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Machine Learning to Identify Drivers of Internal Migration in Coastal Bangladesh

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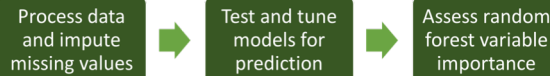
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INTRODUCTION

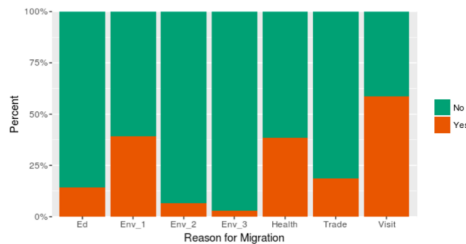
- As climate change increases pressure on vulnerable communities, migration is one adaptation strategy.
- The decision to migrate is highly complex, and is influenced by economic, social, and environmental drivers.
- Bangladeshi communities have long adapted to a dynamic and challenging natural environment. Seasonal migration and livelihood diversification are important adaptation methods, especially rural to urban migration.
- This work addresses a gap in current research by beginning to investigate how different “push” and “pull” drivers of migration might have different variables that contribute to the ultimate decision to move or stay.

METHODOLOGY



DATA AND DATA PROCESSING

- Data was collected by household interviews throughout 40 communities in the southwest area of Bangladesh from 2012 to 2014.
- Multiple imputation with random forest was conducted to address data missing completely at random ($m = 10$).
- Dummy variables were created for each question that included a categorical or ordered response type.
- Random forest (ensemble of decision trees) was selected after assessing predictive ability of different models on complete cases.
- Outcome variables are binary indicators of migration for environmental reasons, education, health, trade, or to visit relatives.
- Random forest models were run for each complete dataset and for each outcome variable (50 models total).



MODELS TESTED FOR PREDICTION

- Each model was trained on a sample of 80% of complete cases of data, and tested on the remaining 20% to test predictive accuracy.
- Model parameters were tuned using cross validation.

Prediction errors (percent) for each model.

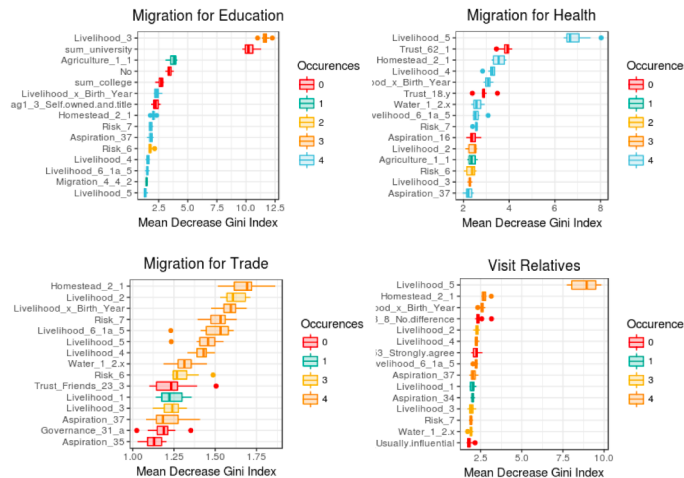
Model	Env_1	Ed	Health	Trade	Visit
Logistic	47.1	44.9	44.1	43.4	42.6
SVM	36.0**	16.2**	36.0**	19.9**	41.2**
Random Forest	35.5	14.7	33.1	19.9**	33.8

**Indicates that the model was unable to predict both “Yes” and “No” values, but predicted only one or the other, resulting in class errors of 0% and 100%.

VARIABLE IMPORTANCE IN RANDOM FOREST MODELS

- Gini Index** is used to measure impurity when building decision trees
- Mean decrease in Gini Index is used to identify top 15 variables of importance in random forest models of each type of migration.

$$Gini = 1 - \sum_j p(j)^2$$



INSIGHTS AND CONCLUSIONS

Type of Migration	Key Variables
All models	<ul style="list-style-type: none"> Livelihood (annual expenditures, daily expenditures, amount of homestead land owned, monthly income) Travel time to primary water source Distance to cyclone shelter Birth Year
Environmental	<ul style="list-style-type: none"> Knowing others who have migrated Environmental damage to home and livelihood
Education	<ul style="list-style-type: none"> Annual expenditure and importance of education Members of household completed university or college
Health	<ul style="list-style-type: none"> Community efforts to dig a pond for drinking water Feeling unsafe traveling to work
Trade	<ul style="list-style-type: none"> Borrowing money from friends Fewer unique variables, higher variance
Visit relatives	<ul style="list-style-type: none"> Low locus of control in community Strong belief that more economic opportunities exist outside of community

Conclusions:

- Environmental migration is uniquely influenced by knowledge of others who have migrated and economic impacts of environmental events.
- Livelihood variables, age, social status, and proximity to water sources are highly important for all forms of migration.
- Imputing missing data significantly impacts results, demonstrating importance.

FUTURE WORK

- Repeat analysis with Bangladesh Environment and Migration Survey (BEMS).
- Develop survival models from survey data to quantify probabilities of migration.
- Use insights from statistical analysis to inform agent-based model to test scenarios and adaptation strategies.
- Utilize multidisciplinary teams to understand the factors that influence human migration as a system, rather than in isolation.



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