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Leveraging Remote Sensing Technologies to Address Incomplete Markets in Crop Insurance

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Abstract

In many agrarian economies, crop insurance schemes are the most prominent among government schemes meant to protect agriculture from the vagaries of nature. A market-based solution for insurance that transfers risks from farmers to insurers has been evasive despite decades of public sector encouragement and funding. The situation of low penetration and unprofitable insurers could be termed an 'incomplete market' and may be attributed to information asymmetry.

With technological advancements in agricultural monitoring and using large scale open-source data about biophysical variables, it has become possible to estimate crop yields and losses at a farm field level. By using objectively collected data from earth observation satellites and weather stations, such estimates can reduce the information asymmetry. We present a prototype of an integrated system that has shown promising results for wheat crop in north Indian plains. Obstacles related to ground (in-situ) data availability and model refinement are to be overcome before the solution is practically implemented. Concerted efforts towards this are warranted from governments, industry and academia to build tech-enabled actuarial models that correctly assess risks in local conditions.

Keywords

Agriculture, crop insurance, FinTech, incomplete markets, remote sensing, risk modelling.

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1. Introduction

Several jurisdictions across the world are seeing crop insurance as a remedy to agrarian distress that is expected to escalate with climate change. High cost of administering a crop insurance policy, given the geographic expanse involved and asymmetry of information between the farmer and the insurer, triggers the problems of adverse selection and moral hazard, eventually leading to market failure. State intervention in the form of subsidised premiums is a typical response in agriculture insurance. Despite receiving public funding for decades, crop insurance initiatives in countries as varied as Brazil, China, India, Spain, and the United States, have not been able to establish a functioning market. In India, the unenthusiastic response from farmers at 30% coverage nation-wide and withdrawal by insurers (Bera, 2019) points to an 'incomplete market'. We deliberate upon a possible disruption in the market through digital technologies suggested by Carter et al. (2017) and others. In the main body of the paper, we first review the situation in the markets for crop insurance, followed by the evolution of technology for agriculture monitoring. In the end, we discuss the prospects of a technology enabled solution in the Indian context.

Advances in remote sensing, data science and machine learning have made it possible to obtain near real time information about crop health in an objective way. Over the last decade, large scale open data initiatives have evolved for disseminating weather-data, satellite-data, and agricultural-data. With the advent of large scale open datasets, various regional as well as global initiatives have come up to monitor crops and to predict farm yields. Agencies around the world are making concerted efforts to collect and process information to estimate agricultural yields at an ever increasing scale.

Extending the crop condition monitoring to insurance applications involves an assessment of the shortfall in crop yields and determination of insurance premiums, where a consensus is emerging among diverse approaches (Ozaki et al., 2008; Zhu et al. 2011; Liu & Ker, 2021). The objectivity, speed and low-cost of these approaches offer an alternate business model with the potential to 'complete' the crop insurance market. Albeit, concerted efforts are warranted to build an ecosystem that could provide affordable insurance to risk-prone farmers, while also ensuring survival of insurers. In this paper, we present our effort using the context of north Indian wheat crop for rabi season.

A desirable solution, in our view, is a 'crop simulation model' that parameterises various stages of crop growth and explains variations in crop yield across time and across different units (farm fields or villages or districts). The proposed solution uses vegetation indices and weather data to obtain information about the history of crop losses, and the current

condition of crops. This remotely obtained information could subsequently be used for risk assessment as well as loss assessment. While the solution developed by us requires further calibration and testing in the real world to establish as a proof of concept, our exploratory studies of system dynamics indicate its potential to desist market failures.

Crop insurance markets have struggled even after decades of public funding, in our view, largely because of the information asymmetry between the farmers and the insurers. We believe that population-level data obtained objectively - with minimal human intervention -through technologies can bridge the asymmetry and help determine an actuarially fair insurance premium. Another reason why crop insurance has not taken off in India is the complexity of the product offered and the presence of basis risk inherent to index-based insurance. Farmers perceive indemnity form of insurance as a more reliable and equitable system, as the payouts are directly linked to their on-field losses. Digital technologies can provide the product features of an indemnity insurance, at a cost, efficiency and speed of an index insurance; thereby ensuring a balance of survival of insurers and affordable product availability to farmers.

A cost-benefit analysis of the digital technologies ecosystem for crop insurance will determine whether the change will be regretted, implying a non-remediable (second-degree) path dependence (Liebowitz & Margolis, 1995), or accepted implying a remediable (third-degree) one. Our direct experience about actuarial models involving digital technologies, as well as the enthusiasm in the community (Murthy et al., 2022b; Carter et al., 2016) are indicative of possible efficiency gains and make a case for a remediable path dependence. This paradigm shift could bring about a societal transformation by unshackling farmers from debt traps, by curbing the use of fertilisers or chemical pesticides and by releasing actuarial sciences from an elite capture.

2. Crop Insurance

2.1 Background

World over, the agriculture sector struggles against a range of manmade and natural factors, such as market volatility, supply chain issues, policy ambiguity and climate change, which is particularly alarming as documented by Lobell et al. (2011) and Olesen et al. (2011). Given the increase in the frequency of climate variability, a range of solutions to address the risks, such as resilient varieties of crops, better farm management, advanced warning systems, agro-advisories, soil conservation, water conservation, etc., have been introduced with varying degrees of success.

In recent years, crop insurance has emerged as an alternative to protect the farmer against crop losses or low yields. This financial instrument safeguards farmers against potential losses in exchange for payment of regular premiums. The introduction of crop insurance can be seen to liberate the farmers from the vicious cycle of debts formed due to exorbitant interest rates charged by informal money lenders. Further, crop insurance transfers risk to the insurance company and the government, thereby encouraging the farmers to adopt technology-driven modern farming methods. Researchers like Li et al. (2022) and Mao et al. (2023) have discovered that the benefits of crop insurance were not only confined to the farmers, but they also helped the environment when farmers reduced the use of agrochemicals and pesticides.

Several insurance schemes have evolved in different agricultural economies around the world. In the United States (U.S. Department of Agriculture, n.d.), the federal crop insurance was established during the 1930s to mitigate yield losses resulting from various natural phenomena. It is the biggest item of the budget of the Department of Agriculture after nutritional supplements. Brazil implemented agricultural insurance products and direct income compensation programs aimed at mitigating fluctuations in farmers' income. These schemes include the Government Premium Subsidies Program for Agricultural Insurance catering to commercial farmers, PROAGRO (Programme of Guarantee of Agricultural Activities) designed for small and medium-sized farmers, the Garantia Safra Program which serves as a Public Sector Pseudo-insurance scheme targeting small-scale farmers, and Bolsa Estiagem specifically tailored for small-sized farmers excluded from the Garantia Safra program (The World Bank, n.d.). In Spain, the framework of agricultural insurance is developed by a collaborative effort between public and private entities. Agroseguro is a public limited company that assumes responsibility for overseeing agricultural insurance operations on behalf of insurance firms affiliated with the co-insurance pool (Burgaz, 2010). In India, the first initiative towards the implementation of crop insurance was taken in the 1970s. Mukherjee and Pal (2017) provide a summary of the evolution of the crop insurance programme in India. At present, two schemes are operating under the ambit of the government, namely Weather Based Crop Insurance Scheme (WBCIS) and Pradhan Mantri Fasal Bima Yojana (PMFBY).

2.2 Index-based Contracts and Indemnity Contracts in Crop Insurance

Two predominant crop insurance models, namely index-based and indemnity have emerged in mitigating agricultural risks. Contract designing of both types has been discussed extensively by Carter et al. (2017). According to them, index-based crop insurance relies on predefined indices, such as weather parameters or yield averages over an area, to determine compensation for losses applicable to all covered farmers in that area. Thus, index insurance

does not compensate policyholders for their actual losses, but for the realisations of the index. On the other hand, indemnity insurance compensates farmers based on the actual losses they have incurred, assessed through field inspections and other suitable methods. The studies conducted by McIntosh et al. (2019) highlight the existence of a trust deficit in index-based insurance, primarily due to perceived inaccuracies in index calculations and consequent dissatisfaction with compensation outcomes. In this regard, Clarke (2016) emphasises various factors contributing to the trust deficit associated with index-based insurance, such as lack of transparency, basis risk, and limited opportunities for customization available to the farmer. In the Indian context, Cole et al. (2013) contend that comprehending an index insurance product presents an even greater challenge to the buying farmer due to the presence of basis risk, resulting in a weak probabilistic connection between the insurance index and individual payouts. Furthermore, Mahul (2000) indicates that desirable risk pooling cannot be achieved in index insurance, and as a result, the systematic risk cannot be diversified. Thus, index-based insurance contracts suffer from a few drawbacks, even though they benefit from an objective measurement of risks and payouts. In the words of Carter et al. (2017), "Indexation eliminates a key element of trust in insurance companies by not necessitating the evaluation of damages by the provider to make payments, which often leads to conflict with indemnity insurance" .

Shirsath et al. (2019) emphasises the importance of farmer satisfaction in driving the adoption of insurance products and underscores the need for scientifically validated weather triggers to enhance the credibility of index-based crop insurance schemes. This emphasis on credibility and validation resonates with the concept of indemnity-based insurance which focuses on actual losses and individualised assessments. Indemnity-based insurance, as highlighted by Kramer et al. (2022), focuses on bridging the trust deficit in the insurance landscape. Due to the challenges faced by index insurance, farmers perceive indemnity as a more reliable and equitable system, as the payouts are directly linked to their specific circumstances and losses. Ghosh et al. (2021) studied the inclinations of farmers toward alternate crop insurance schemes through the implementation of a discrete choice experiment in four different states within India, highlighting the importance of proper loss assessment. To address challenges in loss assessment and a speedy settlement of claims, Carter et al. (2016) suggested employing digital technologies to enhance crop monitoring and yield prediction, thereby enabling insurers to offer products that align with indemnity insurance when estimating losses in large-scale farms. While, by establishing a correlation between meteorological factors and agricultural damages, Hott and Regner (2021) proposed the possibility of utilising a mixture of both types of insurance for intermediate usage. The literature appears to be at a crossroads between the use of innovative digital technologies for indemnity insurance and advancements in index-based insurance. It is our opinion that a

shift towards indemnity insurance with robust technology has the potential to improve the demand for crop insurance by reducing basis risk and thereby winning the trust of farmers.

2.3 Experiences with Crop Insurance

Kramer et al. (2022) review the experience with crop insurance in the developing world, and indicate that many categories of farmers are excluded from the market and affordability is a concern. In China, Ye et al. (2020) find that the area yield insurance is cheaper than farm level insurance (akin to indemnity), yet, it takes greater subsidy to encourage farmers. Mukherjee and Pal (2017) analyse the Indian experience with crop insurance to highlight a dismal record of claims settlement and slow penetration of crop insurance, especially among non-loanee farmers and small and marginal farmers.

Sinha (2004), for instance, attributed the adverse selection and moral hazard characterised by high claims to premium ratio to the uniform premium rates and to the lenders who stand to benefit from payouts. Over time, as the claims experience accumulates, the insurers are expected to be able to price the policies better. However, in India, imperfect market conditions have resulted in an adverse claims ratio, sometimes as high as 165%, that has forced insurance companies to exit (Bera, 2019). The author also reported that the current method of yield measurement through Crop Cutting Experiment (CCE) is flawed and involves subjectivity. According to a study by the implementation agency (Pradhan Mantri Fasal Bima Yojana, 2021), there is a bias in the crop yield estimate through CCEs, creating an artificial risk for the insurer. Insurance companies respond by keeping a cushion - known as loading in the actuarial world - against this underestimation, which results in a higher than adequate premium rate.

Despite massive subsidies, the offtake for insurance products has been dreary at less than half of agriculture sector production, and only 16% in China (Kimura et al., 2022), 20% in India (PMFBY, 2024) and 28% in the United States (Kimura et al., 2022), leaving a large majority exposed to the increasing risks from natural disasters. On the supply side, insurance companies sometimes choose to cede territories (USDA, 2024), or exit the market (Bera, 2019); implying that the risk-return tradeoff is untenable for them. This is indicative of an ‘incomplete market’ where the buyers, sellers and the government are unable to reach an equilibrium, despite the imperative to address this issue crucial to livelihoods and food security.

2.4 Incompleteness of Insurance Markets

The quest for a suitable mechanism for mitigating the myriad risks in agricultural crops has been met with challenges discussed in the preceding paragraphs. The leading cause behind the challenges faced by this sector is the pricing of insurance, i.e. setting the insurance

premium. A high price discourages the farmers from taking insurance, whereas a low price could result in insolvency of the insurer. The situation falls in the category of 'incomplete' markets for insurance. According to Stiglitz and Rosengard (2015), private markets often fail to provide coverage for certain risks, even though the actuarially fair cost of providing such coverage is lower than individuals' willingness to pay. A response to this market incompleteness has been observed in the form of government intervention, such as the provision of crop insurance to farmers. Subsidy programs serve as signals of the government's commitment to promoting insurance purchases. These subsidies play a crucial role in enhancing the insurance market by expanding coverage and mitigating the effects of market incompleteness.

Consiglio and Giovanni (2008) have identified several sources of market incompleteness, including administrative challenges, non-tradability of insurance products, inadequate risk assessments, information asymmetry, and market frictions like transaction costs and operational constraints. According to Kesseler (2008), market incompleteness arises due to adverse selection and moral hazard, which cause the insurance supply and demand curves to intersect in the wrong quadrant. Kesseler suggests that innovative schemes should be developed to address these challenges by fostering collaboration between private players and the government. However, Kesseler also warns about the government intervention while addressing market failure, may reduce the market premiums to levels where actuarially correct pricing becomes infeasible for insurers. Experience with government sponsored schemes in the United States, Brazil, Spain, India and elsewhere shows that subsidies have persisted in the market for crop insurance for decades. It leads to wonder whether crop insurance can ever achieve a market-based transfer of risks, or must a welfare state bear the subsidies perpetually. This quandary led us on our quest for a solution to the incompleteness of risk markets using recent advancements in digital technologies.

3. Can Technology 'Complete' the Markets ?

A congruence of factors is emerging on the crop insurance landscape that could disrupt the agriculture sector in the next decade or so. On one hand, the technologies are rapidly evolving in areas of remote sensing, computer science and crop modelling. On the other hand, societies, institutions, market players and governments are realising the importance of building resilient communities in the wake of climate change, and are prioritising various initiatives on this front, thereby creating a virtuous cycle. In this section, we first summarise the emerging technologies in agriculture, followed by a few noteworthy initiatives being nurtured at different institutions.

3.1 Emerging Technologies in Agriculture Monitoring

In recent years, technology is advancing by leaps and bounds in the agriculture sector. There exist a number of studies focusing on innovations that have been termed inter alia remote monitoring, AgriTech, and precision agriculture. These studies cover a wide range of technologies for example, the use of real-time remote sensing data, thermal and hyperspectral remote sensing, drones in agriculture, Internet of things, mobile-based 'smart' agriculture, etc.

Among these, thermal remote sensing is a promising technology for precision agriculture because it provides a quick measurement of crop stressors before visible symptoms arise. Khanal et al. (2017) emphasised the application of thermal remote sensing in precision agriculture in crop disease diagnosis, mapping soil parameters, drought monitoring, and irrigation scheduling. They also addressed issues with using thermal remote sensing, including air conditions, crop growth stages, and spatial and temporal resolution. Continued efforts have been put into developing and improving remote sensing for agricultural use. Segarra et al. (2020) gave an example of such efforts in their work focused on the improved features and application of Sentinel-2 in precision agriculture. They suggested the combined use of field data and remote sensing data for better crop monitoring. Another piece of remote sensing equipment contributing to the agriculture sector is drones, which are also called Unmanned Aerial Vehicles (UAVs). Rejeb et al. (2022) provided a review of the utility of drones in agriculture and a compilation of use cases. Garcia et al. (2020), highlighted the growing application of drones in precision agriculture and proposed the use of drones to collect information from various agricultural nodes to bring down the cost.

In the domain of remote sensing, earth observation (EO) satellites have been the principal contributor to enabling agriculture from a research and policy making angle. Observations made through satellite sensors in the visible light, infrared spectrum and radio waves have been used for identifying land usage, crop sown and crop health; and developing geographic information system (GIS) based solutions. These observations are typically converted into indices for vegetation conditions, such as Normalised Difference Vegetation Index (NDVI), Leaf Area Index (LAI) and Enhanced Vegetation Index (EVI). This approach has found its way into application areas of economic analyses, national accounts, forecasting, and agriculture policy.

Efficacy of various indices and measures is actively debated in remote sensing literature. Ke et al. (2016) provided an overview of the use of hyperspectral data; however, the study also highlighted the "curse of dimensionality" or our ignorance about which hyperspectral bands are appropriate for vegetation monitoring applications. Another study by Fang et al.

(2019) stated that the LAI retrieval method can be improved through the use of better input information, a canopy model, and retrieval algorithms. On the other hand, NDVI gets saturated easily in areas with high chlorophyll and additionally, it also corrects for the error in reflected light. Therefore, in order to overcome such issues NASA brought forward EVI. These indices can be used individually or combined depending on the scope of the study. For, instance, Murthy et al. (2022a) developed a Crop Health Factor (CHF) using the NDVI, LSWI, Backscatter, and FAPAR for analysing the crop health of paddy

3.2 Institutional Capacity

There are various regional as well as global initiatives utilising the available technology. The Global Agriculture Monitoring (Global Land Analysis and Discovery, n.d.) is a collaborative project by NASA, University of Maryland, and the USDA Foreign Agriculture Service to provide data on crop conditions and data analysis tools. Anomaly Hotspots of Agricultural Production (ASAP), was launched in 2017 by the Joint Research Centre of the European Commission. It is a web-based decision support system with the objective of prevention of food security crises and response planning anticipation. Fritz et al. (2019) highlighted that the primary added benefit of the ASAP system is that it converts accessible meteorological and EO data into brief warning signals that are helpful to decision-makers without requiring a background in geospatial data analysis. It automatically produces alerts about possible issues with agricultural and rangeland output internationally, starting at the first sub-national level. To validate these "hotspots" of possible issues with food security for about 80 countries at high risk of food insecurity, the second component of the system uses experts in agricultural monitoring; these assessments are updated regularly. World Food Programme is another entity that does seasonal and agricultural monitoring. Like the above systems and platforms, it also incorporates and uses weather and EO data. The programme focuses on the humanitarian factors affected by agricultural production. All these initiatives provide timely, accurate, and consensus data. China has also developed and taken steps towards the direction of agricultural monitoring. CropWatch is an agricultural monitoring system in China started in the year 1998 by the Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences. The CropWatch follows a hierarchical approach for crop production monitoring at different scales and also provides an online bulletin on its website about the crop condition of seven regional agro-ecological zones, national levels, and global levels. The bulletin report also covers estimates of the major crops important from the perspective of import and export. Back home, Space Applications Centre Ahmedabad is developing a platform for crop monitoring under the Visualisation of Earth Observation Data and Archival System.

Thus, agencies around the world are making concerted efforts to collect and process information at an ever increasing scale. GEOGLAM is an example of the calibration of technology for agriculture monitoring at global, national, and regional levels. Around the globe, various programmes contribute data and information to it, for instance, Chinese crop monitoring systems CropWatch and ASAP share their data to GEOGLAM. These initiatives showcase the potential of technologies in the modern day agriculture ecosystem, markets and policy. Although most of the technologies are used in crop monitoring, precision agriculture, process control and farm management; their sanguine reassuring experience makes them amenable for adoption in insurance.

3.3 Modelling Crop Yield

International development organisations, institutions of repute, and universities have developed several models of varying sophistications to estimate the yield from agricultural crops, such as World Food Studies (WOFOST), Crop Environment Resource Synthesis (CERES), Agricultural Production Systems Simulator (APSIM), and Decision Support System for Agro-Technology Transfer (DSSAT).

WOFOST is a mechanistic crop growth model that may be customized to generate crop-specific estimations, as described by Huang et al. (2019). Zhuo et al. (2022) devised a data assimilation strategy to integrate the LAI into the WOFOST model. Assimilating LAI into the WOFOST model significantly improved the accuracy of regional wheat yield predictions. DSSAT is a software application programme that includes crop simulation models for over 42 distinct crops. To replicate the outcomes of crop management over multiple years, the DSSAT process involves integrating crop models with datasets pertaining to soil, crops, and weather. The CERES wheat model, as stated by Arora et al. (2007), Jiang et al. (2014), and Jin et al. (2016), is a widely used model that is incorporated into the DSSAT model. While these models have reached an acceptable performance, they can be customised as per the need and improved further. To enhance outcomes, these renowned models in the agriculture domain can be integrated with satellite data and machine learning algorithms.

3.4 Decision Algorithms

Advancements in agronomy have improved our understanding of the optimal values of biophysical variables. With an increase in the number of sensors scanning for changes in biophysical variables, decision making by farmers is now guided by data and algorithms. Automation in farm fields is relying increasingly on pre-programmed logic and shifting towards autonomous systems that require minimal intervention from humans. On a macro

scale, agricultural, economic and weather statistics (for instance Ministry of Finance, 2022) are also based on computerised models built using big data rather than traditional statistical procedures.

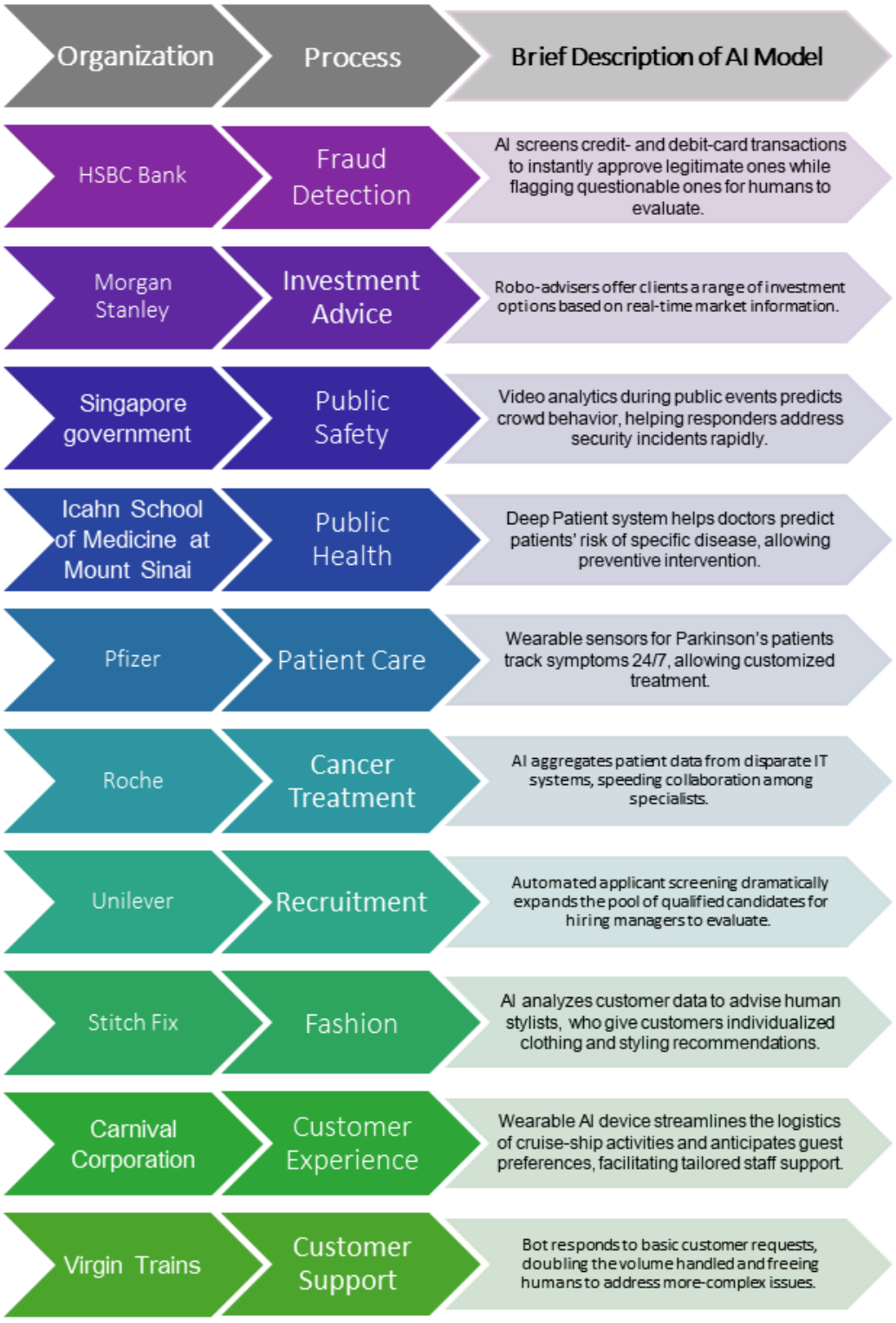
In the crop monitoring field in India, there is a visible thrust towards use of tech-enabled methods. The 'Yield Estimation System based on Technology' (YES-TECH) promoted by the PMFBY recommends five alternate approaches for estimating crop yields. Four of these approaches rely on building a statistical or machine learning (or a combination thereof) model using explanatory variables such as temperature, soil moisture, NDVI, crop management practices and other biophysical parameters. Effectively, the claims settlement process hinges on the back-end algorithm developed for the estimation of yields. All the proposed approaches as well as the existing method of CCEs end up in an area index[1] that is used to determine the loss claims in that area. A basis risk referred in Sections 2.2 and 2.3 prevents a complete indemnification of a farmer and could increase the trust deficit. Furthermore, the validity of any of the approaches is questionable until they pass the test of a real life application. Murthy et al. (2022b) is among the few studies that advocates the use of technology and documents the experiment with Jute crop in West Bengal state. They propose CHF, which is also an approach under YES-TECH, albeit acknowledging it to be a less than perfect metric.

Algorithms and AI models are replacing decision making not only in the insurance sector but also in other walks of life. Some of the prominent examples include anomaly (fraud) detection in financial transactions, expert systems for diagnosis in healthcare, chat-bots based on language models and other examples given in Figure 1. Albeit, there is a "need to train AI agents, explain their outputs, and make sure they are used responsibly" according to Wilson and Daugherty (2018).

[1] The scheme documentation uses the term 'area yield' estimated and indemnity, however, the scheme character is that of an index-based contract. Claims payouts are based on average yield estimated for the administrative unit using CCEs, or YES-TECH.

Figure 1 : Applications of AI Models in Different Sectors

Source : Adopted from Wilson and Daugherty (2018)



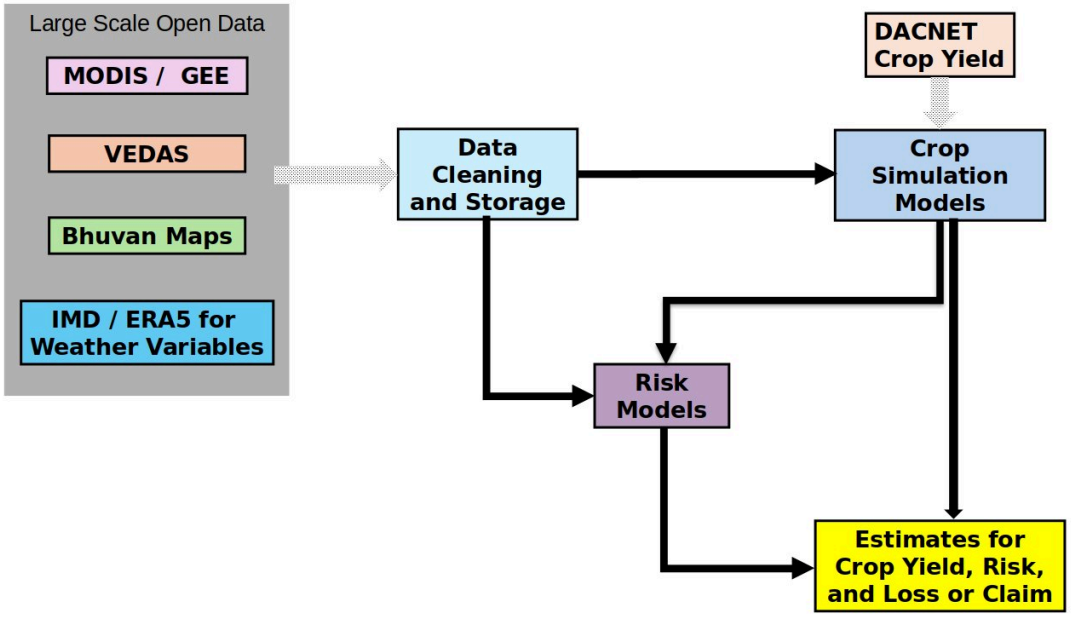
We conclude this section by noting that the crop insurance market is on the cusp of an upheaval with these changes in the political and technological environment. In the next section, we present a possible solution based on our assessment of the state-of-the-art.

4. Applying Technologies to Indemnity Based Contracts

4.1 Overview

With the advent of remote sensing, data science and machine learning, it has now become possible to obtain universal and near real time information about crop health in an objective way. A variety of approaches are available to assess the shortfall in crop yields and consensus about their applicability is emerging. Based on our understanding presented in the preceding sections, a desirable solution is a 'crop simulation model' that parameterises various stages of crop growth and explains variations in yield across time and across different units. The proposed solution (Cf. Figure 2) will use remote monitoring technologies to obtain information about the history of crop losses, and the current condition of crops. This information could subsequently be used for risk assessment as well as loss assessment. We see the solution to be comprised of two parts - a model to estimate crop yield and a model to estimate risks. The model to estimate crop yield uses physically observable input variables, and requires calibration for each crop and each agroclimatic zone. The crop model thus developed comes handy for loss assessment, as well as for building a risk model in the second part of our solution. The risk model applies simulation techniques to characterise variables of interest, and conduct risk assessment. While both models are far from perfection, the concept is reasonably mature for adoption in indemnity insurance. In the subsequent paragraphs, we discuss the technology readiness for their application in the context of the Indian crop insurance programme.

Figure 2 : A Schematic Diagram of the Proposed Technology Solution



4.2 Crop Yield Model

To anchor the tech-enabled solution, we take the Indian context because of our familiarity with the agricultural and socio-economic scenario. We choose wheat crop for the relative homogeneity in its crop management across the Indian geography. Unavailability of high resolution crop masks that specify the crop type growing in each field exposes us to the issues of correctly identifying the area of cultivation. To address this issue, we select only those administrative districts where 90 percent or greater area cultivates wheat during the winter cropping season, also known as Rabi season. Twenty-eight such districts from the two states of northern India are considered as study units. These districts fall in two agro-climatic zones of India a) Upper Gangetic Plains, and b) Trans Gangetic Plains.

To estimate crop yields accurately and consistently, we explored a range of regressors such as solar radiation, length of day, temperature from sowing to anthesis (T1), temperature during grain-filling (T2), sowing date, and NDVI along with its variants. A generic crop yield model may be written as a classical linear normal regression model given by equation (1).

$$y_{it} = \alpha + \beta X_{it} + \gamma t + \varepsilon_{it} \quad \ldots (1)$$

where X_{it} represents input regressors for district i and year t, β is the vector of regression coefficients, coefficient γ captures the long-term trend in agricultural productivity ($\gamma \geq 0$), and ε is the error term.

Among all the candidate regressors for equation (1) like radiation, temperatures, vegetation indices and their offshoots; two regressors offer the simplest and most elegant explanation of variation in our data. The first regressor is the maximum NDVI observed during the season, which is indicative of the maximum vegetation health achieved by the crop and happens to coincide with the grain-filling stage of the wheat crop. The second regressor, PermaNDVI, is the average NDVI observed after harvest that indicates the extent of permanent vegetation such as trees, other crops, grasslands, etc.

For these two regressors, the empirical estimations are robust to a reasonable level as seen from Table 1. The values and signs of the coefficients are consistent with earlier studies and current knowledge base. Evidently, wheat crop yield improves with time indicating yearly productivity improvements of 0.05 tonnes per hectare over the last two decades. The yield is also high for units with higher MaxNDVI and with lower PermaNDVI, i.e. with greater crop biomass. The explanatory power of the model is over 60 percent, which improves to 85 percent if location specific fixed effects are included, both of which are comparable to earlier studies reported with a similar (sub-national) scale. In the current article, we report results without the location specific fixed effects for simplicity. We also established the robustness of our model for out-of-sample prediction accuracy and conducted Chow's prediction failure test before proceeding further. The reported regression model provides the best fit among all regressors attempted and is free from collinearity issues.

Table 1 : Empirical Estimation of Crop Yield

	Coefficient	Std Error	t-statistic	p value
Intercept	2.1306	0.455	4.681	0.000
Year	0.0495	0.005	10.631	0.000
MaxNDVI	3.4184	0.561	6.096	0.000
PermaNDVI	-6.0194	0.499	-12.063	0.000
R^2: 0.612		**Adj R^2:0.609**		**RMSE = 10.7%**
F-statistic: 166.5		**p value = 0.000**		

4.3 Modelling Crop Risks

While crop yield models have undergone significant advancements over time and reached a level of maturity described in Section 3.3, the same cannot be said about risk models. The overarching concern in risk modelling is to derive crop yield distribution which entails a characterization of the risk using the probability of occurrence. Numerous studies have proposed alternative approaches to estimate the probability distribution, but a conclusion

has evaded the community. The debate typically focuses on the suitability of a given distribution function in parametric form, or a distribution estimated through non-parametric methods. Turvey and Zhao (1999) compared parametric distributions and non-parametric distribution to describe the best crop yield distribution. Most recently spatial analysis has been incorporated in estimating yield distribution as weather and pest infestations systematically affect neighbouring regions. Goodwin and Piggott (2009) examined the spatio-temporal characteristics of extreme events, and showed the strength of correlation between yields of neighbours. Here, a problem arises because high correlation diminishes the diversification in the pooling of insurance contracts. With this in mind, in Ozaki's (2008) study, the parameters of the variogram were estimated using the spherical correlation function, which incorporated an average distance at which correlation begins to diminish.

To accurately calculate the risk, BMA (Bayesian Model Averaging) deals with model uncertainty by borrowing additional information from other domains. In BMA, our inference is averaged over all the models in the set of candidate models considered using weights that are derived from Bayes' theorem (Ker et al. 2016). Liu and Ramsey (2023) introduce additional information on weather for conditional distribution by Bayesian methodology through an analytical simulation model and multivariate normal distribution, and find gain relative to other approaches. Further, Vidal (2014) uses the Bayesian analysis of Gumbel distribution to model the maximum intensity of annual rainfall in different geographical regions. Insurance is primarily interested in lower tail probabilities hence the detection of higher moments is of great concern for the efficiency of crop insurance programmes (Zhu et al. 2011).

A synthesis of these diverse approaches to model crop risks can bring about a resilient and adaptive future for agricultural risk management.

4.4 Challenges to Implementation in India

The review of experiences in model building across geographies and domains builds a case for a prototype development in the Indian context. We have attempted to develop a proof of concept for wheat crop in northern states of India with encouraging results and potential viability. Based on our attempt, we foresee several challenges and governance requirements which will determine the adoption of remote sensing in crop insurance.

One of the biggest challenges faced by us in this endeavour was the availability of fine-scale data from farm fields about not only the agricultural productivity, but also the farming practices and even crop or crops sown. The official statistics are collected in India through a sample of at least 24 CCEs in each district, stratified by 2 blocks/tehsils and 2 villages.

Official statistic thus obtained at district level is available (DACNET, n.d.), but the constituent data at village and field level is not made public, or even maintained by state agriculture or statistical departments. Some researchers (Milesi & Kukunuri, 2022) have used the fine scale data from their own CCEs, while other studies have been based on data from experimental fields in agricultural universities. Complete dataset collected through millions of CCEs conducted in India every year can do wonders to improve our understanding of risks with village or field level granularity.

Secondly, Indian skies are cloudy during most days of the main cropping season, limiting the quality of data collected through satellites. UAVs are seen as an alternative, not just to the satellites that get obscured by cloud cover, but also to ground data for identification of crop types and farm management practices. The cost of acquiring this information is indeed cheaper than a ground based measurement. However, the scalability of a UAV based solution remains a challenge because of issues such as shortage of trained manpower and the small window available for data collection during a phenological stage.

A third challenge is the ecosystem for adoption of technology and overall readiness of the market. Implementing a multidisciplinary solution would require specialist inputs from several domains. A system integrator, such as the PMFBY, or the Agriculture Insurance Company of India, must depend on providers of such specialist inputs in the domains of actuaries, agriculture, GIS, image acquisition, IoT, surveying and UAVs. However, notwithstanding the initiatives announced by the government in recent years, only a handful of such providers are available, commercially or otherwise.

Lastly, the challenge of knowing the unknowable future is a hallmark of the insurance industry. While great strides have been made in characterising risks and uncertainties faced by farmers, a broad acceptance of this approach will rest on rapid improvements to model performance. Utilising satellite-derived data in agricultural monitoring and statistical analysis has shown a glimmer of hope to building robust models. A convergence of transdisciplinary studies will pave the way towards solving one of the most important issues for this century, provided that algorithmic biases, data issues, and regulatory framework are addressed.

5. Conclusion

One of the predominant challenges of our times is to build resilient and sustainable communities in the wake of climate change. Coupled with food security, it decides the direction for the future of agriculture. Showing a commitment to the Sustainable Development Goals of the United Nations in these areas, governments across the world are

devoting considerable resources through countless initiatives to protect and nurture the agricultural sector. Crop insurance schemes appear prominently among these initiatives. In the short term, their objective is to protect farmers and the agricultural supply chain from distress by absorbing the risks. In the long run, subsidised crop insurance ought to create a self-sustaining market for risks where the transfer of risks from farmers to insurers is frictionless.

Crop insurance markets have struggled even after decades of public funding, in our view, largely because of the information asymmetry between the farmers and the insurers. We believe that population level data obtained objectively - with minimal human intervention - through technologies can bridge the asymmetry and help determine an actuarially fair insurance premium. A second reason why crop insurance has not taken off in India is the complexity of the product offered and the presence of basis risk inherent to index-based insurance. Farmers perceive indemnity form of insurance as a more reliable and equitable system, as the payouts are directly linked to their specific circumstances and losses. In this communication, we have presented remote monitoring technology and crop insurance programmes as possible mechanisms to overcome the trust issues impeding agriculture in India, and possibly in other parts of the world, particularly the global South.

Large scale open data initiatives for weather-data, satellite-data, and agricultural-data evolved over the last decade, such as European Centre for Medium-Range Weather Forecasts atmospheric Reanalysis version 5 (ERA5), European Data Cube, GeoGLAM, Google Earth Engine, United States Geological Survey, etc. have opened up new possibilities to combine additional sources of information economically and at a scale. We subscribe to the view taken by Carter et al. (2017) that remote sensing can be a remedy for the market imperfections in crop insurance by solving the issues related to data. Academic research and actuarial industry efforts should focus on the identification of correct dataset, explanatory variables and the methodology to assess risks. Literature is replete with alternate approaches to model risks and their drawbacks. Concerted efforts are warranted from governments, industry and academia to build tech-enabled actuarial models that correctly assess risks in local conditions. At present, these efforts are marred with constraints on institutional capacity and data quality that percolate to models. Nonetheless, such models can reduce the adverse selection and ‘complete’ the insurance market by providing affordable products to willing farmers and by ensuring survival of insurers at the same time.

Despite the progress made in satellite data and processing capabilities, the methods employed still fall short of providing nearly real-time, and dependable, information about crops. Large scale data obtained through a wide array of remote sensors carries biases and errors introduced at various stages of data acquisition, processing and correction. Some of the programmes intended to improve data quality, for instance, correction for atmospheric

disturbances, are known to introduce biases. Further, arguments cautioning 'algorithmic' approaches must be taken into account before technology can address the issues faced by the crop insurance sector.

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