The Impact of Risk-Sharing Mechanisms on Smallholder Farmer Climate Adaptation Strategies

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1 Introduction

The impact of climate change on the movement of people has generated considerable attention among policymakers and academic audiences in the past three decades, since the initial 1985 United Nations report that coined the term "environmental migrants" [1]. This is especially a concern in developing countries, whose economies are still heavily dependent on small-scale agriculture and are therefore particularly vulnerable to climatic impacts on livelihoods. Previous work has theorized that smallholder farmers intentionally use migration as a strategy to cope with livelihood risks, which can come from changes in economic, political, demographic, and environmental conditions, among others [2, 3, 4]. With respect to climate risks, rural-urban migration offers farming households a mechanism to diversify their geographic exposure to climate impacts e.g. droughts, floods, and extreme events, as well as risks that are specific to agricultural livelihoods [5, 6, 7].

Migration represents one of several adaptation strategies that farmers could deploy in the face of climate change [8], and there is an open debate in the literature on the extent to which climate may positively or negatively impact migration flows. While several studies from the environmental geography and politics disciplines warn of climate impacts that could displace over 100 million people worldwide [9, 10, 11], scholarship from more traditional migration disciplines tends to emphasize that the most vulnerable members of society may not have the resources to afford migration, and may thus be "trapped" in place by increasing climate stress [12, 13, 7]. Furthermore, uncertainty regarding future policies to build capacity to adapt to climate change at multiple governance scales [14], including new financial instruments that could help poor households better cope with natural disasters [15, 16], further cloud projections about the extent to which climate change will impact the use of migration as a risk management strategy. This study therefore seeks to better understand how rural-urban migration relates to other on-farm adaptation strategies and risk-sharing mechanisms as smallholder farming households, which number approximately 500 million worldwide [17], cope with increasing climate stress.

Recently, several empirical studies have demonstrated a significant relationship between increased temperatures, diminished crop yields, and increased human migration [18, 19, 20, 21]. This effect may be magnified as climate change further increases risks to small-scale agricultural livelihoods through changing temperature and precipitation patterns [22, 23], and through the increasing frequency of extreme events [24, 25]. However, the nature of this relationship is still poorly understood. While previous econometric studies have built our understanding of the conditions under which climatic factors already significantly influence migration, they are typically limited in accounting for changes in populations' demographic structures and adaptive capacities in projecting realistic responses to future climate change [26]. Specifically, they are not well-equipped to understand how migration responses may change as a result of dynamic interactions between changing climatic and societal variables. For example, under what conditions (and for which groups of people) may increased climate risks induce additional migration, and what conditions might deteriorating climatic conditions contribute to "trapping" individuals in place [13]? How does changing access to social capital and the structure of social networks condition individuals' responses to climate change? How does migration complement or substitute for the adoption of other potential adaptation strategies, e.g. diversifying crops, investing in irrigation and soil management techniques, or other forms of livelihood diversification?

One useful set of tools for investigating these questions are agent-based models (ABMs). ABMs simulate how individual decision-makers (generally at the person or household level) make choices based on pre-defined decision-making rules, interactions between agents, and interactions between agents and their environment. ABMs can contribute several insights that are difficult to obtain through econometric studies alone, including non-linear feedbacks between push-pull factors and the migration decisions of agents, the influence of complex social interactions on the decision, and the ability to test model results under different theories of decision-making against observed emergent patterns [27]. However, a common limitation of ABMs is that it becomes more difficult to identify drivers of behavior as increasing levels of complexity are incorporated in the model. Additionally, migration ABMs often suffer from inconsistent decision-making rules regarding the migration decision: these are often modelled using statistical relationships on "push" and "pull" factors of migration, rather than as part of a generalizable model of decision-making that can also incorporate other livelihood options [20]. Thus, it is often difficult to evaluate potential migration outcomes in the context of other livelihood strategies.

Recent climate-migration ABMs provide a useful set of examples for abstracting highly complex decision-making environments into more stylized models (e.g. [28, 29, 30, 31, 32, 33] among others - see Appendix for more details on these). However, there are opportunities to develop more consistent climate - crop yield decision-making relationships in order to better utilize these types of models for policy analysis. First, the structures of social networks themselves have not been seriously examined, and most ABMs assume that network connections are uniformly distributed, or that everyone is connected to everyone else. By contrast, the social network literature indicates that most societies can be characterized by scale-free networks, in which a few agents have many connections, and most agents have few connections [34]. Second, some models incorporate arbitrary rules to guide how when agents choose to migrate (e.g. doubling the probability of migration after a drought has passed an arbitrary time period), rather than embedding livelihood decisions in a consistent framework. Third, almost all ABMs impose an arbitrary set of climate "shocks" (e.g. forcing their models through droughts in predetermined years) rather than relating the probability of extreme events to broader climate scenarios of temperature and precipitation change. Finally, with the exception of Bell et al., ABMs have not explored the possible effects of risk-sharing strategies between agents, either through informal networks or formal government policies. Yet, empirical literature suggests that households intentionally deploy migration as a risk diversifying strategy, using remittances as a way to smooth incomes in the face of livelihood shocks [35, 36, 37]. These questions - the effects of different network structures, consistent decision-making to evaluate tradeoffs/synergies between multiple adaptation strategies, climate shocks that are embedded in long-term climate scenarios, and the impact of formal and informal risk-sharing structures - are fruitful areas that can be productively addressed through ABMs.

Based on gaps identified in the literature, this study seeks to address the following research questions:

- What adaptation outcomes (including, but not limited to, migration) are likely under different climate scenarios?
- How does social network structure impact individual decision-making and community adaptation outcomes?
- What risk-sharing mechanisms (both formal and informal) can help push the community towards a social optimum?

To address these questions, this study builds a generalizable ABM of climate adaptation among smallholder farming communities. The ABM includes multiple climate adaptation strategies, including both on-farm adaptation and rural-urban migration, and seeks to model a more realistic social network structure than previous ABMs in this field. Farming households, which serve as the main decision-making agents, form perceptions about the expected income and risk of each strategy based on a consistent decision-making framework. We then model the impact of increasing climate stress on these decisions, including both long-term changes in crop yields due to rising temperatures, and changing probabilities of extreme droughts. As a policy experiment, we model two different types of risk-sharing mechanisms and their impacts on community outcomes, including wealth, inequality, migration, and income volatility. Additionally, this study contributes to the climate-migration ABM literature by developing a modular structure for incorporating different sources of social and environmental complexity (e.g. bounded rationality, demographic events, and different climate effects). This permits us to better distinguish the implications of each set of assumptions on state variables of interest (e.g. the distribution of household wealth and the proportion of migrants from a community).

2 Model Description

This section describes the structure of the ABM constructed to explore these questions for a stylized smallholder farmer community. The model consists of N = 100 agents, each representing a farming household in the community (household size = 5 people). A full run of the model consists of a 30-year timescale, roughly representing potential climate adaptation scenarios from 2020-2050. In each time step (representing one cropping cycle), agents choose between different climate livelihood strategies, which can be a mix of on-farm management strategies and/or engaging in rural-urban migration. We use the model to track the effects of each of these mechanisms separately on community outcomes of interest, including: the final distribution of household strategy choices, the average community income, GINI coefficient, and the proportion of the community that migrates.

In line with modular and pattern-oriented approaches to ABMs [38, 39], this model is arranged into four modules, or "layers", that progressively introduce more sources of complexity. This structure allows us to test the effect of multiple sets of correlated assumptions on our model results. In the first layer of our model, agents represent economically rational households who seek to maximize the expected utility from these strategies, subject to constraints imposed by their limited resources. The mean value of incomes derived from each strategy remains constant over time, though the actual payoffs derived from these strategies vary across households. The second layer incorporates bounded rationality properties, in which agents are assigned different risk thresholds and rely on their social networks for information. The third layer incorporates demographic parameters, in which agents are assigned different educational levels that correlate with wealth, risk aversion, and accuracy of information. The fourth layer explores how a long-term change in temperature and its impact on the frequency of droughts impact agent decision-making. Finally, we test the impact of multiple risk management mechanisms on the full model. These layers are described in more detail below, and the implications of assumptions in each of these layers is explored in the Results section.

2.1 Layer 1: Economically Rational Optimization

In the first layer of the model, each household i is assumed to have perfect information about the future income distributions for each strategy k, approximating a situation in which government climate forecasts are accurate and widely disseminated (subsequent layers introduce sources of bounded rationality). Households select the strategy that maximizes their expected utility $\mathbb{E}[U(S_i(t), \pi_{ik}(t), \theta_i)]$ over a given time horizon h_i, subject to the constraint that the costs of strategies do not exceed their household savings $S_i(t)$. The payoff for household i for employing strategy k can be expressed as $\pi_{ik}(t) = I_{ik}(t) + R_i(t) - C_{ik}(t)$, where $I_{ik}(t)$ represents the income corresponding to strategy k, $C_{ik}(t)$ represents the cost of strategy k, and $R_i(t)$ represents the remittances received by migrants. The optimization problem can therefore be written as

$$\begin{aligned} &\underset{k}{\operatorname{argmax}}\, \mathbb{E}\left[\sum_{t=t_0}^{t=t_0+h_i} \frac{U[S_i(t), \pi_{ik}(t), \theta_i]}{(1+\rho_i)^{(t-t_0)}}\right] \\ &s.t.\ C_{ik}(t_0) \leq S_i(t_0) \end{aligned} \tag{1}$$

where ρ_i represents household i's discount rate in evaluating strategy costs and payoffs that have different perceived values over multiple years. The time horizon h is set to the same parameter value for all agents in the model.

The set of strategies k available to farming households is $k \in$ [BAU; Diversification; Migration], each with its own expected payoff, risk, and cost. BAU represents "Business as Usual" farming, in which a smallholder farmer plants cereal crops (e.g. rice, maize, and wheat) largely for subsistence, with limited expected potential for income generation I_{BAU}, but also low costs C_{BAU}. Alternatively, farmers could diversify to other crops (e.g. fruits, vegetables, lentils) that may generate more commercial income I_d, but are also likely to come with higher initial costs, C_d, and a higher variance of payoffs among agents.

Finally, households can send a migrant to an urban location; this has an initial up-front cost (C_m), but the household can subsequently benefit from remittances R. In any given year, incomes derived from strategy k, $I_k(t)$, vary across the set of agents according to a Weibull distribution, in which a few agents earn relatively high incomes, while the majority of agents receive less than the mean income. Finally, we incorporate two economic feedbacks in the Base Case Layer. First, we assume that when a household sends a migrant to the city, the remaining members continue farming using either the BAU or Diversification strategy, based on their preferred farming strategy (subject to the same constraint that costs cannot exceed savings). However, migration reduces the amount of labor available for the household's farming activities, and farm productivity therefore declines. Similarly, we assume that payoffs from migration tend to exhibit decreasing marginal returns as a function of the number of migrants from the same household (see Appendix for more details on the specification of strategy payoff distribution and the feedback effects). The Appendix (Section 6.2) contains more information about the specific utility and Weibull functions used for this layer, as well as the Base Case parameter values used to initialize the model.

2.2 Layer 2: Bounded Rationality

The behavioral psychology literature has established several mechanisms through which decision-makers may deviate from rational *homo economicus* behavior assumed in Layer 1, including: risk aversion (individuals are willing to pay a non-zero sum to avoid a gamble), loss aversion (individuals have a steeper utility curve for expected losses than expected gains), and bounded rationality (individuals may not access or use all information available for a decision). Often, the implication of these biases is that decision-makers often stick with their *status quo* behavior, even if changing behaviors may increase their expected utility, but perhaps come with higher short-term risk. Another implication is that decision-makers may be highly influenced by their social networks, both as a means of collecting information, and for establishing a "reference point" for decisions. Thus, the shape and speed of information flow within a social network may significantly affect agents' decision-making.

Layer 2 (Bounded Rationality) seeks to account for this behavior by relaxing some of the assumptions made in Layer 1. In this layer, agents continue to optimize their utility across the strategy set K, and incomes $I_{ik}(t)$ are distributed across the population as in Layer 1. However, agents no longer have perfect information about the future distributions of $I_{ik}(t)$; rather, they must rely on a combination of their own bounded memories, their limited social networks, and partial access to public sources to collect information about strategy incomes. Furthermore, agents are no longer risk-neutral; instead, they have different risk aversion factors, θ_i, that determine their propensity to try new strategies with higher variance. We also introduce a *status quo* bias, λ_i, that controls how likely agents are to consciously re-evaluate their strategy choices, rather than sticking with their current option. To simulate information flow across limited social networks, each agent is assigned a set of network connections that define the peers with which it compares payoffs and gathers information about alternative strategies. The number of connections for each household, j_i, follows a power law distribution such that a few households have a high number of connections and serve as key hubs of community information, while most agents have only a few connections (see Appendix for specification).

Agents' social connections alter their decision-making process in three ways. First, in each time step agents now must pass a "status quo" threshold before deliberately evaluating whether to change strategies. This test consists of comparing agents' current wealth a reference point that accounts for the wealth of their social connections, as well as their own wealth in recent years. Households that perceive they are below this reference point are more likely to be motivated to change their strategy, consistent with empirical research that points to the perception of "relative deprivation" compared to one's neighbors as a key migration push factor [40]. If the status quo threshold is passed, a second way in which social connections influence an agent's behavior is by altering its perception of different strategies' income. Because agents now have imperfect information about the distribution of $I_k(t)$, they no longer accurately perceive the expected income for each strategy ($\mu_k(t)$).

Rather, we assume that they balance the information received from their social networks and their own memories with some information from public sources (e.g. government or media sources). Finally, a third way in which social connections influence agent decision-making is by reducing migration costs. Empirical studies in several migration contexts have established that potential migrants are significantly more likely to migrate with increasing connections to current or returned migrants [41, 42]. Section 6.2 in the Appendix contains more details on how each of these three feedbacks are operationalized in Layer 2.

Finally, the decision-making function utilized for this layer (and subsequent layers in the model) assumes that all households maximize their utility by maximizing their expected income from livelihood strategy options, subject to financial constraints, imperfect information, and varying wealth levels and risk aversion. An alternative interpretation of smallholder farmer decision-making is that households not only seek to maximize income, but also seek to ensure some degree of income stability [36, 37]. We present an alternative utility specification in Appendix (Section 5.2) that explicitly accounts for income volatility in farmers' decision-making, along with a description of key results (Section 5.3). While this alternative specification does not substantially change our results using Base Case parameters, it is sensitive to situations in which decision-makers highly weight income volatility, and highlights the need for further research on smallholder farmers' decision-making objectives.

2.3 Layer 3: Demographic Effects

In previous layers, agents were assumed to share similar demographic characteristics, and important parameters e.g. starting wealth, status quo thresholds, and weighting of public information sources were randomly distributed. However, demographic variables, especially educational attainment, have significant correlations with the ability to process information and adapt to climate risks [43], and assumptions regarding these variables significantly impact projections regarding the future composition of societies [44]. While this model does not seek to account for all sources of demographic heterogeneity, Layer 3 accounts for variation in one of these variables - education - and its correlation with several parameters of interest to the model.

The effect of education is operationalized in the Demographic Effects Layer by assigning each household an educational attainment level, $E_i \in$ [Primary (representing no education - completed primary), Secondary (representing some secondary - completed secondary); and Tertiary (representing any post-secondary education)], consistent with categorizations that are typically used in population projections [44]. For simplicity, these educational levels remain constant over the course of the simulation run. While attainment may differ between male and female heads of household, and between parents and their children, it is assumed in this model that the highest education level of any household member is the most relevant for shaping future livelihood decisions.

In this layer, the education parameter E_i is correlated with multiple parameters that were previously uncorrelated, including:

- Initial savings, $S_i(0)$ (positive correlation). More educated households are assumed to start with greater wealth, on average, than less educated households.
- Risk aversion factor, θ_i (negative correlation). Household with higher education levels are assumed to be more open to new information and strategies, and thus have lower risk aversion.
- Weight given to public information on strategy payoffs, ω_i (positive correlation). Households with higher education are assumed to have more access to public sources of information on opportunities to diversify crops and migrate, and will trust these sources more than households with lower education.

Table 3 in the Appendix displays the specific values used to paramaterize the effects of education on these variables.

2.4 Layer 4: Climate Impacts

In the previous layers, the stylized agricultural community could expect a stationary distribution of incomes from each strategy k. In this layer, we relax the assumption of income stability over time to better reflect the potential impact of increasing climate risk on farming-based livelihoods [45, 22]. We do this by introducing two related climate phenomena: the effect of long-term change in mean temperature on crop yields, and the impacts of increasing frequency of extreme events (e.g. droughts) on farmer incomes.

The first climate phenomenon assumes that the annual mean temperature of the agricultural community increases linearly between 2020 (T_{2020}) and 2050 (T_{2050}). While the rate of change in global mean temperature is projected to be non-linear over long time horizons, a linear rate of change is a fairly accurate approximation over shorter timeframes [46]. The impact of such temperature shifts differ based on geography; for some growing regions at higher latitudes and elevations, small increases in temperature may lead to increases in crop yields by extending the growing season, while in warmer climates, temperature increases are already correlated with yield reductions. For the stylized community in this model, we assume an average decrease in yield of 10 percent for every 1^o C of warming, consistent with global average impact of temperature increases on cereal crop yields [23]. This effect is operationalized by adjusting the mean annual income of the BAU and Diversification strategies as a function of temperature, as specified in the Appendix.

In addition to a gradual decrease in the viability of farming strategies, increasing climate change may also threaten agricultural livelihoods through an increase in the frequency of catastrophic natural disasters, e.g. droughts [47]. Thus, smallholder farmers may make adaptation decisions not only in response to long-term trends, but also to cope with more frequent shocks to their livelihoods. To account for this possibility, a second climate phenomenon represents the possibility of increasingly frequent natural disasters that may more drastically affect income from farming-based strategies. This effect is modelled using a peaks-over-threshold approach under a non-stationary distribution. First, we employ the Standardized Precipitation and Evapotranspiration Index (SPEI) to establish a distribution and threshold for extreme droughts. The SPEI is a normalized index based on historical data (ranging from 1901 to present day) in which 0 represents the mean hydrological balance for any region in a given month, and increases/decreases of 1 unit represents one standard deviation in the historical distribution of the monthly hydrological balance [48]. Thus, an SPEI value of -2 represents a water deficit that is two standard deviations below the mean value for a given month, in a given region, for a given timescale. We assign this value as the threshold for an "extreme drought" for BAU crops (e.g. maize, wheat, and rice) that would likely wipe out most or all of a crop in a particular growing season (representing a 1-in-40 year drought under current conditions). We assume that cash crops likely to be sown in the Diversification strategy are more water-dependent and thus more sensitive to drought risks in rainfed agricultural areas; we use an SPEI value of -1.5 to delineate an extreme drought for this strategy (roughly equivalent to a 1-in-15 year drought).

In each timestep of the model, we assign the community an SPEI number by randomly sampling from the SPEI distribution. We account for the effects of changing mean annual temperature on the distribution of SPEI (non-stationarity) by regressing the lowest SPEI 3-month index in each year on mean annual temperature. Thus, the probability of drought increases over time with increasing temperature, but does so differently for the BAU and Diversification strategies, given their different thresholds. More information on regressions used to relate temperature and SPEI are available in the Appendix.

2.5 Risk Management Mechanisms

As a policy experiment, the full model (with all four layers) is used to explore the the effects of two risk-sharing mechanisms: an informal sharing of remittances between neighboring households, and a formalized index-based insurance program for farmers. Additionally, we explore potential complementarities between these mechanisms through a policy scenario in which both are implemented simultaneously. Each of the risk-sharing mechanisms is explained in further detail below.

2.5.1 Migration Remittances

The first mechanism, sharing of migration remittances, can be conceptualized as a reciprocal risk-sharing norm in which a household's social network facilitates the migration journey through informal means, e.g. providing farm labor support while the migrant is away. In return, the household that sends the migrant is expected to share a portion of its remittances, $\beta * R_i(t)$ with other households in its social network. There is some empirical evidence that remittances are indeed deliberately used as a risk-sharing mechanism, both within households [36, 37] and potentially across multiple households in a community [49, 35].

In this experiment, it is assumed that each household receives an equal fraction of this shared remittance pot $R_{j,i}(t)$, that is:

$$R_{j,i}(t) = \frac{\beta * R_i(t)}{j_i} \tag{2}$$

On the one hand, remittance sharing provides households with an opportunity to diversify income sources from across their network, even if they cannot afford or do not choose to migrate themselves. On the other hand, households who send a migrant now adjust their own expected returns from migration as $(1-\beta) * R_i(t)$ in their objective functions, which somewhat decreases the motivation to send a migrant in the first place. For simplicity, we assume that all households in the community agree to share the same proportion of remittances, β, though we conduct a sensitivity analysis to determine how different levels of β affect the community outcomes of interest.

2.5.2 Index-Based Insurance

The other risk-sharing mechanism explored in this experiment is that of formal index-based insurance for the BAU and Diversification strategies. Under such schemes, an insurer (either a private or parastatal insurance company) provides a payout to insured farmers if certain objective indicators, e.g. number of days above a certain temperature or amount of precipitation in a set time period, pass a pre-defined threshold. This type of insurance has the advantages of reducing the administrative burdens and costs associated with assessing losses under indemnity-based schemes. Additionally, there is some evidence that this reduces "moral hazard" - since insured farmers receive payouts regardless of their actual losses, they still have an incentive to take *ex ante* disaster risk reduction measures [15, 50].

This mechanism is operationalized in the model by introducing a hypothetical insurance company that sells index-based insurance coverage for farming strategy k at an annual premium p_k. For simplicity, the premium is assumed to reflect the actuarially fair value of insurance (i.e. equivalent to expected losses in any given year), though in practice, premiums may be significantly higher than this value. For years in which farmers choosing strategy k experience a disaster, the company commits to disbursing a payout Y_k equivalent to $\mu_k(t)$, the expected income for strategy k in that year. This assumes that the insurance company has accurate information about the long-run expectation of incomes for each farming strategy in the face of increasing climate risk. Note also that the company offers premiums and payouts that are differentiated by strategy k, which may be a strong assumption in regions of the world with less robust climate and crop yield data.

Each year, household i pursuing strategy k decides to purchase the coverage if the following conditions are satisfied:

$$\begin{aligned} p_k &< E_i[P_{k,d}] * Y_k \\ p_k + \sum_k C_{ik}(t) &< S_i(t) \end{aligned} \tag{3}$$

That is, household i will only purchase insurance if the premium offered by the insurer is less than its expected annual losses from a disaster (as perceived by the household). Additionally, the premium (in addition to the costs associated with household i's strategies) must not exceed the household's savings. The key variable in this equation is $E_i[P_{kd,}]$, i.e. the household's perception of the disaster probability for strategy k. To be consistent with the bounded rationality assumptions in Layer 2, it is assumed that households here also have imperfect information about the probability of disasters for any given strategy, and weigh public and social information sources in forming their expectations. Further details on how this is calculated are located in the Appendix.

3 Results

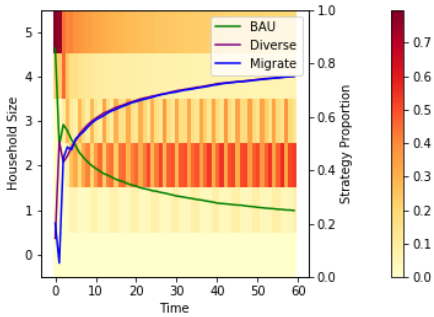
This section presents selected results from our model that develop insights into the most important factors driving household climate adaptation strategies. In the first section, we present results from each of the model's first four layers, illustrating how key variables change as we gradually introduce more complexity. Some of the main outcome variables we track include: the number of households selecting each strategy over time; the average community income, inequality (measured by the GINI coefficient), and overall migrant proportion over time; the breakdown of these variables by households' educational status (for Layers 3 and 4); and households' perceptions of strategy payoffs. Unless otherwise stated, these results represent the average outcomes of 100 model runs for each layer. We run the model for 60 timesteps, where each timestep represents one cropping cycle. As we assume that there are two cropping cycles per year, the model is loosely calibrated on projected climate impacts from 2020-2050.

The second section presents results from one representative model run for Layer 4, in order to more clearly illustrate how shocks (in the form of extreme droughts) impact households' livelihood strategy choices. Section three then presents a few key sensitivities of model results to assumptions made in the bounded rationality and climate layers. In the fourth section, we present results on how the formal and informal risk management mechanisms impact households' strategy choices. Finally, we demonstrate how key results may change in the alternate model specification, where households are assumed to more explicitly evaluate the riskiness of each livelihood strategy in their decision-making.

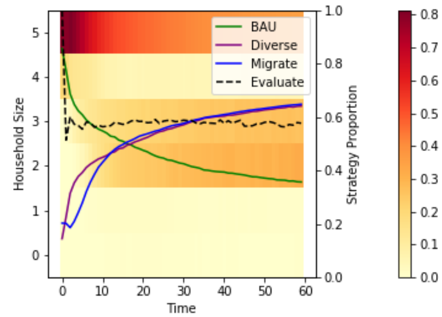
3.1 Base Case Results: Climate Impacts Contribute to Trapped Populations

Fig. 1 displays the distribution of household strategy choices across time for each of the four layers. In Layers 1 and 2, approximately 70-80 percent of households engage in both migration and diversification, and the adoption rates of these strategies are tightly coupled (with a slight gap in Layer 2, where the effect of migrant networks appears to facilitate slightly higher levels of migration). By contrast, only 60 percent of households adopt these strategies by the end of the model run in Layer 3, and even fewer households adopt these strategies in Layer 4 (approximately 40-50 percent). The difference in these results suggest two interrelated phenomena that are driving model behavior: stratifying the population by education creates a layer of agents that generally have few resources and low motivation to change strategies, and the impact of these population characteristics is amplified by the presence of climate shocks. Indeed, significant differences can be observed between strategy choices of households with secondary and tertiary education status on the one hand, and households with primary education on the other hand (Fig. 2). This is particular the case for households with primary education status in Layer 4 - the increasing presence of shocks further reduces their adoption of alternative strategies. Again, the high risk aversion of a majority of agents in this layer, combined with their relative lack of resources to afford alternate options (particularly when shocks are introduced), keeps many households trapped in BAU farming.

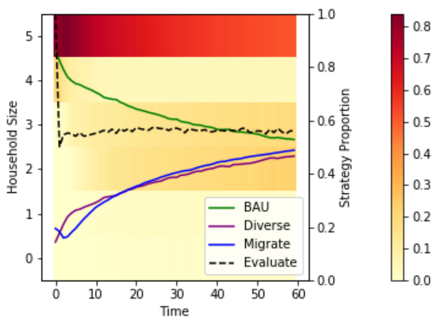
Fig. 3 displays the evolution of three community-level variables - the average community income, proportion of migrants, and inequality - over time, across the four model layers. Here again, important differences can be observed. Average community income increases steadily in Layers 1 and 2, to approximately 600 USD/household/cropping cycle by the end of the model run. Similarly, the proportion of total community members who migrate gradually rises to approximately 40 percent, with cyclical migration and incomes observed in Layer 1. In both cases, the GINI coefficient falls steadily from a peak above 0.4, when the first wave of migration begins, to approximately 0.2 as more households have an opportunity to engage in migration and crop diversification. In Layer 3, there is a significant decrease in community income to approximately 400 USD/household/cropping cycle, while the proportion of community migrants drops significantly below 30 percent. It is also interesting to note that secondary-educated households form the bulk of the initial wave of migrants in the first 10 timesteps, despite comprising only 30 percent of the population. Migration flows in subsequent timesteps reflect an increasing proportion of lower-educated households. This is consistent with observed migration patterns in which middle-income households, and not lower-income households, are often the initiators of rural out-migration waves [40]. Layer 4 displays a much lower average community income - approximately 200 USD/household/cropping cycle - that remains relatively constant after the first 10 timesteps (or 5 years). While inequality does fall from its initial peak, it remains at a relatively high value, around 0.4. Community migration is also substantially reduced to approximately 23 percent of the population, with primary-educated migrants making a



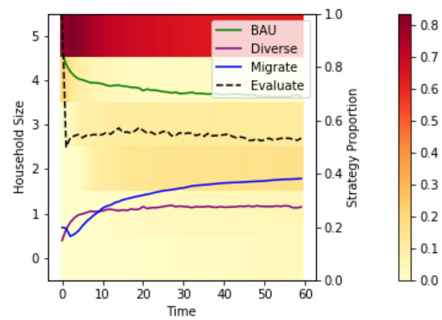
(a) Layer 1 (Economic Rationality)



(b) Layer 2 (Bounded Rationality)

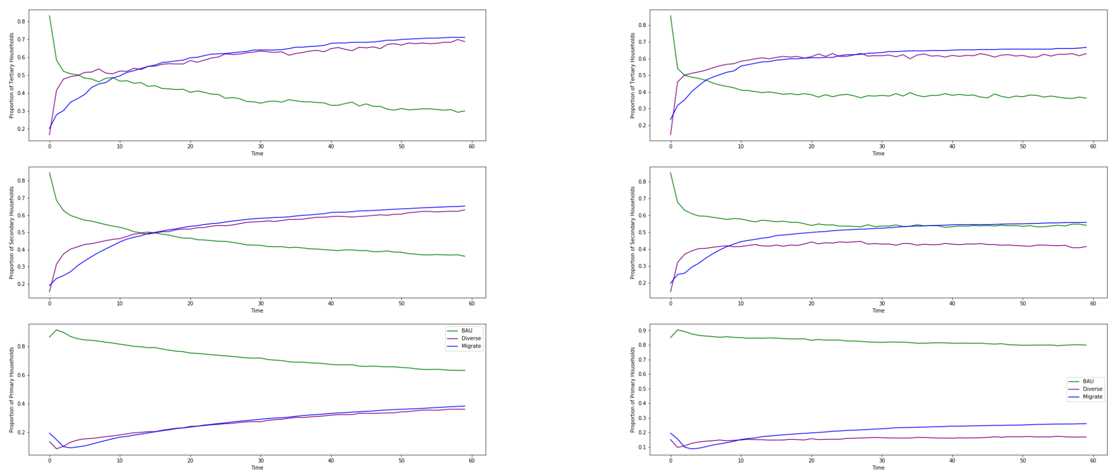


(c) Layer 3 (Demographic)



(d) Layer 4 (Climate Impacts)

Figure 1: Distribution of household strategy choices (solid lines) for: (a) Economic Rationality Layer, (b) Bounded Rationality Layer, (c) Demographic Layer, and (d) Climate Impacts Layer. Note that strategy proportions do not add up to 1 in all time periods, as some households may be engaging in both Migration and one of the two farming strategies. The dashed line in parts b-d indicate the proportion of households who consciously re-evaluate strategy choices in each timestep. The shades of rows in each plot indicate the distribution of agents by remaining village household size (ranging from 0 - no members left in the household, to 5 - all members remain in the village household).



(a) Layer 3 (b) Layer 4

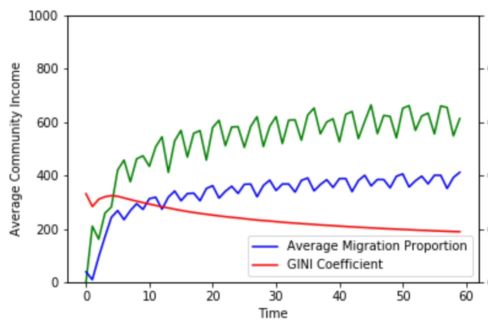
Figure 2: Household strategy choices over time, broken down by educational status. Top = Households with tertiary education, Middle = Households with secondary education; Bottom = Households with primary education. Green lines indicate the proportion of households in each category pursuing BAU farming; blue lines indicate the proportion of households pursuing Migration, and Purple lines represent the proportion of households pursuing Crop Diversification.

smaller contribution to the migration stream.

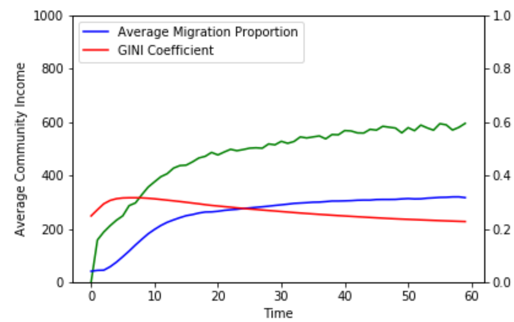
3.2 Immediate Effects of Droughts on Strategy Choices

Figure 4 presents a single model run of Layer 4 to illustrate the effect of droughts on household strategy choices and the flow of migrants for each cropping cycle. For approximately the first 20 timesteps (i.e. up until approximately 2030), households gradually transition from farming BAU crops to engaging in both migration and diverse crop farming (top layer). The number of out- vs. in-migrants fluctuates, but for most cycles up to timestep 20, the number of out-migrants exceeds the number of in-migrants, and there is a net out-migration flow from the community. The transition to Diverse farming is temporarily interrupted by the presence of consecutive Diverse crop droughts in timesteps 5 and 6, which induces some households to revert back to BAU farming. However, this does not interrupt the increasing number of households who engage in migration; in fact, it appears to increase the number of out-migrants in subsequent cycles (though some other cycles show even higher numbers of out-migrants).

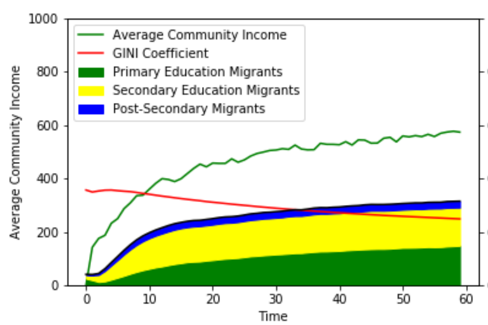
The transition to these alternative strategies peaks around timesteps 20-25 (years 2030-



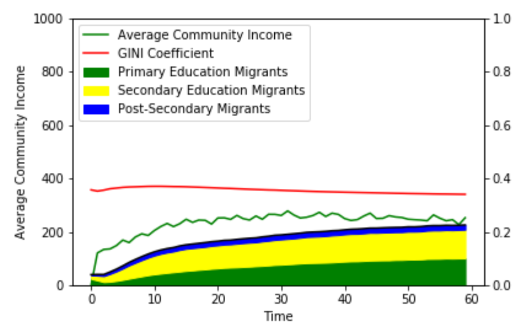
(a) Layer 1 (Economic Rationality)



(b) Layer 2 (Bounded Rationality)



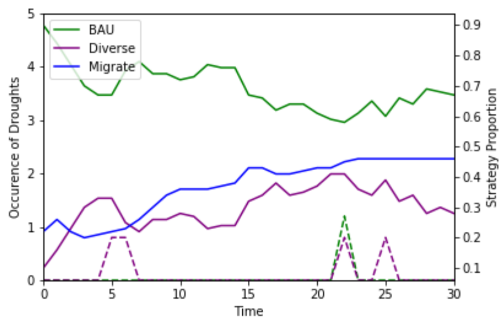
(c) Layer 3 (Demographic)



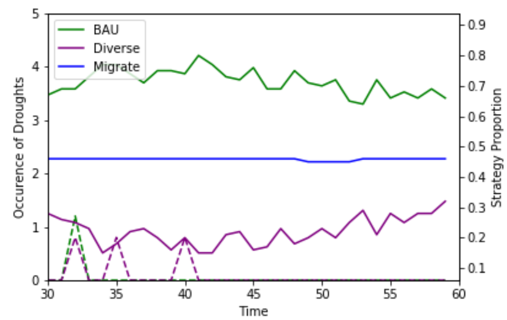
(d) Layer 4 (Climate Impacts)

Figure 3: The evolution of average community income (green line - plotted on left axis), GINI coefficient (red - right axis), and proportion of migrants (blue line - right axis) for: (a) Economic Rationality Layer, (b) Bounded Rationality Layer, (c) Demographic Layer, and (d) Climate Impacts Layer. For the Demographic and Climate Impacts Layers, the composition of migration is also broken down by household educational status.

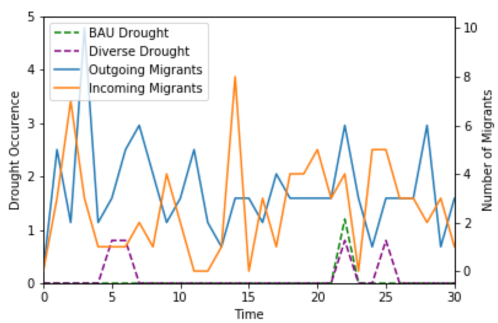
2033), with around 40 percent of households pursuing crop diversification and close to 50 percent pursuing migration. At this point, most households who are able to afford migration and/or diversification have already adopted these strategies. Furthermore, the presence of two diverse crop droughts at this time (along with one BAU crop drought) begins to erode households' farming incomes and increases the perception of diversification as a risky strategy. As such, some households begin to switch back to farming BAU crops, and the adoption of crop diversification drops to around 20 percent by timestep 40 (i.e. year 2040). The number of households engaging in migration remains relatively constant over this time period, although migration "churn" persists - there is an exchange of out- and in-migrants as households continue to re-assess their status quo, strategy payoff perceptions, and savings levels. The relationship between droughts and migration also appears less clear, as some droughts seem to have a negligible effect on migration patterns. This may reflect a situation in which households who have been able to afford migration now have sufficient risk diversification to withstand a shock, while those who have not been able to afford migration can no longer afford to respond (voluntarily) to shocks with this strategy. Finally, some households begin to switch back to crop diversification after several drought-less periods, but this only reaches approximately 30 percent of households by the end of the model run (i.e. year 2050).



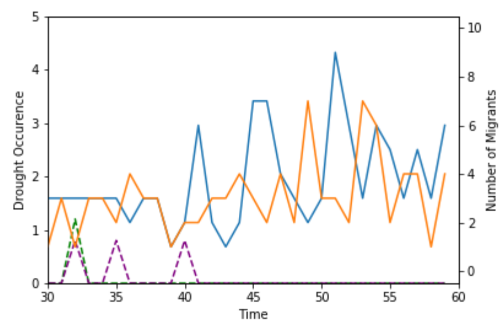
(a) Household Strategy Choices, 0-30 timesteps



(b) Household Strategy Choices, 31-60 timestpes)



(c) Migration Flows, 0-30 timesteps



(d) Migration Flows, 31-60 timesteps

Figure 4: Results from a single model run for Layer 4, illustrating household strategy choices (top) and migration flows into (blue line) and out of (orange line) the community (bottom). Peaks in dashed lines at the bottom of each plot indicate the occurrence of drought in that cropping cycle for Diverse (purple) and BAU (green) crops. For clarity, plots are separated into the first half (0-30 timsteps) and second half (31-60 timesteps) of the model run.

3.3 Sensitivities Regarding Public Information, Climate Scenarios, and Risk Sharing

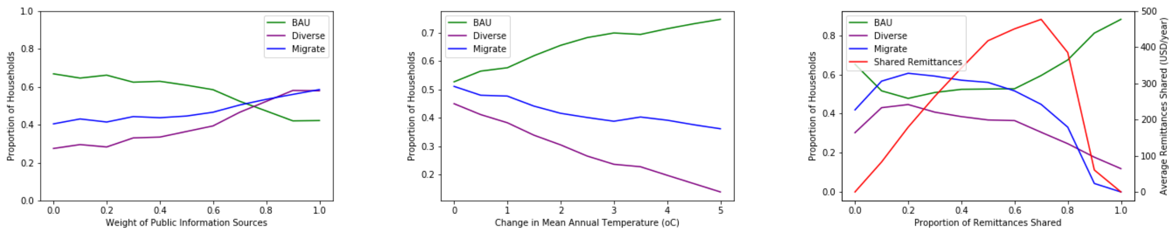
To test the sensitivity of model outputs to our assumed parameter values, we conducted a systematic sensitivity analysis on key parameters listed. All tests were conducted on the results from Layer 4, which represents the most "realistic" layer of the model that incorporates all key sources of complexity, while keeping all other parameters at their Base Case values. Results from the most policy-relevant sensitivity tests are displayed in Fig. 5 below, and the others are shown in the Appendix.

The influence of weighing public information sources, which are assumed to reflect accurate information on strategy payoffs, has a substantial and non-linear effect on model results (Fig. 5, left). At low values of ω, very few households choose the Diversification or Migration strategies, indicating that they likely perceive a lower-than-actual expected utility from their peers regarding these options. Higher values of ω increase the adoption of alternate livelihood options, which has a positive effect on community income and migration, and decreases inequality. Interestingly, there is a sharp non-linearity at around $\omega = 0.6$; values below this threshold do not substantially alter the adoption of migration or overall community migration/inequality, but values above this threshold significantly increase the adoption of diversification and migration strategies. This is likely because diversified cash crops face an increasing frequency of droughts in Layer 4, compared to BAU crops. Over the long-term, the expected income from this strategy is still higher than BAU farming, but households that rely heavily on their social networks for information will strongly weigh the observations in which farmers lost their crops due to extreme drought.

The next sensitivity concerns the effect of increases in mean temperature on model outcomes. In the Base Case, we assume an increase of 1^{o}C in mean annual temperature from 2020-2050; however, temperature increases could be even higher than this for specific regions under various IPCC scenarios [46]. A higher temperature increase affects model relationships in two ways: it contributes to a steeper long-term decline in crop yields, and also increases the frequency of extreme droughts for both BAU and Diverse crops. This leads to a clear negative impact on the adoption of crop diversification and migration. This effect is especially pronounced for values of $1 \leq \Delta_T \leq 3$, which is within the range of expected mean annual temperature changes for South Asia. This range of Δ_T appears to be associated with a steeper drop in the adoption of alternative strategies, perhaps because it is in this range where climate effects sufficiently erode the assets of most households who otherwise could afford alternative strategies.

The final sensitivity analysis anticipates the policy experiment on risk sharing mechanisms. Here ,we assume that households can share a proportion, β, of the remittances they receive from their own family members with other households in their social networks. We vary this β parameter from 0 to 1, and identify an internal optimum between $0.2 \leq \beta \leq 0.3$ that appears to maximize the total number of households who adopt alternative strategies

(Fig. 5, right). For values of $\beta < 0.2$, increases in β increase the incomes of households with connections to migrants, which results in more households being able to afford migration. However, at values of $\beta > 0.3$, migration begins to be less appealing for households who could otherwise afford it, and the number of households who engage in migration begins to decrease. This also reduces the total amount of income entering the community, which prevents other households from eventually being able to afford this strategy as well. We therefore use a value of $\beta = 0.25$ to evaluate the efficacy of the informal risk-sharing mechanism below.



(a) Weight of Public Information

(b) Mean Annual Temperature Change

(c) Proportion of Remittances Shared

Figure 5: Sensitivities of model results to changes in (a) the average weight given to public information sources, (b) the mean annual temperature change between the beginning and end of the model (roughly equivalent to a 2020-2050 time period); and (c) the proportion of remittances shared across household connections.

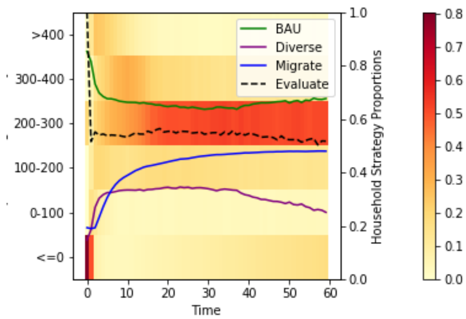
3.4 Policy Experiment: Risk Management Mechanisms

This section presents results of applying the risk management mechanisms described in Section 2.5 to Layer 4 of the Base Case model, which accounts for climate impacts and all other sources of complexity. We investigate the effects of three risk-sharing scenarios: (1) one that only includes an informal mechanism, sharing of migration remittances; (2) one that only includes a formal mechanism, an index-based insurance program; and (3) one that combines both the informal and formal mechanisms.

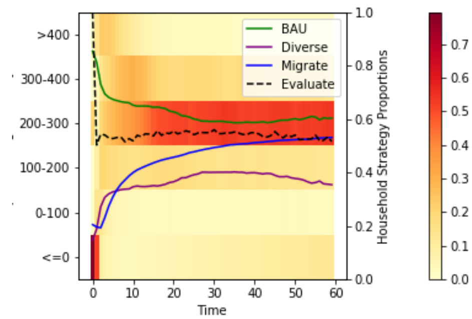
In the first scenario, informal remittance sharing significantly increases the adoption of migration among households, from less than 50 percent without any risk-sharing mechanism (Fig. 6a) to over 60 percent with this mechanism (Fig. 6c). This is likely driven by two factors. First, sharing even a fairly small percentage of remittances (25 percent) with other households in one's network significantly increases their income and ability to withstand shocks from extreme drought. More households are therefore able to afford the initial migration cost, and their migration further reduces migration costs for other households in the network. Second, because there are more households migrating, there are more observations of migration payoffs in the network, which leads to more households accurately perceiving the expected migration payoff of 300-400 USD/migrant/cropping cycle, depending on the number of household migrants (denoted by the colormaps in Fig. 6). Consequently, the adoption of migration occurs more rapidly and persists for a longer time period with remittance sharing. Despite this increase in the adoption of migration, remittance sharing appears to have negligible effect on the adoption of crop diversification, perhaps because it is still seen as too risky by the majority of households.

In the second scenario, a formal index-based insurance policy replaces the informal remittance sharing as the primary mechanism by which farming households can manage increasing livelihood risks from droughts. Although index-based insurance is purchased by several farmers of diverse crops in the early years of the model (Fig. 7a), it seems to have little effect on the overall distribution of household strategy choices (Fig. 6b). Essentially, households remain stuck in the same pattern that was observed without any type of risk-sharing mechanism: approximately 40 percent of households engage in migration, 30 percent switch to diversification, and the majority of households remain trapped in BAU farming. As insurance premiums increase, reflecting heightened drought risk, the number of households holding diverse crop insurance decreases, and few households ever purchase insurance for BAU crops. This result likely reflects financial constraints on BAU farmers that cannot be fixed by index-based insurance alone. Furthermore, while the insurance option improves the perception of Diversification payoffs, most households engaging in subsistence farming cannot afford the upfront costs of switching to this alternative strategy without some additional form of support.

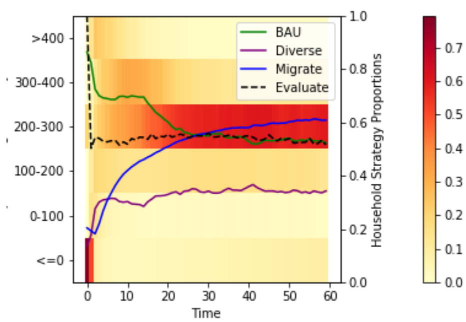
Results from the third scenario (a combination of formal insurance and informal remittance sharing) closely approximate the scenario with only the informal remittance sharing mechanism (Fig. 6d). In both scenarios, approximately 60 percent of households ultimately engage in migration, while adoption of the Diversification strategy does not exceed 40 percent. Although remittance sharing allows households to obtain more income, the proportion of BAU farmers purchasing crop insurance remains very low (Fig. 7b). However, there is a noticeable increase in the purchases of Diverse crop insurance when including both formal and informal mechanisms, particularly in the last half of the model run. This indicates that remittance sharing seems to provide additional income that fairly well-off farmers (i.e. those that can afford the upfront costs of crop diversification) can use for insurance. For BAU farmers, it may be that their expected income from subsistence farming even under "normal" years is so low that they do not deem it profitable to purchase insurance.



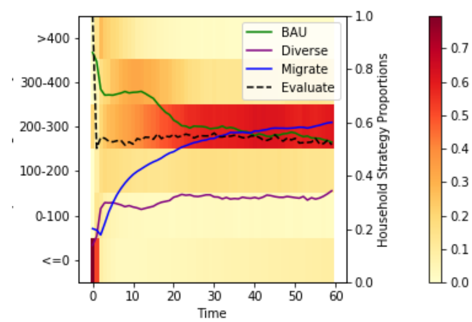
(a) No Risk-Sharing Mechanisms



(b) Index-Based Insurance Only



(c) Remittance Sharing Only



(d) Index-Based Insurance and Remittance Sharing

Figure 6: Distribution of household strategy choices for: (a) no risk sharing mechanisms, (b) only index-based insurance scheme, (c) only remittance sharing, and (d) combining both remittance sharing and index-based insurance. Colormaps represent the distribution of household perceptions regarding the migration payoff.

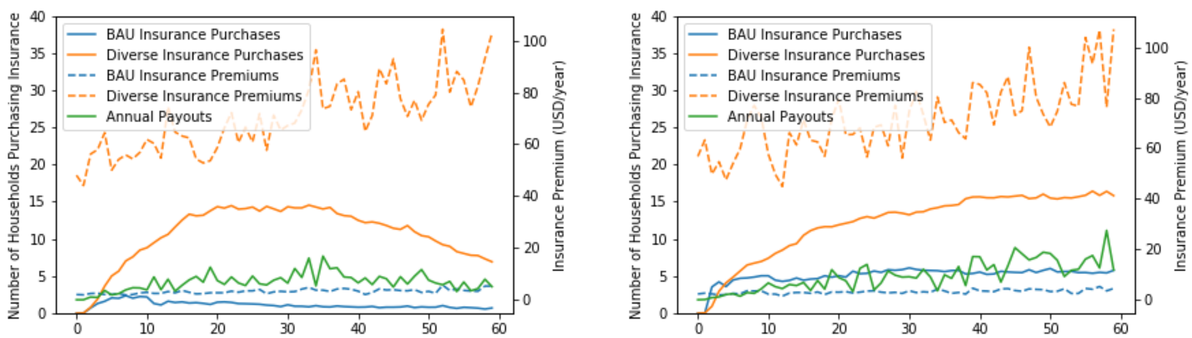


Figure 7: Insurance purchases and premiums for BAU and Diverse crops (a) without remittance sharing and (b) with remittance sharing

4 Discussion

This paper seeks to better understand the impacts of future climate change and multiple risk-sharing mechanisms on smallholder farmer adaptation strategies. To address this question, we developed a model that begins to address several gaps in the emerging field of climate-migration ABMs. First, we embedded the migration decision in a consistent decision-making utility function that agents use to optimize across a portfolio of strategies. While we represented a simplified set of options - BAU farming, crop diversification, and migration - we identified situations in which diversification and migration appeared to be complements (e.g. the risk-sharing experiment with high access to accurate information) and cases in which these alternative strategies are adopted at different rates (as in the risk-sharing experiment with remittance sharing). This represents an improvement over most previous ABMs, in which migration is the outcome of a statistical function that is divorced from other adaptation strategies. Second, we have sought to build this ABM in a modular structure that allows us to gradually introduce new sources of complexity, and identify their effects on key model outcomes. For example, we find that introducing education structure in Layer 3 - which correlates wealth, risk aversion, and access to public information - significantly reduces the adoption of migration and crop diversification compared to Layer 2, which contains the same population-level mean values for each of these variables, but does not correlate them. Such a structure can help identify pre-existing sources of "contextual vulnerability" [51] that are not inherently caused by climate change, but that can be exacerbated by this linkage (as illustrated in Fig. 2).

Third, we model social connections based on "small world" networks that are arguably more representative of real communities, rather than assuming that all agents are equally connected. This makes a difference in key model outcomes; notably, we see a diversity of household perceptions regarding strategy payoffs, as in the risk-sharing scenarios in Fig. 6. This heterogeneity in perceptions - in particular, perceptions that under-estimate the expected strategy payoff - appears to be one factor (among several) that depress adoption of alternative strategies. Fourth, we embed extreme events into a broader climate scenario that links slow-onset changes in crop yields to increasing probabilities of extreme droughts through correlations with mean temperature change. This helps us identify changes in how droughts impact agents' strategy choices: while earlier droughts are correlated with small spikes in temporary out-migration, later droughts do not seem to provoke the same response, likely because most households' assets have been eroded by slow-onset climate effects. Fifth, we compare the effects of formal and informal risk-sharing mechanisms. Our analysis shows that while informal remittance sharing can significantly increase the adoption of migration, formal index-based insurance does not seem to have an appreciable effect on household strategy choices, at least under our base case assumptions. This appears to be driven by a combination of households over-estimating the risk of drought, especially for diverse crops, and low financial assets among BAU farmers to afford insurance premiums.

Our model makes several assumptions regarding parameters relating to behavioral economics, social network interactions, and the effect of climate change on extreme drought, and we test the effects of these assumptions through sensitivity analyses presented in the results and Appendix. While our model displays some sensitivities, several patterns appear robust to a wide range of parameters. First, accounting for climate effects - even a mean temperature increase of only 1^0C - has a noticeable dampening effect on the level of labor-based rural-urban migration. The main drivers of this effect appear to be the erosion of financial assets among farming households, and a feedback effect whereby decreased migration leads to less accurate perceptions of migration payoffs within the community. Second, we find support for the "differentiated vulnerability" concept expressed in Lutz and Muttarak [43], among others. Climate impacts tend to trap households with lower educational attainment more so than households with secondary or tertiary educational attainment, assuming that education is correlated with wealth, risk aversion, and access to public information. Third, we find that an informal risk management mechanism through remittance sharing is effective at addressing some of the constraints imposed by climate change and increases the adoption of migration, though it appears less effective at promoting adoption of crop diversification. Finally, we find that formal index-based insurance on its own appears unlikely to have a significant impact on household strategy choices, driven in part by inaccurate perceptions of drought risk and low financial capacity to afford premiums at cost.

These high-level results lead us to identify a set of tentative policy recommendations to build smallholder farmer resilience to looming climate impacts (subject to model improvements discussed in the next paragraph). In the short term, facilitating the use of informal risk-sharing mechanisms could significantly increase the options available to many smallholder farmers who would otherwise be trapped by climate impacts. Some government policies have already attempted to increase the productive use of migration remittances in sending communities, such as Mexico's "3x1" scheme, in which federal, state, and local governments match remittances that are invested in community projects - though the politicization of this initiative seems to have dampened its initial successes ([52]. Over the medium term, increasing the accessibility to accurate information on climate risks and livelihood options also represents a key government lever. In this model, we assume that all but a few educated elite have poor access to and/or trust in these sources, which seems to accord with surveys of smallholder farmers in a variety of contexts, from Vietnam [53] to Malawi [54]. However, we also show that increased access to accurate information can have a significant impact on the number of households who adopt alternative livelihoods. Targeted information campaigns may need to account for low current rates of literacy, and/or a few well-connected households who have the capacity to influence a significant proportion of other households in their village. Over the longer term, investing in education will likely yield significant dividends in terms of opening alternative livelihood options to farmers. The results from this model suggest that access to public information and openness to take risks, both of which are often correlated with education, matter as much as wealth in the adoption of crop diversification and migration.

Finally, this initial study points to several opportunities for future work on the modelling of smallholder farmer climate adaptation generally, and the climate-migration relationship specifically. As evidenced by initial work presented in the Appendix, explicitly accounting for livelihood risk in the household decision-making function may significantly impact the strategy choices that are generated by these models, if households significantly weigh risk minimization as an objective. Further refinement of this function - e.g. by accounting for different reference points among households - could lead to a better understanding of household livelihood decisions. Furthermore, while we focus this analysis on planned, labor migration, future work could also include a "distress migration" channel that is activated when a household has no more savings, and no option other than to migrate to the city. This might differ from the migration channel we currently model, in that households in distress would likely have less time and resources to plan their migration journey, and thus end up in more vulnerable situations with lower likelihood of earning remittances. Still, this appears to be an important potential outcome of natural disasters and increasing climate risk. As well, including additional risk management mechanisms, e.g. informal loans between households and direct government cash transfers, could allow for a fruitful analysis of a wider set of government policies to build smallholder farmer resilience. This expanded analysis could also include collective adaptation options, e.g. a village (or subset of a village) deciding to pool savings into a public irrigation scheme. Modelling these types of collective adaptation techniques could also introduce pertinent game theoretic considerations that have not yet been analyzed in this work. Finally, a useful avenue for further work would be to develop a benchmark of collective community metrics that would be relevant to smallholder farmers (e.g. maximizing community income, minimizing community inequality, ensuring a minimum level of food security, etc.). This would help better guide policies that could align the individual-level decisions modelled in this analysis with the most socially optimal adaptation pathways. It also highlights a key next step: engaging smallholder farming communities themselves in the further elaboration of this model. This type of participatory research could help develop more realistic decision options and objectives for the model, while serving as a tool to help farming communities elaborate their visions of resilience to future climate change.

5 Appendix

5.1 Further Background Material

The strengths and challenges of ABMs are apparent in their previous applications to the climate-migration relationship. Kniveton et al. [28] developed one of the first such ABMs to predict future migration patterns based on changing climatic conditions, focusing on Burkina Faso as a case study. Agents are assigned migration probabilities based on statistical relationships between historical migration, demographic, and climate data. Social networks are determined by randomly assigning each agent 50 connections to other agents in the community. Hassani-Mahmooei and Parris [29] also build a predictive ABM of climate-induced migration in Bangladesh, but focus on the response to climate-induced shocks, rather than long-term climate change as in Kniveton et al. Decision agents represent blocs of 10,000 individuals of the Bangladeshi population, and evaluate migration decisions by assessing the push, pull, and intervening factors for moving to different districts. Social networks influence these thresholds through an imitation process in which agents emulate the thresholds of agents with higher overall wealth. While these studies provide an initial framework for conceptualizing a climate-migration ABM, they focus specifically on the climate-migration relationship and do not embed the choice to migrate in the context of other potential adaptation strategies.

A more recent set of climate-migration ABMs have sought to endogenize smallholder farmer migration strategies in a broader decision-making process that includes other forms of climate adaptation responses. Smith [30] explores the effects of different rainfall scenarios on internal migration in Tanzania, where the climate-migration relationship is conditional upon the an agent's income and food supply. There are two migration channels: a household can either pursue opportunity-based migration if it can afford the opportunity cost of lost farm labor, or it may be forced to engage in need-based migration if its resilience level drops below a minimum threshold. Entwistle et al. [31] develop future migration responses under various scenarios of rainfall shocks in rural Thailand. Their model allows households to adjust the types of crops and amount of fertilizers used as climatic and soil conditions change; young villagers between the ages of 15-29 can also migrate to the city to earn remittances. Hailegiorgis et al. [32] explore adaptation among nomadic pastoralists in Ethiopia, who decide how to allocate farm resources between crops and livestock, and whether to migrate to different agricultural regions. Agents are more motivated to migrate once their assets fall below a certain threshold, and rely on information from the past three years to estimate payoffs of farming livelihoods in different regions. In contrast, the ABM developed by Bell et al. [33] includes a wider range of livelihood strategies, including agricultural, industrial, and service sector occupations. Decision-making agents are assigned an initial geographic region and can choose to invest in local livelihoods or to migrate to other regions with different livelihood prospects.

5.2 Further Details on ABM Model Specification

5.2.1 Layer 1: Economic Rationality Details

The utility $U_{ik}(t)$ with which agents evaluate their strategy options assumes that households exhibit constant relative risk aversion θ_i, and that households' current wealth, $S_i(t)$, serves as the reference point for evaluating expected increases or decreases in utility from adopting strategy k. Such a utility function takes the shape:

$$U(t) = \begin{cases} \frac{(S_i+\pi)^{1-\theta}-1}{1-\theta} & \text{if } \theta_i \neq 1 \\ \ln(S_i + \pi_i) & \text{if } \theta_i = 1 \end{cases} \tag{4}$$

In the base case layer, we assume that $\theta_i = 0$ for all i, i.e. that all households exhibit risk-neutral behavior.

The general form of the Weibull distribution from which strategy payoffs are obtained is:

$$P(I_k(t)) = \begin{cases} \frac{\kappa}{\mu}(\frac{I}{\mu})^{\kappa-1} \exp^{(\frac{-I}{\mu})^{\kappa}} & \text{if } I \geq 0 \\ 0 & \text{if } I < 0 \end{cases} \tag{5}$$

where μ is the scale parameter and κ is the shape parameter of the distribution. In this layer, values of μ vary by adaptation strategy k, but there is no long-term trend in the viability of the adaptation strategies. This assumption is relaxed in the Climate Impacts Layer.

We model the adjusted farm income, $I_{ik}^{\text{adj}}(t)$, where $k \in$ [BAU, Diversification], as a saturating function of the number of individuals who remain in the village household, $x_k(t)$, and the household's initial draw from the farming income distributions, $I_{ik}(t)$:

$$I_{ik}^{\text{adj}}(t) = I_{ik}(t) * \left(\frac{x^{l_1}}{x^{l_1}+1}\right) \tag{6}$$

where l_1 represents the Hill coefficient, i.e. a parameter that controls the steepness of the saturating function. This functional form ensures that the opportunity cost (in terms of lost farm productivity) is initially minimal for the first migrant who leaves the household, but increases with subsequent migrants, until there are relatively few people left on the farm, which leads to low productivity.

According to the New Economics of Labor Migration theory, households engaging in labor migration as a risk diversification strategy will prioritize sending migrants with the highest earning potential in urban areas and the greatest incentive to remit. By this theory, subsequent migrants from the same household would likely exhibit lower earning potential and/or lower incentive to remit (e.g. an elderly parent). There is some empirical evidence from India that households with multiple migrants tend to exhibit decreasing per capita remittances, compared to single-migrant households [55]. We therefore adjust migration remittances as a function of the number of household migrants as follows:

$$R_i^{\text{adj}}(t) = R_i(t) * \sum_{x=0}^{x=n} \left(1 - \frac{x^{l_2}}{x^{l_2}+1}\right) \tag{7}$$

where n represents the number of migrants from household i at time t, l_2 is the Hill coefficient for migration remittances, and $R_i(t)$ is household i's draw of remittances from the Weibull distribution in Equation 5.

For low values of n (i.e. households that have not yet sent many migrants), economically rational agents will generally perceive that the net present value of expected remittances will outweigh the opportunity cost of lost farm labor. However, depending on the relative values of l_1 and l_2, at some n the expected returns of sending an additional migrant may be less than this opportunity cost, and the household will refrain from sending additional migrants. Such a relationship roughly approximates observed phenomena in South Asian countries that working-age males tend to form the majority of labor migration streams, while females and the elderly/young are more likely to remain in farming occupations [56].

The model is initialized by randomly assigning each household i the following parameters:

- A starting savings $S_i(0)$, drawn from an exponential distribution;
- A starting strategy $k_i(0)$. The initial distribution of $k_i(0)$ can be set by a particular case study of interest.

Table 1 displays Base Case values for key parameters in the Economic Rationality Layer, which are used to generate results in Section 3. The sensitivity of these results to different parameter values is explored in Section 3.3, and further in the Appendix.

5.2.2 Layer 2: Bounded Rationality Details

The social network in Layer 2 is established by randomly assigning each agent a set of connections to other agents in the model. These connections are uni-directional (i.e. A may influence B, but B does not necessarily influence A), and the number of connections established for household i is determined by randomly drawing from a power law distribution of the form:

$$P(j_i) = (j_i)^{-\gamma}, 0 \leq j_i \leq N \tag{8}$$

Parameter	Average Value	Standard Deviation	Notes
I_{BAU}	100	100	Decreases with decreasing household size
C_{BAU}	100	0	
$I_{Diverse}$	750	630	Decreases with decreasing household size
$C_{Diverse}$	300	0	
R	425	700	Per migrant, decreases with increasing migrants
$C_{Migrate}$	500	0	For first year only
l_1	2	N/A	Exponent for decreasing farm productivity
l_2	2	N/A	Exponent for decreasing remittance returns

Table 1: Layer 1 (Economic Rationality) Parameters for one cropping cycle.

where γ is a parameter that controls the steepness of the distribution. Here, connections represent in-edges, in that any connections assigned to household i represent the reference group to which it will compare its wealth and derive information on strategy payoffs.

As noted in Section 2.2, agents combine information about the percentage difference in their own payoffs in time $t-1$ compared to the previous m years (where m represents agents' bounded memories), $\triangledown_{ii}$, and the percentage difference between their payoff in time $t-1$ with the average $t-1$ payoff among their social connections ($\triangledown_{ji}$). The average of these two sources of information (normalized by the number of the agent's connections) must exceed the agent's status quo threshold, λ_i, in order to motivate the household to re-evaluate its strategies. The probability P_i of household i re-evaluating its strategies is thus:

$$P_i = \chi_i(t) \tag{9}$$

$$\text{where} \begin{cases} \chi_i(t) = 1 & \text{if } \frac{(\triangledown_{ii} + \sum_1^j \triangledown_{ji})}{j+1} > \lambda_i \\ \chi_i(t) = 0 & \text{if } \frac{(\triangledown_{ii} + \sum_1^j \triangledown_{ji})}{j+1} \leq \lambda_i \end{cases} \tag{10}$$

Note that in this layer, agents are assumed to equally weight information about changes in their own payoffs over time and that of each of their network connections. It is also assumed that λ_i remains constant for each household throughout the duration of the simulation, as empirical evidence demonstrates that risk preferences are unlikely to change significantly over one's adult lifetime [57].

An additional assumption in this layer is that agents combine information from public sources and their social network in forming perceptions about strategy payoffs. For simplicity, we assume that this public information represents the true expected income of each strategy. However, the degree to which agents rely on public information may be limited by poor literacy or access to information media e.g. websites and newspapers, and/or limited trust in public sources. Thus, they also rely in part on memories of their own income derived from the strategies they deployed in previous years, as well as information received from other agents in their social networks. We also assume that agents forget older information, such that perceived incomes in year t_f only reflect observations within a certain time window, $(t_f - m, t_f)$. we represent the weight that each agent assigns to public information as ω_i, and the weight assigned to "informal" sources (i.e. their own memories and observations from their network) as $1-\omega_i$. This latter information source differs for each household i based on their varied experiences and their different network connections. The perceived utility of any strategy k in time t_f, $\tilde{U}_{ik}(t_f)$, is thus:

$$\tilde{U}_{ik}(t_f) = \omega_i \bar{U}(\pi_{ik,\text{public}}, S_i, \theta_i) + (1-\omega_i) * \bar{U}(\pi_{ik,\text{social}}, S_i, \theta_i) \tag{11}$$

where $\bar{U}$ denotes the average utility perceived from public and social network information sources, respectively (see Appendix for more details on how these quantities are calculated).

The equation that details how each observation is included in this perceived utility is:

$$\begin{aligned}
&\tilde{U}_{ik}(t_f) = \omega_i U(\bar{\pi}_k(t_f), S_i, \theta_i) + \\
&\frac{(1-\omega_i)}{m(j+1)+(m-1)q}\left[\sum_{t=t_f-m}^{t_f-1} U(\pi_{ik}(t), S_i, \theta_i) + \sum_{1}^{j_i}\sum_{t=t_f-m}^{t_f-1} U(\pi_{jk}(t), S_i, \theta_i) + \sum_{1}^{j_i}\sum_{1}^{q_j}\sum_{t=t_f-m}^{t_f-2} U(\pi_{qk}(t), S_i, \theta_i)\right]
\end{aligned} \tag{12}$$

where $\bar{\pi}_k(t) = \mathrm{E}[\pi_k(\mu_k, \kappa_k, C_k)]$
and $q \not\subset J$

Here, $\bar{\pi}_k(t)$ represents the unbiased expectation of a strategy's payoff, $\pi_{jk}(t)$ represents the payoff derived from strategy k by neighbor j in time t, and $\pi_{qk}(t)$ represents the payoff derived from strategy k by neighbor q of j. Each agent forms their perception by summing the utilities of his or her neighbors' payoffs, based on their own risk aversion preferences and their current wealth level. For example, an agent with higher risk aversion would assign a lower utility to a payoff of 1,000 USD, compared to a neighbor who had the same reference point but a lower risk aversion. In any given year t_f, agents form perceptions using information from their own memories and their direct neighbors up until the previous year, $t_f - 1$, and information up until $t_f - 2$ from neighbors two path lengths away, as we assume that it takes an extra cropping cycle for information to be transmitted from one neighbor to the next. An agent's perceived expected utility from strategy k, $\tilde{U}_{ik}(t)$, thus becomes more accurate with a higher weighting ω_i, and through increased network connections, which increase its observations of strategy incomes. In this layer, ω_i is randomly assigned to households through a normal distribution (Table 2). In the Demographic Layer, we intro-

Table 2: Layer 2 (Bounded Rationality) Parameters

Parameter	Average Value (*Scale Parameter)	Standard Deviation (*Shape Parameter)	Description
λ	0.0	0.0	Status quo threshold
θ_i	0.5	0.2	Risk aversion coefficient
ω_i	0.25	0.0	Weight of public information
γ	-2.5	N/A	Exponent for network connections
Avg. degree	4.5		Average number of social connections
m	10	0	Memory of agents (crop cycles)

duce a correlation between ω_i and the educational attainment of the head of household.

Theories on "migrant networks" indicate that networks of current and previous migrants provide potential future migrants with crucial information about safe and efficient ways to reach the city, an economic and social support system to facilitate the migrant's first few months in the city, and help to normalize a process that otherwise might appear daunting or even frightening. In this layer, the effects of social networks on migration propensity are operationalized by adjusting the cost of migration, $C_{iM}(t)$, as a decreasing function of the fraction of an individual's social network that is currently residing in the city, $f_i(t)$. This is governed by the equation:

$$C_{iM}(t) = \begin{cases} c_{0,M}e^{-f_i(t)} & \text{for year } t \\ 0 & \text{for years } t+1, t+2, \ldots \end{cases} \tag{13}$$

where $c^{0,M}$ represents the initial migration cost, without any assistance from one's social network. This assumes that migration requires the household to pay an initial up-front cost for the migrant's trip and initial establishment in the city, and that this cost decays exponentially as a greater proportion of i's social network migrates. After the first year, the migrant from household i is assumed to be self-sufficient and returns any additional revenues earned as remittances for the household (R_{iM}).

Table 2 displays the base case values used for the additional parameters introduced in this layer.

5.2.3 Layer 3: Demographic Effects Details

In this layer, household agents are assigned an educational status (Primary, Secondary, and Tertiary), and each of these statuses is correlated with three parameters: the initial savings level $S_i(0)$, the degree of risk aversion α_i, and the weight of public information sources ω_i. Table 3 displays the proportions of households in each educational attainment category, as

Table 3: Layer 3 (Demographic) Parameters

Educational Attainment	Proportion of households	Savings $S_i(0)$ (Variance)	Risk Aversion α_i (Variance)	Public Weight ω_i (Variance)
Primary	0.65	100 (100)	0.60 (0.2)	0.10 (0.0)
Secondary	0.30	1000 (1000)	0.30 (0.2)	0.25 (0.0)
Tertiary	0.05	2500 (2500)	0.20 (0.2)	0.50 (0.0)

well as the values assigned for each of the three parameters.

5.2.4 Layer 4: Climate Effects Details

The specification for long-term impact of temperature increase on crop yields is as follows:

$$\begin{aligned} \mu_k(t) = \mu_k(t_0) * (1 - \beta_1(T(t) - T_0)) \\ \text{for k in [BAU, Diverse]} \\ \text{where} T(t) = T_0 + \Delta * t \end{aligned} \tag{14}$$

Here, β_1 is the co-efficient relating temperature increase to a proportional change in crop yield (-0.1), and Δ represents the average annual rate of change in mean temperature. A main hypothesis under this scenario is that accuracy of information and the willingness to adopt new strategies becomes increasingly important for accurately perceiving climate risks and securing resilient livelihoods. Therefore, households with a higher number of social connections and low risk aversion are more likely to choose viable livelihoods; these factors are linked with higher educational attainment, which also correlates with a higher initial wealth that enables households to afford new management strategies. By contrast, households with poor social connections and/or low social thresholds are more likely to hold onto farming-based strategies even as these incomes decrease over time. In extreme cases, some of these households may decide to remain with non-optimal strategies until they can no longer financially afford to change, reflecting an emergent "trapped" population [13].

The SPEI is a monthly index of drought severity that accounts for deficits between precipitation and potential evapotranspiration (PET) using data collected on 0.5 x 0.5 degree grids. The SPEI combines two key features of drought indices: it allows for droughts to be calculated on multiple timescales (e.g. measures of 3-month vs. 48-month water deficits)

Table 4: Layer 4 (Climate Impacts) Parameters

Parameter	Average Value (*Scale Parameter)	Standard Deviation (*Shape Parameter)	Notes
Δ_T	1^oC	N/A	Change in mean annual temperature
β_{yield}	-0.1	0.0	Change in crop yield due to 1^oC warming
β_{SPEI}	-0.25	0.0	Change in mean July SPEI03 due to 1^oC warming
τ_{BAU}	-2.0	0.0	Threshold SPEI03 value for BAU extreme drou
$\tau_{Diverse}$	-1.5	0.0	Threshold SPEI03 value for Diverse extreme dro

and explicitly includes temperature as an input for measuring PET. Importantly, it is more strongly correlated with measures of crop yield reductions than other drought indices for most regions in the world [48].

Specifically, we assume that the SPEI 3-month index is the most relevant timescale for agricultural purposes given that most cereal crops' growing seasons are between 3-4 months in most regions of the world. This has also been shown to be most strongly correlated timescale with crop yield changes in the North China Plain [58].

As an initial approximation, we use monthly SPEI and temperature data from 1980-2005 for the Chitwan Valley, an agricultural region in Nepal's mid-Hills ecological belt, which has been a source of significant out-migration in recent decades. Our regression provides a coefficient of -0.247, indicating that an increase of 1^o C in mean annual temperature is correlated with a decrease of 0.247 in the minimum annual SPEI value. The mean value of the SPEI distribution is thus parameterized in our model as a function of mean annual temperature, $T(t)$:

$$\mu_{\text{SPEI}}(T) = \beta_2(T(t) - T_0) \tag{15}$$

where β_2 controls the SPEI-temperature relationship (-0.247 in our base case), and the variance of the distribution is assumed to remain constant.

5.2.5 Risk-Sharing Mechanism Details

In this section, we assume that households form perceptions about the risk of drought for crop k, $E_{ik}(t)$, by combining public and social information sources. Similarly to the Bounded Rationality layer, social information sources combine observations from household i's network connections, as well as its own experiences over the past m years. The full equation that aggregates these public and social information sources is as follows:

$$E_i(t) = \omega_i P(d_k(t)) * (1-\omega_i)[\frac{\sum_{t_f-m}^{t_f-1} d_{ik}(t)}{(m-1)} + \frac{\sum_{t_f-m}^{t_f-1}\sum_j d_j(t)}{j(m-1)} + \frac{\sum_{t_f-m}^{t_f-2}\sum_j \sum_{q(j)} d_q(t)}{j * q(j) * (m-2)}] \quad s.t. q \not\in J \tag{16}$$

Where $d_i(t)$ is a binary variable that takes the value of 1 if household i experienced a disaster in year t, and 0 if it did not. As with Equation 10, j represents the direct neighbors of household i, and $q(j)$ represents the neighbors of j. The variable m represents the length of agents' memories, and $P(d_k(t))$ represents the objective probability of an extreme drought for farming strategy k in year t. As such, households use a combination of objective forecasts on the probability of drought, as well as memories of the frequency of previous disasters for specific farming strategies as a heuristic to forecast the probability of future disasters.

5.2.6 Accounting for Income Volatility in Household Decision-Making

In the main specification of the model, we assume that all households maximize their utility by maximizing their expected income from livelihood strategy options, subject to financial constraints, imperfect information, and varying wealth levels and risk aversion. An alternative interpretation of smallholder farmer decision-making is that households not only seek to maximize income, but also seek to ensure some degree of income stability. This is consistent with empirical and theoretical literature from the New Economics of Labor Migration field, which views migration as one way in which households spread risk and smooth consumption across highly variable economic conditions [36, 37]. Thus, an alternative to the utility function presented in Equation 4 could be to penalize the perceived volatility of each strategy by a coefficient b, as follows:

$$U(t) = \begin{cases} \frac{(S_i + (\pi_k(t) - b_i * \sigma_k(t)))^{1-\theta} - 1}{1-\theta} & \text{if } \theta_i \neq 1 \\ \ln(S_i + (\pi_k - b_i * \sigma_k)) & \text{if } \theta_i = 1 \end{cases} \tag{17}$$

where $\sigma_k(t)$ represents the perceived volatility of a strategy option, expressed as a standard deviation of payoffs. Similar to Equation 11, agents continue to combine information from public and social information sources based on the weighting factor, ω_i, in order to form perceptions about the expected income and risk associated with each strategy.

In this formulation, b represents a measure of an individual's risk preference, i.e. a higher value of b indicates a lower willingness to trade-off risk for expected return [57]. Note that there is a subtle but important difference between risk aversion, which we have denoted as θ_i, and the risk preference parameter b_i. Compared to Equation 4, in which households take the expectation of the perceived utility for each observation of a strategy based on their risk aversion, Equation 9 represents a more explicit way of penalizing strategies that are perceived as more volatile. This may in fact be a more accurate representation of how smallholder farming households evaluate their livelihood options. Consistent with recommendations by Gray et al. [38] to use ABMs as a means of testing the effects of different decision-making theories among agents, we can compare results from our main model specification with those obtained from this alternative decision-making framework that explicitly accounts for income volatility (See Section 5.3).

In determining the socially-derived information, agents also continue to weigh all observations from their own experiences and that of their social connections equally. However, in this modification, agents now weigh this information using the observed dollar values of strategy payoffs π_{jk}, as opposed to the perceived utility from each observation. Equation 12 is now modified as:

$$\tilde{\pi}_{ik}(t_f) = \frac{\omega_i}{m} \sum_{t=t_f-m}^{t_f} \bar{\pi}_k(t) + \frac{(1-\omega_i)}{m(j+1)+(m-1)q} [\sum_{t=t_f-m}^{t_f} \pi_{ik}(t) + \sum_{1}^{j_i} \sum_{t=t_f-m}^{t_f} \pi_{jk}(t) + \sum_{1}^{j_i} \sum_{1}^{q_j} \sum_{t=t_f-m}^{t_f-1} \pi_{qk}(t)] \tag{18}$$

and

$$\tilde{\sigma}_{ik}(t_f) = \omega_i * \sigma_{k,\text{public}}(t) + (1-\omega_i) * \sigma_{k,\text{social}}(t) \tag{19}$$

where

$$\sigma_{k,\text{public}}(t) = \frac{1}{m} \sum_{t=t_f-m}^{t_f} (\mu_k(t) * \sqrt{\Gamma * (1 + \frac{2}{\kappa_k(t)}) - (\Gamma * (1 + \frac{1}{\kappa_k(t)}))^2}) \tag{20}$$

and

$$\begin{aligned} \sigma_{k,\text{social}}(t) = \Bigg[\frac{1}{m(j+1)+(m-1)q-1} * [\sum_{t=t_f-m}^{t_f} (\pi_{ik}(t) - \hat{\pi}_k(t))^2 \\ + \sum_{1}^{j_i} \sum_{t=t_f-m}^{t_f} (\pi_{jk}(t) - \hat{\pi}_k(t))^2 + \sum_{1}^{j_i} \sum_{1}^{q_j} \sum_{t=t_f-m}^{t_f-1} (\pi_{qk}(t) - \hat{\pi}_k(t))^2] \Bigg]^{1/2} \end{aligned} \tag{21}$$

where $\hat{\pi}_k(t)$ represents the mean value of all of household i's observations of payoffs for strategy k (including its own, those of its neighbors, and those of its neighbors' neighbors). In short, each household forms its perception of the expected income for strategy k through a complex combination of the objective expectation from the strategy distribution and what it observes from its social network. Similarly, it forms its perception of the riskiness of the strategy (expressed here as strategy k's standard deviation) through a convex combination of the standard deviation of the strategy's true distribution, and the standard deviation of the observations from its social network. In layers with climate effects, both the mean value and standard deviation of payoff distributions for the BAU and Diversification strategies change over time as climate impacts decrease mean crop yields. As such, the public, objective information received by households reflect the temporal average of the mean and standard deviation of these distributions over the last m years, where m represents the duration of households' memories.

After weighing public and social network information sources to form perceptions of both the expected payoff and standard deviation of each strategy, households next evaluate the utility of these strategies based on Equation 17 above. As an initial approximation, households are assigned a value for b_i equal to their risk aversion, θ_i, such that b_i is bounded by $0 \leq b_i \leq 1$. However, this could be changed in future iterations of the model.

5.3 Additional Results

This section of the Appendix presents additional results that are referred to in the main section.

5.3.1 Additional Sensitivity Analyses

In addition to the sensitivity analyses presented in Section 3.3, Figure 8 presents further sensitivities of model results to parameters in Layers 1-4. For each of these plots, sensitivities reflect the final distribution of household strategy choices in Layer 4.

5.3.2 Results from Alternative Model Specification - Accounting for Risk

Fig. 9 displays key results from model simulations in which Equation 6 is used as the main household decision-making objective function, as opposed to a decision-making function which only seeks to maximize expected income (Equation 1). This figure presents household strategy decisions under four scenarios: (1) accounting for all assumptions in Layer 3, without climate effects; (2) accounting for all assumptions in Layer 4 (with climate effects); (3) accounting for Layer 4 assumptions and also allowing for sharing of remittances between household connections ($\beta = 0.25$); and (4) accounting for Layer 4 assumptions and an index-based insurance scheme.

There are a few differences between the results under this alternative decision-making function, compared to results derived using Equation 1, where households are only concerned with maximizing the expected utility of strategy payoffs. Primarily, there is a substantially lower adoption of the strategy with the most risk, crop diversification, in all scenarios - this is limited to only 20-30 percent of all households. Such a result would be consistent with the hypothesis that as households explicitly penalize the anticipated risk of each strategy, they would be less likely to choose the riskiest strategy. Interestingly, adoption of the migration strategy remains high before accounting for climate effects (Fig. 7a), perhaps

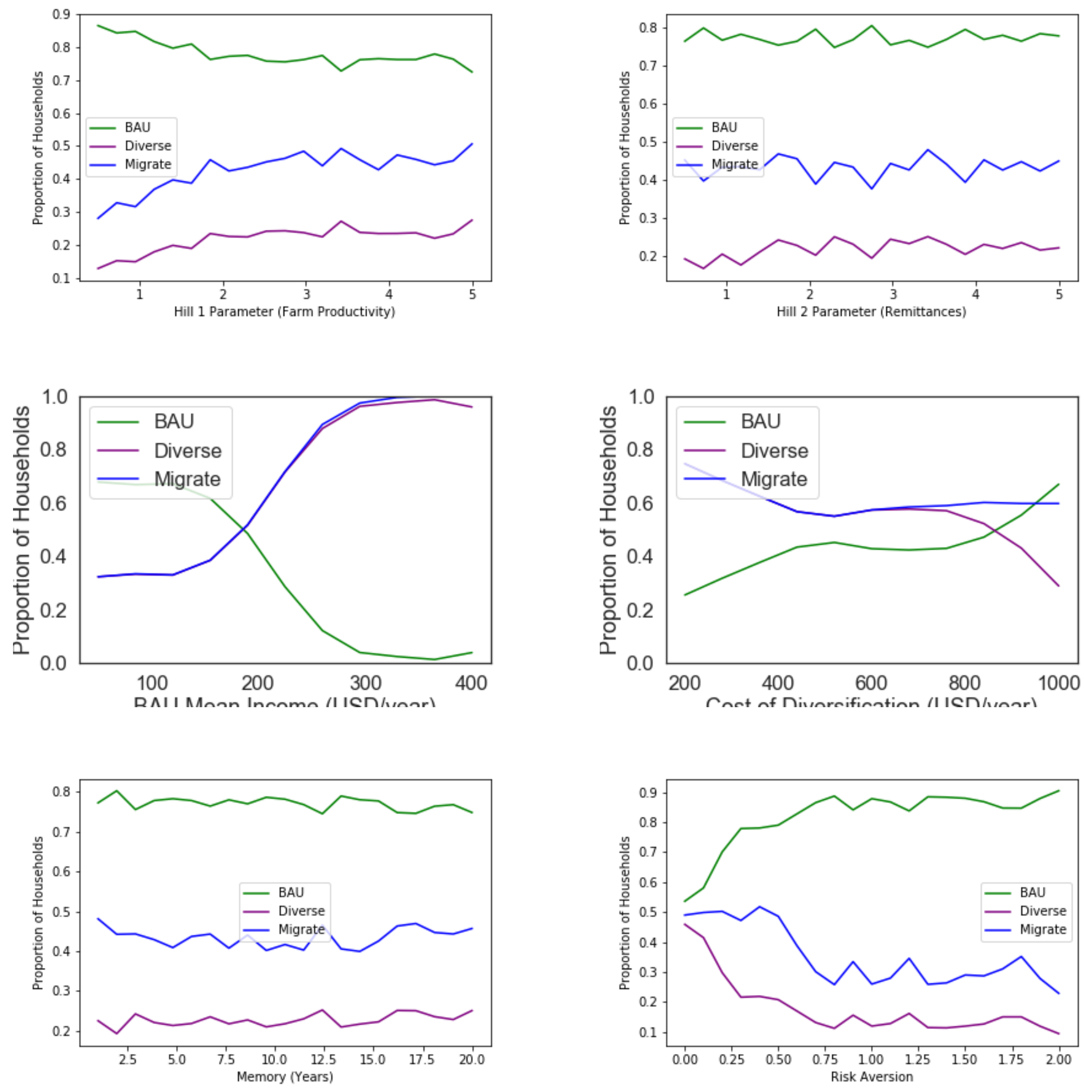
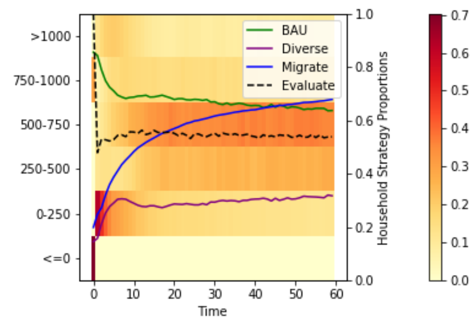


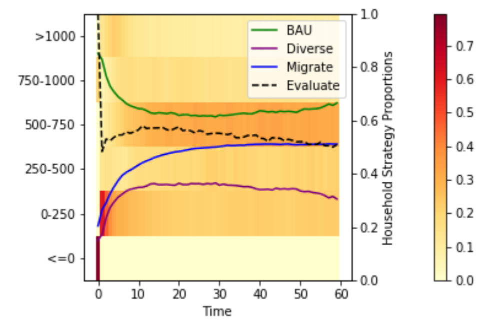
Figure 8: Sensitivity of final distribution of household strategy choices to socioeconomic parameters: (a) the Hill parameter controlling the rate of marginal productivity of farm labor (l_1), (b) the Hill parameter controlling the steepness of declining marginal returns from migration remittances (l_2), (c) the average annual income dervied from the BAU strategy, (d) the annual cost of crop diversification, (e) the duration of households' memories m, and (f) the average risk aversion factor α.

indicating that for most households, the expected benefits in increased income from this strategy outweigh the additional risk that it entails, compared to simply staying with BAU farming. Similarly to the results derived from Equation 1, accounting for climate effects leads to a net decrease in the households who engage in migration, though this strategy remains slightly more popular when accounting for income volatility in the decision-making function (approximately 50 percent of households still engage in migration, compared with 40 percent when volatility is not considered in households' decision-making). This may again reflect the penalties associated with increased risk of the crop diversification strategy under climate impacts, which drives more households to choose migration as the alternative, relatively less risky strategy.

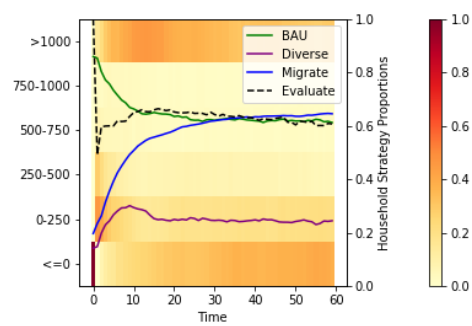
The effects of both types of risk-sharing mechanisms (the informal remittance sharing, and the formal index-based insurance) on household strategy choices are also interesting to note. Similar to the results using Equation 1, the informal remittance sharing increases the adoption of migration back to the original level before accounting for climate effects, around 60 percent of households (Fig. 7c). Curiously, this does not significantly increase the average community income, as households' agricultural income is still diminished from climate impacts. It is also interesting to note that the transmission of information on migration payoffs becomes more bifurcated: even with informal risk-sharing, households are essentially split into those that perceive migration as a high-payoff strategy, and those that have little information or perceive it as a net-loss strategy (colormap on Fig. 7c). This result indicates that some groups of households are able to benefit from risk-sharing, with a high degree of migration, while other groups of households remain trapped in BAU farming. Similarly, the formal index-based insurance mechanism also splits the transmission of information into some groups that perceive migration as highly-profitable, and some that see it as a negligible strategy (Fig. 7d). However, index-based insurance does little to increase the adoption of alternative strategies; in fact, it seems to slightly increase the number of households that stay with BAU farming.



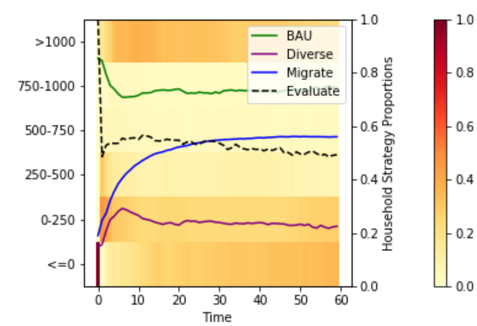
(a) Without Climate Effects - No Risk-Sharing



(b) With Climate Effects - No Risk-Sharing



(c) WIth Climate Effects - Remittance Sharing



(d) With Climate Effects - Index-Based Insurance

Figure 9: Distribution of household strategy choices for: (a) no risk sharing mechanisms and no climate effects, (b) climate effects without risk-sharing mechanisms, (c) climate effects with remittance sharing, and (d) climate effects with index-based insurance. Colormaps represent the distribution of household perceptions regarding the migration payoff.

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