Satellite-Based Assessment of Hailstorm Affected Potato Crop for Insurance Purpose

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Abstract

Assessing the extent of hailstorm affected crop is one of the thrust areas for quantifying mid-season adversaries under crop insurance values chain. This study evaluated the pre- and post-hailstorm responses on spectral bands and vegetation indices derived from Sentinel-2 data for assessing the severity class of the affected potato crop. The potato crop was mapped using pre-event satellite data with overall accuracy of 88% (κ=0.82). Pair-wise Games-Howell t-test showed significant differences among the post-hailstorm potato severity classes in Red, Near Infrared & Short-wave Infra-red (SWIR) bands and Normalized vegetation indices. Percentage change (from pre- to post-event) in band reflectance and vegetation indices showed a better sensitivity in differentiating damage severity. Differential behaviour of SWIR-1 (Band-11) and SWIR-2 (Band-12) were observed within severely affected potato crop under dry and wet soil conditions. Decision matrix based on percentage change in Normalized difference Vegetation Index (ΔNDVI) and Normalized difference Tillage Index (ΔNDVI) could able to capture the damage severity classes with an overall accuracy of 86.7%. Higher proportion of affected area were found to be associated with larger percentage of Potato yield reduction based on measured yield data at Insurance unit level. The proposed methodology could be adopted for operational assessment of the impact of hailstorm events on crops.

Keywords: *Solanum*; NDVI; NDTI; hailstorm; damage; crop insurance

1 Introduction

Since past decades, there has been unprecedented increase in the extreme weather events in the Indian subcontinent, which has made the agriculture more vulnerable and riskier (De et al. 2005; Mohanty, 2020). Hailstorms coupled with unseasonal rainfall is one of such weather extremes mostly observed in the northern to central Indian region during pre-monsoon season (February to April) and causes damage over large area of cultivated winter (*rabi*) crops especially wheat, potato, mustard, gram etc. (Rao et al. 2014). Indian states of Himachal Pradesh, Uttar Pradesh, Punjab, Haryana, Rajasthan, West Bengal, Madhya Pradesh, Maharashtra, Telangana and

Andhra Pradesh are considered to be more vulnerable to hailstorms as the annual probability of occurrence of hailstorm in these areas is more than 50% and also showed significant surge in past years (Chattopadhyay et al. 2017). Hailstorms are sporadic and localized phenomena, difficult to forecast because of limited radar networks, resulting in unavoidable crop losses (Bal et al. 2014). Widespread damages of *rabi* crops due to hailstorms in 2014 and 2015 are well known recent examples (Kulkarni et al. 2015; Bal et al. 2017).

The crop insurance is one of the efficient mechanisms to cope with the hailstorm damage by providing compensation to the farmers as par the yield reduction. In India crop insurance mechanism is based on the area-yield approach. But in case of the hailstorm damage, insurance claims can be raised both based on area-yield approach as well as individual farmer level (PMFBY 2016). Hence, it is very essential to assess the spatial extent and the intensity of the hailstorm damage in near-real time to initiate the compensation, relief or remedial processes. Traditional ground survey-based damage area assessment is laborious, time consuming, cost ineffective and subjected to individual bias, particularly over a large areal extent and relatively inaccessible locations (Bentley et al. 2002). Alternatively, space-based input can help in assessing and quantifying the damaged area through the synoptic, repetitive and multi-band information from satellites platform and in turn would assist informed decision making (Apan et al. 2005).

Remote sensing (RS) has been used since decades for crop discrimination, crop health assessment and crop damages due to different biotic and abiotic agents (Moran et al. 1997). But, limited studies had been found specific to RS based assessment of hailstorm damage. One of the earliest RS-based studies for quantifying the crop losses by hail was done in central Illinois using infrared and standard colour aerial photographs (Changnon and Baron 1971). Thereafter, series of studies had been conducted to showcase the potential of infrared aerial photographs to detect crop-hail damage (Towery et al. 1975; Towery 1980) to support insurance activities. Erickson et al. (2004) used multispectral and hyperspectral airborne data and reported the importance of NIR and red bands in assessing the defoliation in maize. Subsequently many researchers had started using satellite platform for crop-hail damage assessments. Gillis et al. (1990) used Landsat TM data to map damaged area in operational salvage harvest due to hail. Klimowski et al. (1998) observed the hailstorm damage from the geostationary satellite GOES-8 using imageries in visible region. Peters et al. (2000) utilized Landsat TM multispectral data for detection of hail damaged area of corn and soybean. Normalized Difference Vegetation Index (NDVI) derived from Near Infra-Red (NIR) and Red band reflectance is most widely used index for hailstorm damage assessment. Most of the hail damage related studies were based on pre- and post-event NDVI changes (Bentley et al. 2002; Parker et al. 2005; Gallo et al. 2012; Zhao et al. 2012). These researchers have reported a significant decrease of post-event NDVI (in comparison to pre-event NDVI) over the hailstorm damaged vegetation which was completely destroyed, but none of them have commented on the partially damaged crops. In India, limited studies have been conducted to assess the hailstorm damage of crops such as wheat (Ray et al. 2016; Singh et al. 2017) and other mixed crops (Prabhakar et al. 2019) using multispectral satellite data. Singh et al. (2017) has proposed a Percentage Difference Index (PDI), which accounts for the changes in NDVI between normal and current (hail storm affected) years. Such approach is limited over areas with stable cropping pattern where year to year variations of crop calendar is minimal. Space based assessment of hailstorm damage of potato crop is rare. Zhou et al. (2016) used airborne multispectral data and concluded that Green NDVI, NDVI and soil-adjusted NDVI can well assess the hail damage at early stages of potato crop. The present study is the maiden attempt to assess potato crop damaged due to hailstorm over India using satellite observations and ground informations.

Potato (*Solanum tuberosum* L.), also known as “The king of vegetables”, is the third most consumed crop after rice and wheat (Nagar et al. 2019). Indian ranks second in potato production in the world. The area under potato cultivation in India was 2.1 m ha, which give rise production of 52.59 m tons in 2018 (DACFW 2020). Hence, potato plays a very important role in the food and nutritional security of rural India, but the crop is subjected to damage due to hailstorm and unseasonal rainfall periodically (Tiwari et al. 2021). Hailstorms affect the standing potato crop in two ways. The beating action of the solid hails break the foliage, lacerates the stem, disrupt the ridge and furrow structure of the field and partially expose the tuber. The post-hail rainfall causes stagnation of water which leads to the rotting of tuber and secondary infection. The occurrences of hailstorms in India mostly coincide with the tuberization phase of the crop with high above-ground green foliage and cause significant yield reduction (Irigoyen et al. 2011; Jalali 2013). Hence, an objective assessment of the hailstorm damage of potato crop in near-real time using space-based input is need of the hour to support insurance claims.

As discussed earlier, space-based studies to assess the hailstorm related crop damage have predominantly used NDVI (which represents the crop vigour) as an indicator. These studies did not include different short-wave infrared (SWIR) bands which are sensitive to exposed soil, surface wetness as well as non-photosynthetic vegetation (NPV) (Quemada and Daughtry 2016). With the advent of medium resolution (10-20 m) satellite data like Sentinel-2 with wide swath (~300 km), 5 days temporal receptivity, and bands ranging from VNIR to SWIR, the observational capacity has increased tremendously especially for *rabi* season crop like potato (Drusch et al. 2012). Keeping the above-mentioned points in mind, the present study is mainly focussed on identifying spectral bands/vegetation indices that can discriminate different levels of hailstorm affected potato crops. Further, the study also proposes an operation methodology towards objective assessment of the hailstorm affected potato crop which could represent yield loss at insurance unit level.

2 Material and Methods

2.1 Study area

West Bengal experienced a series of hailstorm events accompanied with rains on 25th, 27th and 28th Feb 2019 (NIE 2019; Weather 2019). All the southern districts of West Bengal were more or less affected by it but major damage of potato crops was reported from Hooghly and West Medinipur districts as per the information received from National Insurance Company Limited (NIC), Kolkata. Hence, these two districts were selected for the present study (Fig 1). The study area lies between 21.76º N to 23.22º N latitude and 88.51º E to 87.05º E longitude with mean elevation of 25 m and mean annual rainfall of 1500 mm (ICAR 2017). The area falls under agro-ecological region 15 i.e., Bengal and Assam plains with hot sub-humid to humid eco-sub region. The soil is alluvium with loam to clay loam texture. The geographical area of Hooghly and West Medinipur are 3.13 and 9.28 lakh ha with net sown area of 2.12 and 5.17 lakh ha respectively (Matirkatha 2016). As per the horticultural statistics of 2016 the potato area of Hooghly and West Medinipur districts were 1.11 & 0.86 lakh ha with production of 14.13 & 15.48 lakh tons respectively (Glance 2018).

Insert Figure 1

2.2 Data sets

2.2.1 Ground data

Pre-event ground observations related to the crop type, crop stages, geo-locations etc. were collected during 14-19 February as a part of ongoing FASAL programme (Parihar and Oza 2006) and were further used for classification of the crops in the study area (Fig 2a). Post-event field survey was conducted during 01-05 March 2019 to assess the damages to the crops. The severity of damage to potato crop was recorded through visual inspection and categorized as

"Unaffected" (<20% damage of the canopy foliage), "Moderately-affected" (20-50% damage of the canopy foliage) and "Severely-affected" (> 50% damage of the canopy foliage). The locations of the field data points of the different classes of potato crop affected by the hailstorm are presented in Fig. 2b. Soil moisture variations were also observed in "Severely affected" class as "Dry" and "Wet". Total 54 points were collected over "Unaffected" class, whereas 48 and 61 points were collected over "Moderately-affected" and "Severely-affected" categories respectively. Each field data points were converted to a polygon by considering minimum 3x3 homogeneous pixels and further used for statistics generation. Out of the total points collected over the study area, nearly 75% of the points were used for developing the methodology and the remaining points were used for validation.

Insert Figure 2

2.2.2 Satellite data

Cloud free Sentinel-2 data of two-time epochs i.e., pre-event (19^{th} February 2019) and post-event (01^{st} March 2019) were used in the present study (Fig 2). The surface reflectance product (L2A) of Sentinel-2 were band composited, stacked, exported and downloaded through earth engine cloud computing environment in java script (Gorelick et al. 2017). Subsequent processing of the Sentinel-2 data comprising of six bands (Table 1) were done in ERDAS IMAGINE 16.1 and ArcGIS Desktop 10.6.

Insert Table 1

2.3 Mapping potato crop

Training classes were generated using pre-event ground data (during 14-19 Feb, 2019) and spectral signatures were generated using six bands of sentinel-2 corresponding to 19^{th} February. Training classes comprised of potato, rice, and other crops (chilli, vegetables and scrubs). The classification was done over the agricultural area only, excluding other non-agricultural areas using 1:50000 land use land cover map (NRSC 2014). Major growing crops were classified using Spectral Angle Mapper (SAM) algorithm as described by Kumar et al. (2015) and Zhou et al. (2015). The classification accuracy of the crop map was evaluated using confusion matrices.

2.4 Analysis of variance between severity classes

Band specific reflectance statistics of Sentinel-2 data (both 19th February and 1 March, 2019) over the different categories of potato crop affected due to hailstorm were generated using post event ground truth data points as mentioned in section 2.2.1. These statistics were further analysed to assess the changes in reflectance between the pre- and post-event vis-a-vis the damage severity. The percentage change in reflectance (ΔB) of each band is calculated as per the equation 1.

$$\Delta B = \frac{B_{post} - B_{pre}}{B_{pre}} \times 100 \qquad \text{Equation 1}$$

Where, B_{pre} is the reflectance of a band at pre-event (19th February, 2019) and B_{post} is the reflectance of a band at post-events (1st March, 2019)

Four vegetation indices were calculated using different spectral reflectance (Red, NIR, SWIR) of Sentinel-2 data (Table 2). These are NDVI, Normalized difference Water Index (NDWI), Land Surface Water Index (LSWI), Normalized Difference Tillage Index (NDTI). The band combinations used to generate these indices along with their sensitivity towards different biophysical properties are mentioned in Table-2.

Insert Table 2

The percentage change in VIs (ΔVI) from pre- to post-event is calculated using equation 2:

$$\Delta VI = \frac{VI_{post} - VI_{pre}}{VI_{pre}} \times 100 \qquad \text{Equation 2}$$

Where, VI_{pre} is the VI at pre-event (19th February, 2019) and VI_{post} is the VI at post-events (1st March, 2019). Likewise, ΔNDVI, ΔNDWI, ΔLSWI and ΔNDTI were computed for the three categories of crop damage due to the hailstorm. The ΔB and ΔVI were further analysed statistically towards their sensitivity to explain the severity of the damage and further compared pair-wise using Games-Howell test (Games and Howell 1976).

2.5 Yield reduction due to hail storm damage

Crop cutting experiment (CCE) data of potato at Gram Panchayet (GP) level (administrative unit for crop insurance) for the year 2019 and also for the past five years were analysed. Average yield of the potato crop was calculated by the mean value of last five years of CCE data. Subsequently, percentage yield deviation (ΔY) was computed using the equation 3:

$$\Delta Y = \frac{Yield_{2019} - Yield_{Average}}{Yield_{Average}} \times 100 \qquad \text{Equation 3}$$

Where, $Yield_{2019}$ is GP averaged potato yield (ton ha^{-1}) in 2019 and $Yield_{Average}$ is historical five-year average yield (ton ha^{-1}) of GP. Percent yield deviation data were divided into five yield reduction classes and compared with ΔB and ΔVI.

3 Results and Discussions

3.1 Hailstorm and damage to potato crop

Hooghly and West Medinipur districts of West Bengal state were exposed to hailstorm during 25-28 February, 2019 accompanied with moderate to heavy rainfall causing significant damage to potato crop from falling hails and water stagnation. The daily India Meteorological Department (IMD) gridded rainfall data showed high intensity rainfall over the Hooghly and

West Medinipur districts (Fig. 3). The cumulative rainfall between 25-28 February was found to be more than 100 mm in the parts of districts.

Insert Figure 3

As per the ground truth data collected, there were two prominent standing crops over the two districts i.e., potato and rice. The rice fields were found to be unaffected by the hailstorm-rainfall as they were in the early tillering stage and grown in flooded condition. On the other hand, hails had caused considerable damage to the above ground succulent foliage of the potato crop by breaking/ lacerating it and exposing the below canopy soil. The ridge and furrow structure of the potato field were also disturbed and the potato tubers were exposed partly. The water stagnation due to heavy rainfall further disrupt the soil aeration, causing yellowing of the leaf, rotting of the potato tuber and forced-harvesting in some places.

Fig. 4 showed varying degree severity of damage of the potato crop due to the hailstorm event. The unaffected crops were found have high in leaf greenness and leaf moisture, high ground cover (>80%) and less exposure to the soil. Whereas, moderately affected crops were relatively low in leaf greenness and leaf moisture, canopy cover was found to be moderate (50-80%). The severely affected crop appeared to be yellowish or dried with less canopy cover (<50%), soil is completely exposed showing the ridge-furrow structure of the potato field.

Insert Figure 4

3.2 Spatial distribution of potato crop

The potato crop map generated using pre-event (19th February, 2019) Sentinel-2 data is shown in Fig 5(a). The potato crop was found to be well separated from the other competing crops like rice and vegetables due its typical growth stage having luxurious green foliage and row structure. Hence, potato crop was successfully classified with producer’s accuracy of 94.9% and user’s accuracy of 87.5%. The overall accuracy was found to 88% be with kappa coefficient of 0.82. Potato crop was found to be mostly concentrated in the south-western part of the

Hooghly district and north-eastern part of the West Medinipur district. Tarakeshwar, Pursura and Jangipara blocks in Hooghly; and Chandrokona, Goghat and Keshpur blocks in West Medinipur district were the dominant blocks having large area under potato crop. GP-wise potato area statistics showed that out of total 248 GPs in Hooghly district, 154 GPs were having more than 100 ha under potato cultivation; while in West Medinipur district 77 GPs fulfilled such criterion out of 305 GPs (Fig 5b). GPs with large area under potato cultivation (more than 500 ha) were found to be 72 in Hooghly district and 26 in West Medinipur district.

Insert Figure 5

3.3 Spectral response to hailstorm damage

The surface reflectance (pre-event: 19th February and post-event: 1 March) of six selected bands of Sentinel-2 over the different categories of damage severity of potato crop are shown in Fig.6. It is evident from the graph that there exists a large difference between the NIR (B8) reflectance of pre- and post-event for hailstorm affected potato crop. The magnitude of difference increases with the degree of severity. The mean reflectance of NIR band in "unaffected" crop was 30% with standard deviation (SD) of 3%, while for "moderately affected" and "severely affected" crop it was found to be 25±2.5% and 20±4.6% respectively. Marginal response was also observed over B4 (Red), B11 (SWIR1) and B12 (SWIR2) bands.

Insert Figure 6

To investigate further, four bands (B4, B8, B11 and B12) were selected and the data distribution of these bands during pre- and post-event over the different severity classes were presented in violin-plots (Fig 7). The violin-plot shows the probability density of the data at different values smoothened by a kernel density estimator. Hence, the width of the plot represents the density of the data value and the tapering nature shows the distribution of the data. It is observed that irrespective of the bands, the data distribution of band-reflectance at pre-event remains similar over the different severity classes. It is further verified by Post-hoc Games-Howell tests showing no significant difference among them. Such observation confirms that there were no significant differences in biophysical characteristics of potato crop in term of its vigour, greenness, wetness and canopy cover before the hailstorm took place. Hailstorm cause substantial defoliation of potato crop (Zhou et al. 2016) and same observations were also reported in many other crops (Changnon1971; Chandler et al. 2003). The intensity of the damage off course depends on the kinetic energy or the size of the hails. But, no such data on the size of the hail is available over the study site due to lack of hailpads networks. Nevertheless, varying degree of damages of the potato canopy was observed during the field visit as mentioned in section 3.1. The rainfall further caused wetness differences depending on the drainage capacity of the soil. The changes in the canopy cover and surface wetness are well reflected by the change in shape and position of the violin plots of the post-event observations. There have been substantial changes either in the central tendency (mean) or the dispersion (spread or shape) of the violin plots of the post-event vis-a-vis the pre-event observations irrespective of the bands. The defoliation of the potato canopy cause yellowing of the crop and substantial reduction in the chlorophyll content. The red band (B4) being a chlorophyll absorption band, the mean of the post-event red-reflectance over the unaffected crop was found be significantly different from the affected one (moderately or severely). But the post-event red-reflectance was not found to be significantly different between "moderately affected" and "severely affected" crop. On the other hand, the NIR (B8) region of the spectral band is sensitive to the leaf internal or mesophyll structure. The defoliation causes destruction of the leaf internal structure depending on the severity of the damage. Hence, statistically significant differences were observed between the mean of post-event NIR-reflectance between "unaffected" and "moderately affected", "unaffected" and "severely affected", "moderately affected" and "severely affected" crop. The SWIR-1 (B11) and SWIR-2 (B12) bands were sensitive to the surface wetness (Bidgoli et al. 2020). The surface wetness is attributed both by the leaf and soil moisture. The defoliation caused by the hailstorm substantially reduces the leaf wetness, but the associated rainfall led to the increase in soil moisture. Hence, the combined effect of both has been captured by the SWIR bands. Further, SWIR2 band (2.1 µm) is also sensitive to the fractional vegetation cover as it is close to the cellulose absorption band (Quemada and Daughtry 2016). The mean of post-event SWIR1-reflectance showed significant difference between "unaffected" and "severely affected", "moderately affected" and "severely affected" crop. No significant difference of post-event SWIR1-refelctance was observed between "unaffected" and "moderately affected" crop. On the other hand, post-event SWIR2-refletance was found to be significantly different for "unaffected" and "moderately affected" crop only. It is important to mention here that the dispersion of post-event SWIRs reflectance is very high over the severely affected potato crop. It signifies large variations of the surface wetness and fractional vegetation cover of the severely affected potato crop. In nutshell, it could be concluded that only post-event NIR-reflectance was found to have statistically significant differences between the different categories of damage severities of potato crop. But the NIR reflectance only addresses the changes in the crop vigour or the leaf internal structure. The greenness and surface wetness of the crop are mainly addressed by the Red and SWIR reflectance. As per Fig. 7, Red and SWIR reflectance could partially discriminate the different damage severity classes of the potato crop. Hence, an effort is made to combine these bands to accommodate their sensitivity towards assessing the different damage classes of the potato crop.

Insert Figure 7

3.4 Response on vegetation indices

Converting reflectance of different bands into a normalized index is an effective approach for improving the sensitivity towards assessing the target features (Xue and Su 2017). Hence, we generated four normalized indices i.e. NDVI, NDWI, LSWI and NDTI using the selected four bands as mentioned in the section 3.3. The details of the band combinations are mentioned in Table 2. The variations of the above-mentioned indices during pre- and post-event conditions over the different severity classes are presented in box-plots (Fig 8). It is mentioned in the section 3.3 that all the selected bands (Red, NIR, SWIR-1 and SWIR-2) showed no significant differences between the damage severity classes at pre-event condition (Fig. 7) signifying homogeneous potato crop before the occurrence of the hailstorm. Likewise, the indices derived from these four selected bands did not show any significant differences between the damage severity classes at pre-event condition (Fig. 8). But distinct variations of data distribution of all the four indices over the damage severity classes are observed at post-event condition. As a result, mean of all the four indices showed statistically significant differences between the severity classes during post-event condition (Fig. 8). It is apt to mention here that among all the band-reflectance only NIR (i.e. B8) showed such sensitivity towards separating the severity classes. Hence, there has been a substantial improvement of the sensitivity towards separating the severity classes by combining the bands into normalized indices.

Insert Figure 8

3.5 Temporal changes in band-reflectance and vegetation indices

To assess the severity of the damage objectively the temporal changes (from pre-event to post event) of all the selected bands and the vegetation indices were calculated as described in equation 1 and 2. The mean percentage changes of the band-reflectance ($\overline{\Delta Red}$, $\overline{\Delta NIR}$, $\overline{\Delta SWIR1}$ and $\overline{\Delta SWIR2}$) and the vegetation indices ($\overline{\Delta NDVI}$, $\overline{\Delta NDWI}$, $\overline{\Delta LSWI}$, and $\overline{\Delta NDTI}$) over the different severity classes are presented in Table 3. The variance analysis of these changes was done and the F-values along with its probability of occurrence by chance are mentioned respectively. Post-hoc Games-Howell tests were performed for separation of the mean percentage changes and statistically significant differences between the severity classes are mentioned in Table 3. Out of the four selected band-reflectance, only $\overline{\Delta NIR}$ showed high sensitivity and could able to separate different damage severity classes. $\overline{\Delta Red}$ and $\overline{\Delta SWIR}$ could separate the "unaffected" and "moderately affected" class significantly. Whereas, $\overline{\Delta SWIR2}$ could able to separate "moderately affected" and severely affected" classes. The mean percentage changes of all the vegetation indices i.e. $\overline{\Delta NDVI}$, $\overline{\Delta NDWI}$, $\overline{\Delta LSWI}$, and $\overline{\Delta NDTI}$ were also found to be sensitive. All the metrics of these vegetation indices could able to separate different damage severity classes of potato crop. Similar sensitivity of the ΔNDVI towards the hailstorm damage of potato crop is reported by Zhou et. Al., 2016. But no such report on the sensitivity of ΔNDWI, ΔLSWI and ΔNDTI is found. Importantly, $\overline{\Delta SWIR1}$ was found to have negative changes with the increase in the severity of damage meaning more absorption in SWIR1 band due to net increased in surface wetness. But, the $\overline{\Delta SWIR2}$ showed positive changes with the increase of severity of the damage. Hence, in general the reflectance in SWIR2 have increased due to the hailstorm damage of the potato crop.

Insert Table 3

3. 6 Variabilities of SWIR-reflectance over the severity classes

As mentioned in section 3.3, there were high variabilities/ dispersions of the post-event SWIR-reflectance over the "severely affected" potato crop as evident by the shape of the violin plot in Fig. 7. Further, the differential response of $\overline{\Delta SWIR1}$ and $\overline{\Delta SWIR2}$ over the different severity classes were observed in Table 3. To explain the high variability of SWIR-reflectance, all the field observations over the "severely affected" potato crop were segregated based on the surface soil wetness condition i.e. "Severely affected (dry soil)" & "Severely affected (wet soil)". Further, all the data points of ΔSWIR1 and ΔSWIR2 over the different damage severity classes were put in a scatterplot and shown in Fig.9. The data points pertain to different severity classes were found to form distinct clusters. As the damage severity increases, the severity-isolines of the clusters (shown as dotted line in Fig. 9) were found to be frame-shifted. The slopes of the isolines remained nearly invariant but the offsets were found to be significantly different. The data point over the "unaffected" potato crop were found to be clustered near to the origin, in the first and second quadrant of the plot within 10 to -10 of ΔSWIR1 and ΔSWIR2. On the other hand, data points over the "moderately affected" crop were found to cluster with -10 to -20 of ΔSWIR1 and 10-20 of ΔSWIR2. The data points over the severely affected crop were found to be widely spread over the first, second and the fourth quadrants of the Fig. 9. The data points pertain to "severely affected (wet soil)" were typically found in the fourth quadrant of the plot. Hence, negative values of ΔSWIR2 were found over the "severely affected (wet soil)". As discussed earlier, the hailstorm affected potato crop in two ways. In first case, the aboveground succulent vegetation got damaged by hail without appreciable increase in the background wetness. In the second case, there was appreciable increase in soil wetness in addition to the foliar damage. High soil wetness condition was predominantly observed over the "severely affected" crop and may lead to the tuber rot or force harvesting. These observations of high soil wetness condition were mainly found in the lower ridges of the study area with limited soil drainage condition. The ΔSWIR1 is primarily sensitive to the surface wetness, hence there had been mainly negative changes of ΔSWIR1 due to the hailstorm damage. The ΔSWIR2 is sensitive to fractional vegetation cover (exposed soil surface) and surface wetness as well. In case of "severely affected (dry soil)" categories, there had been significant decrease in the fractional vegetation cover and it exposed of the underlying fine textured dry soil. Thus, it had increased the post-event SWIR2 reflectance and causing positive change in ΔSWIR2. In case of "severely affected (wet soil)" condition the effect of soil wetness on the SWIR2 reflectance superseded the changes (decrease) in fractional vegetation cover.

Hence, we found net absorption in SWIR2 and negative change in ΔSWIR2. Such effect is not observed for SWIR1 reflectance as it is primarily sensitive to the surface wetness. This differential behaviour of ΔSWIR1 and ΔSWIR2 in dry fine textured soil is also explained by Van Deventer et al (1997) using bands of Landsat TM.

Insert Figure 9

3.7 Selecting VIs for affected area assessment

The vegetation indices derived from different band combinations (Red, NIR, SWIR1 and SWIR2) were found to be suitable for delineating different categories of the damage classes of potato crop. But there exists redundancy among these vegetation indices as some similar bands were used to derive it. The guiding principle for remote sensing-based hailstorm damage is based on the fact that the hailstorm induced changes in the biophysical properties of the crop can be detected by one or more vegetation indices. The hailstorm induces stress/damage on potato crop can be addressed using ΔNDVI as shown in the present study (Table 3) and also corroborated by the previous studies (Ray et al. 2016; Prabhakar et al. 2019; Bell et al. 2020). Hence, NDVI was chosen further for decision matrix generation and it mainly represent the crop vigour. Post hailstorm stress on potato can also be caused by water stagnation and other three water indices i.e.ΔNDWI, ΔLSWI and ΔNDTI can address it. To narrow down further, a correlation analysis was performed within these indices. Correlation matrix of these indices at pre- and post-event condition is presented in Table-4. Very high correlation was found between NDWI and LSWI as both indices used NIR and SWIR bands. High correlation is also observed between NDVI and NDWI/LSWI as NIR-reflectance is common for them. Least correlation was found between NDVI and NDTI. The band combination used to derive them were also different. Hence, NDVI and NDTI were further used for decision matrix to delineate different damage severity classes of potato crop.

Insert Table 4

Further, scatterplot between ΔNDVI and ΔNDTI over the different damage severity classes is shown in Fig 10. The plot indicates a clear-cut separation of the three different damage severity classes of potato crop by forming distinct clusters. The majority points of the "unaffected" classes were found at the combination of ΔNDVI≥- 20 and NDTI ≥ -20. The "moderately affected" category was mainly found between -20 >ΔNDVI≥ -30 and -20 >ΔNDTI ≥ -30. Whereas, "severely affected" class was found in ΔNDVI < -30 and ΔNDTI< -30. These observations were further used to frame decision matrix.

Insert Figure 10

3.8 Decision matrix to map the affected area

Based on the detailed analysis of pre- and post-event Sentinel-2 data and the observations made thereafter, the following methodology is proposed to assess the potato crop area affected by the hailstorm (Fig. 11). Assessment of hailstorm damage of a crop requires cloud-free pre-event and post-event satellite observations along with field data points of the crop, its stages, growing environment and the intensity of the damage. In the present study, we used 19th February, 2019 (pre-event) and 1st March, 2019 (post-event) sentinel-2 data to achieve the objectives. The pre-event satellite data along with ground truth points were used to map the potato crop and further analysis was done over the potato crop mask only. Two vegetation indices i.e. NDVI and NDTI were derived using relevant band combinations using pre- and post-event observations (Table 2 and Fig. 11). The percentage change of these vegetation indices between pre- and post-event i.e. ΔNDVI and ΔNDTI were derived to assess the changes in crop vigour and surface wetness respectively. Based on the response of ΔNDVI and ΔNDTI over the different damage severity classes as mentioned in section 3.7 (Fig. 10), these were sliced into different deviation classes as shown in Fig. 11. These deviation classes of ΔNDVI and ΔNDTI were then combined further using decision matrix as mentioned below and also shown in Fig. 12.

- If ΔNDVI ≥ -20 and ΔNDTI≥ -20, the potato crop is "unaffected".
- If -20 >ΔNDVI ≥ -30 and -20>ΔNDTI≥ -30, the potato crop is "moderately affected".
- If ΔNDVI < -30 and ΔNDTI< -30, the potato crop is "severely affected".

It is important to mention here that the combination of ΔNDTI < -30% and ΔNDVI > -20% were non-existent in the study area as large change in ΔNDTI is not possible without significant change in vegetation cover i.e. ΔNDVI (Renier et al. 2015). Hence, such categories of classes were not included in the decision matrix.

Insert Figure 11 and Figure 12

Decision matrix was then implemented over the potato pixels to get the different categories of affected crop over in the study area (Fig 13). Out of the total potato area of 1.21 lakh ha over both the districts combined, nearly 12% of the area was found to be under "severely affected" category and 26% of the area was "moderately affected". The "moderately affected" area was found to have spatial association with the "severely affected area". GP-wise percentage of affected potato area (both severely and moderately) were mapped and presented in Fig.14. The affected areas were mainly found to be concentrated over the Arambagh, Tarakeshwar & Khankul blocks of Hooghly district and Chandrakana & Garbeta block of west Medinipur district. Significant GPs in both the districts were found to be affected by more than 60% of the affected potato area.

Insert Figure 13 and Figure 14

Post-hailstorm field observations (not included to generate criteria for decision matrix) were used for accuracy assessment of the affected area map (Table 5). The "unaffected" potato crop was well classified as evident from high producer's (92.7%) and users (90%) accuracy. The accuracy was found to decrease slightly for other two classes due to omission / commission errors. The producer accuracies were found to be 75.2% and 88.2 % for “moderately affected” and “severely affected” classes respectively. On the other hand, the user’s accuracy of “moderately affected” and “severely affected” classes were found to be 80.1% and 77.3% respectively. The overall accuracy was found to be 86.7 % with kappa coefficient of 0.81.

Insert Table 4

3.9 Hailstorm affected area vis-à-vis potato yield reduction

To assess the match between the hailstorm affected area and yield reduction of the potato crop, we calculated the GP-wise yield deviation from normal (ΔY) using equation 3 as discussed in section 2.5. GP-wise potato yield deviation of the study year (2019) is presented in Fig 15(a). The normal (long-term average) potato yield of the study area (Hooghly and West Medinipur) districts were found to be nearly 20 tones/ha. Large yield deviation was observed due to the hailstorm in year 2019 and potato yield as low as 10 tones/ha were recorded in some pockets of the study area. Majority of the GPs in Keshpur, Daspur-1 and Chadrakona-2 blocks of West Medinipur District; and Khanakul-1&2, Pursura, Jangipara, Dhaniakhali, Singur blocks of Hooghly district were reported large reduction of potato yield. To assess the match between the satellite derived affected potato areas and the reported yield reduction from long term average, the affected (moderate and severely) areas were classified into five classes (≤10%, 10-20%, 20-40%, 40-60% and >60%) and the yield reduction at gram panchayat were also made five classes (<20%, 20-40%, 40-60%, 60-80% and >80%). Under each class of the affected area, the distribution of the GPs having different yield reduction classes were presented in Fig 15b. It was observed that the GPs with more than 60% affected area showed >80% or 60-80% yield reduction. The proportion of high yield reduction classes were found to be reduced as the proportion of affected area decrease. The GPs with <10% affected area was found to be dominated by the yield reduction class of <20%. In nutshell, the yield reduction of potato crop was corroborating well with the % of damage area at GP level. The result could have been improved further by the well distributed sampling procedure to address the local variations.

Insert Figure 15

4 Conclusions

The present study demonstrated the potential of multi-temporal satellite data for objective assessment of potato crop area affected by hailstorm (25-28 February, 2019) in Hooghly and West Medinipur district of West Bengal. Extensive field information, collected over the potato crop before and after the event, revealed that the hailstorm caused significant damage by defoliating the crop canopy and increasing the soil wetness. Pre-event cloud free Sentinel-2 data of 19th February along with the ground information were used to map the potato crop of affected districts with over all accuracy of 82%. This potato crop map was further used to assess the response of different band-reflectance of Sentinel-2 at pre-event and post-event condition. The NIR-reflectance was found to be highly sensitive to the changes in the canopy structure and surface wetness due to hailstorm. Red and SWIR bands were also showed sensitivity towards it. To accommodate the response of multiple bands towards damage of the crop, four different normalized vegetation indices (NDVI, NDWI, LSWI and NDTI) were derived using combinations of Red, NIR, SWIR1 and SWIR2 bands. All these indices showed high sensitivity and could able to separate different damage severity classes of potato crop. Based on the least co-linearity among these indices, NDVI and NDTI were selected to map the affected area. Decision matrix was prepared using the percentage change (pre- and post-event) of NDVI and NDTI over the different damage severity classes and further used it to map the potato crop area into “unaffected”, “moderately affected” and “severely affected” by hailstorm. Overall accuracy of the affected area map was found to be 86.7%. GP-wise yield reduction of potato crop based on the CCE data were also found to be corroborating with the % of the area affected due to the hailstorm. Geospatial map of GP level affected potato crop area was also prepared to facilitate informed decision making. The study has thus established as scientific basis to objectively assess potato crop area affected due to hailstorm. Such value-added products would be very helpful in relief management and crop insurance value chain. Future study may be extended towards assessment of quantitative impact of hailstorm on the yield of potato crop.

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Declarations

Funding: Not applicable.

Conflicts of interest: Authors have not reported any conflict of interest.

Availability of data and material: The satellite data that support the findings of this study are openly available at https://www.copernicus.eu/en/access-data. Other datasets are provided in the manuscript.

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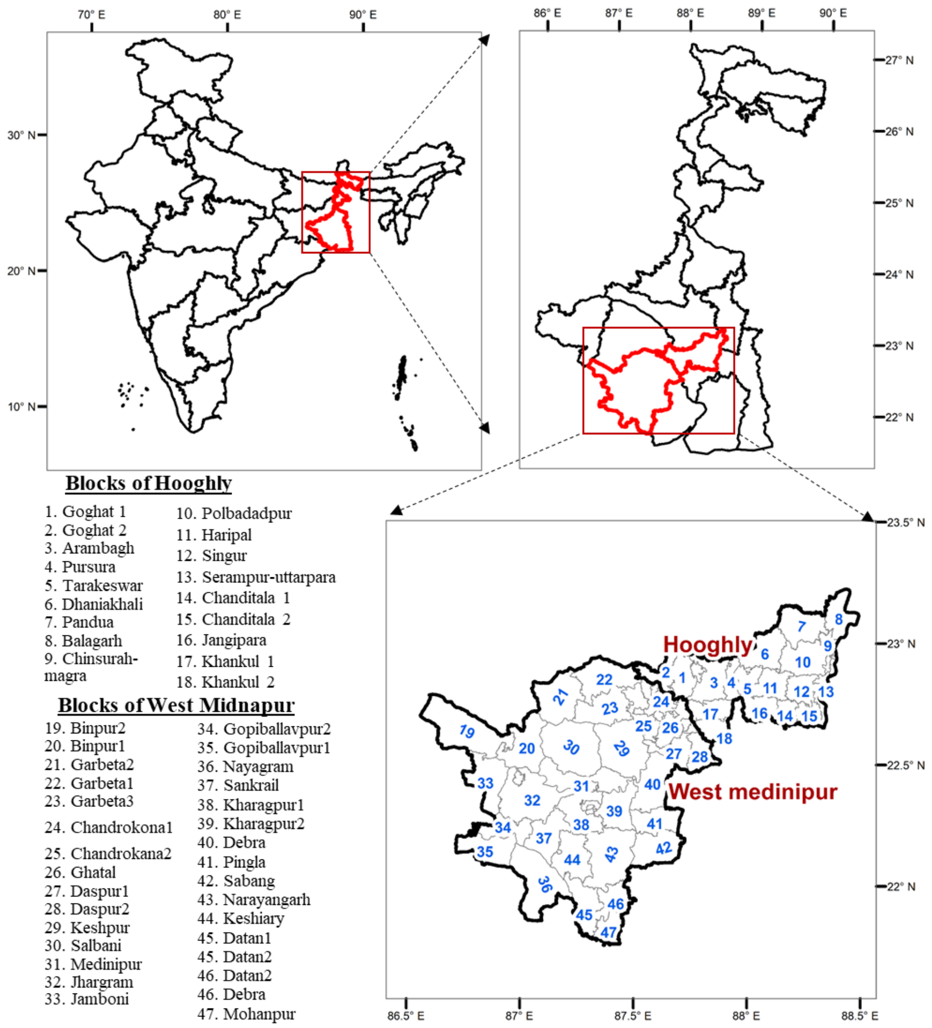

Fig 1 Location of the study area

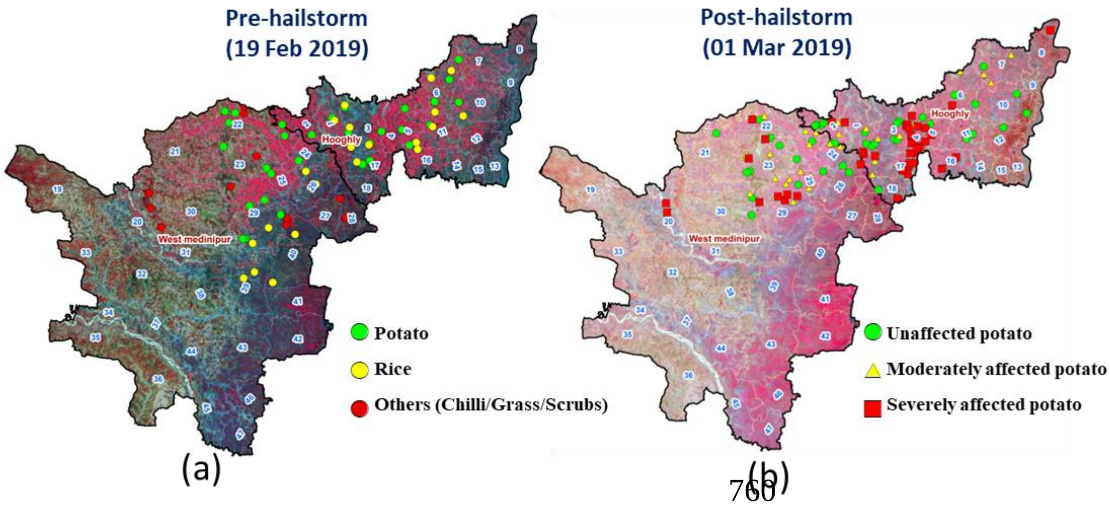

Fig 2 Ground truth points overlaid on Sentinel-2 false colour composites (R:G:B = B8:B4:B3) (a) Pre-event & (b) Post-event.

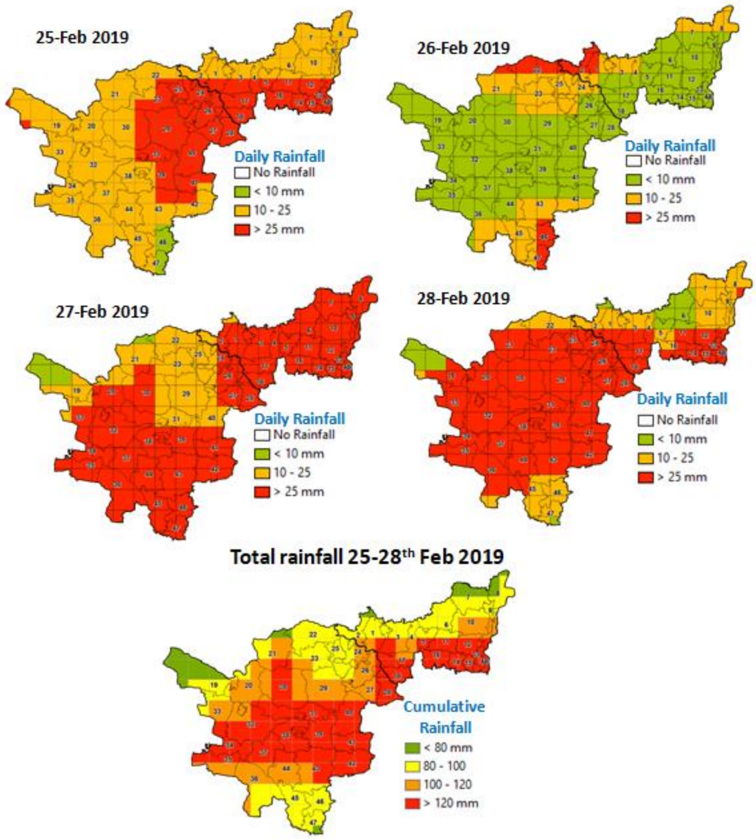

Fig 3 Rainfall over Hooghly and West Medinipur districts of West Bengal during 25-28 February 2019 as represented by 0.1° X 0.1° rainfall by IMD

Fig 4 Field photographs showing severity of damage of the potato crop in the study area due to hailstorm

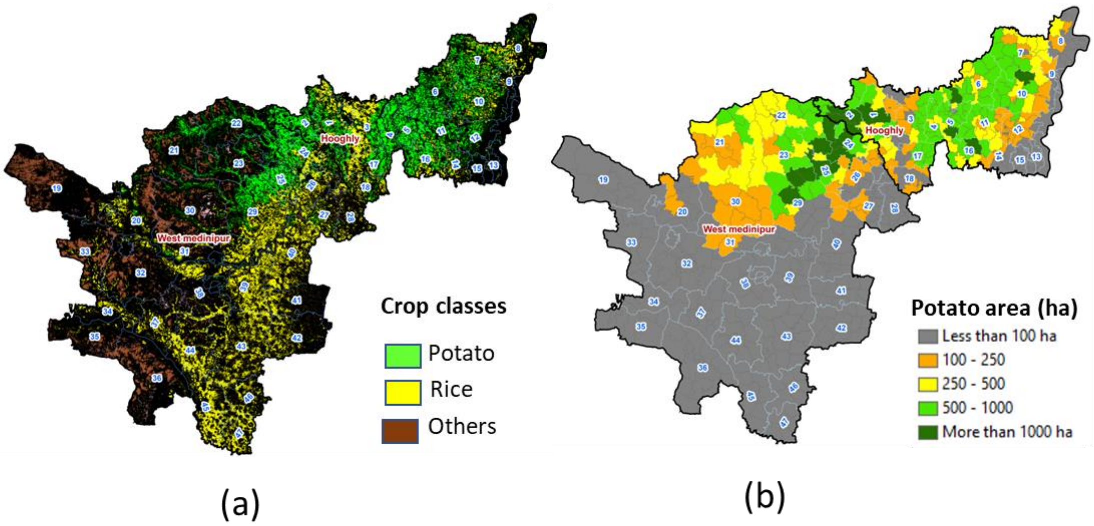

Fig 5 (a) Classified crop map of the study area as on 19th Feb 2019; (b) GP wise area under potato crop

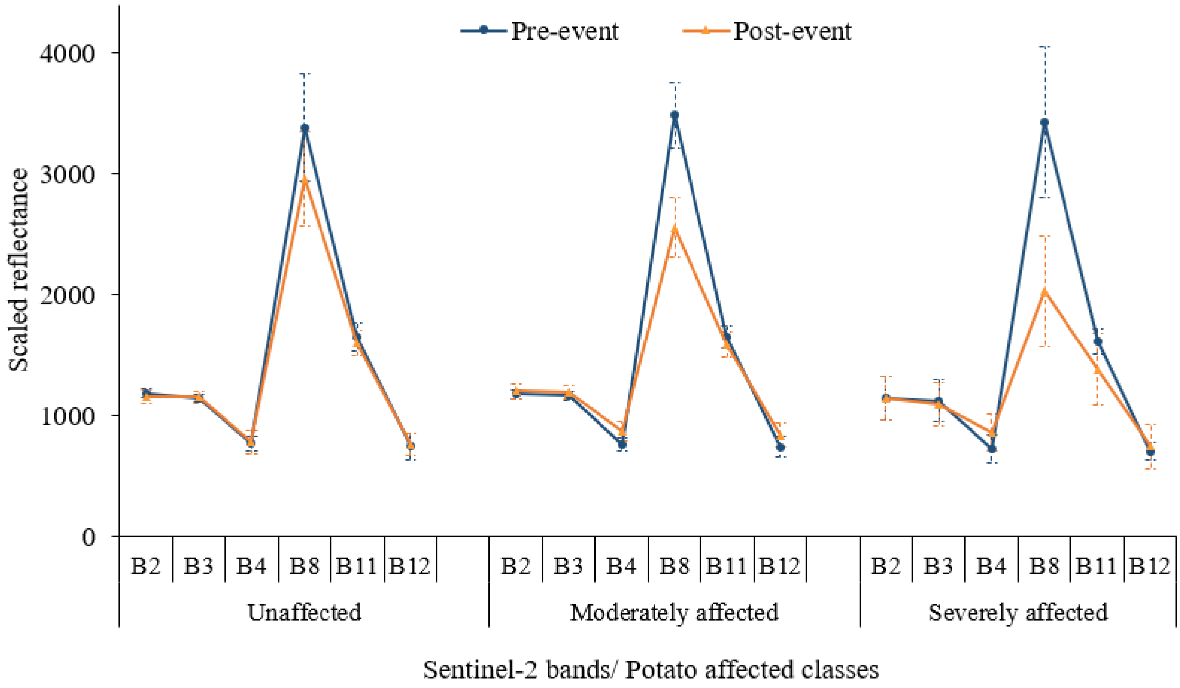

Fig 6 Reflectance of selected bands of Sentinel-2 over the different damage severity classes of potato crop before (19th February) and after (1st March) the hailstorm. Standard deviations are represented as error bars.

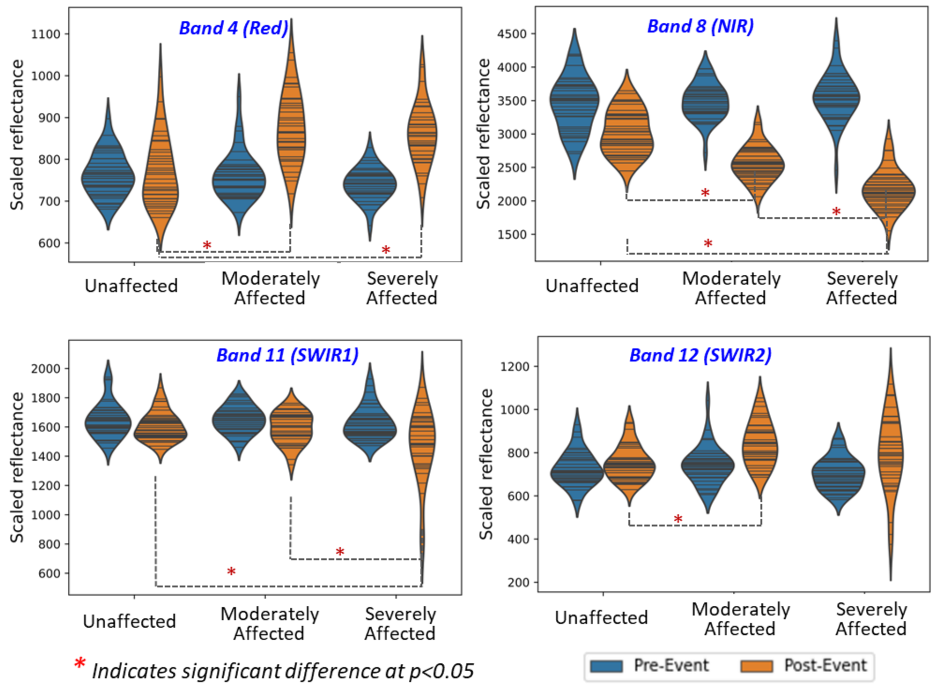

Fig 7 Violin-plot showing the data distribution of the band-reflectance (pre- and post-event) over the different damage severity classes of potato crops due to hailstorm. The band observations significantly (Post-hoc Games-Howell tests) different over the different severity classes are mentioned as *.

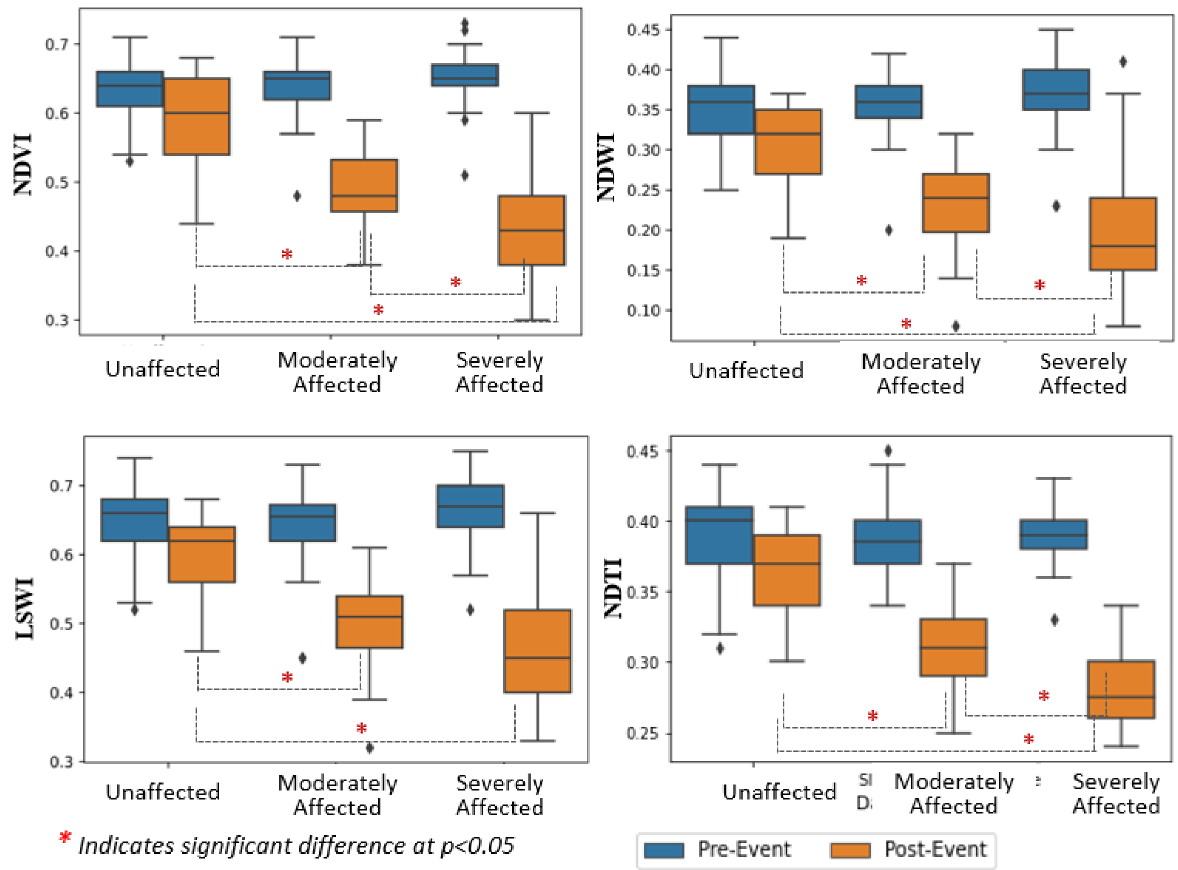

Fig 8 Box-plot showing the variations of different normalized-indices (pre and post-event) over the different damage severity classes of potato crops due to hailstorm. The normalized-indices significantly (Post-hoc Games-Howell tests) different over the different severity classes are mentioned as *.

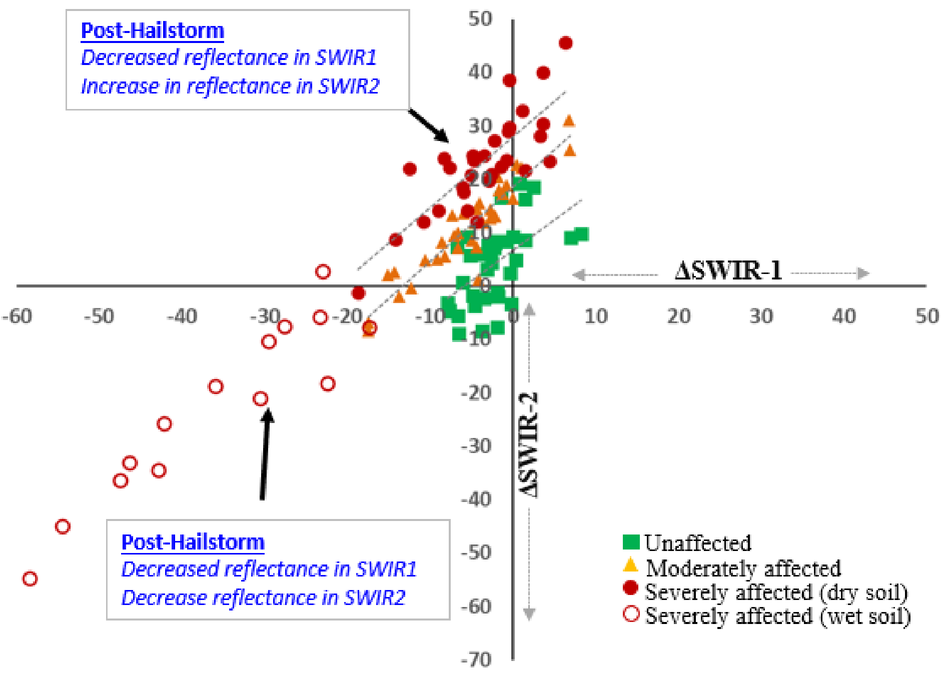

Fig 9 Scatterplot of ΔSWIR-1 and ΔSWIR-2 showing separability of the different damage severity classes of the potato crop

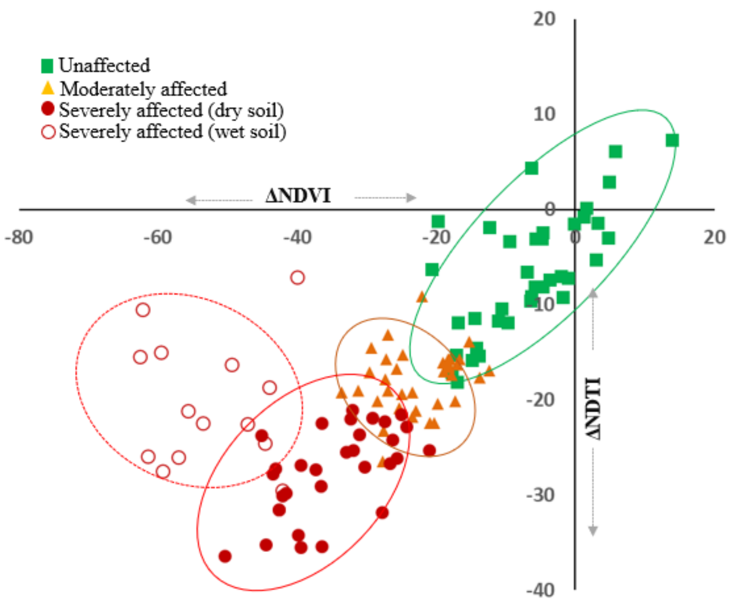

Fig 10 Scatterplot of ΔNDVI and ΔNDTI showing separability of the different damage severity classes of the potato crop.

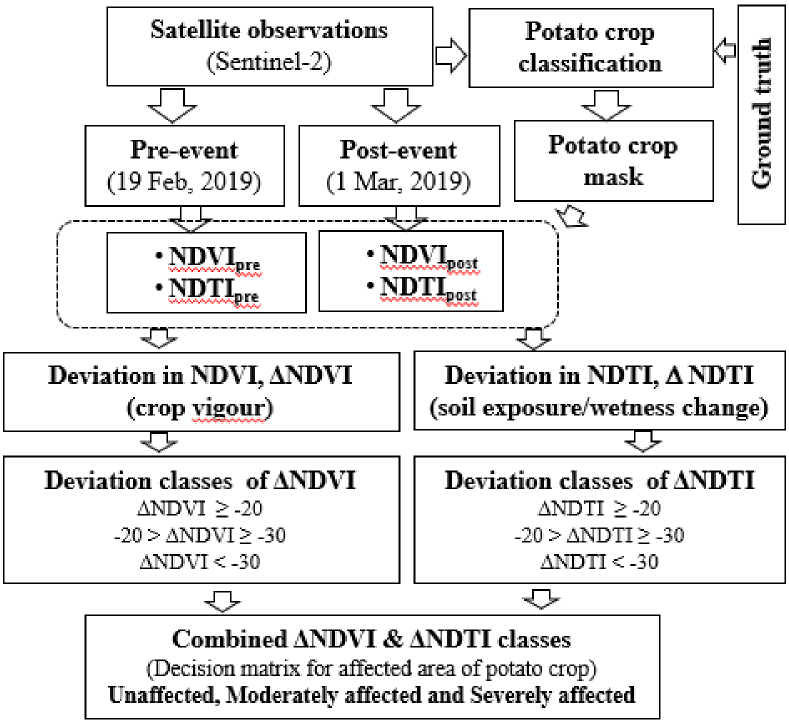

Fig 11 Schematic diagram of the proposed methodology

Increase in soil exposure/wetness change (ΔNDTI)

Decreasing crop vigour (ΔNDVI)

	≥ -20%	-20 to -30%	< -30%
≥ -20%	Unaffected	Moderate	NE
-20 to -30%	Moderate	Moderate	Severe
< -30%	Severe	Severe	Severe

**NE: Non-existent*

Fig 12 Decision matrix of different categories of affected area based on ΔNDVI and ΔNDTI

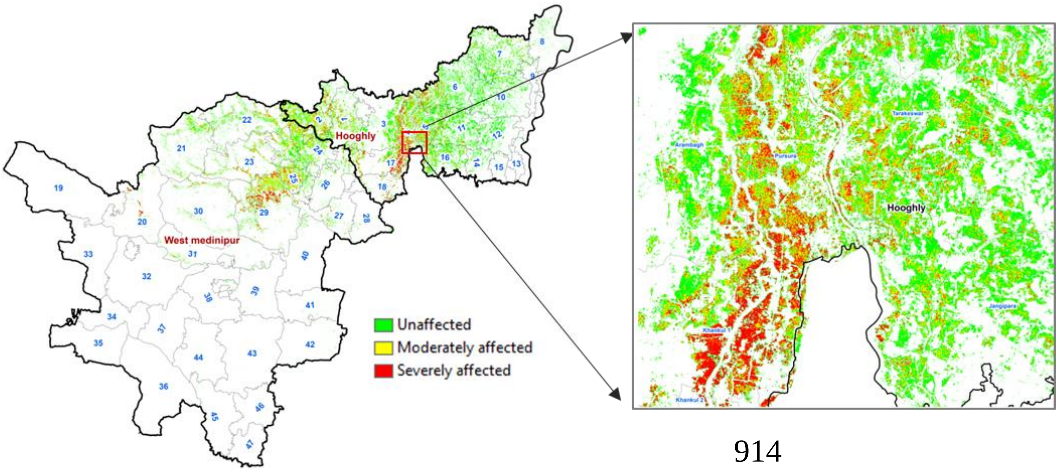

Fig 13 Spatial distribution of the different categories of potato crop affected due to hail storm over Hooghly and West-Medinipur district

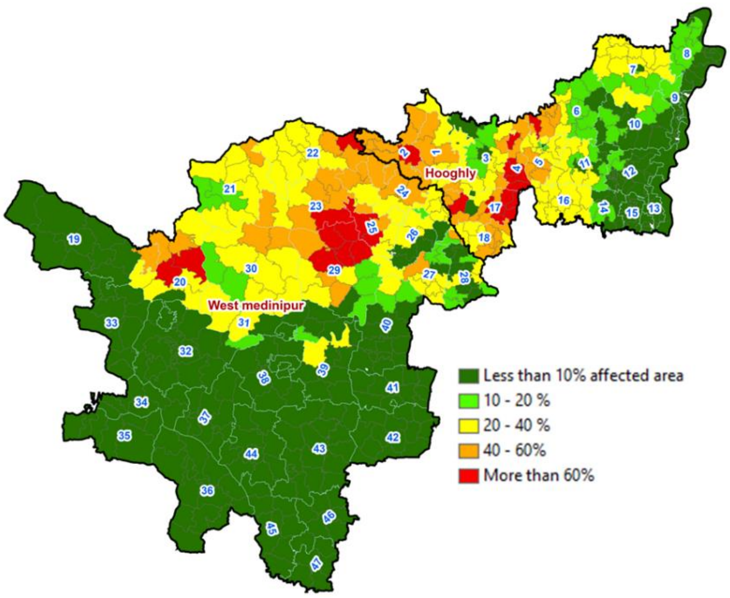

Fig 14 GP-wise percentage of potato crop affected (both moderately and severely) due to hailstorm over Hooghly and West Medinipur

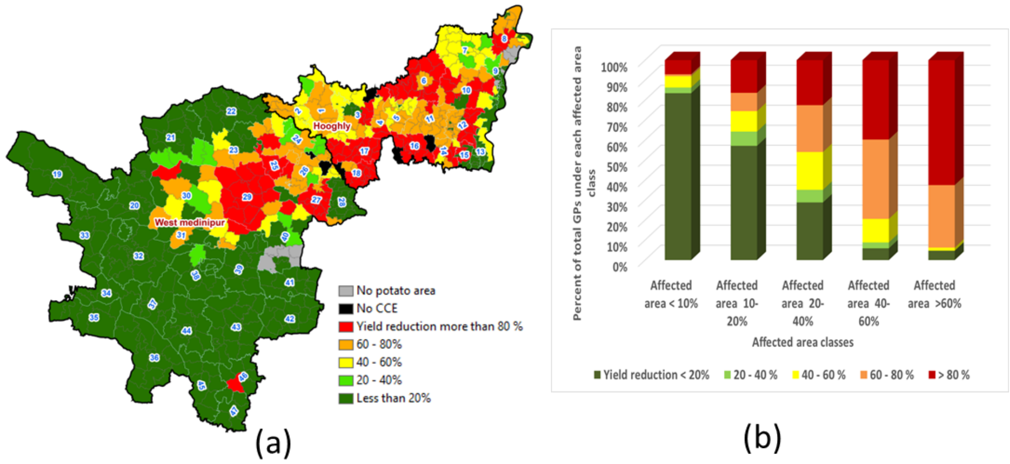

Fig 15 (a) GP wise potato yield reduction in 2019 as compared to historical six years (b) Distribution of GPs into different yield reduction classes under each affected area classes

Table 1 Detailed specification of the Sentinel-2 data used in the present study

Spectral Bands	Central wavelength (µm)	Spatial resolution(m)
B2 - Blue	0.490	10
B3 - Green	0.560	10
B4 - Red	0.665	10
B8 - NIR	0.842	10
B11 – SWIR 1	1.610	20
B12 – SWIR 2	2.190	20

Table 2 Vegetation indices used in the study

Vegetation Indices	Formula	Significance	Reference
NDVI	$\frac{B8 - B4}{B8 + B4}$	• Sensitive to green vegetation • Influenced by leaf chlorophyll and moisture • Represents photosynthetic vegetation fraction	Rouse et al. 1974
NDWI	$\frac{B8 - B11}{B8 + B11}$	• Sensitive to canopy moisture • Influenced by leaf structure and wetness	Gao, 1996
LSWI	$\frac{B8 - B12}{B8 + B12}$	• Sensitive to canopy and soil moisture	Hunt and Rock 1989
NDTI	$\frac{B11 - B12}{B11 + B12}$	• Sensitive to soil moisture and non-photosynthetic vegetation (NPV) • Do not influence much by leaf mesophyll cell structure	Van Deventer et al. 1997

Table 3 Statistical analysis of the mean of percent change (from pre-event to post event) of different band-reflectance and vegetation indices.

Severity classes	N	$\overline{\Delta Red}$	$\overline{\Delta NIR}$	$\overline{\Delta SWIR1}$	$\overline{\Delta SWIR2}$	$\overline{\Delta NDVI}$	$\overline{\Delta NDWI}$	$\overline{\Delta LSWI}$	$\overline{\Delta NDTI}$
Unaffected	37	0.82^{a}	**-11.73^{a}**	-2.40^{a}	3.92^{a}	**-6.55^{a}**	**-13.07^{a}**	**-7.58^{a}**	**-6.45^{a}**
Moderately affected	36	15.13^{b}	**-26.60^{b}**	-3.72^{a}	13.70^{b}	**-23.75^{b}**	**-35.47^{b}**	**-22.56^{b}**	**-19.02^{b}**
Severely affected	46	16.63^{b}	**-38.56^{c}**	-10.13^{b}	12.80^{bc}	**-34.20^{c}**	**-46.80^{c}**	**-30.10^{c}**	**-24.35^{c}**
Variance analysis	F-value	28.0	194.1	16.5	3.6	106.1	44.4	61.4	86.2
	P	.000	.000	.000	.031	.000	.000	.000	.000

N= no of samples. Letters in upper script (a-c) indicate significant difference at P<0.05 (Posthoc Games-Howell tests were performed for separation of means; means with at least one letter common are not statistically significant). The mean values of the severity classes statistically different from each other are mentioned as bold letters.

Table 4 Correlation matrix between different vegetation indices at pre- and post-event of the hailstorm.

Pre-event				
	NDVI	NDWI	LSWI	NDTI
NDVI	1			
NDWI	0.86	1		
LSWI	0.88	0.98	1	
NDTI	0.80	0.91	0.97	1
Post-event				
NDVI	1			
NDWI	0.87	1		
LSWI	0.83	0.99	1	
NDTI	0.78	0.90	0.96	1

Table: 5 Accuracy assessment table for potato damage area classes

Severity classes	Producer's accuracy	User's accuracy
Unaffected	92.7	90.0
Moderately affected	75.2	80.1
Severely affected	88.2	77.3