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DYNAMICS OF INDIVIDUAL AND COLLECTIVE AGRICULTURAL ADAPTATION TO WATER SCARCITY

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ABSTRACT

Drought and water scarcity are growing challenges to agriculture around the world. Farmers can adapt through both individual and community-based collective actions. We draw on extensive field-work conducted with paddy farmers in rural Sri Lanka to study adaptations to water scarcity, including switching to less water-intensive crops, farming collectively on shared land, and individually turning to groundwater by digging wells. We explore how variability in climate affects agricultural decision-making at the community and individual levels using three types of decision-making, each characterized by an objective function: risk-averse expected utility, regret-adjusted expected utility, and prospect theory loss-aversion. We also assess how the introduction of individualized access to irrigation water with wells affects community-based drought mitigation practices. Preliminary results suggest that the growth of well-irrigation may produce sudden disruptions to community-based adaptations, but that this depends on the mental models farmers use to think about risk and make decisions under uncertainty.

1 INTRODUCTION

Future changes in climate will significantly stress agricultural systems around the world. In tropical Asia, research suggests that crop yield decreases caused by climate change could seriously impact food security (Sivakumar et al. 2005). In many South Asian countries, farmers are adapting to existing changes in water availability by pumping groundwater, switching to less water-intensive crops, or leaving the agricultural sector (Shah et al. 2013, Shah et al. 2003). Moreover, farmers' behavior (i.e. their choice of what to grow and what fraction of available cropland to cultivate) in response to an uncertain and changing climate may have a larger impact on agricultural output than the direct effects of climate change on biological crop yield (Cohn et al. 2016).

Simulation models have become important means of assessing the impact of changing climate, technological diffusion, farmer interactions, and farmer decision making on agricultural systems (Baggio et al. 2015, Janssen and Baggio 2016). In this paper, we explore the interactions between water availability and access, farmer decision-making, and collective water scarcity mitigation activities using an agent-based model. The model focuses on agricultural decision making in rural Sri Lanka, an area in which farmers have historically cultivated water-intensive paddy using surface water irrigation systems. We explore how dynamics of increased groundwater irrigation, changes in crop selection, and collective water scarcity mitigation practices vary with the heuristics farmers in rural Sri Lanka use to make decisions under uncertainty. Our preliminary results suggest that farmers individual decision heuristics strongly influence their decision making during periods of extreme water scarcity.

2 BACKGROUND

Sri Lanka is a small island nation off the southeastern coast of India, which is home to nearly 21 million people, 30 percent of whom are involved in the agricultural sector (Department of Census and Statistics 2014). The nation experiences two monsoon seasons annually (Gunda et al. 2016). The northeast monsoon lasts from October to December and brings nearly two-thirds of annual rainfall to Sri Lanka. The southwest monsoon lasts from May to October and brings rain primarily to the southwestern region of the island. This rainfall pattern divides the island into a wet zone and a dry zone and creates two distinct cultivation seasons, the wet *Maha* season and the dry *Yala* season (Samad 2005, Senaratne and Scarborough 2011). Today, the dry zone is home to thousands of surface water irrigation systems in which wet-season water is stored in reservoirs to enable dry-season cultivation. Many farmers in these systems cultivate paddy because rice is the staple food of Sri Lanka, with annual per capita consumption around 100 kilograms (Gamawelagedara et al. 2011) ("paddy" refers to the plant, and "rice" refers to the processed grains).

Climate scientists predict that the prevalence of low rainfall during the dry season will increase in the future (De Silva et al. 2007, Jayawardene et al. 2005, Malmgren et al. 2003). In response to projected changes in water availability and a desire to achieve domestic food security, the Sri Lankan government is encouraging farmers to shift from water intensive paddy cultivation to the cultivation of other field crops (OFCs) such as soy, sesame, chilies, and onions during the dry seasons (Elakanda 2010, Imbulana et al. 2006, Kikuchi et al. 2002). Many farmers have been reluctant to switch to OFC cultivation. In this paper, we analyze survey and qualitative data to inform the construction of an agent-based model (ABM) that explores the role of water scarcity, farmer preferences, and technology diffusion in farmers' decisions to cultivate OFCs or paddy.

Previous work on modeling farmer response to climate change and to potential water scarcity found that when climate forecasts are uncertain, farmers' response depends strongly on the way they think about risks and uncertainty (Jacobi 2014, Podestá et al. 2008, Hansen et al. 2004). Much economic decision analysis and modeling of response to climate change assumes that actors will respond to risks and changes by making rational choices to maximize expected income or wealth, possibly with a degree of risk-aversion (Nordhaus 2008, Kolstad 2011), but a large body of empirical research in behavioral economics has found that people facing decisions under uncertainty often use different heuristics to think about uncertainty and seek different objectives from simply maximizing expected wealth or income (Tversky and Kahneman 1992)

In analyzing the likely response of farmers to water scarcity, we drew on interviews conducted with key decision makers, water managers, and farmers during the 2013 and 2015 dry seasons as well as survey data collected in 607 households in twelve dry zone communities. Our qualitative data suggests that farmers are reluctant to cultivate OFCs for two reasons. The first is a strong cultural preference for paddy cultivation. Sri Lankan farmers have cultivated paddy for centuries and many government programs focus on supporting paddy cultivation. These include fertilizer subsidies, agricultural extension, and government purchase of paddy harvest at a set price (Jinapala et al. 2010). In addition, OFCs are difficult to store, so farmers must bring them to market immediately after harvest. In many cases, this causes market gluts at the end of the season that significantly reduce OFC prices for farmers.

The second reason farmers cite for preferring paddy cultivation is the difficulty of cultivating OFCs during periods of extreme water scarcity. This may seem counterintuitive, since OFCs generally require less water than paddy, but the widespread practice of *bethma* drives many farmers to cultivate paddy when little water is available. *Bethma* is an ancient practice in which farmers divide their fields and cultivate paddy on a subset of the command area. Under *bethma*, permanent field boundaries are temporarily abolished and land is redistributed amongst all farmers who cultivate in the command area. This redistribution process is complex and varies from system to system, but in general, each family received equal-sized parcels of land regardless of the amount of land owned (de Jong 1989, Thiruchelvam 2010). During periods of extreme water scarcity, engaging in *bethma* is the best option for many farmers, as it ensures they are able to achieve modest yields for the season. In recent years, however, the diffusion of agrowells in the dry

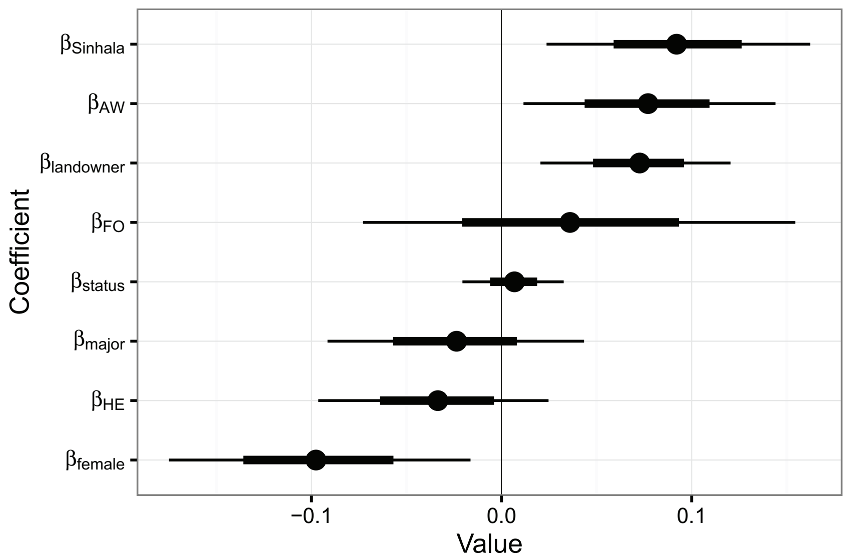

Figure 1: Regression coefficients for choice to grow OFC instead of paddy. The dots show the median of the posterior probability distribution, the thick lines indicate the 66% highest-density interval and the thin lines indicate the 95% highest-density interval.

zone has allowed farmers to cultivate OFCs using groundwater during water scarce seasons (Kikuchi et al. 2002).

3 FIELD RESEARCH

We asked over 600 farmer heads of households whether they regularly planted OFCs in their irrigated fields. Responses y_i were labeled as 1 if farmers regularly cultivate OFCs in their irrigated fields and 0 if they regularly plant paddy in these fields, with $\Pr(y_i = 1) = \text{logit}^{-1}(\beta_i X)$. The respondent-level design matrix X is a set of binary indicators for key demographic variables including agrowell ownership, location in a high-capacity irrigation system, gender, ethnicity, land ownership, location at the head-end of a canal, and farmer organization membership. We also include a measure of socio-economic status constructed using household assets listed by interviewees. Following Gelman et al. (2008), we assign weakly informative Cauchy priors with a mean of zero and a standard deviation of 2.5 to each of the coefficients in the logistic regression except the constant term. We tested to ensure these priors do not unduly constrain the posterior. The data model is as follows:

$$\begin{aligned}\Pr(y_i = 1) = \text{logit}^{-1}(\alpha + \beta_{\text{AW}}\,\text{AW}_i + \beta_{\text{major}}\,\text{major}_i + \beta_{\text{female}}\,\text{female}_i + \beta_{\text{Sinhala}}\,\text{Sinhala}_i \\ + \beta_{\text{status}}\,\text{status}_i + \beta_{\text{landowner}}\,\text{landowner}_i + \beta_{\text{HE}}\,\text{HE}_i + \beta_{\text{FO}}\,\text{FO}_i)\end{aligned} \tag{1}$$

where *AW* is a binary indicator of agrowell ownership, *major* is a binary indicator of location within a large surface water irrigation system, *female* indicates survey respondent sex, *Sinhala* indicates whether the respondent belongs to the dominant Sinhalese ethnic group or to a minority group, *status* indicates high socio-economic status, *landowner* indicates whether the farmer is the legal owner of the land they cultivate, *HE* is a measure of the proportion of paddy fields cultivated by a farmer located at the head-end of their field canal, and *FO* indicates farmer membership in the local farmer organization.

We used the rstan interface to the Stan Hamiltonian Monte Carlo software to perform the regression analysis (Carpenter et al. 2016). Figure 1 shows the results: though none of the effects are very strong, our results suggest that farmers with agrowells, who are Sinhalese, with a relatively high socio-economic status and who own land are more likely to plant OFC during the Yala season. This suggests that farmers who are relatively better off (e.g. Sinhalese ethnicity, male, land owners, located in high-capacity irrigation systems, owning agrowells) will have a higher capacity to engage in risky cultivation practices and will be more likely to cultivate OFCs. As the proportion of farmer fields in the head-end of the field canal increases, farmers are less likely to plant OFCs. Head-end farmers typically receive water before tail-end farmers and do not face the positional water scarcity often faced by tail-end farmers (Chandrapala et al. 2013, Bastakoti et al. 2010).

4 MODEL DESIGN

We developed an agent-based model to study the role of farmer decision-making on adaptation to changing levels of water scarcity. We explore farmer adaptation across varying preference structures, forms of water access, and environmental settings.

This model simulates a single community of farmers, who share a distribution canal (DC) in the Sri Lankan dry zone. The DC is fed by a reservoir and distributes its water equally to a number of field canals (FCs), which carry water to the farmers' fields. Each farmer has a field on one FC. Collective action occurs at the FC level: each season, the farmers sharing an FC vote on whether that FC will collectively practice *bethma* for that season, and the decision follows the majority. This suggests that gradual changes in preference may produce abrupt effects when the number of supporters crosses the majority threshold.

Crop yields depend on access to water: the reservoir level, the amount of rain that falls on the DC (seasonal rainfall is uniform across the DC), and whether an individual farmer has an agrowell. Interviews with local water managers suggest that officials generally think about the level of water in a reservoir categorically (average, below average, or above average) rather than quantitatively, and choose seasonal operating and management strategies for the district accordingly. Similarly, farmers describe seasonal rainfall as wet, normal, or dry.

Here, we present the model structure using the Overview, Design concepts and Details (ODD) protocol (Grimm et al. 2010). All code is available online at https://github.com/eburchfield/agrowell_abm.

4.1 Entities, State Variables, and Scales

The active entities in this model are farmers. Each farmer is characterized by an objective function, socioeconomic status, and agrowell ownership. The objective function characterizes how the farmer makes decisions under uncertainty. Following Podestá et al. (2008), the possible objective functions are risk-averse expected utility, regret-adjusted expected utility, and prospect theory loss-aversion (see Appendix A). Our logistic regression found that ethnicity was an important predictor of cropping decisions, but communities in the Sri Lankan dry zone are ethnically very homogeneous, so we did not include ethnicity in our model.

There are 10 FCs on the DC, and each FC serves 15 farmers. There are no persistent state variables for DC and FC. Each iteration represents one growing season, and the simulations loop through 20 seasons.

4.2 Process Overview and Scheduling

At the beginning of the simulation, the farmers' state variables are initialized. At the beginning of each season (iteration), the level of water in the irrigation system's reservoir is randomly set to high (with 25% probability), medium (50%) or low (25%).

Farmers know that there is a 25% probability of an especially wet season, a 50% probability of a "normal" season, and a 25% probability of an especially dry season. Based on these probabilities, farmers calculate expected utility for different crop choices (growing paddy under *bethma*, growing paddy without *bethma*, growing OFC with *bethma*, and growing OFC without *bethma*). The farmers then rank their preferences and the farmers of each field canal vote on whether to practice *bethma* in that season. After making the *bethma* decision, the farmers choose which crop to grow.

After the farmers make their cultivation decisions, seasonal rainfall is randomly set to wet, normal, or dry and the harvest yield is determined from a payoff table with some stochastic variance. The payoff table lists mean crop yields and variances for growing conditions, which were derived from government reports on crop prices and farmer self-reports of seasonal income reported in survey data. The full payoff table is available at the model repository. Finally, farmers' socioeconomic status is adjusted based on a balance of income and expenses. At this point, farmers who are sufficiently wealthy (socioeconomic status $> 120,000$ rupees, corresponding to one standard deviation above the population mean) will purchase an agrowell, financing it with payments over the following 10 seasons.

4.3 Design Concepts

Basic Principles: When farmers acquire agrowells, they gain an individual ability to irrigate their fields. This reduces their dependence on canal irrigation, which requires coordination and collective action among the farmers who share a canal. Under conditions of water scarcity, we hypothesize that expansion of agrowells may undermine traditional collective adaptations such as *bethma*. This is complicated because farmers must commit to planting before they know what the weather will be, and seasonal forecasts are very uncertain. Thus, the interaction between agrowells and collective action will be mediated by the details of how farmers make decisions under uncertainty.

Emergence: We expect to see emergence occur through the collective decision-making about *bethma* on a field canal. If farmers' cultivation preferences change when they acquire agrowells, a gradual change in the number of agrowells could produce a sudden change in cultivation when a critical number of well-owners tips the balance in voting.

Objectives and Adaptation: Farmers seek to maximize their objective function. Farmers compute their expected profit for each cultivation option, given known parameters (reservoir levels and agrowell ownership), under the probability distribution of seasonal rainfall (low, average, or high). When calculating prospect-theory utility, farmers use their income from the previous growing season as their reference point.

Farmers calculate their objective function for the four possible cultivation decisions—choosing paddy vs. OFC and whether or not to practice *bethma*—and rank the choices from best to worst. They vote for or against *bethma*, with the majority ruling. After *bethma* has been decided for the field canal, each farmer then chooses between growing paddy or OFC.

Sensing: Farmers sense reservoir levels. They do not know what the weather for the upcoming season will be when they make their *bethma* and crop decisions.

Interaction: Farmers on the same field-canal interact by voting on whether to practice *bethma*.

Stochasticity: Farmers are initialized with random socioeconomic status. At each growing season, the reservoir level and rainfall are stochastically generated from the probability distributions described in section 4.2.

Bethma decisions are determined by the majority vote at the field-canal level, but after the field-canal makes this decision each farmer's crop choice is modeled as a Bernoulli process, using a logistic function to map the difference in expected utility between OFC and paddy onto a probability in the interval $[0,1]$. The different utility functions have vastly different natural scales, and these scales change as we change parameters (e.g., from logarithmic to power-law for expected utility), so we scale all of the utilities to bring them to the same range before applying the logistic mapping.

Collectives: Irrigation is managed at the field-canal level, so irrigation decisions (here, the decision whether to practice *bethma*) are taken collectively by all the farmers on the field canal.

Observation: When running the model, we observe the reservoir levels, farmers' income, status, crop decisions, adoption of agrowells, and the field-canals' votes on *bethma*.

4.4 Initialization

Farmers are initialized with an agrowell ownership flag, socio-economic status, an objective function for decision making, and a set of risk parameters. Groups of fifteen farmers are randomly assigned to each field canal.

Farmers' socio-economic status is drawn from a normal distribution with a mean of 100,000 rupees and a standard deviation of 2,000 Rs (Central Bank of Sri Lanka, 2014). A fraction of the farmers with a socio-economic status one standard deviation above the mean socio-economic status receive an agrowell at initialization. We assume that loans for these agrowells have been paid in full prior to initialization. See section 5.1 for tests of sensitivity to these assumptions.

4.5 Submodels:

Crop yields: Crop yields have a complex relationship with reservoir level, rainfall, whether farmers on a field canal practice *bethma* when the reservoir is low, and whether farmers growing OFCs have agrowells. We devised our crop-yield table based on survey data and records from the Sri Lanka Ministry of Agriculture.

Paddy requires a great deal of water. If the reservoir level is normal or high, paddy will produce a full yield, averaging 100,000 Rs of seasonal profit, regardless of the rain. When the reservoir is normal or high and rainfall is normal or low (dry), OFC produces higher incomes than paddy, averaging 120,000 Rs; but in wet years (high rainfall), water damage to OFC and possible flooding reduce OFC yields to 90,000 Rs.

If the reservoir is low, paddy yields will depend strongly on the amount of rain, producing 20,000–40,000 Rs. Practicing *bethma* can raise yields to 50,000–60,000 Rs. For all rainfall conditions, OFC produces 20% more income than growing paddy without *bethma*, but growing paddy with *bethma* produced higher yields for all levels of rainfall.

Agrowells are especially valuable for OFC growers. With an agrowell, a farmer growing OFC can earn 84,000–144,000 Rs: much more than paddy under all conditions except high rainfall with a normal or high reservoir.

This complex payoff table yields interesting dynamics under low-reservoir conditions. Normally, when reservoirs are low, it is economically advantageous for farmers to work together under *bethma*. This produces significantly higher income than either growing OFC or growing paddy without *bethma*. However, once agrowells enter the picture, those farmers who have agrowells can earn far more growing OFCs on their land, and thus they have an incentive to block *bethma*.

Investing in agrowells: Farmers with high socioeconomic status (more than one standard deviation above the population mean) invest in agrowells. An agrowell costs 70,000 Rs, which is paid in annual installments over 10 seasons.

5 RESULTS

We ran a 20-year simulation 100 times for each of four conditions of the farmer's objective function: all farmers using risk-averse expected utility, all farmers using regret-averse expected utility, all farmers using prospect theory, and a mixture with each farmer randomly assigned one of the three objective functions, with equal probability.

Figure 2 shows how the fraction of field-canals choosing *bethma* varied with the penetration of agrowells. Unsurprisingly, no field-canals choose *bethma* when the reservoir has an ample supply of water. But in conditions of water scarcity, the choice of *bethma* depends on the combination of the prevalence of agrowells and the objective functions farmers use to make decisions under uncertainty over the coming season's rainfall.

For risk-averse and regret-averse expected utility, all field-canals choose *bethma* when the reservoir is low, regardless of how many farmers own agrowells, but under prospect theory, *bethma* drops to zero when a large fraction of farmers own agrowells.

Risk-averse and regret-averse expected utilities reference only the possible outcomes, and are weighted proportionally to the probability of each outcome. The prospect theory objective depends not only on the possible outcomes, but also on the reference point (in this case, the farmer's income in the previous season), and the probability weightings are nonlinear (Eq. 8). The panel for mixed objective functions shows that even partial representation of prospect theory among the farmers can have a significant effect on *bethma* decisions, although the effect is much less dramatic than when all the farmers use prospect theory.

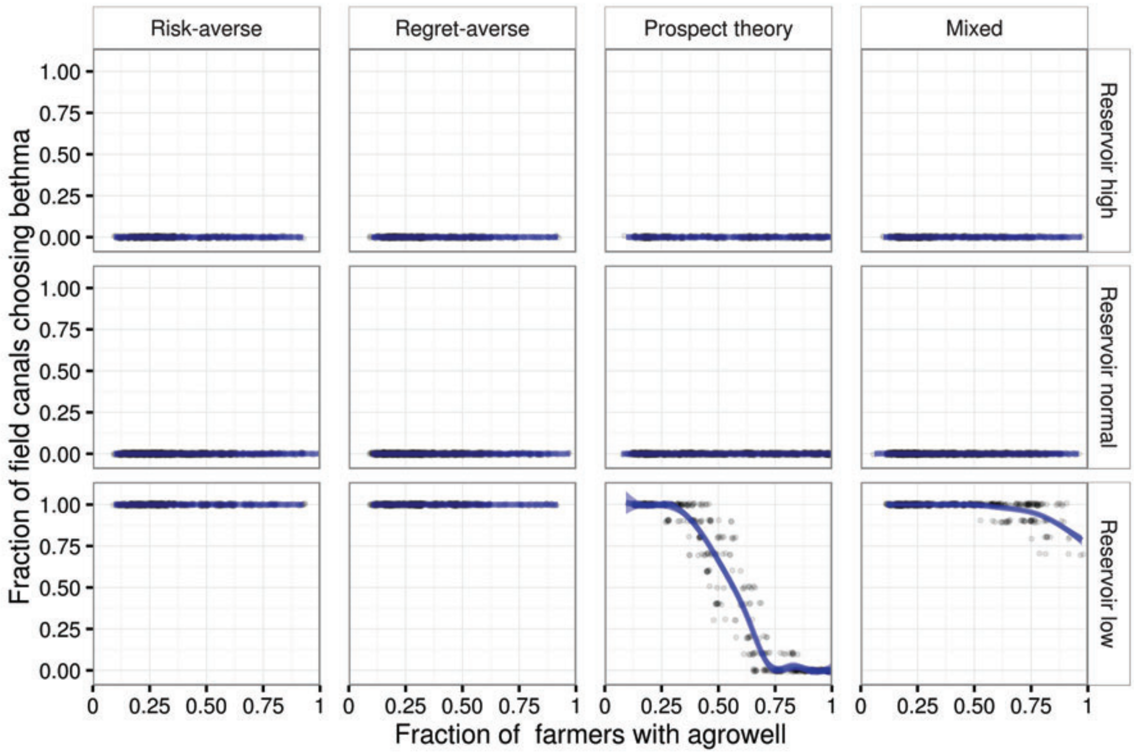

Figure 2: Variation in *bethma* as a function of agrowell ownership for different reservoir levels and different objective function. The figures show the aggregate outcomes over 100 sequences of 20 growing seasons. Dots represent individual model runs and are jittered by 0.02 to aid visualization of overlapping points. The blue lines are lowess-curves.

Figure 3 shows how the individual farmers' profits vary over time, broken down by the conditions of the reservoir. In general, farmers with agrowells have both greater average income and greater variation in income (because they are more likely to plant OFC when reservoir levels are normal or high, which makes them vulnerable to flooding and water damage if the rainfall is heavy that year). When farmers follow prospect theory, the decline of participation in *bethma* leads to growing income inequality in years with low reservoir levels because farmers with agrowells grow OFC without *bethma* and earn 80,000–108,000 Rs, depending on rainfall, but farmers without agrowells only earn 24,000–48,000 Rs, which is considerably less than the 50,000–60,000 Rs they would have earned growing paddy under *bethma*.

5.1 Robustness and Sensitivity Testing

To test how robust our results were to the specific values of the parameters for the objective functions described in Appendix A, we ran an ensemble of simulations using different values for each parameter, both above and below the nominal value, following the example of Podestá et al. (2008), from whom we took values for many parameters, and the methodological recommendations of Railsback and Grimm (2012). For risk-averse expected utility: $r \in \{-0.5, 0, 0.5, 1, 2, 3, 4\}$ (nominal $= 1$, $0 =$ risk-neutral, $< 0 =$ risk-seeking). For regret-adjusted expected utility: all combinations of r as before, $k \in \{0, 0.155, 0.564\}$ (nominal = 0.155), and $\beta \in \{5 \times 10^{-4}, 0.5, 0.9\}$ (nominal = 0.5). For prospect theory: all combinations of $\alpha \in \{0.6, 0.7, 0.8, 0.9, 1.0\}$ (nominal = 0.88) and $\lambda \in \{1, 2.25, 3.5\}$ (nominal = 2.25).

For each objective function and for each combination of parameters, we ran 100 repetitions of 20-year simulations and recorded the fraction of farmers owning agrowells, farmer income, fraction of farmers

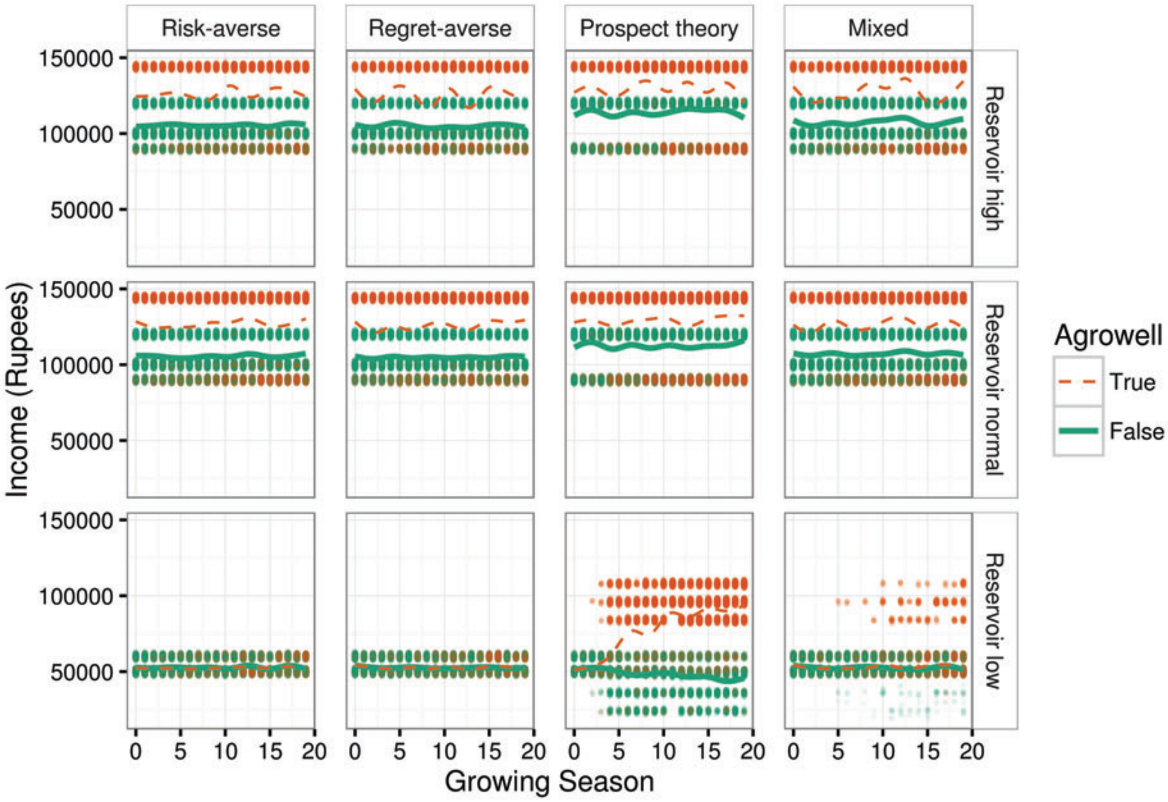

Figure 3: Variation in income over time for individual farmers, grouped by agrowell ownership, for different reservoir levels and different objective function. Each panel shows the simulations in which the reservoir is at a given level for a given season, so a simulation of 20 growing seasons will have dots that appear in the "Reservoir low" panel on those seasons in which the reservoir is low, in the "Reservoir normal" panel for those seasons in which the reservoir level is normal, and so forth. The dots represent individual farmers in 100 sequences of 20 growing seasons. The colored lines are lowess-curves fit to all the farmers in a panel with the corresponding agrowell-ownership. Where the dots form sets of three bands, the different bands correspond to different amounts of rainfall.

cultivating OFCs, and fraction of field canals choosing bethma. For risk-averse expected utility, farmers earned slightly higher incomes and were slightly more likely to install an agrowell for low levels of risk aversion ($r = 0.5$ and $r = 1$). Results presented above used a value of $r = 1$, which follows the empirical literature (Podestá et al. 2008). This value of risk aversion may slightly increase our estimates of farmer income and agrowell installation. For regret-adjusted expected utility, results were not sensitive to variations of the parameters. For prospect theory, as α increased, farmer income increased along with agrowell installation and the cultivation of OFCs. α captures the non-linearity of the value function; it accounts for degree of risk aversion (concavity) in the gain region and risk seeking (convexity) in the loss region.

We varied the rate of agrowell ownership at initialization and also tested setting the remaining term on agrowell loans at initialization to a uniform random distribution between 0 and 10 years. Neither of these variations changed the results substantively.

Space does not permit a detailed quantitative discussion of this robustness and sensitivity testing, but qualitatively, across the range of parameter values, the adoption of *bethma* and farmers' income did not change much, usually by less than the variability between different model runs with the same parameter values, so we conclude that the qualitative results we present here, such as the impact of prospect theory plus agrowell ownership, are robust and do not depend on specific values of these parameters.

6 DISCUSSION

The relationship between agrowells and *bethma* has complicated implications for policy. On the one hand, there is broad agreement among experts that farmers could be better off, both individually and collectively, if they would grow more OFC and less paddy. In particular, the lower water demands for OFC would relieve a good deal of stress on the water supply system and make farmers more resilient to drought. Even when water is plentiful, agrowells can dramatically increase OFC yields. However, this simulation suggests that agrowells may also displace traditional collective responses to water scarcity, such as *bethma*. Agrowells are expensive and are thus out of reach for most farmers today. As successful farmers become wealthier and agrowells proliferate, tensions over *bethma* decisions may grow between farmers with agrowells and those without. In addition, as farmers with agrowells achieve majorities on field canals, farmers unable to afford agrowells may suffer economically, leading to growing inequality, as Fig. 3 shows. However, the relationship between agrowells and *bethma* only occurs for certain decision heuristics (those using prospect-theory objectives), so empirical studies of farmer views of risk and decisions under uncertainty could provide valuable information for policy analysts and decision-makers. This underscores the general observation by experts on risk and decision support that policies for managing environmental risks are more likely to be successful if they are grounded in empirical knowledge of people's actual behavior (Fischhoff 2006). It also highlights the importance of both environmental *and* social uncertainty in driving agricultural outcomes.

This simulation did not address additional complexities of OFCs: markets for selling OFCs are much more volatile than markets for selling rice, both because of government price supports for rice and because OFCs are perishable and refrigerated storage facilities are scarce. If a large number of farmers harvest OFCs at the same time, the market may become glutted, reducing prices. Introducing a realistic demand curve for OFCs into this simulation will be the subject of future work.

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A APPENDIX: OBJECTIVE FUNCTIONS

The farmers' objective functions—the functions they try to maximize when making cultivation choices—follow Podestá et al. (2008).

Risk-averse utility: Farmers seek to maximize profit, but the utility of money declines the more one has ($1000 would make a bigger difference to a person in poverty than to a millionaire). This is formalized with an isoelastic utility function that produces constant relative risk aversion (meaning that utility is scale-invariant so multiplying all monetary values by a constant does not change preferences) (Pratt 1964). The utility of wealth or income w is given by:

$$u_{\text{risk-averse}}(w) = \begin{cases} \frac{w^{1-r}-1}{1-r} & r \neq 1 \\ \ln w & r = 1 \end{cases} \tag{2}$$

where r is a coefficient of risk aversion. Larger values of r correspond to greater risk aversion, negative values to risk-seeking, and $r = 0$ represents indifference toward risk. Following the empirical literature, we use a value of $r = 1$, which corresponds to small risk aversion, with a constant gain in utility for each doubling of income or wealth (Podestá et al. 2008).

Regret-adjusted utility: Farmers compare their profit to what might have happened had they made a different choice and the utility accounts for anticipated regret (Bell 1985, Loomes and Sugden 1982): This utility function determines the expected value of any one possible outcome by comparing it to all other possible outcomes. If the set of possible monetary outcomes (wealth or income) is $\{w_i\}$, then for a given outcome w^*, we define regret as the difference in risk-averse utility (Eq. 2) between w^* and the best possible outcome in the set of w_i (the difference between what you have and what you might have had):

$$\text{regret}(w^*) = \max(u_{\text{risk-averse}}(w_i)) - u_{\text{risk-averse}}(w^*). \tag{3}$$

The regret-adjusted utility is given by:

$$u_{\text{regret-adjusted}}(w) = u_{\text{risk-averse}}(w) - k\left(1 - \beta^{\text{regret}(w)}\right), \tag{4}$$

where k sets the scale for regret (the impact of infinite regret) and $\beta (0 \leq \beta < 1)$ describes the decision-maker's sensitivity to the magnitude of regret (e.g, the impact of doubling regret). Following the empirical literature, we set $r = 1$, $k = 0.155$, and $\beta = 0.5$ (Podestá et al. 2008).

Expected utility: Where the consequence of a choice is uncertain, with possible outcomes w_i whose probabilities are p_i, the expected utility of the choice, under either risk-averse or regret-adjusted utility, is the probability-weighted sum of the utilities of the outcomes:

$$u_{\text{expected}} = \sum_i p_i \, u_x(w_i), \tag{5}$$

where u_x is $u_{\text{risk-averse}}$ (Eq. 2) or $u_{\text{regret-adjusted}}$ (Eq. 4).

Prospect theory: The utility of a given income does not depend on its magnitude, but on how much it exceeds or falls short of some reference value w_{ref} (e.g., expected income), with the pain of losses exceeding the pleasure in equal gains (Tversky and Kahneman 1992). When the consequence of a choice is uncertain, as described above, the prospect-theory utility is given by:

$$u_{\text{prospect}} = \sum_i f(\Delta w_i) g(p_i), \tag{6}$$

where

$$f(\Delta w) = \begin{cases} (\Delta w)^{\alpha} & \Delta w \geq 0 \\ -\lambda(-\Delta w)^{\alpha} & \Delta w < 0 \end{cases}, \tag{7}$$

$$g(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}, \tag{8}$$

$$\gamma = \begin{cases} \gamma_+ & \Delta w \geq 0 \\ \gamma_- & \Delta w < 0 \end{cases}, \tag{9}$$

$\Delta w_i = w_i - w_{\text{ref}}$ is the change from the reference point (e.g., expecting \$100 and getting \$80 makes $\Delta w_i = -\$20$), λ is a coefficient of loss-aversion (how the pain of losing \$100 compares to the pleasure of winning \$100), α describes risk aversion/seeking (analogous to r in Eq. 2) and γ accounts for nonlinear probability weighting. Following the empirical literature, we set $\alpha = 0.88$, $\lambda = 2.55$, $\gamma_+ = 0.69$, and $\gamma_- = 0.61$ (Tversky and Kahneman 1992, Podestá et al. 2008).

REFERENCES

Baggio, J., N. Rollins, I. Perez, and M. Janssen. 2015. "Irrigation Experiments in the Lab: Trust, Environmental Variability and Collective Action". *Ecology and Society* 20:12–20.

Bastakoti, R. C., G. P. Shivakoti, and L. Lebel. 2010. "Local Irrigation Management Institutions Mediate Changes Driven by External Policy and Market Pressures in Nepal and Thailand". *Environmental Management* 46:411–23.

Bell, D. E. 1985. "Disappointment in Decision Making Under Uncertainty". *Operations Research* 33:1–27.

Carpenter, B., A. Gelman, M. Hoffman, D. Lee, B. Goodrich, M. Betancourt, M. A. Brubaker, J. Guo, P. Li, and A. Riddell. 2016. "Stan: A Probabilistic Programming Language". *Journal of Statistical Software*. (in press) http://www.stat.columbia.edu/~gelman/research/unpublished/stan-resubmit-JSS1293.pdf [accessed July 9, 2016].

Chandrapala, A. G., L. K. Chanaka, S. H. De Silva, and H. A. P. Jayalath. 2013. "Irrigation Efficiency and Water Quality of Maduruoya Irrigation Scheme". *Annals of the Sri Lankan Department of Agriculture* 15:25–36.

Cohn, A. S., L. K. VanWey, S. A. Spera, and J. F. Mustard. 2016. "Cropping Frequency and Area Response to Climate Variability Can Exceed Yield Response". *Nature Climate Change* 6:601–604.

de Jong, I. H. 1989. "Fair and Unfair: A Study into the Bethma System in Two Sri Lankan Village Irrigation Systems". Working Paper H005908, International Water Management Institute, Colombo, Sri Lanka.

De Silva, C., E. Weatherhead, J. Knox, and J. Rodriguez-Diaz. 2007. "Predicting the Impacts of Climate Change—A Case Study of Paddy Irrigation Water Requirements in Sri Lanka". *Agricultural Water Management* 93:19–29.

Department of Census and Statistics 2014. "Sri Lanka Labour Force Statistics". Working Paper 64, Sri Lanka Ministry of Finance and Planning, Colombo, Sri Lanka.

Elakanda, S. 2010. "Resource-Based Development: Experience from Mahaweli". Technical report, Center For River Basin Organizations and Management, Central Java, Indonesia.

Fischhoff, B. 2006. "Behaviorally Realistic Risk Management". In *On Risk and Disaster: Lessons from Hurricane Katrina*, edited by R. J. Daniels, D. F. Kettl, and H. Kunreuther, 77–88. Philadelphia: University of Pennsylvania Press.

Gamawelagedara, W. C., Y. M. Wickramasinghe, and C. A. K. Dissanayake. 2011. "Impact of Rice Processing Villages on House Hold Income of Rural Farmers in Anuradhapura District". *Journal of Agricultural Sciences* 6:92–99.

Gelman, A., A. Jakulin, M. G. Pittau, and Y.-S. Su. 2008. "A Weakly Informative Default Prior Distribution for Logistic and Other Regression Models". *Annals of Applied Statistics* 2:1360–1383.

Grimm, V., U. Berger, D. L. DeAngelis, J. G. Polhill, J. Giske, and S. F. Railsback. 2010. "The ODD Protocol: A Review and First Update". *Ecological Modeling* 221:2760–2768.

Gunda, T., G. M. Hornberger, and J. M. Gilligan. 2016. "Spatiotemporal Patterns of Agricultural Drought in Sri Lanka: 1881–2010". *International Journal of Climatology* 36:563–575.

Hansen, J. W., S. M. Marx, and E. U. Weber. 2004. "The Role of Climate Perceptions, Expectations, and Forecasts in Farmer Decision Making: The Argentine Pampas and South Florida". IRI Technical Report 04-01, International Research Institute for Climate Prediction, New York.

Imbulana, K., N. Wijesekera, and B. Neupane. (Eds.) 2006. *Sri Lanka National Water Development Report*. Colombo, Sri Lanka: UNESCO.

Jacobi, J. H. 2014. *A Changing Climate in Sri Lanka: Shifts, Perceptions, and Potential Adaptive Actions*. Ph. D. thesis, Vanderbilt University, Nashville, Tennessee.

Janssen, M. A., and J. A. Baggio. 2016. "Using Agent-Based Models to Compare Behavioral Theories on Experimental Data: Application for Irrigation Games". *Journal of Environmental Psychology*. Advance online publication: https://dx.doi.org/10.1016/j.jenvp.2016.04.018 [accessed July 9, 2016].

Jayawardene, H., D. Sonnadara, and D. Jayewardene. 2005. "Trends of Rainfall in Sri Lanka Over the Last Century". *Sri Lankan Journal of Physics* 6:7–17.

Jinapala, K., S. De Silva, and M. Aheeyar. 2010. "Policies, Institutions and Data Needs for Water Management". In *National Conference on Water, Food, Security and Climate Change in Sri Lanka*, 1. Colombo, Sri Lanka: International Water Management Institute.

Kikuchi, M., R. Barker, P. Weligamage, and M. Samad. 2002. "Irrigation Sector in Sri Lanka: Recent Investment Trends and the Development Path Ahead". Research Report 62, International Water Management Institute, Colombo, Sri Lanka.

Kolstad, C. D. 2011. *Environmental Economics*. 2nd ed. New York: Oxford University Press.

Loomes, G., and R. Sugden. 1982. "Regret Theory: An Alternative Theory of Rational Choice Under Uncertainty". *The Economic Journal* 92:805–824.

Malmgren, B. A., R. Hulugalla, Y. Hayashi, and T. Mikami. 2003. "Precipitation Trends in Sri Lanka since the 1870s and Relationships to El Niño-Southern Oscillation". *International Journal of Climatology* 23:1235–1252.

Nordhaus, W. D. 2008. *A Question of Balance: Weighing the Options on Global Warming Policies*. New Haven: Yale University Press.

Podestá, G., E. U. Weber, C. Laciana, F. Bert, and D. Letson. 2008. "Agricultural Decision Making in the Argentine Pampas: Modeling the Interaction between Uncertain and Complex Environments and Heterogeneous and Complex Decision Makers". In *Decision Modeling and Behavior in Complex and Uncertain Environments*, edited by T. Kugler, J. C. Smith, T. Connolly, and Y.-J. Son, 57–76. New York: Springer.

Pratt, J. W. 1964. "Risk Aversion in the Small and in the Large". *Econometrica* 32:122–136.

Railsback, S. F., and Grimm. 2012. *Agent-Based and Individual-Based Modeling*, Princeton, new jersey 23, 291–308. Princeton University Press.

Samad, M. 2005. "Water Institutional Reforms in Sri Lanka". *Water Policy* 7 (1): 125–140.

Senaratne, A., and H. Scarborough. 2011. "Coping with Climatic Variability by Rain-Fed Farmers in Dry Zone, Sri Lanka: Towards Understanding Adaptation to Climate Change". In *Australian Agricultural & Resource Economics Society 55th Annual Conference Handbook*, 1. Melbourne, Victoria: Australian Agricultural & Resource Economics Society.

Shah, T., A. Roy, A. Qureshi, and J. Wang. 2003. "Sustaining Asia's Groundwater Boom: An Overview of Issues and Evidence". *Natural Resources Forum* 27:130–141.

Shah, T., M. Samad, R. Ariyaratne, and K. Jinapala. 2013. "Ancient Small-Tank Irrigation in Sri Lanka". *Economic and Political Weekly* 11:58–73.

Sivakumar, M., H. Das, and O. Brunini. 2005. "Impact of Present and Future Climate Variability and Change on Agriculture and Forestry in the Arid and Semi-Arid Tropics". *Climatic Change* 70:31–72.

Thiruchelvam, S. 2010. "Agricultural Production Efficiency of Bethma Cultivation in Mahaweli System H". *Sri Lankan Journal of Agricultural Economics* 7:1–20.

Tversky, A., and D. Kahneman. 1992. "Advances in Prospect Theory: Cumulative Representation of Uncertainty". *Journal of Risk and Uncertainty* 5:297–323.

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