

Updated Review

AI-driven Climate–Health Risk Mapping in Bangladesh: A Proposed Framework Integrating Remote Sensing and Machine Learning for Future Early Warning Systems

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Abstract

Climate change is feared to significantly alter the distribution of climate-sensitive diseases in Bangladesh. However, there remains a lack of integrated, data-driven frameworks capable of linking climate hazards with public health risks. This paper proposes a conceptual and methodological framework for AI-driven climate–health risk mapping by integrating remote sensing (RS), Geographic Information Systems (GIS), and machine learning (ML). The proposed framework combines satellite-derived environmental variables, socioeconomic indicators, and health data to construct a composite Climate–Health Risk Index (CHRI) based on hazard, exposure, vulnerability, and adaptive capacity. A Light Gradient Boosting Machine (LightGBM) model is proposed for predictive risk estimation. Although the framework is not yet empirically implemented, it provides a scalable and operational roadmap for future research and policy applications in Bangladesh. The proposed system has the potential to support early warning, targeted interventions, and climate-resilient health planning.

Keywords: Climate Change; GIS; Remote Sensing; Machine Learning; Health Risk; Bangladesh; Framework

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1. Introduction

Climate change is increasingly recognized as a major determinant of public health outcomes, particularly in vulnerable countries such as Bangladesh. The country is exposed to multiple climate hazards including floods, cyclones, salinity intrusion, and rising temperatures (Intergovernmental Panel on Climate Change, 2021).

These hazards influence the spread of climate-sensitive diseases such as diarrhea, dengue, cholera, and heat-related illnesses (World Health Organization, 2023). Despite growing recognition of these linkages, there is a

lack of integrated frameworks that combine climate data, environmental exposure, and health outcomes in a predictive and spatially explicit manner.

This paper does not present empirical findings; rather, it proposes a comprehensive methodological framework for AI-driven climate–health risk mapping to be implemented in future studies.

The objectives of this paper are to:

1. Propose an integrated RS–GIS–ML framework for climate–health analysis
2. Define a composite Climate–Health Risk Index (CHRI)
3. Outline data requirements and analytical workflows
4. Provide a roadmap for future research and policy applications

2. Conceptual Background

2.1 Climate–Health Linkages

Climate variability affects disease transmission through multiple pathways, including:

- Water contamination due to flooding
- Vector breeding influenced by temperature and rainfall
- Salinity affecting drinking water and health

Previous studies highlight the need for spatially explicit risk assessments (Patz et al., 2005).

2.2 Role of GIS and Remote Sensing

GIS enables spatial integration of multi-source datasets, while remote sensing provides continuous environmental monitoring (Kamel Boulos & Geraghty, 2020). These tools are essential for mapping exposure and hazard dynamics.

2.3 Machine Learning for Predictive Health Modeling

Machine learning techniques, particularly gradient boosting models such as LightGBM, offer strong predictive performance for complex, non-linear relationships between environmental variables and disease outcomes (Ke et al., 2017).

3. Proposed Study Area

The framework is designed for application across Bangladesh, with particular focus on:

- Coastal regions (salinity and cyclone exposure)
- Flood-prone river basins
- Urban centers experiencing heat stress

4. Proposed Data Framework

4.1 Climate and Environmental Data

- Satellite rainfall and temperature
- Flood extent (remote sensing)
- Land Surface Temperature (LST)
- Salinity raster datasets
- Digital Elevation Model (DEM)

4.2 Health Data (Future Integration)

- Disease incidence (dengue, diarrhea, cholera)
- Health facility data

4.3 Socioeconomic and Infrastructure Data

- Population density
- Road network
- Healthcare accessibility

5. Proposed Methodology

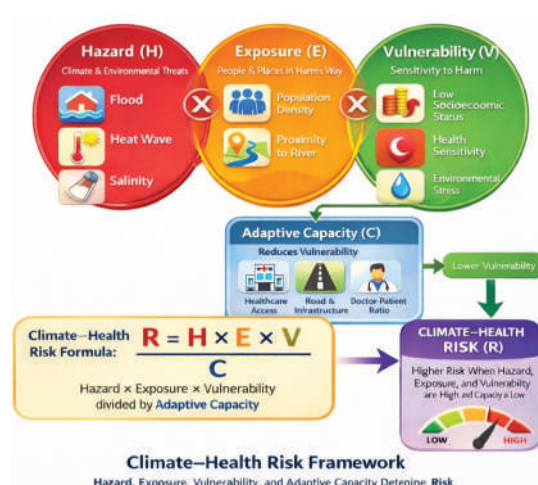
5.1 Conceptual Risk Framework

The proposed Climate–Health Risk Index (CHRI) is defined as: $R = H \times E \times V / C$

Where:

- H = Hazard
- E = Exposure
- V = Vulnerability
- C = Adaptive Capacity

This formulation aligns with established climate risk frameworks (IPCC, 2014).



5.2 Hazard Component (Proposed)

Hazard layers may include:

- Rainfall intensity
- Temperature extremes
- Flood
- Salinity
- Storm Surge
- Heat Wave
- Drought

These variables will be normalized and classified into risk categories.

5.3 Exposure Component (Proposed)

Exposure may be estimated using:

- Distance to rivers (m)
- Flood inundation depth (m)
- Salinity Intrusion Level (PPT)
- Storm Surge Depth (m)
- Drought Intensity (Index)
- Population distribution (No.)

5.4 Vulnerability Component (Proposed)

Potential indicators include:

- Socioeconomic conditions
- Environmental stress
- Health sensitivity

5.5 Adaptive Capacity (Proposed)

Capacity may be represented by:

- Healthcare accessibility
- Road connectivity
- Infrastructure availability
- Doctor-Patient Ratio

5.6 Proposed Machine Learning Model

A LightGBM model is proposed for predicting disease risk.

Potential input features:

- Climate variables
- Environmental indicators
- Exposure metrics
- Vulnerability metrics
- Capacity metrics

Expected outputs:

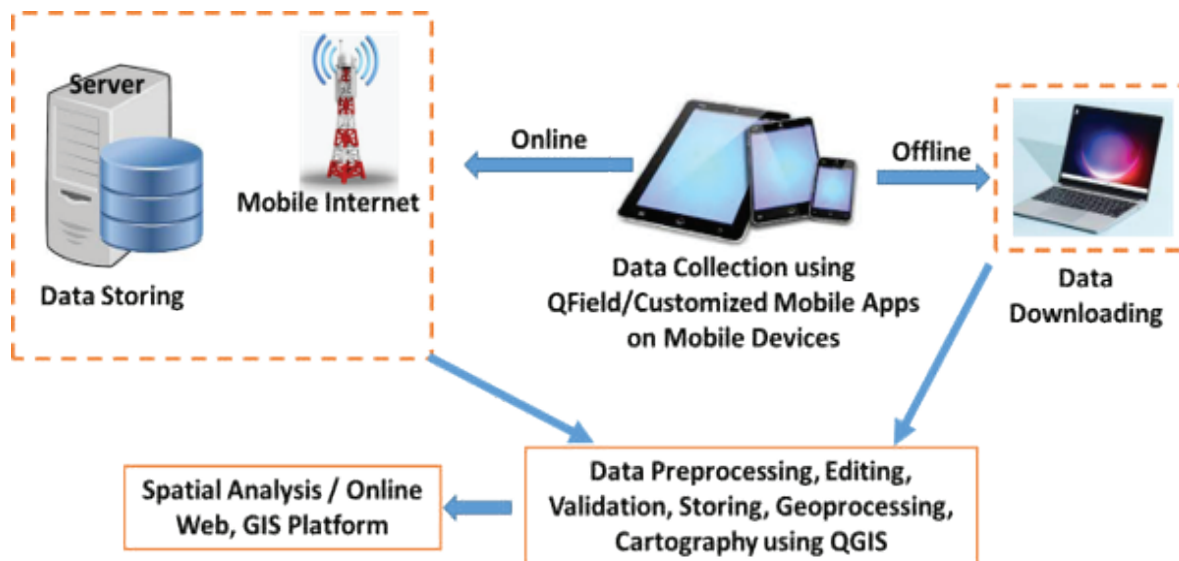
- Disease risk probability
- Hotspot classification
- Disease Outbreak Pattern

5.7 GIS Integration and Outputs

The framework will generate:

- Climate–Health Risk Maps

Below is the Primary Geospatial (GIS) Data Collection System in the field level in addition to the data captured from Satellite Image.



- Disease hotspot zones
- Early warning layers

6. Expected Outcomes (Hypothesized)

Although not yet implemented, the framework is expected to:

- Identify high-risk zones in coastal and flood-prone areas
- Reveal spatial relationships between climate variables and disease risk
- Improve early warning capability for climate-sensitive diseases

7. Discussion

This proposed framework addresses key gaps in existing research by integrating climate, environmental, and health data into a unified analytical system. It emphasizes:

- Multi-hazard integration
- AI-based prediction
- Spatial decision support

The framework is particularly relevant for Bangladesh, where climate risks are intensifying.

8. Policy and Research Implications

- Supports development of Climate–Health Early Warning Systems
- Enables targeted interventions in vulnerable regions
- Provides a foundation for national-scale implementation
- Encourages integration between climate science and public health

9. Limitations and Future Research

As a conceptual framework, this study does not include empirical validation. Future work should:

- Implement the model using real datasets
- Validate predictions with observed health data
- Refine model parameters and weights
- Develop operational decision-support tools

10. Conclusion

This paper proposes a novel AI-driven framework for climate–health risk mapping in Bangladesh. By integrating RS, GIS, and ML, the framework offers a scalable and practical approach for future research and policy applications. Its implementation could significantly enhance climate-resilient health planning and early warning systems.

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