Dynamics of Environmental Change, Livelihoods, and Migration in Bangladesh: An Agent-Based Modeling Approach

By

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For my mother.

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CHAPTER 1

Introduction

1.1 Overview

Future climate change poses a wide variety of threats to human health and well-being ("IPCC - SR15," 2018; IPCC 2022). This is especially true in low-lying coastal communities, where climate change is likely to affect a variety of natural phenomena including storms, sea level rise, coastal inundation, erosion, and precipitation (Nicholls et al. 2007). In addition, climatic changes and environmental stressors will impact livelihood opportunities in vulnerable coastal areas (Nicholls et al. 2008).

One possible human response to climate change and other environmental stresses is migration. Discussions of climate-induced migration have traditionally been framed around a looming crisis of "climate refugees" (Myers 2002). However, this narrative has been challenged as overly simplistic and failing to accurately represent the true complexity of migration decisions (Boas et al. 2019). Recent work has shown that although climate change and environmental pressure can affect population mobility, those impacts may be nonlinear or even negative (Paul 2005; Call et al. 2017). Additionally, environmental factors are rarely the only causes of migration (Obokata et al. 2014). Rather, migration is complex, multi-causal phenomenon that is impacted by both "push" factors (such as political instability, lack of economic opportunity, and lack of natural resources in the location of origin), as well as "pull" factors related to the destination location (including availability of employment, resources, and social capital). Intervening factors such as transportation networks, social ties, and cultural norms can further complicate the decision to migrate (Black et al. 2011a; Amrith 2013; Hunter et al. 2015).

As concern for community displacement increases, it is important to understand the factors that impact migration and what role migration might play in adaptation to environmental stress. The complexity of human migration poses a challenge for researchers who aim to study the effects of environmental changes on population mobility, and questions remain about how to best model human migration to account for this complexity (McLeman 2013; Neumann and Hilderink 2015).

This dissertation adds to existing knowledge of how changing environmental conditions and livelihood opportunities impact migration decisions in coastal Bangladesh. To address this objective, I developed an original agent-based model (ABM) that combines stylized environmental change dynamics with livelihood to investigate how these dynamics impact migration decisions. This research combines established earth sciences and social research with computational modeling to understand the coupled dynamics of human mobility and environmental change in Bangladesh.

1.2 Study Area: Bangladesh

Bangladesh is located on the low-lying deltaic floodplain of the Ganges-Brahmaputra-Jamuna Delta, which includes the Ganges, Brahmaputra, Padma, and Meghna Rivers (Passalacqua et al. 2013) (**Figure 1.1**) In Bangladesh, these major rivers converge and feed into the Bay of Bengal, where approximately 1 billion tons of sediment are deposited annually (Milliman and Farnsworth 2011; Dietrich et al. 2020).

Figure 1.1: Bangladesh and surrounding areas (Image: Google Earth)

Bangladesh falls in a low elevation coastal zone, and as such experiences multiple environmental vulnerabilities such as regular flooding, extreme weather events, and sea level rise (Islam and Sado 2000; Dewan et al. 2007; Dewan and Yamaguchi 2009; Hallegatte 2012; Higgins et al. 2014; Call et al. 2017; McGranahan et al. 2007). Communities on the coastal delta plain of Bangladesh face a particular set of challenges as sediment transport, deposition, and erosion continuously create and destroy land and shape the areas where people live and work

(Auerbach et al. 2015). Additionally, both natural and human changes to the environment are causing shifts in livelihood choices (Ackerly et al. 2015; Tessler et al. 2015). It is estimated that more than 50 million people live in the coastal areas of Bangladesh where they are highly vulnerable to natural disasters and environmental shocks (Ahsan et al. 2011). More than one million people in this area are estimated to lose their homesteads to river erosion every year (Black et al. 2008).

In Bangladesh, migration is a common method of livelihood diversification and adaptation to stressful natural conditions (Black et al. 2005; Amrith 2013; Martin et al. 2014; Alam et al. 2017). Rural to urban migration is the most prevalent form of migration in Bangladesh (Afsar 2003; Bryan et al. 2014; Ackerly et al. 2015; Lagakos et al. 2018, p. 20), especially temporary migration to adapt to seasonal poverty (Khandker 2012). Remittance provided by household members who have migrated can increase livelihood stability in the midst of agricultural instability and seasonal poverty (Call et al. 2017). However, it is unclear how these existing mobility patterns will be impacted by climate change.

Environmentally induced migration has been widely studied in Bangladesh (Afsar 2003; Ahsan et al. 2011; Gray and Mueller 2012, p. 20; Joarder and Miller 2013; Donato et al. 2016; Islam 2017; Call et al. 2017; Chen and Mueller 2018). Much of this research focuses on extreme weather events representing rapid onset environmental change, such as cyclones (Kartiki 2011; Gray and Mueller 2012; Mallick and Vogt 2012, 2014; Lu et al. 2016). Other research considers slower onset environmental change such as salinity encroachment, temperature change, and precipitation (L. Perch-Nielsen et al. 2008; Call et al. 2017; Chen and Mueller 2018). However, there is little agreement between these studies as to how environmental changes will alter migration patterns.

1.3 Environmental Migration Research and Methods

Migration is a complex and multi-causal phenomenon that is driven by multiple factors across temporal and spatial scales. Even where the environment drives migration, it can be compounded by social, economic, and political factors (Walsham 2010; Hunter et al. 2015). A popular conceptual framework of environmental migration that highlights its complexity was proposed by Black et al (2011). The framework, which is shown in an adapted form in **Figure 1.2**, identifies economic, political, social, demographic, and environmental factors as the primary drivers that affect migration decisions. The unique contribution of the framework is that the effect of environmental drivers on a migration decision is dependent on the other factors and the context of the decision. In this way, environmental conditions can directly impact a migration decision, but also impact the decision indirectly through effects on the economic, social, political, and demographic drivers (Black, et al., 2011).

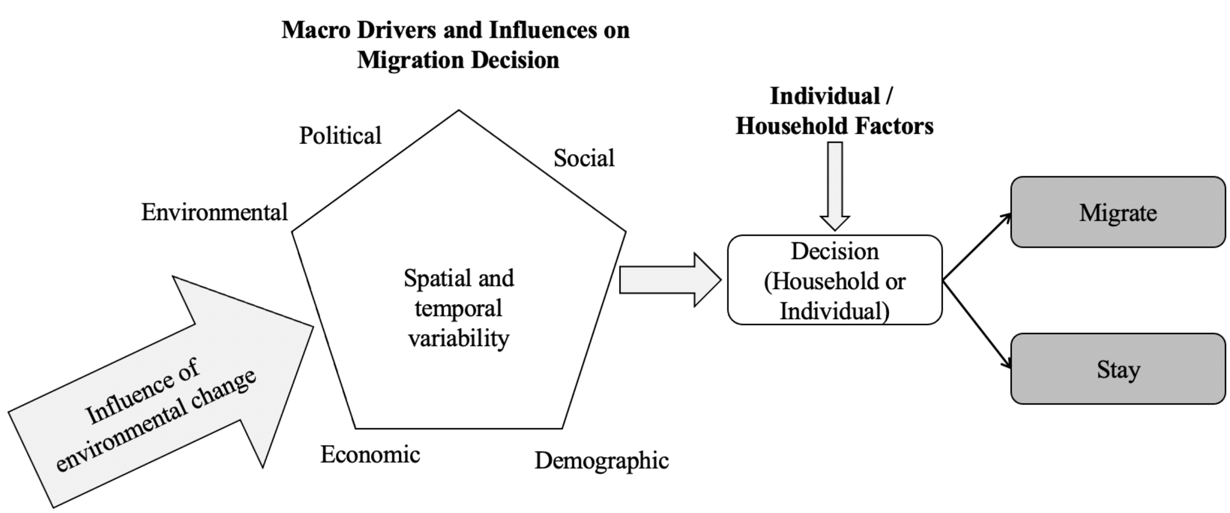

Figure 1.2: Conceptual framework of how environmental change impacts migration (adapted from Black et al., 2011).

Because of the complexity and nonlinearity of environmental migration, the dynamics are still poorly understood and poorly quantified. In general, the study of environmental migration employs a variety of methods from strictly conceptual models (L. Perch-Nielsen et al. 2008; Renaud et al. 2011; Black et al. 2011a), to logistic regression (Koubi et al. 2016), multivariate regression (Hino et al. 2017), statistical analysis (Henry et al. 2003, 2004), and a few agent-based models (Silveira et al. 2006; Kniveton et al. 2011a; Hassani-Mahmooei and Parris 2012; Cai and Oppenheimer 2013; Smith 2014; Thober et al. 2018; Reid Bell et al. 2019). Previous work applied machine learning to two social surveys to identify important predictors of migration in southwestern Bangladesh (Best et al. 2020). One of the datasets used came from the Bangladesh Environment and Migration Survey (BEMS) This survey contains migration, employment, and livelihood histories on more than 3,000 individuals affiliated with 1,695 households. The survey specifically asks for histories of migration within Bangladesh, to India, and to any other country (Donato et al. 2016; Carrico and Donato 2019). The original dataset consists of 1,695 observations of 1,997 distinct variables. The top 15 variables to predict the number of internal migrations a household reported were identified using a random forest algorithm. These variables included latitude, longitude, household characteristics such as number of non-workers and total household members, and socioeconomic indicators including whether or not a home owned a gas or kerosene cooker or a refrigerator. Though the random forest algorithm was able to identify the top predictors of internal migration from the BEMS dataset, it does little to explain how the top variables impact the migration decision or the dynamics of how the variables interact.

Agent-based modeling is a powerful tool to analyze the dynamics of coupled human-natural systems such as environmental migration in Bangladesh as these approaches can simulate nonlinear interactions among individuals and reveal how large-scale collective behavior emerges from individual decisions (Hassani-Mahmooei and Parris 2012). In this way, ABMs represent an opportunity to improve understanding of how environmental change and migration interact in complex social-ecological systems (Thober et al. 2018). Simulation models such as ABMs can address gaps in current understanding by explicitly modeling the linkages and feedbacks between the social and environmental systems. ABMs are also powerful tools because of their ability to describe decision making and the impacts of decisions in great detail (DeAngelis and Diaz 2019). However, Thober et al. find that few existing ABMs of environmental migration fully integrate the social and ecological systems (2018).

One example of agent-based modeling being applied to studying environmental migration in Bangladesh was identified (Hassani-Mahmooei and Parris 2012). Hassani-Mahmooei and Parris developed an agent-based model to simulate migration decisions between districts based on 10 heuristics or migration “rules”, which are primarily based on economics and prospects for livelihoods (2012). The model also includes “push”, “pull”, and “intervening” factors related to climate change scenarios, socioeconomic conditions, house ownership, and employment (Hassani-Mahmooei and Parris 2012). The model can impose climate shocks on agents, pushing them to decide to migrate and then select where to migrate. Combined with population growth and agent mortality, Hassani-Mahmooei and Parris use the model to predict that between 3 and 10 million people in Bangladesh will migrate internally over 40 years (2012).

In ABMs, agent decision-making rules are critically important to the overall model behavior. In ABMs of migration, decision-making has varied from simple numerical models, to heuristics, to more complex behavioral theory (Klabunde and Willekens 2016). A recent review of decision-making rules in ABMs of migration highlighted several suggestions for decision rules, including that the rules should be based in decision theory as well as empirical evidence (Klabunde and Willekens 2016). Despite the complexity of the migration decision and the usefulness of ABMs in implementing decision-making processes, relatively few ABMs of environmental migration include behaviorally or psychologically realistic decision-making rules (Thober et al. 2018). Additionally, few ABMs of environmental migration include social networks. Previous research has established that social networks are important for migration-related decisions (Black et al. 2011c; Hunter et al. 2015). Social networks, especially connections with current or previous migrants can increase the propensity of an individual to migrate by demonstrating feasibility, reducing risks, and increasing benefits of a move (Till et al., 2018). Such dynamics can help to explain chain migration, or movement in which migrants learn about opportunities through social relationships with previous migrants.

Due to the complexity of human migration and the strengths of ABM in studying complex systems, this work primarily utilizes an agent-based approach to study environmental migration in coastal southwestern Bangladesh. Chapters 2 through 4 focus on the development of an original ABM for exploring environmental migration and livelihood dynamics. The development and calibration of this model use a pattern-oriented approach to reproduce previously identified patterns of migration from the empirical literature (Grimm et al. 1996, 2005a). In contrast, Chapter 5 uses output data from several global circulation models (GCMs) of the climate system to look forward into Bangladesh's future and begin to consider how climate change, especially increasing levels of extreme heat, may impact human health and productivity in the region.

1.4 Structure of Dissertation

This dissertation is divided into the following chapters and corresponding research questions:

- **Chapter 1- Introduction**
- **Chapter 2- Reproducing patterns of migration with an economic ABM**
    - Can a simple economic model reproduce identified patterns of environmental migration in Bangladesh?
    - What combinations of community characteristics and livelihood choices in the ABM replicate these observed patterns?
- **Chapter 3- Identifying behavioral dimensions of migration with decision theory**
    - How do different decision frameworks change migration dynamics and sensitivities under environmental stress?
    - What parameters in the behavioral models have significant impacts on migration dynamics?
- **Chapter 4- Exploring network effects on migration**
    - How do flows of information across social networks affect patterns of migration?
    - How do network structure and size impact migration outcomes?
- **Chapter 5- Projections of future extreme heat in Bangladesh**
    - How is wet-bulb temperature in Bangladesh predicted to change under various climate change scenarios?
    - How many dangerous heat days can be expected in Bangladesh by the year 2100?
- **Chapter 6- Conclusions and future work**

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CHAPTER 2

Modeling multi-level patterns of environmental migration in Bangladesh: An agent-based approach

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Abstract

Environmental change interacts with population migration in complex ways that depend on interactions between impacts on individual households and on communities. These coupled individual-collective dynamics make agent-based simulations useful for studying environmental migration. I present an original agent-based model that simulates environment-migration dynamics in terms of the impacts of natural hazards on labor markets in rural communities, with households deciding whether to migrate based on maximizing their expected income. I use a pattern-oriented approach that seeks to reproduce observed patterns of environmentally-driven migration in Bangladesh. The model is parameterized with empirical data and unknown parameters are calibrated to reproduce the observed patterns. This model can reproduce these patterns when the distribution of land ownership is parameterized with a Lomax distribution and high levels of inequality. Future work will compare income-maximizing decisions to psychologically complex decision heuristics that include non-economic considerations.

2.1 Introduction

Understanding how environmental and climatic stress impact human mobility is important for improving fundamental knowledge of coupled human and natural systems, and for applying that knowledge to planning regarding adaptation to climatic change. Human migration is complex, and environmental stress may influence migration decisions in many ways. This complexity has produced a range of approaches to modeling environment-migration interactions, with many unresolved questions about which approach is best (McLeman 2013; Neumann and Hilderink 2015; Piguet 2010).

Agent-based models (ABMs) are an especially promising approach to studying environmental migration. ABMs are particularly powerful in representing dynamics between individual-scale and collective or community-scale phenomena, and to incorporate psychological and sociologically complex decision processes (Thober et al. 2018; An 2012; Klabunde and Willekens 2016). However, only a limited number of agent-based models have been used to study environmental migration (Thober et al. 2018).

Bangladesh presents an ideal location for studying environment-migration dynamics. It is considered one of the most climate vulnerable countries in the world, as well as a location with a naturally dynamic environment and complex history of migration (Amrith 2013). Previous work based on longitudinal migration histories of rural households in Bangladesh found that drought-induced crop loss had a strong effect on internal migration, whereas flooding did not, thus demonstrating the importance of economic disruptions for migration in the region (Gray and Mueller 2012). As a response to environmentally-induced livelihood disruption, Gray and Mueller (2012) observed that as the fraction of the community affected by an environmental event increased, rates of out-migration dropped at first, and then rose after the fraction impacted crossed a threshold. They also found that individual households directly impacted by an environmental shock were less likely to migrate than other households within an affected community.

Here, I present an original ABM of internal environmental migration from rural villages in Bangladesh in which agents make decisions to maximize their household's expected utility in the form of annual income. This work investigates whether an agent-based simulation of local labor markets can reproduce the two key patterns of environmental migration observed by Gray and Mueller (2012) in Bangladesh. The model allows both community-level and household-level dynamics to influence livelihood and migration decisions. This model also serves as a starting point for future investigations into interactions among environmental, social, and behavioral influences on migration.

2.2 Background

2.2.1 Agent-based Modeling to Study Environmental Migration

The impacts of environmental factors on population mobility are complex, and may be confounded or mitigated by economic, political, social, and cultural factors (Obokata et al. 2014; Black et al. 2011; Hunter 2005). Agent-based modeling is well-suited to analyze the interactions between environmental change and migration because of their ability to incorporate nonlinear interactions among individuals and investigate the dynamics by which large-scale collective phenomena emerge from individual actions (Thober et al. 2018). DeAngelis and Diaz (2019) emphasize that ABMs are powerful tools because they can describe decision making and the impacts of decisions in great detail. However, Thober et al. (2018) find that few existing ABMs of environmental migration fully integrate the social and ecological systems.

Pattern-oriented modeling offers a valuable methodological framework for assessing ABMs in terms of their ability to simultaneously reproduce multiple patterns observed in a complex system (Grimm et al. 2005). Pattern-oriented modeling is especially useful when the system exhibits multiple patterns at different scales. Pattern-oriented modeling offers a systematic approach to selecting models and parameterizations and provides clear and useful criteria for testing and validating models (Grimm et al. 1996). I followed a pattern-oriented approach in this work because of the complexity of human migration and the availability of well-known patterns against which to test my model (Gray and Mueller 2012).

Agent-based modeling had not been widely applied to environmental migration in Bangladesh, though two noteworthy examples were identified (Hassani-Mahmooei and Parris 2012; Bell et al. 2021). Hassani-Mahmooei and Parris (2012) developed an agent-based model to simulate migration decisions between districts based on 10 heuristics as well as “push”, “pull”, and “intervening” factors related to climate change scenarios, socioeconomic conditions, and employment. Hassani-Mahmooei and Parris (2012) use the model to predict that between 3 and 10 million people in Bangladesh will migrate internally over 40 years, especially from coastal areas. Bell et al. developed an ABM of household-level migration within Bangladesh, also using a range of “push”, “pull”, and “mooring” factors, though with more complex decision-making by also incorporating individual perceptions and place-attachment (Bell et al. 2021; Bell et al. 2019). They applied this model to migration responses to different scenarios of sea level rise to show that sea level rise is not likely to result in migration away from coasts (Bell et al. 2021). The stark differences in the findings between these two works highlight the existing need to refine ABMs of environmental migration in the region, as well as the importance of selecting the correct decision-making method.

2.2.2 Study Area

Bangladesh is a flat low-lying country located in the Ganges-Brahmaputra-Meghna Delta along the coast of the Bay of Bengal, with a strong monsoon climate. Due to its unique location and geological setting, Bangladesh faces many environmental vulnerabilities including seasonal flooding, frequent exposure to tropical cyclones, vulnerability to sea level rise, and rapid land erosion and accretion (Call et al. 2017; Dewan et al. 2007; Dewan and Yamaguchi 2009; Hallegatte 2012; Higgins et al. 2014; Islam and Sado 2000; McGranahan et al. 2007; Auerbach et al. 2015). Further complicating environmental vulnerability, Bangladesh is also one of the most densely populated countries in the world, with more than 160 million individuals living within an area of just under 150,000 km2 (World Bank 2021). At the same time, most people living in Bangladesh are highly dependent on their natural environment for livelihood opportunities, especially in agriculture and aquaculture (Tessler et al. 2015).

Migration is a common and long-standing strategy in Bangladesh for adapting to challenging environmental and social conditions (Alam et al. 2017; Amrith 2013; Black et al. 2005; Martin et al. 2014). As such, environmentally induced migration has also been widely studied in Bangladesh (Ahsan et al. 2011; Call et al. 2017; Chen and Mueller 2018; Donato et al. 2016; Gray and Mueller 2012, 20; Islam 2017; Joarder and Miller 2013). Regular seasonal migration, both rural-rural and rural-urban, plays an important role in the Bangladeshi economy (Mobarak and Reimão 2020; Lagakos et al. 2018; Akram et al. 2018), but migration in response to acute stress, such as natural disasters, has very different characteristics: it is predominantly rural to urban and of indeterminate duration (Mallick and Vogt 2014; Islam and Mehedi 2016; Kartiki 2011). There is little agreement in the literature as to how environmental changes influence migration patterns, and results vary widely based on specific location, methodology, and type of environmental impact studied.

2.2.3 Patterns of Migration

I use a pattern-oriented approach to developing and validating my ABM. Gray and Mueller (2012) identified two distinct patterns of internal long-distance migration from rural Bangladeshi villages in response to drought-induced crop failure:

- Pattern 1: As the proportion of a community impacted by environmental shock increases, rates of migration initially decrease below the baseline levels, but then increase, especially above a threshold where approximately 20% of the community is impacted. This shows that individual migration decisions are strongly influenced in a non-linear manner by community-level impacts.
- Pattern 2: Households that are directly impacted by environmental shock are less likely to migrate. Migration is costly and affected households may wish to migrate but lack the means to do so.

These patterns serve as the key patterns that this ABM aims to reproduce at the community level (Pattern 1) and the household level (Pattern 2). Both patterns demonstrate that household migration decisions are strongly influenced in a non-linear manner by community-level phenomena. Gray and Mueller speculate that these effects may be due to the economic effects of environmental shocks on communal risk-sharing and local labor markets. Related research in four African countries also finds that environmental impacts on labor markets play a central role in migration (Mueller et al. 2020). My model seeks to test this hypothesis as an explanation for the patterns in the context of purely economic decision heuristics.

2.3 Methods

2.3.1 Model Structure and Entities

My ABM simulates household decisions whether to migrate under environmental stress. I use the model to study relationships between environmental stress and changing livelihood opportunities with regard to their impact on mobility patterns. A complete description of the model based on the ODD protocol (Grimm et al. 2006; Grimm et al. 2010) and model code are available online (Best 2021), and the ODD protocol is available in the **Appendix**. The model is implemented in Python and can be run on an ordinary computer. The model has no explicit spatial character. Each time step represents one year. A single model run of 20 time steps takes a few seconds.

While the model is not explicitly spatial in nature, the virtual environment consists of entities across scales of social engagement. Different categories of entities represent *individuals, households,* and the overall *community*, and each category has its own attributes and behaviors. Individuals are primarily defined by attributes of gender, age, employment at each step of the model, wages, and status as a migrant or not. Each individual is assigned to a household, which is specified by the individuals it contains, land owned, and total wealth. Each household entity also has a defined head of household. The household head is defined as either the oldest adult male individual within the household or, if no male members are present, the oldest adult female member. As the primary economic and decision-making unit within the model, households also keep track of wealth at each step of the model. Households who own land may also hire individuals from other households and keep track of their employees, payments, and expenses. In this way, the economic accounting of the model takes place at the household level. At the next level up in scale, each household belongs to a stylized origin community. The community contains a certain amount of total land distributed across the households, as well as livelihood opportunities in agriculture and both skilled and un-skilled non-agricultural employment options. The community of the model is also the level at which environmental shocks may occur within the environment. At each time step, an "environmental shock" may occur stochastically. If an environmental shock occurs, a specified fraction of the households within the community will be impacted randomly, resulting in loss of agriculture and agricultural wealth. **Figure 2.1** shows a schematic of the model's entities and their relationships.

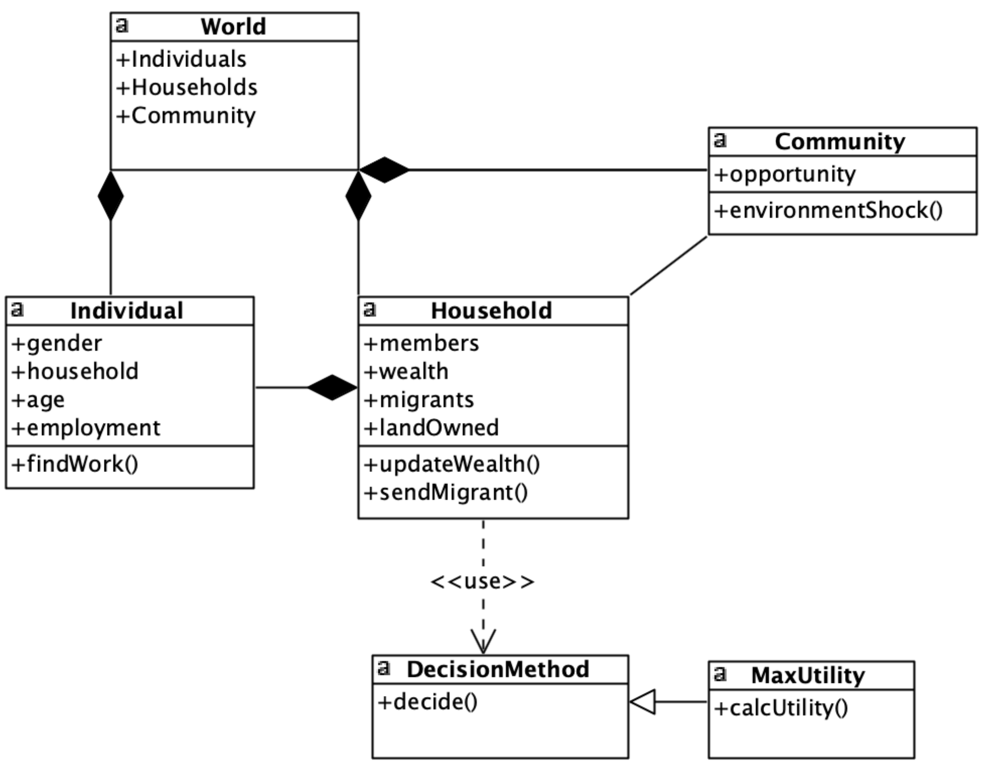

Figure 2.1: Class diagram of model entities with primary variables and operations.

In addition to entities, the model has a series of global variables including:

- *Migration utility* – The annual utility of a household sending a migrant in Bangladeshi taka (BDT)
- *Cost of migration* – The cost of sending a migrant (in BDT)
- *Number of households*
- *Number of individuals*
- *Number of steps to run the model*
- *Wealth factor* – The mean wealth of households. Household wealth is initialized from a normal distribution with this factor as the mean.
- *Shock probability* – The probability of an environmental shock in a time step.
- *Shock severity* – Either a number between 0 and 1 or a probability distribution on the domain [0,1]. When a shock strikes a community, this determines the fraction of households that are affected.

Empirical data from the southwestern coastal region of Bangladesh was used to parameterize the ABM (Carrico and Donato 2019; Adams et al. 2016). For each parameter, the available dataset was used to fit a distribution or obtain estimates of the parameter in the case of salaries and expenditures (**Table 2.1**).

Table 2.1: Data sources and distributions for model parameterization

Model parameter	Distribution	Source
Wealth distribution	Normal	Adams et al. 2016
Household size distribution	Poisson	Carrico and Donato 2019
Land owned distribution	Lognormal	Carrico and Donato 2019
Age distribution	Weibull	Carrico and Donato 2019
Wage and expenditure estimates	NA	Adams et al. 2016

2.3.2 Process and Scheduling

Each simulation begins by creating and initializing individuals, households, and a community. The number of individuals and households remain fixed throughout the model run. Individuals are assigned to a household, and a head-of-household is selected from the adult members. At the beginning of every time step, which represents one year of time, the community faces a stochastic risk of experiencing an environmental shock based on a pre-defined probability. In this case, the annual probability of an environmental shock is set to 0.2. If the environmental shock takes place, a specified fraction of households in the community (initialized at the onset of a model run as the community impact factor) will be directly impacted, resulting in loss of agricultural yields and wealth gained on any land owned.

Next, individuals who are eligible to migrate (males over the age of 14) assess their employment opportunities within the community. Individuals in households that own large amounts of land may work in agriculture on their own land. Individuals in households without sufficient land or that have lost crops to environmental shocks may seek agricultural employment. Households with sufficient land and wealth, which have not lost crops to shocks may seek to hire laborers. In this case, households that are looking to hire agricultural labor may enter an internal labor market. Individuals who are looking for employment may also enter this labor market and attempt to be "hired" by a searching household. The labor market uses a simultaneous double auction approach to match joke seekers with possible employers based on what salary individuals are willing to accept and what households are willing to pay. Individuals who are unable to obtain agricultural employment may seek other employment within the community. A specified number of jobs are classified as "skilled" and pay more than unskilled non-agricultural jobs. At the end of the double auction, some individuals may be left without employment in either agriculture or non-agriculture.

Once all individuals have found or attempted to find employment, each household conducts a calculation of its expected wealth, based on all individuals' expected salaries from their employment. After the household aggregates the total utility of its members, it then decides as a household whether to send a migrant to seek employment outside the community. The model does not account for different possible destinations but treats migration generically as an economic opportunity outside the community. Each household has a DecisionMethod object (**Figure 2.1**), which provides a function that implements the decision. In my initial implementation described in this chapter, all households decide to migrate by maximizing their expected utility, but the model allows for alternate decision heuristics, which can vary from household to household.

If a household elects to send a migrant, then that individual no longer participates in the community but contributes to the household's wealth by sending remittances from his destination at each future time-step. Each household then updates its wealth, each individual ages by one year, and the time-step ends. The wealth at the end of time-step, *t*, is the wealth at the previous time-step, *t-1*, plus the wages of all employed members, plus any income from land that is not affected by environmental shocks, minus any expenses and payments to employees:

$$\text{Wealth}_t = \text{Wealth}_{t-1} + \sum_{i=1}^{\text{individuals}} (\text{Wages}_{i,t}) + \text{LandProductivity}_t - \text{Expenses}_t - \sum_{e=1}^{\text{employees}} \text{Payment}_{e,t}$$

(Eqn. 2.1)

Figure 2.2 shows an overview of the model scheduling for each step. This process repeats for a specified number of steps (years).

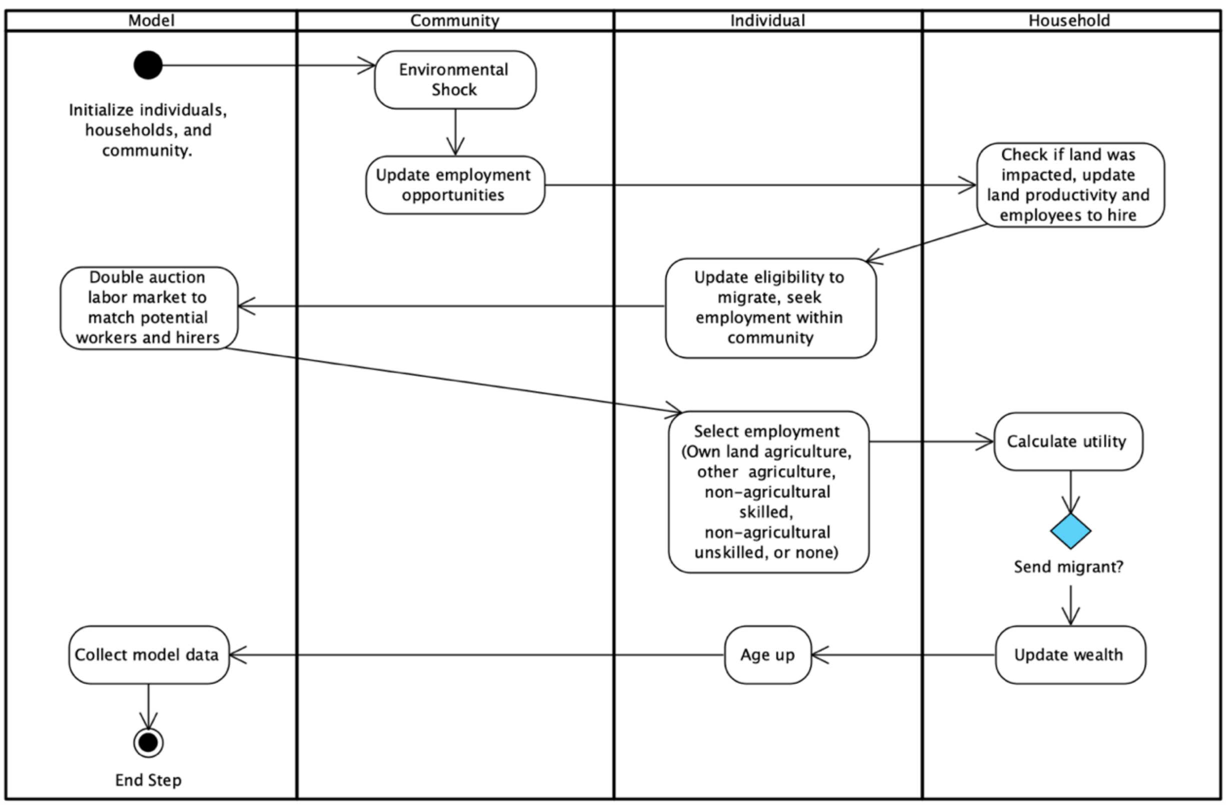

Figure 2.2: Scheduling of each step of the model for community, individual, and household entities.

2.3.3 Migration Decision

Agent decision rules are critically important to ABMs. Decision rules in ABMs of migration have varied from minimalist processes, such as random Bernoulli processes, to simple expected utility maximization, to heuristics with intermediate complexity, to representations of more complex strategic and behavioral theories (Klabunde and Willekens 2016; Thober et al. 2018). In my initial model presented here, households make migration decisions to maximize expected annual income. When the method of decision-making in the ABM is “utility”, then a simple utility maximization approach is used. The premise behind this economic approach is that a household will decide to send a migrant if the decision is economically beneficial. A purely economic model provides one plausible explanation for the observed migration patterns and serves as a baseline for assessing whether a simple economic decision heuristic can reproduce those patterns. I have designed the model to serve as a testbed for comparing different decision heuristics in future research.

At the point of decision-making, each household randomly selects an eligible migrant from its members. Eligible migrants are any male individual over the age of 14. The household then assesses whether that individual’s migration would result in a greater income, compared to the individual’s potential employment within the community. At this stage of the model, the migration decision is a simple binary. The household will elect to send a migrant if it is economically beneficial for the household as a whole (meaning that the benefit of migrating is greater than the individual’s salary within the community). If the migration will increase household economic utility (expected wealth) and the household has sufficient funds to meet the cost of sending a migrant, then that individual with successfully “migrate” from the origin community. After a successful migration decision, a household subtracts the cost of migration from its wealth, and the "migrant" individual agent will only contribute to the model by contributing its income representing remittances at each subsequent step.

2.4 Results

2.4.1 Calibration of Uncertain Parameters

I was unable to find sufficient data for estimates of the cost of migration and the migration utility parameters in the model, both of which are critically important for the migration decision. To calibrate these parameters, I used a pattern-oriented approach to calibration (Grimm et al. 1996; Grimm et al. 2005). I begin by using a Latin hypercube sampling approach, which efficiently samples a parameter space while ensuring that all portions of the space are sampled, to select 100 unique parameter combinations of cost of migration and migration utility across the uncertain parameter space (Stein 1987; Loh 1996; Mckay et al. 2000). I then conduct simulations with the ABM using each of these sampled combinations of parameters. Each unique parameter combination is run with the ABM 100 times across a range of community impact factors from 0 to 1 (0, 0.05, 0.1, 0.2, 0.4, 0.6, 0.8, and 1). Each simulation uses 20 steps (representing 20 years of time) in a simulated community of 700 individuals and 100 households. I can therefore compare the output of the model run with each combination of parameters to my definitions of the community pattern and household pattern. The criteria for matching the community pattern are that the minimum average number of migrations occurs above a community impact of 0 while the maximum average number of migrations occurs above the community impact level at which the minimum number of migrations occurs. This operationalization therefore captures the initial decline followed by increase in migrations as the level of community impacted by the environmental shock increases. The criterion for matching Pattern 2 is that non-migratory households are directly affected by more environmental shocks than migratory households.

Whether or not the parameter combination successfully reproduces both patterns simultaneously is then translating into a binary variable (0 or 1) of "success". Therefore, I can construct a dataset for further analysis that includes each parameter combination and a measure of successful pattern reproduction. I then identified regions of parameter space in which the patterns were satisfied by fitting support vector regression models (SVM) with radial kernels to the data using the Latin Hypercube samples of the migration utility and the cost of migration parameters as inputs and the binary indicator of successfully reproducing the pattern as the outcome variable (for Pattern 1 and Pattern 2). These SVM models predict the success of pattern reproduction across the whole parameter space (**Figure 2.3a,b**). I was then able to identify where these parameter spaces overlap, representing the area that I would expect to successfully reproduce both patterns (**Figure 2.3c**). Overall, 18% of the parameter combinations reproduced Pattern 1, while 27% reproduced Pattern 2. The difficulty of matching both patterns simultaneously is due both to the greater difficulty of matching Pattern 1 and to the lack of overlap between the regions of parameter space that are favorable to Pattern 1 and those favorable to Pattern 2.

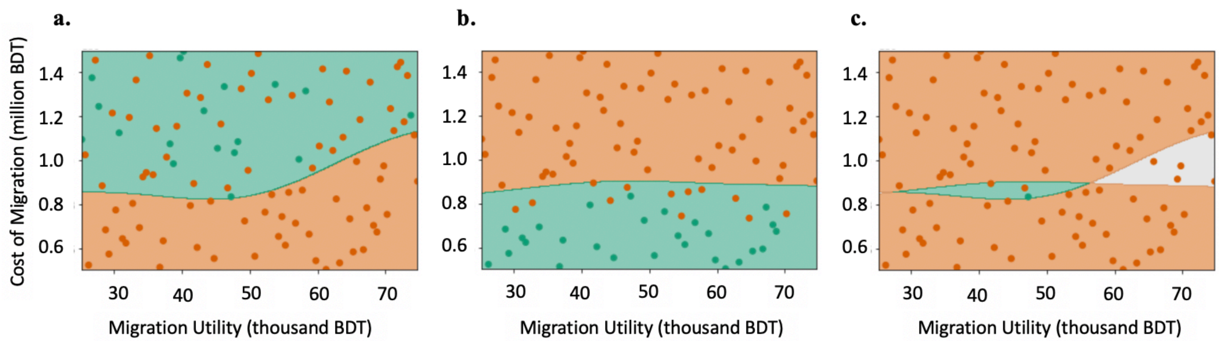

Figure 2.3: Parameter combinations of migration utility and migration threshold and SVM predicted successes of the parameter space for Pattern 1 (a), and Pattern 2 (b). Overlap between the predicted spaces (a) and (b) is plotted with the successes of simultaneously reproducing both patterns (c). Points show parameter combinations sampled in the numerical experiments with green points indicating successful pattern replications and orange points indicating failed pattern replications. Colors show SVM predictions where green represents predicted success and orange represents failure. The unshaded region of (c) represents a region in which neither pattern was replicated.

2.4.2 Pattern Replication

I then ran the model 960 times using a combination of parameter values from the overlapping space for both patterns for which both patterns are predicted to be reproduced well (**Figure 2.3c**), in order to study the model output in greater detail. I used a migration cost of 835,000 BDT (approximately 9,800 USD) and a migration utility of 47,250 BDT (approximately 560 USD), which successfully reproduced both patterns in calibration. I ran 120 batches of simulations, where each batch ran the at varying levels of community environmental impact between 0 (no impact) and 1 (the entire community is impacted). Of these 120 batches, I aggregate the results to assess the patterns.

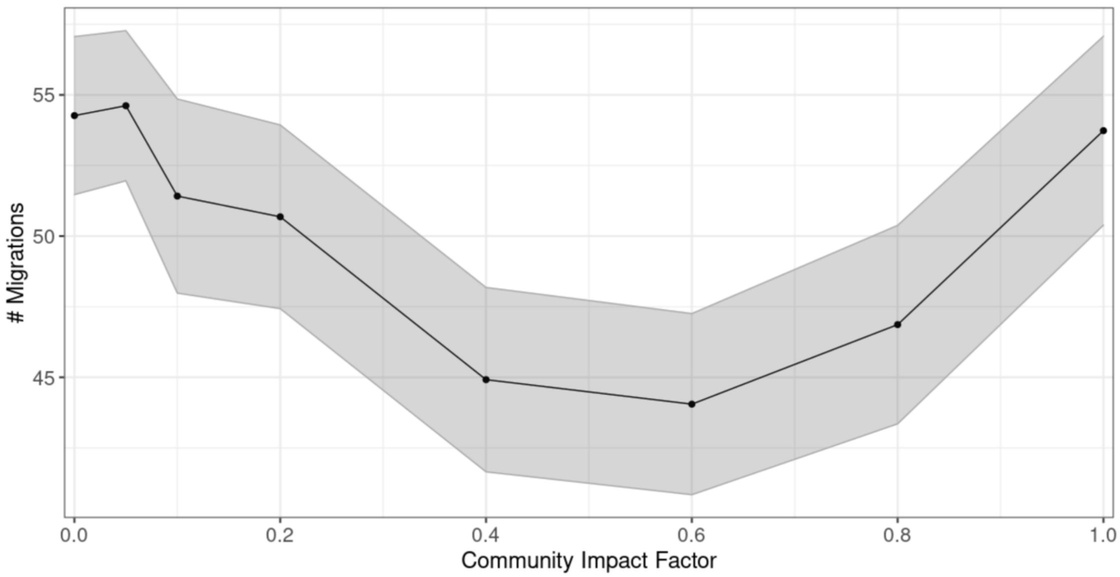

Figure 2.4: Model results of number of migrations in the community by varying levels of community impact. The black lines represent the mean of 120 model runs for each community impact factor, and the gray band represents the 95% confidence interval for the mean.

Figure 2.4 shows the average number of migrations within the community for different levels of community impact. The nonlinear dimension of Pattern 1 is apparent, with a decline in migration occurring as community impact factor increases, followed by an increase in migration after an impact factor of 0.6, consistent with my operationalization of Pattern 1 (**Figure 2.4**). The threshold effect is apparent, though it occurs at higher levels of community impact than predicted.

To explore Pattern 2, I compared households that had migrated during the model run with those that had not and counted how many times each household was directly impacted by an environmental shock (**Figure 2.5**). Here, I observed Pattern 2 at levels of community impact above 0.4. For a community impact factor of 1.0, there are no unaffected households, so I cannot test for Pattern 2. When aggregated across all runs and levels of community impact, Pattern 2 is confirmed: migratory households are impacted an average of 1.41 times with a standard error of

0.012, while nonmigratory households are impacted an average of 1.60 times with a standard error of 0.007, and a chi-squared test finds the difference significant with $p < 0.0005$.

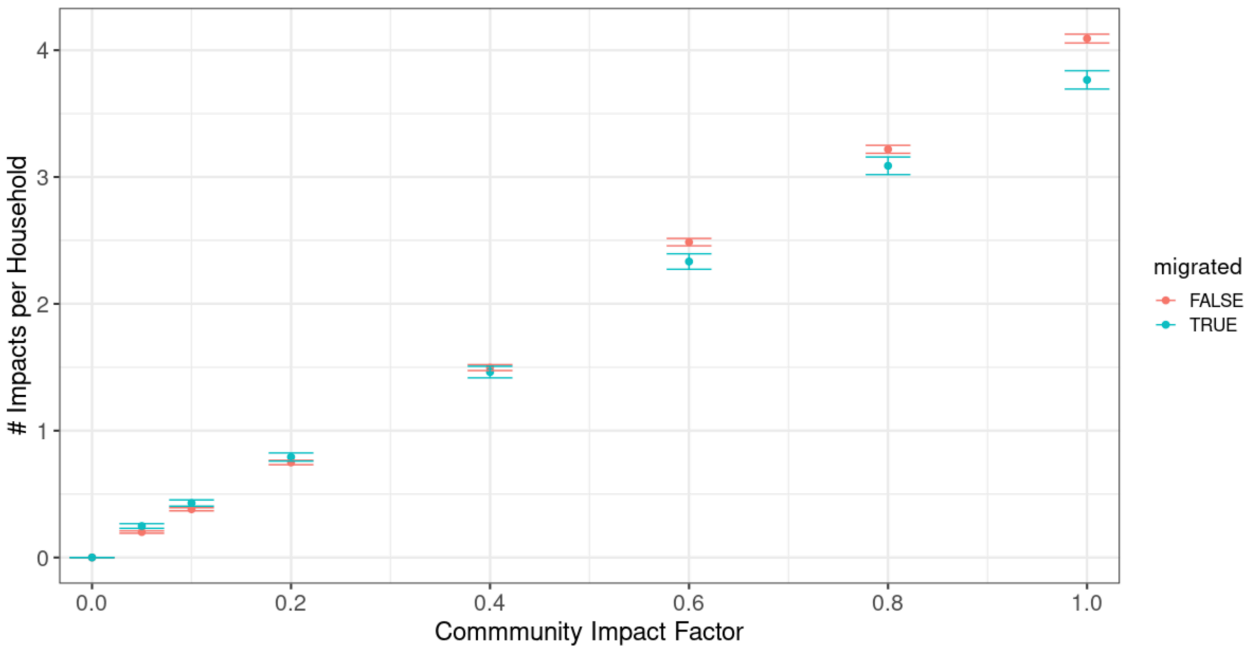

Figure 2.5: Households are divided into those that have migrated (1, blue) and those that have not (0, red). The mean number of times a household was impacted directly by an environmental shock across all 120 trials is plotted with error bars indicating 95% confidence intervals of the mean. For community impact factors above 0.4, Pattern 2 is reproduced: non-migratory households were impacted by more environmental shocks than migratory households were.

These runs confirmed that both patterns were reproduced, but only some aspects of Pattern 1 were reproduced. Some of the variation can be attributed to the inherent stochasticity in the model at initialization, in the timing of environmental shocks, and in determining which households are impacted. This also reflects the inconsistency in reproducing Pattern 1 and the narrow range of parameter space in which both patterns could be reproduced simultaneously.

2.4.3 Exploration of Land Distribution

Upon learning that the model was not reliably reproducing my patterns of interest, I elected to run the model with a different distribution of land ownership within the modeled community. For this version of the model, the distribution of land ownership was parameterized as a Lomax distribution rather than lognormal, as a Lomax distribution fits the survey data well and has been demonstrated as a useful distribution for describing wealth (Lorenz 1905). The single parameter (α) (NumPy 2021) for defining the Lomax distribution of land ownership was taken based on a Gini coefficient calculated from previous survey data from southwestern Bangladesh (Carrico and Donato 2019) where

$$\alpha = \frac{1}{2}\left(\frac{1+Gini}{Gini}\right) \qquad \text{(Eqn. 2.2).}$$

The empirically observed Gini coefficient of land ownership was found to be 0.55. For reference, the national-level Gini index for Bangladeshi income is 0.32, indicating that communities in the study area experience far more unequal distribution of land ownership than income distribution in the country as a whole (The World Bank 2022). In addition to changing the land distribution, I decreased the number of agricultural jobs within the community by a factor of 5 from previous model results. In this updated distribution of land ownership and agricultural job availability, only those households with a higher amount of land owned may elect to hire workers, thus limiting the livelihood opportunities that individuals may seek in the model community.

To assess the community pattern of interest for this version of the model with the updated land distribution, I again visualize the results of total migrations at varying levels of community impact factor (**Figure 2.6**). These results include all 150 sampled combinations of uncertain parameters, each run 100 times at every level of community impact factor. 95% confidence intervals around the mean of all 15,000 model runs are shown in gray. I also see that Pattern 2 is clearly reproduced at community impact factors about 0.4 (**Figure 2.7**).

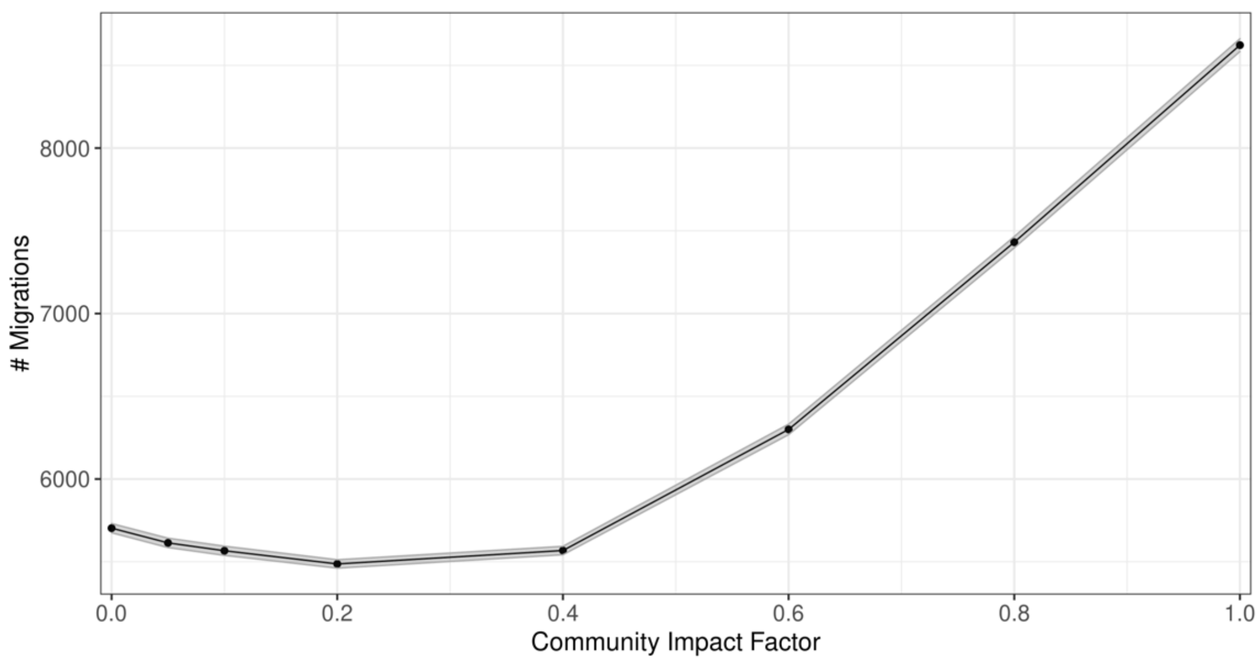

Figure 2.6: Model results based on number of migrations in the community by varying levels of community impact with a Lomax distribution of land ownership. The black lines represent the mean of 150 model runs for each community impact factor and sampled combination of migration utility and cost. The gray band represents the 95% confidence interval for the mean.

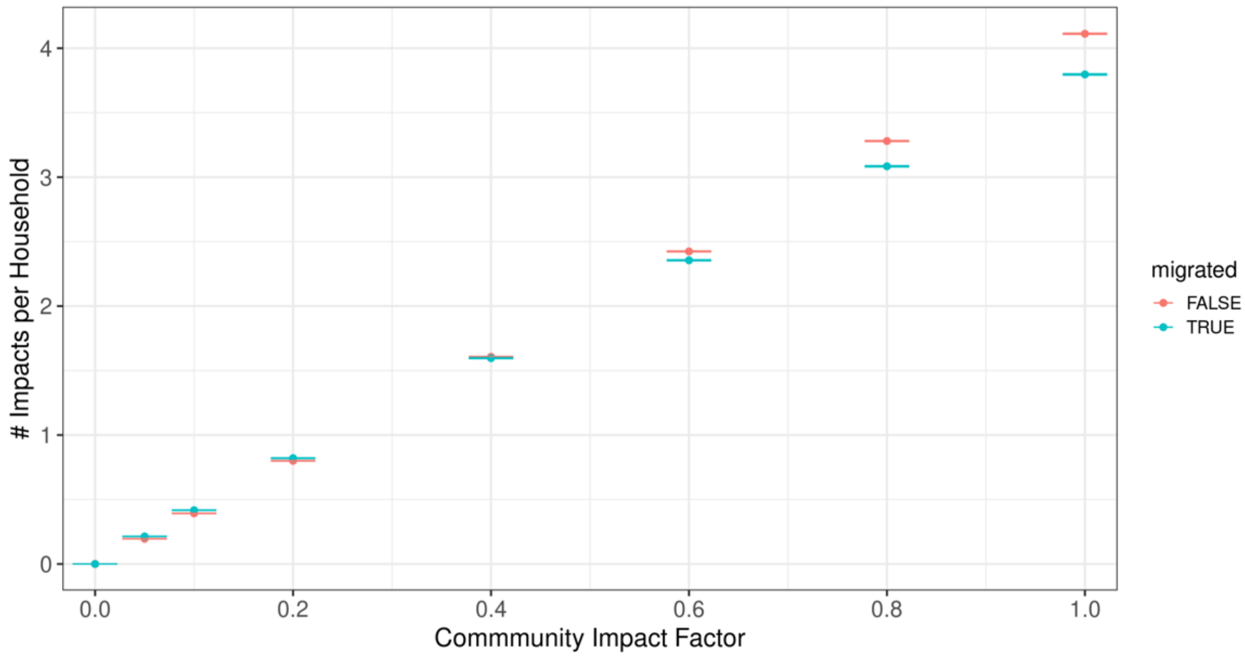

Figure 2.7: For utility maximization results, households are divided into those that have migrated (1, blue) and those that have not (0, red). The mean number of times a household was impacted directly by an environmental shock across all trials is plotted with error bars indicating 95% confidence intervals of the mean. For community impact factors above 0.4, Pattern 2 is reproduced: non-migratory households were impacted by more environmental shocks than migratory households were.

Again, cost of migration and utility of migration (both in BDT) are uncertain parameters that require calibration. For utility maximization with a Gini coefficient of 0.55, 80% of the 150 parameter combinations were able to successfully reproduce the patterns of interest. Results of the SVM predicted parameter space are shown in **Figure 2.8**. These results highlight that the model is now largely insensitive to the cost of migration, while the migration utility is successfully able to reliably reproduce the patterns of interest only below approximately 50,000 BDT (**Figure 2.8**). This suggests that, when land ownership in the modeled community is initialized with an appropriate distribution the utility maximization does very well at reproducing the patterns of interest across a broad range of parameter values. It is worth noting that these costs of migration are very high. One possible explanation is that the cost of migrating may incorporate financial cost as well as psychological costs of migration such as leaving one's home and family.

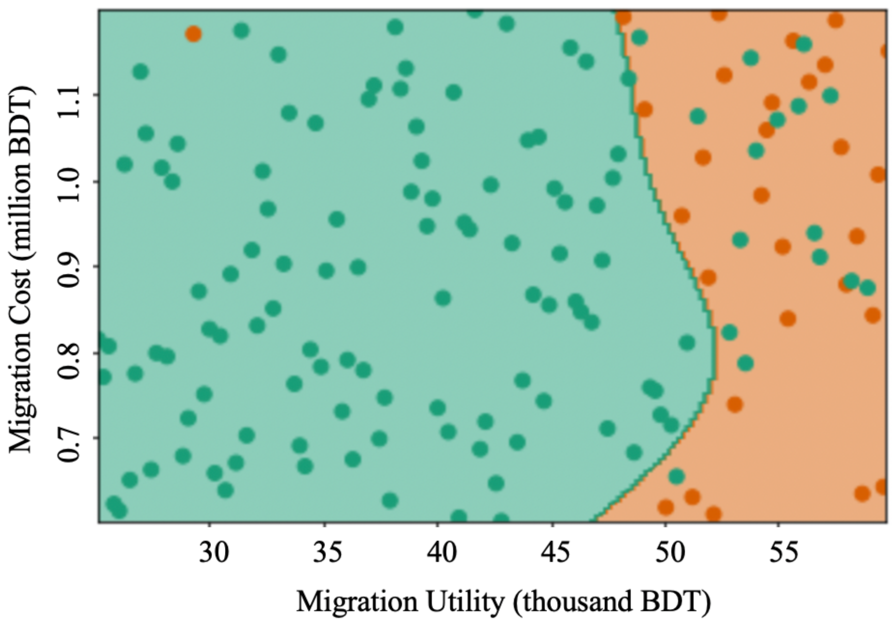

Figure 2.8: Parameter combinations of migration utility and migration threshold with a utility maximization decision method and SVM predicted successes of the parameter space for both patterns of interest. Points show parameter combinations sampled in the numerical experiments with green points indicating successful pattern replications and orange points indicating failed pattern replications. Colors show SVM predictions where green represents predicted success and orange represents failure.

As a sensitivity on the value of Gini coefficient of land distribution, I repeated the model experiments for a Gini coefficient of 0.25 and 0.75. With the utility maximization method, a Gini coefficient of 0.25, representing less inequality in land distribution, was only able to reproduce the patterns of interest across 40% of the parameter combinations, while a Gini coefficient of 0.75 had an 80% success rate. Furthermore, the shape of migrations across levels of community impact factor is impacted by the Gini coefficient, with model runs with a Gini coefficient of 0.25 no longer showing an initial decline in migrations followed by an increase representative of the non-linear nature of the community pattern (**Figure 2.9**).

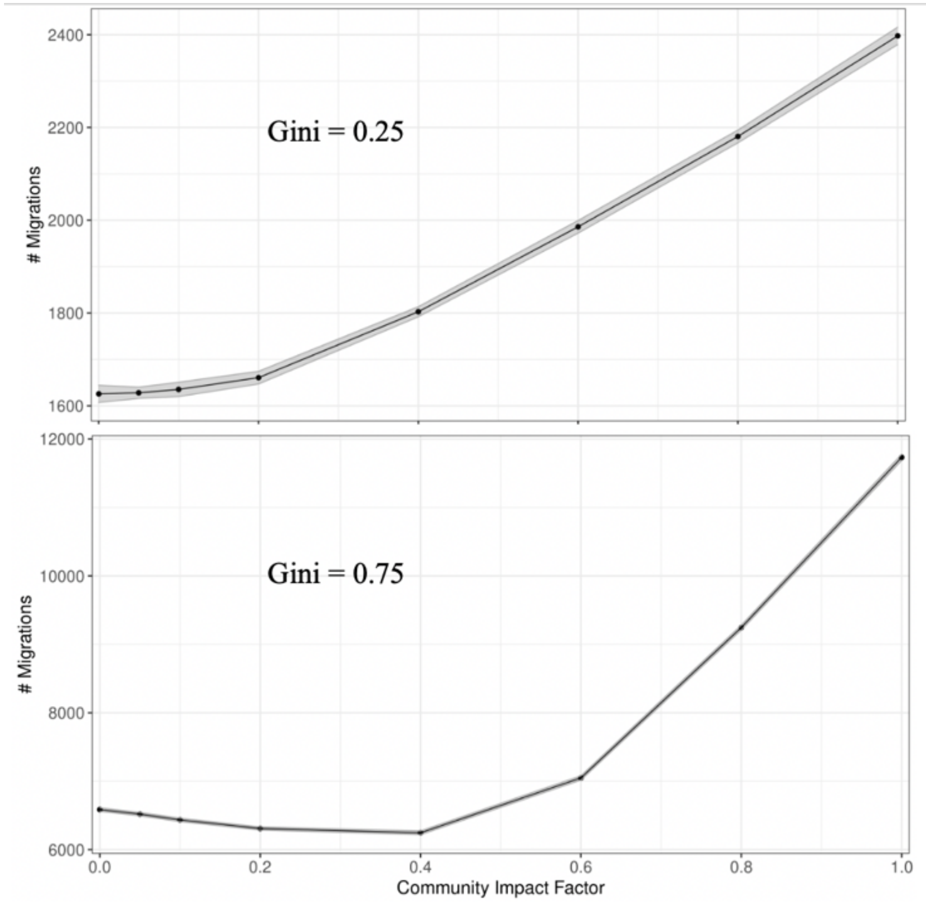

Figure 2.9: Model results based on utility maximization decision method of number of migrations in the community by varying levels of community impact and for a Gini coefficient on land distribution of 0.25 (top) and 0.75 (bottom). The black lines represent the mean of all trials. The gray band represents the 95% confidence interval for the mean.

2.5 Discussion

My model incorporates individual, household, and community-level variables and dynamics in order to simulate environmental migration. The model is parameterized based on available data from Bangladesh (Carrico and Donato 2019; Adams et al. 2016). The uncertain parameters of cost of migration and migration utility (benefit to migrate) are calibrated using a pattern-oriented approach with Latin Hypercube sampling combined with SVM regressions in order to assess the parameter space (**Figure 2.3**). Thus, I demonstrate a novel application of machine learning to model parameterization and calibration.

Results from the initial version of the model using a lognormal distribution of land ownership show that the model is able to reproduce both patterns with varying rates of success. Pattern 2 is reproduced with a high rate of success across the bottom half of the parameter space (**Figure 2.3b**). In contrast, Pattern 1 was only reproduced inconsistently, and primarily in the upper half of the parameter space (**Figure 2.3a**). While the majority of model runs with varying parameter combinations were able to reproduce an increase in migration with increasing scale of environmental impact, the initial decline in migration followed by an increase at an approximately 20% threshold was more difficult to reproduce, which could indicate that the processes that generate the non-linear aspects of Pattern 1 are less fully captured within the current model dynamics. This resulted in a narrow range of parameter combinations that were able to successfully reproduce both patterns simultaneously (**Figure 2.3c**). The high costs of migration that the model predicts may indicate that the patterns are generated when economic opportunities within a community are depleted so much that even high costs to migrate may be worthwhile for households looking for economic opportunity elsewhere.

Despite the lower frequency of success in reproducing the details of Pattern 1, the nonlinear dynamics of the pattern are apparent, even with the lognormal distribution of land (**Figure 2.4**). Pattern 2 is reproduced consistently for aggregated model runs, and when disaggregated by community impact factor, I find that this pattern appears only for community impact factors of 0.4 and above and becomes stronger for larger impact factors (**Figure 2.5**). However, when I change the model so that land ownership is initialized using a Lomax distribution and empirically-derived Gini coefficient, the model performs very well at reproducing the patterns of interest across a wide range of parameter combinations (**Figures 2.6, 2.7, 2.8**). For the community-level pattern of interest, I see that the overall aggregated model runs using the utility maximization method converge narrowly and demonstrate the nonlinear element of this pattern. I also see that, for this method, the threshold of scale of the community impacted by an environmental event above which migrations begin to increase is at approximately 20% (0.2), as expected based on the pattern definition (**Figure 2.6**). The utility maximization method results show that the household-level pattern in which households that are impacted directly by an environmental shock are less likely to migrate, is also reproduced at levels of community impact above 40% (**Figure 2.7**). Overall, 80% of the total 150 unique parameter combinations of migration cost and migration utility were able to successfully reproduce both patterns of interest simultaneously. Evaluation of the parameter space using a radial SVM method shows that this decision-method is insensitive to migration cost in the sampled parameter space and largely insensitive to migration benefit in the parameter space less than approximately 50,000 BDT (**Figure 2.8**).

Interestingly, I also find that the model performance is sensitive to the Gini coefficient used to define the Lomax distribution of land ownership. I see that model performance remains high when higher levels of community inequality (Gini index of 0.75) but declines in successful pattern replication at lower levels of inequality (Gini index of 0.25) (**Figure 2.9**). This non-intuitive finding highlights the importance of land and wealth distribution in the shape of the migration outcomes, where high levels of inequality within the community yield the patterns of interest. These results show that, with the proper land distribution, the utility maximization method reproduced the patterns across the majority (80%) of the parameter space sampled. This suggests that the phenomena that generate the empirical patterns of interest (the underlying processes that produce the patterns of migration found by Gray and Mueller 2012 in rural Bangladesh) are captured in the model structure and utility maximization design. In other words, the patterns are insensitive to the values of uncertain parameters and inseparable from the ABM structure, governed by livelihood choices and an internal labor market.

2.6 Conclusions

I developed an ABM that simulates environmental migration through the impacts of environmental shocks on local labor markets. I used a pattern-oriented approach to calibrating and testing the model based on two patterns of interest in the empirical literature. Pattern 1 captures the dynamics of nonlinear interactions between household and community-level phenomena, with a pronounced threshold of community-impact above which out-migration increases. Pattern 2, in contrast, captures household level dynamics, with households that have not been directly affected by an environmental shock migrating more than households that have been directly affected.

The simple economic model successfully reproduced these patterns with high consistency when the proper land distribution is used. Despite this finding, it is known that decisions to migrate away from one's home village involve far more than economic considerations. There is great hedonic value in connections to one's home community (Mallick and Schanze 2020) and it is also well-known that more generally, considerations such as risk- or loss-aversion and social norms can powerfully influence responses to hazards and opportunities (Beckage et al. 2020; Gilligan 2018; Laciana et al. 2007). Social networks also appear to play important roles in migration decisions (Till et al. 2018; Hunter et al. 2015; Thober et al. 2018). Thus, a purely economic model of decision-making around migration might not be sufficient to reproduce the details of actual human behavior and it is notable that this simple model performs as well as it does. My model does not attempt to capture psychological and sociological aspects of decision-making. In the following chapter, I will investigate more complex decision heuristics.

I designed this model to work as a test bed for comparing different decision be flexible, so new capabilities can be added easily and without disrupting the base structure and scheduling. In addition to incorporating richer decision rules, future work will also investigate the impacts of future scenarios of environmental and climatic change. In the coming decades, growing environmental stress and accelerating change will make it increasingly important to understand how environmental change interacts with population mobility, ABMs have the potential to provide insights into these complex processes.

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CHAPTER 3

Psychological models of decision-making in an agent-based model of environmental migration

Abstract

Environmental migration is an example of a complex coupled human and natural system with dynamics that operate across multiple spatial and temporal scales. Agent-based modeling (ABM) has demonstrated potential for studying such complex systems, especially where individual decision-making is an important component. In this work, I use an original ABM of environmental shocks, livelihood opportunities, and migration decisions to study dynamics of environmental migration in rural Bangladesh. I present results using a behaviorally complex method based on the Theory of Planned Behavior. I hypothesized that a more behaviorally complex decision method which incorporates social networks and community norms would more successfully reproduce the patterns of migration. However, using a pattern-oriented approach to reproduce two key patterns of migration from the empirical literature, I demonstrate that the psychologically motivated decision-making method is less consistently able to reproduce the patterns of interest compared to a simple economic method. Despite this, the level of community inequality in distribution of land ownership remains critically important for patterns of migration outcomes. In this way, my model suggests that community-level inequality has significant implications for migration in the study area.

3.1 Introduction

As climate change and environmental degradation place increased pressure on populations around the world, critical questions remain related to how such environmental stress may influence human migration decisions. Migration is a complex phenomenon influenced by many social, political, and cultural factors in addition to environmental conditions (Hunter 2005; Black et al. 2011b). With this complexity, it is unclear how environmental change interacts with migration and mobility in different contexts (Boas et al. 2019). To study the interactions between environmental change and human migration decisions, environmental migration may be considered as an example of a complexed coupled human and natural system, with aspects that operate across multiple spatial and temporal scales (Liu et al. 2007).

While many studies of environmental migration rely on empirical correlations between environmental or climatic conditions and rates of human migration, agent-based modeling (ABM) has become a potentially useful tool for simulating the dynamics and linkages within a coupled human and natural system that govern environmental migration (Thober et al. 2018). As previously described, ABM is a kind of modeling that simulates dynamics between individual actors (or agents) and their environment (Railsback 2019). A strength of ABMs is their ability to highlight how the combination of individual actions can generate non-intuitive collective behavior at the system level, known as emergence. This makes them a useful tool for studying environmental migration and understanding how large-scale migration outcomes may emerge from individual behaviors (Thober et al. 2018). ABMs also allow for a detailed and deliberate incorporation of decision-making rules into the model (DeAngelis and Diaz 2019).

ABMs of migration and environmental migration use a wide range of decision-making methods from simple probability distributions to complex behavioral models informed by psychology (Klabunde and Willekens 2016). There also exists a tension in modeling of coupled human and natural systems between the idea of "keep it simple stupid" (KISS) and "enhancing the realism of simulation" (EROS) (Jager 2017; Schlüter et al. 2017). It is not always clear, especially when simulating human behavior, how much complexity is needed in a model. Additionally, there are challenges related to operationalizing behavioral theories including uncertainty surrounding how to translate theoretical concepts into code (Ernst 2010; Jager 2017; Muelder and Filatova 2018).

Due to combined environmental and population pressures, Bangladesh is widely considered to be one of the most climate-vulnerable countries in the world. In addition, many citizens of Bangladesh, especially in rural communities, rely on agriculture for livelihood (Ackerly et al. 2015; Tessler et al. 2015). People in Bangladesh are highly mobile, and internal migration, especially seasonally from rural to urban locations for livelihood diversification, is not uncommon (Khandker 2012; Martin et al. 2014; Lu et al. 2016; Alam et al. 2017). In this way, migration can serve as a way for Bangladeshis to adapt to changes in their natural environment as well as seek livelihood opportunities (Black et al. 2005). In this dynamic, complex setting, it is unclear how future climate change and environmental pressure may impact mobility in Bangladesh. The unique combined environmental and human conditions as well as existing patterns of mobility in Bangladesh make it a useful area for studying environmental migration.

In this work, I am interested in studying the dynamics of internal migration from rural communities in Bangladesh impacted by an environmental shock that impacts agricultural livelihoods, such as drought. I present results from my original ABM designed and validated using a pattern-oriented approach, as described in Chapter 2. In this expansion of the model, I present results using a behaviorally complex method of migration decision-making based on the

Theory of Planned Behavior (TPB). I then use machine learning to calibrate and evaluate the effectiveness of each decision-making method in reproducing the patterns used for the pattern-oriented approach. Based on the known complexity of migration decisions, I hypothesize that the decision-making method based on the behavioral psychology TPB will successfully reproduce empirical patterns of environmental migration in rural Bangladesh.

3.2 Background: Decision-Making in ABMs

As mentioned previously, agent-based modeling (ABM) has been demonstrated as a useful tool for studying environmental migration. Simulation models such as ABMs can address gaps in current understanding by explicitly modeling the linkages and feedbacks between the social and environmental systems (Thober et al. 2018). Yet, in ABMs, agent decision-making rules are critically important to the overall model behavior. In ABMs of migration, decision-making has varied from simple numerical models, to heuristics, to more complex behavioral theory (Klabunde and Willekens 2016). A review of decision-making rules in ABMs of migration highlighted several suggestions for decision rules, including that the rules should be based in decision theory as well as empirical evidence (Klabunde and Willekens 2016). Generally, behavioral models of migration posit that a potential migrant will choose to migrate if the move provides an expected benefit such as economic utility or risk reduction and the barriers to migrating are not insurmountably high (Klabunde and Willekens 2016). Within this framework, the decision-making itself may be further complicated by the inclusion of values and norms, network influences, and cognitive processes. This review found that the two most common methods for decision-making within ABMs of migration were utility-based methods and methods based on the Theory of Planned Behavior (TPB) (Klabunde and Willekens 2016). Based on this finding, I elect to implement both methods in my model.

Simpler behavioral models of migration may use a purely economic method of decision-making, such as a utility maximization function. Klabunde and Willekends (2016) refer to these models as "microeconomic expected utility maximization" (2016). They offer an example of a model of migration from East to West Germany based on an expected utility (Heiland 2011). Agents in this simulation make the decision to migrate based on employment opportunities in the destination location. Several other models in Klabunde and Willekens' review (2016) depend on a function to maximize utility in the form of income, social capital, or expected income (Silveira et al. 2006; Biondo et al. 2012).

Klabunde and Willekens also review what they call "psycho-social and cognitive models" of migration decision-making in ABMs, which they use to include models that incorporate theories from social and behavioral psychology (2016). A commonly used example is the Theory of Planned Behavior (TPB). TPB is a popular behavioral theory in which decisions are influenced by agent attitudes towards a behavior, community norms, and agent perceived control over the success of the behavior (Ajzen 1991, 2002). These three aspects are then weighed and integrated to estimate the behavior intention, or likelihood of an agent acting on the behavior. This decision-making theory has been employed by Kniveton et al. in their ABM of migration under drought conditions in Burkina Faso (2011). More recently, TPB, drawing upon Kniveton et al. (2011) was employed in an ABM of migration and changing demographics in the Maldives (Speelman et al. 2021). This theory is of interest because it incorporates multiple levels of influence on the agent decision, including community dynamics and individual perceptions.

It is often unclear what level of behavioral complexity is necessary in ABMs of environmental migration, though the methods used can be critical for model output and insights gained from the model. In the literature, there exists a tension between those who argue for the simplest methods possible (“keep it simple stupid”) and those who argue that models of human behavior must include as much cognitive complexity as possible to more fully capture necessary dynamics (“enhancing the realism of simulation”) (Jager 2017). Ultimately, such decisions and assumptions are determined by the modeler, and the appropriate level of behavioral complexity likely depends on the specific modeling objective.

Beyond the model presented here and in previous work, there are two known examples of agent-based models to study environmental migration in Bangladesh. The models use very different decision-making methods, with Hassani-Mahmooei and Parris (2012) using decision heuristics to determine migration based on previous studies and survey results (Hassani-Mahmooei and Parris 2012). In the second ABM in this context, Bell et al. use more complex decision-making that includes individual consideration of place-attachment and environmental risk perceptions (Bell et al. 2021). Further highlighting the importance of decision-making assumptions in these ABMs, these two models come to almost opposite conclusions, with Hassani-Mahmooei and Parris predicting significant future migration away from coastal regions of Bangladesh, and Bell et al. projecting in-migration towards coastal areas even under future sea-level rise scenarios.

3.3 Methods

3.3.1 Model Structure and Scheduling

My ABM, which was first presented in Chapter 2 of this dissertation, uses a multi-scalar approach to simulating environmental migration by incorporating agents with characteristics and decision-making at the individual, household, and community level within a stylized origin community. Expanding the model from Chapter 2, I incorporate an additional decision-making method based on TPB (**Figure 3.1**). Global-level variables incorporated since the previous version of the model (Best et al. 2021) and expanding from Chapter 2 include:

- *Decision* – Specified method for migration decision-making. Possible values include "utility" for utility maximization, "TPB" for Theory of Planned Behavior, and others.
- *Network type* – Type of network structure for social networks within the community. Possible values include "preferential", "random", "small-world", "fully-connected", and "none". At this stage, the network type is set to "small-world".
- *Network size* – The average number of other households that each household is connected to within the social network. At this stage, the network size is set to 15.

As with the previous version of the model, each model simulation is started by initializing the population of individuals, households, and the community. In this version of the model, at the point of the migration decision, the household then the specified decision-making method to decide whether to send an individual as a migrant. Each household has a *DecisionMethod* object (**Figure 3.1**), which provides a function that implements the decision based on either a utility maximization approach or TPB.

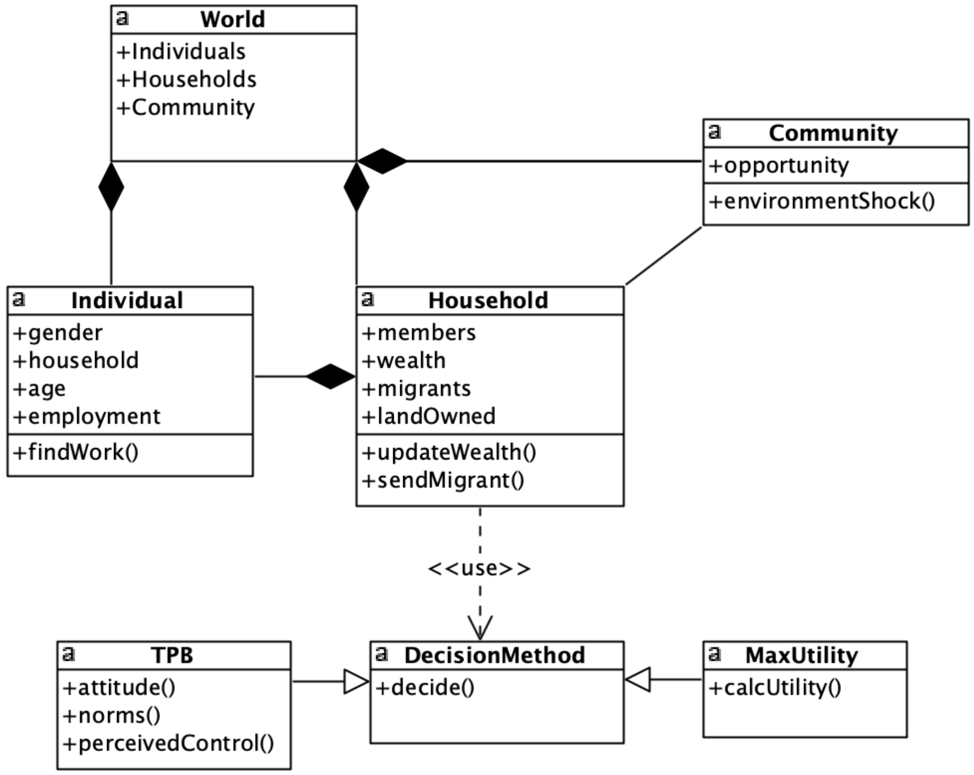

Figure 3.1: Class diagram of model entities with primary variables and operations. The decision method inherits different methods for household agents to make the decision to send a migrant or not. Currently, the decision may be based on a utility maximization (MaxUtility) or theory of planned behavior (TPB).

3.3.2 Decision-making

As described, agent decision-making rules are especially important within ABMs. Decision rules in ABMs of migration have varied from minimalist processes, such as random Bernoulli processes, to simple expected utility maximization, to heuristics with intermediate complexity, to representations of more complex strategic and behavioral theories (Klabunde and Willekens 2016; Thober et al. 2018). I have designed my ABM flexibly to allow for the modeler to specify and test multiple decision-making methods. In this work, I compare a simple economic method of migration decision-making with a more complex, behaviorally informed, method based on the Theory of Planned Behavior (TPB). At the onset of the model run, the modeler may select which method households will use when making a migration decision. As there are multiple plausible methods by which migration decisions may be made, this flexible modeling approach is beneficial in that it does not limit model results and conclusions to a single approach. Other decision-making methods may be more useful for other research questions or implementation in different contexts, and this model allows for simple implementation.

When the decision method in the ABM is set to "TPB", the Theory of Planned Behavior option is used. In this implementation of the migration decision, the households draw upon the Theory of Planned Behavior in which the decision to migrate is based on a behavioral intent (I) informed by a combination of perceived behavioral control (*PBC*), behavioral attitudes (*BA*), and social norms (*SN*) where

$$I = PBC * BA * SN \qquad \text{(Eqn. 3.1).}$$

PBC is a binary variable indicating the deciding household's belief in their ability to successfully migrate if they decide to do so. In the model, *PBC* is based on behavioral control (*BC*). *BC* is calculated as a linear combination of a household's own past experiences with migrating (0 or 1 indicating whether a household has successfully previously sent a migrant), network experiences with migrating (0 or 1 indicating whether any other household within the deciding household's network has successfully sent a migrant), and an asset rate based on the household's wealth and the cost to migrate.

The asset rate is calculated using a logistic function

$$AssetRate = \frac{1}{1 + e^{-kx}} \qquad \text{(Eqn. 3.2)}$$

where *k* is a scaling factor specified at model initialization and *x* is the fraction of a household's wealth that would be necessary to migrate (i.e., meet the cost to migrate). Therefore,

$$x = \frac{wealth_{hh} - migration\_cost}{wealth_{hh}} \qquad \text{(Eqn. 3.3).}$$

From these terms, *BC* is then calculated as

$$BC = w1 * AssetRate + w2 * OwnExperience + w3 * NetworkExperience \qquad \text{(Eqn. 3.4)}$$

where *w1*, *w2*, and *w3* are the weights on each part of behavioral control and must sum to 1. These weights are initialized at the beginning of the model simulation and later calibrated using the pattern-oriented approach. *PBC*, which determines the behavioral intent (*I*) is then based on a random number being less than or equal to *BC*.

Behavioral attitude (*BA*) in Eqn. 3.2 is based on an individual migrant's characteristics and how they related to that individual's propensity to migrate as well as the perceived benefit to migrating. For propensity, a Maxwellian distribution is used with a peak parameter that is informed by the individual's age and perceived benefit to migrate. The Maxwellian distribution is selected because of its flexibility and the ability to define a peak and shape of the distribution informed by empirical knowledge of migration behaviors. Perceived benefit of the migration is calculated using a utility calculation similar to that used in the utility maximization decision-making method and assessing whether or not the migration would result in a net increase of wealth compared to the individual's other employment option.

Finally, social norms (*SN*) are based on the decisions of the household's networked peers. *SN* serves as a scalar on overall behavioral intent *I* and is calculated by

$$SN = 1 + \frac{\#\, HH\ migrated\ in\ network}{\#\, HH\ in\ network} \qquad \text{(Eqn. 3.5)}$$

The ultimate behavioral intent (*I*), as mentioned, is the product of *PBC*, *BA*, and *SN*. A random number is then drawn to determine if *I* translates into a successful migration decision (meaning that the household elects to send the migrant). **Figure 3.2** clarifies the implementation of TPB in this model.

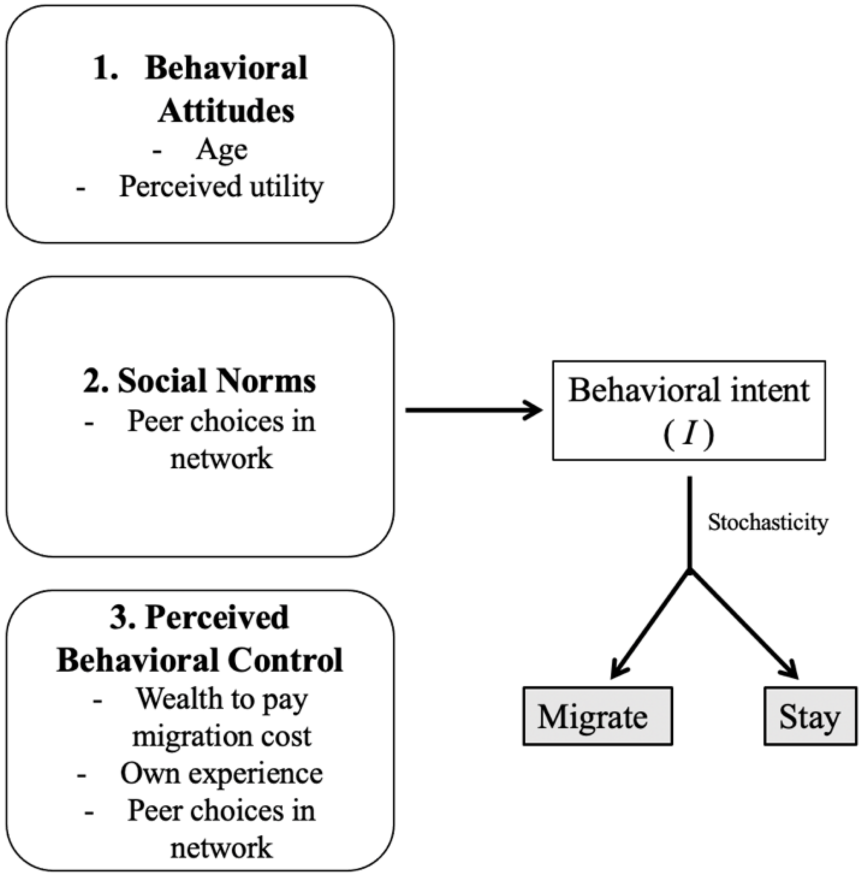

Figure 3.2: Schematic overview of components included in the Theory of Planned Behavior (TPB) method for households deciding whether to send a migrant. TPB combines behavioral attitudes, social norms, and perceived behavioral control to form a behavioral intent.

3.3.3 Pattern-oriented Approach

To assess the model's ability to capture relevant dynamics of environmental migration in the southwestern Bangladesh context, I elect to employ a pattern-oriented approach similar to the approach used in Chapter 2. Pattern-oriented modeling allows us to assess the ABMs ability to reproduce multiple patterns of interest that emerge from the complex dynamics being studied (Wiegand et al. 2003; Klügl and Karlsson 2009; Grimm and Railsback 2012). Here, I utilize the pattern-oriented approach to both calibration and validation of the model.

As a reminder, I identify two patterns of interest related to internal migration from rural Bangladeshi villages influenced by a specific environmental shock of drought-induced crop failure (Gray and Mueller 2012). These patterns are:

- **Community pattern**: As the proportion of a community impacted by environmental shock increases, rates of migration initially decrease below the baseline levels, but then increase, especially above a threshold where approximately 20% of the community is impacted. This shows that individual migration decisions are strongly influenced in a non-linear manner by community-level impacts.
- **Household pattern**: Households that are directly impacted by environmental shock within the community are less likely to migrate. These households may not have the financial means to migrate after experiencing an environmental shock and resulting economic losses.

This ABM aims to reproduce both patterns, which capture outcomes at both the community and household levels.

3.3.4 Machine Learning for Model Calibration

Similar to Chapter 2, I begin by using a Latin hypercube sampling approach to select 150 unique parameter combinations across the uncertain parameter space. I then conduct simulations with my ABM using each of these sampled combinations of parameters. When calibrating the model using the TPB decision method, I have additional uncertain parameters beyond cost and utility of migration calibrated in Chapter 2. With TPB, cost of migration and utility of migration are still uncertain and require calibration. In addition, values of k (**Eqn 3.3**), as well as weights on TPB components *w1*, *w2*, and *w3 k* (**Eqn 3.5**) where $w1 + w2 + w3 = 1$ are uncertain. While the general approach to calibration is the same, I therefore have five uncertain parameters to sample and calibrate simultaneously, rather than just two. Due to the higher dimensionality of the uncertain parameter space, I use a Patient Rule Induction Method (PRIM) rather than SVM. PRIM is a method used for "bump-hunting" or identifying regions of higher concentration of a certain outcome variable (Friedman and Fisher 1999; Nannings et al. 2008). This method allows us to identify areas in the explored TPB parameter space with high concentrations of "success" in reproducing both patterns of interest. The PRIM method is implemented using the *supervisedPRIM* package in R (Shaub 2016).

3.4 Results

3.4.1 Assessing Theory of Planned Behavior

To assess the community pattern of interest, I visualize the results of total migrations at varying levels of community impact factor for the TPB decision method (**Figure 3.3**). For these model runs, I use a Gini coefficient of 0.55 estimated from empirical survey data for initializing the Lomax distribution of land ownership (Carrico and Donato 2019). These results include all 150 sampled combinations of uncertain parameters, each run 100 times at every level of community impact factor. 95% confidence intervals around the mean of all 15,000 model runs are shown in gray. From these results, I see that TPB (**Figure 3.3**) shows an initial decrease in overall outmigration, followed by an increase as community impact factor increases. This is representative of the community pattern of interest.

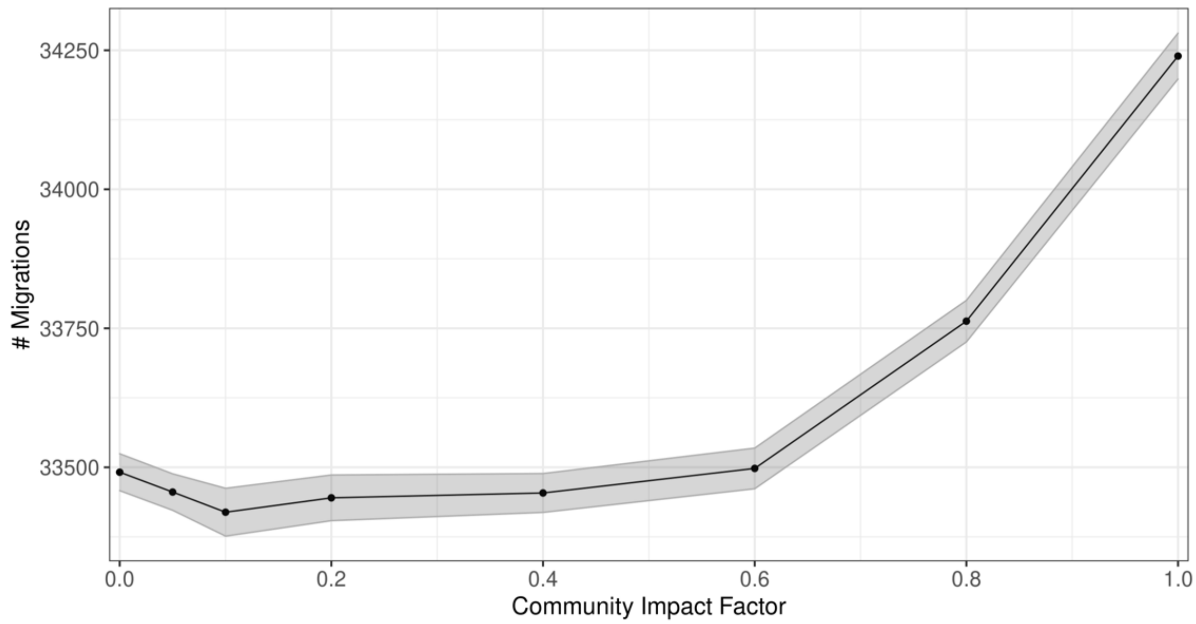

Figure 3.3: Model results based on TPB decision method of number of migrations in the community by varying levels of community impact. The black lines represent the mean of all trials. The gray band represents the 95% confidence interval for the mean.

To assess the household pattern, I divide households from each model run into those that have migrated at all and those that have not during the period of the run. I then compare the number of times that each household was directly impacted by an environmental shock across the migratory and non-migratory households and for each level of community impact factor. I show these results for the TPB (**Figure 3.4**). As previously described, a successful reproduction of the household pattern would be that non-migratory households are impacted by the environmental shocks more frequently than the migratory households. With TPB, the household pattern is not clearly reproduced across the majority of model runs, as there is little difference between migratory and non-migratory households (**Figure 3.4**).

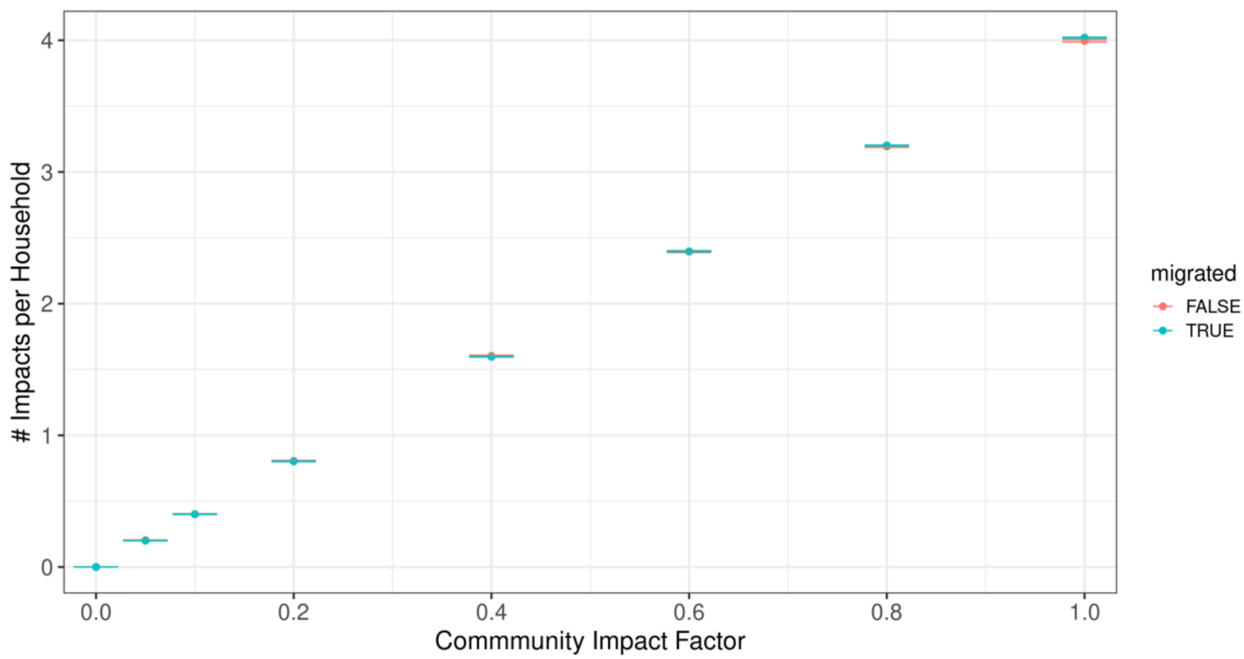

Figure 3.4: For TPB results, households are divided into those that have migrated (1, blue) and those that have not (0, red). The mean number of times a household was impacted directly by an environmental shock across all 120 trials is plotted with error bars indicating 95% confidence intervals of the mean. Pattern 2 is not clearly reproduced.

3.4.2 Evaluating Successful Parameter Space

Results reported thus far have included output from all model runs and uncertain parameter combinations. To assess the successful parameter combinations of the 150 combinations tested, I aggregate the results of all the runs at each combination and evaluate them against the community pattern and household pattern criteria.

For the TPB decision method, cost and utility of migration are uncertain parameters that require calibration, in addition to parameter *k*, and weights on the perceived behavioral control (BC) components. With TPB-based decision-making and a Gini coefficient of 0.55, only 33% of the 150 parameter combinations were able to successfully reproduce the patterns of interest. As the uncertain parameter space is five dimensions, it is more difficult to visualize the PRIM results. However, the PRIM predicts a box around the area of the parameter space where the highest concentration of successful pattern reproduction occurs. The PRIM algorithm predicts this area of success in an area between 30,900 and 63,360 BDT for migration utility, between 807,200 and 1,097,600 BDT for migration cost, between 3.15 and 17.94 for k, between 0.39 and 1.0 for the weight on assets (*w1*), between 0 and 0.53 for the weight on the household's own experience with migration (*w2*), and between 0 and 0.8 for weight on migration experience within the social network (*w3*) (**Eqn. 3.4**).

I can then further evaluate the points in the parameter space that fall within the PRIM predicted area for successfully reproducing the migration patterns of interest. When I evaluate the points within the PRIM area, I see that these points occur when weight on assets (*w1*) is highest, with a mean of approximately 0.5, which *w2 and w3* are smaller and both approximately 0.25 (**Figure 3.5**).

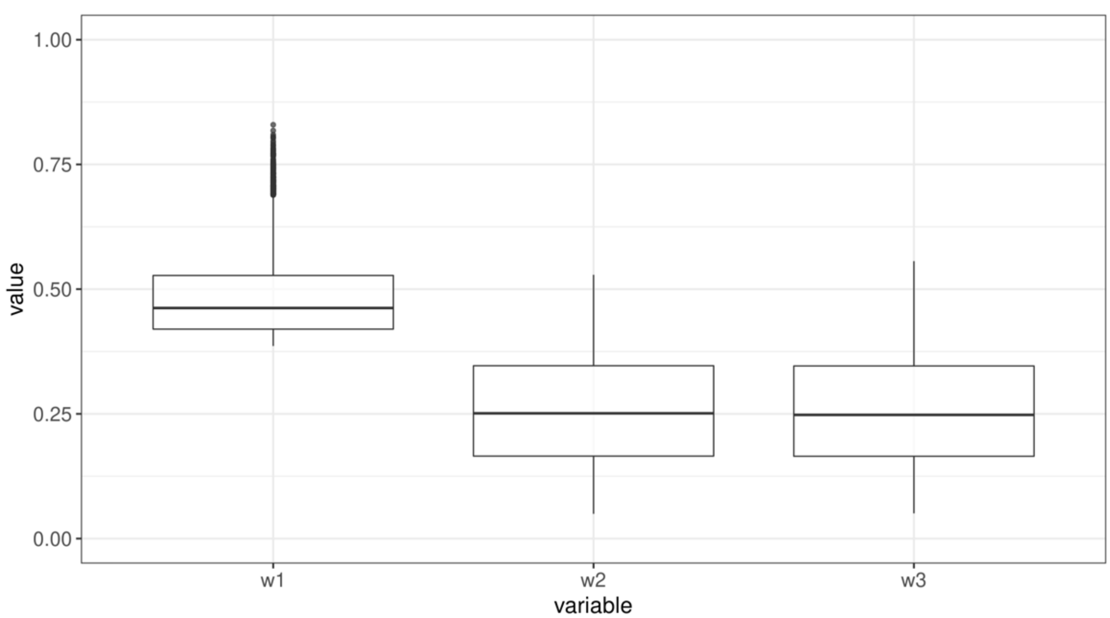

Figure 3.5: Distribution of weights on the components of behavioral control in the TPB decision-making method for parameter combinations that were predicted to successfully reproduce both migration patterns of interest. *w1*, which is the weight on the assets rate.

3.4.3 Importance of Land Distribution

I repeated the model experiments for a Gini coefficient of 0.25 and 0.75. With the TPB method, a Gini coefficient of 0.25 was able to reproduce the patterns of interest across only 27% of the parameter combinations, while a Gini coefficient of 0.75 had a 33% success rate. Again, the shape of migrations across levels of community impact factor is significantly impacted by the Gini coefficient (**Figure 3.6**).

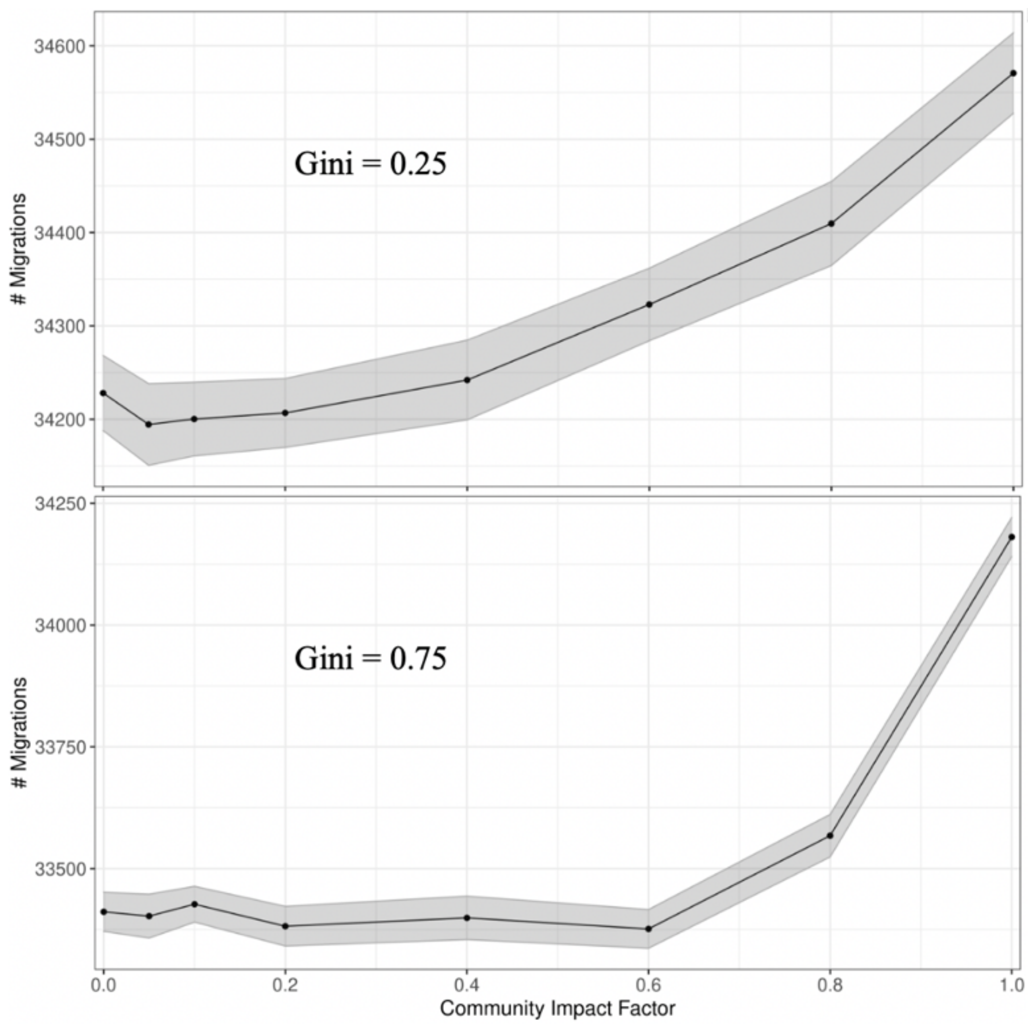

Figure 3.6: Model results based on TPB decision method of number of migrations in the community by varying levels of community impact and for a Gini coefficient on land distribution of 0.25 (top) and 0.75 (bottom). The black lines represent the mean of all trials. The gray band represents the 95% confidence interval for the mean.

3.5 Discussion

In this work, I present results of my original ABM of environmental migration dynamics in rural Bangladesh and incorporate a psychological model of migration decision-making. Importantly, my model is designed to allow for flexibility in the decision-making method utilized by households to decide whether or not to send a migrant. With this flexible ABM, I can evaluate and compare decision-making, which makes the model a useful testbed for studying what factors and psychological processes dominate the emergence of known migration outcomes in the region. Here, I present model results using migration decision method based on TPB, a psychologically complex approach that incorporates knowledge-share across social networks and community norms.

Compared to the utility maximization method first presented in Chapter 2, the TPB method shows a wider spread in migration outcomes, as indicated by the 95% confidence intervals (**Figure 3.3**). Still, in the aggregated results, I see the nonlinear dynamics of the community-level pattern, where migrations initially decline and then increase again as the scale of community impacted by the environmental shock increases. However, the threshold above which migrations increase is predicted at 10% (**Figure 3.3**). The household-level pattern is not clearly reproduced in the aggregated results of the TPB method, as there is not a discernable difference in the number of times migratory households were directly impacted by a shock as compared to non-migratory households (**Figure 3.4**). Overall, the TPB had a lower rate of success (33%) across the total 150 unique parameter combinations of migration cost, migration utility, shape parameter *k*, and TPB-related weights which were able to successfully reproduce both patterns of interest simultaneously. Evaluation of the parameter space using a PRIM algorithm is useful in identifying areas of higher density of successful pattern reproduction. From this, I identify that the TPB is more successful in pattern reproduction when the weight on assets is significantly higher than weights on a household's own past experiences and the past experiences of households within a social network (**Figure 3.5**). The weight on the asset rate incorporates household wealth and economics, suggesting that the TPB performs the best when economics dominate the behavioral control element.

Similar to the results of the utility maximization method presented in Chapter 2, with higher inequality (Gini coefficient = 0.75), I see that TPB model runs maintain their previous rates of successful pattern reproduction. However, the threshold of community impact scale above which migrations begin to increase is shifted higher compared to the initial runs (from 10% to 60% for TPB) (**Figures 3.3, 3.6**). In contrast, less inequality in land ownership (Gini coefficient = 0.25) caused the success rate to decrease and lose the nonlinear element of the community-level pattern (**Figures 3.6**).

While the model using TPB was able to reproduce the patterns of interest at various parameter combinations, the rate of success (33%) was much lower than that of the utility maximization method y (80%). Additionally, the results of the TPB model runs are more highly sensitive to specific parameter combinations. While I can use PRIM to identify the parameter ranges that are more likely reproduce the patterns, the results depend greatly on those values at model initialization. In this way, it seems as though the underlying phenomena that generate the patterns of migration are not inextricable from the model structure when TPB decision-making is used. In this case, the simpler model is more successful in capturing the dynamics of interest. Interestingly, the distribution of land ownership, specifically inequality in land ownership, were critical for model performance with both the simple economic model and the behaviorally complex model. This finding suggests that future environmental migration research in the study area should pay close attention to economic inequality.

3.6 Conclusions

My initial hypothesis for this work was that the behaviorally complex TPB decision-making method would more successfully reproduce the patterns of interest than a simple utility maximization method entirely dependent on economics. I developed this hypothesis due to the known complexity of migration decisions, including the importance of social networks and norms in influencing those decisions (Thober et al. 2018; Till et al. 2018a; Mallick and Schanze 2020). While it remains true that individual migration decisions are personal and complex, my results indicate that a model based on TPB is no better able to capture the decision-making processes to reproduce emerging patterns. This suggests that, in this specific context of rural Bangladesh, behavioral psychology is not better than pure economics when considering the drivers of environmental migration. This finding is important and suggests that modelers should use caution when incorporating behavioral complexity into models, as such added complexity may be unnecessary and hinder performance.

This work also further allowed us to identify the distribution of inequality in land ownership as a critical parameter influencing migration outcomes. This was true for both the utility maximization and TPB decision-making methods, supporting the robustness of this finding. Previous empirical and theoretical work has identified household wealth as an important factor influencing a household's ability to afford to send a migrant and ability to adapt in place after environmental change (Adams 2016; Mallick and Schanze 2020). However, this model identifies community-level inequality, not just individual household wealth as a critical factor for migration outcomes. The idea that community-level inequality is an important influence on environmental migration from a community could have important policy implications for policymakers looking to support resilience in communities in the form of either migration or non-migration (McLeman et al. 2016). This finding may also direct future empirical work in which community-level inequality and migration are more thoroughly investigated.

Finally, this work demonstrates the usefulness of a flexible ABM structure that can serve as a test bed for different decision-making methods rather than assuming a specific method, especially when an ABM is utilized for hypothesis testing. As more ABMs continue to incorporate behavioral psychology in decision-making, this flexibility is important. Some questions in certain contexts may be adequately modeled with simple decision rules, while others may be strengthened by behavioral complexity. This will vary across contexts and different kinds of coupled human and natural systems being investigated.

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CHAPTER 4

Social network size and typology do not significantly impact migration outcomes in agent-based model

Abstract

Social networks have been established as important for human migration decisions, including environmental migration. Despite this, few agent-based models of environmental migration include social network influences, and no known models that investigate the implications of social network size and typology. Here, I use an original agent-based model of environmental migration in Bangladesh to test the impacts of network size and shape on migration outcomes. The model uses a decision-making method based on the Theory of Planned Behavior and includes consideration of the behavior of other households within a network. With this model, I test several network typologies: fully connected, small-world, preferential, and random. I also test various network sizes. Model results show that, in this context, social network typology and size do not significantly change the shape of migration outcomes from the modeled community. Larger networks slightly increase the overall level of out-migration. Results suggest that the role of social networks in influencing environmental migration is context and model specific, but it remains important to consider in future ABM work.

4.1 Introduction

Understanding information transfer through social networks and how that information impacts migration decisions has important implications for the study of human migration. This is especially true in the era of social media and increased information flows through widespread communication technologies such as smart phones (Boas, 2017). Previous research has established that social networks influence migration decisions (Black et al. 2011c; Hunter et al. 2015). Social networks, especially connections with individuals living in a possible community of destination can increase the propensity of an individual to migrate by demonstrating feasibility, reducing risks, and increasing benefits of a move (Till et al., 2018). Such dynamics can help to explain chain migration, or movement in which migrants learn about opportunities through social relationships with previous migrants (MacDonald and MacDonald 1964).

Despite the importance of social networks on migration, few agent-based models (ABM) of migration explicitly include social networks, which may be due to the complexity of modeling these networks (Thober et al. 2018). As part of the complexity of social networks, it is unclear how the typology and size of a network may influence migration decisions. ABMs of environmental migration may be especially useful for exploring such questions, as they can serve as a testbed to vary network effects and see how migration outcomes respond. This work utilizes the original ABM of migration, livelihood, and environmental shock in Bangladesh to test how network size and typology impact migration from a community when agents use a decision-making method based on the Theory of Planned Behavior (TPB) and where social norms influence that decision.

4.2 Background

4.2.1 Social Networks and Migration

Social network analysis aims to understand the relationships between individuals based on social ties (Scott 2017; Bilecen et al. 2018; Bilecen and Lubbers 2021). In general network analysis, based on graph theory, a network consists of a set of nodes or vertices that may be connected by a number of edges (Krause et al. 2007). Information or resources may pass between nodes via edges. Social network theory has had a wide range of applications in behavioral science, psychology, sociology, biology, and more (Krause et al. 2007).

Migration, whether environmentally influenced or not, is understood to be influenced by social networks (Bilecen and Lubbers 2021). For example, the body of research on "chain migration" uses, in part, social networks to explain how migration flows may be perpetuated (MacDonald and MacDonald 1964; Massey and España 1987; Massey 1990; Massey and Aysa-Lastra 2011; Black et al. 2011b). But the effects of social networks on migration are not straightforward. Social network ties and strong community cohesion within an origin may work to inhibit migration, whereas social ties in a potential destination may facilitate migration and destination selection (Haug 2008; de Haas 2010; Till et al. 2018b; Mallick et al. 2021). Having social ties in a destination may migration to that destination more desirable due to the support that those ties may offer (Brooks and Waters 2010; Findlay 2011).

In the case of environmental migration, social networks are also likely important for the migration decision. Especially as most environmental migration is shorter distance, the decision to move and the selection of a destination is likely to be strongly influenced by social network effects (Findlay 2011). Current or former migrants may pass information about migration experience through networks, potentially lowering the cognitive and emotional burden of moving. In addition to information flows, migrants may transfer resources across networks. Remittances received from migrants in a destination can be very important for members of a network that remain in an origin, including for building adaptive capacity and resilience to environmental stress (Warner et al. 2010; Szabo et al. 2018). Despite the theoretical recognition of the importance of social networks in migration-studies, the majority of research in the area remains qualitative (Bilecen and Lubbers 2021).

4.2.2 Social Networks in ABMs of Environmental Migration

As described, ABMs may be especially useful for studying environmental migration, including the role of social networks. In their review of 15 ABMs of environmental migration, Thober et al. consider the inclusion of social networks as one of their review criteria (2018). For their review, social networks are counted only if they are explicitly modeled social connections (including remittances and information exchange). Agents who compare their circumstances to those of other agents without explicitly modeled social linkages are not considered to be part of a social network (Thober et al. 2018). With this definition of modeled social networks, Thober et al. found only four existing ABMs of environmental migration that explicitly include social network effects (2018).

In Berman et al.'s ABM of an arctic community in Old Crow, Yukon, social networks are included in that households can share hunting gear with other households in return for a fraction of the borrowing household's harvest (2004). This exchange between households is meant to represent familial ties within the community, across which households will share resources. However, the networks are abstracted in the model, and households will select a random other household to share resources with (Berman et al. 2004). In this way, the social networks in this model are implemented for resource exchange within the community rather than explicitly related to the migration decision.

For Naivinit et al.'s model of agriculture and labor migration in Thailand, social networks are included in the form of dependents that a household must care for (2010). The presence of dependents in a household impacts an individual's decision to migrate and whether to migrate temporarily or permanently because the dependents require the care of a working household member (Naivinit et al. 2010). In this way, social ties within households are modeled as kinship ties. These kinship connections do impact the migration decision in that they may have a rooting effect on potential migrants who have familial obligations at home. However, this model does not include network interactions between households or any mention of network structures.

Smith includes a more complex representation of social networks in their model of migration and changes in rainfall in Tanzania (2014). Their model includes social influence across multiple levels including at the point of migration decision-making. In this model, agents representing farmers can share information and personal views about migration between both social and labor networks (Smith 2014). These social norms influence the agent decision-making process. In this way, the decision-making is dynamic and influenced by the experiences within the networks. In other words, the behavior of agents can influence the behavior of other networked agents in the future. While the networks effects here are more complex and directly integrated into the migration decision, networks are entirely random and other network structures are not explored (Smith 2014).

The fourth and final ABM that Thober et al. (2018) identify as including social networks is Kniveton et al.'s ABM of migration and changing climate in Burkina Faso (2011). This model, similar to my model presented here, uses a migration decision-making method based on the Theory of Planned Behavior (TPB) (Kniveton et al. 2011b). In this model, agents move around an explicit environment and may exchange information about migration histories with other agents that they encounter. Similar to Smith (2014), agents may influence each other's future decisions through information that they exchange and social influence. In the TPB based decision method, norms are also influenced by peer choices across a network. Again, the network structure is entirely random. Agents in this model are randomly connected to 50 other agents who they may exchange information and experiences with (Kniveton et al. 2011b).

As Thober et al. (2018) identified, very few ABMs of environmental migration include social networks and those that do vary in their complexity and how networks do or do not influence the migration decision. Of the four ABMs that include any kind of network influence, none test different network structures or systematically assess the influences of network typology and size. This work, therefore, begins to fill this gap in the literature by first implementing an explicit social network and then by exploring the role of network typology and size on migration outcomes.

4.3 Methods

4.3.1 Model Structure

For this work, I use the original ABM of environmental migration which has been described in detail in this dissertation. The model is designed to incorporate multi-scalar (community, intra-household, household, and individual) influences on household migration decisions under differing levels of environmental stress within the community. As previously described, each time step of the model represents one year of time, and the model is run for 20 steps for each experimental run. The model is built using an object-oriented approach in *Python3* with entities representing *individuals, households,* and the overall *community.* Each type of entity has unique attributes and behaviors (Best et al. 2021). For example, individuals have attributes of age, sex, and employment. Model runs may be designed at the global-level, where users provide initializing values including run time, number of individuals, number of households, decision-method, and other specifications. For this work, the decision-method is set with a value of "TPB" to specify a Theory of Planned Behavior method. Importantly, the model also includes global variables to specify network typology and network size.

4.3.2 Social Network Effects in Decision-making

My ABM was designed to allow for maximum flexibility in agent decision-making processes. In this way, the modeler can specify at the start of a model run which method household agents will use to decide whether or not to send a migrant at any time step. My previous work demonstrated that a simple utility maximization decision-making method was successful in reproducing empirically based patterns of migration, even outperforming a more complex method based on Theory of Planned Behavior (TPB). However, the more complex, behaviorally informed TPB method allows us to investigate the impacts of social networks where the utility maximization method does not. For this reason, this stage of research focuses on the TPB method.

When the decision method is set to "TPB", consistent with the behavioral theory, the decision to migrate is based on a behavioral intent (I) informed by a combination of perceived behavioral control (*PBC*), behavioral attitudes (*BA*), and social norms (*SN*) (Ajzen 1991, 2002) where

$$I = PBC * BA * SN \quad \text{(Eqn. 4.1).}$$

Network influences come into play for both *PBC* and *SN*. *PBC* is a binary variable representing the household's perceived ability to successfully migrate. Here, *PBC* is based on behavioral control (*BC*). *BC* is calculated as a linear combination of a household's own past experiences with migrating (0 or 1 indicating whether a household has successfully previously sent a migrant), network experiences with migrating (0 or 1 indicating whether any other household within the deciding household's network has successfully sent a migrant), and an asset rate based on the household's wealth and the cost to migrate. From these terms, *BC* is then calculated as

$$BC = w1 * AssetRate + w2 * OwnExperience + w3 * NetworkExperience \quad \text{(Eqn. 4.2)}$$

where *w1*, *w2*, and *w3* are the weights on each part of behavioral control and must sum to 1. These weights are initialized at the beginning of the model. I see, then, that *w3* is the weight on the network effects. In previous stages of this analysis, I showed that empirically based patterns of environmental migration were more successfully reproduced when the highest weight was placed on economic assets (meaning that *w1* was the highest weight). For this work, because I am more interested in the effects of social networks rather than pattern reproduction, I assign a higher value to *w3*, the weight given to social network experience. For these experiments, I set *w3* to 0.7 and both *w1* and *w2* are set at 0.15. *PBC*, which determines the behavioral intent (*I*) is then based on a random number being less than or equal to *BC*.

Network effects also come into play in this model directly with the variable *SN,* which captures the amplifying effect of social norms. *SN* is based on the decisions of the household's networked peers. *SN* is calculated by

$$SN = 1 + \frac{\#\ HH\ migrated\ in\ network}{\#\ HH\ in\ network} \quad \text{(Eqn. 4.3)}$$

In this equation, #HH refers to number of households. Therefore, higher rates of migration within the network will increase the behavioral intent, *I*.

4.3.3 Network Structures

When initializing a new model run, the modeler must set two global variables related to social network size and typology:

- *Network type* – Type of network structure for social networks within the community. Possible values include "preferential", "random", "small-world", and "fully-connected", as described below.
- *Network size* – The average number of other households that each household is connected to within the social network.

Networks between households are implemented using the "NetworkX" package in *Python3* (Hagberg et al. 2008). In general, networks consist of nodes (in this case households), and edges representing connections between nodes (Borgatti and Halgin 2011; Sasaki et al. 2016; Bilecen and Lubbers 2021). Information or resources may be exchanged between nodes across networks.

Networks may have different typologies or structures (**Figure 4.1**). A fully connected network means that each node is connected to every other node, or in this context, all households are connected to one another in a network. The fully connected network is specified using the *complete_graph()* function in NetworkX. As its name suggests, a random network selects other households randomly to be included in a network. The random network is implemented using the *fast_gnp_random_graph()* function in NetworkX, which implements a random network with a specified number of nodes and probability of an edge (Batagelj and Brandes 2005).

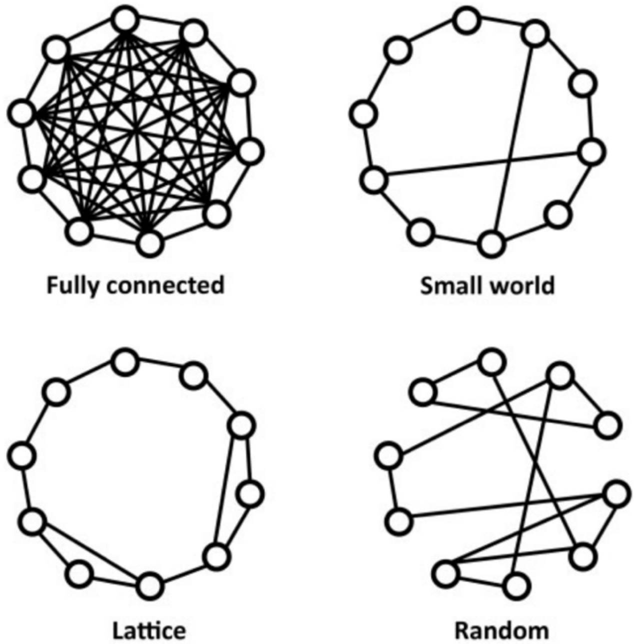

Figure 4.1: Examples of network typologies. From Sasaki et al. 2016.

In this work, I also implement a small-world network and a preferential network. The small-world network is implemented using the *watts_strogatz_graph()* function in NetworkX (Watts and Strogatz 1998). As the name suggests, this function implements a small-world typology as described by Watts and Strogatz (1998). A small-world network is designed as a network structure between completely structured and completely random. In this typology, each node is connected to its k nearest neighbors, with some edges then being replaced by random edges (Watts and Strogatz 1998). The preferential network typology is implemented using the *barabasi_albert_graph()* function in NetworkX, which uses a Barabasi-Albert approach to preferential connections (Barabasi and Albert 1999).

Here, I run model experiments varying the network typology with a TPB decision-making method and with all other parameters held constant. I then vary the network size with a small-world network type.

4.4 Results

4.4.1 Network typology

To first test network typology, I run my model 100 times at varying levels of community environmental impact (community impact factor) for each network typology (fully connected, random, small-world, and preferential). I first assess total migrations across community impact factors for the fully connected community (**Figure 4.2**). I see highly non-linear behavior across the varying levels of community impact to the environmental shock, with an initial increase in migration followed by a decline until an impact factor of approximately 0.6 when migrations increase again (**Figure 4.2**).

Next, I run the same experiment with the remaining network typologies where the average number of connections for each household is 50 (out of 100 possible connections). I show results across the three typologies by decreasing randomness (**Figure 4.3**). I begin with a random network typology (**Figure 4.3a**), followed by a small-world (**Figure 4.3b**), and finally preferential (**Figure 4.3c**). For all the network typologies, I see a very similar shape in the out-migrations by community impact factor as compared to the fully connected network typology. Again, I see an initial increase in migration as environmental impact increases, followed by a decline, and an increase again at a community impact factor of 0.6. The total numbers of migration are also similar between the network typologies, with the random network structure predicting slightly fewer total migrations (**Figure 4.3**).

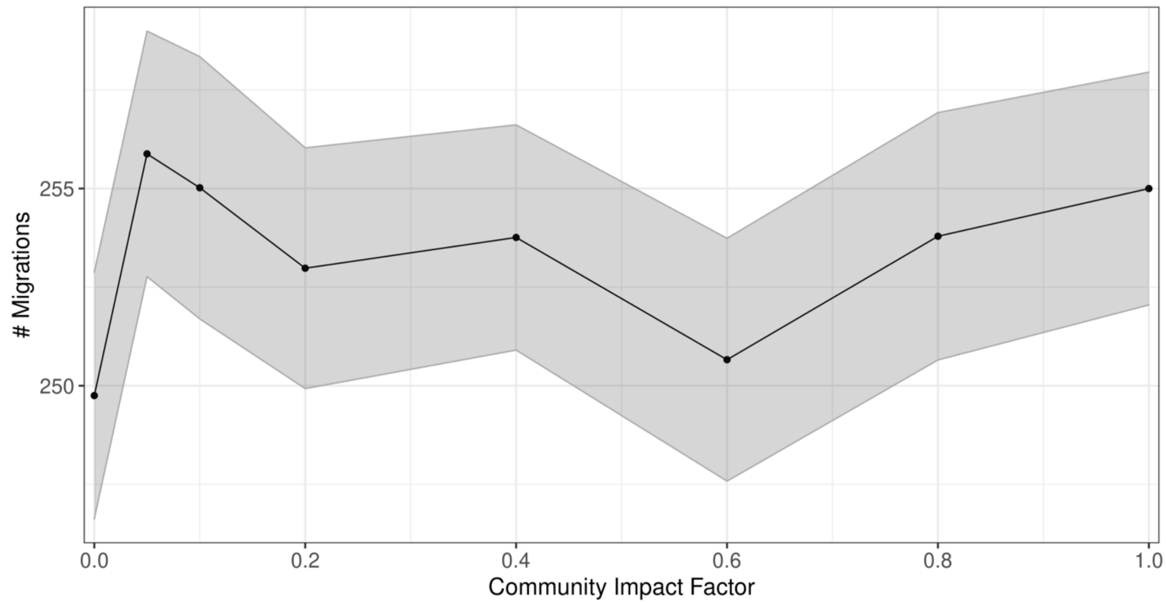

Figure 4.2: Model results of total number of migrations from the community by varying levels of community impact and with a fully connected network typology. The black lines represent the mean of 100 model runs for each community impact factor. The gray band represents the 95% confidence interval for the mean.

I then repeat this experiment of varying network typologies, but this time with households only having a network size of five (out of 100 possible connections). Again, I show results across the three typologies by decreasing randomness (**Figure 4.4**). Like the previous experiment with higher network connectivity, I see similar shapes in out-migration by community impact factor compared to the fully connected typology and between the other typologies.

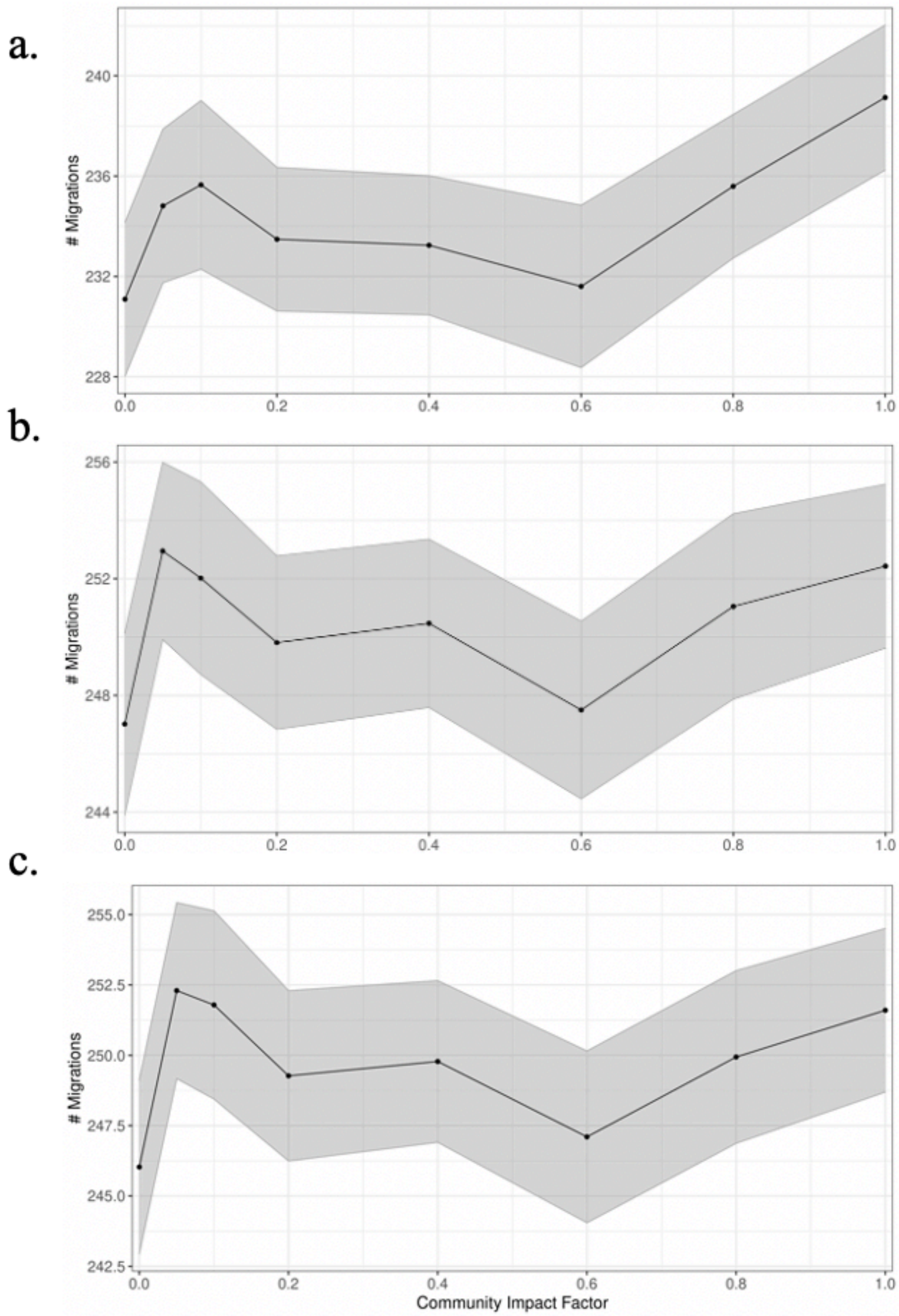

Figure 4.3: Model results of total number of migrations from the community by varying levels of community impact and with a random (a), small-world (b), and preferential (c) network typology and with 50% network connectivity. The black lines represent the mean of 100 model runs for each community impact factor. The gray band represents the 95% confidence interval for the mean.

a.
b.
c.

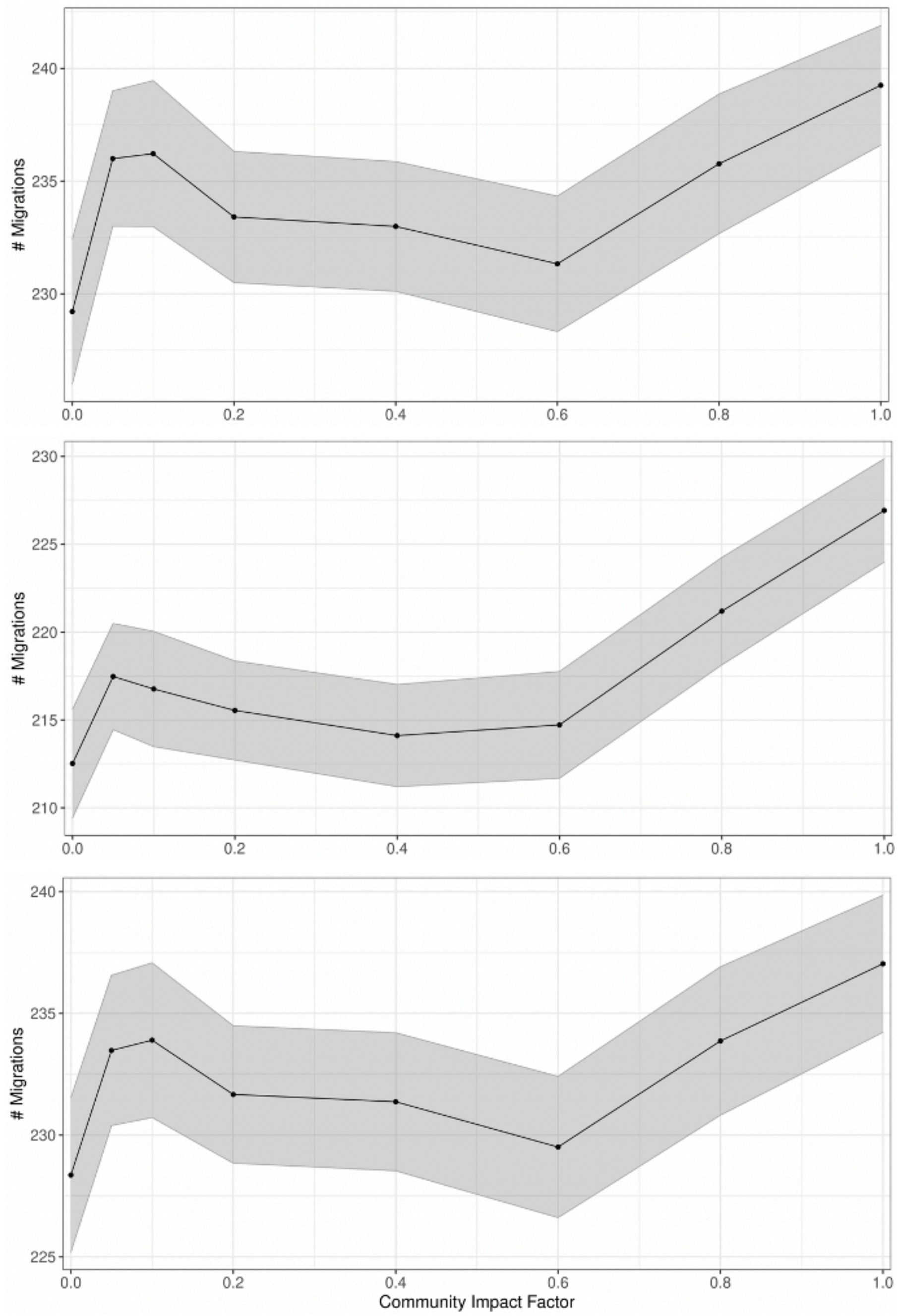

Figure 4.4: Model results of total number of migrations from the community by varying levels of community impact and with a random (a), small-world (b), and preferential (c) network typology and with 5% network connectivity. The black lines represent the mean of 100 model runs for each community impact factor. The gray band represents the 95% confidence interval for the mean.

4.4.2 Network Size

For my experiments to investigate network size, I use the small-world network typology and vary the *network size* parameter which specifies the average number of connections for each household. As mentioned, my previous experiment used a network size of 50. Here, I run the model with network sizes of five, 20, and 75. Again, I run the model for each network size and each level of community impact 100 times (**Figure 4.5**). I show that increasing network size does have a modest effect on overall numbers of out migration, with a network size of five producing the lowest number of migrations across all community impact levels (**Figure 4.5a**). With a network size of five, total migrations do not exceed 230, whereas they exceed 255 with a network size of 75 (**Figure 4.5c**).

Across the network sizes, I again see a similar shape in migration across varying community impact levels. I see an initial increase in migrations, followed by a decline as community impact increases, and an increase again beginning at 0.6. However, only for a network size of five do I see that migrations at the highest levels of community impact eventually exceed migrations at lower levels of impact, which is consistent with the pattern of interest previously used in this work (**Figure 4.5a**). I also see a broader range in the 95% confidence interval bands for the larger networks, suggesting that social networks add variability to the model.

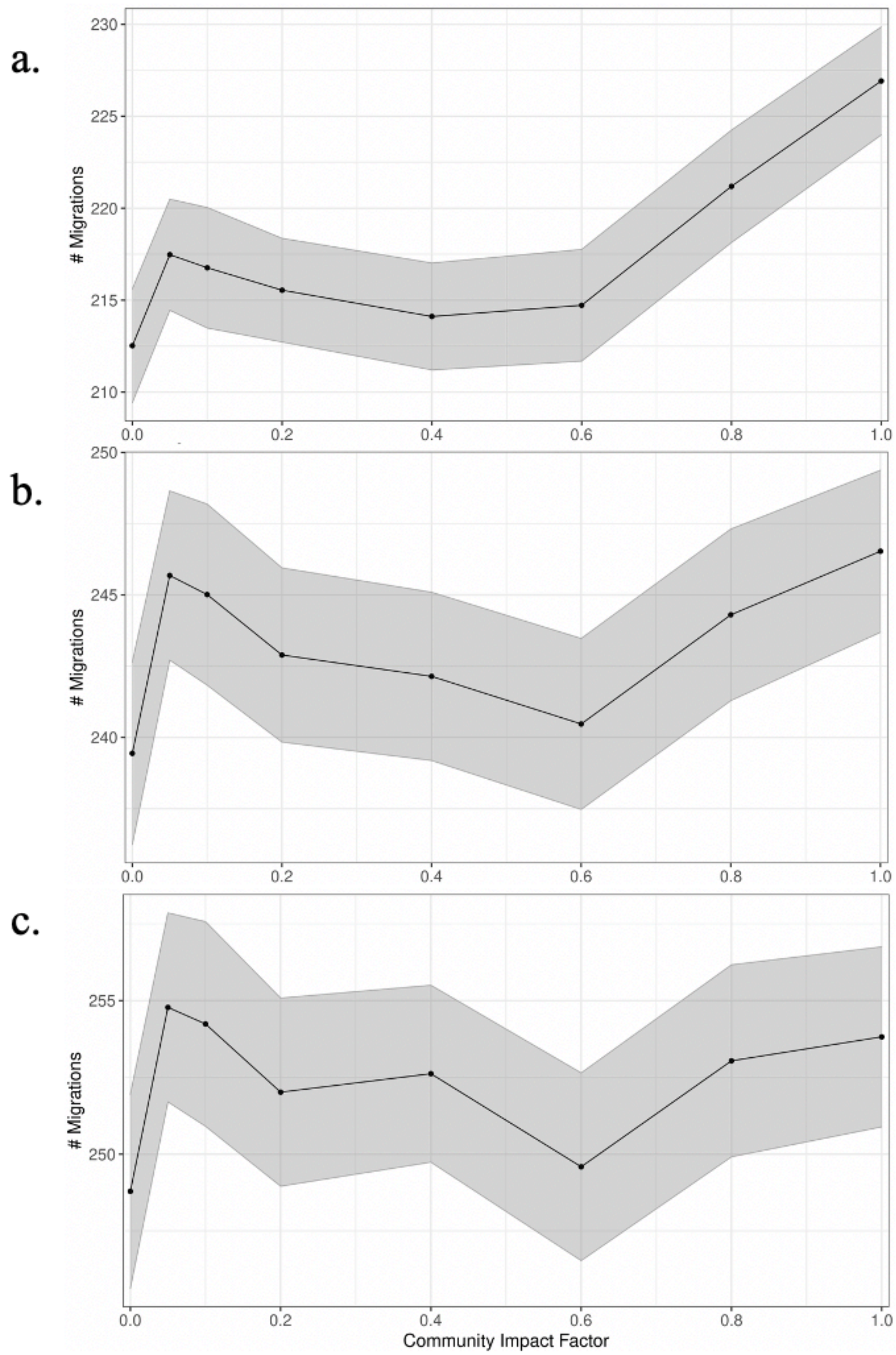

Figure 4.5: Model results of total number of migrations from the community by varying levels of community impact and with a small-world network typology and a network size of five (a), 20 (b), and 75 (c). The black lines represent the mean of 100 model runs for each community impact factor. The gray band represents the 95% confidence interval for the mean.

4.5 Discussion and Conclusions

In this work, I use my ABM of environmental migration in Bangladesh to test the effect of social network typology and size on migration outcomes. I show that network typology does not significantly alter model predicted migrations. For fully connected, random, small-world, and preferential network structures, migrations show similar non-linear behavior across varying levels of community impact to environmental shocks (**Figure 4.2, 4.3, 4.4**). Focusing on the small-world typology, I also demonstrate that the size of the social network has a modest effect on the number of migrations, while the shape of the migration outcome remains largely consistent (**Figure 4.5**).

Admittedly, these (non)results are not the most exciting, but they are important in that they contribute to our understanding of how network size and typology impact outcomes in ABMs. As previously mentioned, very few ABMs of environmental migration include any explicit representation of social networks (Thober et al. 2018). This model incorporates social networks and allows for flexibility in network typology and size. Even though my results show that network typology is largely unimportant for my model under current parameters and formulation, it is necessary that I be able to ask and answer whether or not that is the case. To my knowledge, this is the first such study of network typology in environmental migration ABMs.

My results are also not meant to suggest that social networks are not important for migration when previous research has shown that they are. These findings only suggest that social network size and typology is unimportant for migration predicted from *this* model to study *this* specific context. Another key caveat is that social networks may be important if implemented differently in my model, as different operationalizations of theory in ABMs have been shown to yield very different results (Muelder and Filatova 2018). Also, as I discussed, network effects may operate in many ways to influence migration (such as destination location, “rooting” effects, chain-migration, etc.), and this model only considers the ways that networks may impact social norms and perceived behavioral control. If my model was investigating destination selection or return migration, then the network effects might be very different and possibly significant.

This study lays the groundwork for several opportunities for future work. For example, I plan on investigating how modeled migrations may respond when household agents have heterogeneous network typologies and sizes. I also plan to expand this ABM and incorporate different behavioral theories beyond TPB such as theories related to Protection Motivation Theory and place attachment theory (Rogers 1975; Adams 2016). It is possible that social network size and structure may prove to be important under different methods of migration decision-making. In this case, my model is designed to implement different network structures and systematically compare results.

Though varying social network typology and size for this model and configuration did not drastically change migration outcomes, social networks may prove to be very important for other models of different conditions. For this reason, I suggest that future ABMs of environmental migration, firstly, include social networks explicitly and, secondly, allow for the flexibility to vary network typologies.

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CHAPTER 5

Number of dangerous heat days in Bangladesh will increase with future climate change

Abstract

Extreme heat poses a threat to human health, especially in less developed countries. The combined effect of heat and moisture is captured in wet bulb temperature (WBT). Using an ensemble of climate model runs and adjusted model runs, I present a range of future scenarios of WBT in Bangladesh. Annual number of days exceeding a dangerous threshold of 30 ^{o}C WBT are expected to rise in northern and southern (coastal) Bangladesh under various global warming levels (GWL's) with the potential of exceeding 20 to 30 days based on the most conservative models and exceeding 100 days in adjusted models. Annual consecutive dangerous heat days could exceed 30 days by 2100, suggesting risks of prolonged heat exposure. Maximum annual WBT is shown to likely exceed 32 ^{o}C, with some projections exceeding 35 ^{o}C. Even conservative estimations of warming would also have serious implications for health and productivity.

5.1 Introduction

Future climate change poses a wide variety of threats to human health and well-being (Intergovernmental Panel on Climate Change, 2018; Patz et al., 2007). One such threat is the direct impacts of rising global temperatures and heat stress on human health (Kjellstrom, 2009; Kovats & Hajat, 2008; Luber & McGeehin, 2008; Xu et al., 2020). Heat stress is already the leading cause of fatalities from natural phenomena and heat-related deaths are expected to increase due to anthropogenic climate change (Dahl et al., 2019; Knutson & Ploshay, 2016; Matthews et al., 2017; Sherwood & Huber, 2010). This threat is especially concerning in regions of the world that are less developed and have a large percentage of population that lives and works without access to air conditioning, as these populations are more vulnerable to extreme heat (Lundgren et al., 2013).

Bangladesh is highly vulnerable to climate change (Black et al., 2008; Passalacqua et al., 2013; Walsham, 2010). Rural communities in Bangladesh, where it is estimated that two-thirds of workers are dependent on agriculture as a primary source of livelihood, are especially vulnerable to environmental conditions (World Bank, 2016, p. 200). While future precipitation, flooding, exposure to natural disasters, and even salinity encroachment have received widespread attention by researchers studying climate impacts in Bangladesh, extreme temperatures in Bangladesh have been the subject of fewer studies (Chen & Mueller, 2018; Dasgupta et al., 2015; Haque & Jahan, 2015; Karim & Mimura, 2008).

Extreme heat has direct implications on human health. Exposure to extreme heat is especially dangerous for the very young, very old, and those with preexisting medical conditions (Chan & Yi, 2016; Coffel et al., 2017). Under hot conditions, it is critical for people to be able to cool down either by escaping the heat or by thermal regulating through sweat evaporation, but the ability to cool down through sweat evaporation largely depends on air humidity (Davis et al., 2016). For this reason, indicators of heat stress that depend solely on measures air temperature may not sufficiently capture the impacts of heat on human health. One indicator of heat stress that incorporates both temperature and humidity is wet bulb temperature (WBT), which is utilized for this work (Li et al., 2017; Raymond et al., 2020; Wang et al., 2019; Willett & Sherwood, 2012).

It is broadly understood that humans cannot survive in environments where WBT exceeds 35 ^{o}C, as this is the point where thermal regulation by sweat evaporation is not possible, and core body temperatures will rise (Coffel et al., 2017; A. J. McMichael & Dear, 2010; Raymond et al., 2020; Sherwood & Huber, 2010). Even below the deadly threshold, high temperatures can be dangerous, especially for physical laborers who work outdoors (Kjellstrom, 2009, 2016; Riley et al., 2018). This poses threats to worker health and productivity in places where heat and humidity are high (Dunne et al., 2013). As climate change is projected to increase global temperatures, future WBT is also expected to increase, especially in tropical locations that experience high temperatures and humidity levels (Diffenbaugh & Scherer, 2011; Hyatt et al., 2010). Existing work has shown that some parts of the world may exceed the deadly threshold of 35 °C with future climate change, rendering these places inhospitable to human life without air conditioning (Pal & Eltahir, 2016; Sherwood & Huber, 2010). Not only would this dramatically impact human health, but also energy demand, agriculture, recreation, and more (Kang et al., 2019). For this reason, some scholars have argued that WBT beyond 35 °C may represent a limit to human's ability to adapt to climate change (Pal & Eltahir, 2016).

Though increases in future temperatures pose a threat to human health and socioeconomic growth in Bangladesh, the possible magnitude of such threats is poorly understood and not broadly studied with climate models. Some work has used regional models to predict temperature, precipitation, and monsoon strength across South Asia, without particular focus on Bangladesh (Bhaskaran et al., 2012; Immerzeel, 2008; Rajib Mohammad Adnan et al., 2011; Saeed et al. 2021; van Oldenborgh et al., 2018). Other work has investigated projected changes to temperature and precipitation in Bangladesh by 2100 under climate change scenarios but has not made the connection to human health (Caesar et al., 2015; Islam et al., 2008).

Due to its tropical climate and large percentage of population working outdoors in agriculture and other labor, Bangladeshi communities are highly vulnerable to future heat exposure. To this end, this work investigates future projections of WBT in Bangladesh under various global warming levels (GWL's), using an ensemble of global climate model runs from the Community Earth System Model Large Ensemble Project (CESM-LE) (Kay et al., 2015). Using CESM-LE, I predict how WBT will evolve in Bangladesh by assessing annual days exceeding a dangerous threshold for human health, consecutive days above this threshold, and annual maximum WBT. I further contextualize the results from the CESM-LE model by comparing results to historical weather station data and results from the Coupled Model Intercomparison Project 5 (CMIP5) (Taylor et al., 2011).

5.2 Materials and Methods

5.2.1 Calculating WBT from CESM-LE Model Runs

CESM-LE is an ensemble of 35 model runs, each of which consists of full coupling between land, atmosphere, ocean, and sea ice (Kay et al., 2015). Model spatial resolution is approximately 1° by 1° grids (Kay et al., 2015). I compiled data from each of the 35 ensemble members from the year 1920 to 2100 under RCP 8.5 forcing (Riahi et al., 2011). I extracted variables for daily maximum temperature (T_{max}) in Kelvin, daily minimum temperature (T_{min}) in Kelvin, daily average specific humidity, and daily surface pressure for analysis from model results. I then restricted data to a range of latitude and longitude from 88° to 92.5° E and 20.5° to 26.5° N, representing the geographic range of Bangladesh. I selected two grid cells located in northern Bangladesh and southern, coastal Bangladesh for regional comparison.

From daily data from the CESM-LE, daily WBT was calculated by first calculating near-surface relative humidity (RH) at both T_{max} and T_{min} (daily maximum/minimum near-surface temperature) from near-surface specific humidity (q), and surface pressure (P), using the following equations:

$$e = \frac{qP}{\varepsilon} \tag{Eqn. 5.1}$$

$$RH = 100 \times \frac{e}{e_s} \tag{Eqn. 5.2}$$

where e is the vapor partial pressure of water, is a constant (0.622) based on the specific gas constants for dry air and water vapor, and e_s is the saturation vapor pressure as a function of temperature calculated based on Clausius-Clapeyron's equation. All input values in **Eqn. 5.1** and **Eqn. 5.2** are provided in SI units. RH is in percent from 0 to 100. From RH, the equation from Stull (**Eqn. 5.3)** is used to calculate the WBT with the calculated RH at both T_{max} and T_{min} (Stull, 2011)

$$WBT = Tatan\left[0.151977(RH + 8.313659)^{\frac{1}{2}}\right] + \text{atan}(T + RH) - \text{atan}(RH - 1.676331)$$
$$+ 0.00391838(RH)^{\frac{3}{2}}\ \text{atan}(0.023101RH) - 4.585035 \tag{Eqn. 5.3}$$

where temperatures are in °C.

5.2.2 Comparison to Historical Data

In order to compare CESM-LE results to historical observations, I obtained weather data from 34 weather stations across Bangladesh from the Bangladesh Meteorology Department, capturing daily minimum temperature, maximum temperature, and relative humidity data from 1988 to 2017. Data from one station (Chittagong) were dropped because of data quality concerns. The remaining stations were filtered to split northern and coastal stations. Northern stations were selected as any station with latitude greater than 24.5^{o} N and between 89^{o} and 91^{o} E longitude. Coastal stations were selected as stations with less than 23.5^{o} N latitude and between 89^{o} and 91^{o} E longitude. This filtering resulted in a remaining 3 stations in northern Bangladesh (Rangpur, Mymensingh, and Bogra) and 9 stations in coastal Bangladesh (Khepupara, Patuakhali, Bhola, Satkhira, Barisal, Khulna, Madaripur, Jessore, and Chandpur) (**Fig. S5**).

Historical *RH*, which is a single daily value representing daily maximum *RH*, was adjusted to calculate an estimated daily average *RH.* This was done by calculating daily average temperature (T_{av}) as the average between daily T_{max} and T_{min} and then calculating the saturation pressure (e_{sat}) at T_{av} and $T_{max.}$ *RH* at T_{max} was then calculated as the reported *RH* multiplied by the ratio of P_{sat} at the daily average temperature and P_{sat} at the daily $T_{max.}$ This adjusted *RH* and historical T_{max} were used to calculated daily maximum WBT at each weather station (Stull, 2011). Annual mean $T_{max},$ *RH,* and WBT from the northern and coastal stations were compared to annual maximum values from CESM-LE (**Fig. S1, S2**).

For northern Bangladesh, mean CESM-LE T_{max} is, on average, 0.64 °C cooler than mean historical data. For coastal Bangladesh, mean CESM-LE T_{max} is, on average, 2.3 °C cooler than mean historical data. In northern Bangladesh, mean model *RH* is an average of 9.0% less than mean historical *RH.* In coastal Bangladesh, mean model *RH* is an average of 0.97% less than mean historical *RH*. Finally, mean maximum annual predicted WBT for northern Bangladesh is 2.4 °C less than mean historical WBT while mean annual maximum predicted WBT for coastal Bangladesh is 2.3 °C cooler than mean historical WBT. Despite these discrepancies, mean model results fall within a standard deviation of historical data for each of the variables assessed (**Fig. S1, S2**). This comparison to historical data indicates that estimates of WBT from the CESM-LE model ensemble are likely conservative, as they underestimate T_{max}, *RH*, and WBT. Furthermore, the model is unable to reproduce extremes in the historical data.

5.2.3 CESM-LE Adjustment Informed by CMIP5

To further assess the validity of CESM-LE predictions, I compared results of the CESM-LE runs to results from the fifth phase of the Climate Model Intercomparison Project (CMIP5) obtained from colleagues at the National Oceanic and Atmospheric Administration (NOAA) (Taylor et al., 2011). CMIP5 data used in this analysis was from the same climate model used in CESM-LE but with slightly updated physics. CMIP5 also allowed us to consider RCP 4.5 and RCP 6.0 emissions scenarios, which represent more optimistic future emissions.

Annual mean T_{max} from CMIP5 was, on average, 1.6 °C warmer than CESM-LE in northern Bangladesh, and 0.77 °C warmer in coastal Bangladesh. CMIP5 annual mean *RH* was approximately 2.4% lower (drier) in northern Bangladesh and 2.5% higher (wetter) in coastal Bangladesh as compared to CESM-LE. These differences corresponded to WBT that was higher by, on average, 0.75 °C in northern Bangladesh and 1.09 °C in coastal Bangladesh. These results again indicated drier, cooler conditions predicted with CESM-LE, especially in coastal Bangladesh. Based on this finding of differences between CESM-LE and CMIP5 model predictions, I devised a method to adjust the CESM-LE predicted WBT based on the relationship between CESM-LE and CMIP5 data.

I evaluated the difference between CMIP5 daily maximum WBT and CESM-LE daily maximum WBT. To do so, daily values were plotted in density plots for both models from the years 1950 to 2100, representing 55,114 observations for coastal and northern Bangladesh each in order to select an appropriate method for adjusting CESM-LE results. I fit a linear regression to the data using the *lm( )* function in R against several variables, including *RH*. The intercept, coefficient, and R^2 results for coastal and northern Bangladesh linear models are given in **Table S1**. CESM-LE *RH* was selected as the variable based on which to conduct the adjustment of CESM-LE versus CESM-LE WBT due to a higher value of R^2 for test regression. I also fit a LOESS model to the data to allow for non-linearity. Both the linear model and LOESS model were plotted on the density plots (**Fig S6).**

The linear model and LOESS model of difference in WBT as a function of CESM-LE *RH* were used to conduct the adjustment of CESM-LE model results based on CMIP5 results. To apply the adjustments, the linear and LOESS models previously fit to the data were used to predict the difference between CESM-LE and CMIP5 based on CESM-LE predicted *RH*. This difference was then applied to each daily CESM-LE maximum WBT for each ensemble member.

Finally, I compare the adjustment annual mean WBT max from CESM-LE, linear adjusted CESM-LE, LOESS adjusted CESM-LE, CMIP5, and historical data (**Fig. S7**). Though there are challenges associated with the historical weather station data due to uncertainties, I see that both the linear and LOESS adjustments to the CESM-LE data bring the predicted WBT closer to the WBT calculated from the weather station data. A full description of adjustment methodology can be found in **Supporting Materials** in the Appendix. The adjustments to CESM-LE predictions help to highlight the spread of possible future scenarios and inherent uncertainty in the climate models.

5.2.4 Assessing GWLs

Due to limitations of RCP's, especially the possibility that RCP 8.5 may be an unrealistically extreme scenario, I focus my results on the impacts of GWL's of 1.5° C, 2.0° C, 3.0° C, and 4.0° C (Burgess et al., 2020; Ho et al., 2019; Pielke & Ritchie, 2021; Ritchie & Dowlatabadi, 2017b, 2017a). GWL's allow us to move beyond the idea of emissions scenarios, and instead focus on outcomes at various levels of warming.

With the CESM-LE RCP 8.5 data, I establish a 30-year reference period of 1950 to 1970 and use NASA observational GISS Surface Temperature Combined Land-Surface Air and Sea-Surface Water Temperature Anomalies (Land-Ocean Temperature Index, LOTI) to adjust for preindustrial levels (GISS Team, 2020; Lenssen et al., 2019). 30-year periods corresponding to GWL's in global CESM-LE model output were calculated for each of the 35 CESM-LE ensemble members based on previously established methodology (Abiodun et al., 2019; Naik & Abiodun, 2020). These time intervals for each GWL were then applied to the CESM-LE data and adjusted CESM-LE results.

5.3 Results

5.3.1 Annual Dangerous Heat Days

I use a WBT threshold of 30 °C to define dangerous conditions, as this is a level that would be dangerous for outdoor workers and other individuals with increased vulnerability to heat exposure while still falling within a range where human adaptation may be possible (Kjellstrom et al., 2009). This level also corresponds to a “dangerous” heat stress risk level according to the NOAA National Weather Service Heat Index, with WBT above 31 ^{o}C corresponding to “extreme danger” (Im et al., 2017). Using daily WBT, I estimate the annual number of days above the 30 ^{o}C threshold for northern and coastal Bangladesh at daily maximum and minimum temperatures (**Fig. 5.1**). At the baseline, under a GWL of 0 ^{o}C, WBT in Bangladesh does not exceed the dangerous level of 30 ^{o}C based on the unadjusted CESM-LE, but after a GWL of 3 ^{o}C the annual number of days above this threshold increases rapidly (**Fig. 5.1**). By a GWL of 4 ^{o}C, the mean of the model ensemble predicts more than 21 days annually above the danger threshold at daily maximum temperatures in northern Bangladesh, and more than 12 days in coastal Bangladesh. At this GWL, both areas are expected to also experience at least one day where the minimum WBT exceeds the 30 ^{o}C threshold. Upper bounds of the unadjusted ensemble predictions estimate 71 dangerous days in the north and 61 in the south. However, the CESM-LE adjustments based on CMIP5 show that days annually above the danger threshold may start increasing as early as the 1.5 ^{o}C GWL, especially in northern Bangladesh, and reach as many as 100 days in both northern and coastal regions by a GWL of 4 ^{o}C (**Fig. S3**).

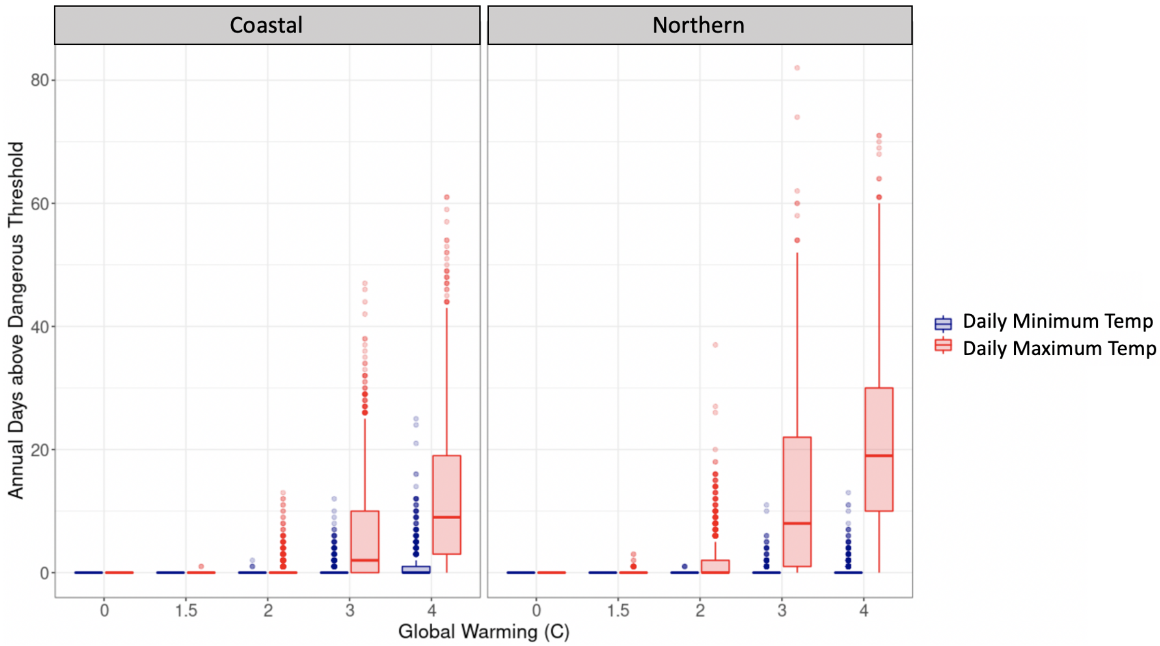

Figure 5.1. Annual number of days above 30 ºC WBT dangerous threshold by GWL. CESM-LE predicted annual days above dangerous threshold of WBT at daily maximum temperature (red) and daily minimum temperature (blue) under baseline (0), and GWL's of 1.5, 2, 3, and 4º C. Solid line in boxes represents the median, while top and bottom limits of colored boxes indicate 75% and 25% percentiles respectively. Vertical lines span to the largest value within 1.5 times interquartile range above 75% (up) and the smallest value within 1.5 times the interquartile range below 25% (down).

5.3.2 Consecutive Dangerous Heat Days and Prolonged Heat Exposure

Prolonged exposure to extreme heat, without relief, may increase risks to human health (Sharma et al., 2019). For this reason, the days where minimum temperatures exceed a dangerous threshold can provide additional insights into future human health risks. My analysis suggests that up to 13 days may be above the dangerous threshold at daily minimum temperatures in northern Bangladesh, and up to 25 days in coastal Bangladesh with 4 ºC of global warming for the unadjusted CESM-LE output (**Fig. 5.1**). To further investigate risks of prolonged exposure to extreme heat, I also analyzed annual consecutive days above the 30 ºC WBT threshold (**Fig. 5.2**). Consecutive days above the dangerous threshold at the maximum daily temperature could exceed

30 days in both northern and coastal Bangladesh under a GWL of 4 °C in unadjusted CESM-LE projections. In addition, the number of consecutive days where the dangerous WBT threshold is exceeded at the daily minimum temperature is also expected to rise. Here, coastal Bangladesh could experience between 5 and 15 consecutive days of dangerous heat without any relief, even at night, while northern Bangladesh could experience up to 10 days of dangerous heat without relief. The adjustments suggest even more severe prolonged heat exposure, with coastal Bangladesh potentially experiencing more than 30 and northern Bangladesh experiencing more than 20 consecutive days of extreme heat without relief **(Fig. S4)**.

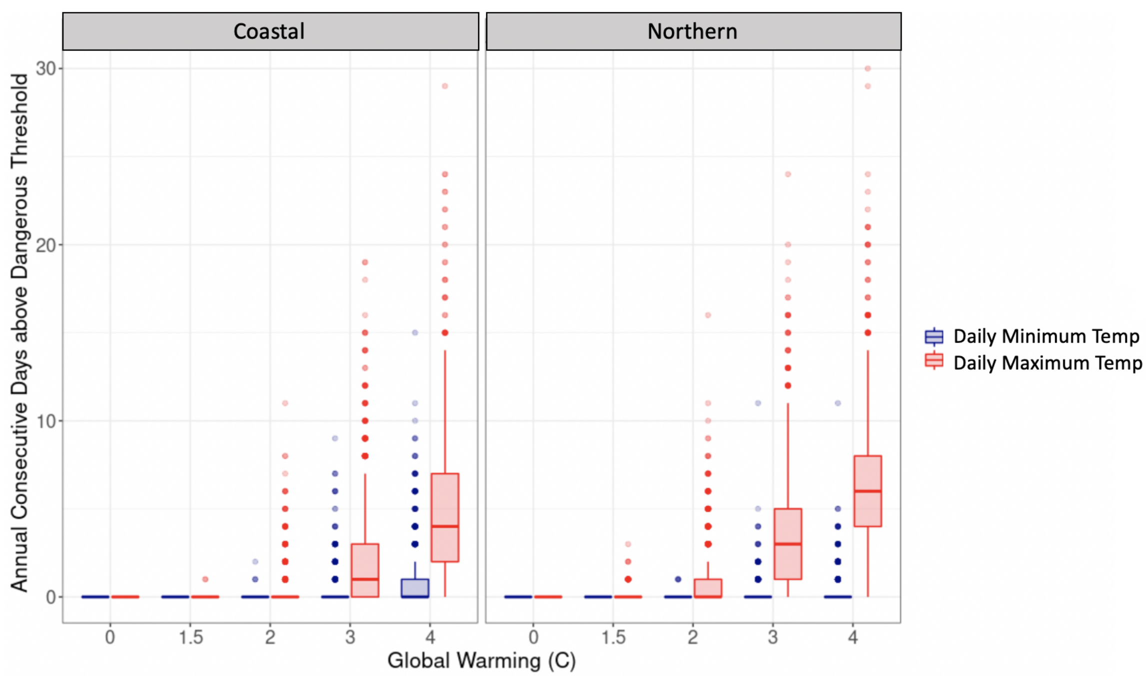

Figure 5.2. Annual number of consecutive days above 30 °C WBT dangerous threshold by GWL. CESM-LE predicted annual consecutive days above dangerous threshold of WBT under various GWL's at daily maximum and daily minimum temperatures for northern and coastal Bangladesh.

Bangladesh experiences a tropical monsoonal climate, with the rainy season lasting from June to October every year. By dividing each year of data into a rainy season from June to October, and a dry season capturing the remaining months, I can assess the seasonality of extreme WBT. Especially in coastal Bangladesh, the majority of annual days above a dangerous threshold occur during the rainy season (**Fig. 5.3**).

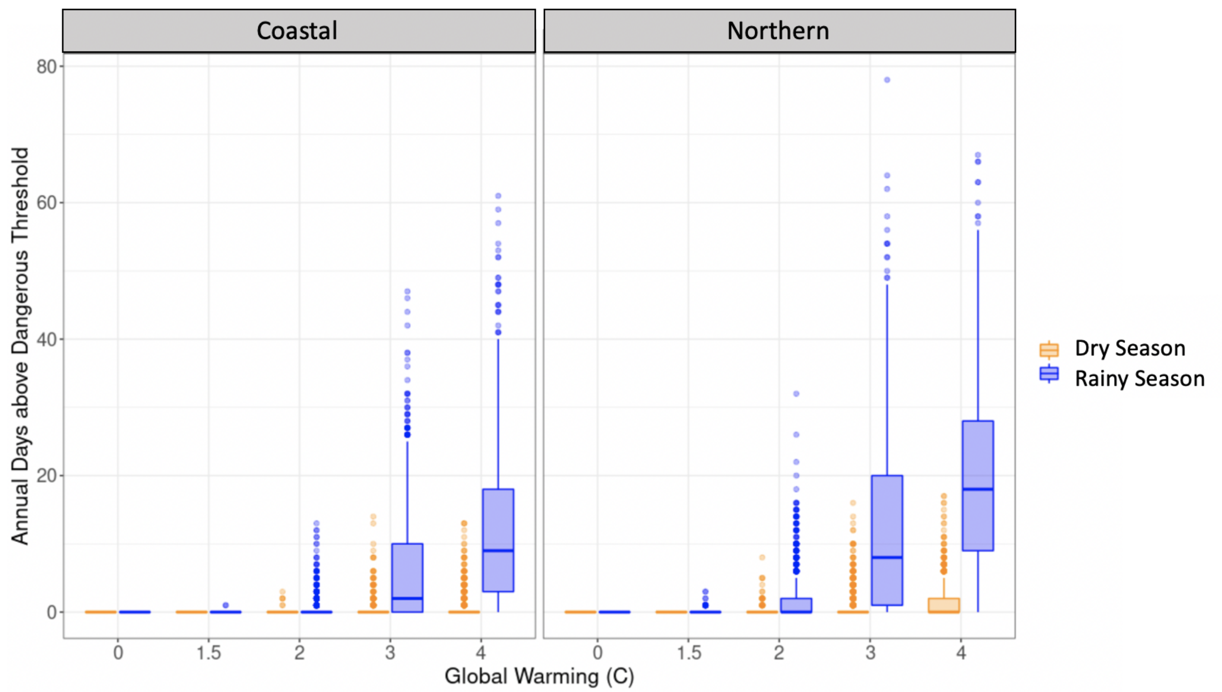

Figure 5.3. Annual number of days above 30 ºC WBT dangerous threshold divided into rainy and dry season by GWL. Model predicted annual days above dangerous threshold of WBT for northern and coastal Bangladesh split into rainy season (June – October) and dry season.

5.3.3 Annual Maximum WBT

I am also interested in annual maximum WBT, not just the number of days exceeding a dangerous threshold, as even a single day of extreme heat can be dangerous. Though results show that WBT in Bangladesh is not expected to exceed the deadly 35 ºC threshold in the unadjusted CESM-LE runs, it is expected to exceed 32 ^{o}C in both northern and coastal Bangladesh under a GWL of 4 ^{o}C (**Fig. S8**). The adjusted models show that maximum WBT could exceed 33 ^{o}C in both northern and coastal Bangladesh, with the LOESS adjustment showing exceedances of 34 ^{o}C even under the 3 ^{o}C GWL (**Fig. S8)**. In northern Bangladesh, the LOESS adjustment predicts that WBT could exceed 34 ^{o}C with a maximum prediction of 35.3 ^{o}C, exceeding the 35 ^{o}C deadly threshold. In coastal Bangladesh, the linear and LOESS adjustments are quite similar, and predict a maximum WBT between 32.1 and 33.7 ^{o}C.

5.4 Conclusions

These results highlight the potential dangers of future increases in WBT in Bangladesh under different GWL's. At a GWL of 4 ^{o}C, my results indicate that as many as 40% of days out of every year could exceed a level that is dangerous for the health of vulnerable people and outdoor laborers. Such a scenario could have implications for communities in coastal Bangladesh who already experience severe environmental challenges such as frequent cyclones, flooding, and salinity encroachment. Even under lesser GWL's, these results suggest that extreme heat as a result of anthropogenic climate change will be a challenge that Bangladesh will face in the future. By analyzing consecutive days above the dangerous threshold, my results also suggest that Bangladeshis living in coastal communities will experience more days without any relief from the heat. While wealthier households will be able to escape the heat with access to air conditioning, poorer households will not have such an escape (Im et al., 2017). The seasonality of dangerous WBT may pose additional challenges for people trying to adapt to extreme heat, as the monsoon season is also a time when annual flooding and waterlogging are likely to occur, creating additional environmental pressures.

In this work, it is also important to consider annual maximum WBT. The adjustments did show the possibility of WBT exceeding the deadly threshold of 35 ^{o}C in northern Bangladesh. However, even the conservative maximum WBT of 32 ^{o}C predicted would undoubtedly result in increases in mortality and morbidity for Bangladeshi communities, especially in individuals who are very old, very young, or have a pre-existing medical condition. 32 ^{o}C WBT could also have health impacts for the majority of the Bangladeshi individuals who earn their livelihood through physical labor outdoors, including agricultural workers, rickshaw drivers, and others. Physical limitations on productivity caused by heat could further entrap already vulnerable laborers into conditions of poverty (Diffenbaugh & Burke, 2019). Due to uncertainties in these models, it is difficult to assert whether or not WBT in Bangladesh will reach the 35 ^{o}C deadly threshold in the future. Despite this, comparison to historical data highlights that both CESM-LE and CMIP5 do not sufficiently capture extremes in meteorological conditions. Historical data shows that WBT's exceeding 33 ^{o}C, though rare, have already been recorded in Bangladesh, and it is reasonable to expect that such conditions will become more frequent and reach 35 ^{o}C with future warming.

Beyond the obvious impacts on human health and productivity, the projected increases in WBT from this analysis would likely also have impacts on food production, access to freshwater, disease transmission, and energy use in Bangladesh, to name a few (A. J. McMichael & Dear, 2010). It is also possible that these changes in WBT could result in human migration, as people leave increasingly inhospitable environments in attempt to adapt (Cattaneo & Peri, 2016; C. McMichael et al., 2012; Mueller et al., 2014; Xu et al., 2020). Future work is necessary to explore these additional implications of WBT increases in Bangladesh. This work does not attempt to quantify losses in terms of human health or productivity associated with future increases in WBT in Bangladesh, though it is clear that the effects would be significant. This work is also unable to detect finer scale spatial differences in WBT across Bangladesh, such as differences between urban and rural environments, which would be important to understand in future work (Fischer et al., 2012; Oleson et al., 2015).

5.5 References

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CHAPTER 6

Conclusions

6.1 Summary

As I have consistently discussed in this work, environmental migration is highly complex. The decision for a household or an individual to migrate or stay in an environmentally vulnerable location is influenced by factors that cross multiple spatial and temporal scales. These processes are especially complicated in Bangladesh, where a dynamic natural environment, highly mobile population, and unique social setting converge.

The purpose of this work was to develop an original ABM and use that model to explore environmental migration dynamics in Bangladesh. In Chapter 2, I present the initial version of the ABM using a simple utility maximization decision-making method. I asked the research questions: 1) Can a simple economic model reproduce identified patterns of environmental migration in Bangladesh? and 2) What combinations of community characteristics and livelihood choices in the ABM replicate these observed patterns? I found that a simple economic model reproduces the patterns of interest with a high level of success when the distribution of land ownership is initialized correctly. I also developed and demonstrated a machine learning method combined with a pattern-oriented approach for model calibration to identify successful parameter combinations.

Chapter 3 expanded my ABM to include more complex decision-making based on the psychological Theory of Planned Behavior. I found that the simple utility maximization method performed better than the more complex method at reproducing the migration patterns of interest. As with the utility maximization method, I found that the distribution of land ownership in the simulated community was critically important for migration outcomes with the TPB method. Specifically, using a Lomax distribution to initialize household land ownership based on an empirical Gini coefficient significantly improved model performance. The finding that community-level inequality plays a key role in migration outcomes is important and could inform both policy and future research.

In Chapter 4, I investigate more fully the role of social networks within the ABM. I test several different network structures and sizes and compare the migration outcomes across model runs. I find that the network structure does not have a significant effect on migration outcomes with the model, while increasing network size does increase overall rates of outmigration. This result suggests that network typologies are less important than expected within the model. This is consistent with my findings that, for these patterns and in this context, economics are dominant in the migration decisions of agents.

Finally, in Chapter 5 I deviate from my focus on the ABM to look towards the future of the climate in Bangladesh. I find that wet bulb temperature is expected to increase in Bangladesh in the future under all global warming scenarios tested. Wet bulb temperatures could reach dangerous levels by 2100, especially during the humid and hot monsoon season. These high temperatures are expected to be especially dangerous for outdoor workers and people who do not have access to air conditioning.

6.2 Future Work

There is much future work needed to continue to understand these dynamics and several immediate opportunities to expand the ABM. As a next step in this research, I aim to work with social psychologists to further develop the representation of decision-making in my ABM to incorporate additional psychological theory. Eventually, I plan to develop a participatory game to collect data from communities in Bangladesh so that stakeholder input can be directly incorporated into the model design. Data collected from the game will provide insights into how players weigh different factors to make a migration decision, as well as how decisions are made under uncertain conditions. In this way, the model can continue to be expanded in a straight-forward way and used as a test bed for various theories. In addition, I aim to expand the model to include destination locations rather than just origins. This modification would enable the model to be used to also consider the ways in which social networks influence destination selection and decision-making surrounding return migration.

In general, more research is needed to understand how environmental change and climate change may interact with human mobility, especially as climate change pressures continue to increase. In conducting this research, communities must be at the forefront and local voices should be centered. Specifically, researchers should consider how our research can be useful in supporting the decisions of households that are impacted, whether they choose to migrate or to stay in place. There is significant opportunity to expand participatory modeling methods in this area.

Finally, while agent-based modeling and other forms of modeling are undoubtedly useful in studying environmental migration, they are not the only relevant methods. Beginning to understand environmental migration requires transdisciplinary collaboration as well as sincere community engagement. Ultimately, we must remember that this work is about people and their decisions, aspirations, and wellbeing. Future work should consider how to incorporate individual input, stories, and lived experience into all stages of research and modeling.

APPENDIX

A. ODD FOR AGENT-BASED MODEL OF ENVIRONMENTAL MIGRATION IN BANGLADESH

Kelsea Best

1 OVERVIEW

1.1 Purpose

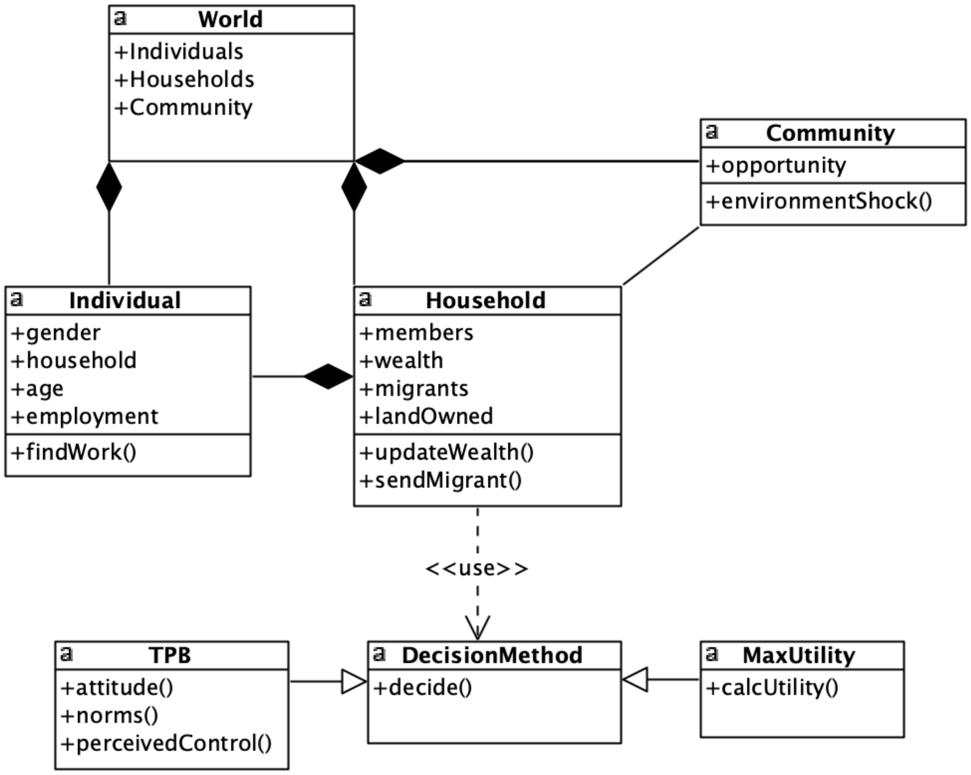
The purpose of the model is to simulate household migration decisions in Bangladesh under environmental pressure. The model seeks to understand how environmental stress in the form of drought and drought-induced agriculture loss, as well as changing livelihood opportunities, impact mobility patterns. The model allows the user to implement multiple decision-making frameworks including decision-making informed by utility maximization, theory of planned behavior, protection motivation theory, and a mobility-potential based method.
Future versions of the model will also explore how social networks impact migration decisions through the exchange of information and resources between origin and destination locations, including different kinds of destinations.

1.2 Entities, state variables, and scales

This model consists of **individuals** and **household** entities. Individuals have a gender, age, and employment, as well as a household that they are assigned to. Households consist of individuals. Other entities include the **decision class** and **community class**. The household will access the decision method from the decision class in order to decide whether or not to send a migrant. The decision class allows for the user to select a decision-making method from available methods including utility maximization and Theory of Planned Behavior (TPB).

Each household is connected to a **community** entity. In the simple model, the community represents the origin location. The community has associated employment opportunities. In a later version of the model, destination locations will be incorporated as types of community including Dhaka, Khulna, and another rural location. These destinations will also have associated employment opportunities that individuals can assess. Destinations will also have an associated risk and cost to move. Communities, individuals, and households are all situated within an environment which will stochastically experience a shock at a given time step. An environmental shock will impact community opportunities as well as individual households.

Agents will also keep track of their location where they are residing at each time step. To represent social networks, agents will be able to exchange information about migration histories and wealth histories freely with a random set of other households.



UML diagram of the model structure

1.2.1 Global variables

- decision – decision method to be used to make migration decision (options include "utility", "tpb", "pmt", "mobility", or "hybrid")
- shock_method – type of environmental impact simulated, this can be "shock" for a stochastic environmental shock or "slow_onset" for a gradual impact
- mig_util – utility to migrate successfully
- mig_threshold – wealth threshold to migrate
- num_hh – number of households
- num_individuals – number of individuals
- init_time – initialization time (automatically 0)
- tick – tracks time progression in model
- ticks – total number of ticks for model to run
- migrations – tracks overall migrations taken globally
- wealth_factor – factor to initialize household wealth
- ag_factor – productivity factor for land that households own

- origin_comm – origin community (calls community class)
- comm_scale – proportion of community that is impacted by an environmental shock
- jobs_avail – number of non-agricultural jobs in community
- network_type – type of social network for agents to use (options include “small_world”, “random”, “preferrential”, or “none”)
- network_size– size of each household’s social network
- individual_set – stores individuals and data
- hh_set – stores households and data

There are also several global variables related to specific decision-making methods including weights for TPB and PMT (w1, w2, w3 such that w1 + w2 + w3 = 1, k which is a scaling factor, and threshold which is the household threshold for PMT.)

1.2.2 Individual class variables

- unique_id
- age
- gender (‘M’ or ‘F’)
- hh – stores idea of household that individual belongs to
- employment
- salary
- employer
- can_migrate –True/ False if inidivdual is eligible to migrate
- head –True/ False if individual is a head of household
- migrated – True/ False if individual has migrated
- wta – Salary that individual is willing to accept from a potential employer

1.2.3 Household class variables

- unique_id
- wealth – total wealth in household
- hh_size – size of household (integer)
- individuals – data frame that stores individuals that belong to that household
- head – stores individual who is head of household
- land_owned – value of land owned by household
- network– other households within the social network
- network_moves – how many times a household within the social network has sent a migrant
- land_impacted – True/False if household’s land was impacted by environmental shock
- wta – willing to accept
- wtp – willing to pay
- employees – stores employees hired by household
- payments – stores payments household owes to employees
- expenses – stores any household expenses
- total_utility – utility of household summed over individuals

- total_util_w_migrant – utility if household sends a migrant
- num_shocked – tracks how many times a household is impacted by an environmental shock
- land_prod – stores how much wealth a household gains from its land. If a household is not impacted by a community shock, then this is currently ag_factor * land_owned. If a household's land is impacted, then this is zero.
- secure – True/False if household has enough wealth to pay for basic food. This represents whether or not a household falls beneath a poverty threshold. Currently, this security threshold is based on the World Bank definition of poverty as less than $1.90 USD per person, per day.
- wellbeing_threshold – Calculates the threshold below which a household is not secure. Based on the World Bank definition of poverty as less than $1.90 USD per person, per day, or approximately 20,000 BDT per year per member of household.

- someone_migrated – tracks how many times the household has sent a migrant

Theory of Planned Behavior (TPB) specific household variables include: - control – perceived behavioral control - attitude – household attitude towards migration - network_fact – impact of social network on social norms - w1, w2, w3 such that w1 + w2 + w3 = 1 – weights aspects of perceived behavioral control - k – logistic regression scale for asset rate

1.2.4 Decision class variables

- outcome – True/ False for outcome of decision

1.2.5 Community class variables

- impacted – True/False if community is impacted by environmental shock
- scale – Percent of community impacted by environmental shock
- jobs_avail – Number of low-paying non-agricultural jobs available in the community (i.e., construction, rickshaw driver, etc.). This may decrease if the community is impacted by an environmental shock.

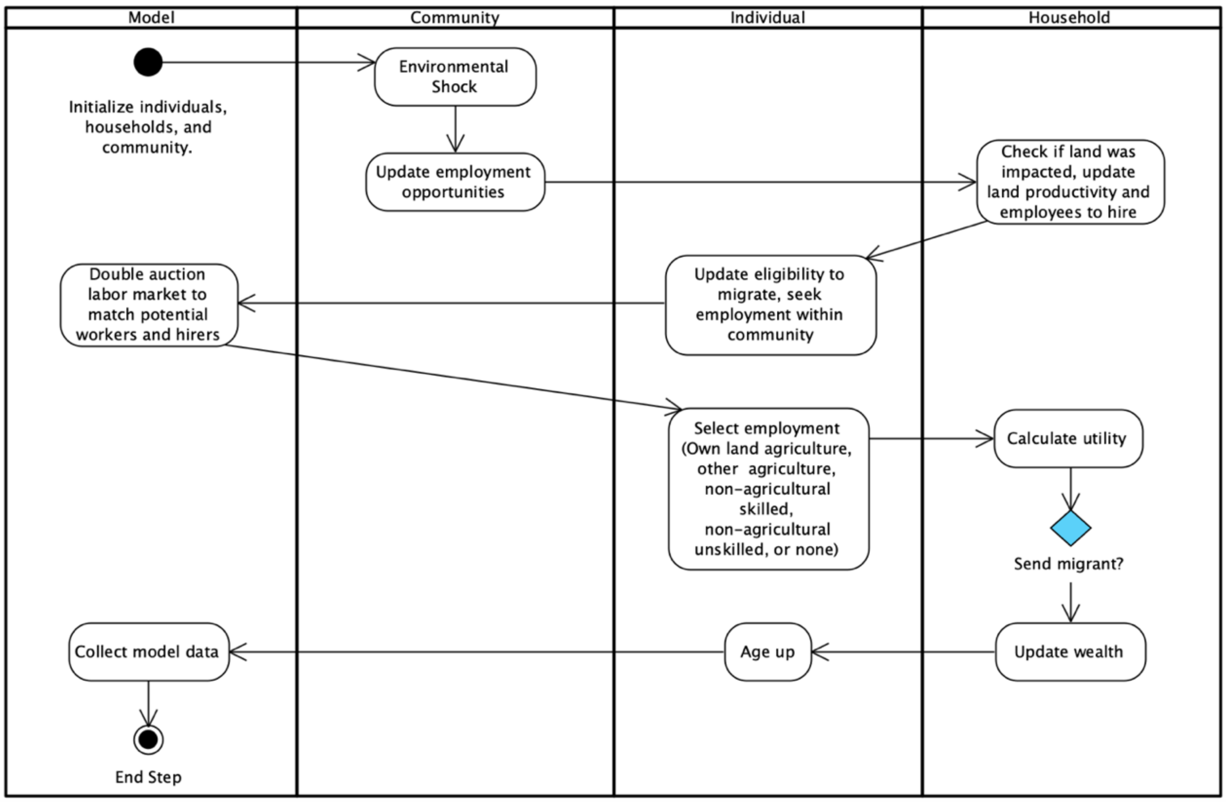
1.3 Process overview and scheduling

Each simulation starts with creation of a set of individuals, households, and a community. Individuals are assigned to a household, and households assign a head of household. These individuals and households are stored in data frames. Initial individual and household traits can be set randomly or pre-assigned.

At each step, the origin community will face a probabilistic risk of drought as an environmental shock, if the "shock_method" is set to "shock", which will impact agriculture and employment opportunities. Households will check to see if their land has been impacted by the environmental shock. Individuals will then update their eligibility to migrate and then assess employment opportunities within the community and select an opportunity based on utility and being able to perform the job (for example, old enough to work in agriculture and owning land). If the "shock_method" is specified as "slow_onset", then instead the agricultural productivity of the land in community gradually declines by a specified percentage at each step.

After each individual has selected an employment opportunity within the community, the household will aggregate utility across individuals and then, at the household level, the decision to send a migrant or not will be assessed based on the decision-making method implemented by calling the decision class. This decision will be recorded. If a household elects to send a migrant, then that individual will no longer participate in the ABM but will contribute to the household's wealth at each step of the model (until later versions in which the agent will go to a specific destination and later have the option to return-migrate). Eventually, there will be a probability of the migration failing, in which case the migrant will not contribute to the household's wealth. Eventually, households can also decide to move based on exchanging information and resources across their networks as well as past experience.

The number of ticks will increase by 1 at each step, and each individual will age by one year. Data will be collected at each tick and stored in data_set.



Sequence of actions

2 DESIGN CONCEPTS

2.1.1 Basic Principles

This model is based on the literature on environmental migration, which describes both push and pull factors as being important in migration decisions, as well as the importance of social networks. The ABM is used to attempt to reproduce patterns of migration in response to flooding and drought-induced crop failure in rural Bangladesh (Gray & Mueller, 2012). Three key patterns that are identified in this work are:

- As the proportion of a community impacted by crop loss increases, rates of migration also increase, especially above a threshold of approximately 20% of community households impacted. Therefore, community-level impacts are important for household migration, and a critical threshold may exist.
- Households that are directly impacted by crop loss are less likely to migrate, suggesting that a barrier exists to migrating for more vulnerable households.
- Wealthier households are more likely to migrate.

The decision-making elements of the model are based on behavioral theories including Theory of Planned Behavior, Protection Motivation Theory, and Motivation Potential.

2.1.2 Emergence

Emergence will arise in the form of how rates of migration change throughout the model run. When specific destination locations are included, emergence could also provide insights into where migrants will move and future populations in each destination and origin community. It is also possible that comparisons across networks of agents will show that certain networks are more mobile than others, which will be evident by comparing migration histories.

2.1.3 Adaptation

Individuals and households adapt to changes in their environment by changing their livelihood choices as opportunities in the community change. In later versions of the model, households may also adapt by updating their beliefs about migration based on past experiences or experiences of other households within their networks, which in turn impacts their likelihood of making a migration trip. Sending a migrant is, of course, another adaptation that households can make.

2.1.4 Objectives

Agents evaluate an objective based on the decision-making method to maximize utility, minimize risk, or a combination.

2.1.5 Learning

Agents will learn both from their own experiences as well as the experiences of agents in their network.

2.1.6 Prediction

Agents do not make predictions about the future, but they may consider risks associated with a decision based on own histories or histories of other agents in their network.

2.1.7 Sensing

Agents are able to sense all of their own traits and the traits in their current community. They are also able to assess migration histories of agents in their social network.

2.1.8 Interaction

Households interact by sharing information about their migration histories and wealth histories with other households within their network. Household agents can give and receive information within their network and make decisions based on this information. Households can also transfer resources in the form of remittances across their networks.

2.1.9 Stochasticity

Stochasticity may be included in the initialization of the model in terms of agent traits and social network connects. Stochasticity is also present in the implementation of environmental shock risk at each step. Stochasticity will be incorporated to determine whether or not a migration trip was successful, based on a probability of failure.

2.1.10 Collectives

Households connected by social networks can share information about their migration experiences with one-another. They can also share resources.

2.1.11 Observation

The model records all household migration histories, histories of environmental impact, and tracks wealth over time. On the larger level, the model will also track populations in origin and destination communities over time, total migrations, and the evolution of wealth in the community.

3 DETAILS

3.1 Initialization

Currently, the model is initialized with a number of ticks for the model to run, number of individual agents, number of household agents, a decision method to be used, and a migration utility. Agent (household and individual) traits can be randomly initialized based on a parameterization from BEMS data or other sources of data.

3.2 Input data

None.

3.3 Submodels

3.3.1 Model level functions

- generate network This creates the social network based on the total number of households in the community, the size of each network, and the type of network. Network type is specified by the model user as part of model initialization and can include random, small-world, preferential, or none. This function then generates a graph object that is passed to each household to implement their own social networks.

- double_auction Individuals who are looking for employment and households that are looking for employees can enter the double auction. Individuals will look for households whose wtp is greater than their wta. If they find such a household, their salary will be set as the average between wtp and wta, and their employer will set to that household id. The individual's id will be appended to the household's employer list. The double auction will run for a specified number of rounds or until there are no longer any individuals looking for work or households looking to hire. Individuals who are unable to find employment within the double auction may attempt to take a lower paying, non-agricultural job if there are avail_jobs within the community.

- data_collect Collects data from the model at each step including migration histories and wealth.

- tick_up Ticks the model up at the end of each step, ages each individual, and resets the community's environmental schock.

3.3.2 Household class functions

- gather_members Households collect individuals to be in their household. They randomly select the number of individuals given by hh_size from the individual set.

- assign_head Households assign head of household to the oldest male member of the household. If there are no male members, then the oldest female is assigned as head of household.

- check_land Ask households to check to see if their land has been impacted in the case of an environmental shock. If a household's land is impacted, then their wealth experiences a stochastic decrease, and their land productivity goes to zero.

- migrate Households select a potential migrant from their set of individual household members who are eligible to migrate. Households may then decide, based on the decision method to send a migrant by calling the decision class. If the household does decide to send an individual migrant, then someone_migrated is increased by 1, and the individual no longer participates in the model beyond contributing to household wealth.

- sum_utility The household sums the total utility across all individuals. This is done by asking each individual in the household what his/her salary is and summing them for the household. Here, the household also checks if it is secure or not (above poverty threshold), based on the total earnings.

- hire_employees If a household's land has not been impacted, then it updates the number of employees that it can hire based on its land owned and its wtp. Household updates its wtp and wta. wtp is calculated as the household's land_productivity / (num_employees + 1). wta is calculated as the household's wellbeing_threshold / hh_size.

- update_wealth At the end of each tick, all households update wealth by summing across the employment of individuals within the household (or migrants that have successfully migrated). Updated wealth is calculated as:

$$Wealth = PreviousWealth + AllSalaries + LandProductivity - Expenses - PaymentsToEmployees$$

- set_network The household sets its network based on the model's graph object generated by generate_network(). Each household stores a list of other households that it is connected to in its network.
- check_network The household checks to see if other households within its social network have been impacted by an environmental shock and if they have sent a migrant. In this way, each household can learn from its own experiences as well as the experiences of its network.

3.3.3 Individual class functions

- age_up Individuals increase their age by 1 after each tick.
- check_eligibility Individuals check to see if they are eligible to migrate (currently, only male individuals older than 14 years old are eligible).
- find_work Each individual will look for work within the community. Individuals with a large amount of land (representing large land owners) may work in agriculture on their own land. If an individual is not part of a household with enough of its own land (small land owners or landless), the individual may seek agricultural employment with another household by entering the internal. labor market. If wtp > wta, then the individual may gain employment with another household. If supply is not greater than demand, then the agent does not find work in agriculture with another household. Individuals who are unable to obtain employment in the labor market may also attempt to seek non-agricultural employment by checking the avail_jobs within the community. There are a specified number of jobs that are "skilled" and pay more than "unskilled" non-agricultural jobs.

3.3.4 Community class functions

- shock Probabilistically experience a drought year based on the annual risk. If a drought occurs, then community work opportunities will be updated based on a decline in the utility of agriculture.

3.3.5 Decision class functions

- decide This part of the model will implement the decision method for households to decide whether or not to send a migrant. If the decision conditions are achieved, then outcome is updated to True.
  - utility_max - simple utility maximization
  - tpb - Theory of Planned behavior. Households draw upon the Theory of Planned Behavior in which the decision to migrate is based on a behavioral intent (I) informed by a combination of perceived behavioral control(PBC), behavioral attitudes (BA), and social norms (SN). Where $I = PBC * BA * SN$

PBC is a binary variable based on behavioral control (BC). BC is a combination of a household's own past experiences with migrating (0 or 1), network experiences with migrating (0 or 1), and an asset rate based on the household's wealth and the cost to migrate. The asset rate is calculated using a logistic function:

$$AssetRate = 1/(1 + e^{-}k * x)$$

where k is a scaling factor specified at model initialization and x is (the household's wealth - the cost to migrate) / the household's wealth.

BC is then calculated as

$$w1 * AssetRate + w2 * OwnExperience + w3 * NetworkExperience$$

where w1, w2, and w3 are the weights on each part of behavioral control and must sum to 1.

PBC is then based on a random number being less than or equal to BC.

Behavioral attitudes (BA) are based on an individual migrant's characteristics and how they related to that individual's propensity to migrate as well as the perceived benefit to migrating. For propensity, a Maxwellian distribution is used with a peak parameter that is informed by the individual's age and gender where men or more likely to migrate than women. Perceived benefit is a binary (0, 1) using a utility calculation and assessing whether or not the migration would result in a net increase of wealth compared to the individual's other employment option.

Finally, social norms (SN) are based on the decisions of the household's networked peers. SN serves as a scalar on PBC and BA and is given by

$$SN = 1 + (migrationsinnetwork/migrationsize)$$

The behavioral intent (I), as mentioned, is the product of PBC, BA, and SN. A random number is then drawn to determine if I translates into a successful migration decision (meaning that the household elects to send the migrant).

- pmt - Protection Motivation Theory. Households draw upon Protection Motivation Theory in which the decision to migrate is based on a threat appraisal (T) followed by a coping appraisal (A).

The threat appraisal (T) is based on perceived vulnerability (V) and severity (S). S is based on the number of times the community has been impacted by an environmental shock, while V is based on the amount of wealth that a household stands to lose if impacted by an environmental shock.

$$T = SxV$$

where T must then exceed a threat threshold to move to the coping appraisal.

From there, coping appraisal (A) is based on response efficacy (RE), self-efficacy (E), and cost efficacy (CE). RE is based on past migration experiences in the network, E is based on the household's own past experience migrating, and CE uses the same logistic function form as the asset rate in TPB.

Then,

$$A = w1 * RE + w2 * E + w3 * CE$$

again, where w1, w2, and w3 are weights on each element and must sum to 1.

A random number is then drawn to determine if A translates into a successful migration decision (meaning that the household elects to send the migrant).

B. Supplementary Materials for Chapter 5

Chapter 5: Number of dangerous heat days in Bangladesh will increase with future climate change

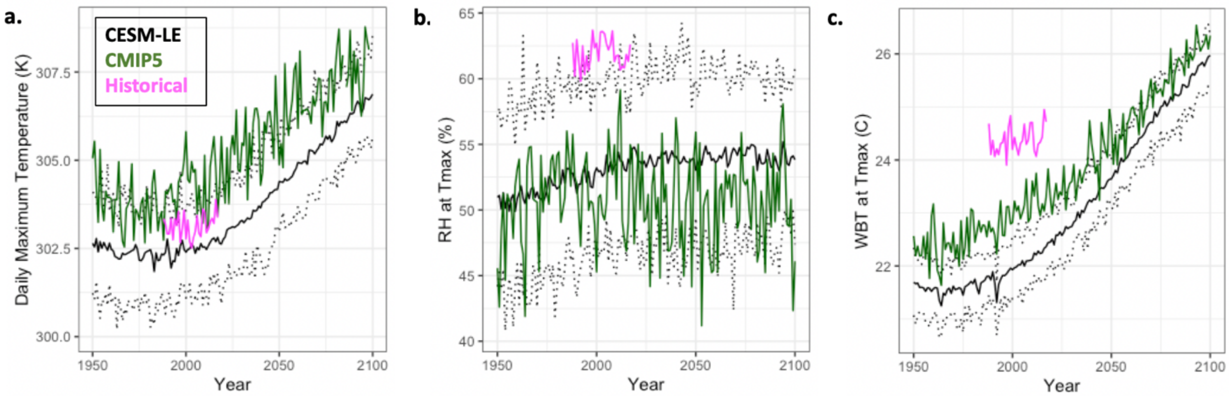


Fig. S1. Comparison of average maximum temperatures and relative humidity between CESM-LE and CMIP5 in northern Bangladesh. Average daily maximum temperature (a.), daily relative humidity (b.), and daily WBT (c.) for northern Bangladesh. Black lines represent the CESM-LE runs (mean is sold, dashed lines are upper and lower bounds of ensemble members), green line represents CMIP5 run, all under RCP 8.5, and pink line represents mean of historical weather station data.

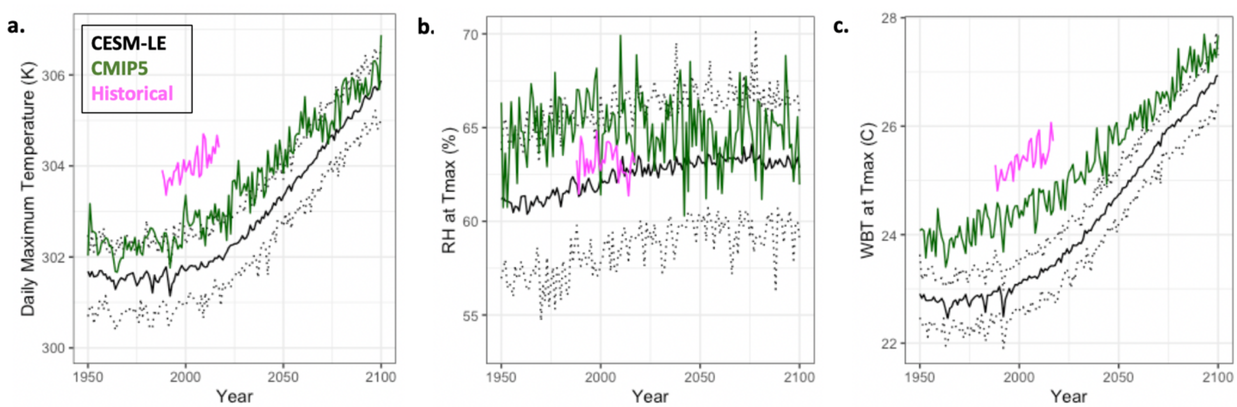


Fig. S2. Comparison of average maximum temperatures and relative humidity between CESM-LE and CMIP5 in coastal Bangladesh. Average daily maximum temperature (a.), daily relative humidity (b.), and daily WBT (c.) for northern Bangladesh. Black lines represent the CESM-LE runs (mean is sold, dashed lines are upper and lower bounds of ensemble members), green line represents CMIP5 run, all under RCP 8.5, and pink line represents mean of historical weather station data.

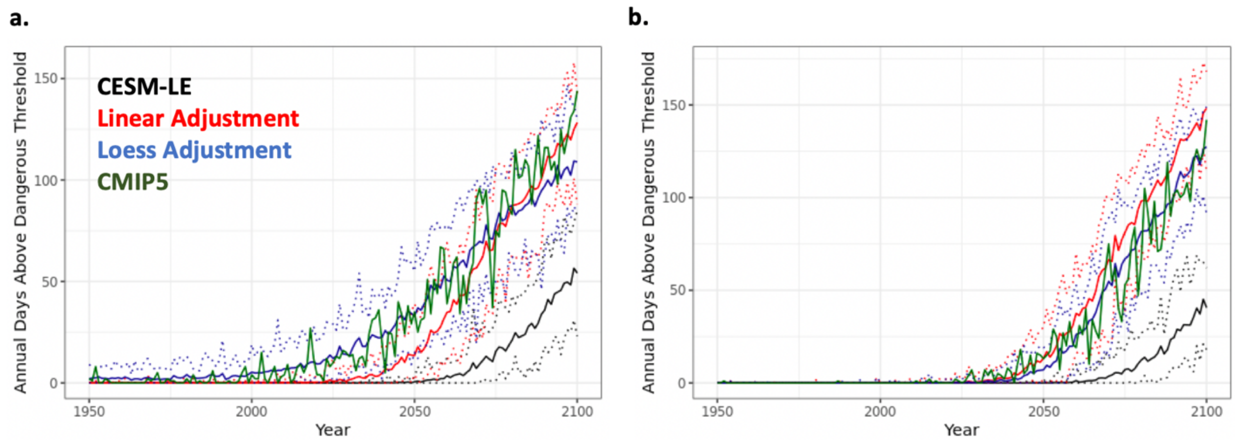


Fig. S3. Annual days above 30 ºC WBT dangerous threshold for CESM-LE and two CMIP5 adjustments. Annual days above a 30 ºC dangerous threshold are indicated for raw CESM-LE model predictions, CESM-LE predictions adjusted with a linear regression, and CESM-LE predictions adjusted with a LOESS regression, and CMIP5 predictions. Solid lines indicate the average of the 35 model ensemble members, and dashed lines indicate the upper and lower ranges given by the ensemble. Results indicated for northern (a.) and coastal (b.) Bangladesh.

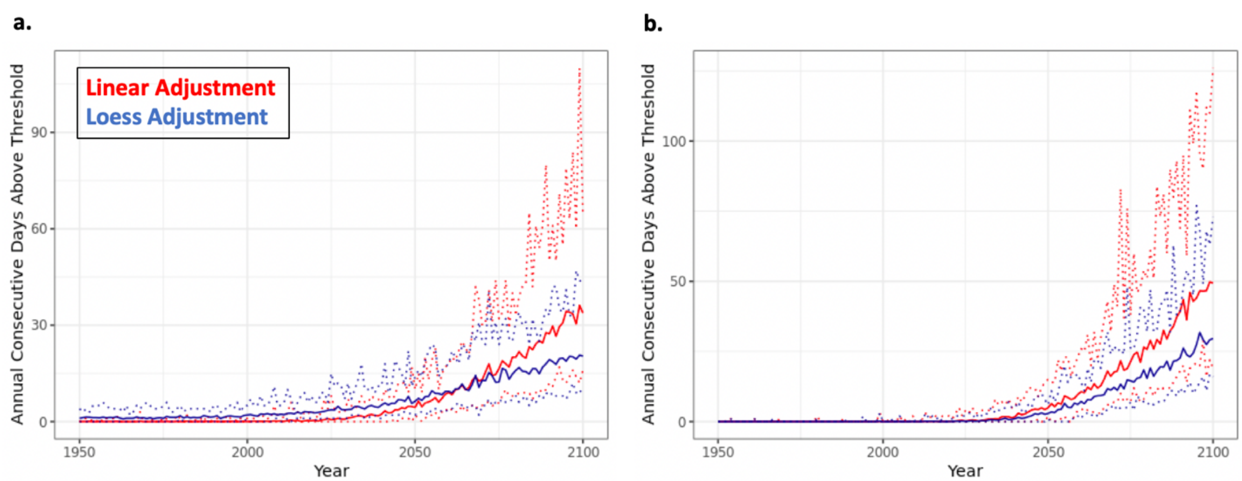


Fig. S4. Annual number of consecutive days above 30 ºC WBT dangerous threshold, CMIP5 adjusted models. Model predicted annual consecutive days above dangerous threshold of WBT for northern (a.) and coastal Bangladesh (b.) from the year 2000 to 2100 at daily maximum temperatures. Solid lines indicate the average of the 35 model ensemble members, and dashed lines indicate the upper and lower ranges given by the ensemble.

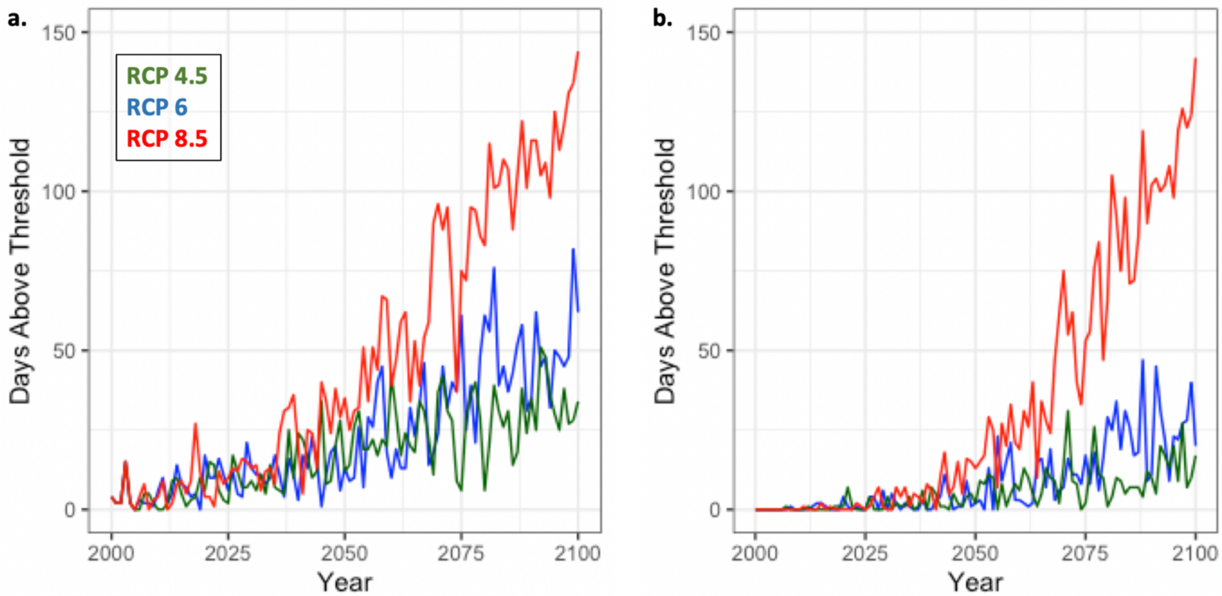


Fig. S5. CMIP5 predicted annual number of days above 30 ºC WBT dangerous threshold under three RCP emissions scenarios. Model predicted annual days above dangerous threshold of WBT for northern (a.) and coastal (b.) Bangladesh from the year 2000 to 2100 at daily maximum temperature.

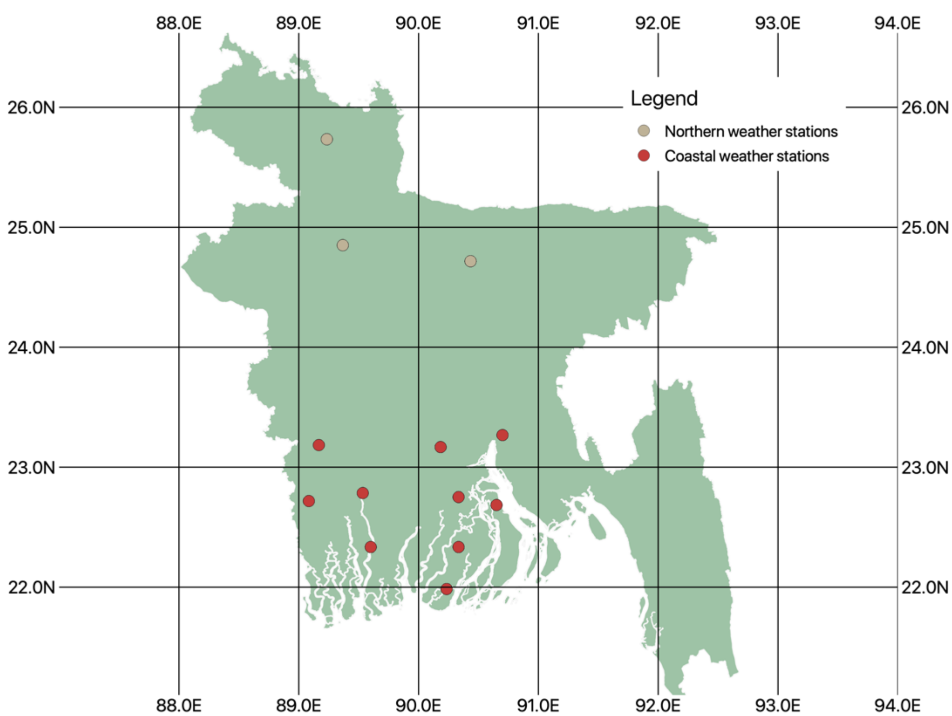


Fig. S6. Locations of weather stations used for historical comparison. Map of Bangladesh indicating the locations of weather stations used for historical comparison.

Table S1. Linear regression results for coastal and northern Bangladesh. Results for linear regressions in both regions are shown for difference between CMIP5 and CESM-LE daily maximum WBT as a function of CESM-LE daily maximum RH and as a function of CESM-LE daily maximum WBT.

Linear Model	Region	Intercept	Coefficient	R^2
Diff WBT ~ CESM-LE RH	Coastal	-0.540886	0.026176	0.04003
	Northern	-0.7607331	0.0283621	0.04763
Diff WBT ~ CESM-LE WBT	Coastal	-0.10378	0.04958	0.01404
	Northern	-0.287218	0.044784	0.01002

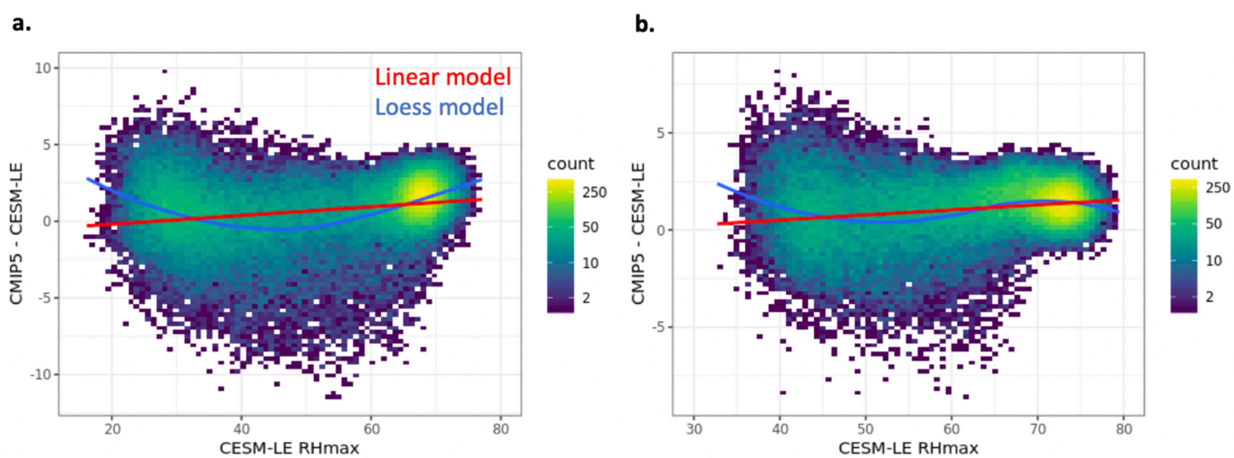


Fig. S7. Density plots of differences between CMIP5 and CESM-LE daily maximum WBT versus CESM-LE daily maximum RH. Daily difference between CMIP5 and CESM-LE ensemble mean daily maximum WBT was plotted against CESM-LE ensemble mean daily maximum *RH* for the years 1950 to 2100 to evaluate an appropriate adjustment to CESM-LE model predictions informed by CMIP5. Daily values are shown with color representing density and linear regressions (red line) and LOESS regression (blue line) are plotted. Results indicated for northern (a.) and coastal (b.) Bangladesh.

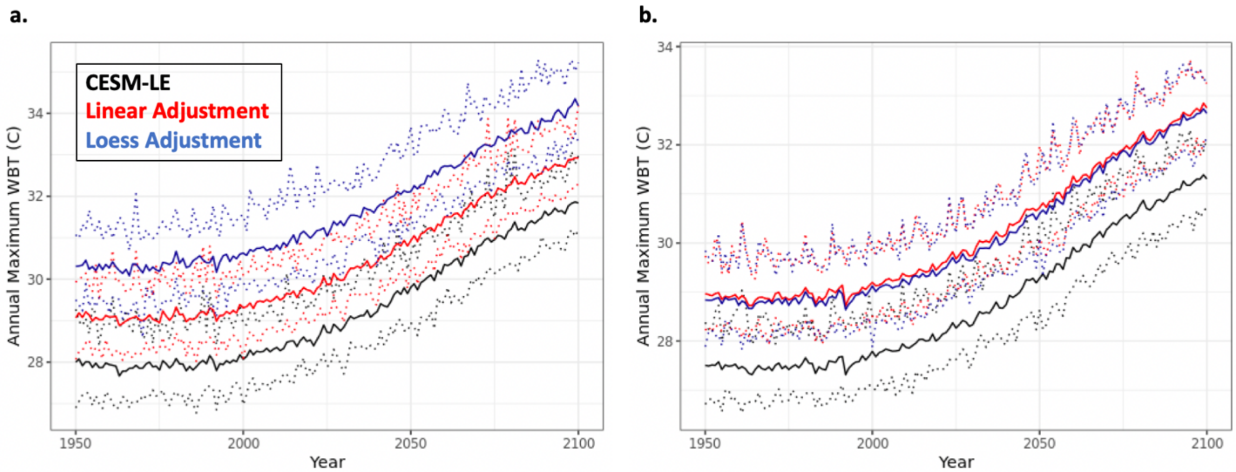


Fig. S8. Maximum annual WBT from 1950 to 2100 for both CESM-LE and adjusted CESM-LE. Maximum annual WBT in northern (a.) and coastal (b.) Bangladesh are relatively steady from 1950 to 2000 and then begin to increase steeply through 2100. Solid lines indicate the average of the 35 model ensemble members, and dashed lines indicate the upper and lower ranges given by the ensemble.

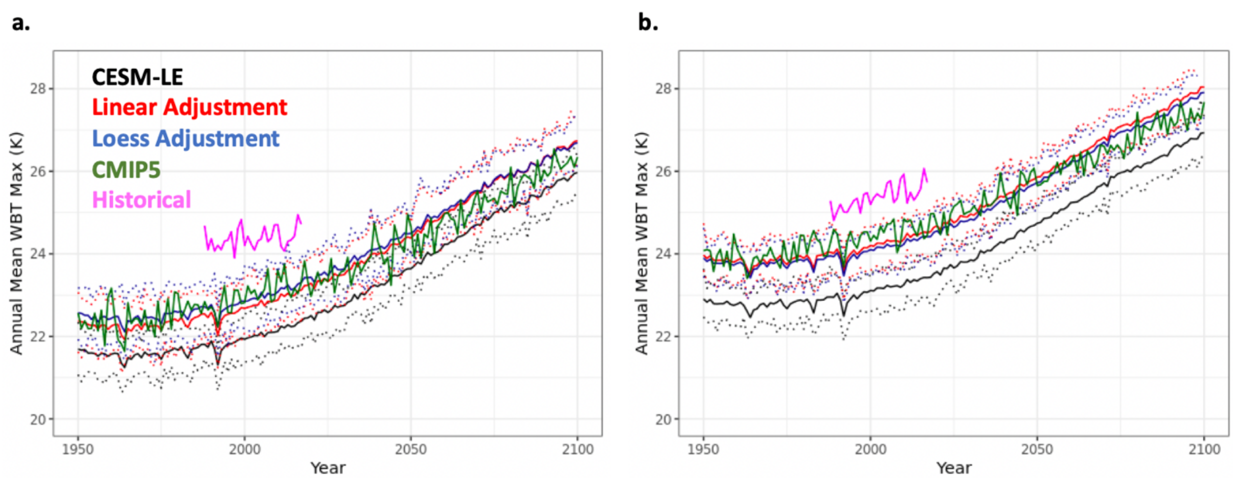


Fig. S9. Annual mean maximum WBT for CESM-LE, CESM-LE adjustments, and CMIP5. Annual mean maximum WBT are displayed for raw CESM-LE model predictions (black), CESM-LE predictions adjusted with a linear regression (red), CESM-LE predictions adjusted with a LOESS regression (blue), CMIP5 (green) model output, and historical data (pink) from 1950 to 2100. Solid lines show ensemble means, and dashed lines show the maximum and minimum range of values from each ensemble. Results indicated for northern (a.) and coastal (b.) Bangladesh.

Full Description of CESM-LE Adjustment Informed by CMIP5 Results

Evaluating appropriate adjustment

In order to make an appropriate adjustment of the CESM-LE model output informed by the CMIP5 results, we further investigated the relationship between CESM-LE and CMIP5 data. To begin, we evaluated the difference between CMIP5 daily maximum WBT and CESM-LE daily maximum WBT versus several variables, including CESM-LE WBT and CESM-LE RH. Daily values were plotted in density plots for both models from the years 1950 to 2100, representing 55,114 observations for coastal and northern Bangladesh each in order to select an appropriate method for adjusting CESM-LE results.

In addition to the density plots (Figure S7), we fit a linear regression to the data using the *lm( )* function in R. The intercept, coefficient, and R^2 results for coastal and northern Bangladesh linear models are given in **Table S1**. CESM-LE RH was selected as the variable based on which to conduct the adjustment of CESM-LE versus CESM-LE WBT due to a higher value of R^2 for test regression, demonstrating a better explanation of the relationship between the CESM-LE value and the difference between CESM-LE and CMIP5 WBT.

For coastal Bangladesh, the model predicts an increase of ~0.026 K/% Kelvin difference between CMIP5 WBT and CESM-LE WBT with every percent increase in CESM-LE *RH*. For northern Bangladesh, the model predicts an increase of ~0.028 K/% Kelvin difference between the models for every percent increase in CESM-LE *RH*. Both models have a low R^2 . This low explained variance is largely caused by differences in differences in short-term atmospheric variability (weather) between the CESM-LE and CMIP5. When the regression is recalculated with 10-year averages to reduce weather-related noise, the R^2 becomes 0.1815 for coastal Bangladesh and 0.1569 for northern Bangladesh.

The *loess*( ) function was also used to fit the LOESS model to the data. A LOESS (short for local regression) is a non-parametric approach that fits multiple regressions locally and allows for non-linearity. Both the linear model and LOESS model were plotted on the density plots (**Fig S7**).

Adjustments applied to CESM-LE data

The linear model and LOESS model of difference in WBT as a function of CESM-LE *RH* were used to conduct the adjustment of CESM-LE model output based on CMIP5 results. We determined that these adjustment methods were more appropriate than applying a constant adjustment to CESM-LE WBT because of the closer relationship between humidity and WBT. In addition, the differences between the CESM-LE output and CMIP5 were not constant over time. We applied both a linear and LOESS adjustment to account for the potential nonlinearity in the relationship. The application of two different corrections further allows for studying uncertainties associated with the particular choice of the correction itself. To apply the adjustments, the linear and LOESS models previously fit to the data were used to predict the difference between CMIP5 and CESM-LE based on CESM-LE predicted RH. This difference was then added to each daily CESM-LE maximum WBT for each ensemble member.

Results indicate that the predicted annual number of days above the 30 ºC dangerous threshold are sensitive to the adjustment and the adjustment method (**Fig. S3, Table 1**). The raw CESM-LE predicts approximately 56 days above the dangerous threshold, while the linear adjustment predicts 128 days, and the LOESS adjustment predicts 109 days in northern Bangladesh by 2100. In coastal Bangladesh, the raw CESM-LE model predicts 45 days, the linear adjustment predicts 148, and the LOESS adjustment predicts 127 days above the dangerous heat threshold by the year 2100. Similarly, results of annual maximum WBT are sensitive to the choice of adjustment method, though the choice of adjustment method is less important for coastal Bangladesh, while the LOESS adjustment significantly increases predicted maximum WBT in northern Bangladesh as compared to the linear adjustment (**Fig. S8**).

When we compare annual mean WBT between CESM-LE model to the adjustments, we see that the differences in annual mean WBT are more modest. In coastal Bangladesh, the mean difference in mean annual maximum WBT is approximately 1 K for both the linear and LOESS adjustments. In northern Bangladesh, this difference is even less with a mean difference of 0.75 K between the raw model and linear adjustment, and 0.87 K between the raw model and the LOESS adjustment. **Fig. S9** shows these differences in annual mean WBT and includes CMIP5 results for comparison. We see that both adjustment methods cause the CESM-LE ensemble results to more closely follow CMIP5 results. We also can observe that CMIP5 output, which consists of a single observation of a model run, is much noisier that an ensemble with CESM-LE, even when looking at annual means of WBT. However, the adjustments of CESM-LE remove the noise associated with the single observation from CMIP5, further demonstrating the value of an ensemble of models in their ability to offer more stable results in addition to ranges of uncertainty caused by variation in 'weather' between the different ensemble members.

Comparisons of adjusted and raw CESM-LE data, CMIP5 data, and historic data

Finally, we compare the adjustment annual mean WBT max from CESM-LE, linear adjusted CESM-LE, LOESS adjusted CESM-LE, CMIP5, and historical data (**Fig. S9**).

Though there are challenges associated with the reliability of the historical weather station data due to uncertainties in the station data collection, the linear and LOESS adjustments to the CESM-LE data bring the predicted WBT output closer to the WBT calculated from the weather station data (Fig. S9). However, the historical weather data station data still shows higher WBTs on average than either the adjusted CESM-LE or CMIP5.