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# Rising Waters: Can We Use Machine Learning to Accurately and Effectively Predict Bangladesh's Floods and Hydrological Data?

Audience: Central and local governments of Bangladesh

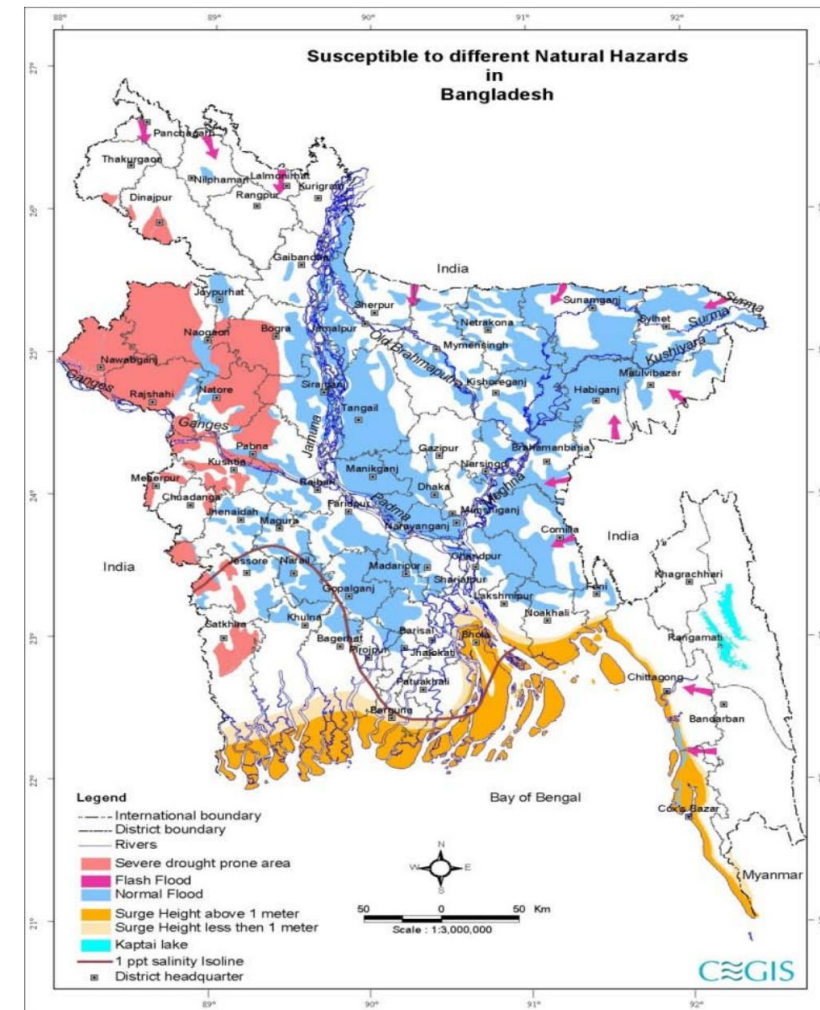
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MIDS W201 | MON 4PM PT | GROUP 2

# Bangladesh is subject to catastrophe due to floods

- Population of ~165 million people.
- Located at the delta of the Padma and Jamuna rivers in the northeastern part of the Indian subcontinent.



# Bangladesh is subject to catastrophe due to floods

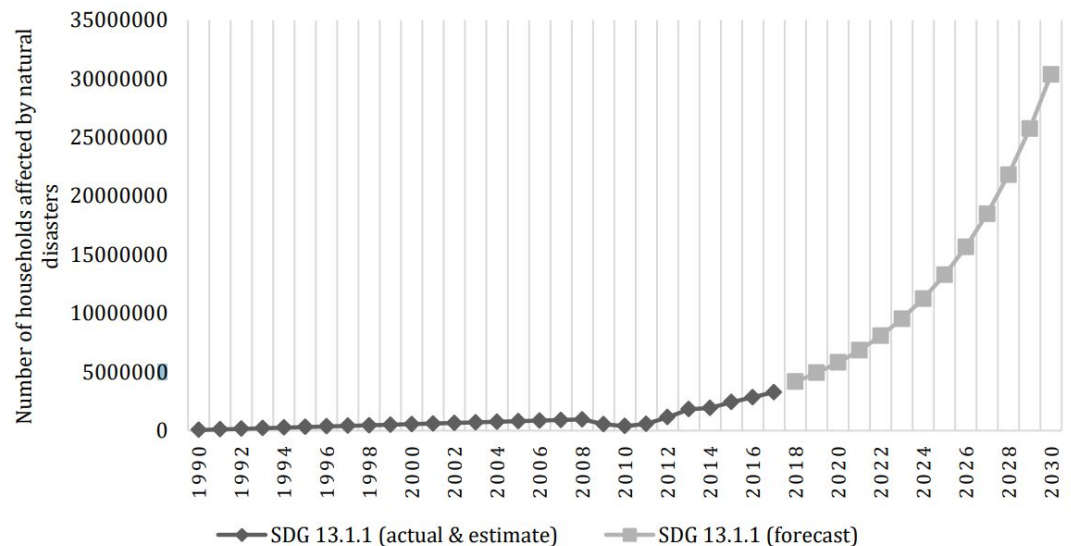
- 2020: heavy monsoons caused nearly 25 percent of the country to be submerged
  - ~2 million displacements
  - Hundreds of deaths
- Going forward, the UN estimates that the number of households to be impacted by natural disaster will grow exponentially.



# Data

- Bangladesh Disaster Related Statistics
- Bangladesh Water Development Board (BWDB)  
Data:
  - Historical water level data across all of the nation's major rivers
- Bangladesh Meteorological Department (BMD)  
Data
  - Daily rainfall and temperature data
- NOAA Global Integrated Surface Dataset:
  - Meteorological data such as humidity, wind, cloud coverage, and historical patterns of extreme weather such as cyclones

## Bangladeshi households impacted by weather events: p



# Study design

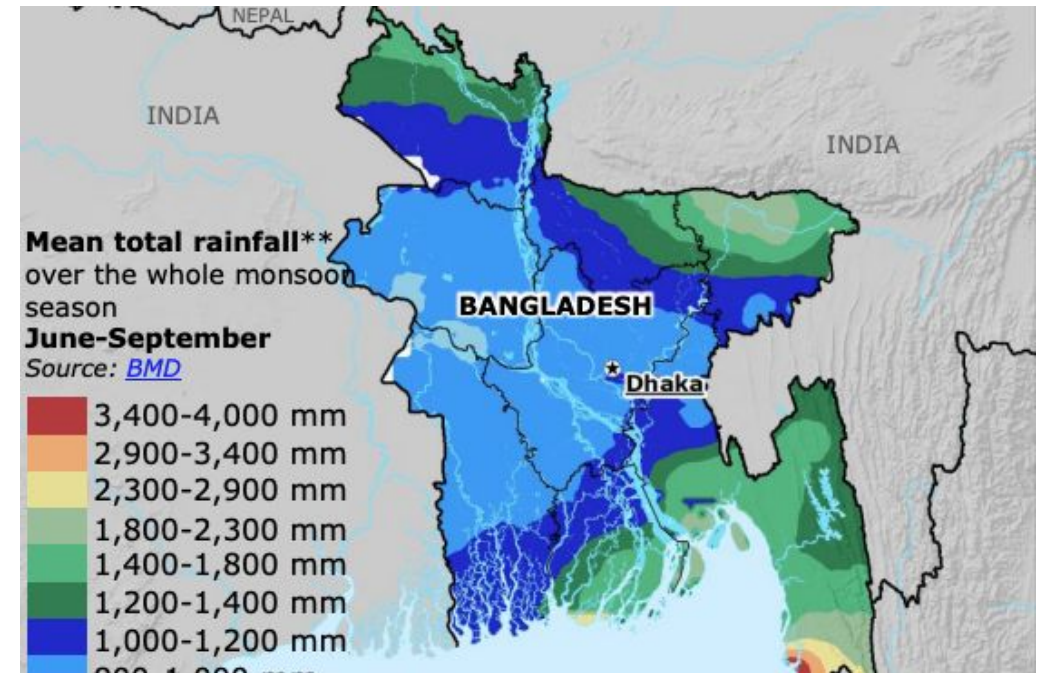
- Quantitative study
- Establish baseline predictive method used by government
- Capture mix of historical and live data
- Feed captured data to train model
- Calculate predictive ability of our model against baseline prediction





# Sample

- Stratification based on flood-prone geographical areas
- Use latitude and longitude points from dataset for grouping
- Interpolate for missing values



Source: United Nations Office for the Coordination of Humanitarian Affairs

# Variables and/or Intervention

- Hydrological/meteorological data:
  - Precipitation, river flows/levels, storm surges



# Statistical Methods

$$NSE = 1 - \frac{\sum_{t=1}^T (Q_o^t - Q_m^t)^2}{\sum_{t=1}^T (Q_o^t - \bar{Q}_o)^2}$$

- **Nash-Sutcliffe efficiency coefficient (NSE)**

- Assesses predictive ability of hydrological models
- One minus ratio of the error variance of model divided by the variance of the observed

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Predicted_i - Actual_i)^2}{N}}$$

- **Root Mean Squared Error (RMSE)**

- Square root of predicted minus actual data divided by



# Potential Risks

- Overfitting
- Parameter instability of model
- Communication with stakeholders and local community
- Fair and equitable access to results
- Regional variance



# Deliverables

After 3 years, we will provide:

- Technical details of predictive model (e.g. accuracy, # of projection days)
- Live test results of new model
- Summary report with recommendations





Thank You