Appendix A: Model Overview, Design Concepts, and Details

Overview

Model Software: Powersim Studio 10 Expert

Purpose: The purpose of this model is to evaluate the impact of seasonal forecasts on a farmer's net agricultural income. The net income is a function of the crops planted, actual seasonal weather, and market conditions. The farmer being simulated is a simplified representation of farmers in System MH.

Entities, state variables, and scales: The entity in this model is an adaptive farmer who uses seasonal forecast information to select crops. To understand the impact of the seasonal forecasts, the net income of the adaptive farmer is compared to a farmer who uses climate information instead of seasonal forecast information to select crops (hereafter referred to as "climate" farmer) and a farmer who plants only rice (hereafter referred to as "rice-alone" farmer) every season.

Both the climate and adaptive farmers are characterized by heuristics, wherein the farmer's experiences over time influence their future decisions. Based on findings from games played in the field, we also simulate the influence of education on the adaptive farmer's net income; a farmer with less than grade 9 education demonstrates more randomness in their crop selection decision. For all three planting approaches, the decisions are not constrained by a farmer's bank balance and are assumed to occur uniformly across the farmer's field, hypothetically assumed to be one acre. The three planting approaches were simulated for three climate scenarios: 1) climate consistent with historical conditions, 2) drier climate, and 3) a wetter climate.

The model is calendar-independent with each time step representing one dry (locally referred to as "yala") season. The simulations are run for 64 dry seasons, which occur once per year. There is no spatial distribution of fields, farmers, or weather within the model.

An overview of the model's components and layout in Powersim are provided in Figures A1 and A2 respectively.

Process overview and scheduling: The model actions are executed in the following order each season:

1. Season begins (and the adaptive farmer receives a weather forecast)
2. Farmer selects a crop based on their planting approach
3. Reality ensues with actual weather and market conditions
4. Farmer obtains a net agricultural income
5. Farmer updates their rationale for planting given actual weather and market experiences
6. New season begins

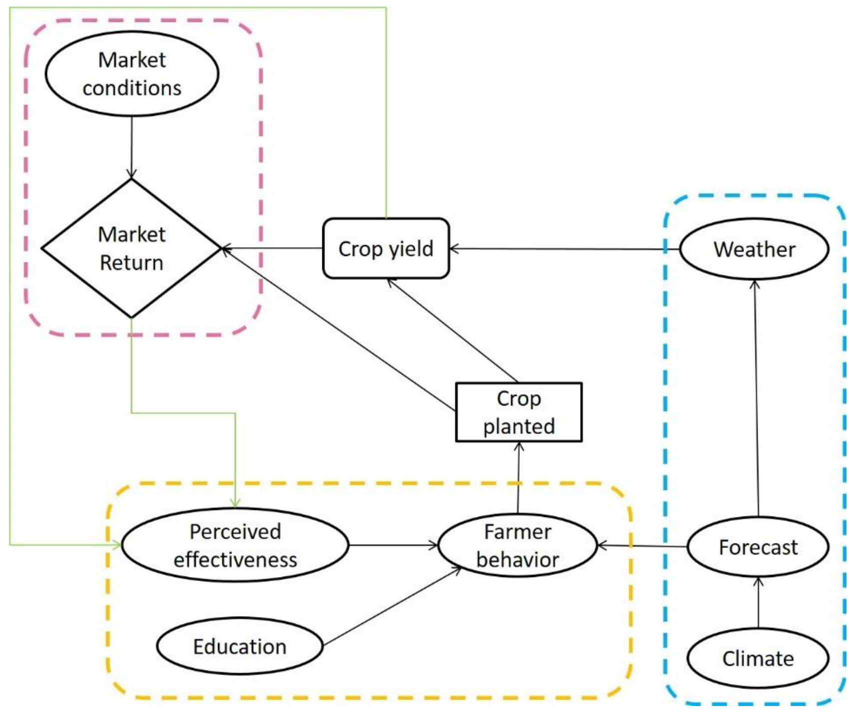

Figure A1. Influence diagram of hydrological (dashed blue), economic (dashed purple), and farmer behavior (dashed orange) components of the system dynamics model. The two green arrows note the updating process of the farmer's perceived effectiveness (i.e., prior experience) of the adaptation practice of crop diversification at the end of each season.

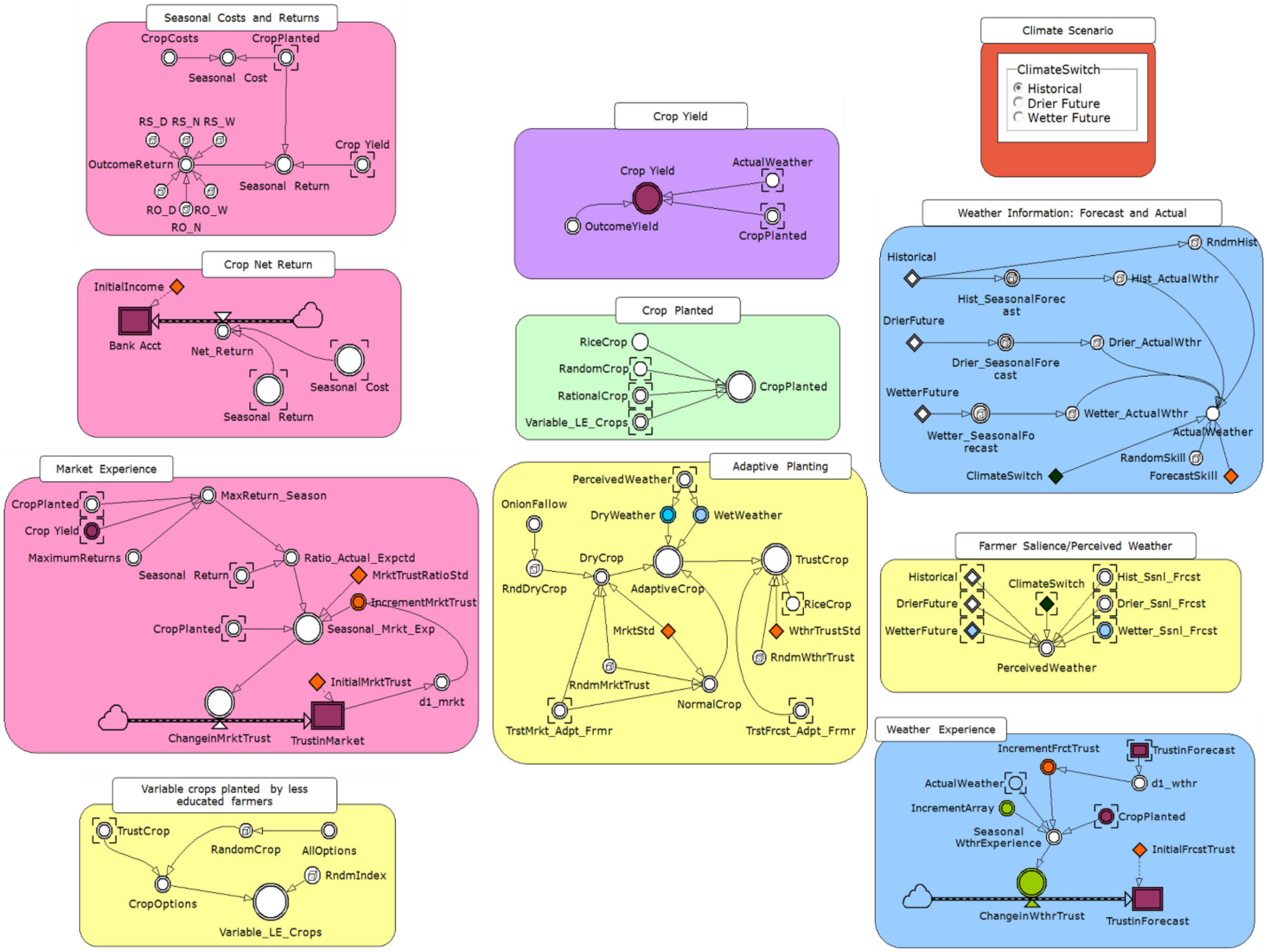

Figure A2. Snapshot of simulation set-up in Powersim Studio 10 Expert, a system dynamics software.

Design Concepts

Emergence and Observation: The model's primary output is net agricultural income over time. Important secondary outputs include farmer's trust in forecast and trust in the market; these outputs emerge from how the farmer's planting decision compares to the season's realized weather and market conditions. Our analysis focuses on the impact of different planting approaches and climate conditions on the outputs of interest. Even though changes in forecast and market trust do not influence the rice-alone farmer's planting decision, these outputs are generated for comparison purposes. Outputs from Powersim were written to Excel files and processed in R.

Adaptation and Learning: The rice-alone farmer does not adapt their decisions between seasons. The adaptive (and climate) farmer, on the other hand, updates their rationale for crop selection based on their experiences with the weather and market. If the farmer's trust in the forecast or market decreases below a threshold, the farmer becomes risk averse. Specific learning traits of the adaptive farmer are described in detail below.

Objectives: The farmer's objective is to maximize their net agricultural income. However, this objective is not explicitly incorporated into their planting approaches except implicitly as part of the risk aversion behaviors of the adaptive farmer.

Prediction: The rice-alone farmer predicts the return for their crop is constant, which is reflective of the current price floor policies for rice in Sri Lanka (Herath et al., 1982). The climate and adaptive farmers predict their crop returns will be at least 80% of their maximum return; if below this value, then their trust in the market decreases.

Sensing: The climate and adaptive farmers are assumed to have perfect knowledge of the climate conditions and seasonal forecasts respectively. These farmers are also assumed to have perfect knowledge of the maximum returns for crops but not the exact returns for soybean or onions.

Interaction: Although game findings indicate that farmer behaviors changed when they interacted with fellow players (Figure A3), this dynamic is outside the scope of model analysis. Therefore, there are no interactions in the model.

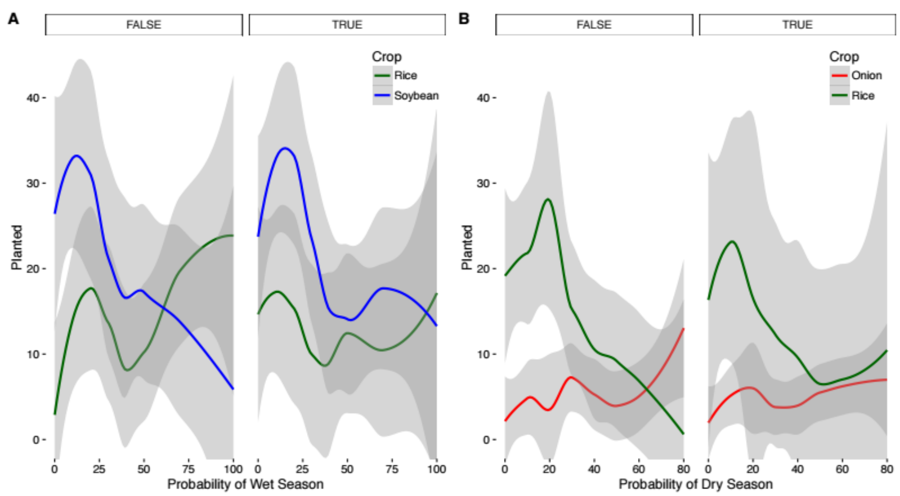

Figure A3. Impact of collaboration on farmer crop selections of A) rice vs soybean as a function of wet season probabilities and B) rice vs onion as a function of dry season probabilities. Lines represent average values while shaded regions represent 95% confidence interval for a LOESS fit to the data. When there is collaboration (i.e., condition is true) in rice-soybean comparison (A), farmers were more likely to plant soybean over a wider range of wet season probabilities. As for rice-onion comparison (B), when there is collaboration, farmers were more likely to plant rice over a larger range of dry season probabilities.

Stochasticity: There are two main stochastic components of the model: 1) weather and 2) market returns for soybean and onions. Each model run is initiated with one of three climate conditions from which the forecast and subsequently the weather are randomly generated (see subsections on "Climate scenarios" and "Actual weather"). The market returns for soybean and onions are randomly generated from a uniform distribution of a range of returns (see subsection on "Market return").

Collectives: There are no collectives in the model.

Initialization: Each model run is initialized with one of the three climate scenarios. All three farmers begin with net agricultural income of 0, 80% trust in the forecast, and 70% trust in the market; initial trust levels were chosen based on impressions gained from interviews in the field.

Input Data: In addition to the initialized values, the values in Table A1 are default parameters used in the model set-up across the climate scenarios.

Table A1. Default parameter values used in model simulation

Parameter	Value
Forecast skill	70%
Threshold at which trust in forecast is lost	30%
Threshold at which trust in market is lost	50%
Ratio of actual return to expected return at which farmer's trust in market is updated	0.8

Details

Climate scenarios*:* The climate scenarios are binned in deciles across probabilities that rainfall during the season is dry, normal, or wet. A general trend towards drought at our study site has been observed by Gunda et al. (2016) but Seo et al. (2005) note that the dominant climate change being observed at a seasonal level in Sri Lanka is increased variability. Therefore, the three climate scenarios considered in the model are:

1. Historical climate during the dry season: 40% dry – 40% normal – 20% wet
2. Drier climate: 50% dry – 40% normal – 10% wet
3. Wetter climate: 30% dry – 40% normal – 30% wet

The historical probabilities were determined from assessing drought indices at Anuradhapura using 131 years of data generated by Gunda et al. (2016) (Figure A4). No extreme conditions (i.e., floods and droughts) are considered in the model. The categorical approach (i.e., dry, normal, and wet) is consistent with field findings, which indicate that local water managers generally think about water availability in categorical rather than quantitative terms (Burchfield and Gilligan, 2016).

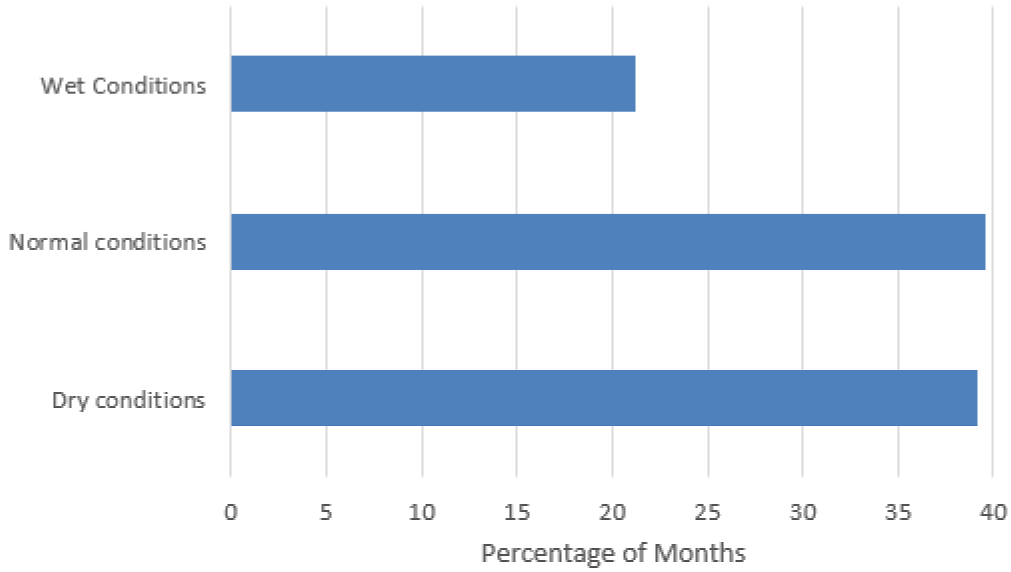

Figure A4. Percentage of months between 1881 and 2010 that were classified as wet, normal, and dry conditions based on the Palmer Drought Severity Index values at Anuradhapura. Data generated by Gunda et al. (2016).

Seasonal forecasts: For a given climate scenario, a seasonal forecast is generated by randomly sampling the corresponding climate probabilities.

Actual weather*:* Actual weather is generated by randomly sampling the seasonal forecast but is moderated by the forecast skill. For a forecast skill of 70%, for example, the actual weather generated is drawn (on average) from the generated forecast probability 70% of the time and from historical conditions (regardless of the actual climate) the remaining 30% of the time. For a forecast skill of 100% then, the actual weather generated is drawn from the generated forecast probability 100% of the time.

Crop options: The adaptive (and climate) farmer has the option of planting rice, soybeans, onions, or leaving their field fallow.

Crop decisions: As aforementioned, both the climate and adaptive farmers select crops based on their ongoing experiences with the weather and market. Based on the game findings (Figure A5), both farmers use the following logic to translate the ternary weather probabilities to actual crop decisions:

- If the probability of wet weather is >=70%, plant rice
- Else if the probability of wet weather is <30% and the probability of dry weather is >=60%, plant onions or leave field fallow
- Else, plant soybeans

Based on the ADAPT-SL survey data, the farmer chooses to plant onions (instead of leaving their field fallow) 75% of the time. If the farmer's planting decisions do not match the actual weather, they lose trust in the forecast. If the farmer's trust in the forecast drops below a threshold (default: 30%), then the farmer exhibits risk averse behavior by just planting rice – a behavior observed and documented in many regions of South Asia, including Sri Lanka (Thiruchelvam, 2005; Hertzog et al., 2014; Jain et al., 2015). This model set-up also reflects our ADAPT-SL survey findings that as a farmer's predictability of rainfall decreased, they were less likely to plant non-rice, or other food crops (OFCs). Similarly, if the farmer's market return for a crop is not at least 80% of their expectations, they lose trust in the market. If the farmer's trust in the market drops below the threshold, they exhibit risk averse behavior by planting rice instead of soybean and leaving fields fallow instead of planting onions (see subsection on "Trust heuristics").

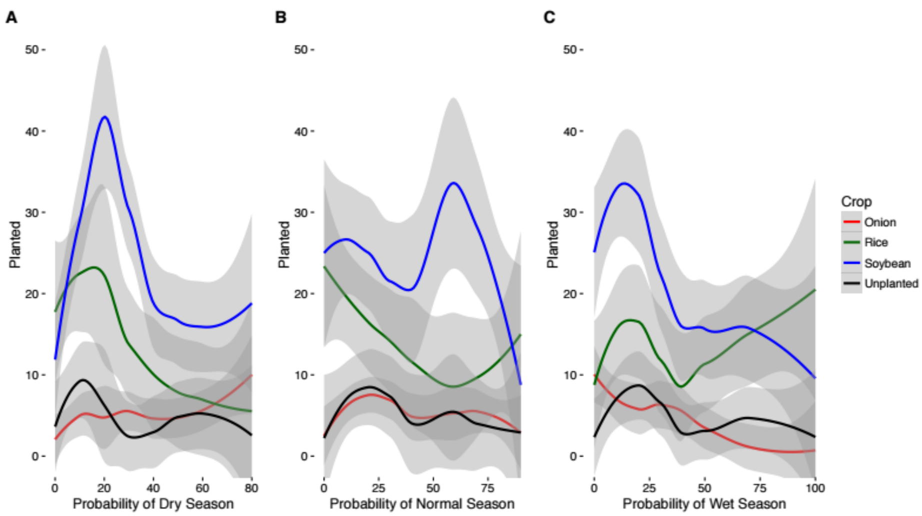

Figure A5. Planting decisions as a function of weather probabilities for A) dry season, B) normal season and, C) wet season. Lines represent average values while shaded regions represent 95% confidence interval for a LOESS fit to the data. Generally, farmers preferred to plant soybean except when the probability of wet or dry weather is high, in which case farmers opted to plant rice or onions over rice respectively.

Crop yield: Crop yields are binned into three categories: successful, normal, and poor. We assume that the farmer has the necessary knowledge to plant and maintain their crops and that the crop yields are not biophysically constrained (e.g., by soil type) on their hypothetical field. Therefore, the crop yields are purely a function of water availability. Both rice and soybean require more water for a bountiful crop while onions perform better in drier conditions due to root rot issues (Brouwer and Heibloem, 1986). So assuming that Huruluwewa is at average capacity, wet weather is needed for successful rice and soybean crops while dry weather is needed for a successful onion crop (Table A2).

Table A2. Crop yields as a function of weather conditions.

	Dry	**Normal**	**Wet**
Rice	Poor	Normal	Successful
Soybean	Poor	Normal	Successful
Onion	Successful	Normal	Poor
Fallow	None	None	None

Education: Our game results show that farmers with more education (i.e., greater than grade 9) moved more quickly towards planting rice under increasingly wet probabilities of weather (Figure A6). Therefore, we created a binary education variable that only impacts the implementation of the adaptive farmer's planting approach. If the farmer's education is less than grade 9, then there is some variability in their adaptive behavior; half of the time, the farmer makes a decision following the rationale outlined above and the other half of the time, the farmer chooses an option at random with a preference for planting rice 70% of the time and one of the other options (i.e., soybean, onion, or fallow) the remaining 30% of the time. This heavier weighting towards rice in the stochastic component reflects the positive association between education and predictability of rainfall in the ADAPT-SL survey data; our data shows that farmers who are less educated were less likely to state that they could predict rainfall; the ADAPT-SL survey data indicates that a farmer's predictability of rainfall is related to the likelihood the farmer is to plant OFCs (see subsection on "Trust heuristics").

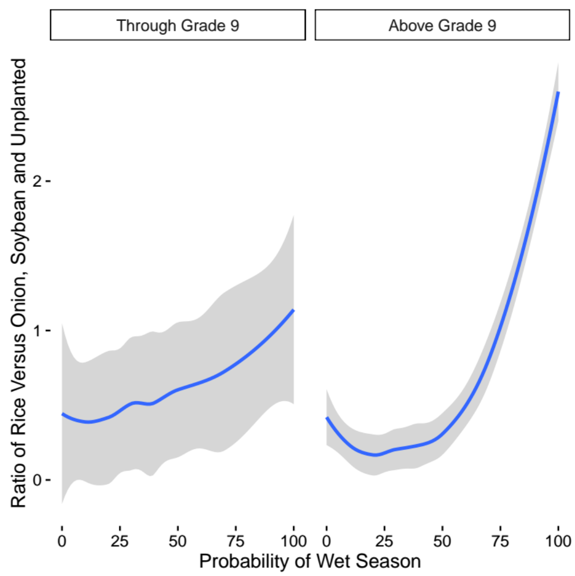

Figure A6. Impact of education on farmer crop selections. Lines represent average values while shaded regions represent 95% confidence interval for a LOESS fit to the data. Less educated farmers planted more rice at lower probabilities of wet season whereas more educated farmers moved more quickly towards planting rice as the probability of a wet season increased.

Market return: Market return is modeled as a function of crop yield and market conditions. Consistent with current Sri Lankan policies, we model rice with a fixed return while returns for soybean and onions are market-dependent; market returns for soybean are less variable than those for onions given the presence of futures contracts (whereby farmers enter agreements with businesses to buy the crop at an agreed price) in System MH. In the model, the returns for soybean and onions are randomly drawn from a uniform distribution of the ranges specified in Table A3. The market relationships in Table A3 were established based on aggregate data for costs (including both labor and materials) and returns from agricultural statistics books (Department of Agriculture, 2010-2011).

Table A3. Crop costs and returns (x 30,000 Sri Lankan Rupees), normalized per acre (Source: Department of Agriculture, 2010-2011). Crop returns are a function of crop yield.

Crop planted	Cost	Returns		
		Successful	Normal	Poor
Rice	1	3	2	1
Soybean	2	3-5	2-4	1-3
Onion	5	5-15	4-12	3-7
Fallow	0	0	0	0

Trust heuristics*:* We use a cognitive model for trust in our simulation; specifically, trust is as an accumulation of experiences over time and can influence behavior in the future (Earle and Siegrist, 2008; Hoogendoorn et al., 2012). Trust heuristics are an important aspect of farmer behavior since the farmer's efficacy beliefs/perceived effectiveness of a particular behavior are strongly correlated with their intent to perform that behavior in the future (Esham and Garforth, 2013; Truelove et al., 2015). The rice-alone farmer is not influenced by heuristics in the model; for the climate and adaptive farmers, we assume that there is an immediate feedback at the end of each season for the next season's decisions.

Trust in the forecast and trust in the market are modeled as percentages bounded between 0 and 100 (Sutcliffe and Wang, 2012), with the specific trust level representing the probability that the farmer decides to rely on their rationale; this approach is similar to the concepts of graded trust and subjective probability discussed in Lorini and Demolombe (2008) and Castlefranchi et al. (2003) respectively. At the end of each season, the farmer's trust in the forecast is updated by their experiences using Eq. [1]:

$$Trust_{t+1} = Trust_t + I_t A_t, \qquad [1]$$

where t is a season number, I_t is the increment for trust change in forecast, and A_t is the seasonal adjustment; recall that the farmer is initialized with 70% trust in the forecast. The increment for trust change is calculated each season as the minimum difference between the actual trust level and the boundary conditions (0% and 100%). By making the increment a function of the actual trust levels, our model captures the basic assumption that people with high trust are more likely to be tolerant of failures/bad experiences (Jonker and Truer, 1999; Sutcliffe and Wang, 2012).

The seasonal adjustment value, A_t, is based on prospect theory principles that people generally value losses more than gains (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981). Using the farmer's crop yields as the reference point for weather observations, the adjustments were defined as follows:

- If their crop has a successful yield: +6%
- If their crop has a poor yield: -10%

This approach is similar to the methodology employed by Ziervogel et al. (2005), where farmers lost trust in the forecast when their crop yields were poor. If the farmer's trust in the forecast drops below a threshold of 30%, then the farmer reverts to the risk averse behavior of planting rice. This model set-up is consistent with our ADAPT-SL survey findings that as a farmer's predictability of weather decreases, they are less likely to plant OFCs. The farmer continues to update their heuristics regarding weather predictability (relative to their crop planted) throughout the simulation.

The heuristics associated with market trust also follow Eq. [1]. Specifically, the next season's trust is influenced by the current season's actual returns and the increment of change is a function of the actual trust level and the minimum distance to the boundary conditions. Furthermore, the adjustments each seasons are based on the farmer's expected return for each crop (assumed to be 80% of the maximum return possible for soybeans and onions as the default):

$$A_t = \begin{cases} +6\% & if\ \dfrac{actual\ return}{expected\ return} \geq 0.8 \\ -10\% & if\ \dfrac{actual\ return}{expected\ return} < 0.8 \end{cases}$$

If the farmer's market trust falls below the threshold of 50%, then they lose trust in the market and opt to plant rice instead of soybean and leaving their field fallow instead of planting onion. Again, similar to forecast trust heuristics, the farmer continues to update their market heuristics regarding market predictability throughout the simulation.

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