Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo and M. Loper, eds.

MODELING MULTI-LEVEL PATTERNS OF ENVIRONMENTAL MIGRATION IN BANGLADESH: AN AGENT-BASED APPROACH

Kelsea Best
Jonathan Gilligan

Department of Earth and Environmental Science
Vanderbilt University
5736 Stevenson Center
Nashville, TN, 37240, USA

Ao Qu

Department of Mathematics
Vanderbilt University
1326 Stevenson Center Ln
Nashville, TN, 37212, USA

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. We 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. We 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, but only for a narrow range of parameters. Future work will compare income-maximizing decisions to psychologically complex decision heuristics that include non-economic considerations.

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

978-1-6654-3311-2/21/$31.00 ©2021 IEEE

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, we 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 BACKGROUND

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). We 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 our 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 Paris (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 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 km^2 (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.

2.3 Patterns of Migration

We use a pattern-oriented approach to developing and validating our 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). Our model seeks to test this hypothesis as an explanation for the patterns in the context of purely economic decision heuristics.

3 MODEL DESIGN

3.1 Model Structure and Entities

Our ABM simulates household decisions whether to migrate under environmental stress. We 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). 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.

This model has entities representing *individuals, households,* and *communities*. Individuals have attributes of gender, age, and employment and corresponding wages, and are assigned to a household. Households consist of one or more individuals and have attributes of wealth, land, employees, payments and expenses. Each household also has a decision method, which it uses to decide whether or not to send a member to seek work outside the community. Each household belongs to a community. The community has employment opportunities in agriculture and in skilled and unskilled non-agricultural occupations.

Communities are situated within an environment, which stochastically produces environmental "shocks" that impact employment opportunities in the community and the wealth of affected households. Figure 1 shows a schematic of the model's entities and their relationships.

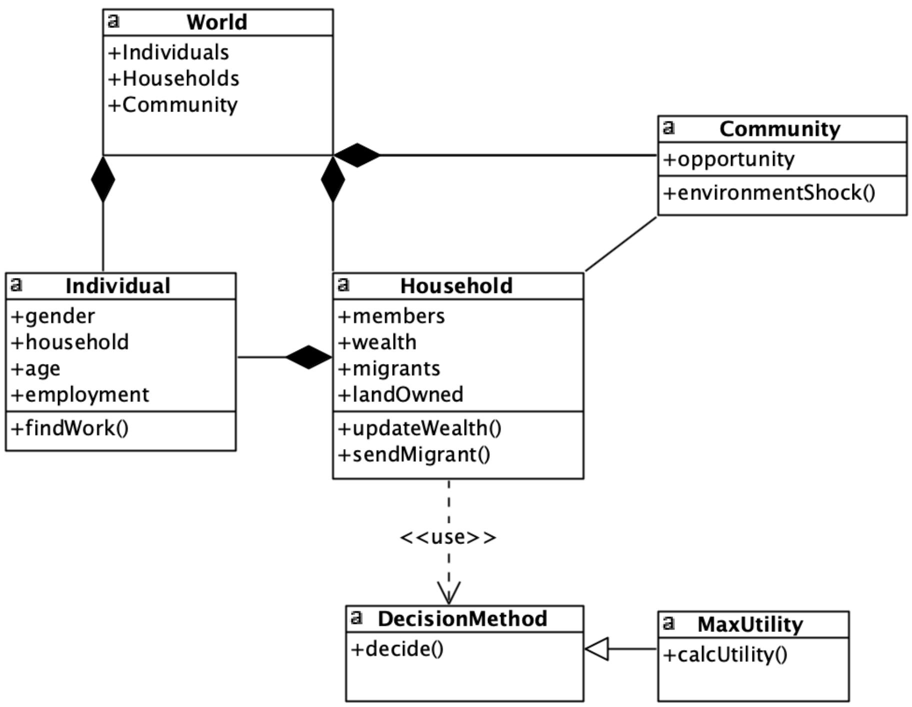

Figure 1: Class diagram of model entities with primary variables and operations.

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

- *Migration utility* – The 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 1).

Table 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

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. Each time-step represents one year. Each year begins with the community facing a stochastic risk of an environmental shock, which causes some households to lose their crops for the season. If a shock occurs, the fraction of households that lose their crops is determined by the magnitude of the shock, which is either a constant value or is drawn from a probability distribution, as specified by the global *shock severity* variable.

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. 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. A labor market uses a simultaneous double auction to match job seekers with employers and establish wages for agricultural work.

After each individual has selected an employment opportunity within the community, the household aggregates the total utility of its members and 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 1), which provides a function that implements the decision. In our initial implementation, all households decide 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:

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

Figure 2 shows an overview of the model scheduling for each step. This process repeats for a specified number of steps (years).

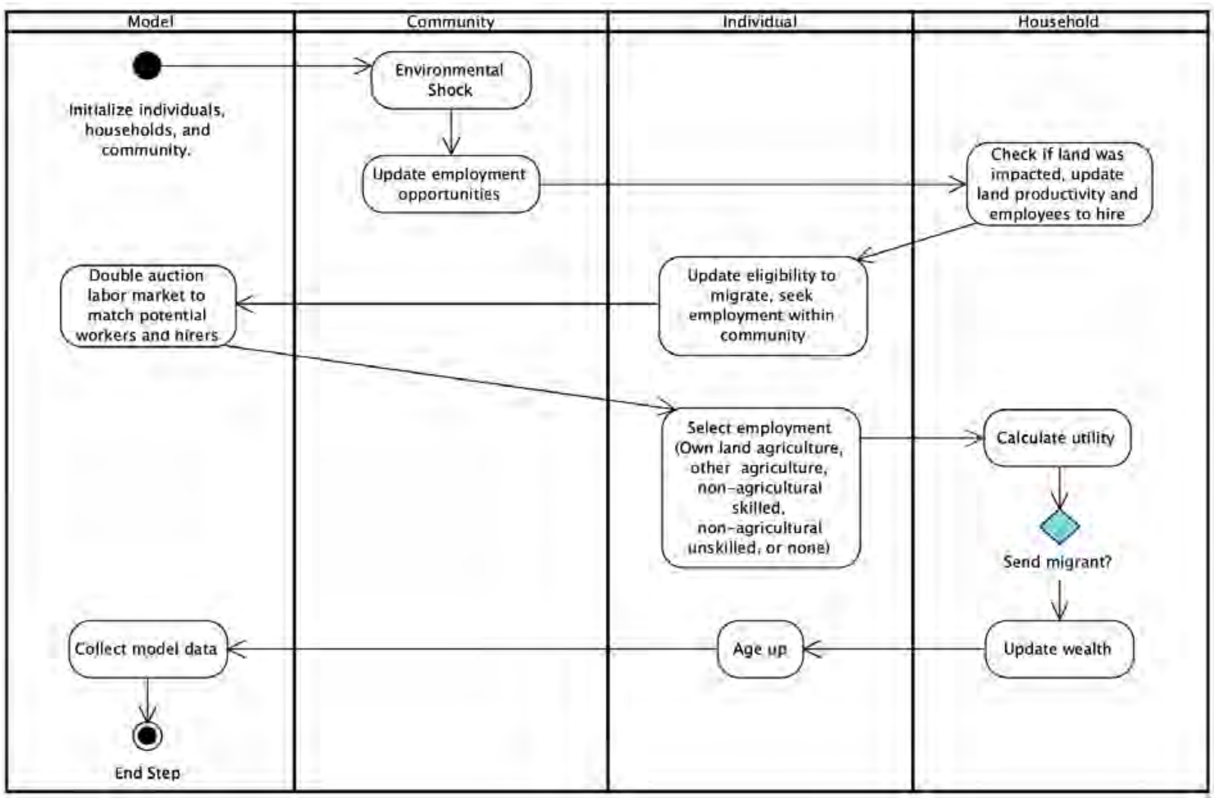

Figure 2: Scheduling of each step of the model for community, individual, and household entities.

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 our model, households make migration decisions to maximize expected annual income. A purely economic model provides one plausible explanation for the observed migration patterns and also serves as a baseline for assessing whether a simple economic decision heuristic can reproduce those patters. We have designed the model to serve as a test-bed 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. If the migration would be beneficial for the household and the household has sufficient wealth to meet the cost of migration, then that individual will "migrate" and only contribute to the model by contributing its income representing remittances at each subsequent step. After a migrant is initially sent, a household subtracts the cost of migration from its wealth.

4 RESULTS

4.1 Calibration of Uncertain Parameters

We were 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, we used a pattern-oriented approach to calibration (Grimm et al. 1996; Grimm et al. 2005). We used Latin hypercube sampling to cover a wide parameter space for 100 unique combinations of cost of migration and migration utility. We then ran the model 20 times for each parameter combination and otherwise the same initialization of a test community with 100 households and 700 individuals, and compared model results to each of our patterns of interest. Each model was run for 20 steps (20 years). This allowed us to identify values of the parameters that could successfully generate the patterns.

We assessed the successful parameter combinations by aggregating the results of each of the 20 runs for each combination and using a binary variable to indicate whether or not the model satisfied each pattern for that combination of migration utility and cost of migration. The criteria for matching Pattern 1 are that the mean number of migrations for a shock with a community impact factor of 0.2 are less than for no shock and that the mean number of migrations for a shock with an impact factor of 0.6 is greater than for no shock. The criterion for matching Pattern 2 is that non-migratory households are directly affected by more environmental shocks than migratory households.

We 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 3a,b). We were then able to identify where these parameter spaces overlap, representing the area that we would expect to successfully reproduce both patterns (Figure 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.

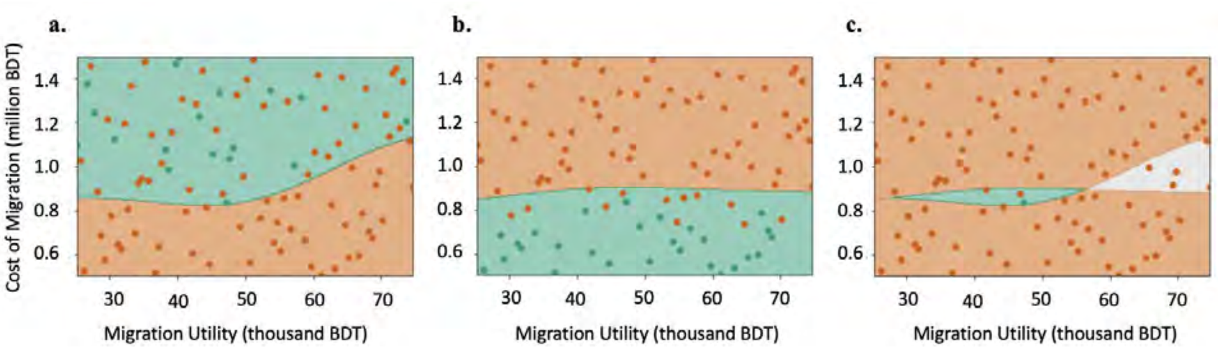

Figure 3: Parameter combinations of migration utility and migration threshold and SVM predicted successes of the parameter space for Pattern 1 (a), and Pattern 2 (b). Overlap between the predicted spaces (a) and (b) is plotted with the successes of simultaneously reproducing both patterns (c). Points 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.

4.2 Pattern Replication

We 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 3c), in order to study the model output in greater detail. We 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. We 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, we aggregate the results to assess the patterns.

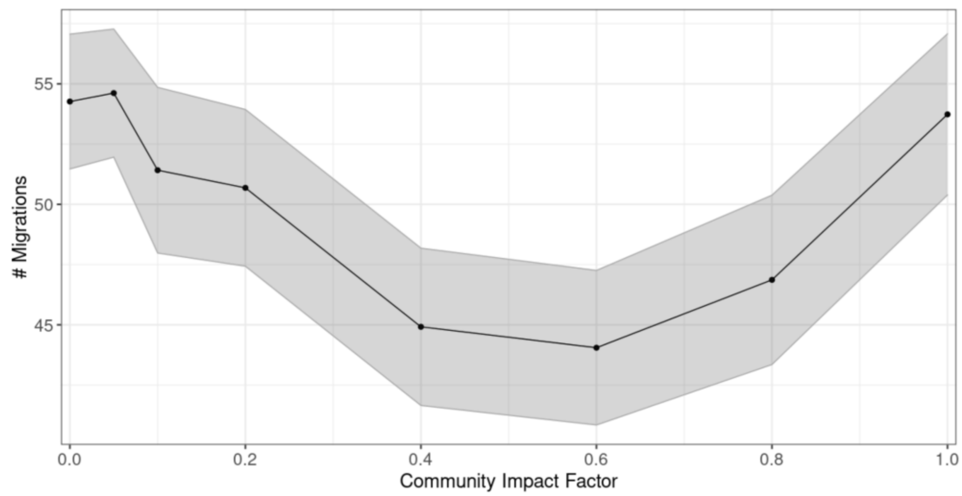

Figure 4: Model results of number of migrations in the community by varying levels of community impact. The black lines represent the mean of 120 model runs for each community impact factor, and the gray band represents the 95% confidence interval for the mean.

Figure 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 our operationalization of Pattern 1 (Figure 4). The threshold effect is apparent, though it occurs at higher levels of community impact than predicted.

To explore Pattern 2, we 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 5). Here, we 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 we 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 $p < 0.0005$.

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.

5 DISCUSSION

Our 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 3).

Results from this calibration 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 3b). In contrast, Pattern 1 was only reproduced inconsistently, and primarily in the upper half of the parameter space (Figure 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 3c).

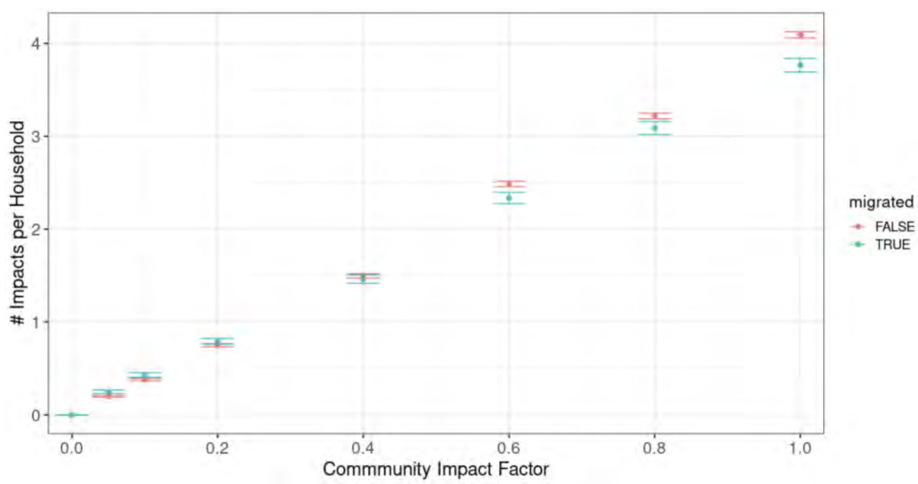

Figure 5: Households are divided into those that have migrated (1, blue) and those that have not (0, red). The mean number of times a household was impacted directly by an environmental shock across all 120 trials is plotted with error bars indicating 95% confidence intervals of the mean. For community impact factors above 0.4, Pattern 2 is reproduced: non-migratory households were impacted by more environmental shocks than migratory households were.

Despite the lower frequency of success in reproducing the details of Pattern 1, the nonlinear dynamics of the pattern are apparent (Figure 4). Pattern 2 is reproduced consistently for aggregated model runs, and when disaggregated by community impact factor, we find that this pattern appears only for community impact factors of 0.4 and above, and becomes stronger for larger impact factors (Figure 5).

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. In addition, the difficulty in reproducing both patterns simultaneously suggest that the interactions occurring between community and household scale may be more complex than the current model accounts for.

6 CONCLUSIONS

We developed an ABM that simulates environmental migration through the impacts of environmental shocks on local labor markets. We used a pattern-oriented approach to calibrating and testing the model. We identified 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.

Our model successfully reproduced these patterns, but inconsistently, and only for a few combinations of parameters representing the cost and utility of migration. One possible explanation for these results suggest would be that, while economic considerations are important in driving migration decisions, non-economic considerations may also be important. Our model does not attempt to capture psychological and sociological aspects of decision-making, so it is not surprising that it has only limited success in reproducing the patterns of interest. In future work, we will investigate more complex decision heuristics.

We 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.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. CNH 1716909. We thank Dr. Bishawjit Mallick for extensive discussions in which he provided valuable insights.

REFERENCES

Adams, H., W.N. Adger, S. Ahmad, A. Ahmed, D. Begum, A.N. Lázár, Z. Matthews, M.M. Rahman, and P.K. Streatfield. 2016. “Spatial and Temporal Dynamics of Multidimensional Well-Being, Livelihoods and Ecosystem Services in Coastal Bangladesh”. *Scientific Data* 3(1): 160094.

Ahsan, R., S. Karuppannan, and J. Kellett. 2011. “Climate Migration and Urban Planning System: A Study of Bangladesh”. *Environmental Justice* 4: 163–170.

Akram, A.A., S. Chowdhury, and A.M. Mobarak. 2018. *Effects of Emigration on Rural Labor Markets*. New Haven, CT: Yale University. http://faculty.som.yale.edu/mushfiqmobarak/papers/MigrationGE.pdf.

Alam, G.M.M., K. Alam, and S. Mushtaq. 2017. “Climate Change Perceptions and Local Adaptation Strategies of Hazard-Prone Rural Households in Bangladesh”. *Climate Risk Management* 17: 52–63.

Amrith, S.S. 2013. *Crossing the Bay of Bengal: The Furies of Nature and the Fortunes of Migrants*. Cambridge, MA: Harvard University Press.

An, L. 2012. “Modeling Human Decisions in Coupled Human and Natural Systems: Review of Agent-Based Models”. *Ecological Modelling* 229: 25–36.

Auerbach, L.W., S.L. Goodbred Jr, D.R. Mondal, C.A. Wilson, K.R. Ahmed, K. Roy, M.S. Steckler, C. Small, J.M. Gilligan, and B.A. Ackerly. 2015. “Flood Risk of Natural and Embanked Landscapes on the Ganges–Brahmaputra Tidal Delta Plain”. *Nature Climate Change* 5: 153–157.

Beckage, B., K. Lacasse, J.M. Winter, L.J. Gross, N. Fefferman, F.M. Hoffman, S.S. Metcalf, et al. 2020. “The Earth Has Humans, so Why Don’t Our Climate Models?” *Climatic Change* 163(1): 181–188.

Bell, A.R., C. Calvo-Hernandez, and M. Oppenheimer. 2019. "Migration, Intensification, and Diversification as Adaptive Strategies". *Socio-Environmental Systems Modelling* 1: 16102–16102.

Bell, A.R., D.J. Wrathall, V. Mueller, J. Chen, M. Oppenheimer, M. Hauer, H. Adams, et al. 2021. "Migration towards Bangladesh Coastlines Projected to Increase with Sea-Level Rise through 2100". *Environmental Research Letters* 16(2): 024045.

Best, K. 2021. *Bestkb/Environmental-Migration-ABM.* Zenodo. 10.5281/zenodo.4526330. https://zenodo.org/record/4526330, accessed 24th July, 2021.

Black, R., W.N. Adger, N.W. Arnell, S. Dercon, A. Geddes, and D. Thomas. 2011. "The Effect of Environmental Change on Human Migration". *Global Environmental Change* 21: S3–S11.

Black, R., C. Natali, and J. Skinner. 2005. *Migration and Inequality*. World Bank Washington, DC.

Call, M.A., C. Gray, M. Yunus, and M. Emch. 2017. "Disruption, Not Displacement: Environmental Variability and Temporary Migration in Bangladesh". *Global Environmental Change* 46: 157–165.

Carrico, A.R., and K. Donato. 2019. Extreme Weather and Migration: Evidence from Bangladesh. *Population and Environment* 41(1): 1–31.

Chen, J., & Mueller, V. (2018). "Coastal climate change, soil salinity and human migration in Bangladesh". *Nature Climate Change*, *8*(11), 981–985.

DeAngelis, D.L., and S.G. Diaz. 2019. "Decision-Making in Agent-Based Modeling: A Current Review and Future Prospectus". *Frontiers in Ecology and Evolution* 6. https://www.frontiersin.org/articles/10.3389/fevo.2018.00237/full.

Dewan, A.M., M.M. Islam, T. Kumamoto, and M. Nishigaki. 2007. "Evaluating Flood Hazard for Land-Use Planning in Greater Dhaka of Bangladesh Using Remote Sensing and GIS Techniques". *Water Resources Management* 21:1601–1612.

Dewan, A.M., and Y. Yamaguchi. 2009. "Using Remote Sensing and GIS to Detect and Monitor Land Use and Land Cover Change in Dhaka Metropolitan of Bangladesh during 1960–2005". *Environmental Monitoring and Assessment* 150: 237–249.

Donato, K.M., D.S. Massey, K.M. Donato, A.R. Carrico, B. Sisk, and B. Piya. 2016. "Different but the Same: How Legal Status Affects International Migration from Bangladesh". *The ANNALS of the American Academy of Political and Social Science* 666: 203–218.

Gilligan, J.M. 2018. "Climate Modeling: Accounting for the Human Factor". *Nature Climate Change* 8: 14.

Gray, C.L., and V. Mueller. 2012. "Natural Disasters and Population Mobility in Bangladesh". *Proceedings of the National Academy of Sciences* 109: 6000–6005.

Grimm, V., U. Berger, F. Bastiansen, S. Eliassen, V. Ginot, J. Giske, J. Goss-Custard, et al. 2006. "A Standard Protocol for Describing Individual-Based and Agent-Based Models". *Ecological Modelling* 198: 115–126.

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

Grimm, V., K. Frank, F. Jeltsch, R. Brandl, J. Uchmański, and C. Wissel. 1996. "Pattern-Oriented Modelling in Population Ecology". *Science of The Total Environment* 183: 151–166.

Grimm, V., E. Revilla, U. Berger, F. Jeltsch, W.M. Mooij, S.F. Railsback, H.-H. Thulke, J. Weiner, T. Wiegand, and D.L. DeAngelis. 2005. "Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology". *Science* 310: 987–991.

Hallegatte, S. 2012. "A Framework to Investigate the Economic Growth Impact of Sea Level Rise". *Environmental Research Letters* 7: 015604.

Hassani-Mahmooei, B., and B.W. Parris. 2012. "Climate Change and Internal Migration Patterns in Bangladesh: An Agent-Based Model". *Environment and Development Economics* 17: 763–780.

Higgins, S.A., I. Overeem, M.S. Steckler, J.P.M. Syvitski, L. Seeber, and S.H. Akhter. 2014. "InSAR Measurements of Compaction and Subsidence in the Ganges-Brahmaputra Delta, Bangladesh". *Journal of Geophysical Research: Earth Surface* 119: 1768–1781.

Hunter, L.M. 2005. "Migration and Environmental Hazards". *Population and Environment* 26: 273–302.

Hunter, L.M., J.K. Luna, and R.M. Norton. 2015. "Environmental Dimensions of Migration". *Annual Review of Sociology* 41: 377–397.

Islam, M. R. (2018). "Climate Change, Natural Disasters and Socioeconomic Livelihood Vulnerabilities: Migration Decision Among the Char Land People in Bangladesh". *Social Indicators Research*, *136*(2), 575–593.

Islam, M.R., and H. Mehedi. 2016. "Climate-Induced Human Displacement: A Case Study of Cyclone Aila in the South-West Coastal Region of Bangladesh". *Natural Hazards* 81: 1051–1071.

Joarder, M.A.M., and P.W. Miller. 2013. "Factors Affecting Whether Environmental Migration Is Temporary or Permanent: Evidence from Bangladesh". *Global Environmental Change* 23: 1511–1524.

Kartiki, K. 2011. “Climate Change and Migration: A Case Study from Rural Bangladesh”. *Gender & Development* 19: 23–38.

Klabunde, A., and F. Willekens. 2016. “Decision-Making in Agent-Based Models of Migration: State of the Art and Challenges”. *European Journal of Population* 32: 73–97.

Laciana, C., E. Weber, F. Bert, G. Podestá, X. González, and D. Letson. 2007. *Objective Functions in Agricultural Decision-Making: A Comparison of the Effects of Expected Utility, Regret-Adjusted Expected Utility, and Prospect Theory Maximization*. Working Paper, Center for Research on Environmental Decisions (CRED), Columbia University.

Lagakos, D., A.M. Mobarak, and M.E. Waugh. 2018. *The Welfare Effects of Encouraging Rural-Urban Migration*. Working Paper. National Bureau of Economic Research. http://www.nber.org/papers/w24193.

Mallick, B., and J. Schanze. 2020. “Trapped or Voluntary? Non-Migration Despite Climate Risks”. *Sustainability* 12: 4718.

Mallick, B., and J. Vogt. 2014. “Population Displacement after Cyclone and Its Consequences: Empirical Evidence from Coastal Bangladesh”. *Natural Hazards* 73: 191–212.

Martin, M., M. Billah, T. Siddiqui, C. Abrar, R. Black, and D. Kniveton. 2014. “Climate-Related Migration in Rural Bangladesh: A Behavioural Model”. *Population and Environment* 36: 85–110.

McGranahan, G., D. Balk, and B. Anderson. 2007. “The Rising Tide: Assessing the Risks of Climate Change and Human Settlements in Low Elevation Coastal Zones”. *Environment and Urbanization* 19: 17–37.

McLeman, R. 2013. “Developments in Modelling of Climate Change-Related Migration”. *Climatic Change* 117: 599–611.

Mobarak, A.M., and M.E. Reimão. 2020. “Seasonal Poverty and Seasonal Migration in Asia”. *Asian Development Review* 37: 1–42.

Mueller, V., Sheriff, G., Dou, X., & Gray, C. (2020). “Temporary migration and climate variation in eastern Africa”. *World Development*, *126*, 104704.

Neumann, K., and H. Hilderink. 2015. “Opportunities and Challenges for Investigating the Environment-Migration Nexus”. *Human Ecology* 43: 309–322.

Obokata, R., L. Veronis, and R. McLeman. 2014. “Empirical Research on International Environmental Migration: A Systematic Review”. *Population and Environment* 36: 111–135.

Piguet, E. 2010. “Linking Climate Change, Environmental Degradation, and Migration: A Methodological Overview”. *Wiley Interdisciplinary Reviews: Climate Change* 1, 517–524.

Tessler, Z.D., C.J. Vorosmarty, M. Grossberg, I. Gladkova, H. Aizenman, J.P.M. Syvitski, and E. Foufoula-Georgiou. 2015. “Profiling Risk and Sustainability in Coastal Deltas of the World”. *Science* 349: 638–643.

Thober, J., Schwarz, N., & Hermans, K. (2018). “Agent-based modeling of environment-migration linkages: A review”. *Ecology and Society*, *23*(2).

Till, C., J. Haverkamp, D. White, and B. Bhaduri. 2018. “Understanding Climate-Induced Migration through Computational Modeling: A Critical Overview with Guidance for Future Efforts”. *The Journal of Defense Modeling and Simulation* 15: 415–435.

World Bank. 2021. Bangladesh | Data. *World Bank*. https://data.worldbank.org/country/bangladesh, accessed 24th of July, 2021.

AUTHOR BIOGRAPHIES

KELSEA BEST is a PhD candidate in Earth and Environmental Science at Vanderbilt University. Her research focuses on using quantitative methods to study environmental migration in coastal Bangladesh. Her email is kelsea.b.best@vanderbilt.edu and her website is https://www.kelseabestresearch.com/.

AO QU is a junior undergraduate math major at Vanderbilt University. His research interests primarily lie in operations research and smart urban systems. His email is ao.qu@vanderbilt.edu.

JONATHAN GILLIGAN is an Associate Professor of Earth and Environmental Science and Civil and Environmental Engineering at Vanderbilt University and director of Vanderbilt’s Climate and Society Grand Challenge Initiative. His e-mail address is jonathan.gilligan@vanderbilt.edu and his website is https://www.jonathangilligan.org/.