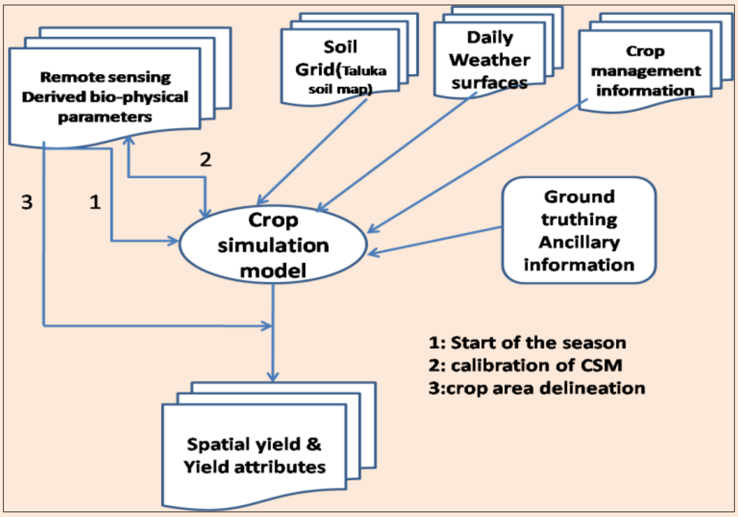
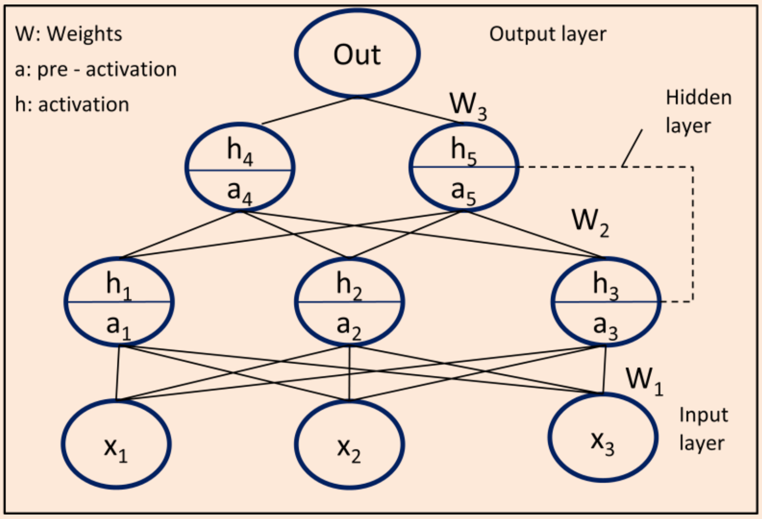
Technical Report

Replacing CCE-yield estimates with modeled-yield estimates for crop insurance





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15	**Abstract (with Keywords)**	Growing concern on the quality of the yield data of the Crop Cutting Experiments (CCEs) is limiting the effectiveness of crop insurance in the country. The need for improving the yield estimates using remote sensing and other technologies is well recognized and the research in this direction has gained momentum in recent years. This report documents the scope for replacing the current CCE-based yield estimates with model-based yield estimates for crop insurance. A quick review of the recently published research and the results of the studies carried-out by us formed basis for this report. It is observed that modeling crop yields at local scales such as Insurance Units is complex and is constrained by scarcity, scale and quality of input data related to weather, soil, crop variety, crop management etc. Therefore, more focused research is needed for replacing the current CCE-yield estimates with modeled yield estimates.			

Executive Summary

Growing concern on the quality of the yield data of the Crop Cutting Experiments (CCEs) is limiting the effectiveness of crop insurance in the country. The need for improving the yield estimates using remote sensing and other technologies is well recognized and the research in this direction has gained momentum in recent years.

This report documents the scope for generating and adopting the modeled-yield estimates in lieu of CCE-yield estimates in crop insurance by reviewing the recently published research and the results of our studies.

Road map for improving the crop yield data for insurance includes three strategies namely (1) Improve the current CCE process through smart sampling, (2) Reduce the CCE number through optimization techniques and (3) Replace the CCE-yields with modeled yields.

Smart sampling for selecting the existing fixed number of plots and use mobile technology for digital recording of the CCE process are now being followed in the country. These interventions have improved the quality of CCE data to certain extent, but not to the desired extent.

Studies on optimization of CCEs have demonstrated that the number of CCEs can be reduced by about 40-50% for major crops like paddy, wheat, rabi jowar etc. However, critical elements like sampling/model error and calibration of historic yield data limit its operational implementation.

The three widely adopted approaches for yield modeling are Semi-empirical, Crop Growth Simulation and Artificial Intelligence models.

Semi-empirical methods are based on bio-chemical process of plant – light absorption for photosynthesis, radiation use efficiency, stress factors, accumulated biomass and grain yield. These models are found to be performing well at regional scales for some of the crops. Availability of precise information on crop variety, planting and harvest date and derivation of water stress and temperature stress factors are critical elements in this methodology for local level application.

Crop growth models simulate the plant processes to estimate various bio-physical parameters and final crop yield. All these models are best designed for point based application. These models need intensive parameterization such as genetic coefficients of crop varieties, crop sowing time, crop management practices – fertilizer applications, irrigation supplies, pest/disease occurrence, local weather parameters etc. These data intensive models tend to perform poorly when applied in spatial perspective covering IUs/Blocks/Taluks.

Artificial Intelligence (AI) has become popular in solving the non-linear relationships between the variables particularly in the bio-physical framework involving crop yield estimation. AI includes Machine Learning (ML) and Deep Learning (DL) models. In recent years, AI models have gained momentum for crop yield estimation. Critical issues in these models are feature

selection, optimization of model parameters, consistency of results, scale etc. These models are also data intensive, if the estimates are targeted at local scales.

The key challenges with yield modeling methodologies that impact the indemnity assessment and basis risk in crop insurance are (a) generation of modeled yield estimates for the past years, (b) consistency of model errors and control on such errors and (c) ability to parameterize all the crop risks that occur during crop's life cycle. These models use bio-physical variables such as soil moisture, LAI, APAR etc which are currently available at much coarser resolutions. Downscaling of these variables to finer scales is associated with uncertainties, affecting the accuracies of the models.

Magnitude and direction of model errors in the yield estimates of past and current years are very critical in determining the indemnity values for claims settlement and minimizing the basis risk.

District/state level crop yield estimation using the above models is still not operational in the country even for principal crops, due to various limitations. Crop yield estimation at local scales such as IUs, is more challenging than that of district/state level, due to higher variability and lesser scope for parameterization. Similarly, yield estimation for non-cereal crops is more challenging than that of cereal crops, due to various reasons.

Therefore, more focused research is needed for replacing the current CCE-yield estimates with modeled yield estimates in crop insurance. Cereal crops may be targeted first and based on the outcome; such research for non-cereal crops may be initiated.

Till the methodology for generating modeled-yield estimates is ready, technology interventions to reduce dependence on the CCE-yield data can be explored by developing yield-proxy indicators at least for major crops.

In this direction, AICIL and NRSC developed and implemented an innovative index-based insurance scheme linking pay-outs to satellite based crop performance index rather than yield measurements. The scheme, first of its kind in the country, was successfully implemented in 2020-21 for different crops in West Bengal state. Such technology-driven index-insurance insurance schemes may trigger a paradigm shift in the crop insurance system benefitting all the stakeholders.

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1.0 Introduction

Globally, agriculture is exposed to multiple hazards leading to frequent crop losses. As a result, crop insurance has become an indispensable risk management tool in agriculture sector (Vermeulen et al., 2012). Better management of agricultural risks is one of the important strategies to address the current challenges of food security, income security and climate resiliency of Indian agriculture. Increasing crop risks coupled with low growth and outreach of crop insurance signify huge potential for crop insurance in India. A robust system of crop insurance is the need of the hour to reduce the impact of covariate risks in agriculture and promote innovations and investments in farming sector.

Agricultural risk sharing through crop insurance has been in existence in many counties, in many forms for many decades (Skees et al. 2005) but most of these products are being supported by huge subsidies from the Governments (Ibarra and Skees 2007). Highly subsidized agricultural insurance products have serious implications on the sustenance of crop insurance in the future (Atwood 1996, Barnet 2004, Mahul 2010). Therefore, the need for developing innovative crop insurance products that are actuarially stronger, has been largely recognized by both developed and developing nations in recent years (Anonymous 2014, Leblois and Quiron 2013).

India has a long history of implementing various crop insurance schemes with improvements from time to time, to insulate the farming community against various cultivation risks (Mishra 1996, Singh 2013). Traditional crop insurance was introduced in the country in the year 1965 followed by Comprehensive Crop insurance scheme (CCS) in 1980's and 1990's, weather based insurance schemes in 2003 and National Agricultural Crop Insurance Scheme (NAIS) in 2004 and Modified NAIS (MNAIS) in 2010 (Anonymous 2014). In the existing crop insurance schemes, estimation of loss and indemnity payment are decided by weather index or crop yield index over an area. NAIS and MNAIS, the most popular area-yield crop insurance schemes, have faced serious limitations – subjective crop yield measurements, inadequate coverage, accuracy and transparency (Anonymous 2014). As a result of these deficiencies, basis risk has increased and indemnity payments have consistently exceeded the premiums even in years of good weather conditions (Rao 2010, Anonymous 2014).

Pradhan Mantri Fasal Bima Yojana (PMFBY) being implemented in the country from kharif 2016, is an area-yield insurance contract that has many positive features to compensate for multiple risks during the entire life cycle of the crop season. Use of technologies viz. remote sensing, mobile and data analytics is mandatory for effective implementation of the scheme.

Despite bringing improved versions of crop insurance schemes from time to time, the biggest challenge in the crop insurance continues to be generation of accurate crop yield data in the insurance units (Anonymous 2014, Murthy 2018). Availability of reliable, current and historical crop yield data, particularly in developing countries poses a serious challenge for objective assessment of crop loss, pricing and indemnity payment in area-yield index schemes (Smith and Watts 2009). Limited number of yield measurements and subjectivity in measurements are serious limitations in the current system of Crop Cutting Experiments (CCEs). As a result, the estimated yield of an insurance unit tends to deviate from the true yield level leading to data disputes and delay in claims settlements.

Bias in the CCE-yield data is generally on the lower side as observed from various reports, news items and views of different stake holders. Such under-estimation of crop yields in the insurance units, has cascading effects on the entire chain of insurance. Yield data quality disputes delay the claims settlement process. Reduced yields attract higher payouts, reflecting higher risk and higher cost of insurance (premium rate) in subsequent years. Increased premiums are the result of artificial risk caused by biased yield. Thus, the purpose of crop insurance compensating for natural risks will be defeated once the data-induced artificial risk creeps in to the system.

Another impact of the biased data is that it reduces the threshold / guaranteed yield of the crop for an insurance unit which is based on the average of preceding 5-7 years yield in the insurance unit Therefore, the probability of experiencing less than the threshold yield (which is already on lower side due to past series of biased data) gets minimized gradually over a period of time. As a result, the insured farmers would be either not indemnified or partially indemnified despite facing crop losses. Consequently, the crop insurance contract will become a futile and pointless risk management instrument rather than risk reducing instrument, as the farmers may end-up paying the premiums without getting the compensation for crop loss in return.

Therefore, the current thrust area in crop insurance is development of technology interventions to improve the yield data and strengthen crop loss assessment system. This report documents the opportunities and challenges for improving the crop yield data for crop insurance. Emphasis is placed on the scope for replacing the current CCE-based yield estimates with modeled-yield estimates for crop risk assessment. This is done based on quick review of the recently published research papers and the results of the studies carried-out by us.

2. Strategies for improving the yield data

Technology interventions in the form of using satellite data and mobiles to improve crop yield estimation are largely recognized and promoted (Raju and Ramesh 2008, World Bank 2011, Anonymous 2014). Various limitations in the current system of crop yield estimation in the insurance units along with ways and means to improve the system by using satellite, mobile, GIS technologies and data analytics were well documented by Murthy et al. (2018).

Department of Agriculture, Cooperation and Farmers Welfare (DACFW), Ministry of Agriculture, Government of India has taken-up many initiatives to improve crop yield estimation procedure ever since the launch of PMFBY in 2016 (www.pmfby.gov.in). Bringing technologies in to crop yield estimation mechanism of PMFBY is one of the prime tasks being addressed by various agencies in the country. Realization of this goal is in progress through step-by-step implementation of new techniques in a phased manner. This is because the new techniques have to be tested for consistency of results and scalability.

Improving the crop yield estimation using technologies includes three major strategies

- Improve the current CCE process through smart sampling,
- Reduce CCE number through optimization techniques and
- Replace CCE through alternate methods.

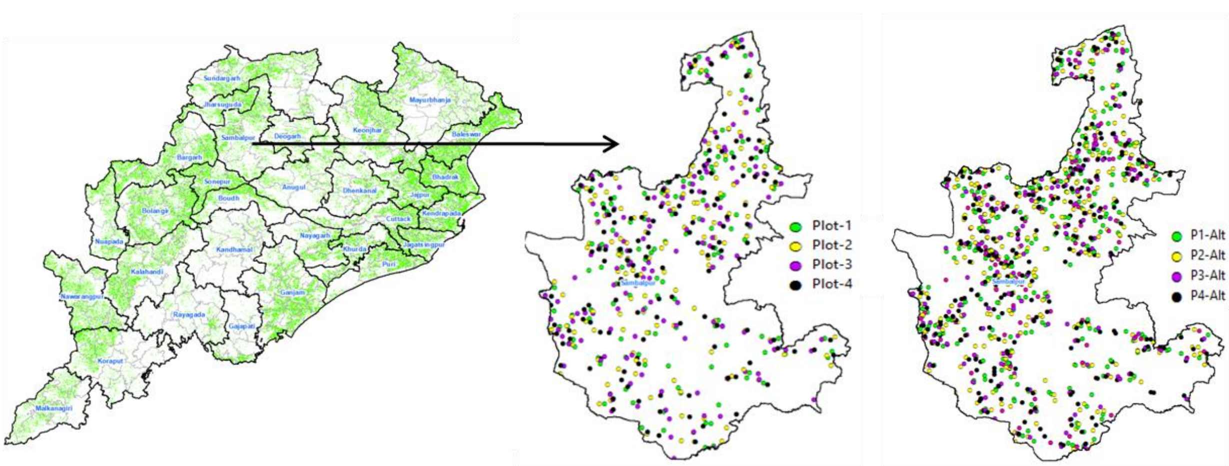
2.1 Improve the current CCE mechanism

The most ideal approach is to increase the number of CCE in each insurance unit and follow digital process for executing the crop cutting procedure. This will lead to statistically sound estimates with transparent process and objective measurements. Multiple factors – logistics, economics, time lines, trained man power etc. prohibit the implementation of this approach. Moreover, the historic yield data which were derived from limited CCE measurements and the current yield data based on increased-CCE measurements are not comparable. Calibration of historic yield data is a big challenge.

The second approach is adoption of smart sampling for selecting the existing fixed number of plots and use mobile technology for digital recording of the crop cutting process. CCE-fields selection (Fig.1) through satellite based smart sampling technique replacing the existing random number methodology, was first developed and implemented by NRSC (ISRO) and Department of Agriculture, Government of Odisha, in Odisha state in 2018-19 (Murthy et al. 2019). Subsequently, it is being up-scaled to many districts from 2019-20, by MNCFC at the initiative of DACFW, Ministry of Agriculture and Farmers Welfare, Government of India. Thus, smart sampling with Mobile-app based recording of crop cutting have improved the quality of CCE data to a certain extent, but not to the desired extent.

Figure 1 Smart sampling based CCE-fields selection in Odisha state

(a) Paddy crop map (b) CCE-field locations (primary plots and alternate)



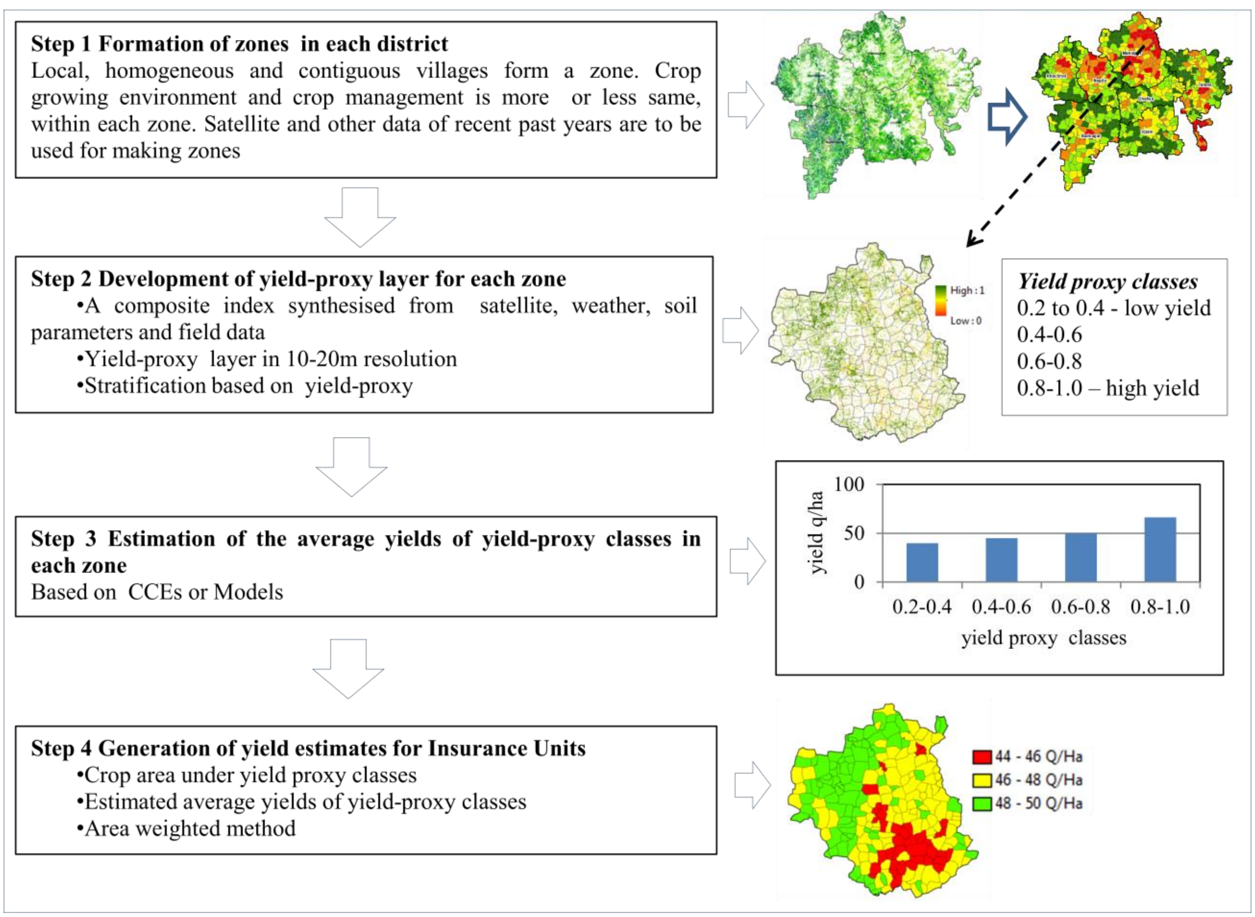
2.2 Reducing the sample size in CCE

In the CCE-reduction methodology, CCEs are conducted at aggregated level say Block/Taluk and the resulting yield data is used to derive the estimates at IU level.

NRSC and AICIL have developed and tested the methodology for CCE reduction for wheat crop in Ujjain district under a collaborative project (Fig. 2). The first approach involves conducting CCE in a limited number of fields determined on the basis of different yield indicators. This yield data will be used to develop empirical/semi empirical models with yield indicators. These models are then applied to generate yield estimates at disaggregated level i.e., insurance units. These models vary from place to place and with crop stages.

The second approach is to divide the distinct into homogeneous zones on the basis of weather, soil and crop parameters. These zones are localised, contiguous and represent similar crop growing environments. The crop yield proxies developed based on satellite and other indices better capture the variability in localized areas. For each zone, wheat crop yield proxy was developed using NDVI, LSWI and back scatter ratios. The yield proxy has ranged from 0-1 and each zone was divided in to five yield proxy classes. Now, actual crop yield value corresponding to each yield proxy class was estimated by conducting CCE. The CCE derived average yield of different yield proxy classes are used to estimate the yields of individual insurance units within the zone, through area weighted approach. Results indicated that CCE number can be reduced by about 40-50% without compromising with accuracy. However, there is a need to replicate the methodology for one more season to check the consistency of results. Many agencies have developed techniques for CCE-reduction but the reports on outcome are not available in public domain, to draw any conclusions.

Figure 2 CCE-reduction methodology framework



Critical issues in CCE reduction methodology are; (a) strong yield proxy at appropriate resolution/granularity, (b) optimal grouping of insurance units, (c) sampling/model error in the estimates and (f) calibration of historic yield data.

2.3 Replacing CCE yield data with Modeled yield data

Crop yield estimation is a complex problem because many factors such as weather, soil, crop variety, crop management etc are involved. Such estimations at local scales like insurance units in India is even more challenging and complicated than regional scale estimations because capturing variability at local scales demands higher degree of parameterization. Replacing CCE yield data with modeled yield data is being attempted by many agencies in the country. There are four widely followed modeling approaches for generating yield data;

- Empirical – parametric regressions
- Semi-empirical
- Crop simulation models
- Artificial Intelligence (AI) models

2.3.1 Empirical model – parametric regressions

Parametric regression functions are developed using yield and spectral and agro-met variables. Satellite indices covering single or multiple growth stages are employed. This approach is very primitive in nature because of limited parameterization and lack of generalization. Quite often they result in large error of estimates due to weak predictive power of independent variables. Therefore, this approach is not suitable for crop insurance applications.

2.3.2 Semi-empirical model

It is based on Radiation Use Efficiency (RUE) model proposed by Monteith, 1977. This model is based on bio-chemical process of plant – light absorption for photosynthesis, radiation use efficiency, stress factors, accumulated biomass and grain yield. It is recognized as a better approach than simple empirical modeling. Its strength lies in adopting a process-based framework with limited parameterization.

Tripathy et al. (2014), adopted this model for generating wheat yield estimates at District and State level in India and suggested its operational use for regional estimations. The modeled yield and observed yield are with close relationship at State level with R^2 of 99% but with poor relationship at district level with R^2 of 55%. They have attributed such a drastic fall in accuracy of modeled yield estimates from state to district level, to identification of planting dates. Therefore, application of this model at finer scales such as insurance units which are much smaller regions within districts may not produce accurate yield estimates due to inadequate parameterization. MNCFC (DACFW) adopted this technique to generate yield proxy in the smart sampling methodology for CCE fields selection but the evaluation reports are not available to understand the sensitivity of the yield proxy at local level like insurance units.

Chen et al. (2020) used this model for estimating the yields of canola, barley and wheat and found that the model has explained 87%, 69% and 83% of the observed field scale grain yield variability. Dong et al. (2020) implemented this model for estimating winter wheat yield in Kansas state of the USA and found that estimates were able to explain 69% of variability in the reported yields at county level, when wheat variety was included in the model. Without variety information, explaining power of the model is reduced to 64%. There are many other studies across the world on this model, producing mixed results. In most of the studies, yield estimation was attempted at aggregated level to characterize the yield gaps or to assess inter annual variability of yield. There are no proven cases of applying this model to generate yield estimates at local scales.

Critical elements of RUE model application that impact the accuracy of yield estimates are summarized as under;

- precise information on crop variety, planting and harvest dates
- empirical derivation of FAPAR with NDVI
- derivation of water stress and temperature stress factors

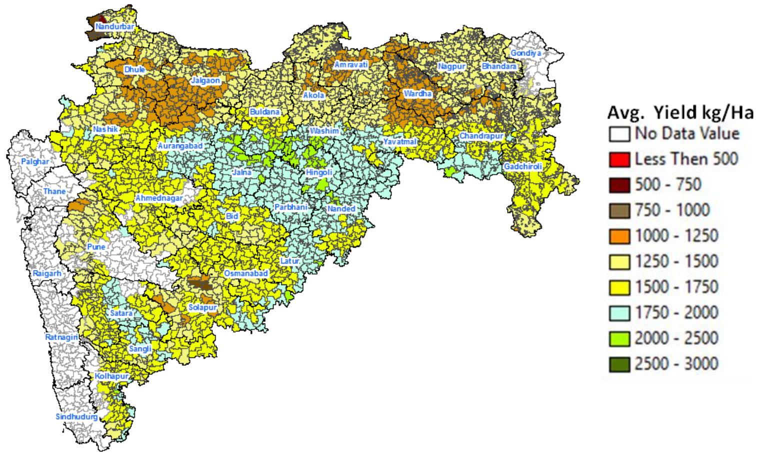
Temperature and water stress are the two important limiting factors and quantifying these two parameters at local scales like insurance unit remains a big challenge. This model would result in potential yield rather than actual yield if the stress factors are not accounted with right data and technique. The model cannot be applied for part of the season, because constant RUE is applicable only when the entire crop growth season is considered. Availability of cloud free moderate resolution (10-30m) NDVI and LSWI datasets throughout the crop season may not be possible. Most of the research reported on this model adopted coarse resolution data, which are not suitable for insurance needs.

2.3.3 Crop simulation models

Crop growth models simulate the plant processes to estimate various bio-physical parameters and final crop yield. These models need intensive parameterization starting from genetic coefficients of crop variety under cultivation, crop sowing time, crop management practices – fertilizer applications, irrigation supplies, pest/disease occurrence etc. These are highly reliable point based or location specific models due to availability of input parameters in experimental plots. These models better serve the needs of plant breeders in their experiments while developing new varieties. All these models are best designed for point based application. When applied over larger geographies, these models perform poorly due to limited parameterization and inadequate representation of varied crop growing environments (Hochman et al. 2009, Palaso et al. 2011, Kamir et. al. 2020, Manivasagam and Rozenstein 2020). Regional scale application of these models is well reported despite accuracy levels are poor. Adoption of crop simulation approach to meet the yield data needs at local scales i.e., smaller geographic units like insurance units is also expected to result in poor accuracy levels. More research is needed to customize these models to suit the crop insurance requirements, particularly to address parameterization, scalability and accuracy factors.

We have implemented DSSAT crop growth simulation platform to simulate soybean and cotton crops growth and yield. This work is being carried-out under MahaAGRITECH project a collaborative project of Department of Agriculture, Government of Maharashtra, Maharashtra State Remote Sensing Applications Centre and NRSC (ISRO). Input data used in the model includes daily max & min temperature (Source: IMD AWS), Daily Solar Radiation (IMD AWS), Daily Rainfall (IMD AWS), Soil data - Depth wise texture, BD, pH, Organic carbon, water holding capacity etc. (NBSSLUP soil map at 50K), crop management - Start of the sowing and irrigation information derived from satellite images and used to drive simulation, other management factors taken as per the standard local practices. Soybean yields were generated at revenue circle level for kharif 2019, as shown in Fig. 3. These estimates were found to be with 70-80% accuracy based on first level validation analysis. Model improvement activities are in progress.

Figure 3 Simulated soybean yields, kharif 2019, Maharashtra



2.3.4 AI models (Machine Learning / Deep Learning based regressions)

Crop yield has high variability across space and time owing to variations in weather, edaphic, management factors and genotypes. Spectral data of a crop is the integrated manifestation of the effect of all the above factors and hence, satellite data has significant role in regional crop yield assessment. Since decade, remote sensing spectral data has been incorporated into different statistical, agro-meteorological, and simulation models for crop yield assessment. Each approach has its own limitation like statistical methods are location specific and parametric in nature while agro-meteorological and simulation models are highly data intensive. Therefore, Artificial Intelligence (AI) has gained importance in solving the non-linear relationships between the variables. AI includes Machine Learning and Deep Learning models, such as the random forest (RF), support vector machine (SVM), and different variant of neural network models (NN). In recent years, AI models have gained momentum in crop yield estimation. Satellite derived vegetation indices, meteorological data, hydrological variables and edaphic factors are used in these models (Jiang et al. 2004, Jeong et al. 2016, Ma et al. 2016).

2.3.4.1 Soybean yield estimation

This work is also being carried-out under MahaAGRITECH project along with crop simulation models. The current study covers three of the major soybean growing districts of Maharashtra namely Latur (for Tehsil level yield estimation), Akola and Washim (for Circle level yield estimation).

For Tehsil level yield modeling (TLM), seven input features were used - MODIS derived season maximum FAPAR, season maximum NDVI and season maximum LSWI, LPRM-AMSR2 derived average soil moisture during June-July period and August-September period and cumulative rainfall and rainy days during June to September. Soybean yield data at Tehsil level during 2012 to 2018 was used to train the model and 2019 yield data was used for model validation.

For Circle level yield modeling (CLM) the input features include Sentinel 1 derived season maximum VH backscatter, dynamic range of VH from the start of the season to the maximum vegetative stage of the crop, and area under the VH curve between the start of the season and maximum vegetative stage, Sentinel 2 derived season maximum NDVI and cumulative rainfall and rainy days during June to September. Here, both the training and validation was performed on stratified samples of 2019 dataset. Yield data of 75% circles were used to train the model and the rest 25% were used for validation.

Different deep neural network (DNN) configurations were tested via brute force algorithm and it was found that a configuration of, input-36-36-18-18-output, performs well on TLM where as a configuration of, input-256-128-32-output, performs well on CLM. Since the data density of all the features used in the modelling is different, Adam optimizer was selected as an optimiizer with a learning rate of 0.001.Leaky RelU activation function and Root Mean Square Error (RMSE) loss function were used in both the models. To avoid over fitting and to ensure overall model generalization, different regularization criteria were applied during the training process. These were: early stopping criteria based on training and validation loss, dropout of 0.2 in each layer and a scheduler which reduces the learning rate of the optimizer by a factor of 0.1 after every 50^{th} epoch.

In TLM, the training and validation RMSE was found to be 173 Kg/Ha and 187 Kg/Ha respectively, whereas, in CLM, training and validation RMSE was found to be 113 Kg/Ha and 109 Kg/Ha respectively. Even though the RMSE's are slightly on a higher side, but the spatial distribution of the predicted soybean yield suggests that the trend in yield variability is well explained by the proposed DNN models. Soybean yield estimates as Tehsil and Circle level for the year 2019 are shown in Fig. 4 and the comparison between the reported yield and the predicted yield is shown in Fig. 5.

Figure 4 Soybean yield estimates for the year 2019

(a) Tehsil level yield in Latur district (b) Circle level yield in Akola and Washim districts

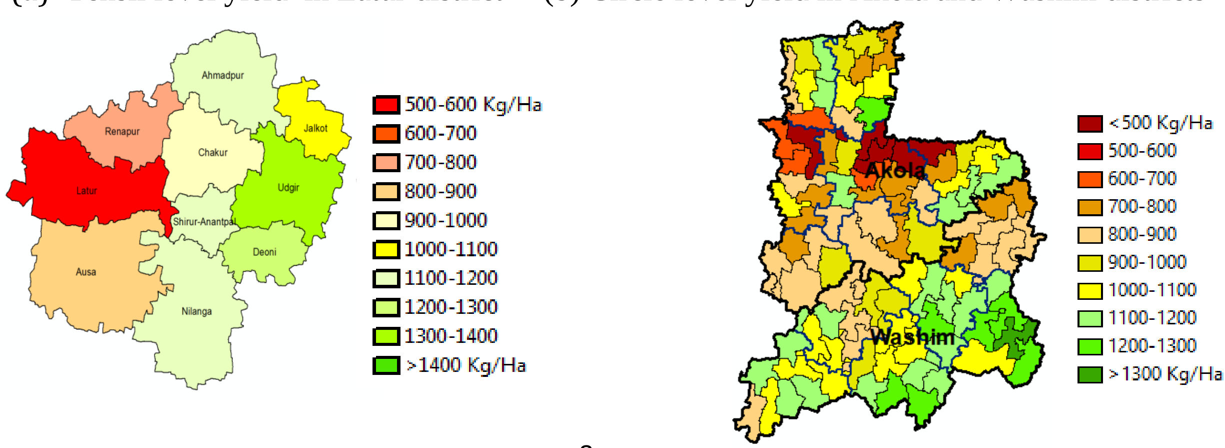


Figure 5 Tehsil wise reported yield and predicted yield, Latur district

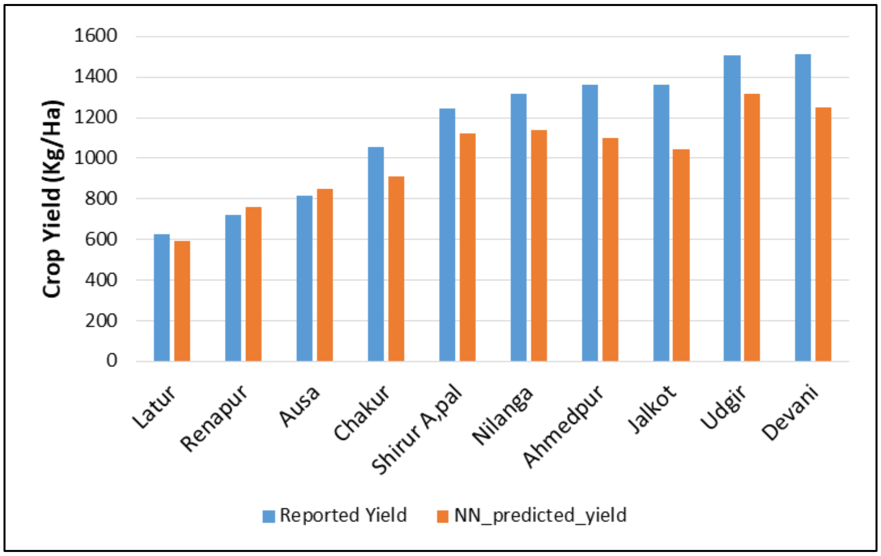


Figure 6 Circle wise reported and predicted yield, Akola and Washim districts

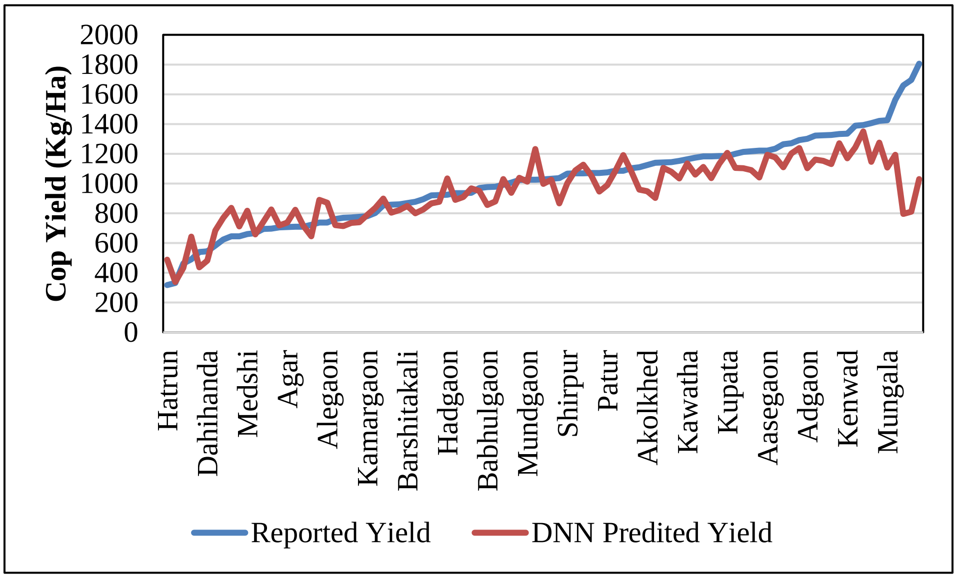


Fig. 6 compares the DNN predicted circle level yield with the actual yield. It can be deduced that the error in model estimate at lower yield ranges are significantly less than those at higher yield range. By doing further analysis, we found that the model performance was fairly good in lower and medium yield ranges but at higher yield ranges there was under-estimation.

2.3.4.2 Wheat Yield estimation in Ujjain district

In this project, CCEs for wheat crop were conducted for the study, at 178 location spread across 10 Gram Panchayats (GPs) of the Ujjain district in an area of 5m X 5m each. Grain weights along with its moisture content were measured in-situ and afterwards, all the yield data were brought to a common grain moisture content of 14 percent. The crop yield ranges from 7 Q ha-1 to 60 Q ha-1.

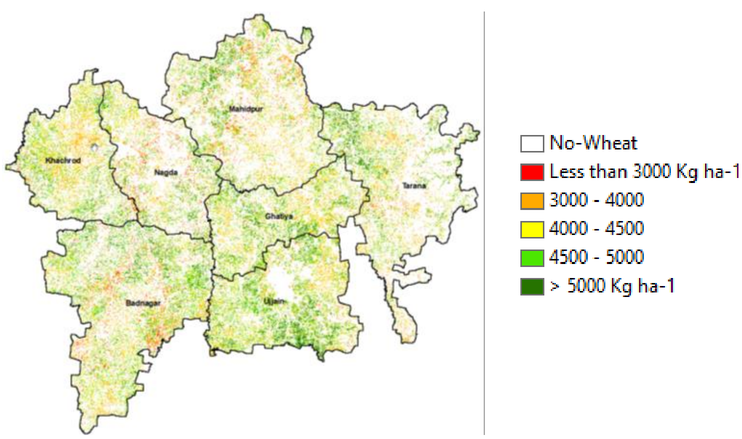
Random Forest (RF) technique was used to model the wheat crop yield by utilizing time series NDVI& NDWI (Sentinel 2), GPP (LandSat 8) and XPR (Sentinel 1) datasets from 1st fortnight of November 2017 to 2nd Fortnight of March 2018. 75% of the dataset were used to train the model and 25% of the dataset were used for model validation. The modeling was done sequentially by injecting indices one after other into the RF model. This led to four different combinations of input features: (a) Using only temporal NDVI, (b) Temporal NDVI & Temporal NDWI together, (c) Temporal NDVI, NDWI & GPP together and (d) All the four temporal indices together into the RF model.

It was observed that at each successive addition of a variable in the model, there was significant improvement in R^2 and RMSE. From the initial stage, there was decrease of about 25% in model RMSE when all the four indices were utilized for modelling. RF model's assessment of validation dataset with different combination of input feature is presented in Table 1. Subsequently, the RF model trained on temporal NDVI, NDWI, GPP and XPR {stage 4} dataset was implemented across Ujjain district and wheat crop yield for rabi 2017-18 was estimated (Fig 3).

Table 1: RF model performance with different combination of input features

Modelling stage	Parameters used in RF model (all temporal)	Number of parameters	RMSE (Q/Ha)	R^2
Stage 1	NDVI	10	9.8	0.69
Stage 2	NDVI+NDWI	20	8.7	0.76
Stage 3	NDVI+NDWI+GPP	28	7.6	0.83
Stage 4	NDVI+NDWI+GPP+XPR	38	7.4	0.85

Figure 6 Wheat yield estimated using Random Forest model



Klompenburg et al. 2020 reviewed the research publications on Machine learning / deep learning algorithms on crop yield prediction and indicated that the most challenging aspects are selection of best model and best input datasets and suggested further research to address these challenges. They found that the most used data sets in the model are features on temperature, rainfall, and soil type, and the most applied algorithm is Artificial Neural Networks. Despite numerous research reported on crop yield estimation using various models, the performance of these models are still to be improved to desired levels (Filippi et al. 2019). ANN based machine learning model performed well for predicting rice yields in Bangladesh (Islam et al. 2021)

Any deep learning model requires large volume and variety of dataset during training process. Therefore, to achieve at stable and robust DNN model for yield prediction, a large volume of crop yield data at all yield ranges (low, medium, high) is required. In the presented case of yield estimate at aggregated and disaggregated level, the data availability at lower and higher yield ranges were limited and hence we observed inaccuracies in model prediction in those ranges.

Critical issues in the operational use of AI models are are model selection and optimisation of model parameters, consistency of results, scale of model development etc. These models are also data intensive, if the estimates are targeted at local level i.e., insurance units.

2.3.5 Hybrid approaches

Combination of crop model and empirical model was adopted by Lobel et al. (2015), for estimating the yields of soybean and maize across multiple regions and years covering Midwestern US, Crop model derived yield and bio-physical indices and weather based indices are used to train the statistical models and these models are applied on satellite and weather indices to generate yield estimates. The model estimates have captured 35% variability in maize yield and 32% variability in soybean yield. The authors conclude that many avenues exist to improve the model performance.

2.3.6 Summary of recent research on yield modeling

By reviewing the recently published literature on crop yield estimation, the results and critical factors reported are summarized in Table 2. Although this review is not exhaustive, the results thereof provide fairly good indications on the opportunities and limitations for implementing technology based yield estimation in crop insurance.

Table 2 Summary of the results of the recently published papers on crop yield estimation

S.no	Author and study details	Purpose / Target	Results and uncertainty factors
		I. Semi empirical model (Light Use Efficiency)	
1	Dong et al. (2020) Winter wheat, Kansas, US. Assessment of the interannual variations of yield at regional level	Assessment of the interannual variations of yield at regional level	Explained 64% of spatial variations without using crop varieties data and 69 % variations when using varieties data. Captured 82% of the inter-annual variability in yield Critical inputs – (a)crop variety, (b) crop growing period and (c) latent heat flux dataset at finer resolution
2	Chen et al. (2020) Nationwide estimation for Canola, wheat and	Regional /National for generating yield data using Technology	Explained 87%, 69% and 83% of yield variability for Canola, wheat and Barley respectively. Errors are significant at field scale level

	Barley crops in Australia		High spatial resolution information on date of sowing, crop growth and meteorological data play a key role
3	Tripathy et al. (2014) Yield estimation in India	District/State level yield estimation	Regressions between Modelled yield and observed yield produced R^2 of 99% at State level and 55% at district level. Identification of precise sowing date is a critical factor
II. Machine Learning / Deep Learning models			
3	Klompenburg et al. (2020)	**Review paper**	Many algorithms are being used. No specific conclusion on best performing model. Choice of features and scale are critical factors.
4	Kamir et al. (2020) Wheat yield estimation in Australia	For yield gap analysis and identification of yield gap hotspots. Comparing different techniques of machine learning regressions	Climate and NDVI time series have improved the models. data Yield predicting power of different algorithms range from 55% to 73%. Over predictions in the areas having low wheat area. Predictor variables, adequacy of training data and crop growing environment determine are critical factors
5	Son et al. (2020) Rice yield estimation Taiwan, Regional scale MODIS NDVI	Planning and policy making, used coarse resolution datasets	Predictions compared to Govt. statistics, Mean Absolute Error ranged between 7.1% and 11.8%. Agreement index between the two estimates ranged between 0.81 to 0.84. Mixed pixels and cloud cover cause uncertainties.
6	Islam et al. 2021 Boro rice yield estimation in Bangladesh	Yield predictions for farm risk management, insurance premium decisions etc. Parametric and non-parametric regressions with NDVI at maturity stage.	R2 values of the regressions between modeled and observed yield range from 0.84 to 0.91. Limited parameterization, crop risks that occur at the end of season are not accounted. Models performed well in 2/3rd of area only.
7	Holzman et al. (2018) Soybean, wheat and corn yield estimation in Argentina	Regional scale estimations. Regression models. Yield, crop water stress and solar radiation are the parameters	R2 values ranged between 0.55 and 0.82 TVDI computed from coarse resolution LST and EVI needs to be improved with finer resolution data. Mixel pixels, cloud cover, LST retrieval accuracy, varying relations between TVDI-Radiation-Yield are uncertainties
III. Crop Simulation Models			
8	Manivasagam and Rozenstein 2020	**Review Article**	Challenges with implementation of these models over larger geographies include parameterization and clibration of models, scale of inputs and integration of RS based bio-physical parameters are core issues.
9	Pazhanivelan et al.	Crop insurance	Accuracy 86-91% at district level, 82-97% at

	(2019) Rice yield estimation in India		Block level
10	Setiano et al. (2019) Rice yield estimation in south and south-east Asian countries.	Generation of paddy yield estimations using SAR data and simulation models, at regional/Province scale	Normalised Root Mean Square Error of yield estimates ranged from 10-15% in different Provinces/States.
IV. Hybrid models (Simulation and empirical models)			
11	Lobell et al. (2015) Maize and Soybean crops in Mid-western US	Providing crop yield data where ground estmates are not generated, Crop management decisions and Scientific research. crop yield data where ground estimates are not made	The model has captured 35% variability in maize yield and 32% variability in soybean crop. Scope exists for improving the models with additional parameters and field data.

2.4 Model error and its impact on indemnity

Impact of model errors on crop loss indemnity assessment needs to be examined before using modeled-yield estimates in crop insurance. Currently, indemnity levels for different crops in different seasons range from 70-90%. Indemnity level of 90%, means 90% of normal yield is guaranteed by the crop insurance contract. Normal is the average of past 7 years yield. Area-yield insurance contract guarantees certain % of normal yield called Threshold Yield (TY). The per cent shortfall from the TY is applied on the sum insured to arrive at compensation pay-out, for a given IU.

The error in the modeled yield estimates of the current and past years plays a crucial role in the use of such estimates for indemnity assessment and pay-out execution under crop insurance contracts. The impact of model error on indemnity is showcased here using a test data set in Table 3.

If the errors are not accounted, the current year's yield 3500 kg/ha, is greater than the TY by 12% and hence no indemnity is to be paid, as indicated in the Table.

The error in the modeled estimates is assumed to be varying from 10 to 25% on both sides (+/-) and accordingly the actual yield estimates after adjusting the error are shown in Table 3. Negative error indicates that the yield is under estimated and positive error indicates over-estimated yield. Magnitude and direction of error in the yield estimates of current and past years impact the indemnity. For example, if the model error is same, say -10% or -20%, or -25%, for the current as well as past years, the resulting indemnity % is constant, even after correcting the estimates for error as seen in Table 3. This is a hypothetical situation and the probability of its occurrence is very less.

Table 3 Test data on modeled-yield estimates for simulating indemnity values

		Actual yield after applying the model error (%)							
Year/details	Modeled yield kg/ha	-10%	-15%	-20%	-25%	+10%	+15%	+20%	+25%
Current year (Y_n)	3500	3889	4118	4375	4667	3182	3043	2917	2800
Past years									
Y_{n-1}	4000	4444	4706	5000	5333	3636	3478	3333	3200
Y_{n-2}	2900	3222	3412	3625	3867	2636	2522	2417	2320
Y_{n-3}	3500	3889	4118	4375	4667	3182	3043	2917	2800
Y_{n-4}	3800	4222	4471	4750	5067	3455	3304	3167	3040
Y_{n-5}	3200	3556	3765	4000	4267	2909	2783	2667	2560
Past years average	3480	3867	4094	4350	4640	3164	3026	2900	2784
Threshold yield - TY (90%)	3132	3480	3685	3915	4176	2847	2723	2610	2506
% dev. from TY	12	12	12	12	12	12	12	12	12
Indemnity (%)	0	0	0	0	0	0	0	0	0

In the scenario of positive error in the current year and negative errors in the past years' estimates, the indemnity outcomes with corrected yield estimates are shown in Fig. 7. Here, it is evident that +10% model error in the current year leads to an indemnity ranging from 9 to 24% corresponding to the errors of -10% to -25% for the past years (Fig 7a). Model error of +25% in the current year resulted in the indemnity levels of 20 to 33% corresponding to the model errors of -10 to -25% in the past years.

If model errors in the yields of historic years are on negative side, the yields will be underestimated and hence the threshold yield will always be on lower side. This leads to reduced indemnity situation in the current season, if the errors are unaccounted.

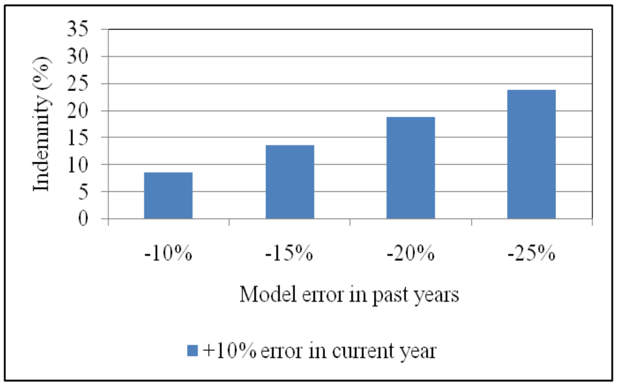
If the model error in the yields of past years is on positive side, the yields are over-estimated and hence the threshold yield will always be on higher side. This leads to higher indemnity value for the current season.

In the situation where the model error of the past years is on positive side and that of current year is on negative side, the resulting indemnity for the current year will be on higher side, with uncorrected estimates.

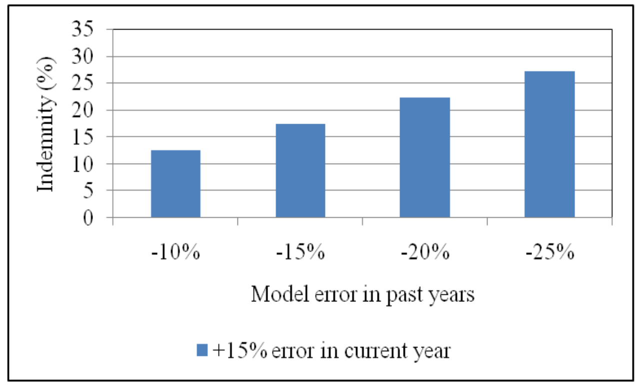
While using modeled yield data in crop insurance, the indemnity value consists of actual yield reduction due to crop risk as well as yield changes due to model error. Higher the model error larger is the deviation of indemnity from the reality and larger is the basis risk. Therefore, magnitude and direction of model errors in the yields of past and current years play a critical role for adoption of modeled-yield estimates in crop insurance.

Figure 7 Simulation of indemnity using the modeled- yield estimates for insurance payouts

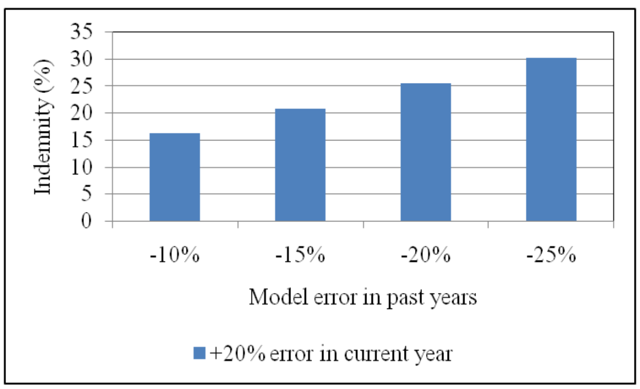
(a) +10% model error in the current years's yield estimates



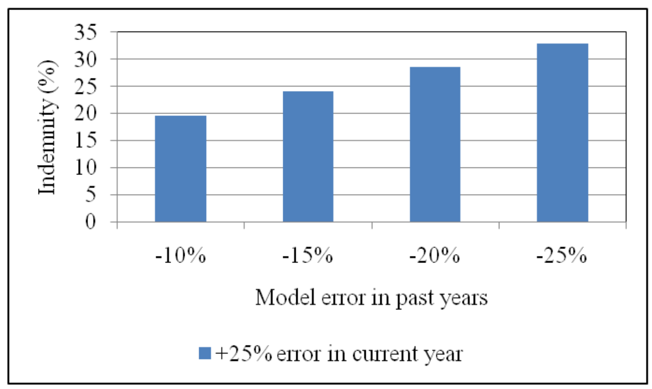
(b) +15% model error in the current years's yield estimates



(c) +20% model error in the current years's yield estimates



(d) +25% model error in the current years's yield estimates



2.4.1 Basis risk

Review by Smith and Watts (2009) indicates that index-based insurance schemes in developing countries are faced with serious problems of basis risk and non-availability of historical data, making the scalability and sustainability of agricultural insurance in the long run, a big challenge.

In the area-yield insurance, indemnity is based on the yield loss experienced at the insurance unit level. There is a possibility that a farmer who suffered crop loss may not be indemnified and also a farmer who experienced no yield loss could be indemnified. Basis risk indicates the probability that the crop loss is not compensated or indemnified. Consequently, in such insurance units, farmer-participants face the un-indemnified risk and forego the premium as well, thus making the insurance, a risk-enhancing contract.

There are two important elements in the modeled-yield estimates that impact the basis risk;

- model errors and their variability from year to year as discussed above and
- ability of the models to parameterize all the crop risks that have occurred during the crop season.

If any of the crop risks are not adequately captured, it leads to underestimation of crop loss. Generally, these risks include (a) Unseasonal rains/Floods/Cyclones (submergence, lodging, panic harvest etc), (b) Weather aberrations such as hot and dry winds, rise in temperatures (poor grain setting and grain development), (c) Weather induced pest/disease incidence and (d) Pest incidence following floods (BPH in rice)

2. 6 Merits and demerits of different strategies for improving yield data

Different strategies for improving the crop yield data in the insurance units and their merits and limitations are summarized in Table 4.

Table 4 Strategies for improving the crop yield data for crop insurance

Strategy	Scope of adoption
Improve CCE	Increase the CCE number (to 10/12 per IU), smart sampling for fields selection and smart phones for digital recording of crop cutting process. **Advantages** • Statistically valid yield estimates **Limitations:** • Operational feasibility due to huge increase in CCE number • Still prone to human bias • Calibration of past years data/estimates
Reduce CCE	Reduce the CCE number using Technology based yield proxies, sampling estimates and empirical modelling **Advantages** • improves quality, timeliness and economics of CCE • Reduces moral hazard to some extent **Limitations:** • Sampling / model error • Modelling errors • Calibration of past years data/estimates
Replace CCE (modelled yield)	Modeled yield estimates through semi-empirical, simulation, Machine Learning/Deep learning, hybrid models **Advantages** • No CCE and hassle free • Reduces moral hazard • Timely availability of data and estimates **Limitations:** • Model parameterisation • uncertainty/error in estimations • Calibration of past years data/estimates

3. Conclusions and way forward

The biggest challenge in the crop insurance continues to be generation of accurate crop yield data in the insurance units. Improving the area-yield insurance either through (a) increasing/optimising CCE number or (b) adopting technology-based estimation is yet to be realised due to various factors discussed in this report.

Research on technology-based crop yield estimation using Crop Simulation and Artificial Intelligence models has gained momentum in recent years.

The key challenges with yield modeling methodologies that impact the indemnity assessment and basis risk in crop insurance are (a) generation of modeled yield estimates for the past years, (b) consistency of model errors and control on such errors and (c) ability to parameterize all the crop risks that occur during crop's life cycle. These models use bio-physical variables such as soil moisture, LAI, APAR etc which are currently available at much coarser resolutions. Downscaling of these variables to finer scales is associated with uncertainties, affecting the accuracies of the models.

Magnitude and direction of model errors in the yield estimates of past and current years are very critical in determining the indemnity values for claims settlement and minimizing the basis risk.

District/state level crop yield estimation using the above models is still not operational in the country even for principal crops, due to various limitations. Crop yield estimation at local scales such as IUs, is more challenging than that of district/state level, due to higher variability and lesser scope for parameterization. Similarly, yield estimation for non-cereal crops is more challenging than that of cereal crops, due to various reasons.

Therefore, more focused research is needed for replacing the current CCE-yield estimates with modeled yield estimates in crop insurance. Cereal crops may be targeted first and based on the outcome; such research for non-cereal crops may be initiated.

Quantifying the frequent and localized phenomena that affect the crop production is a main challenge in the area-yield crop insurance (Ibarra and Skees 2007). Carter et al. 2016, found that yield risk is not predicted by the index insurance in some of the agro-ecological regions of their study area.

Insurance products have to developed meeting the local crop growing conditions, for effective transfer of risks; otherwise such products may produce maladaptive outcomes (Muller et al 2017). Innovative measures including the use of technology have to be constantly introduced in insurance to overcome the challenges of agriculture insurance such as moral hazard, fraudulent claims etc and ensure the sustenance of these contracts (SwissRe 2013).

Way forward

Replacing the CCE or reducing the dependence on CCE is the need of the hour to address the ever increasing crop yield measurement risks in crop insurance. Till the operational methodology for generating modeled-yield estimates is ready, technology interventions to reduce the dependence on CCE-yield data by using yield-proxy indicators for major crops needs to be developed.

In this direction AICIL and NRSC developed an innovative index-based insurance scheme linking pay-outs to crop performance proxies rather than measured losses. The scheme, first of its kind in the country, was successfully implemented in 2020 crop season in West Bengal state. The conventional 'Area-yield approach' has been replaced by 'Area- crop performance/crop health approach'. A composite index called Crop Health Factor (CHF), has represented the crop performance by incorporating multiple physical and biophysical parameters related to crop health. It is a quantitative measure of crop health and its overall performance. CHF deviation from the past years' average decides the crop loss and insurance pay-out in the current season. End-of-the crop season risks like hailstorms, floods, cyclones have also been accounted in the crop performance.

This new index-insurance is has many advantages over the conventional yield-based scheme in terms of transparency, objectivity and ease of implementation. There is scope for improving the index with additional features. Such technology-driven index-insurance insurance schemes may trigger a paradigm shift in the crop insurance system benefitting all the stakeholders.

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