Agricultural Systems 218 (2024) 104014

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Risk-based evaluations of competing agronomic climate adaptation strategies: The case of rice planting strategies in the indo-Gangetic Plains

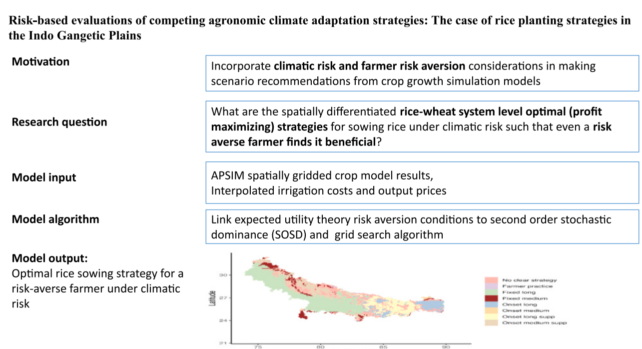
Maxwell Mkondiwa [a], Anton Urfels [b,c,d,*]

[a] CIMMYT International Maize and Wheat Improvement Center, New Delhi, India
[b] International Rice Research Institute (IRRI), Los Baños, the Philippines
[c] Water Resources Management Group, Wageningen University & Research, Wageningen, NL
[d] College of Agriculture and Life Sciences, Cornell University, Ithaca, NY, United States of America

HIGHLIGHTS

- Risk is insufficiently accounted when evaluation agronomic climate adaptation options
- We improve existing risk-assessments to better evaluate agronomic climate adaptation options
- The value of the framework is especially strong in areas where different options compete
- Enable spatially mapping climatic riskiness of agronomic adaptation options and identify least risky and highest performing ones

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Jagadish Timsina

Keywords:
Sustainable agriculture
Spatial economics
Climate resilience
Irrigation
Smallholder farmers

ABSTRACT

CONTEXT: Adjusting crop planting dates and variety durations is emerging as a crucial climate change adaptation strategy for many cereal systems. Such strategies include harmonizing crop planting with the onset of the rainy season or planting at specific recommended calendar dates. Evaluations of these strategies mostly consider yield and yield variability, but focus less on financial risks associated with different planting strategies and importance of risk aversion behaviour of the farmers in their decision to adopt the strategies.
OBJECTIVE: Here, we present a novel framework that uses a computational spatial ex-ante approach for risk-based evaluations of agronomic adaptation options. This framework allows development agronomic adaptation recommendations that consider climate risks for risk-averse famrers.
METHODS: We use a second order stochastic dominance approach that is paired with computational optimization—Golden section search algorithm. This approach allows a distributional assessment of risk and uncertainty by providing bounds at which even a risk averse would benefit from changing practices. This contrasts with conventional methods that do not consider farmers' risk aversion, e.g. mean-variance or conditional value at risk optimization methods. To demonstrate our approach, we compare the yield risks and economic risks associated with readily available gridded crop simulation outputs for various rice planting strategies across the Indo-Gangetic Plains (IGP)– a major region experiencing food insecurity and climate impacts.

* Corresponding author at: International Rice Research Institute (IRRI), Los Baños, the Philippines.
E-mail address: a.urfels@irri.org (A. Urfels).

https://doi.org/10.1016/j.agsy.2024.104014
Received 1 March 2024; Received in revised form 21 May 2024; Accepted 25 May 2024
Available online 31 May 2024

RESULTS AND CONCLUSIONS: The findings provide quantitative evidence about the riskiness of previously recommended rice planting date strategies. The risk-based assessment corroborates the recommendation for planting long-duration varieties at the monsoon onset with or without supplemental irrigation (covering about 22% of IGP area) in the Eastern IGP, and at state-recommended planting dates (covering about 38% of IGP area) in most of the Western and Middle IGP. Importantly, our risk-based assessment shows where the results are not as clear cut and which strategy is the least risky. This is especially important in the Middle IGP where farmers appear to have more flexibility to achieve comparable outcomes with several planting strategies.
SIGNIFICANCE: In conclusion, the proposed approach provides a useful and novel tool for comparing different agronomic climate adaptation strategies from an economic risk perspective in a spatial framework.

1. Introduction

Climate change is predicted to have a largely negative impact on the agricultural systems of low and middle income countries (IPCC, 2022). To adapt, farmers and policy makers must choose between several competing agronomic response options. Deriving recommendations for rice planting in the rice-wheat cropping systems of the Indo-Gangetic Plains (IGP) is a case in point. In the IGP, rice is planted in the monsoon season from June to October (also called kharif) while wheat is grown as an irrigated crop in winter season from November to April (also called rabi). Climate impacts on agricultural systems of the IGP are among the most severe globally (IPCC, 2022), as, e.g., late monsoon onsets delay rice sowing in the Eastern IGP and push wheat crops into periods of high terminal heat stress – while farmers in the Western IGP use free electricity to plant their rice crops early in the hot summer months and contribute to groundwater depletion.

Recent compelling evidence suggests that advancing the planting date of rice to match the monsoon onset is a crucial adaptation option for farmers in the Eastern IGP – and might help to alleviate groundwater depletion in the Western IGP (Newport et al., 2020; Urfels et al., 2021; Urfels et al., 2022; Wang et al., 2022; Ishtiaque et al., 2022; McDonald et al., 2022; Montes et al., 2023). To test this hypothesis, Urfels et al. (2022) and subsequently, working with the same datasets, Montes et al. (2023) use gridded crop simulations for the Indo-Gangetic Plains to investigate the impact of different rice planting strategies (combining sowing dates, variety duration and irrigation) on system level productivity, resilience, and environmental benefits. However, most farmers are risk-averse and not only interested in long-term profit maximization and yield outcomes (Ruzzante et al., 2021). It is thus important to consider economic risks and not just average yield and yield variability when evaluating agronomic adaptation strategies. For example, recent studies by Hurley et al. (2018) and Suri (2011) have shown that year to year variation in economic returns to adopting technologies can result in lower levels of adoption of generally profitable agricultural innovations – but approaches for evaluation agronomic strategies from a risk perspective remain scarce. The main aim of this paper is to develop a framework of managing climatic risk by making climate risk considering (or robust) recommendations on rice sowing strategies in the IGP using evidence from crop growth models.

Researchers usually evaluate these options based on average yield levels, water use, and income across years with varying weather conditions and provide subsequent recommendations (Kakraliya et al., 2018; Tesfaye et al., 2019). However, comparing these different indicators and assessing acceptable levels of variability is not straightforward resulting in recommendations based on qualitative expert judgement and mean comparisons that disregard downside risks. Using means for evaluation of agronomic response options is especially inadequate for risk-averse smallholder farmers that seek to minimize any losses they may have to incur (Ruzzante et al., 2021). How, for example, shall one evaluate an adaptation strategy that, across several years, has been shown to require an average of 50 mm additional water use to gain 300 kg of yield, 10% more income and increase yield variability by 5%?

To address this knowledge gap, we deploy a climatic risk proofing framework to select suitable adaptation strategies for risk-averse farmers. To demonstrate our approach, we evaluate the riskiness of adopting various rice planting strategies across the IGP by re-evaluating the results of crop the model simulations of various rice planting strategies across the IGP by Urfels et al. (2022).

This paper contributes to two strands of literature. The first strand of literature is on stability analyses of agricultural technology benefits based on ex-ante cropping system assessments (Urfels et al., 2022). Montes et al. (2023) used inter-annual standard deviation to analyse the stability of the planting date scenarios. Urfels et al. (2022) used deviation from the mean caloric yield for each of the years when a shock occurred as a measure of yield instability. These measures of yield stability, while a step better than mean comparisons, they do not consider robustness of the optimal decision to risk aversion of the farmers. In addition, these measures do not consider higher order moments beyond mean and variability that may matter for distributional comparisons. In addition, we argue that mean comparisons do not consider the trade-offs for achieving highest returns and reducing uncertainty. Up to date, most studies address uncertainty by, for example, using model ensembles or Monte Carlo simulations (Iizumi et al., 2009; Rosenzweig et al., 2013). But these approaches only allow for establishing confidence in the mean and variation around it and do not adequately take into account the implied risks to farmers.

These limitations are addressed in the second strand of literature which focuses on the spatial risk assessment of economic benefits of agricultural innovations (Nalley and Barkley, 2010). This literature attempts to optimize on the trade-offs of achieving the highest return and lowest uncertainty therefore allows one to choose strategies that are more robust. Using modern portfolio theory (Markowitz, 1959) which suggests that a strategy to maximize average returns may be a suboptimal strategy, (Nalley and Barkley, 2010) used a mean-variance analysis to optimally select wheat varieties that achieve highest return and lowest risk. This strategy still suffers from the limitation of using a subset of moments (mean and variance) of the distribution. The stochastic dominance approach was developed to resolve these concerns in selecting robust strategies (Levy, 2016). Using long-term weather data, crop simulation model results, spatially explicit observed maize prices, and fertilizer prices; Hurley et al. (2018) simulates whether weather risk affects the adoption of fertilizer and improved maize seeds. They use heterogeneity in soils and climate in a calibrated crop growth model to simulate the distributions of yields across adoption of fertilizer and improved maize seed scenarios.

We specifically follow the approach proposed by Hurley et al. (2018)[1] to estimate willingness to pay bounds for a risk-averse farmer to likely adopt an alternative rice planting date strategy. The key idea of the willingness to pay bounds is that there is an amount of economic gain that will make one choose a new strategy in the sense of second order stochastically dominating the base strategy. Similarly, there is an amount that would make them indifferent. The algorithm uses a golden section search optimization approach to select the maximum and

[1] A similar computational willingness to pay bounds approach to second order stochastic dominance is used in the finance literature to evaluate put and call options (for details, see Levy 1985).

minimum numbers that satisfy these conditions. This algorithm allows the check of whether a strategy is better than the other at different quantiles of the distribution and will compute the quantile and value at which this switch occurs thereby providing the bounds which Hurley et al. (2018) call “willingness to pay bounds”. We depart from their approach in three substantial ways. First, instead of fertilizers and improved varieties, we consider multiple management changes including sowing dates, irrigation amounts, and varieties differing on duration to maturity. This allows a more realistic comparisons of the benefits of the interrelated crop management decisions rather than a piecemeal and partial analysis of specific decisions. Second, we consider a rice-wheat multi-crop system unlike Hurley et al. (2018) who focus on maize only. This has the added value that the optimal decision in one crop may be suboptimal for the next season there providing the trade-offs that farmers make when making adjustments in one crop. Third, we do not only consider pairwise comparisons but also use the willingness to pay bounds to select the best strategy among multiple competing options. This has the advantage that we can select one optimal strategy among the many to recommend for risk-averse farmers. Our application shows how this risk-assessment framework can handle increasingly complex decisions.

The rest of the paper is organized as follows. We present next the methods focusing on the computational risk assessments. In section 3 we present results and discussion of the yield and economic benefits of alternative planting date strategies. We finally conclude in section 4.

2. Methods

In this section, we showcase and explain our risk-assessment framework which departs from the conventional risk assessments that use mean-variance optimization. The mean-variance optimization literature attempts to optimize on the trade-offs of achieving the highest return and lowest uncertainty therefore allows one to choose strategies that are more robust. Using modern portfolio theory (Markowitz, 1959) which suggests that a strategy to maximize average returns may be a suboptimal strategy, (Nalley and Barkley, 2010) used a mean-variance analysis to optimally select wheat varieties that achieve highest return and lowest risk. This strategy still suffers from the limitation of using a subset of moments (mean and variance) of the distribution. The stochastic dominance approach from which the approach in this paper is based was developed to resolve these concerns in selecting robust strategies (Levy, 2016). We first explain the proposed framework from a theoretical perspective. Subsequently, we briefly explain how we use the gridded Agricultural Production Systems Simulator (APSIM) simulation outputs from Urfels et al. (2022) to illustrate our approach.

In short, we illustrate our approach in the Results section by (i) comparing the different planting strategies by crop and their yield risks, (ii) systems level revenue, and (iii) system level partial profits. Finally, (iv) we determine the most optimal planting strategy for risk-averse farmers for each grid-cell across the IGP. To determine which strategy performs best from a risk perspective, we use a novel method to estimate willingness to pay bounds through a stochastic dominance approach to determine which rice planting strategies are both economically beneficial and least risky. To assess economic returns, we multiply the simulated yield outcomes with spatially explicit price data for rice and wheat. Since the only variable cost of in the simulation is irrigation amount,[2] we consider their impact on the outputs and calculate partial profits using common irrigation cost of US\$1.26 per m^3 (Shah et al., 2009; Urfels et al., 2020) and multiply it with the total irrigation amount required in each simulation.

The remainder of this Methods section provides an overview of (i) our risk assessment approach (section 2.2–2.3) and (ii) details on the input data (section 2.3).

2.1. Computational spatial ex-ante economic model under risk aversion

The framework uses a two-step approach: First we evaluate systems-level yield risks and subsequently systems level economic risks. For both yield risks and economic risks, we assess adaptation options through a willingness to pay (WTP) lens that considers both economic performance and riskiness. The guiding question is: How much would a farmer be willing to pay for an adaptation option and still be clearly better off than with the baseline? To assess this, we assume that an adaptation option is suitable for risk-averse farmers if the distribution (not just the average) of yield and economic outcomes supersedes the baseline so that the chance of having inferior outcomes is reduced. Using the so called ‘second order stochastic dominance’ (SOSD) – a well-established measure in decision theory for comparing the riskiness inherent in two distributions – we assess whether the adaptation option is less risky than the baseline (i.e. negative outcomes less likely). Below we provide an overview of how SOSD works for our case. For more details regarding SOSD and risk aversion, please see Levy (2016) and Meyer (1977) for a detailed explanation.

2.2. Comparing the riskiness of two agronomic adaptation options

To evaluate the riskiness of an adaptation option regarding either yield or economic returns, we compute spatially explicit willingness to pay bounds in rice and wheat yield equivalents that define, for a risk-averse farmer, whether that farmer would adopt a technology or not. SOSD provides an estimate of which option is risker and Hurley et al. (2018) computational modelling helps to assess how much better it is. Importantly, our WTP bounds are not symmetrical and, in principle, the WTP bounds we use can be thought of as follows (i) how much the cumulative distribution of the adaptation option can be shifted to the left (i.e. the benefits uniformly reduced) and still outperform the baseline (lower bound), and (ii) how much the cumulative distribution function can be moved to the right (i.e. the benefits uniformly increased) before it is entirely on the right side of the baseline (upper bound). In other words, how much is a farmer will a farmer gain (willing to pay) when adopting the adaptation strategy (lower bound). And how much would a farmer need to pay in addition to adopting the adaptation option to reduce his risk of losing against the baseline to zero (upper bound).

To demonstrate this approach, we use a hypothetical experiment shown in Fig. 1. We consider three cumulative distribution functions for scenarios *G*, *Q* and *F*. Based on mean comparisons, *G* is clearly better than *F* and *Q*. If we think in terms of distributional differences, *G* is clearly better than *Q* because the cumulative distribution curve of *G* is wholly to the right of *Q*. This is also called first order stochastic dominance. Consider the next case, where *G* and *F* are having crossing cumulative distribution functions. Visually, it can be assessed that *G* has a higher mean and much lower likelihood of low performing outcomes. G has a higher mean and is less risk. This is, G second order stochastically dominates *F*. Since the cumulative distribution function of G and F are crossing each other, neither distribution first order stochastically dominates the other.

Lastly, consider the case of *F* and *Q*, they are crossing each other and have the same mean. It is difficult to visually assess which one is more risky – i.e. determine the second order stochastic dominance ordering for these technologies.

The lower WTP bound that makes any risk-averse farmer prefer new technology (in this case scenarios other than the baseline) can be derived using second order stochastic dominance (see Hurley et al., 2018) for detailed derivations). If both lower bound and upper bound are positive, then any risk-averse farmer will prefer the new technology. Conversely, if both lower bound and upper bound are negative, then any risk-averse farmer will stick to the old technology. If however, the lower bound is negative and the upper bound is positive, then it is requires an explicit understanding of risk preferences—information not easily available—to determine which distribution is preferred. We use Octave

[2] Partial profit = crop yield x crop price -irrigation cost.

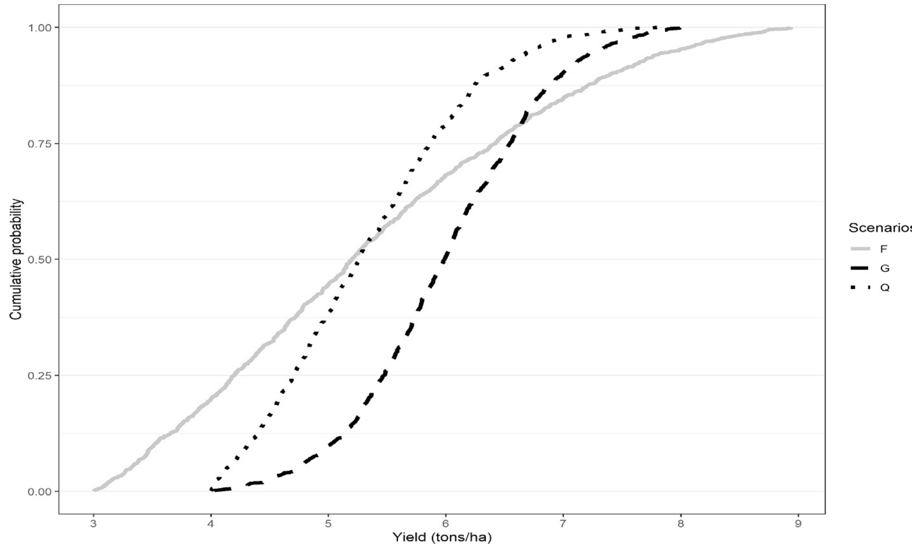


Fig. 1. Hypothetical stochastic dominance assessment.
Note: We use a truncated normal distribution with four parameters: minimum (a), maximum (b), mean, and standard deviation (sd). The parameters used for each of the scenarios are as follows: G = rtruncnorm (n = 1000,a = 4,b = 8, mean = 6,sd = 0.8), Q = rtruncnorm (n = 1000,a = 4,b = 8, mean = 5,sd = 1), F = rtruncnorm (n = 1000,a = 3,b = 9, mean = 5,sd = 2).

for the computational analyses.

Proceeding with the three different hypothetical distributions (G, Q, F) to illustrate our case, we show in Table 1 results from using our approach to compute upper and lower willingness to pay bounds. The WTP bounds are positive for the comparison between Q and G as well as F and G.

The sign for the WTP bounds gives the evaluation of the benefits of the technology for a risk-averse farmer. If both upper and lower bounds are positive, the farmer is willing to pay for that strategy. The upper bound is the amount of money that would pay just to stay with the new technology and thus abandon because it is second order stochastically dominated, while the lower bound is the amount that would pay just to be indifferent between the new strategy and the base strategy. For negative WTP for upper and lower bound, it shows that they would need to be paid to accept the proposed strategy. Lower bound is the amount of money that they would accept to abandon their existing strategy. Upper bound is the amount of money that they would accept just to be indifferent between the new strategy and their existing strategy.[3]

Table 1
Hypothetical distributions and willingness to pay bounds.

Panel (a): Truncated normal distribution parameters for the hypothetical distributions

Truncated normal parameters	G	Q	F
N	1000	1000	1000
Min = a	4	4	3
Max = b	8	8	9
Mean	6	5	5
SD	0.8	1	2

Panel (b): Willingness to pay bounds from computational second order stochastic dominance assessment

	Q(base) vs G	Q vs F	F vs G
WTP lower bound (ton/ha)	0.036	0	0.499
WTP upper bound (ton/ha)	0.763	0.218	1.384
Interpretation	G SOSD Q	Not clear	G SOSD F

2.3. APSIM spatially gridded crop model scenarios

The data used in this paper was based on gridded APSIM crop growth simulation model results for climate variables for the period 1982–2015 reported in Urfels et al. (2022).[4] The model was run using $0.05^\circ \times 0.05^\circ$ spatial resolution input data and the original study includes extensive performance evaluation for validating the results and modelling setup with other datasets on reported phenology and yield outcomes. Seven scenarios from crop simulation results reported in Urfels et al., (2022) are considered. The scenarios correspond to variation in irrigation, varietal duration and the planting of rice at the onset of the monsoon. Table 2 shows the details for the scenarios. We used the fixed long (S1) scenario as the baseline scenario. This scenario involves planting long duration rice variety at a fixed recommended date based on a state recommendation. We considered this as the baseline scenario instead of the farmer practice (S0) because S1 had observations for all pixels in the area of interest unlike the farmer practice which due to limitations of data had a limited number of pixels.[5]

The APSIM model results are coupled with spatially gridded rice and wheat prices from the Landscape Crop Assessment Survey (LCAS; https://systems-agronomy.github.io/lcas/) data interpolated using a random forest model based on population density and back of the envelope spatially gridded irrigation costs approximated for rented tubewells (most expensive) as 1.26 USD per m^3 (Shah et al., 2009; Urfels et al., 2020). To calculate system revenues, we used grid cells level prices of rice and wheat to compute the revenues of following each of the

[3] R and octave code to replicate the analyses for a subset of the data are available here: https://eia2030-ex-ante.github.io/WTP_Bounds_SOSD_Risk_Model/.

[4] The gridded APSIM crop simulation model setup incl. Input data of varying soil, climate, and management data and results are available here: https://git.wageningenur.nl/urfel001/igp-simulation-setup.

[5] We did robustness analyses with farmer practice as baseline in a limited geographical space. The decision of which scenario to use as the baseline does not alter the results.

Table 2
Rice planting strategy scenarios.

Scenario number	Rice planting strategy	Description
S0	Farmer practice	Farmers' practice baseline without nutrient and water limitations to understand current limits
S1	Fixed long (baseline scenario)	Planting long duration variety at a fixed recommended date (state recommendation)
S2	Fixed medium	Planting medium duration variety at a fixed recommended date
S3	Onset long	Planting long duration rice variety at the onset of monsoon
S4	Onset long supp	Only providing supplementary irrigation for planting long duration varieties at monsoon onset
S5	Onset medium	Planting medium duration variety at monsoon onset
S6	Onset medium supp	Supplementary irrigation for planting medium varieties at monsoon onset

scenarios. The grid cells level prices are obtained by interpolating prices from the Landscape Crop Assessment Survey (LCAS) for 2017/18 season. We then use these economic indicators in the stochastic comparisons.

2.4. Systems level economic benefits and risks

For cropping system assessment, we focus on the revenues and partial profits (revenue-cost of irrigation) derived from both rice and wheat. Willingness to pay is therefore in monetary terms rather than quantity terms. We use the same approach as stated above to determine if it is beneficial for a risk-averse farmer to adopt the planting date strategy. When the revenue and partial profit WTP is compared between the baseline and the proposed strategy, we get the revenue and profit potential for the farmers in each grid cells.

3. Results

Here we present results to evaluate the yield and economic risks associated with different rice planting strategies that were simulated across the Indo-Gangetic Plains. We first present results for rice and wheat yields and subsequently assess the performance for system level economic returns and their risks. We use the state recommended calendar dates for rice planting as a baseline (not the farmers' practice) as it is a more clear-cut strategy (one calendar date for each the Western, Middle, and Eastern IGP) than the remotely sensed farmers' practice.

3.1. Risk adjusted yield benefits of different rice planting strategies in the IGP

Figs. 2 and 3 provide a geographical overview of where each strategy outperforms the baseline. While the results generally corroborate the findings from the previous crop simulations reported in Urfels et al. (2022), the risk-based framework allows us to identify spatially demarcated zones where risk-averse farmers might want to switch strategies and where multiple strategies can work similarly well for risk-averse farmers – a feature that could only be assessed through visual assessment in the previous study.

3.1.1. Rice yields and their riskiness

Table 3 shows the descriptive statistics on the willingness to pay bounds (ton/ha) in rice yield equivalent for the planting date scenarios in comparison to the fixed date with long duration variety planting strategy. The WTP summary rows show the percentage of farmers who are more likely to (a) benefit, (b) be worse off or (c) be indifferent between the planting date strategies. Only 31% of the farmers would find the planting long duration rice varieties at the monsoon onset (S3) as beneficial followed by planting medium duration varieties (S2) at the recommended calendar dates medium (30%). For farmer practice (S0), the average and median WTP bounds (both lower and upper) are negative implying that farmers are overall worse off using their current rice planting strategies.

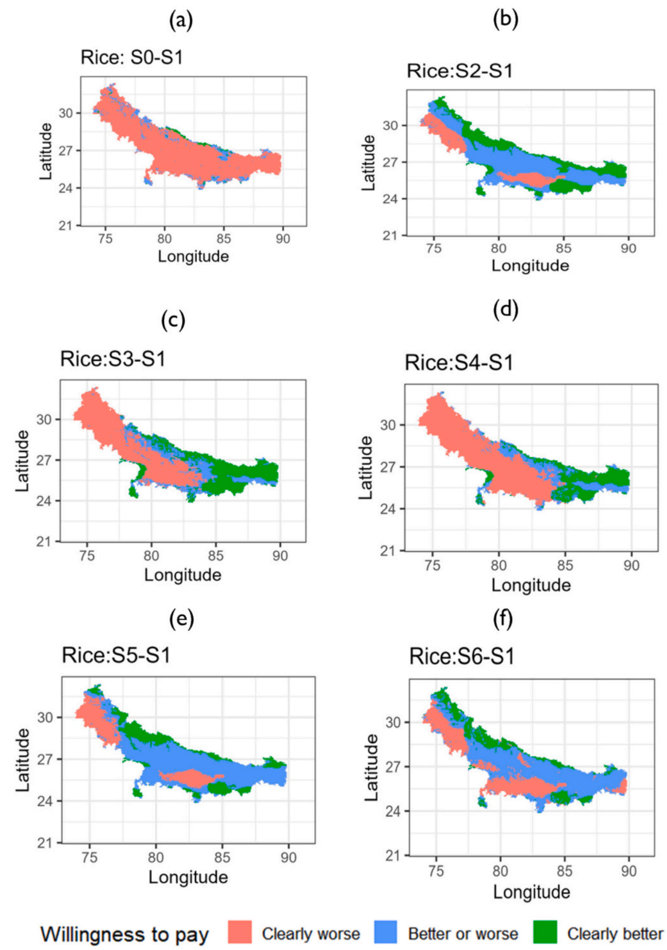


Fig. 2. Willingness to pay (rice yield ton/ha) for the strategy against a fixed long duration variety reference strategy (S1) using second order stochastic dominance. Note: S0 to S6 are as defined in Table 2 where S0 = farmer practice, S1 = fixed long (baseline), S2 = fixed medium, S3 = onset long, S4 = onset long supplemental irrigation, S5 = onset medium, S6 = onset medium supplemental irrigation.

Fig. 2 shows for which grid cells the proposed planting strategy is clearly better, clearly worse, or neither better or worse than the state recommended planting dates with long duration varieties (S1). Among these, planting a long duration variety with monsoon onset (S3) seems to provide much advantage in the eastern part of IGP. The western part seems to benefit more from the fixed date recommendation with long duration varieties (S1). The yield trends have been discussed in Urfels et al. (2022), pointing out the Middle IGP is a transition zone. The risk-based approach corroborates these findings and provides additional insight into the transition areas where we can clearly demarcate when one strategy supersedes the baseline, and where several strategies provide comparable benefits (e.g. see Fig. 2c).

3.1.2. Wheat yields and their riskiness

Like in rice, the results for wheat show how rice planting strategies affect the wheat crops – which is grown directly after rice harvest and its planting date thus strongly dependent on the rice planting date. Table 4 shows descriptive statistics of the willingness to pay bounds in wheat yield equivalent (ton/ha) for the scenarios in comparison to fixed date

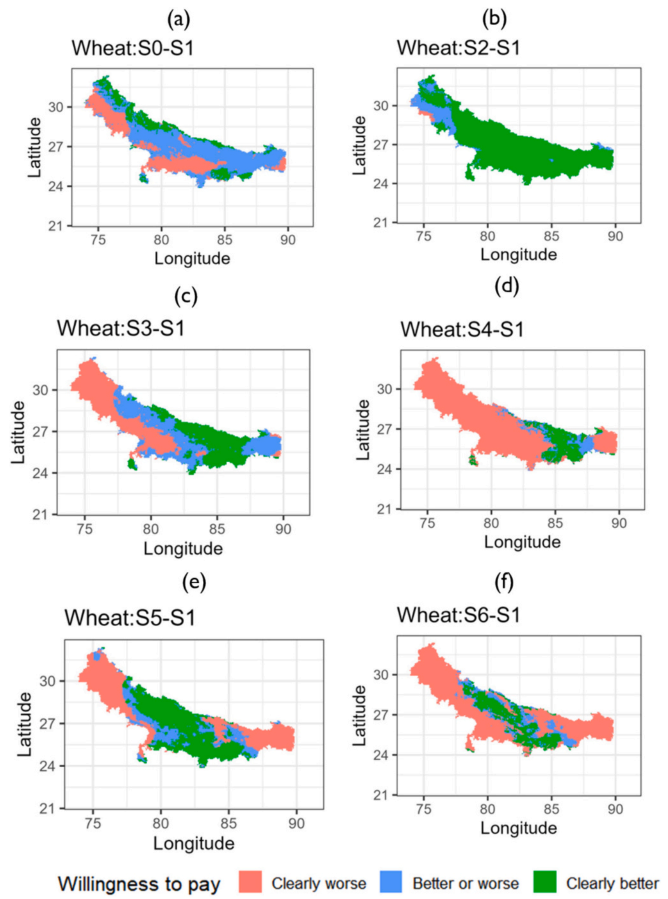


Fig. 3. Willingness to pay (wheat yield ton/ha) for the strategy against a fixed long duration variety reference strategy using second order stochastic dominance. Note: S0 to S6 are as defined in Table 2 where S0 = farmer practice, S1 = fixed long (baseline), S2 = fixed medium, S3 = onset long, S4 = onset long supplemental irrigation, S5 = onset medium, S6 = onset medium supplemental irrigation.

recommendation with long duration rice variety rice planting strategy (S1) (here after called fixed long strategy). Column (S0-S1) shows the comparison between farmer practice (S0) and fixed long strategy (S1). It is apparent from the lower bound estimates, almost 90% of farmers have negative WTP lower bound for the farmer practice strategy (S0) when compared with the fixed long strategy (S1). For about 25% of these, even the upper WTP is negative. Farmer practice is a good strategy for risk-averse farmers for only about 4% of the grid cells. For wheat the best strategy seems to be planting medium duration varieties and state recommended calendar dates (S2) in that most of grid cells (86%) will benefit with higher wheat yields as compared to the fixed long rice planting strategy (S1).

However, there is a clear spatial structure to these results. Fig. 3 shows the spatial distribution of willingness to pay classifications categorizing strategies on wheat yield worse than, better than, and not different from the fixed long rice planting strategy (S1). Fixed planting of a medium duration rice variety (S2) seems to be the best strategy to ensure higher wheat yields across most locations in the IGP except in the northwestern IGP where one would be indifferent (12%). Besides, the Eastern IGP also performs well with planting long duration varieties at the monsoon onset, which is much earlier in the Eastern IGP than in the Western IGP.

3.2. System-wide economic benefits for a risk-averse farmer

The above yield-based risk assessment likely matter most to subsistence farmers. Most farmers in the IGP, however, sell some parts of their produce (Urfels et al., 2023). Fully evaluating the system level risks thus requires an economic evaluation across both crops. We first provide an overview of the revenue and associated risks, followed by a more profit-oriented analysis that includes partial costs incurred for irrigation as this is the only cost variable that varies across the scenarios.

3.2.1. System revenues

Table 5 shows the descriptive statistics for the willingness to pay bounds. Starting with the percentage of grid cells that would benefit from each of the scenarios as compared to the baseline (S1), the WTP summary rows show that farmers' practices (S0) is the worst performing strategy across the IGP (column 3) with 89% losing compared to the state recommended planting dates (S1). This is followed by planting medium duration varieties at the monsoon onset with constrained

Table 3
Rice WTP bounds with fixed long as baseline, IGP.

Bound	Statistics	S0-S1	S2-S1	S3-S1	S4-S1	S5-S1	S6-S1
Upper bound	Mean	−1.03	1.90	0.76	0.41	1.32	1.01
	Std.Dev	1.36	1.75	2.50	2.38	1.79	1.76
	Min	−5.65	−2.47	−5.58	−5.65	−4.23	−4.38
	10th percentile	−2.17	−1.60	−2.26	−2.35	−1.65	−1.53
	25th percentile	−1.85	1.32	−0.58	−0.88	0.66	−0.47
	Median	−1.33	2.48	0.04	−0.30	1.77	1.53
	75th percentile	−0.45	3.04	3.18	2.86	2.38	2.20
	90th percentile	0.15	3.52	4.11	3.68	3.06	2.93
	Max	5.92	5.64	5.73	5.65	10.95	8.90
Lower bound	Mean	−3.53	−0.73	−1.42	−2.02	−1.27	−1.49
	Std.Dev	1.68	1.73	2.60	2.47	1.78	1.68
	Min	−7.83	−4.69	−7.02	−6.16	−7.02	−7.20
	10th percentile	−5.53	−2.47	−5.13	−5.19	−2.75	−3.20
	25th percentile	−4.62	−2.03	−3.76	−4.41	−2.28	−2.52
	Median	−3.71	−1.15	−0.71	−1.87	−1.51	−1.82
	75th percentile	−2.32	0.35	0.18	−0.14	−0.34	−0.54
	90th percentile	−1.89	1.92	1.90	1.18	1.16	0.73
	Max	4.84	5.05	4.79	4.66	8.50	6.49
WTP summary	Clearly better (share)	0.02	0.30	0.31	0.21	0.21	0.18
	Not clear (share)	0.11	0.52	0.21	0.19	0.59	0.53
	Clearly worse (share)	0.87	0.18	0.49	0.60	0.21	0.29
	Number of cells	17,411.00	17,412.00	17,420.00	17,421.00	17,421.00	17,421.00

Note: The number of cells are lower for S0-S1, S2-S1 and S3-S1 due to missing information in some of the grid cells.

Table 4
Wheat WTP bounds (ton/ha) with fixed date-long variety scenario as baseline, IGP.

Bound	Statistics	S0-S1	S2-S1	S3-S1	S4-S1	S5-S1	S6-S1
Upper bound	Mean	−0.50	1.00	0.22	−0.88	0.17	−0.65
	Std.Dev	0.83	0.46	0.64	1.19	0.70	1.14
	Min	−5.47	−0.08	−1.16	−4.06	−1.56	−4.19
	10th percentile	−1.89	0.28	−0.58	−2.55	−0.76	−2.19
	25th percentile	−0.71	0.71	−0.18	−1.78	−0.42	−1.63
	Median	−0.29	1.09	0.08	−0.79	0.20	−0.50
	75th percentile	0.00	1.34	0.54	−0.06	0.75	0.29
	90th percentile	0.28	1.53	1.28	0.77	1.11	0.75
	Max	1.59	1.99	2.05	1.91	1.78	1.61
Lower bound	Mean	−1.94	0.49	−0.37	−1.69	−0.37	−1.62
	Std.Dev	1.45	0.37	0.83	1.45	0.79	1.47
	Min	−7.00	−0.55	−2.29	−6.67	−2.29	−6.67
	10th percentile	−3.88	−0.02	−1.49	−3.69	−1.50	−3.65
	25th percentile	−3.15	0.27	−0.90	−2.97	−1.01	−2.83
	Median	−2.14	0.49	−0.37	−1.64	−0.21	−1.70
	75th percentile	−0.58	0.70	0.15	−0.52	0.28	−0.17
	90th percentile	−0.04	1.07	0.79	0.29	0.47	0.24
	Max	1.34	1.34	1.62	1.49	1.35	1.23
WTP summary	Clearly better (share)	0.04	0.86	0.28	0.15	0.40	0.20
	Not clear (share)	0.20	0.12	0.35	0.09	0.19	0.14
	Clearly worse (share)	0.75	0.01	0.37	0.76	0.41	0.66
	Number of cells	17,421.00	17,421.00	17,421.00	17,421.00	17,421.00	17,421.00

Table 5
Gross revenue WTP (thousand rupees/ha) bounds with fixed long as baseline.

Bound	Statistics	S0-S1	S2-S1	S3-S1	S4-S1	S5-S1	S6-S1
Upper bound	Mean	−23.99	34.99	8.37	−14.67	14.30	1.49
	Std.Dev	25.96	28.30	41.11	47.53	29.59	31.35
	Min	−144.09	−28.54	−84.72	−125.24	−64.90	−89.49
	10th percentile	−56.03	−15.52	−45.24	−74.99	−26.87	−37.83
	25th percentile	−39.27	22.03	−19.37	−51.28	−4.45	−19.90
	Median	−24.18	41.04	1.34	−18.60	15.28	−1.92
	75th percentile	−12.33	56.10	39.14	20.11	36.06	25.19
	90th percentile	1.85	66.82	69.81	56.16	53.93	45.26
	Max	87.55	91.16	96.57	86.07	132.20	108.48
Lower bound	Mean	−73.43	−1.39	−18.36	−43.68	−16.67	−28.19
	Std.Dev	36.34	25.91	43.02	49.08	28.35	30.59
	Min	−177.76	−59.94	−123.07	−139.93	−119.55	−151.45
	10th percentile	−113.83	−28.09	−77.92	−109.68	−46.58	−65.46
	25th percentile	−94.35	−20.99	−53.41	−86.66	−30.70	−43.60
	Median	−72.95	−6.29	−13.44	−42.45	−19.58	−29.30
	75th percentile	−56.20	16.31	10.49	−3.30	−1.85	−11.96
	90th percentile	−29.14	36.79	37.99	22.05	20.96	11.44
	Max	83.40	69.35	87.03	76.56	113.90	83.34
WTP summary	Clearly better (share)	0.02	0.42	0.36	0.23	0.23	0.16
	Not clear (share)	0.09	0.42	0.16	0.14	0.44	0.32
	Clearly worse (share)	0.89	0.16	0.48	0.63	0.32	0.52
	Number of cells	17,456.00	17,456.00	17,456.00	17,456.00	17,456.00	17,456.00

irrigation (S6) (column 8) that results in 52% of cells clearly worse off than the baseline.

These results show that there is no one size fits all strategy and we further investigate the spatial structure to better understand the performance of different rice planting strategies across the IGP. Spatially, there are pockets for which a risk-averse farmer would not switch to the recommended fixed date with long duration variety strategy (S1) especially in the central grid cells of Bihar. Again, the spatial structure of the results shows where, due to interannual weather risks, farmers may fare best to choose one specific strategy and where they might be similarly well off with more than strategy (Fig. 4).

3.2.2. System partial profits

When considering partial profits as incurred by the varying irrigation costs, the results again show that there is no one size fits all solution for the IGP with no single rice planting strategy outperforming others. Table 6 shows descriptive statistics for willingness to pay for partial profits (revenue-irrigation costs) for each of the planting date strategies as compared to fixed date-long duration rice variety strategy (S1). As with productivity and revenue comparisons, farmer practice (S0) is a worse strategy for about 85% of the grid cells in IGP. None of the strategies dominate across the entire IGP as can be seen in Fig. 5.

The preceding results have been interpreted on the basis of whether the strategy is better, worse or unclear based on whether the lower bound and upper bound are all positive, all negative or only lower bound is negative respectively. We use bounds in making this determination because in a distributional comparison of the adaptation options it is not possible to pin down one value. The use of willingness bounds however has another advantage beyond what we have shown with discrete choices, i.e., better, worse, unclear. It is that the magnitude of each of the bound provides insights on downside and upside risk as well as the ambiguity of the adaptation option (the wider, the more ambiguous).

On average for example, planting long duration rice at monsoon onset remains less risky and overall beneficial for farmers up to a reduction in partial returns by the lower WTP bound of Rs. 12,300 per ha (~US$ 153.75 at an exchange rate of 1:80). This could happen, for example, if there was an increase in irrigation or a decrease in grain prices, both of which are common and likely scenarios. At the same time,

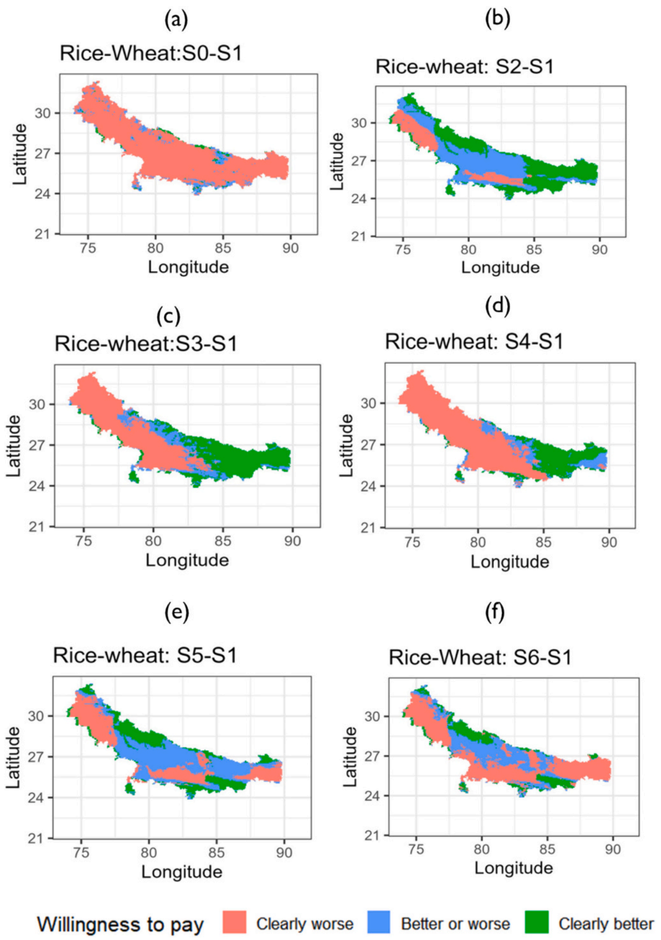


Fig. 4. Spatial distribution of revenue WTP (where to target the scenarios). Note: S0 to S6 are as defined in Table 2 where S0 = farmer practice, S1 = fixed long (baseline), S2 = fixed medium, S3 = onset long, S4 = onset long supplemental irrigation, S5 = onset medium, S6 = onset medium supplemental irrigation.

a uniform increase of US$ 201.5 would render this strategy risk-free vis-a-vis the baseline strategy. Given that no average farmer or pixel exists for which these two average bounds would occur simultaneously, these

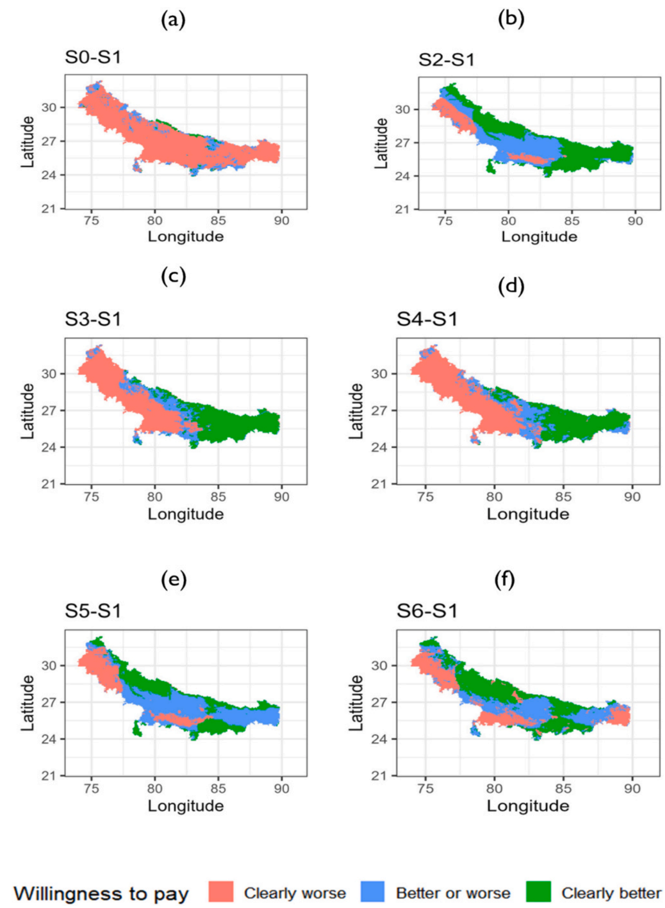


Fig. 5. Spatial distribution of partial profit WTP (where to target the scenarios). Note: S0 to S6 are as defined in Table 2 where S0 = farmer practice, S1 = fixed long (baseline), S2 = fixed medium, S3 = onset long, S4 = onset long supplemental irrigation, S5 = onset medium, S6 = onset medium supplemental irrigation.

Table 6
Partial profits WTP (thousand rupees/ha) descriptive statistics.

Bound	Statistics	S0-S1	S2-S1	S3-S1	S4-S1	S5-S1	S6-S1
Upper bound	Mean	−15.31	40.40	12.30	7.84	23.80	25.40
	Std.Dev	22.82	28.98	42.88	46.27	31.34	34.62
	Min	−97.77	−25.01	−80.65	−95.69	−62.89	−82.90
	10th percentile	−36.40	−10.73	−42.52	−49.44	−21.58	−17.54
	25th percentile	−26.88	24.88	−16.26	−27.25	7.19	−1.91
	Median	−18.74	47.15	2.00	1.43	24.04	23.22
	75th percentile	−8.09	62.14	48.44	41.74	48.21	52.55
	90th percentile	6.10	72.21	77.33	79.22	63.93	74.15
	Max	99.85	96.57	103.13	112.42	137.49	129.42
Lower bound	Mean	−50.40	3.51	−16.12	−24.19	−8.78	−5.70
	Std.Dev	26.63	25.83	44.08	47.57	28.33	32.81
	Min	−126.29	−54.20	−115.70	−112.73	−103.66	−118.82
	10th percentile	−79.57	−23.43	−73.37	−82.82	−38.10	−47.72
	25th percentile	−66.27	−16.27	−54.83	−66.11	−23.19	−23.23
	Median	−52.75	−0.94	−13.87	−28.33	−12.87	−6.43
	75th percentile	−35.94	20.98	16.24	13.97	6.85	12.31
	90th percentile	−21.19	41.44	44.49	43.67	29.05	36.92
	Max	89.66	76.40	90.44	97.08	120.33	99.99
WTP summary	Clearly better (share)	0.02	0.49	0.37	0.31	0.32	0.38
	Not clear (share)	0.13	0.37	0.18	0.21	0.48	0.35
	Clearly worse (share)	0.85	0.14	0.45	0.48	0.21	0.27
	Number of cells	17,420.00	17,420.00	17,420.00	17,420.00	17,420.00	17,420.00

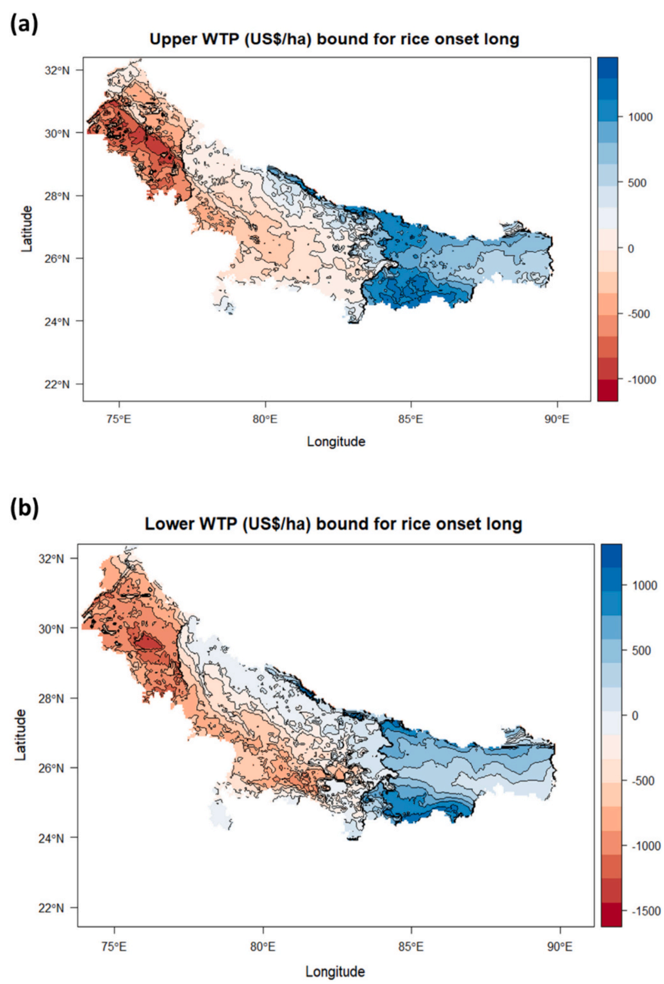


Fig. 6. Quantitative analysis of willingness to pay bounds for onset-long strategy.

numbers are best evaluated at pixel level as shown in Fig. 6. There are areas of the Eastern IGP where partial profits of the onset-long strategy are almost risk-free requiring reduction of profits of over US$1000 for any risk-averse farmer to consider the baseline. These areas can be clearly prioritized for the onset-long strategy. Of course, profit data is only partial, and a full real-world recommendation should consider more comprehensive profit analyses - but even such partial analyses based on crop modelling results can provide decision makers with valuable ex-ante insights into the riskiness of adopting different climate adaptation strategies.

3.2.3. Recommended rice planting date strategy per grid cell

Lastly, the risk-based evaluation approach allows us to compare all of the rice planting strategies against each other and identify which strategy performs clearly better and with less risks involved than any other strategy and where several competing strategies might result in similar economic benefits as well as risks. In other words, the above analysis has made binary or pairwise comparisons – while the most important question is: Which strategy should be recommended where? To derive this optimal scenario, we calculate the maximum upper bound WTP among the scenarios and the maximum lower WTP. If one single scenario clearly pays more and clearly induces less risks than the others, we select that scenario for that particular grid cell. As a result, Fig. 7 shows the optimal rice planting date strategy. As much as a 38% of the area of interest benefits most from following a fixed date planting with long rice variety strategy (S1). Much of this is in the western part of the IGP. In terms of area, this is followed by about 19% percent of the pixels for which we couldn't clearly assign the best strategy for risk averse farmers. The next preferred strategies include onset, long duration variety with supplemental irrigation (13.54%), onset medium with supplemental irrigation (13.00%), onset with long duration variety (8.72%), and fixed date with medium duration variety (6.54%). The least preferable strategies are farmer practice (0.44%) and planting of medium duration rice at the monsoon onset (0.5% of the pixel area).

4. Discussion

Importantly and in addition to the findings of Urfels et al. (2022) and Montes et al. (2023), the framework in this paper shows that in parts of the Eastern Gangetic Plains providing only supplemental irrigation rather than full irrigation is economically beneficial from a risk perspective. The same is true for some areas in the northern parts of the Middle and Western IGP – indicating importance of climatic and soil variability. In addition to cited prior works (Urfels et al., 2022; Montes et al., 2023) which formed the basis of the analysis and used APSIM crop growth model, the results can be compared to two recent studies (Wang et al., 2022; Wang et al., 2024) which rely on regionally calibrated

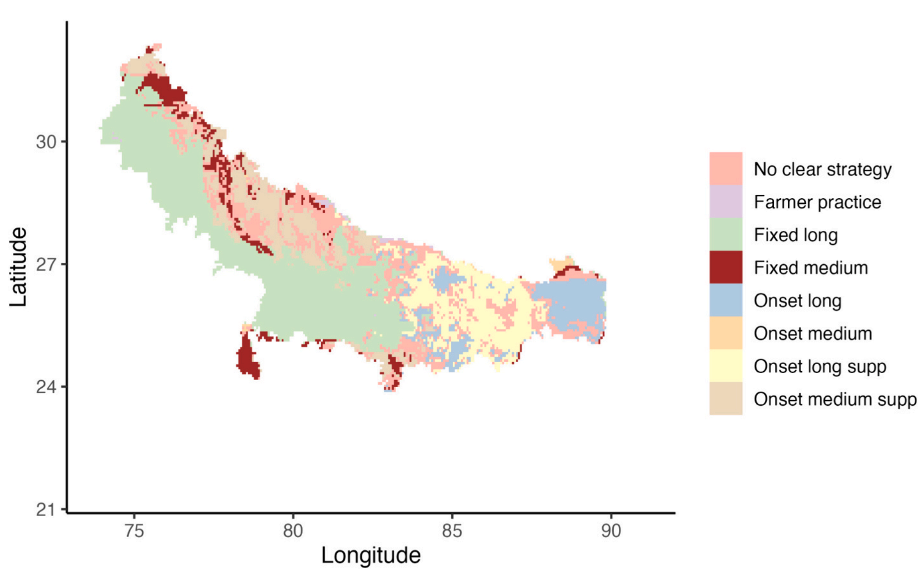


Fig. 7. Optimal rice planting date strategy derived from our optimisation approach using second order stochastic dominance.

Environmental Policy Integrated Climate (EPIC) agronomic model. Importantly, our analytics show that, from a risk-perspective, not all regions might have one single best planting strategy and that identifying a singular optimal strategy or planting date does not consider farmers' risk averse attitudes. We thus suggest that more attention should be paid to evaluating crop modelling and optimization studies form a risk perspective to identify broader bands of best-bet recommendations in such areas – rather than focusing on single optimal suggestions.

4.1. Value of a risk-based evaluation approach in face of climatic risks

The IGP is a hotspot of climate change impacts in that though it supports the most intensive crop production, it also suffers from frequent droughts, volatile monsoon onsets, and heat stress. Farmers delay rice planting in dealing with these environmental and climatic impacts (McDonald et al., 2022) thereby suffering substantial yield penalties. Without affordable irrigation infrastructure, timely rice planting becomes very risky for the farmers as evidenced by the recent El Nino event and late monsoon – causing farmers to fallow and reduce rice area. Similar issues of importance of timing and precipitation variability affect other farming systems elsewhere. Recommendations therefore require to consider riskiness evaluation and will need to include also field evaluation of riskiness after the first pass model ex-ante simulations as we do in this paper.

Climate variability and change has prompted a rethinking of how the agricultural research and development community can develop climatic risk considering innovations. These are innovations that are expected to be resilient to present and future climatic shocks. In that regard, crop modelling has become the key approach of assessing how different agronomic innovations perform under varying historical realizations of weather. In this paper, we have demonstrated that a nuanced understanding of risk in evaluating such crop model results can generate insights and provide a basis for making climate risk considering recommendations to smallholder farmers. This approach then allows researchers and farmers to understand the plausible strategies they can follow in order to maximize profits even in years when the weather is extreme.

Besides the farmers and researchers, the approach provides policy decision makers with a prioritization and targeting framework for extension support services that advances only the strategies that are more likely to be accepted by all the farmers in the location. This then reduces wastage of resources especially when risk neutral and profitable technologies are promoted in locations where most farmers are risk-averse. The task of figuring out the risk aversion preferences of the farmers in non-trivial and not possible for each of the individual pixels. The approach we use innovatively circumvents this challenge by placing conditions and extent under which any risk-averse farmer will still find the proposed strategy beneficial.

4.2. Limitations and future research

There are several key limitations to the proposed approach. First, it is computationally heavy especially if the gridded analysis is conducted for larger spatial scales. This challenge can be resolved by reducing the number of pixels in each analysis because the approach uses each pixel separately such that the optimal strategies will not differ based on number of pixels. Second, it requires many years of data to characterize the empirical cumulative distribution function. The analyses use the period 1982–2015 data which covers enough variation of climatic variability. In the context of long-term trials and surveys, it is difficult to find such longitudinal datasets at scale. Future research that combines these data sources and Monte Carlo simulations would allow the use of the approach in empirically grounded analyses. Third, as compared to other outcomes-based risk analyses like the mean-variance or conditional value at risk approach, the approach in this paper simply recommends the best strategy but not an optimal combination or diversified portfolio of options (literature started by Markowitz, 1959). Fourth, given that the risk evaluation approach relies on crop model outputs, any limitations of the crop model are propagated in our approach. For example, the gridded APSIM crop model we use has no N limitation and no irrigation to isolate the effect of sowing dates in addition to not having many interactions including with crop management and local socioeconomic conditions which may limit the ability of the farmers to change to the proposed strategy. For example, due to groundwater access challenges, some farmers may not be able to irrigate on time. While we acknowledge these limitations, they are not necessary for the merit of this paper in that the paper is aimed at showcasing a methodology for evaluating risk regardless of the nature of the crop model used.

5. Conclusion

We have shown in this article how a spatially explicit risk-assessment framework can provide evidence on how different agronomic climate adaptation strategies can be adequately evaluated for risk-averse farmers. This work builds on an approach proposed by Hurley et al. (2018) and uses computational second order stochastic dominance to calculate lower and upper bounds for which any risk-averse farmer will be willing to adopt an alternative rice planting date strategy. The results for the IGP provide further evidence that early sowing (at monsoon onset) of long duration rice is a suitable strategy (for 22% of the IGP) for risk-averse farmers of the rice-wheat rotation system in eastern IGP (e.g., Bihar) – while planting at state recommended dates and growing medium duration varieties is a better option in the Western and Middle IGP. Importantly, we also show that farmers in the Middle IGP have more flexibility to choose among competing options without jeopardizing incomes or increasing risks. With weather variability expected to further increase globally and affecting smallholder farmers disproportionately, risk-assessment approach can provide a robust and climatic risk considering framework for evaluating various competing climate adaptation options for risk-averse smallholder farmers that not only benefit from higher long-term gains but also seek to minimize losses in any given year.

CRediT authorship contribution statement

Maxwell Mkondiwa: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anton Urfels:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgements

This study was conducted as part of the Cereal Systems Initiative for South Asia (CSISA; https://csisa.org/) supported by the United States Agency for International Development (USAID) and Bill and Melinda Gates Foundation (BMGF). This study was also suppored by the CGIAR Asian-Mega-Deltas Initiative, CGIAR Excellence in Agronomy Initiative, CGIAR NexusGains Initiative. These initiatives are supported by a variety of donors. For details, please visit www.cgiar.org. We thank Terrance Hurley for sharing the prototype Matlab code for the computational risk model. The content and opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the donors or supporting initiatives.

References

Hurley, T., Koo, J., Tesfaye, K., 2018. Weather risk: how does it change the yield benefits of nitrogen fertilizer and improved maize varieties in sub-Saharan Africa? Agric. Econ. 49 (6), 711–723. https://doi.org/10.1111/agec.12454.

Iizumi, T., Yokozawa, M., Nishimori, M., 2009. Parameter estimation and uncertainty analysis of a large-scale crop model for paddy rice: application of a Bayesian approach. Agric. For. Meteorol. 149 (2), 333–348. https://doi.org/10.1016/j.agrformet.2008.08.015.

IPCC, 2022. Summary for policymakers. In: Press, C.U. (Ed.), Intergovernmental Panel on Climate Change.

Ishtiaque, A., Singh, S., Lobell, D., Balwinder, S., Fishman, R., Jain, M., 2022. Prior crop season management constrains farmer adaptation to warming temperatures: evidence from the indo-Gangetic Plains. Sci. Total Environ. 807, 151671 https://doi.org/10.1016/j.scitotenv.2021.151671.

Kakraliya, S.K., Jat, H.S., Singh, I., Sapkota, T.B., Singh, L.K., Sutaliya, J.M., Sharma, P. C., Jat, R.D., Choudhary, M., Lopez-Ridaura, S., Jat, M.L., 2018. Performance of portfolios of climate smart agriculture practices in a rice-wheat system of western indo-Gangetic plains. Agric Water Manag 202, 122–133. https://doi.org/10.1016/j.agwat.2018.02.020.

Levy, H., 2016. Stochastic Dominance. Springer, Cham. https://doi.org/10.1007/978-3-319-21708-6.

Markowitz, H.M., 1959. Portfolio Selection. Yale University Press. https://doi.org/10.12987/9780300191677

McDonald, A.J., Balwinder, S., Keil, A., Srivastava, A., Craufurd, P., Kishore, A., Kumar, V., Paudel, G., Singh, S., Singh, A.K., Sohane, R.K., Malik, R.K., 2022. Time management governs climate resilience and productivity in the coupled rice–wheat cropping systems of eastern India. Nature Food 3 (7), 542–551. https://doi.org/10.1038/s43016-022-00549-0.

Meyer, J., 1977. Second degree stochastic dominance with respect to a function. Int. Econ. Rev. 18 (2), 477–487. https://EconPapers.repec.org/RePEc:ier:iecrev:v:18:y:1977:i:2:p:477-87.

Montes, C., Urfels, A., Han, E., Balwinder-Singh., 2023. Planting Rice at monsoon onset could mitigate the impact of temperature stress on Rice–wheat Systems of Bihar, India. Atmosphere 14 (1), 40. https://www.mdpi.com/2073-4433/14/1/40.

Nalley, L.L., Barkley, A.P., 2010. Using portfolio theory to enhance wheat yield stability in low-income nations: an application in the Yaqui Valley of northwestern Mexico. Agric. Resour. Econ. Rev. 35 (2), 334–347. Retrieved 2010-08, from. https://ageconsearch.umn.edu/record/93223/files/JARE_Aug2010_10_pp334-347.pdf.

Newport, D., Lobell, D.B., Balwinder, S., Srivastava, A.K., Rao, P., Umashaanker, M., Malik, R.K., McDonald, A., Jain, M., 2020. Factors constraining timely sowing of wheat as an adaptation to climate change in eastern India. Weather, Climate, and Society 12 (3), 515–528. https://doi.org/10.1175/WCAS-D-19-0122.1.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M., 2013. The agricultural model Intercomparison and improvement project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. 170, 166–182. https://doi.org/10.1016/j.agrformet.2012.09.011.

Ruzzante, S., Labarta, R., Bilton, A., 2021. Adoption of agricultural technology in the developing world: a meta-analysis of the empirical literature. World Dev. 146, 105599 https://doi.org/10.1016/j.worlddev.2021.105599.

Shah, T., Ul Hassan, M., Khattak, M.Z., Banerjee, P.S., Singh, O.P., Rehman, S.U., 2009. Is irrigation water free? A reality check in the indo-Gangetic Basin. World Dev. 37 (2), 422–434. https://doi.org/10.1016/j.worlddev.2008.05.008.

Suri, T., 2011. Selection and comparative advantage in technology adoption. Econometrica 79 (1), 159–209. https://doi.org/10.3982/ECTA7749.

Tesfaye, K., Khatri-Chhetri, A., Aggarwal, P.K., Mequanint, F., Shirsath, P.B., Stirling, C. M., Jat, M.L., Rahut, D.B., Erenstein, O., 2019. Assessing climate adaptation options for cereal-based systems in the eastern indo-Gangetic Plains, South Asia. J. Agric. Sci. 157 (3), 189–210. https://doi.org/10.1017/S0021859619000492.

Urfels, A., McDonald, A.J., Krupnik, T.J., van Oel, P.R., 2020. Drivers of groundwater utilization in water-limited rice production systems in Nepal. Water Int. 45 (1), 39–59. https://doi.org/10.1080/02508060.2019.1708172.

Urfels, A., McDonald, A.J., van Halsema, G., Struik, P.C., Kumar, P., Malik, R.K., Poonia, S.P., Balwinder, S., Singh, D.K., Singh, M., Krupnik, T.J., 2021. Social-ecological analysis of timely rice planting in eastern India. Agron. Sustain. Dev. 41 (2), 14. https://doi.org/10.1007/s13593-021-00668-1.

Urfels, A., Montes, C., Balwinder, S., van Halsema, G., Struik, P.C., Krupnik, T.J., McDonald, A.J., 2022. Climate adaptive rice planting strategies diverge across environmental gradients in the indo-Gangetic Plains. Environ. Res. Lett. 17 (12), 124030 https://doi.org/10.1088/1748-9326/aca5a2.

Urfels, A., Mausch, K., Harris, D., McDonald, A.J., Kishore, A., Balwinder, S., van Halsema, G., Struik, P.C., Craufurd, P., Foster, T., Singh, V., Krupnik, T.J., 2023. Farm size limits agriculture's poverty reduction potential in eastern India even with irrigation-led intensification. Agr. Syst. 207, 103618 https://doi.org/10.1016/j.agsy.2023.103618.

Wang, X., Folberth, C., Skalsky, R., Wang, S., Chen, B., Liu, Y., Chen, J., Balkovic, J., 2022. Crop calendar optimization for climate change adaptation in rice-based multiple cropping systems of India and Bangladesh. Agric. For. Meteorol. 315, 108830 https://doi.org/10.1016/j.agrformet.2022.108830.

Wang, X., Wang, S., Folberth, C., Skalsky, R., Li, H., Liu, Y., Balkovic, J., 2024. Limiting global warming to 2 °C benefits building climate resilience in rice-wheat systems in India through crop calendar management. Agr. Syst. 213, 103806 https://doi.org/10.1016/j.agsy.2023.103806.