Summary for Policymakers

Forecasting Assam's Loss and Damage Finance Needs using the ICRIER '*Prakriti*' model

April 2025

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Introduction

The frequency and intensity of extreme weather events (EWEs) such as droughts, heat waves, extreme precipitation, and tropical storms are expected to increase as indicated in the IPCC's Sixth Assessment Report (AR6). Between 2000-2019, the global cost due to climate change was estimated to be US$ 2.86 trillion (Newman & Noy, 2023). According to WMO (2023), Asia was the most disaster-affected region with 79 hydro-meteorological hazard events in 2023 alone, 60 percent of which were associated with floods.

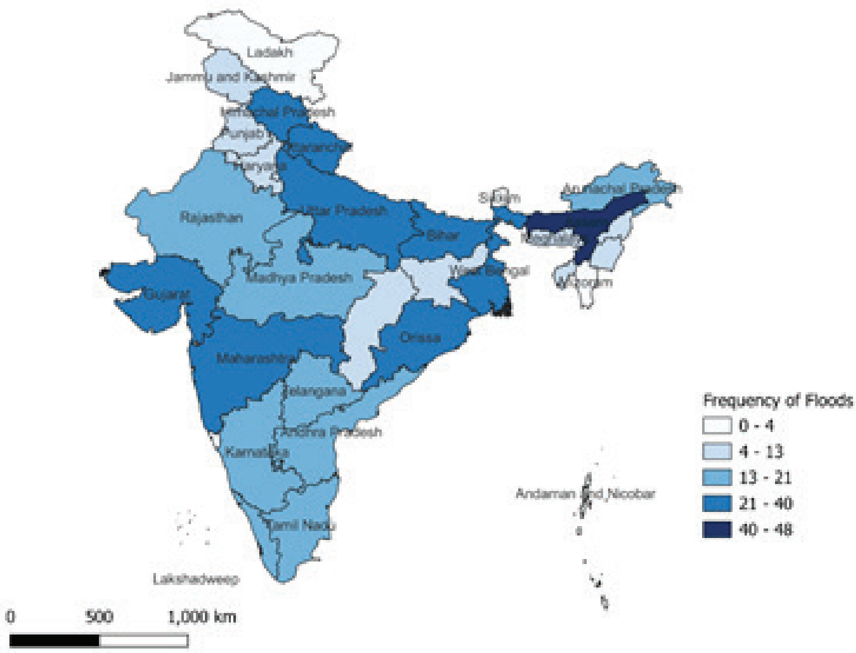
India is the sixth most affected country due to EWEs in the period 1993-2022 as reported in the Climate Risk Index (2025). The average number of EWEs has been increasing continuously over the last five decades (Ray et al, 2021). Especially, quick-onset events such as floods and cyclones occur within a very short timeframe, resulting in catastrophic damage to economies, livelihoods, and communities. Realizing the urgency, a dedicated loss and damage fund was established at COP 27 and made operational at COP 28.

Analysis of EM-DAT data for India reveals that damage costs of floods constituted 63.10 percent of the total disaster costs during the period 1990-2022 (Goldar et al, 2024). In a study conducted by CGIAR (2012) to find the global flood hotspots, flood events from 1990-2011 were analysed, and India was found to share the highest portion of such events, ranking first (3,996 flood events). The data availability on flood damages reported by government agencies in India is limited to damages in public infrastructure, crop area affected, and livestock loss. Indirect economic losses, such as disruptions in supply chain, labour availability, production, and revenue losses, tend to spill over beyond the directly affected areas and are difficult to estimate (Newman & Noy, 2023). This warrants a focus on understanding floods more to measure the indirect economic losses and the ripple effects involved to forecast the Loss and Damage finance needs for such flood events.

State Selection

Floods are a recurrent phenomenon in India during the monsoon season (June-September), adversely impacting the infrastructure, food security, and livelihoods. The National Commission on Floods estimated that 400 lakh hectares of land area are prone to floods in India. According to "The National Climate Vulnerability Assessment" report (Dasgupta et al., 2020), some of the states that are at the top of the list with higher vulnerability are Assam, Jharkhand, Odisha, Bihar, and West Bengal. IMD data for 1995-2020 reported around 1058 climatic disaster events affecting almost the entire country. Floods were the most frequent disasters during this period, covering 29 of the 36 states and Union Territories. Based on the annual average frequency of floods, Bihar tops the list, followed by West Bengal and Assam (Gupta et al., 2021). Also, analysis of EM-DAT data for the period 2000-2023 shows that out of the 502 flooding events, Assam tops the list, followed by Uttar Pradesh, Bihar, and Gujarat (Figure 1). Therefore, based on EM-DAT data and IMD data, and taking into consideration the vulnerability aspect of states, it can be concluded that Assam leads the list of states most affected and vulnerable to flood-related disasters.

Figure 1: State-wise Flood Frequency



(Source: Authors' construction using EM-DAT (2000-2023))

Research Objective

While direct disaster impacts in India have been studied from the vantage of geospatial analysis (Tripathi et al., (2019), Mishra et al., (2022)) or damage cost approaches (Bahinipati & Venkatachalam (2016); Patankar (2019)) or econometric modelling (Panwar & Sen (2019), Amarsinghe et al., (2020)), there are critical gaps in estimation of total costs:

1. Few studies have sought to compute damages via the economic system. Details regarding losses suffered by industrial production processes are missing or inadequate. Data regarding damages is usually collected from grey literature or government sources, but these have a limited scope and only cover aspects such as people affected, displaced or dead, damages to crop and livestock and public infrastructure.

2. There is disproportionate focus on direct impact of natural disasters. Disaster losses are transmitted across the industrial supply chain and have a contagion effect over other sectors, impacting even non-affected areas. Since such losses are distributed over space and time, obtaining information on them is difficult and consequently, it remains an area of study that is under-explored.

3. The impact of any disaster is a function of the intersection of the area affected by a hazardous event and the urban and regional landscape of that area at that point of time. Approach to disaster adaptation planning by state governments tend to focus only on the spatio-temporal trends of the hazard event itself (e.g., its intensity, frequency etc.) and ignore the spatio-temporal trends and patterns in the urban and regional landscape.

Our study would build on existing work to eliminate the above gaps and add to existing literature by developing an Input-Output (IO) modelling framework at a sub-national level that captures both direct and indirect losses due to natural disasters. This framework would be complemented by a GIS-based modelling and simulation approach, incorporating spatio-temporal trends and patterns in urban and regional landscapes, to augment comprehensive disaster adaptation planning at the sub-national level. The study is organized into three parts: the ***Prakriti*** **2.0** model, which addresses the first two research questions; a geospatial model, which explores the third; and a flood forecasting model, designed to project how flood events in Assam evolve under different climate change scenarios.

Methodology

1. The '*Prakriti*' 2.0 model

The ***Prakriti*** model uses an IO framework to represent the economy as a matrix of inputs and outputs across sectors, describing how one sector's output serves as another's input through linear equations. This allows the model to capture the impact of disaster-induced disruptions to the economic system.

Earlier Model

The authors' previous work (Goldar et al., 2024) introduced the ICRIER ***Prakriti*** Disaster Management Model to assess two disaster-affected Indian states—Assam (flooding) and Andhra Pradesh (cyclones). The model translated direct damage figures from these disasters into annual production loss values to compute the impact on Gross State Value Added (GSVA) and employment. Following Lenzen et al. (2019), data on infrastructure losses were collated for 37 regional input-output (RIO) sectors using public infrastructure loss statements and ASI data. The productivity of capital was computed and multiplied with annualized asset losses to calculate annual production loss values. The gamma matrix, containing production loss coefficients for each affected sector, was then calculated. Reduced consumption levels due to disasters were captured as x_1=x_0-Δx leading to effects on value added and employment:

$$\Delta Q = q(I - A)^{-1}\,\Delta x, \text{ and}$$

$$\Delta E = e(I - A)^{-1}\,\Delta x$$

where q and e are value-added and employment coefficient matrices, respectively. This model primarily captured the backward linkages of disaster impacts, including the immediate and subsequent losses in jobs and value added across the economy.

Current Model

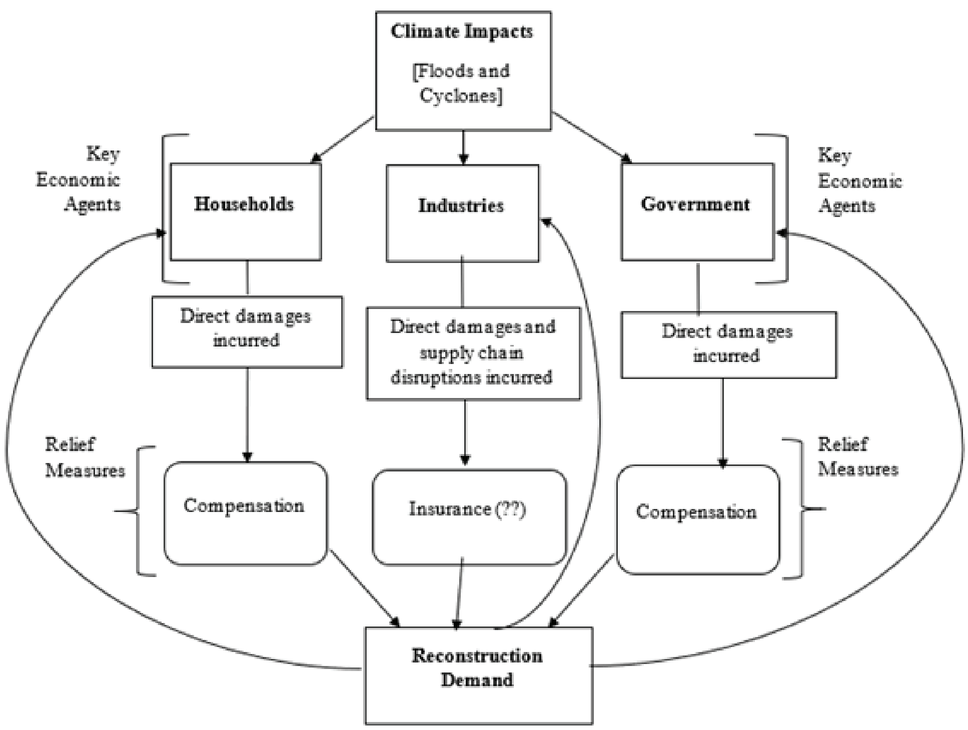
The updated model is modified using the adaptive regional input-output model (ARIO) developed by Hallegatte (2014). It retains some of the elements of the previous model, such as estimation of direct damages using government data sources and industrial surveys. Additionally, industry stakeholder consultations were conducted to estimate state-specific parameters for the modelling exercise. This involved details such as maximum capacity utilisation, time taken post-disaster to resume production, price changes in inputs, inventories maintained, etc. For data on insurance claims and inventories, the authors looked into data sources such as CMIE Prowess and MoSPI's Annual Survey of Industries.

These direct damages are converted to reductions in production in the states. The estimation of indirect damages, on the other hand, is carried out using the modelling structure given below. While the earlier model had been coded using Stata MATA, the current version of the model has been written in GAMS as the system of equations had to be optimised for a deriving a solution.

The model aims to enhance the ICRIER-***Prakriti*** Disaster Management Model by incorporating the following elements:

- Limitations to production capacity following a disaster, including both backward and forward linkages of such disruptions. The model uses a time step of 1 month to showcase post-disaster impacts.
- Impacts of adaptive responses, such as utilizing maximum production capacity, drawing down inventories, rationing demand, and substituting inputs from outside the state or country.
- Insurance mechanisms to simulate post-disaster resilience.
- The influence of reconstruction demand.
- The role of government relief programs.

Figure 2: ARIO Schematic



(Source: Authors' construction)

The framework thus simulates decision-making at the economic agent's level to identify optimal post-disaster strategies. The ARIO model has been made dynamic to address future disaster impacts by incorporating projected economic shifts, sectoral growth patterns, and technical progress. Unlike standard IO models, which often represent disasters as abrupt shocks that halt production entirely, the present approach offers an advancement. It captures the rational behaviour of economic agents as they respond to the aftermath of a disaster, allowing for a more realistic simulation of the impacts of increasingly frequent and severe disasters.

Thus, the work builds on existing work by developing a comprehensive optimisation and IO modelling framework to assess direct and indirect impacts of future climate-induced disasters and devise optimal strategies for relief, prevention, and reconstruction.

2. Geo-spatial model

An effective disaster adaptation strategy for Assam should combine the existing early warning and infrastructure improvement (e.g. construction and maintenance of embankments) based system with a more comprehensive stochastic landscape change modelling framework that factors in the future growth and development of various urban-regional complexes of the state. Urban-regional complexes can be envisaged as clusters and urban centres along with the rural settlements that surround them.

Torsten Hägerstrand's Monte Carlo based approach to simulate spatial diffusion can be considered as the theoretical and methodological basis of the FUTure Urban-Regional Environment Simulation (FUTURES) modelling framework used in the present study. FUTURES is a patch-based, stochastic, multi-level land change modelling framework for urban-regional growth scenario simulation (Petrasova, et al., 2016). The modelling framework is made up of three interacting sub-models (Meentemeyer et al., 2015) with a dynamic feedback system (feeding the output of the model at each time-step of simulation as the input for the subsequent time-step)

A. POTENTIAL sub-model

The POTENTIAL sub-model uses multi-level logistic regression to create a probability surface which quantifies the likelihood (potential) of each cell unit of the base satellite image of the study area to transform from non-developed land to developed land. The sub-model first allocates an original potential score of each cell of the satellite image through the following multi-level (i.e. across multiple sub-regions) regression equation:

$$S'_{[i][j]} = A_{[j]} + \sum_{v=1}^{n} \beta_{[j][v]} * X_{[i][j][v]} + \beta_{[j][Dp]} * Dp_{[j][i]}$$

Where:

$S'_{[i][j]}$ = Original potential score of cell i in sub-region j

$A_{[j]}$ = Intercept for sub-region j

$\beta_{[j][v]}$ = Coefficient of predictor variable v in sub-region j (total n variables)

$X_{[i][j][v]}$ = Value of predictor variable v in sub- region j at cell i

$\beta_{[j][Dp]}$ = Coefficient of development pressure variable in sub-region j

$Dp_{[j][i]}$ = Value of development pressure variable in sub-region j at cell i

B. DEMAND sub-model

The Development Pressure variable is an extremely important variable that adds a dynamic feedback loop to the FUTURES framework. It quantifies the effect of surrounding development on any given cell i based on a distance decay effect. It is computed using the following gravity equation:

$$Dp_{[i]} = \sum_{k=1}^{n_i} \frac{State_k}{d_{ik}^{y}}$$

Where:

$Dp_{[i]}$ = Development pressure on cell i

Statek = Binary variable showing state of kth neighbouring cell (developed state = 1 ; undeveloped state = 0)

n_i = Number of neighbouring cells within a specific range with respect to cell i

d^y_{ik} = Power function of the distance (d) between cell i and cell k

The coefficient y in d^y_{ik} controls the effect of distance decay. If a is high then the effect of surrounding developed cells decreases faster as distance from cell i increases and if it is low then effect decreases more slowly as distance increases.

The DEMAND sub-model estimates the total quantum of future land that would transform from undeveloped to developed as a relationship between the trend of population growth of the study region over a period of time and the amount of developed land (as derived from land use classification of satellite imagery) over that same period. At every time step, there would be a certain number of developed cells produced to satisfy the land requirement of the population based on the relationship. The relationship is assumed to be linear (to project the trend based on linear least squares regression) in the current exercise.

C. PATCH GROWING ALGORITHM (PGA) sub-model

The PGA sub-model is the main engine of the FUTURES modelling framework and adds the stochastic element to it. It transforms undeveloped cells to developed cells using a Monte Carlo approach. It first drops a "seed" randomly across the POTENTIAL probability gradient. It then generates a random number between 0 and 1 and compares it to the probability value of the cell in which the seed is located. If the random number is larger than the probability value of the cell then the seed is allowed to survive and the cell is allowed to develop and grow a patch by trying to convert other cells around it. If the random number is lesser than the probability value of the cell then the seed dies.

PGA then converts the transformed cell into a patch by checking the probability score of surrounding cells using another gravity equation:

$$S_i = \frac{S'_i}{d^\alpha}$$

Where:

S_i = Composite potential score of cell i

S'_i = Original potential score of cell i computed by POTENTIAL sub-model.

d^α = Power function where d is the distance between cell i and the seed cell, and a is the coefficient controlling the effect of distance decay. A high value of a produces more compact patches, simulating a more compact development process and a low value creates more scattered patches simulating a more scattered, sprawl like development.

Finally, the probability that an undeveloped cell i becomes developed is given by the logistic function:

$$P_i = \frac{e^{S_i}}{1 + e^{S_i}}$$

The growth of a patch continues until it is stopped by parameters computed from the calibration of size and shape of patches based on the analysis of patches in land use maps used as inputs to FUTURES. This process of allocation and transformation of cells continues until the total quantum of developed cells as determined by DEMAND is reached.

The final output from PGA comes in the form of maps for each time-step of the simulation period showing the amount and location of new land development. In each iteration the new land developed is allowed to exert its own influence on future land development using the development pressure feedback variable.

3. Flood Forecasting Model for Assam

A 2D hydraulic model was developed using HEC-RAS software to simulate the movement of water across the Brahmaputra floodplain under present and future climate conditions for various rainfall return periods. The model integrated rainfall hyetographs derived for different return periods and high-resolution SRTM DEM data was used to represent terrain, and land use and land cover (LULC) information to account for surface roughness and infiltration variations. Using a Rain-on-Terrain approach, the model captured the spatial and temporal dynamics of flooding, including direct rainfall contributions, flow pathways and water depths.

This comprehensive setup enabled detailed simulation of inundation patterns, offering valuable insights into flood risks and aiding in effective flood management and planning for the Brahmaputra River basin. The calibration of the HEC-RAS hydraulic model was done using the August 2018 flood extent data, which provided valuable insights into the model's performance. While the model achieved a 65% match with observed flood extents, limitations due to the lack of observed hydrological data and the scale of the study area are acknowledged.

Results and Discussion

1. The *'Prakriti'* 2.0 model

Preliminary results from the work show that the extent of direct damages from the 2016 floods in Assam were ₹10534 crore. This includes information gleaned from the relevant Flood Memorandum for 2016 (₹10,242 crore) as the extent of damage assessed across sectors (livestock, crops, houses, health, etc.) by the state. The authors additionally assessed the value of private damages incurred by firms to be ₹292 crores. This estimation is based on reduction in asset values of buildings, plant and machinery, ICT, and change in stock (inventories) as note by the MoSPI's Annual Survey of Industries.

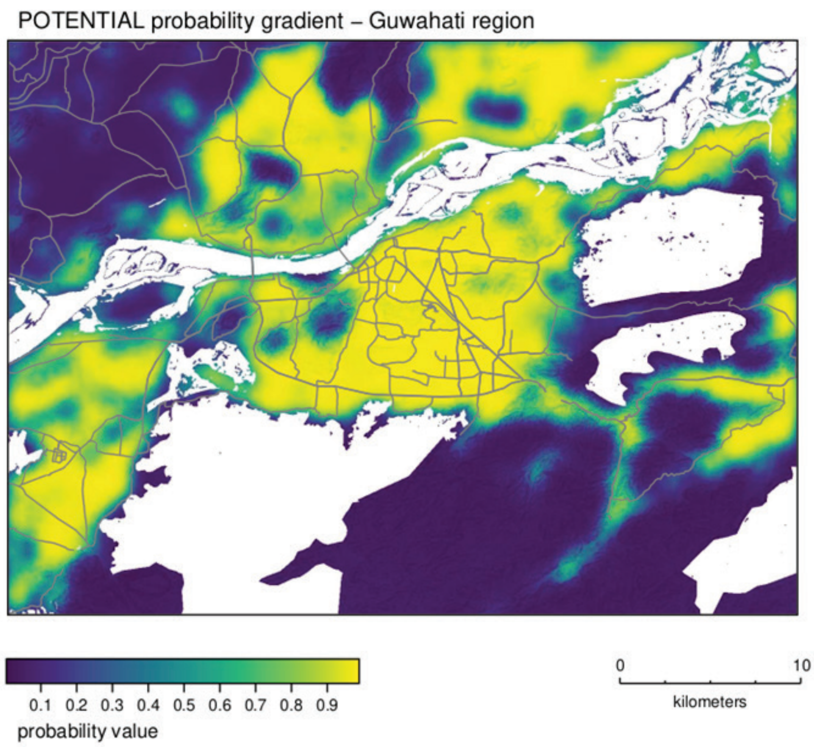
Like before, as a part of **the *Prakriti* 2.0** ARIO model, the loss of value in assets, assuming a certain asset life and discount factor, was converted to an annualised value of ₹2,701 crore. across households, private corporations and government utilities. Assuming that the compensation paid only covers a certain part of actual losses, and the loss in assets leads directly to reduction in production possibility (via the capital-output ratio), Assam's floods in 2016 translated into an output loss of ₹6,689 crore. This amounts to 2.62% of the SDP for that year.

2. Geo-spatial model

The FUTURES modelling framework was applied to the Guwahati urban region, located in a high flood-risk zone of Assam. Covering about 1,400 sq km, the region is mapped at a 30-meter resolution (matching Landsat imagery), with each cell representing 900 square meters map. The results of the DEMAND sub-model are derived using linear regression, with population of the main urban centre in the region as the independent variable and the amount of land needed for development (in cell units with 1 cell = 900 sqm) as the dependent variable.

The following map (Figure 3) shows the probability surface computed by the POTENTIAL sub-model. Each cell unit is given a probability value ranging from 0 to 1 showing the probability that it has to become developed.

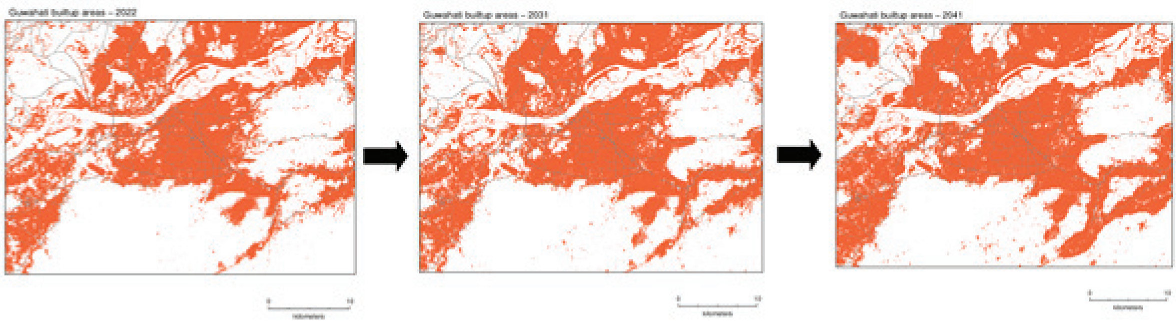
Figure 3: Computation of probability surface by POTENTIAL sub-model



(Source: Authors' construction)

The following maps (Figure 4) show the results of the computation of the PGA sub-model. Although the outputs of the PGA sub-model are in the form of separate maps for each year of the simulation, only three time-steps have been shown here. The results of the simulation show the probable spatial distribution of future land development in the three urban-regions

Figure 4: Built-up area expansion in Guwahati urban-region computed by PGA sub-model



(Source: Authors' construction)

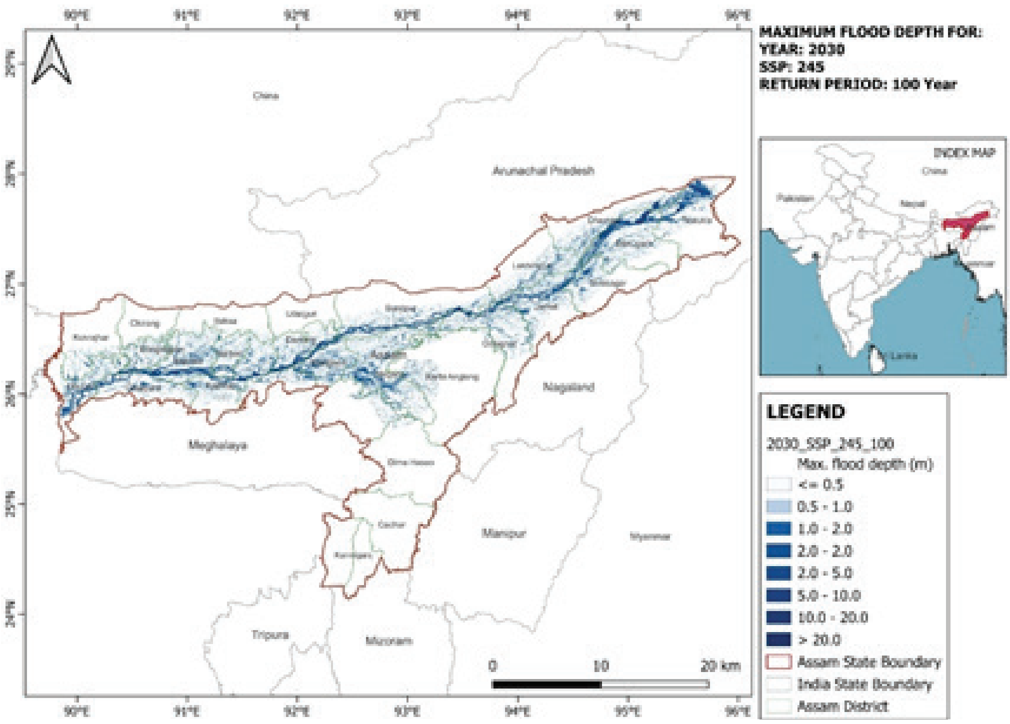
The results of the FUTURES modelling framework provide an opportunity to study the probable spatial distribution of developed land in the future. Integrating such a landscape modelling and simulation approach to the mainstream disaster adaptation strategy of the state of Assam will allow for a more comprehensive disaster adaptation planning exercise. It will enable the decision makers to track which geographical areas in the disaster-affected regions of the state will experience what kind of development in the future, and that will help optimise planning efforts to minimise disaster losses and damages. For example, in the case of Guwahati, the planners would be able to track probable future hotspots of urban flooding based on the spatio-temporal trend of built-up area formation.

3. Flood Forecasting Model for Assam

Projected changes in flood extent across different future time periods (2030, 2050, and 2070) and under two climate scenarios: SSP 245 (moderate emissions scenario) and SSP 585 (high emissions scenario) were analysed. The analysis is based on flood extent projections for different return periods (5-year, 10-year, 25-year, 50-year, and 100-year), which indicate the probability of extreme flooding events.

It was found that future flooding will increase, even under SSP 245, the moderate emissions scenario, where flooding increases by 7% for 100-year (larger and rarer) floods (Figure 5). while frequent floods (5-year, 10-year) show smaller increases (~3%). This indicates that extreme events are worsening more than regular floods. Under a high-emission scenario (SSP 585), the situation was worse: flooding under SSP 585 is almost double the increase compared to SSP 245. There is a 12.06% increase in 100-year floods by 2070 (vs. 7.07% under SSP 245). This means that if emissions continue unchecked, the state will face significantly worse flooding.

Figure 5: Maximum Flood Depth for 100-Year Return Period



(Source: Authors' construction)

Policy Perspectives and Way Forward

As discussed previously, the present data collection with regard to flood-related losses and damages mostly covers the people affected, displaced or dead, damages to crops and livestock, and public infrastructure and ignores the losses and damages experienced by industries. Flood-related losses are transmitted across the industrial supply chain and have a contagion effect over other sectors, impacting even non-affected areas. This implies the need for policy interventions to undertake a more **comprehensive approach to the assessment of flood-related losses and damages.**

Considering the significant impact on industries that are more vulnerable to flood-related risks, there is a need for policy interventions at the sub-national level to support business recovery. These include specific policy measures that target vulnerable industries, such as coke and cement in the state of Assam, which are more exposed to climate risks. These policy interventions may include subsidized insurance schemes, disaster relief funds for the industries, and low-interest loans for the industries to rebuild their businesses. These measures would aid in quicker recovery of investment demand in the state. Additionally, there is an acute need for more investment in infrastructure for disaster-proofing to help ensure quicker recovery, enhanced resilience and long-term economic stability.

The results of the modelling exercises provide a framework for assessment of the full extent of economic damages suffered by a state, while also offering a method to evaluate the evolving vulnerabilities due to changes in development patterns, urbanization and land use changes in the future. This exercise has been undertaken at sub-national and district levels, to serve as an illustrative case for the application of the modelling framework for assessing damages and informing disaster adaptation planning. The study is important from the **disaster planning** perspective (permissible land use and land use change, disaster evacuation and shelter plans, engineering designs for public works) and **fiscal provisioning** at the state and local levels for disaster preparedness and relief work.

Disaster impacts are localised, shaped by the region's unique topography, disaster risk profile and socio-economic characteristics. Some key determinants of regional vulnerabilities include demographic and economic factors such as industrial patterns and sectoral composition. Over-reliance of a region on certain industries or sectors can heighten the risk of livelihood and business disruptions.

This sets the stage for replicating the analysis undertaken in this paper across different regions to ensure accurate assessments of disaster-related economic costs and business disruptions in context-specific settings. The scope of such analysis may extend beyond other states or districts with their distinct risk profiles, to include industrial regions, economic clusters and corridors that transcend conventional administrative boundaries.