points have been collected manually with the android app ‘Mapmarker’ and Google Earth. Further, pre-processing of satellite imageries such as resampling, mosaicking and sub-setting have been done with the Sentinel Application Platform (SNAP) software. Crop classification and acreage estimation was conducted using Maximum Likelihood approach. It is the first time an attempt was made to estimate cropping intensity using geospatial technology in the upper Gangetic plains of Uttarakhand state. Rice and sugarcane areas of 108,884 ha and 11,479 ha, respectively, were estimated from the October 13, 2021 image. Pea crop area was estimated as 6,227 ha from December 7, 2021 image. Using March 6, 2022 image, wheat and mustard crop areas were estimated as 105,334 ha and 2,018 ha, respectively.

Keywords: Crop classification, Sentinel-2, Image processing software, Crop acreage estimation, Multiple cropping Index, Cropping Intensity

1. INTRODUCTION

Throughout human history, the reliance on land for food production and economic development has had a profound impact on the global landscape. Meeting the demands of a growing population and developmental activities has placed immense pressure on the planet's soil (Foley et al 2011; Weinzettel et al 2013) This has led to changes in land use and land cover (LULC), which in turn have contributed to environmental degradation and various hazards worldwide (Stabile 2014). These changes include climate change, increased water extraction, alteration of the hydrological cycle, degradation of water quality, loss of biodiversity, accelerated surface erosion, and depletion of soil nutrients. Such extensive shifts in LULC can adversely affect agricultural systems (Turner et al. 2007).

In India, agriculture is a significant source of income for households. However, the conversion of agricultural land into non-agricultural land, is reducing the available land for farming (Pandey and Seto 2015). The country's growing population drives higher demand for food. To ensure food security, crop production must increase annually and per unit of area. Achieving this goal requires efficient management and sustainable use of natural resources. Mapping the LULC is crucial for effective natural resource management (Lesslie et al. 2006). Crop mapping, along with its implications, plays a vital role in food security, economic planning, and environmental policies (Ozdogan 2010). Traditional manual surveying methods for crop mapping are time-consuming, labour-intensive, and limited to a small number of accessible fields (Gilbertson et al 2017). For mapping larger areas, satellite images are a viable option (Thenkabail et al. 2010). Satellite remote sensing provides periodic, large-scale observations of ground objects, making it an advanced tool for regional crop-type characterization (You and Dong 2020). A successful example of crop-type mapping using Sentinel-2 images was demonstrated in Maharashtra state, India, where the major crops of the Sangamner district were classified by Vijayasekaran (2019). Crop classification using satellite imagery can be carried out through different approaches. When analysing satellite images for feature mapping, classification of any feature can be conducted with numerous methods which vary in their way to identify classes and in their accuracy (Briem et al 2002). The maximum likelihood classifier calculates the probability of a particular pixel for every class and then allocates that pixel to the most likely class (Ahmad and Quegan, 2012).

Information on crop acreage estimated over time and space can be utilized to synthesise quantitative variables such as cropping intensity (Ray et al 2005). Cropping intensity is defined as the number of crops grown by a farmer on the same field in an agricultural year (Raut et al 2011). Cropping intensity indirectly provides a measure of cropland usage with respect to time from the same piece of land. The Udham Singh Nagar (USN) district of Uttarakhand comes under fertile zone of upper Gangetic plateau where agriculture is intensively followed. Keeping in view all these facts, the present study has been conducted to extract information regarding crop cover of the Udham Singh Nagar (USN) district of Uttarakhand state and to estimate the cropping intensity using multidate Sentinel 2 satellite images.

2. MATERIAL AND METHODS

Details of the present study area, collection of the satellite image, software tools used in the study, ground-truth observations made and methodologies applied are described in this section.

2.1 Study Area

The study was conducted at the Udham Singh Nagar district of Uttarakhand state, which lies under the fertile Gangetic plateau of India (Fig 1). The district size is 2,579 km^2, making it the ninth-largest district in Uttarakhand. It lies between the latitudes of 28° 53' N and 29° 23' N and the longitudes of 78° 45' E and 80° 08' E. This district is under sub-tropical and sub-humid climatic conditions with clearly established monsoons (rainy season), as well as winter and summer seasons. The rainy season begins in the middle of June and extends up to September. The winter season starts from October up to February, and is followed by the summer season from March until June (Malik et al 2018)**.** Udham Singh Nagar district is popularly called "*Chawal ki Nagari*" which signifies that the most important occupation for the population of this district is agriculture. The main crops grown during the rainy season are paddy and sugarcane and the main crop grown in the winter season is wheat, while summer corps are mainly mustard and pea. Sugarcane is grown through all seasons.

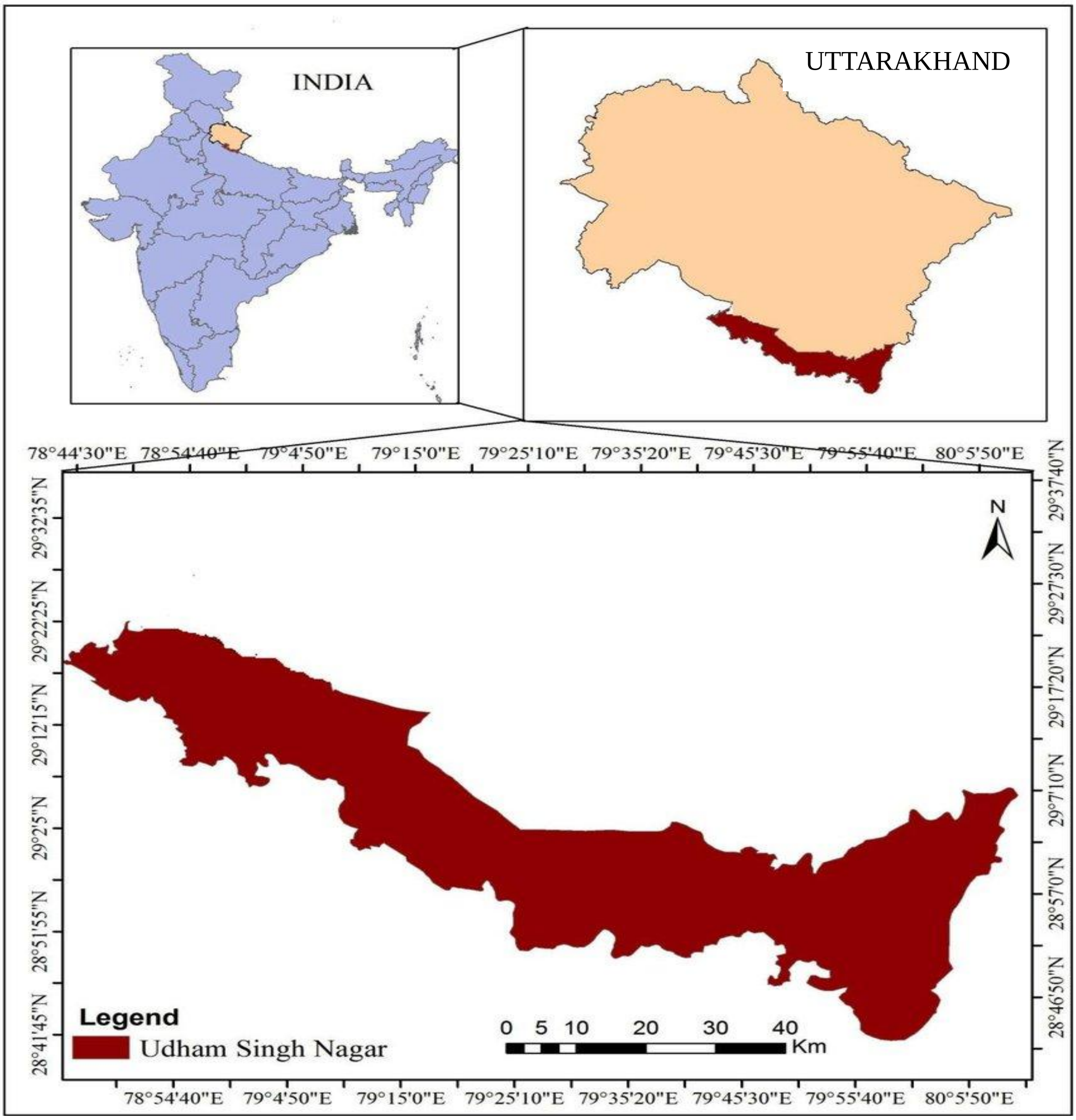

Fig. 1. Location map of Udham Singh Nagar district

2.2 Software used

Different image processing and GIS softwares were used in the present study to make the classification process much easier. SNAP 8.0 (SeNtinel Application Platform) software developed by the European Space Agency (ESA) is suitable to view, analyse and process sentinel satellite data. Downloaded satellite data which is in *.zip* format can be directly opened in SNAP without any extraction (Djamai and Fernandes 2018). There is no need of layer stacking of the images if the mosaicking process is carried out in SNAP which saves time. Thus, the SNAP 8.0 version was used in the current study to resample, mosaic and sub-setting the region of interest. Another free open-source GIS software, QGIS 3.18-Zurich

(Quantum GIS), was used to digitize the district boundaries of the Udham Singh Nagar district. Using the digitized district boundary of the Udham Singh Nagar district Udham Singh Nagar district image was carved out. This image is further analysed using Environment for Visualizing Images (ENVI) which is a popular image processing software that is used by scientists, image analysts, researchers and GIS and remote sensing professionals (Ranjan et al. 2014). ENVI is used in order to pre-process and analyse satellite imageries quickly. In the present study, ENVI 4.7 was used for the training and classification of images using maximum likelihood classifier. Ground truth points which were harnessed for accuracy assessment and training of the image, are collected using an android app named ‘Map Marker’.

2.3 Data sources and collection

Sentinel-2 satellite image with 5-day temporal resolution and 10 m spatial resolution from the EU Copernicus Programme is best suited for monitoring vegetation at a small scale (Xiong et al. 2017). Therefore, freely available Sentinel-2 satellite data having a high spatial resolution of 10 m and good spectral resolution with 13 bands have been selected in the present study. Four tiles of Sentinel-2 satellite cloud-free images required to cover the Udham Singh Nagar district were downloaded from the official website (https://scihub.copernicus.eu/).

The rice crop is generally sown in the second fortnight of June and harvesting starts in the third week of October. The crop reaches its maximum vegetative stage in the month of September (Chetan, 2018). Cloud-free images of Sentinel-2 were not available during September month. The nearest cloud-free image with respect to the maximum vegetative stage of the rice was therefore utilized in the present study. Sugarcane reaches its maximum stage six to seven months after planting (Everingham et al. 2007). Since sugarcane is majorly planted in February, maximum vegetation is reached in the mid of October. As a result, rice and sugarcane crops were classified and their respective acreage was estimated by using the same image dated October 13, 2021. As the present year data on area covered by crops and area of built-up land is not available, previous year (2019-20) data were taken from the Directorate of Economics and Statistics official website (https://eands.dacnet.nic.in) whereas actual forest area was retrieved from the Forest Survey of India, 2019 report. Arumugam et al (2021) reported that the waterbodies area in Udham Singh Nagar is 6,272 ha. As the data regarding the ‘Other’ class was not available, this class is not taken in comparison.

Pea crop is generally sown from the end of October to the first week of November. It reaches its maximum vegetation stage in December (Pandey and Uniyal 2018). Other winter crops like wheat and mustard are at the seedling stage during that month. It was not possible to differentiate pea from other winter season crops using the same image. A Sentinel-2 satellite image dated December 7, 2021 was thus used to differentiate only pea. Pea crop was seen as light red colour in standard FCC image while 'other' class was seen with slightly reddish to a dull cyan colour. As wheat and mustard have their maximum vegetation during the month of February (Naram 2016), the image dated 15 February 2022 was used for wheat and mustard crop differentiation. Wheat crop is seen as bright red colour whereas mustard crop is visualised in pinkish red colour in FCC image (Ranjan and Nain 2013). Hence, in the present study, three Sentinel-2 satellite images were used and major crop acreage was estimated season-wise.

Ground truth data points were collected during different seasons throughout the Udham Singh Nagar district by collecting information regarding previous and present crops from the farmers. In addition, three field surveys were undertaken. A first field survey was undertaken on 10 November 2021 in the Rudrapur- Kichcha block and latitude and longitude information were collected for fields of rice, sugarcane, fields as well as other established crops. In the Udham Singh Nagar district, the rice crop is generally followed by wheat. But some farmers establish a short-duration pea crop just after rice and before wheat (Naram 2016). On December 27, 2021, a second field survey was conducted to collect latitude and longitude information of the pea crop. Similarly, a third field survey was undertaken on March 6, 2022 to collect latitude and longitude information of wheat and mustard fields. The collected ground truth points were divided in the ratio of 70:30. 70% of the ground truth collected points were used for training of the software and the other 30% is used to test the accuracy of the classified images.

2.4 Data processing

Four tiles of sentinel-2 satellite images (*RKT, RMT, RLT* and *RLS)* were downloaded in order to cover the whole Udham Singh Nagar district. Image mosaicking is often a very necessary process to cover the full and large region of interest (ROI) for various remote sensing applications (Li et al 2019). In SNAP, mosaicking two or more Sentinel-2 satellite image L2A multi-pixel size products with varying spatial resolutions requires that all associated bands have the same spatial resolution (Javhar et al 2019). Resampling was carried out with respect to NIR band (B8) which has a 10 m spatial resolution which is followed by mosaicking. With the help of the Udham Singh Nagar district vector layer, the subset of the Udham Singh Nagar district was carved out from the mosaicked Sentinel-2 imageries.

This Udham Singh Nagar district image is then analysed in ENVI-4.7 software for training and classification purposes. In supervised image classification, the quality of the training process determines the success of image classification (Lillesand et al 2015). Training of the data set was carried out with the help of ground truth points collected through Google earth, field surveys and personnel experience. Image classification was carried out in next step using maximum likelihood classifier (Fig 2). The maximum likelihood classifier calculates the probability of a particular pixel for every class and then allocates that pixel to the most likely class. Then a confusion matrix was generated by using 30% of the total ground truth points collected which were kept for accuracy assessment purposes. The confusion matrix assesses the accuracy for each class as well as for the whole image. It includes Overall Accuracy (OA), Producer accuracy, User accuracy and Kappa coefficient (Lillesand et al 2015).

OA is the ratio of pure pixels in the classified image to the total number of pixels and is expressed in percentages.

$$OA = \frac{Number\ \ of\ pure\ pixels \times 100}{Total\ number\ \ of\ pixels}$$

Another statistical parameter for accuracy assessment is the Kappa coefficient (k^) which reflects the difference between actual agreement and the agreement expected by chance. It is given by,

$$\text{k\^{}} = \frac{Observed\ \ accuracy\ -chance\ agreemen\ t}{1-chance\ agreement}$$

After classifying the image, class statistics were calculated and compared with reported area. After estimating acreage of each crop using the multi-temporal satellite images, cropping intensity of the whole Udham Singh Nagar was calculated using Multiple Cropping Index. The number of crops grown by a farmer on the same field in an agricultural year constitutes the cropping intensity (Raut et al. 2011).

Multiple cropping index (MCI): It is defined as the ratio of the total area cropped in a year to the land area available for cultivation and is expressed in percentage.

$$MCI = \frac{100 * \sum_{i=1}^{n} a_i}{A},$$

Where n is the total number of crops, a_i is the area occupied by the i^{th} crop planted and harvested within a year and A is the total cultivated land area available.

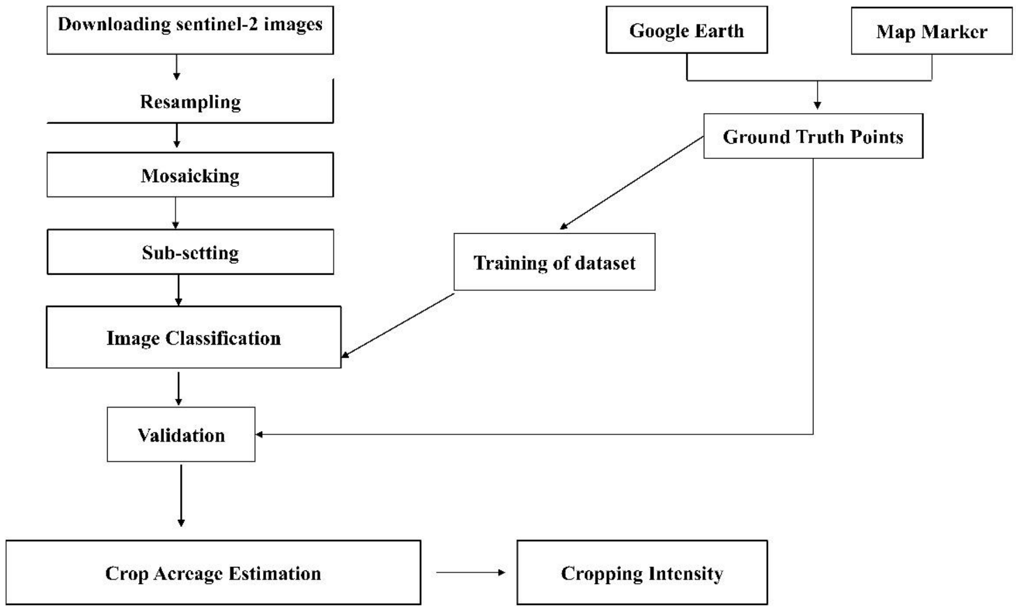

Fig. 2. The flowchart of the methodology followed

3. RESULT AND DISCUSSION

3.1 Crop classification and accuracy assessment

3.1.1 Rice and Sugarcane crop classification

The main crops grown during the rainy season in Udham Singh Nagar district are rice and sugarcane and in the winter season, mainly wheat followed by mustard and pea is grown in larger areas. The Sentinel-2 satellite imagery dated 13/10/2021 was used to discriminate and delineate the rice and sugarcane crops. According to the estimate, the rice area occupied 108884 ha area whereas the sugarcane crop occupied 11479 ha of the total area of the Udham Singh Nagar district. The Forest area covered 43814 ha followed by built-up land which occupied 36650 ha of land. Waterbodies accounted for 6272 ha of the total area. The overall Accuracy calculated was 74.91% for the rainy season the and kappa coefficient was 0.69 (Table 1). The low accuracy was because of the mixing of the built-up land class and the 'other' class. This is due to the similar spectral signature of fallow land and built-up land. The spectral signatures of fallow lands and built-up land may be similar and can cause a decrease in classification accuracy (Sinha et al. 2020). Producer accuracy of rice class was 100% which represents all the reference pixels are correctly classified. And user accuracy of rice is 85.77% which represents 85.77% of the pixel rice class in the image actually represents rice class in the field. Similarly, producer accuracy and user accuracy of sugarcane were 61.90% and 86.67% respectively. Due to mixing between rice and sugarcane low producer accuracy in the case of sugarcane is observed. Rao et al. (2008) demonstrated that rice and sugarcane variants' spectral properties were fairly similar, making it challenging to distinguish between these two crop species.

Table 1. Confusion matrix percentage based

Classes	Rice	Sugarcane	Forest	Built-up land	Water bodies	Others	Total
Rice	100.00	38.10	3.90	0.00	0.00	0.00	7.84
Sugarcane	0.00	61.90	0.00	0.21	0.00	0.00	0.45
Forest	0.00	0.00	96.10	0.00	0.00	0.00	21.56
Built-up land	0.00	0.00	0.00	17.29	0.00	2.45	5.37
Waterbodies	0.00	0.00	0.00	0.00	100.00	0.00	23.30
Others	0.00	0.00	0.00	82.50	0.00	97.55	41.48
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

3.1.2 Pea crop classification

Generally, pea crop sowing ranges from the end of October month to the first week of November. It achieves its maximum vegetation stage during the month of December. So, the Sentinel-2 image dated 07/12/2021 was used for the differentiation of the pea crop. Pea crop was seen as light red colour in standard FCC image while ‘other’ class was seen with slightly reddish to a dull cyan colour. Using the number of pure pixels in each class, OA was calculated which was 98.65% and the kappa coefficient was 0.98 (Table 2). Producer accuracy of pea crop was 77.55% and user accuracy was 100% which signifies a better pea crop classification

Table 2. Confusion matrix percentage based on the image dated 07/12/2021

Class	Pea	Others	Built-up land	Water bodies	Forest	Total
Pea	76.55	0.00	0.00	0.00	0.00	1.70
Others	23.45	88.89	2.24	0.00	0.00	3.86
Built-up land	0.00	9.72	97.76	0.00	0.00	21.80

Water bodies	0.00	1.39	0.00	100.00	0.00	42.80
Forest	0.00	0.00	0.00	0.00	100.00	29.83
Total	100.00	100.00	100.00	100.00	100.00	100.00

3.1.3 Wheat and mustard crop classification

Since both crops show their maximum vegetation stage during February month, a Sentinel-2 satellite image dated 15/2/2022 was used in the present study to differentiate between these two crops. Wheat crop is seen as bright red colour whereas mustard crop is visualised in pinkish red colour in FCC image. Wheat crop is shown in green colour in the classified image (Fig 3) while mustard with the maroon colour.

Table 3. Confusion matrix generated for image classification dated 15/02/2022

Class	**Wheat**	**Mustard**	**Forest**	**Built-up land**	**Water bodies**	**Others**	**Total**
Wheat	99.74	1.03	0.00	0.00	0.00	0.00	19.44
Mustard	0.26	96.91	0.00	0.00	0.00	0.00	2.40
Forest	0.00	0.00	100.00	0.00	0.00	0.00	2.65
Built-up land	0.00	0.00	0.00	93.24	0.00	1.73	34.74
Waterbodies	0.00	0.00	0.00	0.00	100.00	0.00	21.26
Others	0.00	2.06	0.00	6.76	0.00	98.27	19.52
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Kappa coefficient value of 0.96 along with OA of 97.08% signifies better classification (Table 3). Producer accuracy and user accuracy of wheat were 99.74% and 99.87% respectively. In the case of the mustard crop producer accuracy was 96.91% and user accuracy was 97.92%.

As the main goal of the study is to classify the crop and estimate their acreage, measures of accuracies pertaining to each crop class is as shown in (Table 4). The error of omission gives the idea about the proportion of observed features that are not classified whereas the error of commission represents the proportion of other features that are wrongly classified in the given class (Wang et al. 2020). It measures the error in each class in both ways. The error of commission and error of omission in the case of rice was 14.23% and 0.00% and that of

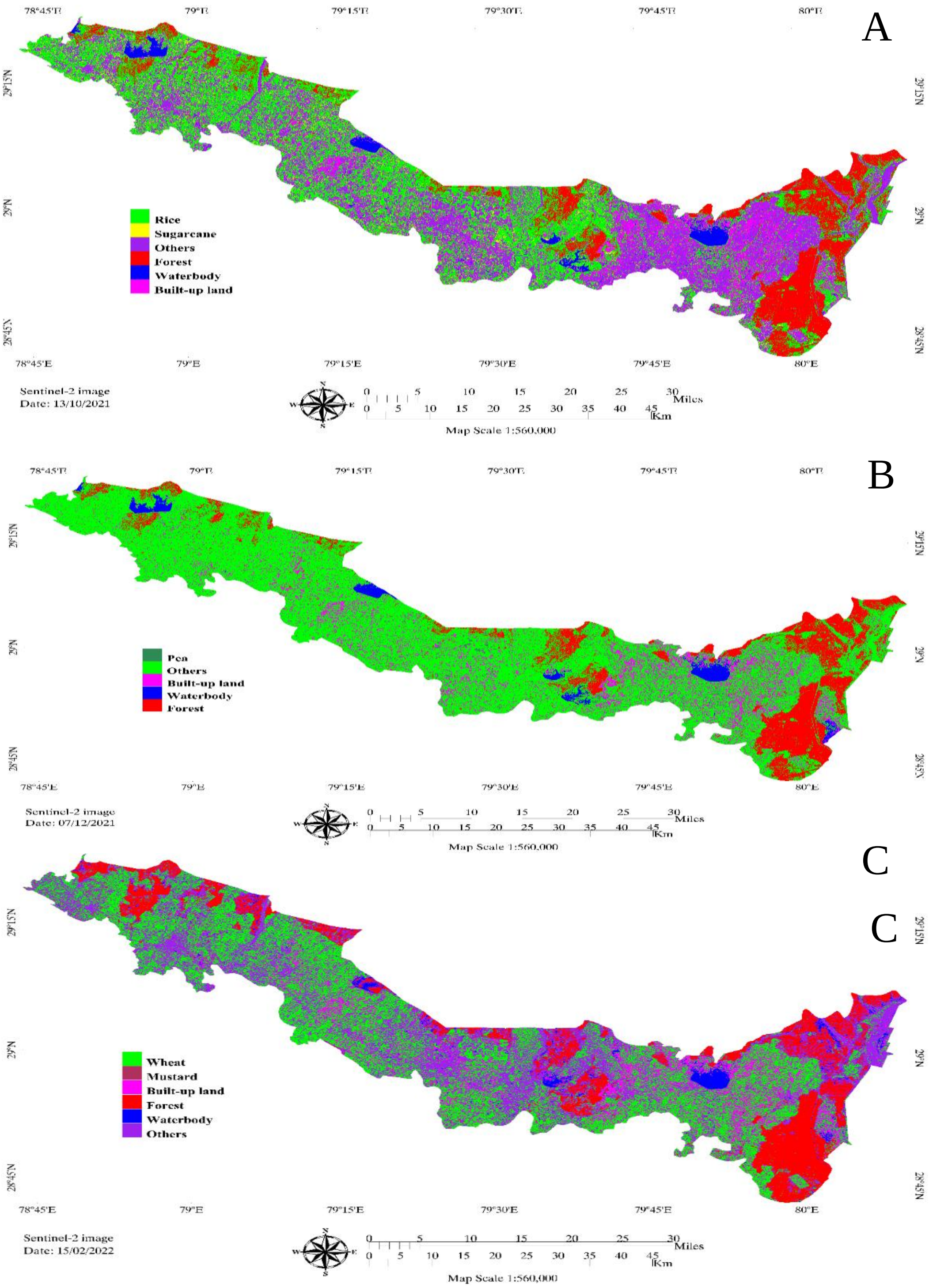

Fig. 3. **The classified image of Udham Singh Nagar** A) Rice and Sugarcane B) Pea C) Wheat and Mustard

sugarcane was 13.33% and 38.10% respectively with respective producer accuracies of 100.00% and 61.90% in rice and sugarcane class. User accuracy of rice is 85.77% and that of sugarcane is 86.67%. Similarly, in the case of winter crops like pea, wheat and mustard the reported producer accuracies are 77.55%, 99.74% and 96.91% and user accuracies are 100.00%, 99.87% and 97.92% respectively. The wheat crop was associated with the least error of commission of 0.13% and the least error of omission of 0.26%. All these values represent accuracies crop classification is higher and reflects fairly good classification.

Table 4. Classification accuracies of each crop class

Crop	Producer Accuracy, (PA) (%)	User Accuracy, (UA) (%)	Error of Commission (%)	Error of Omission (%)
Rice	100.00	85.77	14.23	0.00
Sugarcane	61.90	86.67	13.33	38.10
Pea	77.55	100.00	0.00	22.45
Wheat	99.74	99.87	0.13	0.26
Mustard	96.91	97.92	2.08	3.09

3.2 Crop acreage estimation and calculation of cropping intensity

After carrying out statistically sound classification, the class statistics option in ENVI 4.7 software was used for crop acreage estimation. According to the estimate, the rice area occupied 108884 ha area whereas the sugarcane crop occupied 11479 ha of the total area of the Udham Singh Nagar district. A comparison was made between the estimated and reported area as shown in Table 5. It shows rice area was classified more accurately than any other class with a difference of 53 ha only. Sugarcane crop area was classified with the difference of 2668 ha area. Pea occupied 6272 ha according to estimation but the reported area was 4144 ha. Wheat crop acreage was estimated as 105334 ha whereas the reported area was 104706 ha. In the case of the mustard crop estimated area and reported area were 2018 ha and 3192 ha respectively. The coefficient of determination which is denoted by R^2 is calculated using MS-EXCEL which shows the resemblance between the estimated and reported area. Its value varies from 0 to 1. Value '0' denotes no resemblance and the value of '1' denotes perfect resemblance (Orelien and Edwards, 2008). The calculated value of R^2 was 0.999 which indicated a very good agreement between the estimated and reported area. A common way to quantify the discrepancies between values (sample and population values) predicted by a model or estimator and the values actually observed is to use the root-mean-square error

(RMSE) which can be used to assess the accuracy of remote sensing products used in spatial data analysis (Bourennane and King, 2003). The lower the RMSE value, the better the performance is. %RMSE (per cent Root Mean Square Error) is calculated which indicates the error percentage. Its value was found to be 0.70 which denotes very less error in the estimation.

Table 5. Comparison between estimated and reported area of each crop class

Crop	Reported (2019) (ha)	Estimated (ha)	Difference	R^2	RMSE (%)
Rice	108884	108937	-53	0.999	0.70
Sugarcane	11479	14147	-2668		
Pea	6272	4144	2128		
Wheat	105334	104706	628		
Mustard	2018	3192	-1174		

Using the estimated crop acreage, MCI for whole Udham Singh Nagar district was calculated Putting all the variables in the equation MCI was computed which has a value of 174.4%. This indicates 74.4% of the cultivated area is resown in winter season. High cropping intensity has been an important strategy for increasing harvest area and crop production without expanding physical cropland. It also indicates there is a scope to increase the cropland by 25% during the winter season which can contribute to the increased production.

CONCLUSIONS

Accurate and timely mapping of crops plays a pivotal role in ensuring food security, shaping economic strategies, and guiding environmental policies. These crop maps are indispensable tools for agro-environmental evaluations and monitoring water usage in agriculture. Precise crop classification is vital for effective agricultural management and monitoring activities. Satellite remote sensing, due to its ability to provide comprehensive large-scale observations of ground objects, has emerged as a cutting-edge tool for characterizing crop types and their regional distributions. In this study, high-resolution multispectral images captured by the Sentinel-2 satellite on October 13, 2021, December 7, 2021, and March 6, 2022, under the auspices of the European Space Agency (ESA), were employed for classification purposes. Ground truth data points were meticulously collected using the 'Mapmarker' Android app and

Google Earth. The satellite images underwent various pre-processing steps such as resampling, mosaicking, and sub-setting, facilitated by the Sentinel Application Platform (SNAP) software. Utilizing the Maximum Likelihood approach, this study marked the inaugural effort to estimate cropping intensity in the upper Gangetic plains of Uttarakhand state utilizing geospatial technology. The classification results from the October 13, 2021 image indicated rice cultivation covering an area of 108,884 hectares and sugarcane spanning 11,479 hectares. Additionally, pea crops were estimated at 6,227 hectares based on the December 7, 2021 image. The March 6, 2022 image revealed wheat cultivation over an area of 105,334 hectares and mustard crops covering 2,018 hectares. In summary, the Sentinel-2 satellite imagery proved to be an effective tool for crop classification and acreage estimation, particularly when accounting for crop phenology. Leveraging the SNAP 8.0 software significantly reduced processing time as it eliminated the need for layer stacking. The subsequent image processing conducted in ENVI-4.7 software yielded prompt and accurate results. The major crops in Udham Singh Nagar district, namely rice, sugarcane, pea, wheat, and mustard, were classified using the Maximum Likelihood method, resulting in closely aligned estimates with reported areas. Furthermore, the study calculated the district's cropping intensity using the Multiple Cropping Index (MCI), which stood at 174.5%. This information can be leveraged for informed agricultural planning to optimize cropland usage efficiently.

Data Availability: The datasets analysed during the current study are available from the European Space Agency’s Copernicus website (https://scihub.copernicus.eu/)

Code availability: SNAP software is available to download through official website https://step.esa.int/main/download/snap-download/

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