Improving performance of index insurance using crop models and phenological monitoring

Working Paper No. 337

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Abstract

Extreme weather events cause considerable damage to livelihoods of smallholder farmers globally. Whilst index insurance can help farmers cope with the financial consequences of extreme weather, a major challenge for index insurance is basis risk, where insurance payouts correlate poorly with actual crop losses. We analyze to what extent the use of crop simulation models and crop phenology monitoring can reduce basis risk in index insurance. Using a biophysical process-based crop model (APSIM) applied for rice producers in Odisha, India, we simulate a synthetic yield dataset to train non-parametric statistical models to predict rice yields as a function of meteorological and phenological conditions. We find that the performance of statistical yield models depends on whether meteorological or phenological conditions are used as predictors, and whether one aggregates these predictors by season or crop growth stage. Validating the preferred statistical model with observed yield data, we find that the model explains around 54% of the variance in rice yields at the village cluster (Gram Panchayat) level, outperforming vegetation index-based models that were trained directly on the observed yield data. Our methods and findings can guide efforts to design smart phenology-based index insurance and target yield monitoring resources in smallholder farming environments.

Keywords

index insurance, crop yield, APSIM, leaf area index, phenological monitoring.

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Contents

Acronyms

CCE	Crop cutting experiment
PMFBY	Pradhan Mantri Fasal Bima Yojana
GP	Gram Panchayats
APSIM	Agricultural Production System sIMulator
NDVI	Normalized difference vegetation index
RTM	Radiative transfer model
LAI	Leaf area index
EVI	Enhanced Vegetation index

1. Introduction

Agriculture plays a critical role in supporting livelihoods and food security for rural households across the developing world (Castañeda et al., 2018). Designing strategies to protect farmers against crop losses caused by adverse weather conditions such as droughts or floods has become a key priority for governments and donors, particularly given expected increases in the frequency or intensity of extreme weather events in the coming decades due to climate change (Afshar et al., 2020). One of these strategies is to provide smallholder farmers with agricultural insurance, which offers financial protection from losses associated with extreme weather. In recent years, several agricultural insurance programs have been rolled out at scale, and large amounts of money have been invested in these programs. For instance, in the monsoon season of 2019, India's national insurance scheme, the Pradhan Mantri Fasal Bima Yojana (PMFBY), covered more than 33.5 million hectares of land through subsidized crop insurance, with gross insurance premiums amounting to more than USD 3 billion.[1]

In developing countries, the main type of crop insurance being offered to smallholder farmers is index-based insurance. Unlike traditional insurance schemes, which is based on the direct verification of crop yield losses for each insured field, payouts from index insurance are made on the basis of an empirical relationship between a proxy index and expected yield losses (Dalhaus & Finger, 2016). Proxies used include weather indices, satellite vegetation indices, or area-yield indices, whereby yields are measured for a sub-sample of fields through crop cutting experiments (CCEs) to estimate an average yield over a given region, and payouts are made when these average yields fall below a threshold that is based on historical yields for the region. Using an objective observable index in claims settlement helps provide more

[1] Data are estimated from Pradhan Mantri Fahsal Bima Yojana, Ministry of Agriculture & Farmers Welfare, State Wise Business Statistics as on 02.11.2020. https://pmfby.gov.in/pdf/2020-11-02%20-%202019%20Kharif.pdf.

timely payouts and reduces costs of loss verification for insurers, making coverage more affordable for farmers and potentially improving farmers' willingness to pay for insurance (Kos & Kloppenburg, 2019). Uptake has been generally low, though, in part due to high levels of basis risk, that is, a mismatch between the index – and thus insurance payouts – and actual yield losses (Clement, Wouter Botzen, et al., 2018).

One component of basis risk is design risk, which arises from limited data availability (Hellin et al., 2019). In particular, the limited availability of observed yield data inhibits the identification and definition of reliable weather and vegetation indices that accurately predict yield losses. Whilst this is not a limitation for area-yield index insurance, high costs of conducting representative samples of CCEs in heterogeneous smallholder farming environments can lead to biased estimates of average yields, and thus basis risk. Another important driver of basis risk relates to the temporal specification of the variables used to predict crop yields. Most index-based insurance schemes trigger payouts based on indices that are defined over fixed calendar periods, often relating to the average timing of key phenological stages in a given agricultural system (Enenkel et al., 2018; Miller et al., 2020; Vroege et al., 2019). In reality, the timing of a crop's sensitivity to weather may vary significantly across fields due to differences in management practices such as variety and sowing dates, as well as meteorological conditions, which affect rates of crop development (Van Oort et al., 2011). Failure to consider this heterogeneity may lead to inaccurate estimation of yield losses and basis risk (Bucheli et al., 2020; Ceballos & Robles, 2020).

In an effort to address these challenges, we analyze to what extent the integration of crop models and phenological monitoring can help reduce these design and temporal basis risk, respectively. Biophysical crop simulation models can be leveraged to generate larger synthetic yield datasets, which can then be used to train weather- or satellite-based index models (Bandara et al., 2020; Blanc, 2017; Yin & Leng, 2020) or support spatial targeting of limited numbers of CCEs that can be conducted as part of area-yield insurance products. However, to date, this approach has not been widely applied in the context of index insurance design, with limited evidence about its performance at spatial scales relevant for insurance applications (e.g. field, farm or village) or in comparison with index models derived empirically from available observational yield datasets. Approaches to reduce temporal basis risks have focused on developed countries, where detailed phenological monitoring networks exists (Dalhaus et al., 2018). In contrast, there has been limited attention on how to embed phenological information in the design and implementation of index insurance in smallholder environments, for example through use of satellite or in-situ phenology monitoring systems or technologies (Hufkens et al., 2019; Parkes et al., 2019).

We address these knowledge gaps through a case study on rice yield estimation in the state of Odisha, India, an area of extensive rainfed rice production, where agriculture is highly exposed to risks posed by monsoonal rainfall variability. We demonstrate how the integration of crop models, phenological monitoring through satellite remote sensing, and machine learning techniques can support the design and implementation of smart phenology-based index insurance products at spatial scales relevant for smallholder communities. Our findings highlight the opportunity for robust and scalable yield estimation by combining satellite data with machine learning and crop modelling. We show that this approach can significantly outperform models that rely solely on satellite imagery. At the same time, our results demonstrate several remaining challenges that need to be addressed in order to accurately and reliably estimate yields at plot scales in smallholder farming environments.

2. Methodology

In the following subsections, we outline our methodological approach to estimate rice yields. In Section 2.1 we provide information about the case study area, including key characteristics of agricultural production in Odisha. In Section 2.2, we describe the modelling approach used to develop a database of synthetic yield data for our study area, followed in Section 2.3 by the statistical techniques used to relate simulated yield data to relevant crop, phenology, and weather conditions. In Section 2.4, we discuss the process for validating statistical models against both synthetic and observed yield data. We also contrast performance of our models with estimates of yields derived directly through regression analysis using satellite vegetation indices.

2.1 Study area and observation data

Our analysis focuses on rice yield estimation in the state of Odisha in eastern India (Figure 1). Agricultural production in Odisha is dominated by small-scale farmers, with most rice production occurring during the summer monsoon season (Kharif). Rice production in the region is mainly rainfed, reflecting the relatively limited access to affordable and reliable irrigation water supplies in eastern India. Monsoonal rainfall variability is therefore a key production risk for many farmers. For example, a late onset of the monsoon leads to delays in rice transplanting, resulting in yield losses due to use of older seedlings and exposure to end of season temperature stress (Balwinder-Singh et al., 2019). Similarly, a lack of access to irrigation limits farmers' ability to protect crops against dry spells during the season, which can have damaging impacts on yields if droughts occur around critical development stages such as anthesis and grain filling (Cornish et al., 2015).

To support our analysis of alternative yield estimation approaches, observed yield data were collected through CCEs for a total of 80 paddy rice fields located in two blocks of Jajpur district, Odisha. Yield data were collected in late 2019, following the end of the 2019 summer monsoon season that was characterized by above average rainfall and early starting time. Rice fields were sampled from 20 Gram Panchayats (GPs)—clusters of nearby villages—as GPs are the primary spatial unit to estimate area-yields in the context of the Indian Government's National Crop Insurance Program (PMFBY). In each of the selected GPs, field staff would randomly select among consenting farmers the fields of 5 farmers for seasonal monitoring. Monitoring was done through smartphone images of the crops, and at the end of the season, as the crop had reached maturity, field staff collected yield data through CCEs. Field sizes range from 375 to 800 square meters (mean of 630), which are typical of smallholder farming in eastern India.

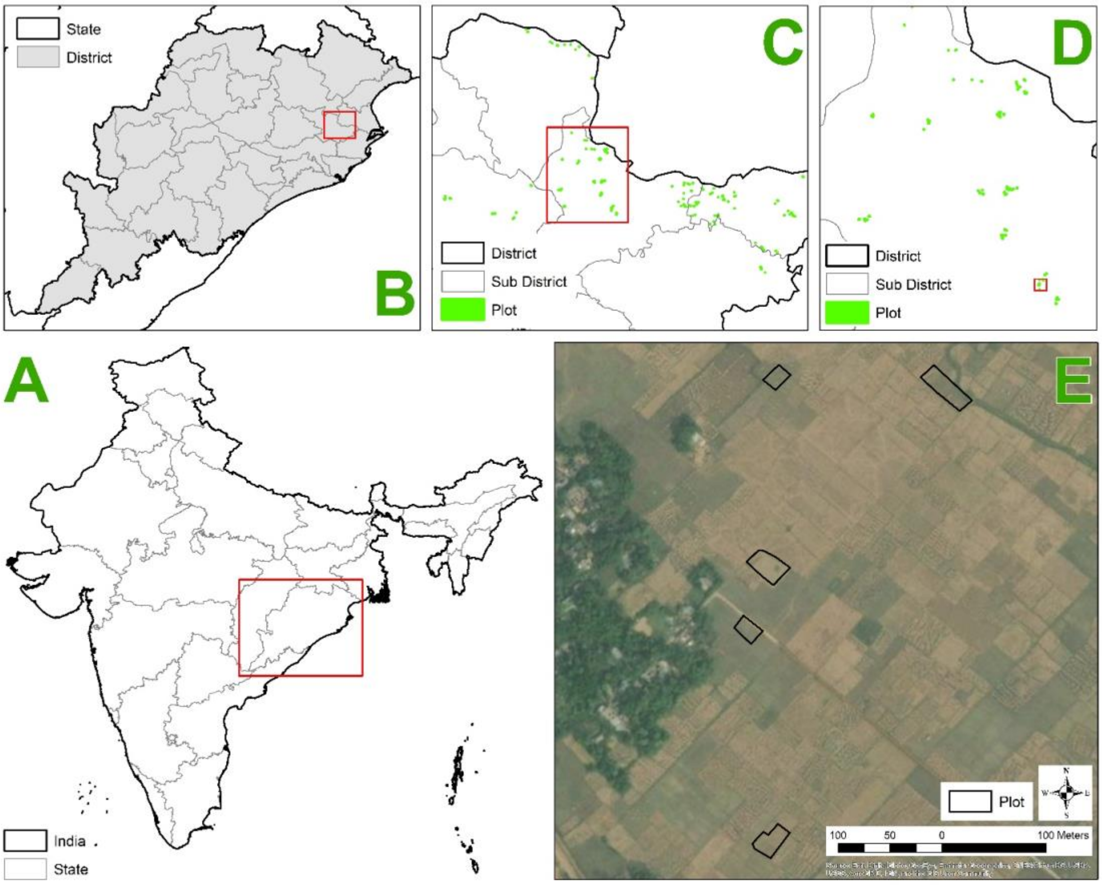

Figure 1: The map of study area with zoom level increasing from country scale (panel A) to the plot scale (panel E)

2.2 Synthetic yield data generation

Designing index insurance products requires establishing a relationship between crop yields and one or more predictors (that is, the variables used to operationalize the insurance 'index') that can be monitored and observed at a lower cost than would be required to manually verify yields directly through surveys or CCEs. However, limited availability of in-situ yield data represents a major barrier to estimating these relationships accurately and reliably. Resulting biases in the estimated relationships between yields and predictor variables or indices introduce basis risk. An increase in data availability could help address such basis risk. We therefore analyze whether index performance can be enhanced by relying on ensemble process-based crop simulations to generate synthetic yield data, representing yields across a range of potential weather conditions and agricultural management practices that would be infeasible to observe directly through in-situ data collection.

To develop a database of synthetic yield data, through a process-based crop model–APSIM (Agricultural Production System sIMulator)–we simulate the response of rice yields across a range of potential weather conditions and management practices in our study area. APSIM's rice module, ORYZA2000, is a dynamic physiological model of rice development, which has been widely applied for studies of both rainfed and irrigated rice production systems across south and southeast Asia (Balwinder-Singh et al., 2016, 2019; Gaydon et al., 2017). Thus, the synthetic yield data go beyond the limited observation data stemming from the CCEs, which will be used only to validate the statistical models, not to train the statistical models.

APSIM simulations consider a range of plausible weather and management practice scenarios observed in our study region. Specifically, we varied the parameters in the model specifying sowing dates (from 15 May to 15 Aug on one-week intervals), seedling ages (from 25 to 40 days on 5 days intervals), planting density (100, 150, or 200 plants per square meter), number of hills (from 30 to 45 hills on 5 hill intervals), and fertilizer amounts (50, 100, or 150 kilograms of urea per hectare) in accordance to information on typical management practices drawn from published literature (Balwinder-Singh et al., 2016, 2019) and state-level agronomic advisory documents (Dhaliwal & Kular, 2014). We carried out APSIM simulations for each combination of parameter values (2016 in total) for 100 weather years, resulting in a total of 201,600 unique yield simulations. Weather time series used in the crop simulations were developed using a weather generator (LARS-WG) and relying on 39 years of historical observed meteorological data between 1981 and 2020, obtained from ERA5 v5.1.3 (including daily minimum and maximum temperature, total precipitation, and solar radiation).

For each simulation, we defined crop growth parameters in APSIM according to the dominant local rice cultivar – MTU7029. MTU7029 (often referred to as Swarna rice) is a long-duration variety, for which parameters in APSIM have been calibrated and validated previously by Balwinder-Singh et al. (2019). All simulations assumed that rice was transplanted into a clay loam soil – the dominant soil type for rice production areas in the region based on spatial analysis of soil texture data provided by SoilGrids (Hengl et al., 2017) – with hydraulic properties determined using pedotransfer functions (Saxton and Rawls., 2006). Specifically, the volumetric water contents used in our analysis for the lower limit, drained upper limit, and saturation levels were estimated as 18%, 32.3%, and 46.1% respectively, with saturated hydraulic conductivity assumed to be 20 mm/day and 1 mm/day for the top five and bottom soil layers (out of six), respectively, in line with APSIM guidelines for ponded transplanted rice simulations (*Single season crop simulations - APSIM*, n.d.).

2.3 Statistical yield models

The variables that are used as predictors of yields in index insurance can vary in terms of the underlying type of data (such as various weather variables or indicators of crop development such as leaf area index) and the temporal period over which each predictor is aggregated (for instance, whether one uses the average for the entire growing season versus the average for a specific phenological stage), along with the spatial scale at which yields are estimated (plot versus village, GP or district aggregation).

To assess the implications of these choices, we fit 28 alternative statistical models that vary in terms of the underlying assumptions about which variables and what level of temporal aggregation are most useful for explaining variations in the synthetic yield data generated by APSIM as described in Section 2.2 (Figure 2). Specifically, the 28 alternative model specifications developed consider different unique combinations of three potential meteorological and agronomic predictor variables (that is, temperature: T, precipitation: P, and LAI: L, resulting in seven unique predictor combinations of T, P, L, TP, TL, PL, and TPL), along with four different assumptions about the time period over which each predictor is aggregated for yield prediction on a given plot.

The four different temporal specifications that we consider in our analysis include: (1) fixed season – FS – representing a typical or 'normal' cropping season between August and November; (2) dynamic season – DS – where variables are aggregated according to plot-specific information about the start and end date of the crop growing season; (3) fixed growth stages – FSTG – where variables are aggregated by fixed crop growth stages timings instead of the timing of the full season; and (4) dynamic growth stages – DSTG – where variables are aggregated by dynamic crop growth stage timings relying on plot-specific information about the start and end dates of each stage. In the FSTG and DSTG models, we divide the rice season into four main stages – transplanting, panicle initiation, flowering, and grain filling – resulting in a total of four unique predictor variables (one per stage) for each meteorological and agronomic predictor.

For each temporal model specification, predictor variables are aggregated by either averaging daily values within the period (for minimum and maximum temperature), or by calculating the cumulative sum (for precipitation) or integration (for LAI) of the variables over the specified period.

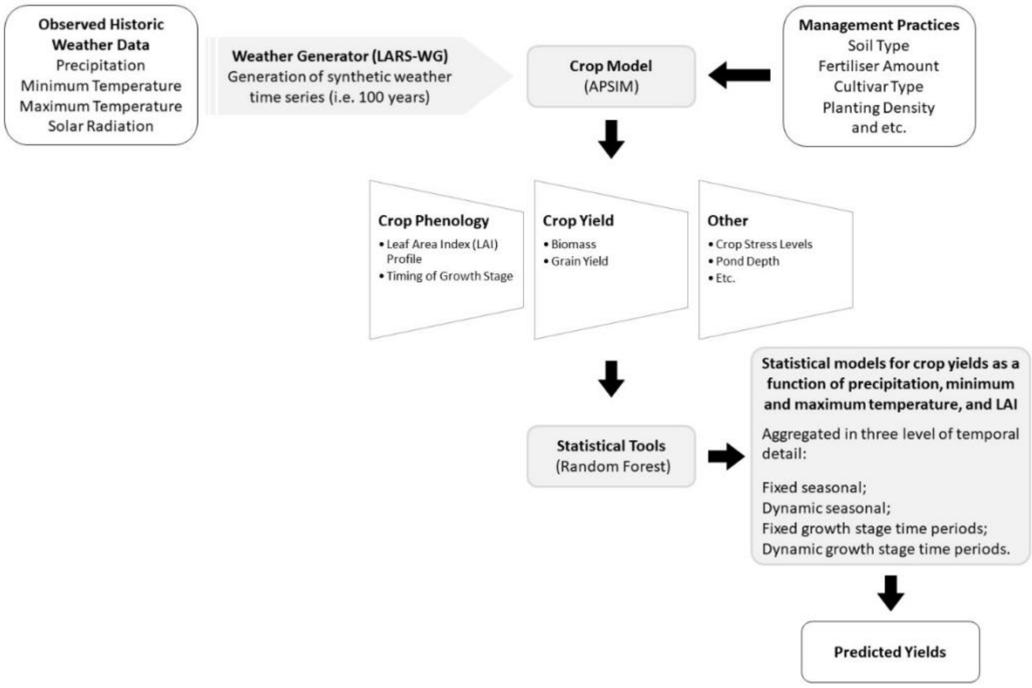

Figure 2. Overall procedure of coupling process-based crop models and statistical models to emulate synthetically generated APSIM crop yields. First, APSIM is used to simulate crop phenology, LAI, yields and other state variables for a range of potential weather conditions and management practices. Through random forest analysis, statistical index relationships are then developed relating simulated yields to different combinations of weather and agronomic predictors varying in their combination and temporal aggregation

Each of the 28 models was fit using random forests (RF) (Breiman, 2001), a cumulative learning algorithm for regression and classification problems based on decision trees and bagging (bootstrap aggregation). Many studies have demonstrated the effectiveness of the RF model in modeling agricultural biophysical processes, particularly those that are nonlinear (Everingham et al., 2016; Jeong et al., 2016; Sakamoto, 2020). During the training process, RF builds a 'forest' from regression trees that are developed from a bootstrap sample of input datasets. Each bootstrap sample contains two-thirds of the input dataset while the remaining samples that are not included in training, are used to validate the model and assess the importance of predictor variables. Once the model construction terminates, predictions can be done by considering the expected value of all individual predictions of regression trees in the forest. We performed this RF analysis using the randomForest package v 4.6-14 (Liaw &

Wiener, 2002) in R, and considering the default parameters (e.g., number of trees) suggested by package developers in R environment (R Core Team, 2018).

2.4 Validation of Statistical Yield Models

We first compared the ability of each alternative model design to reproduce synthetic yields simulated by APSIM, focusing on the R-Squared and Root Mean Square Error (RMSE) of yield estimates in comparison with the actual APSIM simulated yields. For this analysis, we split 201,600 simulated yield observations into training and validation samples through a random selection, considering 80% of the observations as training data and the remaining 20% of the observations as data not used during the development phase of the statistical models.

After identifying the best performing statistical model for emulating APSIM simulated yields, we seek to evaluate the ability of this model to reproduce observed yields in our study area. To determine yields for each of the 80 unique fields in our observed yield dataset (Section 2.1), we obtained weather and crop development observations for the 2019 rice growing season over our study region. Daily time series of precipitation and temperature (minimum and maximum) were obtained from the ERA5 reanalysis dataset at 0.25° x 0.25° resolution (Hersbach et al., 2020). Timing of rice growth stages was determined from NDVI time series–interpolated from discrete values obtained from Sentinel-2 satellite imagery–for each of the 80 fields in our sample. Specifically, we assumed that the minimum NDVI value at the inflection point on the rising limb of the curve corresponds with the transplanting date, and that harvest occurs when the NDVI time series equals 0.25 on the falling limb. Timing of other growth stage transitions was determined based on typical time from transplanting to reach the start of each stage for Swarna rice: 41 days, 61 days and 75 days for start of panicle initiation, flowering and grain filling, respectively.

LAI time series for each field were generated based on spectral band data obtained from Sentinel-2 and Landsat-8 imagery retrieved through Google Earth Engine (Gorelick et al., 2017). Estimates of LAI were generated for each cloud free pixel based on spectral band data provided by Sentinel-2 and Landsat-8 imagery using an inverted radiative transfer model (RTM) (Jacquemoud et al., 2009). The RTM inversions were developed by running the PROSAIL model 5000 times to generate synthetic reflectance data for a range of possible combinations of rice canopy, leaf and soil properties (Table 1), following parameter ranges reported in previous applications for rice LAI estimation (Campos-Taberner et al., 2016). We use the simulated reflectance data to develop statistical models between the spectral bands collected by Sentinel-2 and Landsat-8 to LAI using a procedure similar to the RF approach described previously in Section 2.3. To develop statistical models for LAI, we split data equally at random between training and validation. The validated RTM model is subsequently used to convert observed reflectance on a given field into a discrete estimate of rice LAI for each available cloud-free observation, which is then converted to a continuous LAI time series for each field by fitting a double logistic function.

Estimated yields were compared with observed data from CCEs using R^2, RMSE, and Normalized Room Mean Square Error (NRMSE) statistics at two spatial scales: (1) plot scale (80 observations), and (2) GP scale (20 observations, with an average of 4 plots per GP). As noted previously, the latter equates to a spatial scale similar to a cluster of nearby villages, which is the lowest level of governing institutions in India's administrative structure. Importantly, GPs form the primarily spatial unit for area-yield insurance within the Indian government's national crop insurance program, which at present relies on data from manual CCEs to verify crop yield losses and any resulting payouts to farmers. Understanding performance of our methods at this scale therefore is of particular importance for understanding potential opportunities and challenges for satellite data and crop models to help reduce costs and time associated with crop insurance in India.

Table 1. Canopy, leaf and soil parameter ranges and distributions used within the PROSAIL RTM simulations. The parameters were drawn from a truncated normal distribution (TND), with the exception of solar zenith angle, observer zenith angle, and relative azimuth angle.

Parameter Name	TND Mean	TND Std.	TND Lower Bound	TND Upper Bound
Structure Parameter	1.5	0.3	1.2	2.2
Chlorophyll content	45	30	20	90
Brown pigment content	0.25	0.1	0.1	0.5
Dry matter content	0.05	0.005	0.003	0.011
Dry/Wet soil factor	0.9	0.25	0..3	1.2
Leaf area index	3.5	4.5	0	10
Leaf angle distribution	60	20	30	80
Hotspot parameter	0.2	0.2	0.1	0.5
Parameter Name	Uniform Distribution (minimum Value)		Uniform Distribution (maximum Value)	
Solar zenith angle	15		90	
Observer zenith angle	-12		12	
Relative azimuth angle	6		6	

3. Results

3.1 Performance of Statistical Models in Emulating APSIM Simulations

We first compare the performance of different model specifications (with varying predictor variables and varying levels of temporal aggregation for these variables) in terms of their ability to reproduce the synthetic yield data generated using APSIM. This is equivalent to selecting the best performing index for the design of an index insurance product. Figure 3 summarizes the performance (left: R^2, right: RMSE) of each candidate model during validation against the validation data not used during training of the RF models.

From inspection of Figure 3, two trends are apparent. First, the models more accurately reproduce heterogeneity in APSIM-simulated rice yields when considering greater temporal disaggregation of predictor variables (i.e., moving from left to right along a row in Figure 3). The greatest improvement in model performance is found when including predictor variables disaggregated by crop growth stage (DSTG models). The RMSE error across potential models reduces by 5% to 85% (with an average of 47%) and 8% to 80% (with average of 50%) when input variables are aggregated by fixed and dynamic growth stage as opposed to over the fixed and dynamic seasonal –FS and DS – models respectively. However, the reduction in RMSE in yield estimates from aggregating predictor variables over a dynamic aggregation approach compared to a fixed aggregation approach is much smaller (40-86% with an average of 60% across models considering different combinations of temperature, precipitation, and leaf area index predictors).

The second noticeable trend from examining Figure 3 is that model performance improves by integrating multiple weather and crop predictor variables. A comparison of alternative model configurations using unseen validation datasets in Figure 3 (i.e., comparing across rows in each figure panel) shows that the best model performance in terms of both R^2 and RMSE is achieved when combining temperature, precipitation, and leaf area index predictors. Reliance on a single variable alone appears to reduce the capacity of our models to accurately capture the variability in crop yields simulated by APSIM. Leaf area index alone is found to be the least robust individual predictor of yields, with models based on temperature, precipitation, or a combination of these two variables generating significantly more accurate yield estimates. For example, for dynamic stage model specifications, the RMSE of models considering only leaf area index as a predictor is 572.9 kg/ha compared with 238.7 kg/ha for models including only weather predictors (temperature and precipitation) – an increase in RMSE of approximately 140% when only using leaf area index as a predictor of yields.

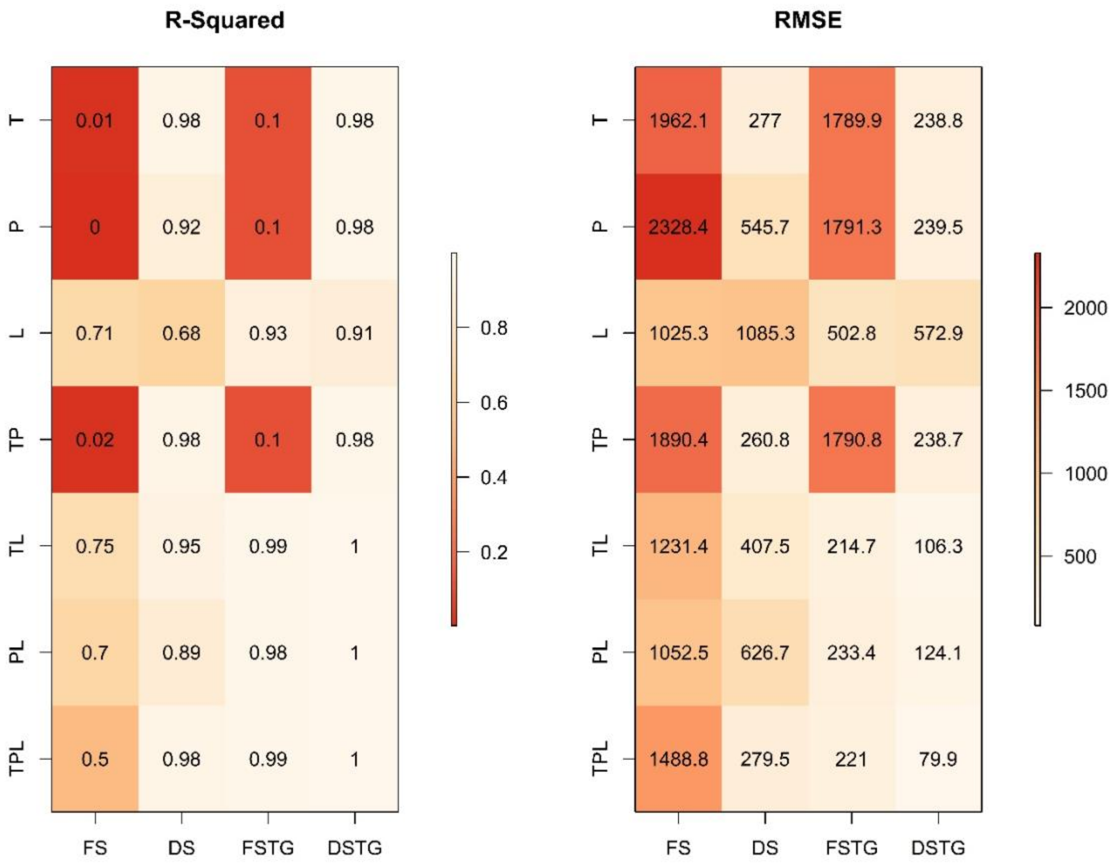

Figure 3. Performance of statistical models in emulating synthetic APSIM simulated rice yields. Statistical model labels denote the different model predictor variables (vertical axis) and temporal aggregation of predictors (horizontal axis) considered in each specification, where T: Temperature, P: Precipitation, L: LAI, FS: Fixed Season, DS: Dynamic Season, FSTG: Fixed Crop Growth Stage, DSTG: Dynamic Crop Growth Stage. R^2 and RMSE are reported for out-of-sample validation based on a retained 20% of the 201,600 unique yield simulations performed using APSIM.

3.2 Performance of Statistical Models in Estimating Crop Yields at plot and GP Levels

For application in the context of agricultural insurance, it is important to assess the ability of statistical models to reproduce not only synthetic yields simulated by APSIM but also observed yield in real world smallholder farming environments. We therefore evaluate the ability of our best performing 'index' (i.e., model specification considering temperature, precipitation and LAI predictors disaggregated by growth stage; see Section 2.4 and 3.1) against observed yields from CCEs conducted in Jajpur district in the state of Odisha in eastern India, at the plot level (80 observation points) and averaged by GP level (20 observation points).[2]

We find that our statistical model, developed based on the synthetic yield data simulated using APSIM, explains around 54% of the variance in observed rice yields at GP level, with an RMSE of 546.27 kg/ha (Figure 4b and Table 2). Performance of yield estimation at plot level is lower, with our model able to explain approximately 26% of observed yield variability with an RMSE of 860.1 kg/ha (Figure 4a and Table 2). Model accuracy is lower when predicting observed yields than when predicting APSIM simulated yields, likely due to constraints imposed by the spatial resolution of weather data, gaps in LAI time series caused by cloud cover, and uncertainties in the underlying radiative transfer model used to translate spectral data obtained from Sentinel-2 and Landsat-8 into estimates of rice LAI during the season. However, an R^2 of 0.54 for GP-level yields suggests that such an approach may offer a useful tool for the design of index insurance products at this scale, for example in the context of

[2] We use the observed yield data to validate our approach; that is, to analyze whether a statistical yield model that was estimated using synthetic data, simulated using biophysical crop models, and implemented using real-time monitoring of weather conditions and crop phenology, has predictive power. We do not aim to identify the best-performing model using the observed yield data because of limitations in observed yield data availability, specifically, a lack of sufficient variation across space and time to reliably estimate our statistical yield models—this is the exact same challenge in index design that motivated our use of crop simulation models.

supporting area-yield index insurance products within the Indian Government's PMFBY crop insurance program.

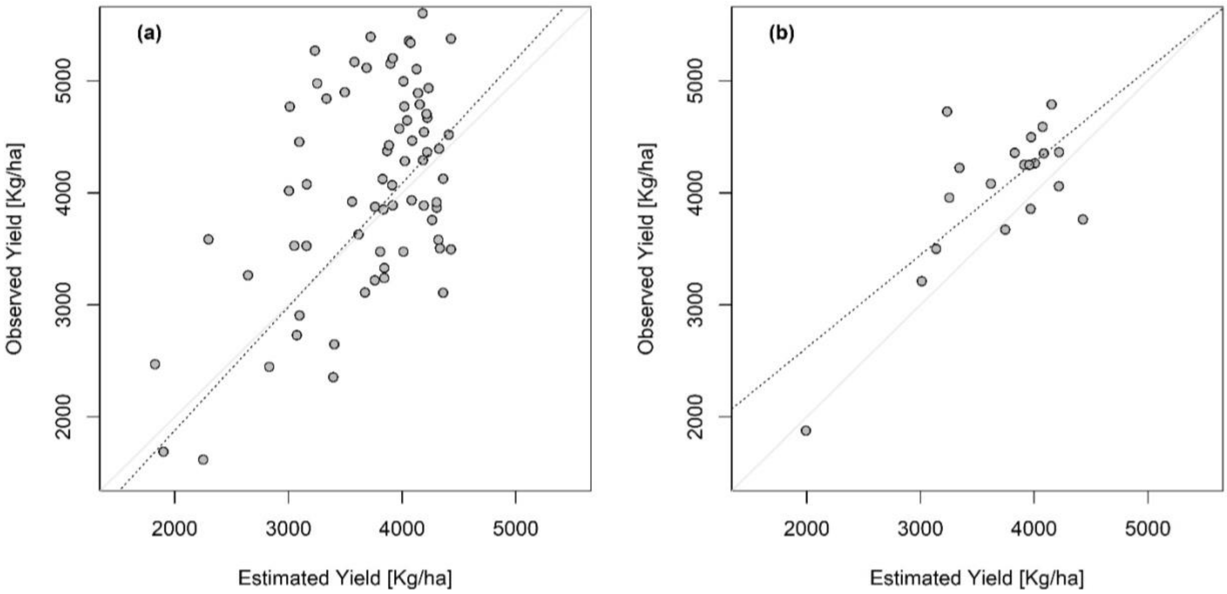

Figure 4. Scatterplot comparing estimated and observed rice yields (kg/ha) at: (a) plot, and (b) GP spatial scales.

3.3 Comparison of Statistical Models Developed Based on Vegetation Indices and Process Based Crop Model Simulations.

As previously highlighted, a common challenge when developing and designing index insurance products is the limited availability of yield observation datasets to train underlying models that quantify yield losses based on proxy data. To evaluate the value provided by using crop models to generate larger synthetic yield training datasets, we compare the performance of our models reported in Section 3.2 with plot and GP level yield estimates derived using statistical vegetation index (VI)-based models developed by using observed yield data from CCEs. This is a common approach underlying design of many existing index insurance products in India and other parts of the world (Brock Porth et al., 2020; Kölle et al., 2020; Turvey & McLaurin, 2012), and, as such, understanding what – if any – improvements in accuracy are obtained from using crop models alongside satellite data is critical to understand the value added from more complex approaches.

We consider two alternative potential VI-based yield models, using as predictors the average values of either NDVI or EVI. In each case, the used predictor is disaggregated by averaging over the four main rice crop growth stages to match best performing model stemming from Section 3.2. We develop each statistical VI model using the RF approach, with VI values for each field and growth stage calculated using spectral bands data and observations of growth stage timings obtained from Sentinel-2 and Landsat-8 for each field, as described in Section 2.3. Note that we train these alternative models by using a bootstrap approach (1000 times) and validate them through a k-fold validation scheme by considering 5-folds with 16 observation in each of them to minimize risks of overfitting, which could occur if all yield data were used in training and validation. We do not include weather data as an additional predictor in these models, given that the coarse resolution of available gridded weather products means that there is insufficient spatial variation to adequately capture effects of spatial weather heterogeneity in model training. Moreover, it is common for index insurance products to typically consider only vegetation indices or only weather data as predictors, with relatively little attempts to date to combine these predictors in index insurance contracts.

Similar to the trends observed in the previous analysis of statistical yield models that were derived based on APSIM simulated yield data, we find an improvement in the performance of VI-based models when aggregating yield estimation from plot to GP level (Table 2). However, comparing the performance of VI and crop model derived yield estimates at the same spatial scale, predictions by our crop model approach far outperform the predictions from both VI models. For example, at GP scales, our preferred model captures 54% of observed yield variability, while VI-based models capture on average only 39% of yield variability (36% and 42% for the NDVI- and EVI-based model, respectively). VI-based models are also associated with larger RMSEs; on average, RMSEs are 12% higher than in the statistical yield model that we estimated from APSIM simulations.

Moreover, VI-based models are also associated with higher levels of uncertainty depending on which data are included in model training (for instance, we find a 47.63 standard deviation of RMSE values of 1000 bootstrap EVI based yield estimations at the GP scale). Where the total number of yield observation data are limited, as is the case here, and is common in almost all smallholder environments, this result suggests that use of APSIM or other crop models can play an important role in improving the accuracy and robustness of yield-index relationships necessary for designing index insurance products, relative to satellite vegetation indices alone.

Table 2. Accuracy Assessment of Statistical Models Developed Based on Vegetation Indices and Process-Based Crop Model Simulations. CCE: Crop Cutting Experiments, GP: Gram Panchayat, Standard deviations are shown in parentheses.

Model	Plot Level			GP Level		
	R^2	RMSE	NRMSE	R^2	RMSE	NRMSE
NDVI	0.11 (0.03)	990.82 (36.09)	0.24 (0.01)	0.36 (0.07)	633.45 (47.05)	0.16 (0.01)
EVI	0.11 (0.03)	1000.20 (35.44)	0.24 (0.01)	0.42 (0.09)	590.49 (47.63)	0.15 (0.01)
Crop Model	0.26 (0)	860.08 (0)	0.21 (0)	0.54 (0)	546.27 (0)	0.14 (0)

4. Discussion

Relative to other forms of insurance and risk financing, index insurance schemes can provide a relatively low cost and easy-to-implement solution to protect smallholder farmers against production risks posed by extreme weather events and climate change (Barnett & Mahul, 2007; Clarke et al., 2012). However, the value of these products for farmers and insurers is strongly predicated on the ability to base insurance payouts on index relationships that reliably and accurately quantify crop yield losses at disaggregated spatial and temporal scales (Clement, Botzen, et al., 2018).

We show that combining crop modelling and satellite-based crop phenology measurements can provide a scalable solution for deriving the relationship between yields and proxy indices at spatial scales relevant for agricultural insurance. Our findings highlight that accounting for field-level heterogeneity in crop phenology and combining multiple types of predictor variables, including both weather and leaf area indices, can significantly enhance model accuracy, in particular when aggregating to spatial units larger than an individual plot; which is common for area-yield index insurance in smallholder farming systems such as those in our study area (Shirsath et al., 2019). It is also important to note in this regard that in the crop model simulations, we only used publicly available information on typical ranges of cropping practices and varieties to generate synthetic yield training data; we did not measure these variables to implement crop models at the plot level, which adds to the scalability of this approach.

Our findings do not support a finding from previous research combining earth observation data and crop models: that yields can be estimated using either a single (peak or aggregated total) value of LAI for the season, or multiple LAI predictors that relate to specific satellite image dates but are not directly correlated with crop growth stage timings (Burke & Lobell, 2017; Jain et al., 2017, 2019). Due to the lack of variation across space and time of our field level observations, we were unable to validate all model combinations and aggregation levels with field measurements. Nonetheless, the comparison of models derived from simulated data in terms of their ability to capture heterogeneity in simulated yields suggest that disaggregating predictor variables by crop development stages enhances the accuracy of predicted yields relative to simpler seasonal aggregation. This will be true especially when heterogeneity in phenology between fields and seasons is large due to differences in farm management practices, crop varietal choices, and weather conditions. We also find that insurance index performance can be improved further by combining LAI and weather predictor variables, which we attribute the ability of weather data (in particular temperature predictors) to capture crop yield losses associated with deficient grain filling or pollination that would not be fully captured by changes in LAI alone (Waldner et al., 2019).

Although the value of phenology data for improving yield estimation and index insurance has been demonstrated previously (Conradt et al., 2015; Dalhaus et al., 2018; Ortiz-Bobea et al., 2019), these studies have focused on developed countries where extensive and longstanding phenological monitoring networks exist. We show that it is possible to replicate some of these improvements in yield estimation accuracy, and we highlight for smallholder environments the potential to reduce basis risk in index insurance using satellite-derived information on the timing of key development phases. The value of phenological information is largest when considering not only heterogeneity in the timing of the start and onset of the crop growing season but also in the timing of specific individual growth stages. This result is consistent with evidence suggesting that effects of extreme weather on yields of rice and other crops are strongly dependent on the timing of shocks during the season, with potential for larger yield losses if weather-related shocks occur during critical growth periods such as anthesis (Barlow et al., 2015; Cornish et al., 2015). Critically, only adjusting the seasonal time period for index insurance contracts – for example to account for potential impacts of delayed transplanting of rice in years for with late monsoon onset (Balwinder-Singh et al., 2019) – would fail to exploit the true value of phenological information for yield estimation.

While our results suggest potential benefits of using crop model simulations to support the design of agricultural index insurance products, several approaches could be used to improve the accuracy of yield estimation at the plot level, which would aid both the design of plot-level index insurance and the accuracy of larger scale area-yield index insurance. For example, in this study we rely on a relatively simple satellite-based method for estimating intra-seasonal crop phenology. Integration of in-situ imagery, for example taken by farmers through smartphones at regular intervals during the season (Hufkens et al., 2019), could help to reduce uncertainties in satellite-derived of growth stage timings while also providing a supplementary source of information to help to validate fitted LAI time series. Such data would be especially valuable for crops grown during the rainy season, a period where substantial gaps in satellite imagery often occur due to high levels of cloud cover. In addition, in-situ imagery could provide a mechanism for detecting crop damage that may be difficult to reliably correlate with weather or vegetation indices, for example mechanical damage to crops caused by flooding, wind and hailstorms, or pests and diseases (Ceballos et al., 2019). These factors are a potentially important driver of errors in plot-level yield estimation, suggesting that integration of in-situ imagery should contribute to reduce basis risk especially at these finer spatial scales. A further factor that may explain the larger errors in yield estimations observed in our analysis at the plot versus GP scales is the coarse resolution of weather data available in our study region. The ERA-5 reanalysis dataset used in this study has a spatial resolution of 0.25 x 0.25 degrees (approximately 25km x 25km), which is sufficient to capture heterogeneity in weather conditions between GPs but not between individual plots within a GP. Given the important role of weather data in yield estimation (Section 3.1), this suggests that provision of finer resolution weather data could play an important role in supporting reductions in basis risk of index insurance products. However, development and validation of fine-scale weather data products remains challenging in many smallholder environments due to the limited density and completeness of in-situ weather records (Norton et al., 2013), in contrast to more extensive monitoring networks found in regions such as Europe and North America (Dalhaus & Finger, 2016).

Finally, a key finding from our analysis is that the use of crop models provides added value for yield estimation beyond the use of statistical models based solely on satellite vegetation indices. Nevertheless, it is important to note that while our analysis considers two of the most commonly used vegetation indices for index insurance and yield estimation (NDVI and EVI), alternative types and combinations could have been used. For example, studies by Enenkel et. al. (2018) (Enenkel et al., 2018), and Mollmann et al., (2020) (Möllmann et al., 2020) showed that developing more complex statistical models using multiple types of vegetation indices from different satellite datasets (e.g., Sentinel-1 or Sentinel-2) can yield more robust crop yield information. Hence, future research should seek to evaluate a broader range of vegetation index models to further explore the added value provided by integration of crop models alongside satellite and other data sources. Moreover, future analyses should also consider how trade-offs between the two types of methods are affected by the amount and completeness of observational yield data and satellite imagery used to train statistical VI-based models. We hypothesize that the added value of crop models will be highest in environments where observational yield datasets are smaller, where satellite imagery is strongly affected by cloud cover, and where small plot sizes pose a challenge for remote sensing with currently available resolutions of satellite imagery; each of these are common characteristics of smallholder farming environments that are the focus of this study.

5. Conclusions

Index-based insurance provides a potential solution to transfer risks caused by crop failure away from smallholder farmers, providing farmers with a timely payout in the event of a poor harvest without the need for expensive manual verification of yields as in the case of traditional indemnity insurance. However, basis risk, that is, a poor correlation between actual yield losses and losses estimated based on the insurance index, remains a key challenge to scaling index insurance, reducing farmers' willingness to pay for insurance products and their ability to adapt to climate variability and change. In this study, we evaluate the potential to improve the accuracy of index insurance by combining process-based crop models, satellite-derived phenological metrics, and geospatial weather data to design index insurance products, focusing on a case study of rainfed rice production in the state of Odisha in eastern India.

We show that when accounting for field-level heterogeneity in crop development and timing of extreme weather events, it is possible to reliably estimate rice yields without the need for extensive observational yield training datasets, and without having to apply real-time data-demanding plot-level crop simulations. Our analysis demonstrates that yield estimation is improved by considering both agronomic (i.e., leaf area index) and meteorological (i.e., temperature and precipitation) drivers of yield variability. Performance also increases when aggregating individual plot-level estimates to village or GP-level scales, suggesting that approaches proposed in this paper may have value in reducing reliance on the time and resource intensive CCEs that are typically used to support assessment of losses in area-yield index insurance products in India.

Our findings further show that the accuracy of yield estimation by our preferred crop model and satellite information approach significantly outperforms models based solely on satellite vegetation indices and is consistent with existing research using crop models and satellite data for yield estimation in India, even though these studies have typically focused on crops such as wheat where satellite imagery is much less affected by cloud cover. Overall, our results highlight the potential of technologies such as crop modelling and satellite remote sensing to support smart phenology-driven index insurance contracts, with potential for further improvements in yield estimation accuracy as high-resolution satellite and in-situ crop monitoring becomes increasingly viable in smallholder environments.

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