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Designing weather index insurance of crops for the increased satisfaction of farmers, industry and the government

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ABSTRACT

Weather-based crop insurance is a powerful tool for stabilizing farmers' income by providing timely payouts directly linked with weather parameters. However, its performance can be marred by faulty design, leading to high basis risk and insufficient payouts. This paper presents a new methodology for contract design for weather-based insurance, field tested in India. By combining agro-meteorological statistical analysis, crop growth modelling and optimization techniques, a heuristic model is developed which generates superior contract design which yields better and frequent payouts at no extra cost of subsidies (in terms of premium rates). The study also presents 'Farmer Satisfaction Index' as a powerful evaluation tool in determining the effectiveness of insurance products through measurement of basis risk. The method is backed by results from implementing the proposed model in many districts of Maharashtra, India. The proposed contract performed better than the existing insurance contract with 50 and 72 percent increase in Farmers Satisfaction Index for Soybean and Pearl Millet, while increasing correlation of payouts with yield losses and reducing the overall loss-cost ratio. Selected triggers effectively captured climatic risks in important crop growth phases. These results were consistent for pay-outs evaluated for long-term time series of 100 years of synthetic climate data. Findings indicate the use of recommended approach can lead to increased satisfaction of farmers, insurers and policymakers alike.

1. Introduction

Income from crop production has historically known to be unstable. Climatic stresses and/or other factors can cause sudden losses resulting in highly volatile returns, especially in the case of rainfed areas. Growing evidence suggests historical food insecurity across the globe because of climatic influence (Niles and Salerno, 2018; Ray et al., 2015). Changing climate in the future is expected to further exacerbate variability and reduction in agricultural production, affecting rural livelihoods at the global scale (Arnell et al., 2016). Risk management from changing climate is hence considered vital in protecting agriculture and promoting development (Jensen and Barrett, 2017). Crop insurance has been recognized as an effective hedging strategy against extreme weather events and is often used to mitigate unexpected losses (Panda, 2013; Platteau et al., 2017). Crop insurance primarily acts as a contingency risk management strategy where premiums are paid by participant farmers and losses are claimed when yields fall below a stipulated level. However, area yield-based crop insurance is burdened with many issues like high basis risk (risk where the insurance contract

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does not trigger payments in the event of crop loss, often due to faulty design and/or wrong selection of climatic variables), poor operational mechanisms and faulty design of insurance product with high premiums (Carter et al., 2014). Consequently, weather-based crop insurance (henceforth WBCIS) was developed as an alternative to traditional agricultural insurance. By directly linking weather parameters to payouts, WBCIS offered a transparent and more effective mechanism in which claim payments are not based on crop yields derived from crop cutting experiments and market factors; but on objectively measured, manipulation free readings given by weather stations (Brown et al., 2011). Specifically, for weather events like the deficit and excess rainfall, droughts and extreme temperature, WBCIS is a conceptually better proposition, as it is more suited to the progressive impact of such events on crops, which gradually accumulates over time and causes crop failures. It has thereby reduced transaction costs and omitted the problems of basis risk, moral hazard and adverse selection compared with traditional insurance (Kuwata et al., 2015; Swain, 2015). Globally, WBCIS is increasingly being used to compensate crop losses (Clement et al., 2018).

India is one of the largest countries in agricultural insurance after the United States and China (Swiss Re, 2014). The national crop insurance scheme (known as Pradhan Mantri Fasal Bima Yojana) is an area-based yield insurance scheme launched in 2016. Although it covers the majority of area under crop insurance, weather-based index insurance scheme had an area coverage of 1.7 million hectares in the country in 2016 (Gulati et al., 2018). Under this scheme, claim payments to farmers are linked directly to weather parameters like rainfall, humidity and temperature (Adivappar et al., 2014). Triggers are developed, which are critical or threshold values of selected weather indices at which pay-outs from the insurance contract commences. They are generally developed from current and historical weather data and are monitored at nearest weather stations (Clarke et al., 2012). Although satellite weather data is increasingly being recognized as an important source for designing index insurance in developing countries (Enenkel et al., 2018), weather-based insurance in India is still primarily dependent on station weather data. Diversifying from area-yield based insurance; WBCIS utilizes rainfall and temperature indices apart from historical yield data. In India, WBCIS provides coverage for both rainy and post-rainy season. It covers all the major crops including cereals, pulses, oilseeds and annual horticultural crops. Risk coverage extends from sowing to crop maturity, but may vary with individual crop and specific area. Any adverse weather event during the crop season entitles the insured farmers a payout, subject to deviation in weather triggers defined in the "payout structures". The scheme is highly subsidized by the government and it has been made mandatory for all cultivators availing institutional credit. Total sum insured is distributed among various crop growth phases and critical weather indices. These weather indices are usually developed in consultation with experts.

Despite being an improvement over traditional yield-based insurance products, WBCIS has not generated anticipated impact. Most of the farmers in impact studies have cited delay in claims settlement and insufficient payouts as major pitfalls against greater uptake of the scheme amongst farming community (Zevenbergen, 2014; Raju et al., 2016). Demand for WBCIS among farmers is profoundly impacted by premium rates and basis risk, as documented in recent research (Hill et al., 2016). On the contrary, subsidizing premium rates to cover up basis risk and make insurance products more palatable to the farmers is a costly proposition for the government and insuring agencies alike (Ricome et al., 2017); and climate change may even force premium rates to go higher (Tack et al., 2017). Many index insurance projects have thus not been able to create high demand, even after subsidies and significant extension efforts. Basis risk is often cited in insurance literature as the single biggest hurdle for the spread of weather insurance in agricultural areas (Jensen et al., 2016; Doms et al., 2018). The crux of an effective index insurance lies in the design of its weather triggers and coverage of production risks (Marr et al., 2016). An index insurance product is rendered ineffective for farmers when it is unable to give payouts for yield losses. Thus, the effectiveness of the product can be greatly increased by its better linkage with production risks. In fact, high demand for index insurance has been documented when additional supporting factors like index effectiveness, favourable pricing options, credit facilitation and policy support have been provided (Jensen et al., 2018; Chantarat et al., 2017; Carter et al., 2017).

2. Objective

As illustrated above, claims settlement in case of WBCIS is solely dependent on triggers set for weather parameters. It co-creates potential for high basis risk, as often inappropriate trigger values and faulty weather indices are used to generate ineffective contracts and yield losses at field levels are rarely translated into actual payouts for the farmers (Elabed et al., 2013). Adequate hedging against yield fluctuations should thus be an important goal for index insurance, for which it is necessary to establish clear weather-yield relationships. Efficacy of WBCIS can be greatly increased by calibrating weather indices to maximize the correlation between claim payments and yield losses (Clarke and Wren-Lewis, 2016; Morsink et al., 2016; Clarke et al., 2012). Agro-meteorology based statistical analysis and crop growth modelling can be effectively used for such calibrations and to rectify faulty weather indices (Zhu et al., 2015). However, they are sporadically used due to lack of corresponding weather and crop production data at the local level and triggers are often developed based on expert judgement (Shen et al., 2015). The present agricultural insurance narrative thus needs a potential model to improve insurance contracts with greater results for all stakeholders alike. In this paper, we present a new methodology to develop efficient weather triggers and improve overall WBCIS performance. Specifically, we aim:

a) To develop and evaluate a methodology for developing best performing weather based index insurance product built on statistical analysis, crop growth modelling and optimization framework.
b) To develop an evaluation index for succinctly measuring farmer's satisfaction with WBCIS product.
c) To illustrate the methodology in terms of improved performance of WBCIS in a pilot study in Maharashtra, India.

3. Methodology

3.1. Conceptual framework

A synergistic methodology combining statistical analysis, dynamic crop growth modelling and optimization framework was developed for the study (Fig. 1).

First step was to develop a robust weather-yield response model. This was achieved by developing and standardizing models obtained from statistical analysis of historical data. Historical observed yield data and weather parameters were subjected to stepwise regression to determine significant variables affecting yield levels. Forward stepwise selection model was used as a building block and weather variables were added subsequently. The variables were included on the basis of minimum threshold of p-value (threshold of p-value was 0.05 or lower). However, to retain consistency with existing contract design, some non-significant weather variables were also included. Consequently, three models were developed a) excessive rainfall model (with positive deviation from mean monthly rainfall); b) deficit rainfall (with negative deviation from mean monthly rainfall) and c) combination model (with both deficit and excessive rainfall). Crop growth modelling (through DSSAT) was then used to develop simulated yield data for the same time period. Crop growth models simulate the effects of daily changes in soil, weather and agronomic management practices on crop growth and yield. Therefore, it is easier to isolate direct yield change attributable to a specific weather parameter or management input; and hence a better relationship with weather parameters. All simulations were done under rainfed mode (no irrigation) as Kharif crops grown in the region were all rainfed. The input data required for simulations was used from different sources, for example, soil data was taken from National Bureau of Soil Survey and Land-use Planning and daily weather data was taken from weather stations located in the districts. The model settings (variety, fertilizer rates, crop calendars etc.) was based on prevailing farming conditions in the study districts from government reported statistics (National Food Security Mission, official district profile). Simulated yields were then used for developing a second crop-yield response model. Previous research has presented a strong case for combining statistical and simulation methods to construct strong weather indices for best results (Lampayan et al., 2015). Crop

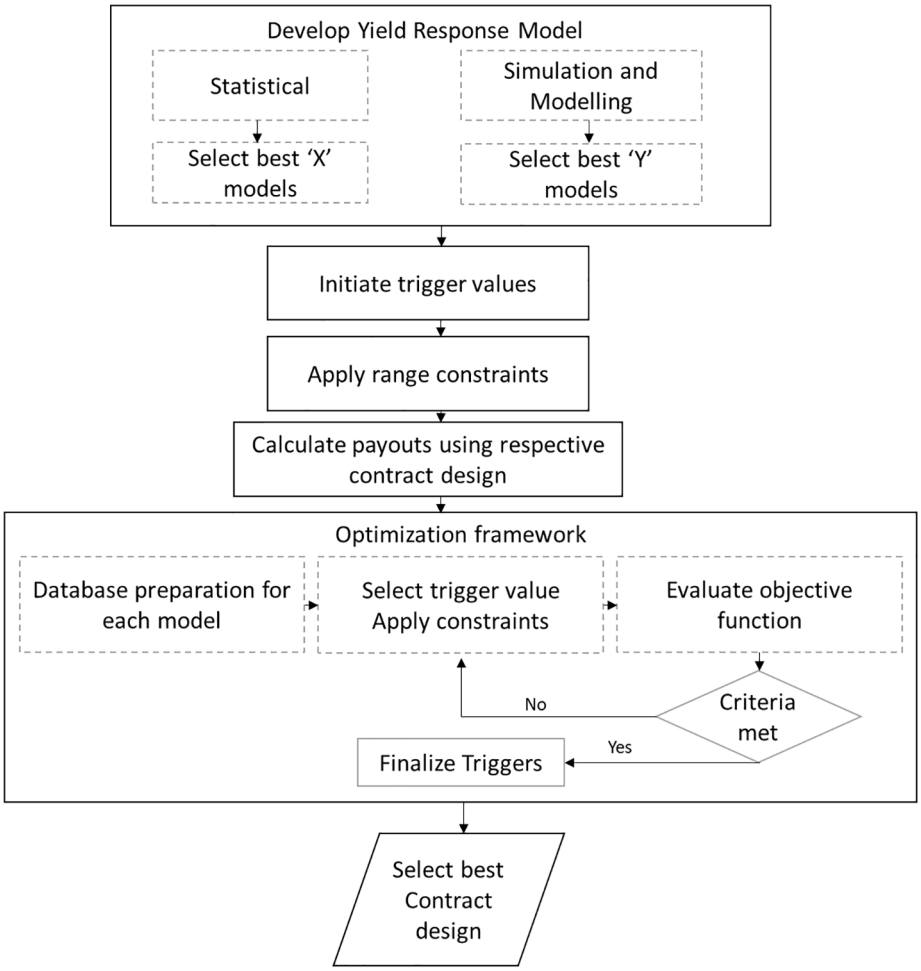

Fig. 1. Flowchart of methodology used to develop triggers for Weather Based Crop Insurance Scheme (WBCIS).

Table 1
Parameters used in the optimization framework for improving contract performance.

Performance parameter	Definition
Farmer Satisfaction Index	Satisfaction index is a measure which combines the pay-out difference and correlation between the pay-outs. Mathematically it is correlation weighted pay-out difference (%) and it is scaled to 10, maximum (10) for best fit and 0 for worst
Farmer Satisfaction Index (True Payments)	Satisfaction index in above definition when measured only for those years where yield loss was observed
Claims ratio	It is the ratio of claims payable as per the contract and premium collected
Premium (percentage)	Amount of Premium payable under the contract, as a percentage of Sum Insured

simulation modelling is also helpful in cases where historical data is insufficient or missing, a widely prevalent hurdle for many regions. Several crop models have been used in agricultural insurance like Decision Support System for Agrotechnology Transfer (DSSAT) for India and Système d'Analyse Régionale des Risques Agroclimatiques (SARRA) with parcel level water balance (SARRA-BIL) for Senegal (Dingkuhn et al., 2003). Crop growth modelling was done using DSSAT, which has been calibrated previously to reported yield datasets (Jones et al., 2003). Second step involved identifying trigger values of selected weather parameters, which would initiate pay-outs under the contract design. After obtaining regression models from observed and simulated data, trigger values were calculated. Range constraints were applied, to keep triggers under statistical bounds (standard deviation of the weather coefficient derived from the data series or standard error derived from regression equation). Payouts were then calculated for selected trigger values. Final step involved using goal setting under optimization framework, to select contract with best performance under specified goals. Optimization is a commonly used tool in insurance to systematize models, fix pricing levels and check model sensitivity to constraints (Carson et al., 2013). Optimization techniques have also been used in crop insurance to design better insurance models (Turvey, 2012). Open solver (in excel) was used for optimization and SPSS Statistical tool was used for analysis. The main stakeholders of any WBCIS scheme are farmers, insuring agency and government (which provides the subsidy). Accordingly, three goals were identified for optimization a) maximum payouts for farmers b) low claims ratio for insuring agency and c) minimal premium rates (lesser subsidy required) for the government. Each of these goals (or objective function) were evaluated based on whether the optimized trigger values were within statistical and crop-physiological bounds. The objective function used for the revised contract was maximization of farmer satisfaction index, which aims at maximizing pay-outs corroborating with yield losses. Optimization framework described here helped in developing a new contract which gave consistent payouts with yield losses, within reasonable bounds of claims ratio and premium level. This was achieved by selecting appropriate performance parameters (Table 1). These parameters were standardized within statistical bounds of weather triggers (as discussed previously in Step 2).

3.2. Farmer satisfaction index

A farmer satisfaction index was developed as one of the parameters to measure farmer's agreeability with redesigned WBCIS scheme. The concept of satisfaction index has been extensively used in life and non-life insurance (Haumann et al., 2014). It serves as a reliable indicator in providing valuable insights into factors affecting uptake of insurance products across the industry. It has proved beneficial for all stakeholders including consumers, industry and policymakers alike (Taylor, 2001).

Using similar principles, this paper attempted to create farmers' satisfaction index for the specific crop insurance model. Extension of satisfaction index to agriculture has been limited. Yazdanpanah et al., 2013 presented a modified customer satisfaction index for measuring satisfaction of crop insured farmers in Iran, using American Customer Satisfaction Index (ACSI). These survey techniques, brings better insights into the product design. While the direct approach can yield a significant understanding of farmer behaviour towards an insurance product, it is often cumbersome and requires a periodic survey of farmers. This paper proposes an indirect approach, by linking required pay-outs (based on actual yield losses) and given pay-outs. The index serves as a proxy indicator for basis risk, and was developed to measure the ability of an insurance contract to give required pay-outs. Basis risk can be decomposed into two main components- insured peril basis risk (resulting from the inability of the insurance contract to cover risks which can hamper crop yields) and production smoothening basis risk (resulting from poor linkage of triggers with actual yield loss). This index can thus measure both forms of basis risk, which were not captured well earlier while trigger development (Morsink et al., 2016). Mathematically, average farmer satisfaction index (for all the years) is defined as

$$Farmer\ Satisfaction\ Index = \rho(pr, pg) * (100 - \sum (pd)/n) \tag{1}$$

where ρ(pr,pg) represents the correlation between pr (pay-outs required) and pg (pay-outs given) and pd is the pay-out difference (a difference between pay-out required based on yield loss and pay-out given based on contract design) and n is the number of years.

The index in its current form treats under and over-payments in a similar manner which might not be able to capture the welfare implications of index insurance. For example, resource-constrained farmers are worse-off, if they don't get a payout from index insurance when a production shock occurs. Alternatively, it is possible that such farmers receive a payout from index insurance in the absence of a production shock, which is unfavourable for the insuring agency and government in the long run (Clarke, 2016; Morsink et al., 2016). However, it is a simple index which can capture basis risk and can be used to guide contract design for safeguarding multiple stakeholders interest.

4. Data and case study

This paper presents findings from applying the above discussed methodology (for trigger development) to WBCIS in the state of Maharashtra. The state is host to many different types of climatic risks including floods and droughts. To develop the model, historical agricultural and weather data were collated for the particular insurance sites. Crop yield and meteorological time series data were obtained from district stations. Time series data was available from 1991 to 2012. Historical weather and yield data was analyzed for spatial and temporal trends. Existing contracts were obtained from the district and analyzed for understanding the current index insurance structure. Contracts were designed for the deficit and excessive rainfall. Deficit rainfall was characterized by rainfall volume (cumulative rainfall volume, mm) and distribution (maximum length of dry spell, days). The dry spells relate to the number of consecutive days with rainfall less than 2.5 mm, as defined by the Indian Meteorological Department (IMD). Excess rainfall trigger is activated if sum of two consecutive days rainfall exceeds a given threshold value. Other insurance parameters such as sum insured, premium and minimum threshold payment by district and crop, were collected from existing insurance contract. Some contracts used double triggers and had provisions to carry forward rainfall from phase to phase. Crop durations were split into two to five distinctive phases depending on each crop (Soybean and Pearl Millet). In this paper, we present a detailed analysis of one district Ahmednagar. Ahmednagar is host to different climatic risks namely erratic rainfall pattern and climatic stress. Fig. 2 represents climatic risks in the case study area of Ahmednagar district.

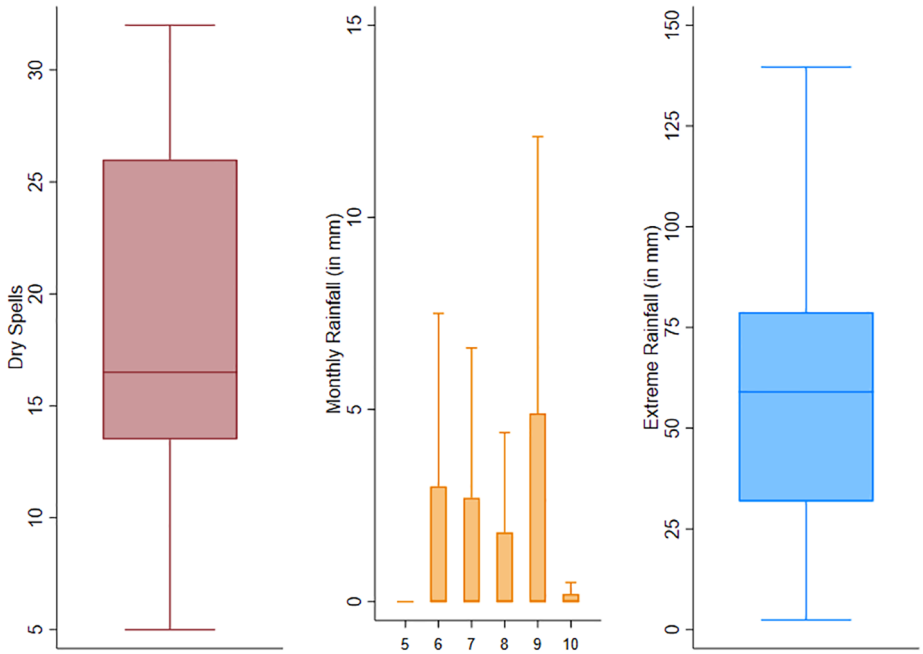

Fig. 2. Climatic Variability in Ahmednagar Maharashtra (1991–2012). The left panel denotes variability in number of dry spells in the crop growing season (May to October). The middle panel denotes variability in monthly rainfall (with months from May to October). The right panel denotes variability in extreme rainfall over the crop growing season. Rainfall data taken from weather stations.

5. Results and discussion

5.1. Regression results

Statistical analysis of yield and weather data gave insights on the inherent precariousness of crop production systems in the district. Being a primarily rainfed area, crop production was observed to be highly volatile. Yield levels were observed to be highly variable with the coefficient of variation being as high as 59% for some crops.

Using crop growth modelling and statistical analysis, best crop-yield response model was developed. Values of excessive rainfall from existing contract were kept constant while others (rainfall volume and dry spells) were transformed. Multiple regression was used to build final crop yield– climate model. Model fits were much stronger with simulation yields as compared to observed yield data (Table 2). This was anticipated as crop growth modelling gives simulated yields entirely based on climate data (excluding other exogenous factors), whereas historical yields vary widely because of many other factors including idiosyncratic shocks (random shocks which have little or no correlation with the expected trend).

Table 2
Regression results for crop yield-response model.

Yield (kg/Ha)	Pearl Millet Reported Yield	Pearl Millet DSSAT Yield	Soybean Reported Yield	Soybean DSSAT Yield
Rainfall				
Phase 1	1.129	0.934	6.526	−0.174
	(0.623)	(0.739)	(3.406)	(1.785)
Phase 2	−0.076	0.962	2.409	0.571
	(0.671)	(0.796)	(1.508)	(0.790)
Phase 3	0.445	1.187*	−0.115	1.665**
	(0.440)	(0.521)	(0.970)	(0.508)
Dry Spell	−5.68	−7.40	−23.590	−5.058
	(4.25)	(5.03)	(11.606)	(6.084)
Extreme Rainfall				
Phase 1	–	–	−14.231	2.228
			(7.171)	(3.759)
Phase 2	–	–	−0.460	−0.458
			(3.255)	(1.706)
Phase 3	0.924	−2.267	−3.426	−5.948
	(1.511)	(1.792)	(4.221)	(2.213)
Phase 4	–	–	1.619	−1.696
			(3.741)	(1.961)
Constant	551.45*	1219.16***	1606.984**	2074.056***
	(224.70)	(266.41)	(457.383)	(239.739)
R Square	0.75	0.794	0.79	0.843

Note: Multiple regression was performed with yield as dependent variable on rainfall parameters. Details of existing contracts are provided in the supplementary information. The analysis is presented for the district of Ahmednagar.

5.2. Trigger development

After finalizing crop response model through regression, triggers were developed. The existing contract was designed in a manner, where different climatic variables (like dry spells, rainfall volume and excess rainfall) were divided into different phases based on local crop growing calendar (for example the first phase for rainfall volume in soybean was from 20th June to 6th July). These phases often corresponded with crop growth phase in the district. Base trigger values of different weather parameters under different crop growth phases were calculated using crop water requirement of the particular crop for the district using FAO CropWat tool and trigger values of existing contracts. Range constraints (upper and lower limits) were then applied to these base values on the basis of regression coefficients obtained above or one standard deviation of the parameter in the weather data. Goal setting was then applied based on objective (maximizing farmer satisfaction index or minimizing claims ratio) and the model was run for optimization of the trigger value.

Each goal setting under the optimization framework affected the weather triggers differently (Fig. 3). In soybean, the optimization for the proposed contract lead to change in trigger value in all three phases. For example, the greatest change in trigger value occurred in phase 3 (the new trigger value reduced by 45 mm from the existing contract). Similarly, after the optimization procedure for the proposed contract design, the trigger values for excessive rainfall saw the highest change in phase 2 and 4. Climatic stresses either in terms of dry spells or excessive rainfall are particularly harmful at maturity (phase 2) and reproductive plant growth phases (phase 4). Correspondingly in the proposed contract, trigger values were adjusted in specific phases to compensate for such climatic stresses, by payouts. Similar changes in contract design were done for Pearl Millet (not shown in Fig. 3).

INDEX: Aggregate of rainfall unit over respective phases	Rainfall Volume (mm)	PHASE - I	PHASE - II	PHASE - III
Proposed Termsheet	STRIKE I (<)	10	-10	6
	STRIKE II(<)	-25	-35	-45
	EXIT	0	0	0
Termsheet- Maximum Satisfaction Index	STRIKE I (<)	12	24	6
	STRIKE II(<)	-25	-35	-45
	EXIT	0	0	0
Termsheet- Minimum Claims Ratio	STRIKE I (<)	-16	-55	6
	STRIKE II(<)	-25	-35	-45
	EXIT	0	0	0

INDEX: Maximum of 2 consecutive days cumulative rainfall	EXCESS RAINFALL (multiple event)	PHASE - I	PHASE - II	PHASE - III	PHASE - IV
Proposed Termsheet	STRIKE I (>)	-10	25	10	40
	EXIT	0	-100	0	30
Termsheet- Maximum Satisfaction Index	STRIKE I (>)	-14	39	10	40
	EXIT	-4	-69	0	30
Termsheet- Minimum Claims Ratio	STRIKE I (>)	-13	39	10	40
	EXIT	-2	-69	0	30

Fig. 3. Change in contract design for a) Rainfall volume and b) excess rainfall after optimization for Soybean. Strike denotes the critical level of weather variable at which the insured becomes eligible for pay-out based on the contract. The exit is the threshold or end point of weather variable at which the insured becomes eligible for full sum insured, according to the contract design.

5.3. Effect of optimization on contract parameters

Effect of different objectives on triggers and contract performance was then analyzed under the optimization framework. Clear trade-offs were recognized while evaluating contract performance for different goal settings. Theoretically, an ideal contract design from farmers' perspective would have maximum satisfaction index, minimum premium and lowest claims ratio. However, such a contract wouldn't have much value as a business proposition for insurers and government agencies. Maximization of any three of the key contract variables- Satisfaction Index, Claims ratio and Premium percentage lead to decrease in the other two. Therefore, developing an optimal contract required a balance between the three variables. Fig. 4 captures how contract parameters change for each goal setting and their relationship. It clearly shows a dramatic increase in correlation (yield loss and payouts) and farmer satisfaction index from existing to the proposed contract. Claims ratio decreased whereas a slight increase in claims frequency was observed under the proposed contract. Maximizing Farmer Satisfaction Index also increased claims ratio which is often not desirable by insuring agencies. Similarly, minimizing claims ratio leads to an increase in premium rates, thereby increasing the financial burden of the government.

The trade-offs can also be captured by showing how contract parameters change at different trigger levels (Fig. 5). For the proposed contract, the selected trigger level (0) for rainfall volume shows the highest satisfaction index and lowest claims ratio. Both farmer satisfaction index and correlation follow a similar pattern with trigger change, with the corresponding decrease in trigger value, both the parameters decrease sharply. Increase in trigger value causes only a minor decline in satisfaction index but decreases the claims ratio substantially. Therefore, the proposed trigger value is optimum for maximizing farmers' satisfaction and decreasing the claims ratio.

Final trigger development was then developed based on goals of maximizing satisfaction index at the same time keeping claims ratio at a low level and maintaining premium rates at the same level (Fig. 6).

Above methodology was also replicated for Pearl Millet. The resulting contract performed significantly better compared to existing contract in all parameters. Although there was a slight increase in claims ratio, there was a marked increase in the satisfaction index. Results from both crops signified adaptability of the proposed methodology under different crops.

Crop insurance is a very important agricultural risk management strategy which involves many stakeholders. It is often linked to institutional credit to reduce the incidence of loan defaults (Carter et al., 2016). It serves as a tool for policymakers to protect production systems and improve the diffusion of institutional credit in rural households. Despite widely known influence of weather

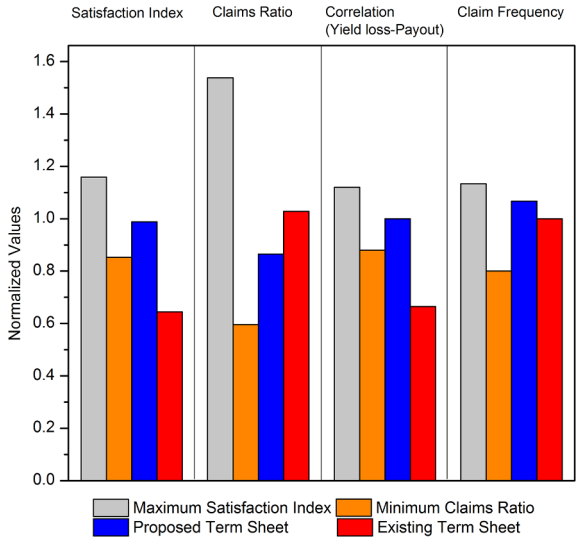

Fig. 4. Trade-offs under Optimization Procedure, the figure shows the performance of contracts for soybean, under different goal settings. The four scenarios for optimization are shown in the legend (Maximizing Satisfaction Index, Minimum claims ratio, existing contract and proposed contract).

on farm harvests, demand for WBCIS has not grown in tandem amongst cultivators (Michler et al., 2016). Even lucrative subsidies from the government and low premium rates from insuring agencies fail to attract farmers on a large scale. While there are a host of other barriers for adoption of new insurance products and participatory exercise can alleviate them successfully (Patt et al., 2009), a faulty product is unlikely to be preferred by the farmers. It has been demonstrated how the reception of payouts by farmers is the most compelling factor in determining uptake of the insurance product than being enrolled in an insurance scheme historically (Hill et al., 2016). Farmer satisfaction from the insurance is thus rooted in payouts which this paper tries to capture through farmer satisfaction index. Although farmer satisfaction is vital for the success of any agricultural insurance product as they are primary

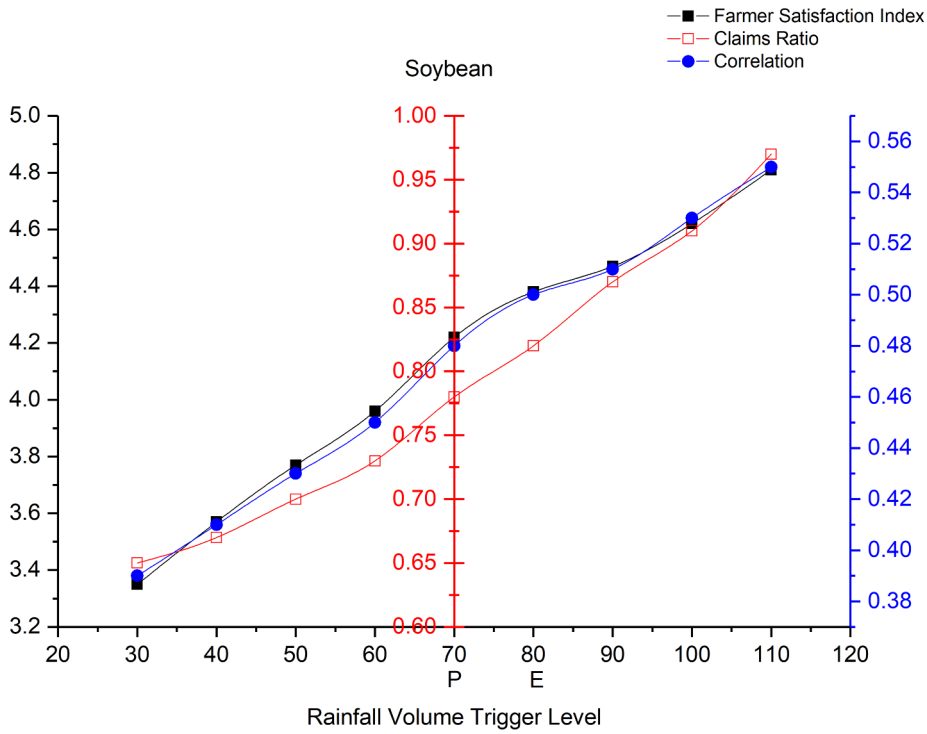

Fig. 5. Trade-offs under Optimization Procedure, the figure shows the effect of trigger change on farmer satisfaction index, claims ratio and correlation of rainfall volume trigger in phase 2 of the proposed contract of soybean. Levels P and E denotes trigger value for proposed and existing contract design.

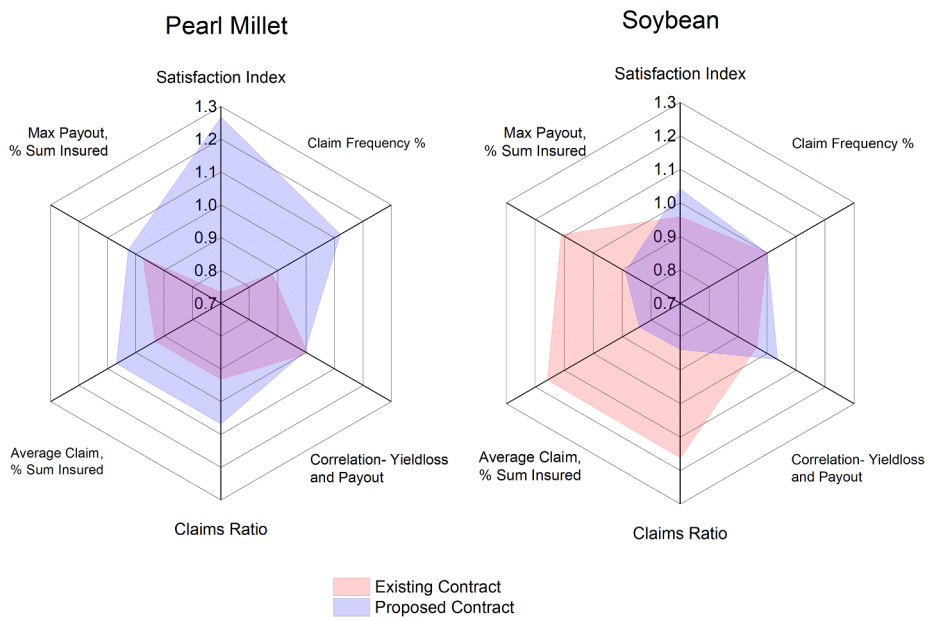

Fig. 6. Comparison of proposed and existing contracts for two crops in the district of Ahmednagar. Values of different contract parameters are normalized for comparison.

stakeholders, it cannot be isolated from other important factors. WBCIS cannot operate on excessive subsidies leading to unrealistic premium rates, nor can it afford to be unprofitable for insuring agencies. Developing scientifically validated weather triggers as described by us is likely to lead to improved satisfaction of all the stakeholders of crop insurance. The methodology used here ensured rational bounds of premium rates, reducing premium wherever possible while taking care of claims ratio and index effectiveness. The optimization of premium rates helped in reducing the subsidy burden of the government. While it continues to be highly subsidized by the government, growing literature questions the role of subsidy in making agricultural insurance viable (Goodwin and Smith, 2013). Therefore, it should be feasible and give benefits as a good business proposition both for the government or for private insurers. In short, from a good insurance scheme, the insurer must gain positive actuarial income and farmers should benefit from need-based pay-outs. However, insurance may also lead to a decrease in farmers adaptation (Müller et al., 2017; Annan and Schlenker, 2015). Bundling insurance product with different agricultural technologies and credit linkages can help in overcoming some of these issues (Foltz et al., 2013).

Results from using the suggested methodology have given optimum results for all the relevant stakeholders for two rainfed crops. There are limitations to the application of the proposed insurance contract presented here for irrigated areas. Weather triggers of dry spells and excessive rainfall may not be appropriate for irrigated areas, and the insurance contract has to be redesigned to cover the climatic risks being faced in such areas (like temperature effects etc.). Similarly, weather triggers may also be developed for coverage

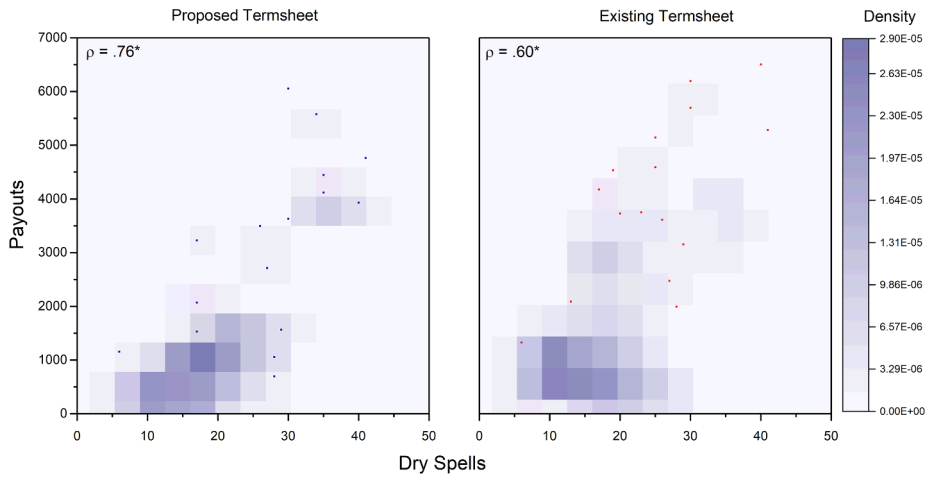

Fig. 7. Kernel Density estimates for 100 year runs of weather trigger (number of dry spells) and payouts by existing and proposed contract of soybean in Ahmednagar district, Maharashtra. Pearson's correlation coefficient with significance level is also shown.

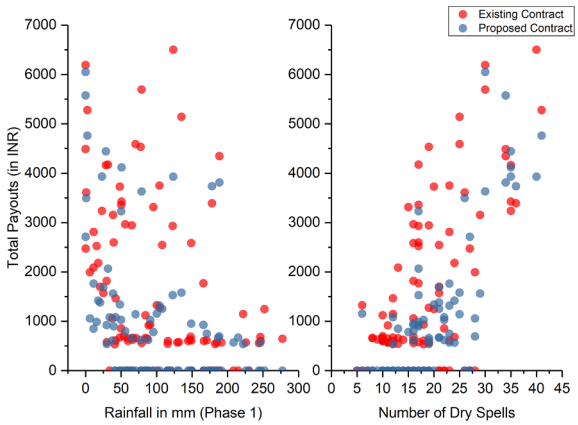

Fig. 8. Relationship of total payouts with a) rainfall in phase 1 and b) number of dry spells for existing and proposed contract of soybean in Ahmednagar district, Maharashtra.

against disease conducive weather events. However, the integrated methodology presented here, based on both statistical and biophysical modelling can help in redesigning of the insurance contract. Optimization framework presented in this study helped in arriving at a tradeoff model, where different parameters could be fixed in an optimum operating space for viability. Not only did the suggested approach increased overall benefits to the farmers, but it also aided in making WBCIS more inclusive by simplifying the design of the contract for a better understanding from farmers. Existing contracts were too complicated for participant farmers to understand and such complexities have been known to cause aversion of farmers towards crop insurance products in general (Akter et al., 2016). The new contract removed the intricacies of multiple strike rates and carryover rates, making them more acceptable. Very few insurance products are able to cater to different stakeholders congruently. The methodology adopted in this research is a workable technique through which such objectives can be achieved. A multimethod approach using statistical analysis of historical yields and supplementing it with biophysical crop growth modelling helped in developing a robust crop response model. Optimization framework then maximized different contract parameters based on pre-determined goals. Use of crop growth modelling may act as a limitation due to lack of expert knowledge to handle such models, however appropriate training and skill building can help in scaling out of such multi-method approaches for better index design.

The proposed contract gave superior and need-based payouts than the existing one, even in long-term. To illustrate, we calculated payouts from existing and proposed contract of soybean, based on projected weather parameters for 100 years using a stochastic weather generator (Jones and Thornton, 2013). Fig. 7 shows how pay-outs determined by new contract are more contiguous and linear with dry spells, as compared to the existing contract. As can be seen, the existing contract gives very high payouts even when dry spells are low and simultaneously, give low payouts when dry spells are high. Similarly, for rainfall volume existing contract leads to overpayment by giving payouts even when rainfall is high (100–200 mm), as compared to a proposed contract which shows better relationship of payouts with rainfall (Fig. 8). New triggers under the proposed contract, are better linked to climatic stresses through the improved agro-meteorological statistical model. The proposed contract, smoothens the production risks by giving balanced payouts according to climatic stress which is reflected in increased correlation.

6. Conclusion

The study aimed at presenting an alternative index-insurance model by modifying existing methodology and coupling crop modelling and optimization techniques with statistical analysis for better and more efficient weather indices. The approach is backed by findings from applying the said methods to existing WBCIS scheme in the state of Maharashtra. Evidence from field testing highlights the potency of proposed WBCIS design in developing a win-win insurance model for all the relevant stakeholders by a) increasing farmer satisfaction by better correlation of pay-outs with yield loss b) production risk smoothening by decreasing redundant pay-outs to farmers and increasing overall margin to the insuring company c) reduction in the total sum insured and farmer's share in the premium, making it more attractive for farming community and, d) overall decline in amount of subsidy to be provided by the government. The model can help in creating a robust and sustainable insurance scheme and serve as an effective hedge against increasing climatic disturbances.

Declaration of Competing Interest

The authors declare no competing interests.

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https://ccafs.cgiar.org/donors. The views expressed in this document cannot be taken to reflect the official opinions of these organizations.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2019.100189.

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