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The Applicability of Remote Sensing and Geospatial Technologies for Mapping the Damaged Wheat Crop due to Waterlogging

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Abstract

Accurate assessment of crop acreage and damage at the field level is essential for agricultural planning, crop insurance, and disaster management. The present study evaluates the applicability of remote sensing and geospatial technologies for wheat crop mapping and waterlogging assessment at the cadastral (Khasra) level. The LISS-III satellite imagery with a spatial resolution of 23.5 m was utilised to delineate wheat-sown areas in five villages. Revenue cadastral maps containing Khasra boundaries were georeferenced and integrated with the satellite imagery to facilitate field-level crop identification and ownership-based assessment. The results demonstrated a high degree of spatial correspondence between satellite-derived village boundaries and official revenue records. For example, the geographical area of Bagga Kalan village estimated from satellite imagery was 365.76 ha, which closely matched the officially recorded area of 367 ha. An accuracy assessment conducted through extensive field verification revealed an overall wheat-mapping accuracy of approximately 96% in Bagga Kalan village. Furthermore, integrating satellite imagery with cadastral maps enabled the precise identification of waterlogged agricultural fields in Lohgarh village that were affected by canal breaches. Thus, the study demonstrates that remote sensing can accurately identify wheat-sown fields at the Khasra level and detect waterlogging, thereby supporting crop insurance agencies in assessing damage and facilitating compensation to affected farmers.

Keywords: Crop damage, GIS, Remote Sensing, Satellite, Wheat, Waterlogging

Introduction

Agricultural land covers 33% of the world's total land area (Anon, 2011a). More than 50% of the population is engaged in agriculture, making it the primary source of livelihood in many countries. Agricultural land is decreasing day by day due to the rapid growth of urbanisation and industrialisation. Crop production was reduced due to climatic hazards, insects/pests, and animals/birds. Wheat production was reduced by 21% due to excess rainfall in Canada and Russia (the largest wheat exporter), resulting in losses of 40% of grain crops (Anon, 2011c). Rabi crops were damaged due to thunderstorms, wind, hailstorms, and heavy rainfall in the states of Madhya Pradesh (2.4 lakh ha), Haryana (17.5 lakh ha), and Punjab (2.60 lakh ha) (Anon, 2015).

Agricultural risk-sharing through crop insurance has existed in many countries, in many forms, and for many decades (Skees *et al*., 2005). Crop production has been a subject of interest from time immemorial, mainly to levy taxes on crop produce by the rulers. However, after independence, the government's focus has been on obtaining pre-harvest crop estimates for planning crop imports and exports. In addition, paying compensation to farmers in times of crop losses, essentially due to the vagaries of nature, such as floods, hail, etc., has become an important aspect of governance. The estimates of crop losses are generally based on the Girdawari system, a manual method in which patwaris physically visit agricultural fields to record losses. However, this system is fraught with malpractices in general reporting without proper verification in the field or laced with other motivational reasons. Given that agriculture is the mainstay of India, with 54.6% of the population engaged in agriculture and allied activities (Anon, 2011b), paying compensation is vital to prevent farmers from committing suicide during crop losses. The government has roped in crop insurance companies to pay compensation to farmers. As with any other insurance entity, the requirement is based on actual losses. This, therefore, requires first mapping crops at the agricultural field level (Khasra level) to understand whether the crop was sown at all and whether there were any losses to crops in the intervening period between sowing and harvesting. A practical application of remote sensing was reported in Churu village, Rajasthan, where the net-sown area of gram crops in the region was 2.34 Lakh hectares as per remote sensing data, but 5.38 Lakh hectares were insured.

The country has a long history of implementing various crop insurance schemes, with improvements over time (Mishra, 1996). Traditional methods, such as G*irdawari* to record crop losses, are time-consuming, costly, and may lack transparency. However, contrary to this, Remote sensing techniques are faster, cost-effective and scientifically robust. GIS and remote sensing-based spatio-temporal mapping is an effective tool for visualising and analysing the spatial and temporal variability of soil, water, and crop attributes (Chinchmalatpure *et al.*, 2018; Vibhute *et al.*, 2024). Crop mapping is a crucial research area within environmental remote sensing and the cornerstone for producing crop-specific land cover data (Stevan and Clarke, 2013; Thenkabail *et al.*, 2018; Weiss *et al.,* 2020). The present work focuses on losses to the wheat crop due to waterlogging at the field level. The work reported was carried out as part of a master's thesis in 2015-16, but it remains relevant given the current demand for crop insurance. The recent floods in Punjab in 2025 have once again forced us to provide a mechanism for crop insurance. The focus of the work reported is to classify large areas for wheat crop at the field level using remotely sensed satellite data, using a very limited field visit, and identify wheat fields damaged by waterlogging to save on time and cost, while achieving a high level of accuracy. The objective of this study is to evaluate the effectiveness of remote sensing and GIS techniques for mapping wheat crops and identifying waterlogging damage at the cadastral (Khasra) level.

Materials and Methods

Study area and data used

The work was carried in villages Bagga Kalan (Hb No 122), Nurpur Bet (Hb No 123) of Ludhiana district of Punjab representing areas with dominant wheat crop and villages Sarmastpur (Hb no 149), Bal (Hb No 150) of Jallandhar district of Punjab where mixed cropping is generally witnessed was chosen so as to understand if the satellite technology can work in both type of areas. However, these areas did not experience any flooding, and the study area was therefore extended to Lohgarh village in Sirsa district of Haryana, which had extensive damage to wheat fields due to flooding caused by a breach in the canal. Satellite images used were LISS-III of date of pass Feb 10, 2016, with spatial resolution of 23.5 m which are comparable in relation to field sizes in Punjab and Haryana, were used for classifying the study area for wheat crop.

Cadastral maps were digitised in ARC-Map software and overlaid on high-resolution satellite images of WV-II (spatial resolution of 0.5 m). The WV-II satellite images used were pre-processed and geometrically corrected to help identify the Khasras as shown on the cadastral map (Fig. 1).

The selected villages were fully consolidated, with agricultural fields having a regular geometric shape. The standard field size was 40 × 36 Karam, corresponding to one Khasra (or Qila), which is equivalent to approximately 67 m × 60 m in SI units. This represents the smallest land parcel unit in Punjab and is depicted as yellow rectangular polygons in Fig. 1. A 67 m × 60 m grid was generated in GIS as vector data and overlaid on the WorldView-2 (WV-2) satellite imagery. The grid was aligned to match the agricultural field boundaries as closely as possible. Figure 1 illustrates the Khasra (field) boundaries, shown in yellow according to the cadastral map, overlaid on the high-resolution WV-2 satellite image. Since the satellite imagery was already georeferenced, the field boundaries generated in vector format inherited spatial coordinates and could be accurately overlaid on other georeferenced satellite images of the same area.

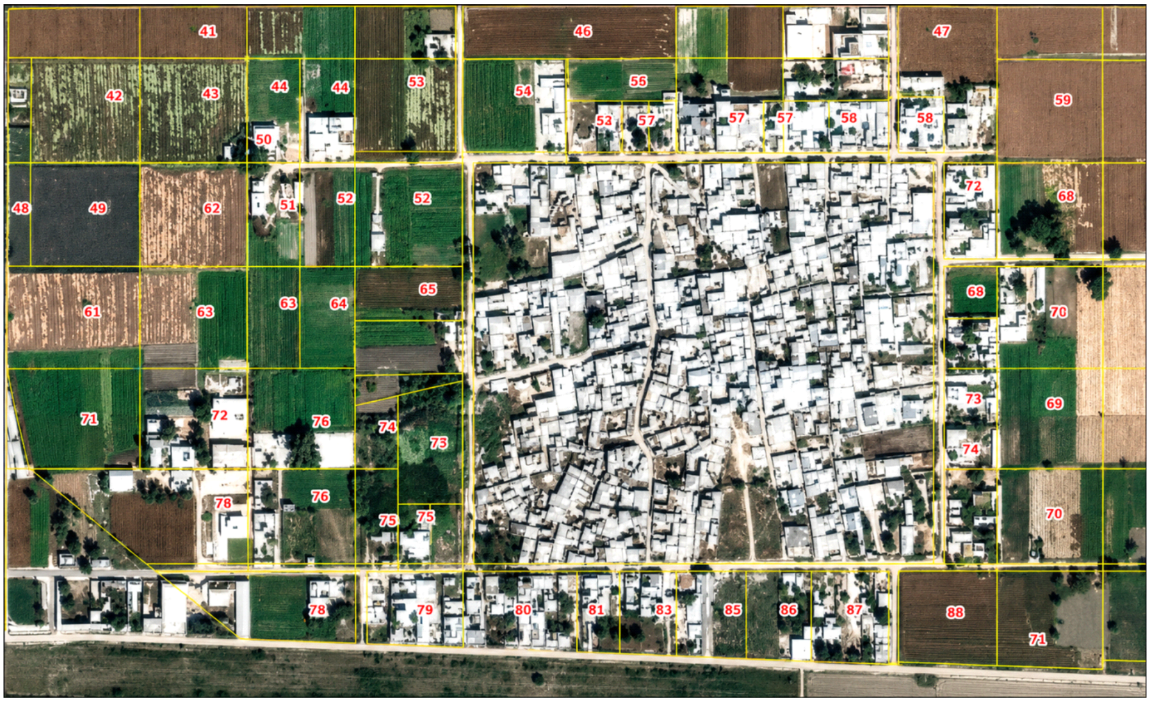

Fig. 1 Cadastral (yellow lines) overlaid on HRS satellite data of village Bagga Kalan

Remote Sensing has been used worldwide in several land cover projects, especially for crop inventory. For example, large area crop experiment (LACIE) (Printer *et al.***,** 2003) and Crop acreage and production estimation (CAPE) (Navalgund *et al.,* 1919). The LISS-III satellite images of the study area, comprising the four villages, were classified based on field visits conducted around 11 Feb 2016 (near the satellite overpass date, which also corresponds to the maximum vegetative growth of the wheat crop). Supervised Image classification technique: The Maximum Likelihood classifier (MLC) was used to classify the satellite images into various ground-based classes. Digital classification of satellite images involves three stages. The first stage is the training stage, in which areas of known ground identity (such as wheat, sugarcane, etc.) are identified on the ground by visiting the area of interest, and these areas are then demarcated on the satellite images as training sites. There are usually very few locations in the study area. The training areas are used to generate statistics from satellite images corresponding to the land classes in the study areas. These statistics are used to train the classifiers (make rules for each land class). In the second stage, the trained classifier (MLC) classifies the whole image into various information classes. In the third stage, the accuracy of classification is tested on a sample of points from the classified image, using field-collected data, excluding those used in the training stage.

The classified map is then overlaid with cadastral information, such as yellow vector lines, as shown in Figure 1. Thus, the classified map, overlaid with the cadastral map, shows the Khasra fields sown with wheat. The Khasra polygons are then populated with attributes, such as wheat, to represent Khasras that fall under the wheat category as per the satellite-classified map.

However, if there is waterlogging in the fields between the maximum vegetative stages of wheat in February and harvesting in mid-April, a satellite image of, say, April, post-waterlogging, is overlaid with Khasra polygons and land-cover class attributes such as wheat. Areas that are waterlogged appear black on the False Colour Composite (FCC) of satellite images. The black colour is because water absorbs all incident sunlight, so nothing reaches the satellite sensor; therefore, the black colour. Thus, Khasras, which are under wheat and later up to harvesting, can be overlaid on satellite images post-waterlogging to help identify khasras that are sown with wheat but affected by waterlogging, as can be inferred from the black colour on the satellite images occupied by wheat Khasras. This information is expected to help identify fields (Khasra level) where wheat was sown and affected by waterlogging, eventually helping pay compensation to farmers.

Results

The work was carried out for four villages of Punjab. However, the work of village Bagga Kalan is demonstrated herewith. A field visit in Bagga Kalan village was undertaken on 11 February, 2016, near the time of satellite overpass. The ground data pertaining to classes that included wheat, fodder, Oats, and vegetables were populated for each of the fields (khasra level) on a cadastral map of the village Bagga Kalan and on a crop map prepared (Fig. 2) using conventional field-visit methods. Thus, the prepared crop map reflects the actual classes in the village at the field

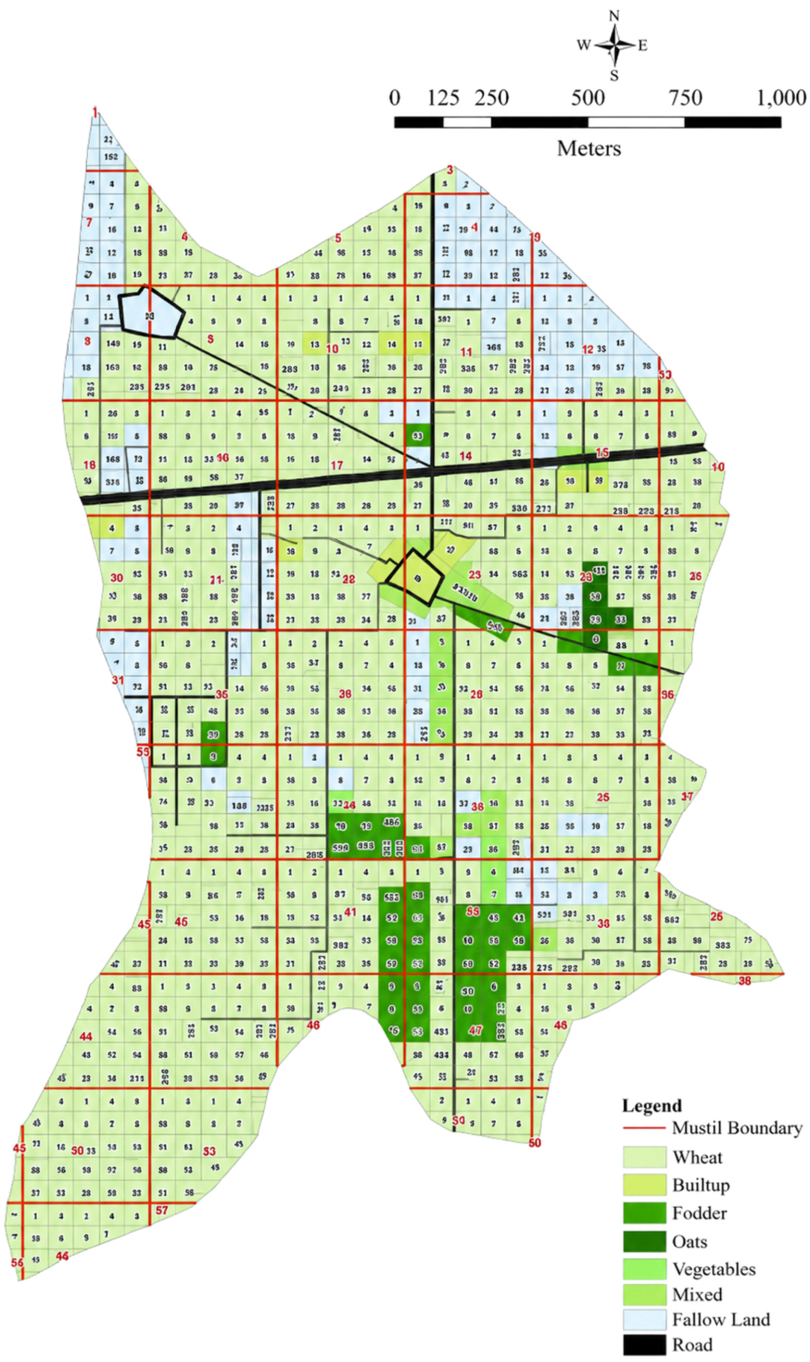

Fig. 2 Land use/cover map of Bagga Kalan at Khasra level based on field visit during 11 February, 2016

level, as can be seen with the naked eye, and represents the ground reality. However, a ground-based survey is very time-consuming, especially when carried out over large areas, such as the entire State of Punjab. Hence, remote sensing techniques are employed to reduce time and cost in obtaining information on crops sown at the field level.

To quickly classify the village into various land-use/cover classes, satellite images are classified into categories. This involves collecting locations of a few samples (Locations were taken for each land class from the crop map, Fig. 2, to train the MLC classifier). About 104 locations were collected across all classes to train the MLC classifier, and a separate sample was used to assess classification accuracy. The classified map (Fig. 3) was generated by applying the trained classifier on the satellite image. Thus, the crop map generated from field inputs (Fig. 2) and the one

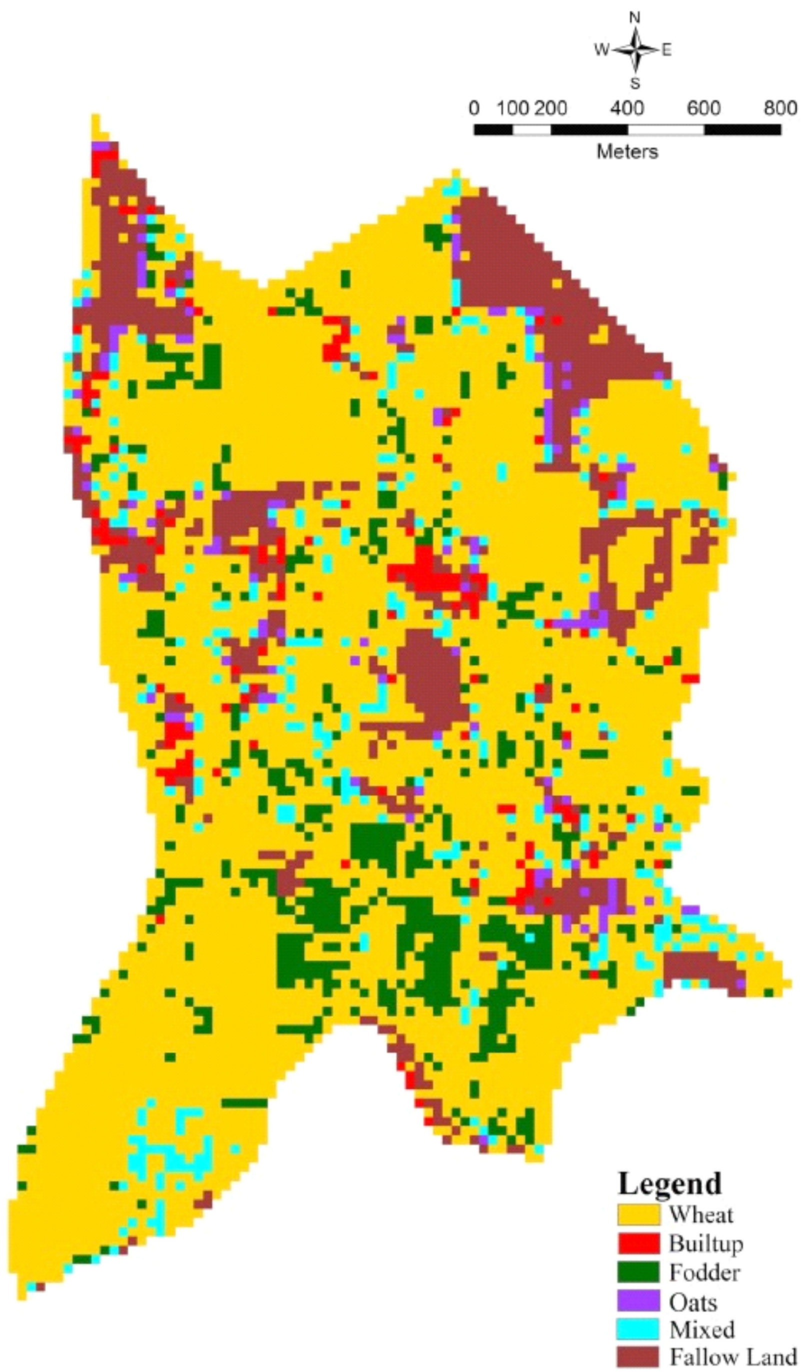

Fig. 3 Land use/cover map of Bagga Kalan based on classification of satellite images

Table 1. Comparison of Area under various classes with observed and satellite imagery in village Bagga Kalan

Class	Area from crop map (field work), ha	Area from classified map (satellite driven), ha
Wheat	283.78	274.79
Built-up	5.86	7.71
Fallow	48.53	46.88
Fodder	17.01	22.54
Mixed	7.56	9.59
Oats	2.02	4.25
Vegetables	1.62	0.00
Total Area	366.38	365.76

generated from satellite imagery (Fig. 3) were visually compared to assess the accuracy of the satellite-driven map at a few common locations, with regard to the categories present at those locations, for quantitative accuracy analysis.

The crop map was created by populating all the Khasra (field) maps of the village with respect to various land-cover classes during the ground visit (Fig. 2). The classified map generated was overlaid with the revenue map of the village, called the Khasra map, which helped to identify crops in each of the fields individually. Training samples were drawn from this map and aligned with the satellite image to generate statistical parameters for each class. A maximum likelihood classifier (MLC) was used to classify the satellite image for the whole village. Thus, two maps were created: one crop map based on actual classes as per field visit and another classified map drawn from a satellite image based on limited samples of classes from the field driven crop map

A visual inspection of the two maps (Fig. 2 and Fig. 3) demonstrated that the wheat crop was correctly classified. Area comparison between the two maps (Table 1) also confirms that the wheat crop area, the focus of the study, is the same in both cases. Comparison of the area of village Bagga Kalan from the cadastral map used for the crop map based on ground visits (366.38 ha) and that derived from the satellite image (365.76 ha) is very close to the village area of 367 ha as per the revenue-based area as available in the village directory of the revenue department.

However, to put the accuracy in numerical form, a confusion matrix was constructed (Table 2), a widely used method for accuracy assessment in remote sensing. It is a simple cross-tabulation of the mapped class from the satellite-classified map against those observed on the ground (field-driven crop map) for a sample of cases (Canters, 1997; Campbell, 2002; Foody, 2002). The confusion matrix suggests that, out of 48 wheat crop locations from the ground (Crop map drawn by field visit) versus the classified map from the satellite image, 46 samples were correctly classified as belonging to the wheat class, yielding an accuracy of 95.83%. The only confusion was with respect to the mixed class, which may be due to the mixture of wheat class with other classes, such as built-up in the land parcel. Hence, the study demonstrated that satellite image classification based on small-field data can produce a classified map with high accuracy for the wheat sown area. The area in the erstwhile Punjab, current Punjab, and Haryana together is dominated by the wheat crop, and it is expected that satellite-classified data would be sufficient to accurately depict the locations of wheat areas on the ground.

However, there were no losses to the wheat crop from floods in the selected villages. As such, the study was extended to village Lohgarh in

Table 2. Confusion matrix for village Bagga Kalan

Classified → / Reference ↓	Wheat	Built up	Fodder	Fallow land	Vegetables	Oats	Mixed
Wheat	46	0	0	0	0	0	2
Built up	0	6	0	1	0	0	0
Fodder	0	0	16	2	0	0	0
Fallow land	0	0	2	19	0	0	0
Vegetables	0	0	0	3	0	0	0
Oats	0	0	1	0	0	2	0
Mixed	2	1	1	0	0	0	0

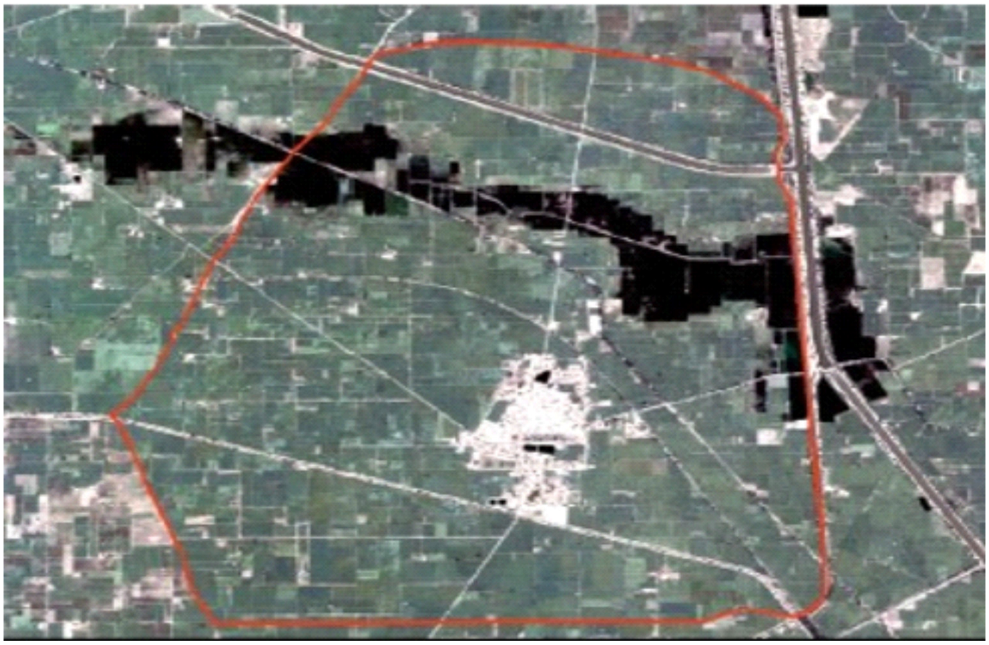

Fig. 4 Satellite image of Lohgarh Village showing waterlogging (black colour) due to a breach in the canal

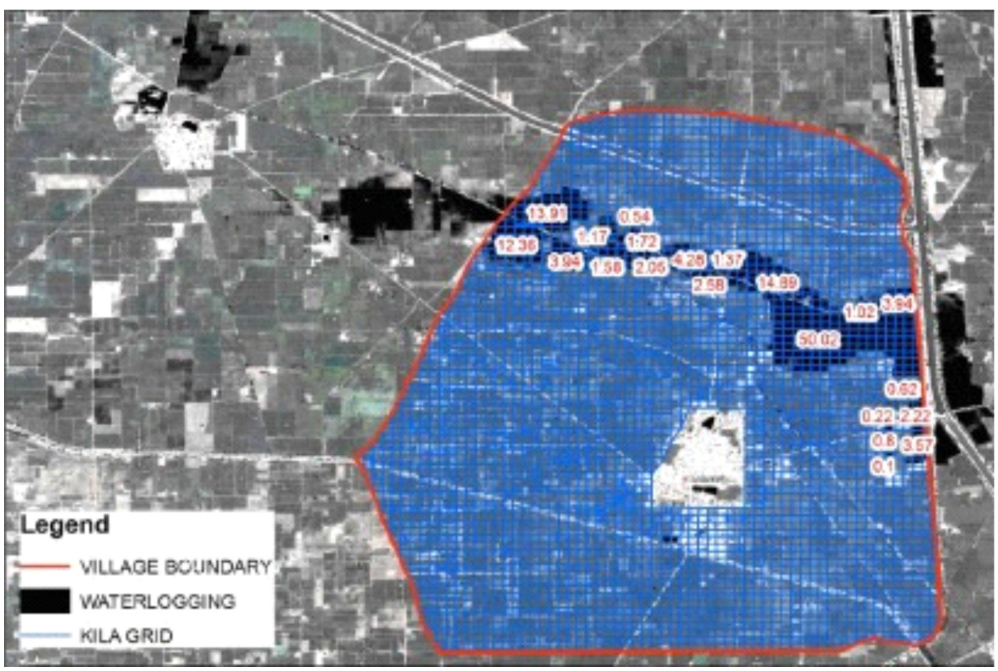

Fig. 5 Wheat fields damaged by waterlogging in Lohgarh village overlaid with Khasra boundaries

Haryana, which witnessed waterlogging in agricultural fields. The methodology was repeated for Lohgarh village.

Figure 4 clearly shows that the black colour in the satellite image indicates the area flooded, causing damage to the wheat crop. The waterlogging in the fields is due to breach in canal running on right side (East) of the village. The black colour is due to water absorbing all incident sunlight, so nothing reaches the satellite sensor. The Lohgarh village is dominated by wheat crop and overlaying cadastral data on satellite image (Fig. 5) clearly shows the fields (Khasras) affected by waterlogging.

Conclusions

LISS-III Satellite data can be used for overlaying cadastral data very accurately. This helps determine whether the field is sown with a wheat crop, which is primarily required by crop insurance companies to validate the field's crop type. Second, if the area is affected by waterlogging, such as in the present study at any given time in the wheat crop growth cycle, post-waterlogging satellite data can help determine whether the field is sown with wheat and affected by waterlogging. Thus, the problem reduces to two dates: a satellite analysis date for mapping wheat crops very accurately, and another date when the area is waterlogged to help determine whether a field sown with wheat crops later becomes waterlogged. Mapping the wheat crop at the Khasra level can also be done with high accuracy. This, in turn, can help insurance companies focus only on areas affected by waterlogging and pay compensation to farmers whose wheat fields are waterlogged. Future studies may integrate high-resolution satellite data and machine-learning classifiers to improve classification accuracy for mixed cropping systems and enable timely completion of analysis over larger areas.

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