Technology Assessment Using Satellite Big Data Analytics for India's Agri-Insurance Sector

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Abstract

Over half of India's employment is attached to the agriculture sector and their survival is dependent on the performance of farms. The uncertainty in performance of farms due to weather fluctuations and other risks is tackled by providing insurance cover. However, policymaker's choice of administrative measures for estimating crop loss has resulted in inaccurate data collection, opened vulnerability to politicization of the process and created bottlenecks to operate at scale. These problems have led to skewed timelines for data collation, lack of confidence of the data produced by the agri-insurance providers and caused long drawn delays in settling claims made by farmers. In this paper, we present a case study on the assessment of using satellite big data as a technology deployed in Northern India to solve the aforementioned problems between the stakeholders in the agri-insurance claim settlement process. Satellite big data based analytics provides an independent data source and decision-making platform for the agri-insurers to conduct an assessment for calculating the indemnity payments. The results showcase how transparency brought in by the satellite big data analytics curbs the plausible exploitation of claim settlement process and leads to increased efficiency and efficacy in settling farmer claims.

Managerial relevance statement

The present work explores a digital transformation of decision making of agri-insurance operations using satellite big data analytics. Our study demonstrates how satellite data analytics can be leveraged to streamline the data collection, collation process on crops and

thereby highlight the possibility of passing on the benefits of digitalisation of the operations to small and marginal farmers in India. By utilizing the satellite big data, we showcase insights on crop yield, crop acreage can be obtained and contrast it with the problems in the legacy manual methods. The real-world setting of the case study allows us to explore how satellite big data analytics can improve decision making in insurance claims settlement operations for small and marginal farmers. The transparency brought in by digitalisation using satellite big data analytics also has the potential to improve the ethicality of the decisions made towards insurance claims. This study captures the integration of digital transformation for societal benefits and provides early evidence for adoption in developing countries.

Keywords: Big data analytics, Digitalisation; Satellite imagery, Agriculture, Insurance, India.

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INTRODUCTION

Grand societal challenge (GSC) is defined as specific critical barrier(s) that, if removed, would help solve an important societal problem with the high likelihood of global impact through widespread implementation [67]. One such GSC is to promote "poor as suppliers" in emerging countries. We consider the agricultural sector as the research context as it accounts for approximately 28% of the global employment. Further, the sector assumes importance since small farmers represent a significant proportion of the farming population attributed to high population density and sluggish growth in cultivable land. Also, these farmers are key to ending hunger and undernutrition worldwide and therefore it is important to contribute to their profitability for greater food security [76].

We consider India for our empirical setting due to the existing problems prevailing and the impact it creates by serving the second largest population in the world. Small and marginal farmers (<2 hectares) operate on 85% of the 138 million farm holdings [1] contributing to half of employment of India's workforce and making up 18% to its GDP [2]. India's farm sector remains largely driven by rain-fed means with estimates of 80% of farms dependent on monsoons for crop production [3]. The uncertainty in performance of farms therefore affects over 100 million families in India. With 10281 farmers committing suicides in 2019 largely attributed to the inability of farmers to pay back loans [77], the agricultural supply chain in India is likely to face disruptions if the current trends continue. One of the major factors contributing to issues in agricultural supply chain is the lack of crop insurance to the farming community.

The use of crop insurance has been an institutional response to provide cover to the weather, pest and natural risks that are faced by farm communities in India and dates back to over five decades since its first adoption. With the introduction of Pradhan Mantri Fasal Bima Yojana (Prime Minister's Crop Insurance Scheme), there were approximately 40 million adopters of crop insurance in India with 38.5 million hectares of land insured for a total of ₹133,106 crore ($20.5 billion) for the monsoon of 2016 [4]. Accuracy in crop loss assessment is one of the key yardsticks to disburse crop insurance claims. In each planting season, based on the crop yield estimates, 'average loss' is calculated for the insurance claim settlement process. Researchers observing crop loss settlement for small and marginal farmers in India have found that this process has major loopholes in implementation that includes insufficient data collection conducted to estimate the 'average' loss, bogus data for acting just as formalities on paper, lack of trained professionals conducting to collect data, and tremendous scope for corruption [5].

In addition, absence of agro-meteorological data [6], lack of digitized farm records [7], and lack of historical performance of farms are identified as key challenges to achieve transparency in claim settlement and scale in crop insurance. These challenges are affecting the operations of insurers by creating inertia in the claim settlement process. According to the Government of India's own task force [8], the process to settle claims has embraced timelines of 6-12 months. For claims of summer monsoon of 2016, media reports indicated that insurers had not paid 83% of the claims until March 2017 [9].

Digitalisation offers tremendous opportunities to leverage information technologies to address such problems in operations and supply chains. More recently, researchers have been investigating the application of digitalisation in areas such as purchasing [10], increasing productivity [11], operations management [12] and manufacturing servitization [13]. The use of digitalisation through the application of big data analytics is a one such area that is gaining interest within the supply chain and operations research context [14]. Digital transformation is leading to increased competitiveness through cost reduction and enhancement of productivity to better support decision-making processes [15]. However, assessing the right technology for a given problem seems to be a challenge in global societies. As the agri-crop insurance sector lacks high density data which involves farmers, farm lands, crop types, weather etc, practitioners have moved towards technology that can collect high volume data in real time. One such data collection means is to harness satellite imagery. Satellite imagery data is often characterized by information which is having volume, variety and velocity, which is in turn one of the key characteristics of big data [16]. For example, the European Union satellites produce about 10 TB of data per day and is available freely for the public to utilize [17]. We believe satellite big data is one such subset within the big data analytics that finds itself underutilized in the supply chain and operations research context.

In this present work, we showcase how digitalisation based on satellite big data can be leveraged to improve decision making by enhancing the accuracy, completeness and consistency of underlying information. This would help assess the utility and application of technology in solving GSC. We present our research question (RQ) below:

> **RQ –** How satellite big data analytics be leveraged to improve decision making in insurance claims settlement operations for small and marginal farmers in India?

We adopt a case-study approach to address this research question. We attempt to demonstrate the digitalisation by data-driven decision making of using satellite big data analytics for the purposes of estimation of cotton crop acreage and changes in crop yield in settling crop insurance claims in India. The scope of utilization of satellite big data analytics for claim settlement in agri-insurance context includes establishment of historical performance of individual farms, monitoring of the entire crop cycle from planting to harvest, classification of crops at individual farm level, assessment of crop health and yield during the harvest period, and estimation of damages caused by risk events. The results obtained in our study showcases the tremendous opportunity to remove bottlenecks and trust deficits between the key stakeholders that support agriculture and thereby delivering better agri-financial services to the communities of small and marginal farmers in India. Digitalisation using satellite big data analytics assists decision making related to claim settlement for agri-insurance operations, which ensures quick settlement of economic losses due to crop failure to small and marginal farmers in India.

This paper is organized as follows. We have reviewed the use of analytics as well as satellite data at an industry-level. An introduction to the current procedures and their associated challenges in crop insurance administration in India is then presented and explained from the context of its effects on small and marginal farmers. We then highlight the methodology in utilizing satellite big data analytics and explain its application in the context of decision-making by agri-insurance providers. Following it, we present the case from a district in northern India and the challenges encountered by insurance providers in working with the legacy administrative processes and data. The results of adopting satellite big data analytics and the research findings are then presented based on technological, societal and administrative machinery perspectives. The paper concludes providing an insight of what the future holds for the expansion of satellite big data analytics as an integral part of policy making and operations of various stakeholders within the agriculture value chain.

LITERATURE REVIEW

There are several ways in which researchers and practitioners have defined or interpreted the concept of digitalisation. Digitalisation has been conceived as a '*process of converting analog streams of information into digital bits*' by Brennen and Kreiss [19]. It has also been broadly presented as '*technology of digitalising information*' by Siu and Wong [20]. For the sake of our study, we find the definition by Hennelly *et al.* [21] of '*use and adoption of external digital technologies by organizations, to improve their supply chain and operational performance*' very appropriate. Digitalisation has been at the forefront of initiatives such as Industry 4.0 to not only drive scalability and flexibility of processes [22] but also help in decision making [14].

The concept of big data is one such technology in digitalisation that has gained traction in the supply chain, production and operations context [23]. This is based on the premise that the use of big data technology can positively impact performance to enable data-driven growth [24]. Big data has been applied to various fixing problems in manufacturing [25], operations management [26] or supply chains [27]. Big data can also be applied to specific value chains such as agriculture. For example, researchers have recently investigated the use of big data in purchasing of food produce [27], supply chain of fisheries [28] and sustainability of production of agricultural produce [29]. The outcome of such studies have the potential to support an integrated approach to effective and efficient decision making in agri-chain by considering harvesting time window constraints, yield perishability, seasonality, and weather uncertainties [30]. However, one must realize that technology should be in place to support big data generation. For instance, satellite imagery can produce large amount of data continuously and process the same through different technologies to derive meaningful outcomes. Such large amount of data generation at real time for large interval of time provides decision makers with sufficient evidence to apply analytics for meaningful insights.

From a developing country context, the use of big data analytics products has been recognized as one of the means of transforming agriculture to achieve greater inclusive growth, raise efficiency of complementary factors affecting farms, and reduce transaction costs [31]. Developing countries who traditionally may not have had long-term or large-scale investments in decision support tools in agriculture can take advantage of the current trends decreasing computational costs and increased computational capabilities to go beyond just providing information and introduce advanced analytics with decision support tools to support their stakeholders [32].

Today's satellites are generating big data that can support the development and adoption of tools in decision making [33]. In the past decades, the bottleneck in the proliferation of the usage of the satellite data has been its availability and coverage over areas of interest and the cost to acquire them [34]. With the emergence of satellite constellations and their inherent capacity for data collection [35], satellite-based data has transformed itself into big data [36]. For instance, the Copernicus program of the European Commission with its Sentinel satellites produces approximately 10 TB of Earth Observation data per day [17]. Satellite data can help derive indicators such as the Normalized Difference Vegetation Index (NDVI) that can be used to analyse health of live vegetation is a useful application of satellite-based remote sensing data in agriculture for understanding and explaining crop yield [37].

Specific to the Indian context, Dayasindhu and Chandrashekar [38] have discussed how India's own satellites have been underutilized and have not witnessed the advantages of innovations built on top for these capabilities translating into positive effects for the economy. This also concurs with research that points to the inability of governments to harness big data at national scale to more likely to hamper its ability to harness the potential of big data [39]. We are attempting to discuss such a translation by addressing the resolution of operational problems in the decision-making process for crop insurance claims settlement and reflect on the utility of digitalisation based on satellite big data analytics in creating a positive impact in potentially resolving the bottlenecks. This also allows us to capture how a non-tailored technology to the agriculture sector such as satellite big data can still help support the needs of the stakeholders supporting the growth of the sector at national scale. We believe that our research is perhaps one of the earliest documented cases that studies the adoption of digitalisation based on satellite big data analytics in a developing country within the realm of agri-financial services. Given the democratized access to satellite big data itself, there are lessons from this case study for stakeholders in other developing countries as well as other parts of the agriculture value chain. This also extends the argument of new technologies aiding farmers with information that can rapidly change the dynamics of operational landscape in supply chains of developing countries [40].

THEORETICAL FRAMEWORK

We address our research question through the framework of technology assessment [68]. Technology assessment is defined as the form of policy research which analyse and examine the short term and long-term consequence of any application of technology [70]. Literature suggest that it is important to understand modulation of technology developments and the dynamics of such modulation [71]. In other words, it is important to understand the context in which the technology is used, the strategic side of technological implementation and most importantly the alignment of technology with the issue at hand. Obviously, the tangible impact of any technological intervention assumes paramount importance [69]. Research points out that in addition to the scientific investigation of the conditions and consequences of technology, one must focus towards societal evaluation [68].

We believe that this research focusses on the key dimensions of technology assessment for the following reasons. First, it follows a scientific approach towards understanding the role of satellite imagery in collecting data and using that data to derive meaningful outcomes for the crop insurance sector. Second, through the lens of technology assessment, we attempt to document the impact of the technology (satellite imagery-big data) in an objective manner thereby contributing to the impact assessment of technology. Third, our research tries to link and argue the alignment of the issues in the crop insurance sector with the choice of technology being implemented in this study. Here, we try to address both the modulation of technological development and also its relevance of society. The degree at which farm sector in developing nations are burdened due to lack of insurance, inability to access cheap credit mandates researchers to delve deeper into the technology assessment dimension. The accuracy in technology assessment will decide not only the sustainability of the technology, but also impact key stakeholders that aim to develop new markets (crop insurance) and at the same time help farmers improve earning potential which in turn may boost other sectors such as farm machinery, suppliers of fertilizers, pesticides, etc.

Past research in the interface of technology assessment and satellite is limited in the management and policy discipline. For instance, Hall [73] was one of the first few papers that assessed the role of satellite technology for climate change issues in polar regions. Hadjimitsis et al. [74] explains the role of satellite remote sensing technology in analysing the atmospheric pollution in large cities close to airports. In the context of agriculture, Jahns and Koegl [75] used the technology assessment framework to evaluate the positioning and navigation of farm vehicles in Germany. Hence, there exists an opportunity to understand more on the emerging technological applications in solving important societal challenges in the management discipline.

METHODOLOGY

The technology assessment theoretical framework needs to be applied through an empirical approach to address our research question. We therefore, introduce this methodology section by explaining the rationale of our exploratory study in the agricultural sector. We then describe the research context under which the empirical setting is established.

Rationale

We use a case study approach for three reasons. First, our study is exploratory in nature [41]. In other words, we intend to assess and show how satellite big data as a technology can help alleviate the problems of crop-insurance sector in the Indian agricultural sector. One of the major problems in the insurance sector is that they lack capabilities to analyse and extract insights from big data sources such as satellite imagery. Hence, intermediaries should collaborate with insurance players and help them extract decision intelligence from the rich data. Second, it helps us to understand the “how” and “why” questions while we understand the process of addressing the existing concerns [72]. Third, case studies are needed to capture the impact of data-driven practices. For instance, Akhtar *et al.* [18] highlight the lack of case studies in data-driven practices. Our case study is based on the assessing the crop indemnity pay outs for the crop yield losses for the Bhiwani district in the Northern Indian region for the Kharif (monsoon) seasons of 2016-17. We have not randomly sampled the case study setting, but rather we have picked it to for its fit with the research question itself [42]. Also, case studies-based research is also prominently used by researchers in big data analytics-based research [43]. Further, through the use of a case study approach, we are able to provide an outlook for resolving an operational bottleneck within a value chain (i.e., settling of indemnity payments within the agri-insurance operations).

Research Context

We have chosen to use convenience sampling in selecting the setting (e.g. the region and the time period) of the case study. The convenience sampling of crop yield investigation in the Bhiwani district was based on several local factors that bridge the research team and the teams involved in the agri-insurance operations. This includes knowledge of the proximity of the research team to the geography and the ability to work closely with the local stakeholders involved in the agri-insurance operations. One of the prime factors contributing to the choice of the Bhiwani is that the authors and the research team could leverage their social capital to gain insights from the local stakeholders and understand the intricacies for the adoption of a digitalisation-based solution. We believe that the solution discussed in this paper can be easily scaled and replicated across the entire Indian geography. The case study itself stands as a litmus test based on the experience of a single geography and crop harvest season.

AGRI-INSURANCE IN INDIA – CURRENT PROCEDURES AND ASSOCIATED CHALLENGES

The crop insurance program is federally administered but with the involvement of the States in data collection. The risks covered under the crop insurance scheme [44] are provided in Table 1. The State in consultation with insurance companies agree and approve on indemnity levels of 70%, 80% and 90% corresponding to high, moderate and low-risk level for notified crops and regions. The administration of crop insurance needs an agreement upon basis by policy makers and insurance companies to structure the insurance scheme. *Area yield index* is a compromise that the policymakers have chosen to be the basis of average yield as collection of accurate information at the individual farm level has historically been too expensive and cumbersome [45] and area yields typically mitigate adverse selection and moral hazard problems [46]. The other popular index that is used in several developing countries is the *weather-based index*. This index typically uses Automatic Weather Stations (AWS) installed over a certain geographical area to record rainfall, temperature, humidity, and wind speed to base the payout on negative deviation in rainfall ('pay per MM deviation'[1]). *Weather-based index* has been proclaimed as suitable for low income countries [47] but faces several challenges [48] such as non-availability of sufficient density of AWS, inability to cover farm-based losses (such as pests, diseases, etc.), and imperfect correlation between farm yield and weather index. India has deployed both *area yield index* and *weather-based index* schemes to administer crop insurance [49]. Both of these approaches do pose some basis risk for the farmers and insurance providers due to the information asymmetry in the cycle of administration [50]. We address the challenges in the area yield index within the purview of

[1] Loss estimates are based on a trigger (e.g. rainfall accumulation falls below a certain designated threshold) beyond which all policyholders in the area covered receive the insurance payout.

this paper since the farmers were registered on the basis of the area yield within the region of interest.

TABLE 1 - RISKS COVERED UNDER CROP INSURANCE IN INDIA

Type of risk	Description of risk
Prevented Sowing/Planting Risk	Adverse seasonal variations such as major rainfall deficit preventing the insured area from sowing.
Standing Crop Risk	Non-preventable hazards such as weather and farm-related events, which include drought, floods, landslides, cyclones, inundation, pests, and diseases.
Post-Harvest Risk	Coverage to crops that are being dried in cut and spread condition on the field after harvesting against unseasonal rains or cyclonic events.
Localized Calamities Risk	Coverage against losses incurred on isolated farms in the notified areas due to localized risks of hailstorm, landslide, and inundation

The primary dataset for crop insurance program using area yield index in the underwriting process is the average crop yield. The crop yield estimation is done by the means of sample survey using Crop Cutting Experiments (CCEs), which involve selecting a 5 x 5m (25 sq.m) area in a field, harvesting the crop in that area and finally weighing the produce leading to an estimate of the yield per acreage (average yield). Additional data sources such as the records of produce arriving at the local mandi (market) can be used as an estimate of how much produce has reached the local market and it helps in tracking the local produce. CCEs are mandated to be conducted by the States who then have to collate the data and share it with the insurance companies to use the average yield data in determining the tune of insurance to be paid to the insured farmers. Threshold yield is calculated based on average yield for the last seven years, excluding up to two declared calamity years. The average crop yield for the current season is then compared with the threshold yield to determine the extent of compensation. As per the manual on Crop Estimation Survey [51], the method generally adopted for estimating the average yield of a crop and sampling error (at the stratum level) is simple arithmetic mean of plot yield (net) within it. The stratum means are then combined using area under the crop in the stratum to give a weighted average yield for the district. The average yield for the state is arrived at as a weighted mean of district yield with corresponding crop area as weight. Symbolically, the district average yield can be represented as,

$$\bar{X} = \mathrm{d} \times \mathrm{f} \times \frac{1}{\sum_{i=1}^{k} a_i} \times \sum_{i=1}^{k} (a_i x_i) \tag{1}$$

Where x_i = sample arithmetic mean of the net yield of sample cuts in the i^{th} stratum,

a_i = net area under the crop in the i^{th} stratum.

k = number of strata in the district.

d = driage factor (i.e. allowance for driage).

f = conversion factor for converting the yield per cut to yield per hectare.’

Once the estimation of the average yield for a given area is determined, the difference between the threshold yield and the average yield is used to then pay out the indemnity to the farmer as grievance redressal by the insurance company.

$$Claim = \frac{Max(Threshold\ Yield - Average\ Yield, 0)}{Threshold\ Yield} * Sum\ Insured \tag{2}$$

The threshold yield for a crop is the average yield of top 5 yields from past seven years of that season multiplied by applicable indemnity level (70%, 80% or 90% as agreed upon by the State and the insurance companies) for that crop. Note that in this scheme which uses area index, there is no method to track yields of individual farms. According to this scheme, every insured farmer of a particular loss-calculated area becomes automatically eligible for a payout.

Challenges in data collection

There are several challenges that arise in the entire process beginning from the data collection to the final reporting made to the insurance industry. The coordinates to conduct CCEs are generated using stratified random sampling to ensure that they are not cherry-picked, which eventually may lead to biased average yield results. The challenge with randomly generated coordinates has been with lack of access to some of the locations by officials conducting CCEs and therefore introduces risk of either drastically moving the location where CCE is conducted or reporting numbers based on adjacent CCE coordinates. CCEs although may sound as a very simple process to an expert in the sector, there is still the need for scientific processes to be followed in order to produce accurate results at every individual CCE. The sheer volume of the number of CCEs to be conducted and efforts required to collate it over a large geographical area like India makes it extremely challenging and difficult.

A recent report on 'Enhancing technology use in agriculture insurance' [8] by the task force in National Institute for Transforming India (NITI) Aayog, a Government of India's own think tank, found several discrepancies in using CCEs, which include:

- **Cost of conducting CCEs** – According to recently available data, a total of 900,000 CCEs are conducted in India as a part of the General Crop Estimation Survey (GCES). As it is recommended to conduct at least 4 CCEs per crop at the insurable unit level, India has a total of 230,000 such units (representative of total villages). With an estimated cost of a minimum of $16 (Rs. 1000) per CCE, the cost for conducting CCEs themselves pose a challenge.
- **Resources to conduct the CCEs** – Since the yield needs to be determined around the harvest period, the CCEs are to be conducted almost simultaneously in all geographies. This poses the challenge of availability of trained manpower to conduct the CCEs, monitoring them and reporting the results on time.
- **Quality of the CCE data** - The time and cost incentive design and the laborious process involved in CCEs add further limitations as it introduces human bias and measurement errors. The quality of the reported CCE data is often challenged due to the limitations of not having met the volume, timeline, and collation of results as prescribed. Issues such as re-submission of CCE data also add to the poor data quality. Issues in the quality of data pushes the insurance industry to not accept the data as a reliable input for underwriting process.

Other bottlenecks in insurance industry

Historical yield plays a role in calculating threshold yield as it uses average yield data for last 7 years in the computation. In several cases, even with the CCE data being accepted for the season, the non-availability of previous yield data at the insurance unit level for the insured crop adds to lack of reliable data in calculating the threshold yield.

The State government makes the data on CCEs available to the insurance company for guiding the underwriting process. Apart from the data sharing, the insurance company is invited to have its representatives during the CCEs, adding to the trust in the process of collecting yield data. However, due to the large number of CCEs to be conducted, the insurance companies do not have sufficient manpower to be able to deploy in all CCEs.

Since the State is in control of the entire CCE process, the CCE data may also be subject to manipulation under political pressure. For instance, getting lower yield declared during CCEs can appease the farming communities within a particular region and thereby generate vote banks for upcoming elections. The insurance companies need to be able to challenge the results produced via the CCE process for a particular risk zone to ensure that they are not being subject to losses due to artificial scenarios supported with false or inaccurate data. It is important to note that the reverse may also be true, where the insurance industry increases its profits by getting the CCE data to be intentionally suppressed to show higher average yields. This further highlights the need to have an extremely transparent, robust and auditable structures and processes from the perspective of all stakeholders in the agriculture value chain.

The bottlenecks created in the entire process of data collection, collation, dissemination, acceptance for the present season and the availability of reliable data for previous years add to the inertia in calculating the indemnity payments and eventually lead to delays that can be between six to twelve months. These bear an effect into the future credit available for the small and marginal farmers. Banks refuse sanctioning of loans for upcoming cropping seasons without receiving the full repayment of already sanctioned credit.

Bhiwani case study - Potential of satellite big data analytics

Although we did rationalize our sample selection of Bhiwani district to address our research objectives, we formally introduce the Bhiwani case study in this section to explain the micro level characteristics and issues prevalent in the district by taking the example of Cotton as the crop under consideration. We further highlight the relevance and need for satellite big data analytics for addressing the challenges of crop insurance.

Cotton is one of the major crops grown in Bhiwani district of the Haryana state with rice and bajra (pearl millet) being the other major crops [52]. One of the characteristics of cotton is that farmers are able to harvest (pick) the crop in multiple time windows (e.g. picking twice in a 4-week period) during the same harvest season. In 2016, better prices and farming practices had led to a good crop, prompting farmers in the cotton belt of Haryana (of which Bhiwani is a part) to shift to cotton farming. However, cotton yield was reported lower than expected for the Kharif season of 2017. But there were no reasons reported in the media for the lower cotton yield, unlike in the adjacent district Sirsa, where whitefly attack was stated as a reason for bad crop condition [53] during the same time.

In the present case, out of the 890 CCEs conducted in the district of Bhiwani, only 274 were co-witnessed by the representatives of the insurance companies. Sceptical of the reports of lower crop yield, the insurance company wanted to triangulate the claims made using the data reported via the CCEs. As per the Pradhan Mantri Fasal Bima Yojana (PMFBY) operational guidelines, insurance companies administering crop insurance to farmers under this scheme can use satellite remote sensing derived indices such as the NDVI and Normalized Difference Wetness Index (NDWI) (a satellite derived indicator used to monitor changes in water content in vegetation) for estimating losses and settling claims. These indices can also be used for confirming crop yield data provided by the state government when the yield estimates reported at the insurance unit level are abnormal.

Satellite big data

Remote sensing technology provides an unbiased vision of large areas and is widely used in assessment and forecasting of crop yield on a regional basis. Satellite images allows the accumulation of valuable information for the determination of relationships with ground truth data by using spectral characteristics of the fields and expected harvest. In this case, the satellite big data is leveraged to determine the extent of crop damage, approximate crop area and yield to validate the authenticity of CCEs conducted for cotton crop for Bhiwani district in Haryana for 2017's Kharif (monsoon) season.

Temporal satellite imagery data of 2016 and 2017 over Bhiwani district is used for comparative analysis and to determine the extent of damage and authenticity of the CCE data. On the basis of Sentinel 2B and Landsat-8 satellite imagery[2] for June to November of 2016-2017, time-series NDVI and NDWI for Kharif season are used to estimate the acreage of sown area for cotton crop. The satellite data is used to derive the NDVI and NDWI based indices for the region in question. The results from the analytics help by providing an independent estimate of the acreage and the health of the cotton crop. The government reported village wise CCE-based crop data for 2016 and 2017 and the corresponding satellite

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[2] Sentinel-2B and Landsat 8 are European and American optical mapping satellites carrying high-resolution multispectral cameras that provide open access to imagery for agriculture and forestry, among others allowing for prediction of crop yields and health.

data derived estimates can then be compared to derive conclusions for the decision on insurance claims settlement.

Satellite big data analytics

The satellite imagery is procured based on the Region of Interest (ROI) and time of interest. The process begins by geometric error correction in the procured imagery. Geometric error is distortion in the satellite imagery due to the satellite orbit parameters. Post this process, radiometric correction of the imagery is performed to remove the noise by considering various factors such as incident sunlight, terrain reflectance and atmospheric attenuation. Post the completion of basic image processing of geometric and radiometric correction, the imagery of the ROI is extracted from single or multiple images by clipping parts at different swaths and creating a mosaic of the ROI images. To create a time series analysis, **t**he images of ROI at different times are stacked together to one single image. At this point in time, the analytics process is ready to be kicked off starting with the application of an agriculture mask to extract only the agricultural region from the ROI. From the extracted agricultural region, the specific crop region is extracted by using the crop's spectral and temporal features. Depending on the geographic boundaries of interest, the ROI crop classification image is broken down based on the vector shapefiles of villages to perform a village wise crop health assessment.

Validating the estimation of crop acreage accuracy via the satellite big data processing algorithms is an important step to gain confidence in the correlation between the statistical estimation performed over remotely sensed satellite data and the ground truth. The firm developing the algorithms achieved this by conducting a series of independent boundary measurement and then comparing them with the estimates of the acreage obtained from the trained algorithms for the crop. In the case of Bhiwani, the accuracy of algorithms in estimating the acreage was found to be 88%. Similarly, the crop yield estimations are assessed via the satellite big data and the accuracy of the yield estimates is verified by using a software-based model which is trained by conducting a series of CCEs. These algorithm validation steps are witnessed by independent experts from the sector to have no internal bias by the firm. Satellite big data also has the potential to estimate the crop yield [54] and thereby is capable of complementing or replacing the CCEs [55]. In the case of Bhiwani, the satellite data is used to estimate the total crop acreage and the health of the crop. Satellite data based yield estimates were not utilized in the case of Bhiwani since an agreement on the crop acreage and the crop health between the parties involved precede an agreement on the total. In Figure 1, we present a pictorial comparison of the data collection journey from the legacy solution to the satellite-driven digitised solution while highlighting the challenges in the data collation and data collection process and the outcome of the digitised solution.

Legacy Solution

Data Collection: a) Crop Cutting Experiment (CCEs) are conducted in randomised locations are used to manually weight yield by removing crops in a 5m X 5m patch; b) 4 CCEs per crop at the insurable unit level (230,000 such unit's representative of total villages) at a cost of $16 (Rs. 1000) per CCE needs to be conducted.

Data Collation: Historical data for 7 years needed to calculate threshold yield as it uses average yield data.

Challenges

Data Collection: a) High cost of conducting CCEs; b) Manual and labour-intensive process; c) Time window to conduct tens of thousands of CCEs is very small hence requiring trained human resources in a short time span is difficult; d) Human Bias and Measurement errors; e) Co-observers are needed to ensure reliability of CCE's.

Data Collation: a) Data going back 7 years for the CCE locations used for the current season may not be available; b) Lack of historical data at insurance unit level for the insured crop adds to lack of reliable data in calculating the threshold yield.

Digitized Solution

Data Collection: a) Satellites collect data of an entire region where individual farms are segmented according to the ownership; b) Multiple satellites can be used to collect data from different satellite operators; c) Data from several satellites (such as Sentinel) are available for free.

Data Collation: Satellite data over the past 7 years for the region of interest can be procured from different satellite operators/sources to estimate the type of crop and the crop yield.

Outcome

Data Collection: a) Reduction of the cost of conducting CCEs; b) Increased reliability of the data as a result of removing manual labour; c) Improved quality of the estimates of the crop yield; d) Removal of human bias and ability to compare results from multiple data sources from different operators; e) No cost or low cost of access to satellite data.

Data Collation: a) Easier access to historical data for any farm location; b) Increased reliability of information on the crop; c) Higher trust due to independently verifiable nature of source with satellite data.

FIGURE 1: A COMPARISON OF LEGACY VS SATELLITE-BASED DIGITALISED SOLUTION FOR AGRI-INSURANCE

RESULTS AND DISCUSSION

We discuss the outcomes of digitalisation of decision-making leveraging satellite big data analytics on the basis of addressing the bottlenecks in the working with the legacy process of CCE-based administration as well as using the results to potentially streamline the operational aspects of the decision-making processes for the crop insurance claims. We do this by comparing the results on the basis of using the CCE-based data reported for the Bhiwani district using the legacy process as well as through the satellite big data analytics found evidence.

Contention 1: Removing the underlying data vulnerability

It is important to acknowledge the bottlenecks caused by the vulnerability of the data by the legacy processes in the crop insurance claims settlement lifecycle. The large number of CCEs to be conducted sets a limitation on the insurance companies to have co-observers deployed at all CCEs. This gap in co-witnessing data collection is a bottleneck in the ability of the insurer to trust the data set in its entirety. The current process of estimating the actual yield (estimate of the realized average crop yield in an insurance unit) is based on CCE data. However, the conduction, collection and collation of the CCE data is done by the agricultural department of the state government while the final yield estimate calculations are done by the planning department. We believe that adopting democratized data sources such as satellite big data can leapfrog the challenges in trust issues in the process as well in reporting the dataset.

The reported datasets for the Bhiwani district itself provide evidence such challenges. In the case of Bhiwani, errors were found in translation of the CCE data into actual yield estimates when the data from the two departments of the government were put together to test for correlation. By simply plotting the locational coordinates provided by the State reveal that 22 out of 890 CCEs used in the determination of the average yield fall outside the Bhiwani district boundary. These create an anomaly in the eventual declaration of actual yield for the blocks that consider these locational coordinates. Based on the findings presented in Figure 1, the insurer can challenge the government authorities for a re-calculation of average yield for the contested villages where the invalid data points were used in the yield calculation. However, it also provides the basis for the insurer to use the CCE data from the blocks that are unaffected by the invalid data points to carry them through further in the underwriting process.

The variation in village-wise actual yield (as estimated by the planning department) and CCE yield (as produced by agriculture department) is plotted in Figure 2 as a histogram with the CCE data points being considered only if there were three cotton pickings during harvest completed at one site. It was found that the cotton yield in 114 villages out of 435 villages have reported CCE based village-wise cotton yield greater than the average yield provided by the government for claim settlement. This observed difference on the translation of the CCE data into actual yield projects a low correlation between the two datasets, raising questions about the authenticity of the calculations of the actual yield based on the CCE data by the government.

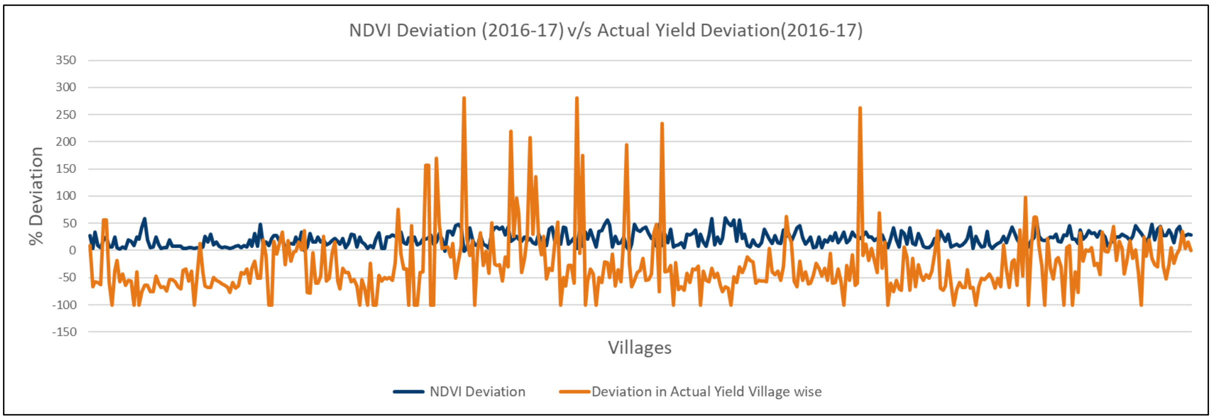


FIGURE 2 - VILLAGE-WISE TOTAL YIELD FROM CCE VS ACTUAL AVERAGE YIELD

Based on these results, the insurer can again challenge the government authorities for a re-calculation of average yield for the contested villages where the actual yield is lower than the CCE yield. However, it also provides the basis for the insurer to use the actual yield from the blocks that are unaffected by the data bias to carry them through further in the underwriting process.

Given that the data from the satellites is both independent and democratized in terms of access, the usage of satellite data as a basis to render decisions can create trust between the stakeholders. There may be adoption concerns on completely replacing the established legacy processes. A practical middle ground may be using a combination of both CCE and satellite big data sources to create a litmus test to the data collected within the legacy process. This can increase the moral and ethical barriers in reporting the underlying data which holds the administrators accountable within the landscape current operations.

Contention 2: Capturing errors within the legacy dataset acting as basis for underwriting

The premise of the 'area-based approach' being that the conditions at farm level as well as weather at a given localized area being very similar, the results expected in capturing the average yield in this approach should translate to yields that have low deviations (~<10%) between adjacent areas/blocks. However, the actual yield data in the case of several adjacent villages in Bhiwani is not indicative of this.

The deviation between adjacent villages in actual yield (Figure 3) is found to be between 1-30% for 52 villages and 30-60% for18 villages. The satellite big data based assessment reveals that drastic change in crop condition happened between 2nd October, 2017 and 22th October, 2017, which may be indicative of the first and second pickings around these dates. It was found that 346 of the 435 villages saw a change in intensity of crop condition by 30% or lesser (Figure 4).

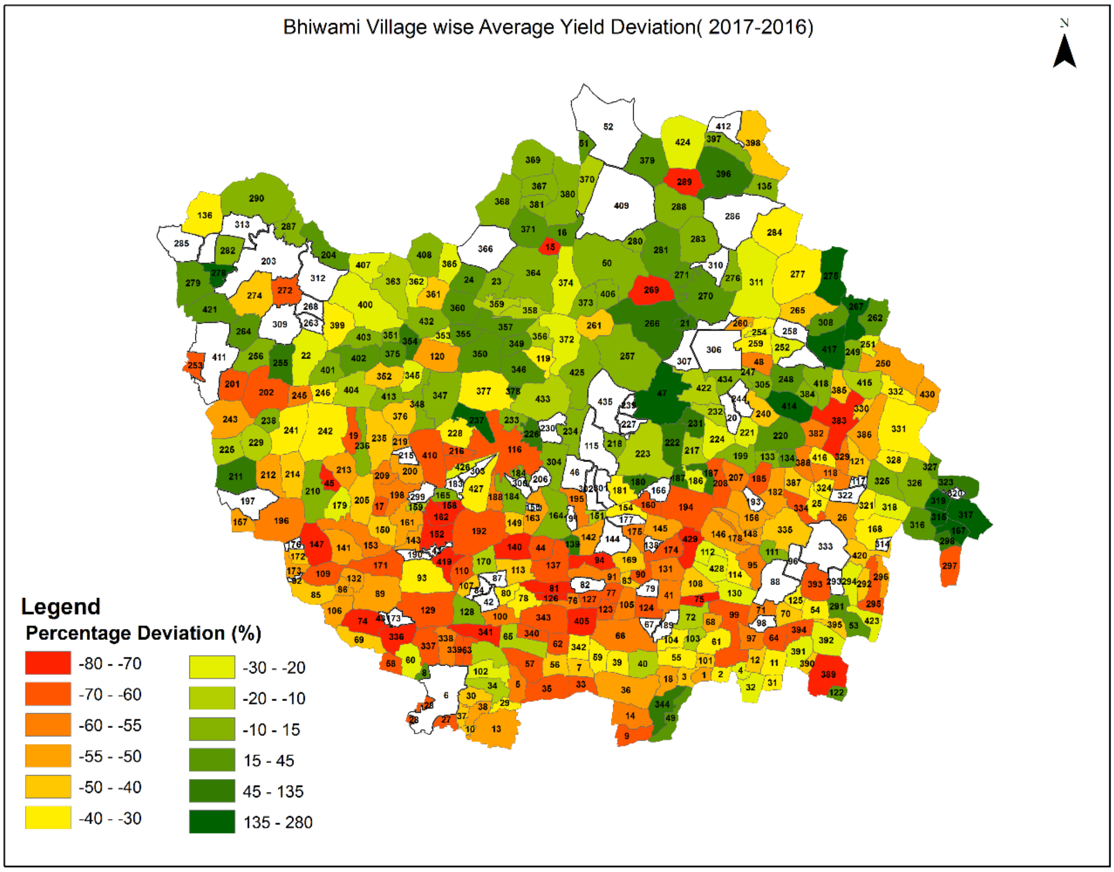
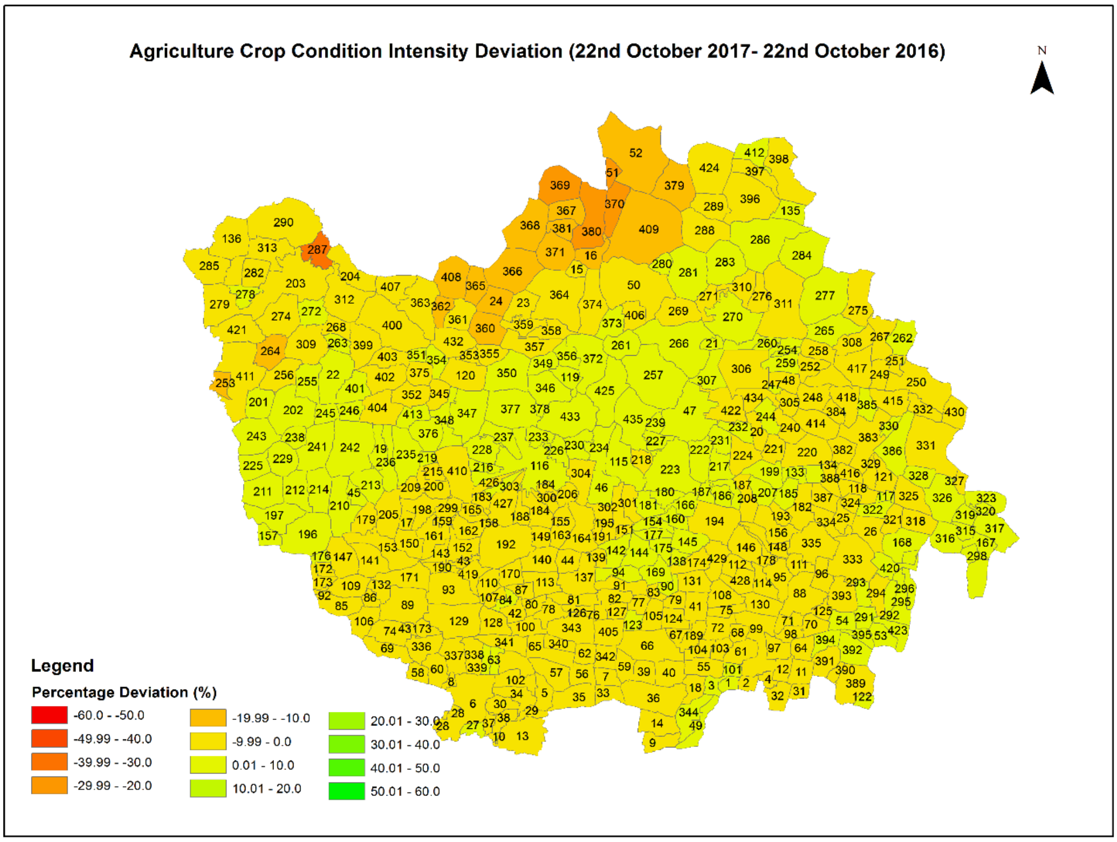


FIGURE 3 - YIELD DEVIATIONS IN ADJACENT VILLAGES



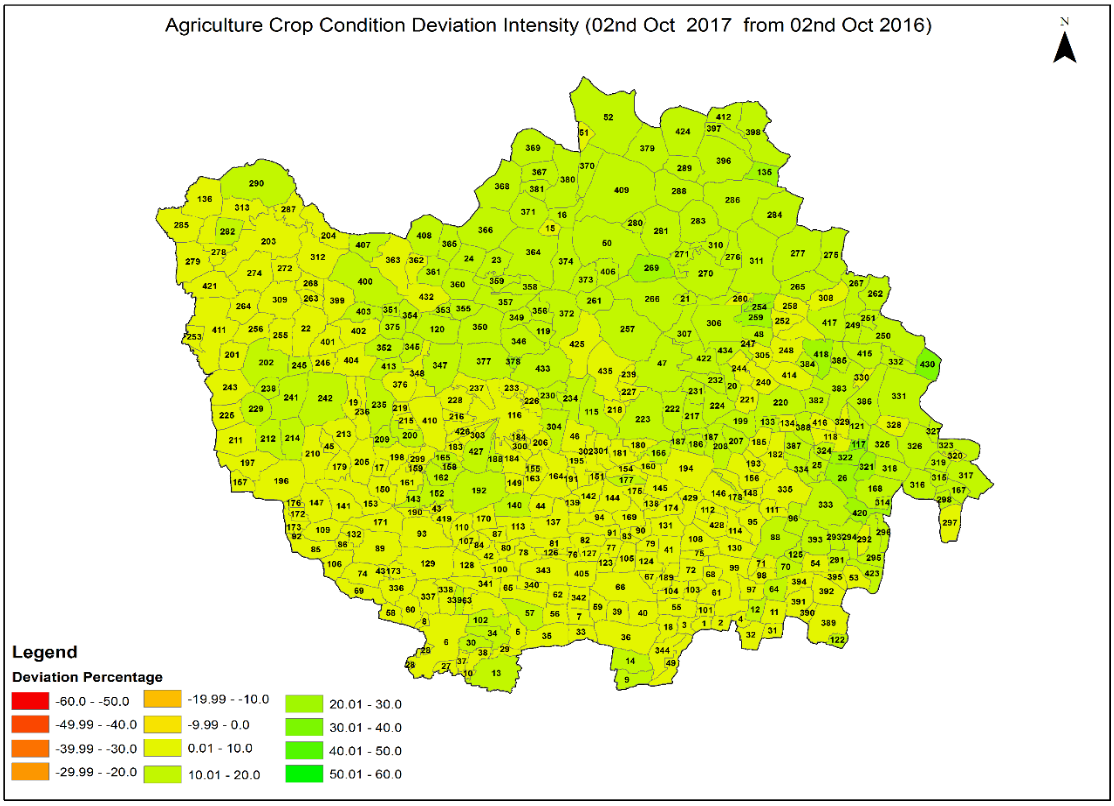


FIGURE 4 - COMPARISON OF CROP YIELD BETWEEN 2-22, OCTOBER, 2017

Adjacent villages in Bhiwani district have very high deviation (from positive to negative) as per the government cotton yield data, raising questions about its validity. Given the premise of area-based approach of yields to be similar among adjacent blocks, the large deviations in actual yields between adjacent villages brings the timing of the CCEs into the limelight since cotton being a crop that can be harvested over multiple pickings. The results from this analysis provides the grounds for the insurer to challenge the government data based on the time series analysis of yield against the timeline of CCEs being conducted to estimate the actual yields.

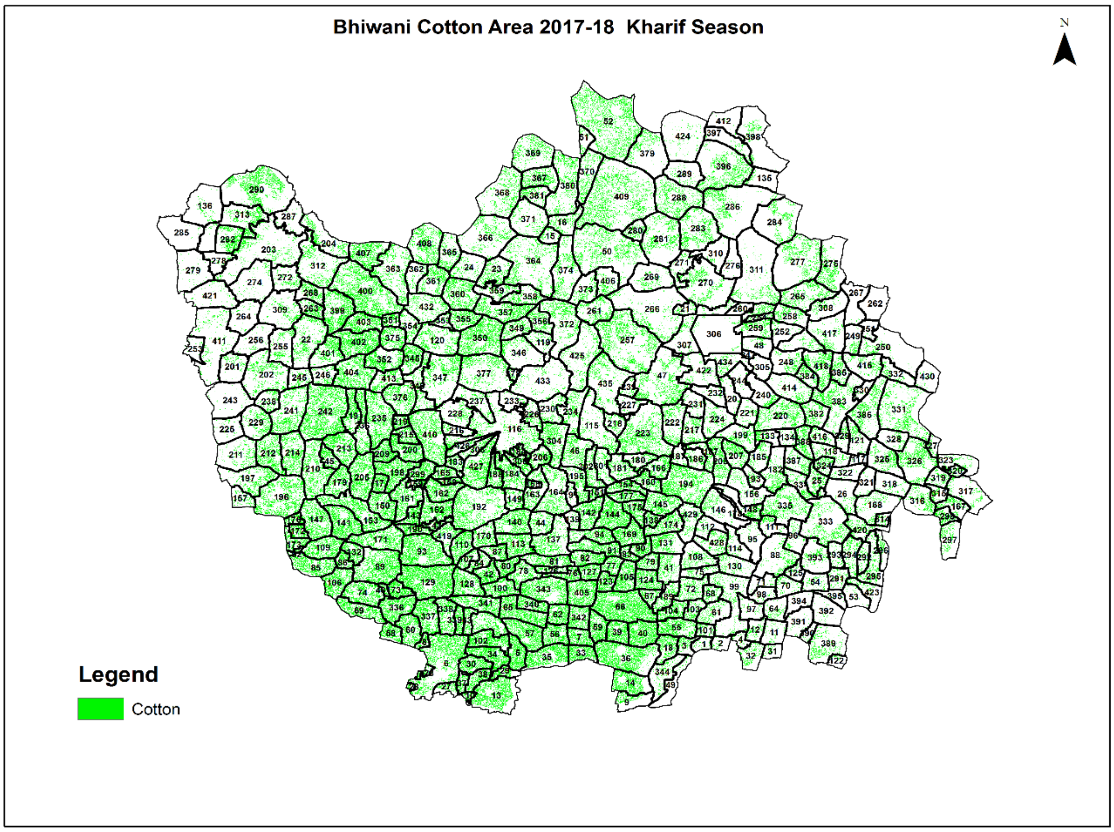
Contention 3: Estimation of cotton crop acreage

Given the culture of mixed-farming (multi-cropping) by small and marginal farmers in India, one of the important sources of information needed in the underwriting process is the total acreage of the insured crop. With the current process of determining the total crop acreage being based on land-based physical surveys conducted by the government, the insurer either has to invest into co-observing the survey or simply depend on data provided to them on total acreage. Estimation of the total crop acreage by creating an independent source of information for the insurer to be able to contest any large deviations in the declared crop acreage is an opportunity to bridge the gap in trust.

Figure 5 shows cotton crop acreage for 2016 and 2017 based on the crop classification and village-wise estimation produced post the processing performed on satellite imagery. Table 2 provides the cotton acreage for 2016 and 2017 comparing the data provided by the government against that produced by satellite analytics. For the year 2016 and 2017, difference in the cotton crop acreage figures (with the government claiming higher crop acreage) stands at 21.3% and 18.3% correspondingly.

TABLE 2 – TOTAL DISPUTED LAND ACREAGE FOR 2016 AND 2017

Year	Government Acreage (Ha)	Satellite Analytics Acreage (Ha)	Dispute (Ha)	Dispute (%)
2016	87,600	68,969	-14,750	-21.3
2017	1,13,900	93,039	-20,861	-18.3



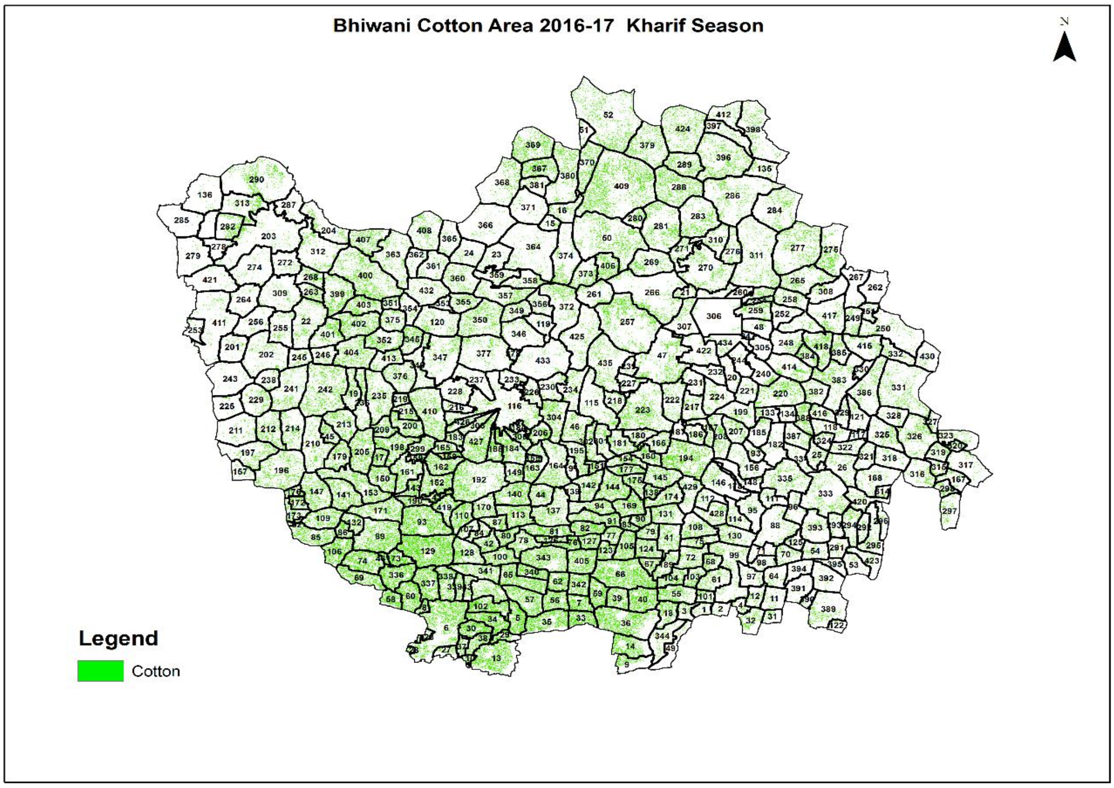


FIGURE 5 - VALIDATION OF COTTON ACREAGE WITHIN THE AREA OF INTEREST

Since the deviation in results are high, a block level acreage comparison is performed (Table 3) to closely evaluate the difference between the two datasets. The block level data highlights that except in some blocks (Tosham, Badhra, Dadri-1, and Kairu), the deviations between the results generated from satellite analytics estimated acreage and government's acreage data is much higher. These ambiguity in area estimates implies that the insurance industry can challenge the government to possibly reconsider cotton sown area data. At the same time, it offers the opportunity to the insurer to fast-track the underwriting process for the blocks where the deviation is below acceptable margins. Further, within the disputed blocks of larger deviations, the insurer can conduct the underwriting process in two stages. The first stage involves carrying out underwriting process for the claims that can use the satellite data-based crop acreage estimation and based on the settlement reached between the insurer and the government. The second stage can involve clearing the underwriting process for the disputed acreage. These steps shall ultimately benefit the farm community in reducing the processing claims and providing timely relief.

TABLE 3 - BLOCK-WISE DISPUTED LAND ACREAGE FOR 2016 AND 2017

Block	2016		2017	
	Satellite Analytics Acreage (Ha)	Dispute (%)	Satellite Analytics Acreage (Ha)	Dispute (%)
Loharu	12,000	1%	13,700	-26%
Bhiwani	7,700	-49%	9,100	-37%
Tosham	6,200	-25%	11,600	-1%
Bhiwani Khera	5,800	-52%	6,200	-52%
Dadri-I (Bond Kalan)	4,400	-21%	6,200	9%
Dadri-II (Dadri)	5,000	11%	6,700	31%
Badhra	13,500	2%	17,000	1%
Siwani	3,800	-24%	6,300	-19%
Kairu	4,300	0%	6,000	7%
Behal	5,900	-24%	10,000	-34%
Total	**68,900**	**-21%**	**93,000**	**-18%**

Contention 4: Estimation of cotton crop yield

CCEs as a single source of data is a bottleneck in estimating the average yield of crop and with the data mainly generated by the government's own representative. The drawbacks of the insurer not having enough resources to co-observe all CCEs affects the reliability of the data and forms the basis of contention over the estimates of average crop yield.

The government data for cotton yield for Kharif 2016 showed significant drop considering the output for the following year of 2017. There can be several reasons for the drop-in output such as lack of rains, irrigation issues, pests, etc. In order to understand the reason for the estimated lower yield for 2016, a comparative analysis of crop intensity using time series NDVI maps is conducted. 2016 and 2017 planting to harvest is compared to analyse the change in crop condition and output yield within various blocks of the Bhiwani district.

In order to identify the reason for the change in crop vigour and deviations in yield of cotton crop, soil moisture time-series data (generated by combining thermal satellite image data with local weather parameters) was analysed at the village level along with local precipitation data and demarcation data of irrigated and non-irrigated cotton growing areas. This is performed to identify the condition of supply of water (continuous irrigation or any drastic reduction in water content in the soil) and to avoid false inclusions.

Utilizing the wetness profile at the village level plotted for the years 2016 and 2017, the change in intensity of the wetness profile reveals noticeable changes. This information is then corroborated with the rainfall information for both the years, as provided by the government. Although unusually high rainfall was recorded in 2017, as against the same month in the year 2016, the crop wetness condition deviation in was very low. Hence the impact of rains on the actual yield of cotton in Bhiwani was ruled out.

The average NDVI values when compared between the year’s 2016 and 2017 (Figure 6) corroborates the deterioration of crop condition in 2016. However, there is a significant deviation between the government reported data of crop yield and the data from the satellite analytics. The results showed that government reported data projected lower yield figures. These deviations were spotted through statistical linear relationship between NDVI and CCE data. This forms the basis to check possible reasons for the anomaly in the underlying data by finding a correlation of the data at the village level. The number of villages with negative deviation in actual yield data of 2016 and 2017 is found to be 131 of the 435 villages which have deviation of more than 50%. The variation in NDVI (crop condition indicator) and actual average cotton yield as determined via the CCEs across all villages was analysed. There was no correlation found between these two datasets as should be expected, potentially due to incorrect reporting of actual cotton yield.

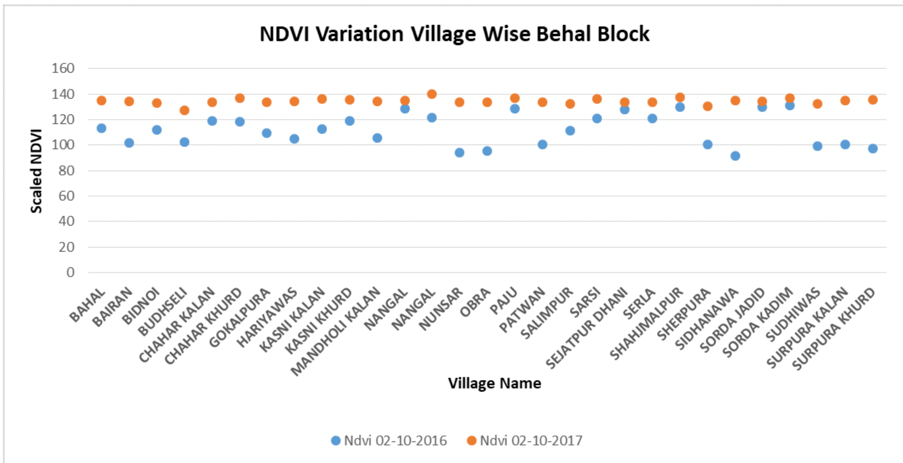


FIGURE 6 - VARIATION IN CROP YIELD BETWEEN 2016 AND 2017

Digitalisation based on integration of better information in supply chains enable responsiveness [56]. Digitalisation of decision-making using satellite big data analytics provide the insurer the ability to overcome the challenges in determining the factors causing damages instead of simply relying on crop surveys, media reports or simple weather-based reporting. The localization to the individual farm level through satellite big data allows the insurer to make a case for not only accurately determining the plausible source of crop damage and therefore lower yield, but also in estimating the extent of damage at the localized farm level. This provides the impetus for the insurer to fast-track claims independently in areas that have deviations to acceptable ceiling in crop yield against the government provided data and negotiate with the government for the datasets where the deviations are large towards a settlement. Economic influence and growth is an identified pillar for sustainable production in agriculture supply chains [57]. The usage of satellite big data analytics provides the foundation to providing economic equity to small and marginal famers. The use of satellite big data analytics to drive decision making adds richness to case study literature within digitalisation since the study itself is purely based on real-life setting. From the perspective of studying the deployment of technologies that are beneficial to farmers in developing countries, researchers often look at technologies that farmers can directly use by themselves and can benefit from development these technologies can help for their farm lands [58]. Our study shows there is tremendous scope to have a large-scale deployment of satellite big data analytics to support operations that can directly transfer socio-economic benefits to small and marginal farmers.

Discussion

The case study of Bhiwani provides insights into the real-world application of digitalisation of decision-making using satellite big data analytics be leveraged to improve decision making in insurance claims settlement operations. Through the case study, we provide an insight into the real-world integration of novel technologies in knowledge creation and dissemination which ties into the operations of the stakeholders supporting small and marginal farmers. The case study provides concrete evidence of how disparate data in the big data context can be brought together to provide informed decision making and allows plausible integration of big data analytics into the interrelated nature of institutions and business entities' supporting processes in agriculture value chain. The case study showcases how satellite big data based analytics provides the grounds for the insurers in developing countries to conduct an independent assessment into the total acreage of the crop as well as the total yield of the crop which act as the two main parameters that are a factor in calculating the indemnity payments. The bottleneck created by the lack of trust in the data provided to the insurers on acreage and yields for conducting the underwriting process has the potential to be resolved via negotiations between the parties, paving the way to claims settlement to the affected farm communities. Digitalisation using satellite big data analytics provides one such approach using which we have demonstrated the utility of data-driven practice for the purposes of estimation of cotton crop acreage and changes in crop yield within the crop insurance context. This paper gives an important foundation from the perspective of GSC too. Our findings provide evidence that GSC such as the one explained in this paper can be systematically addressed through satellite big data analytics and provides motivation for similar projects in the agricultural sector concerning losses in the food supply chain.

There is immense scope for the greater integration of data-driven avenues to be integrated into agriculture supply chains in emerging markets. For instance, the satellite big data analytics approach would work best for countries such as India where 85% of agricultural land holdings is less than 2 hectares. In other words, where farm size is small, satellite imagery analytics could be very effective. Further, in areas where farm size is large, there is immense potential of satellite imagery big data combined with other technology such as drones etc for effective precision driven farming and surveillance in the agriculture sector. Hence, policy agents may rely on this solution approach as an effective tool and scale up initiatives across different parts of India irrespective of the farm size. With India gaining success in satellite missions in recent past, the viability of scaling up such operations and using complimentary technology seems positive. Similar arguments hold true for emerging nations especially countries in the Asian sub-continent who can imitate such approaches by deploying satellite imagery technology.

RESEARCH IMPLICATIONS

The case study discussed in the paper can spark interest adoption of digitalisation in both horizontally (within the space of agri-financial services) and vertically (extension to other parts of agriculture value chain). Within the landscape of agri-financial services, the osmosis of the satellite big data analytics into banking and insurance practices provides the opportunity to create interlinkages between the two sectors to facilitate transparency and efficiency in the entire lifecycle of the use of agri-financial services by farmers. Exploration of such seamless information sharing between the credit supply side and the downstream risk management side of the agriculture markets in developing countries can reduce the volatility in markets, provide a more transparent basis for agronomy policy making, encourage greater private sector and foreign investment. There is also scope to integrate satellite big data into supply chain design strategies to improve coordination across the value chain [59].

Similarly, longitudinal studies of crop health and yield enabled by satellite big data is not only of interest to policy makers or agri-financial services sector, but also to the trading and supply chain markets. There is clearly scope for utilization of satellite big data analytics as an integral part of decision technologies in agribusiness problems including agro-econometric forecasting, crop planning, procurement, and vendor price/risk assessment [60]. The analytics based insights on performance of crops also have potential for integration into improving risk management models [61].

We believe our research context presents an important contribution to the discussion on tackling GSC through management research [67]. Our findings support the argument that through coordinated and collaborative effort from different stakeholders involved in the supply chain, GSC can be addressed to a great extent. In our case, we find our technology partners can address the issues of critical stakeholders, i.e., insurance providers, in the supply chain.

Further, our paper builds on the understanding of constructive technology assessment [71] by focusing on the modulation dimension of technological assessment. Further it highlights the role of societal impact [68] in terms of providing opportunity for higher income for farmers. It supports the overarching goal of social robustness of technology by addressing grand societal challenges in developing nations [67]. Also, it documents the strong impact of satellite imagery in creating big data for onward analysis through different analytical techniques [69].

Practice implications

The present work showcases how the use of satellite big data analytics in agri-financial institutions supporting cultivation by small and marginal farmers in developing countries can be a part of the basket of tools which can drive dynamic capabilities in the upstream of agriculture. From a practice perspective, the study provides evidence of the maturity of the technology, scalability of it to large geographical areas. This should provide impetus for the government in India to conduct some independent pilots on the possibility of replacing CCEs and testing the deployment of satellite big data analytics for crop yield and health assessment at the federal level.

The results of the case of Bhiwani provide several key evidences for the agri-insurance providers to contest the basis of the data provided by the government. One of the major outcomes from an operations perspective of the insurers is the ability to overcome the bottleneck to have physical presence of personnel to witness CCEs. Satellite big data analytics affords them to have a combination of both personnel (where available) and an analytics-driven solution to arrive at decisions based on first-hand evidence. The findings reported using satellite big data as an independent source of information provide the insurers to fast-track claims settlement where the deviation of yield against the CCE yield data is not significant and at the same time try to take a two-stage approach to settling claims in villages where further negotiations on the basis of the data needs to be carried out.

Policy implications

The case study provides evidence of the value created for stakeholders supporting the agriculture supply chain by integrating independent streams of data and providing a digitalisation-driven solution for efficient decision making. There is tremendous scope for policy makers to employ such analytics-driven solutions through pilot projects and scale successful solutions to address other agronomy problems within the supply chain. Proactive employment of technology-driven effective policy making for agronomy problems holds the potential to address the accelerated need to adapt to climate change [62]. Ultimately such solutions improve the management of risks associated with increasing climate change and its effect on farmers and food systems.

One such example within the Indian agronomy policy making context is the transition towards using individual-based approach to crop insurance from an area-based approach. The

Government of India has so far used 'area-based approach' for crop insurance owing to the higher administration costs involved in individual ex-ante assessment of risk as well as ex-post assessment of loss for estimating individual premium and disbursal of claim payment [63]. Satellite data analytics has the potential to be the centrepiece of the key enabling technologies to transition from area-based approach to individual-based approach in crop insurance. Adoption of individual-based approach can help provide tailored redressal solutions to individual farms and their tillers against the current practice of clubbing several farmers and their holdings. The greater transparency created through the process can provide the foundation for improved administrative decision making (e.g., expansion of the scope of crops being covered in crop insurance schemes). The spill overs moving to individual basis may lead to other positive externalities such as increased participation by the private sector in rural agriculture, creating tighter credit supply side linkages, and contributing to better forecasting models for food security.

Societal implications

Satellite big data analytics allows addressing the needy farmers by delineating the decision making for settlement of claims submitted through a verifiable and scalable model. The transparency brought in by the satellite big data curbs the plausible exploitation of claims filing and settlement for political gains and holds great potential for improved ethicality of the decisions made to approve (or not approve) the insurance claims.

Access to microcredit has been effective in providing better access to agriculture inputs, adoption of modernization, improved farm/nonfarm linkages leading to smoothening risk for small and marginal farmers and increasing farm incomes [64]. However, most of the microfinance schemes fail due to lack of screening capabilities of unproductive borrowers [65]. Research has highlighted the need for interlinkage between credit contracts and index insurance in low collateral environments as a necessity to internalize the positive externality that insurance affords on the lender's portfolio [66]. Therefore, the circling back of the satellite data analytics into the supply side of credit shall have positive implications for better decision making and risk management of the microcredit lending community. As a result, the expansion of microcredit has a direct impact on the expansion and coverage of crop insurance and can potentially contribute to increasing the overall pie within the crop insurance segment.

Limitations and future research

The case study that we have presented uses a single geography and a single incident to explore the research question. This comes as a methodological constraint that we have to accept to be able to set a reasonable set of boundary conditions for the case study. Within the scope of this paper, the digitalisation solution described may indeed have a bearing on the policymakers with the plausible adoption of satellite big data analytics to replace the traditional method of CCE. With the expected saving in cost, time and efficiency of rolling out such new technologies, the agri-economic effects into policy making due to the adoption of big data analytics shall be an interesting phenomenon to study. Given the potential for the fast-paced proliferation of the digitalisation described in the present work, there is immense potential for adoption of such analytics services by corporations in their supply chain intelligence. We believe there is scope to study the ethical aspects that may emerge from adoption of such digitalisation technologies by other potential users such as banks, corporations, investors, etc.

Acknowledgments

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