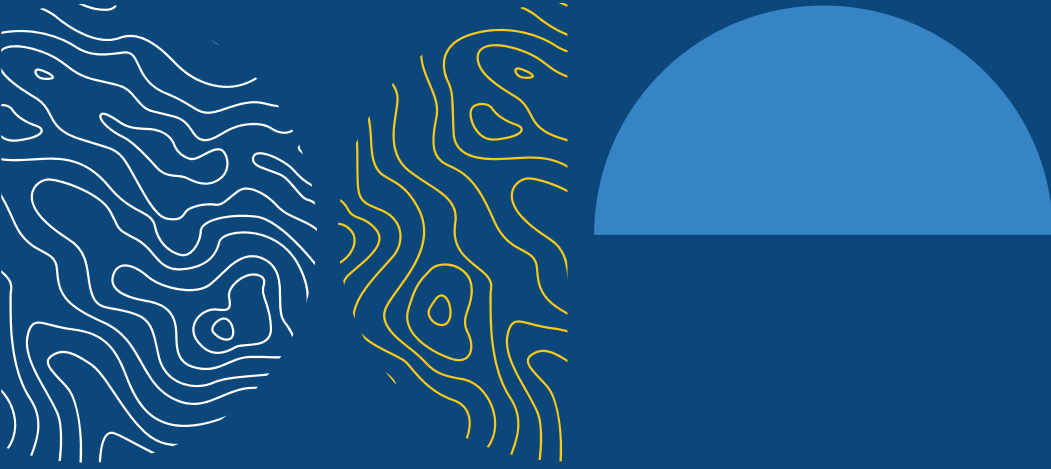




Impact Forecasting Toolkit

Paving the way towards
Impact Forecasting



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Paving the way towards Impact Forecasting



Funded by
European Union
Humanitarian Aid



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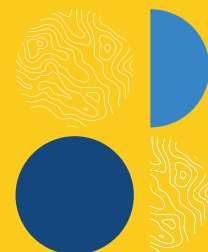


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List of Acronyms

AA	Anticipatory Act
BMDWRF	Bangladesh Meteorological Department’s Weather Research & Forecasting
BOB	Bay of Bengal
DRR	Disaster Risk Reduction
EWS	Early Warning System
ECMWF	European Center for Medium-Range Weather Forecast
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
IBF	Impact-based Forecasting
IF	Impact Forecasting
INFORM	Index for Risk Management
INSTANT	Integrated Forecast Dissemination Portal
RIMES	Regional Integrated Multi-Hazard Early Warning System
TCs	Tropical Cyclones
VCI	Vegetation Condition Index



P refix

Hydrometeorological hazards, particularly tropical cyclones, pose a recurring threat to lives, livelihoods, and economic stability in vulnerable regions worldwide. Despite advancements in meteorological forecasting, the persistent gap between hazard prediction and actionable risk communication continues to undermine disaster preparedness and response. In Bangladesh, a country disproportionately affected by cyclones originating in the Bay of Bengal, early warning systems have historically reduced fatalities through timely alerts and infrastructure improvements. However, generic forecasts often fail to address the nuanced vulnerabilities of individual communities, resulting in varied impacts across the region with different livelihood sectoral damage.

The critical challenge lies not in predicting what the weather will be but in communicating what the weather will do. While vital, traditional hazard-centric forecasts lack granularity in translating meteorological data into localized consequences. This limitation leaves disaster managers and communities unprepared to prioritize resources or implement targeted interventions, particularly in regions with heterogeneous exposure and vulnerability profiles.

To address this gap, the Cyclone Impact Forecasting (IF) Toolkit demonstrates the paradigm shift toward impact-based decision-making. By integrating high-resolution hazard forecasts with dynamic vulnerability indices and sector-specific exposure data, this methodology enables the generation of location-specific impact scenarios. Grounded in multidisciplinary collaboration, the toolkit synthesizes advanced forecast products, socio-economic datasets, and remote sensing insights to quantify risks at both national (district) and sub-district (upazila) levels. For instance, during Cyclone Remal (2024), the integration of vegetation health indices allowed precise forecasting of agricultural losses, guiding preemptive harvests and asset protection in high-risk areas.

Developed in partnership with the Bangladesh Meteorological Department (BMD) and the Department of Disaster Management (DDM), this toolkit emphasizes operational scalability of IbF and IF specially for compound hazards like tropical cyclones. It leverages Bangladesh's existing early warning infrastructure while incorporating national and sub-national-level socioeconomic and exposure data to generate detailed impact scenarios. This impact scenario can subsequently serve as the baseline for effective early and anticipatory actions, such as targeted evacuations, resource prepositioning, and sector-specific resilience measures. The result is a robust framework that bridges the divide between meteorological accuracy and communitycentric risk reduction.

By transitioning from traditional forecasts to a impact-driven approach, this initiative represents a significant advancement in disaster risk management. It not only enhances the precision of early warnings but also fosters a culture of proactive preparedness, ultimately reducing economic losses and safeguarding vulnerable populations. As climate change intensifies cyclone frequency and severity, the adoption of such innovative tools will be pivotal in building adaptive resilience across coastal regions globally.

Background

Bangladesh's coastal regions face disproportionate exposure to tropical cyclones, enduring approximately 25% of all cyclones generated annually in the Bay of Bengal (Alam et al., 2003; Dube et al., 2009). These events have historically inflicted catastrophic human and economic losses, a trend projected to intensify with rising sea surface temperatures and sea levels (Dasgupta et al., 2010). The country's existing risk management framework—comprising cyclone shelters, embankments, volunteer-led preparedness programs, and mass media alerts—has reduced fatalities over decades. However, systemic gaps persist in translating forecasts into actionable, location-specific guidance, particularly for communities with diverse vulnerability profiles.

The national cyclone warning system, originally designed for maritime ports, exemplifies this limitation. For instance, a standardized “Great Danger Signal No. 10” issued for the port of Mongla triggers blanket evacuations across entire districts, irrespective of localized hazard intensity or community resilience. While critical for port operations, such one-size-fits-all alerts inadequately address the spatially variable risks faced by inland and coastal populations. A cyclone forecasted to generate 150 km/h winds in a densely populated deltaic region may warrant different preparedness measures than the same storm impacting a sparsely inhabited coastal belt. Yet, under the current system, both scenarios receive identical warnings, leading to either resource misallocation or public complacency.

The effectiveness of modern forecasting systems relies on synthesizing high-resolution hazard forecasts with granular socio-economic and exposure datasets to contextualize risks. Precision of forecasting Hazard is achieved through advanced meteorological tools such as the European Centre for Medium-Range Weather Forecasts (ECMWF)'s high-resolution forecast products, which generate high-resolution predictions for wind and rainfall, enabling dynamic risk mapping. These hazard forecasts can be further complemented by vulnerability and exposure information collected through primary, secondary, and even satellite products to generate more meaningful impact scenario. Together, these technical advancements transform static meteorological data into actionable insights, ensuring forecasts addresses not only weather conditions but also how it will impact vulnerable populations and critical sectors. These technical innovations underpin Impact-based Forecasting (IbF) and Impact Forecasting (IF), methodologies that shift the focus from predicting weather conditions to understanding what the weather will do.

The success of such approaches relies on the four pillars of the Early Warning System (EWS): risk knowledge, monitoring, warning communication, and response capability. A “people-centered” EWS requires seamless collaboration between meteorological agencies, disaster management authorities, and local governments to convert static forecasts into dynamic action plans. This approach can subsequently aid in customizing evacuation protocols in accordance with community mobility constraints or pre-positioning supplies based on projected agricultural losses. While challenges persist, particularly in real-time data integration and hyper-local validation, the adoption of IF represents a transformative leap in reducing potential damages through early actions. By bridging the gap between global-scale models and community-scale vulnerabilities, this toolkit is pioneering a replicable framework for cyclone resilience, one that aligns meteorological precision with humanitarian imperatives.

Chapter



1



Chapter 1: Introduction to Key Terminologies



1.1 Hazard

A hazard is defined as the possible occurrence of a natural or human-induced physical event or trend that could result in loss of life, injury, or other health impacts, along with damage to or loss of property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources (IPCC, 2022). Similarly, WMO (2015) defines hazard as any element related to hydrometeorological, geophysical, or human-induced that presents a risk to life, property, or the environment (WMO, 2015). Hazards do not constitute disasters but become so when interacting with vulnerable populations and exposed assets. Hence, it is essential to consider a hazard's frequency, magnitude, duration, and spatial extent to identify potential impact areas. For instance, data on weather predictions, meteorological conditions, and specific hazard information related to cyclones are useful when illustrating a hazard layer.



1.2 Exposure

Exposure encompasses scenarios in which individuals, livelihoods, species or ecosystems, environmental functions, services, and resources, along with infrastructure and economic, social, or cultural assets, are situated in regions susceptible to adverse effects (IPCC, 2022). In the event of a hazard, the people, assets, or elements that may be affected are defined under exposure. The exposed elements must be located in hazard-prone areas as otherwise, no such risk of disaster exists (WMO, 2015). For instance, Human beings and tangible human assets (buildings and critical infrastructures) are some indicators that belong to this category.

Exposure and vulnerability are not always mutually inclusive; for instance, inhabitants living inside Pucca housing are less exposed than those in Kutcha houses despite a similar level of vulnerability due to location. Exposure is also

time and space-dependent: the geographic location of the exposed element can determine its level of exposure. To highlight a situational scenario, during a thunderstorm, a private car on the road would be less exposed than a crane despite the same hazard (WMO, 2015; IPCC, 2014). The dynamic nature of exposure makes it difficult to gather such statistics (WMO, 2021). Information that can impact economic well-being, such as fisheries, aquaculture, and agriculture production data, can also fall under exposure data. As such, exposure data can range from population density to road density to agricultural area (WMO, 2021; INFORM, 2022).



1.3 Vulnerability

Vulnerability refers to a community's inability to cope with a hazard effectively. The exposed elements (human beings, livelihoods, and assets) are susceptible to adverse effects from that hazard (IPCC, 2022; WMO, 2015). The vulnerability of the exposed element varies based on time and space. For example, it is possible to lower the vulnerability of the coastal population in a cyclone-prone area by increasing the capacity for cyclone shelters. Following the cyclone Gorky in 1991, the number of multi-purpose cyclone shelters increased in the coastal areas of Bangladesh, which reduced the vulnerability of many inhabitants (WMO, 2021; Haldi et al., 2021).

Vulnerability is directly proportional to lack of coping capacity and inversely to adaptive capacity. It can be further divided into sensitivity and adaptive capacity (IPCC, 2014). The level of sensitivity indicates the extent to which a system or population is impacted by a hazard, with more sensitive communities experiencing more significant harm. Adaptive capacity refers to the capacity to deal with, adapt to, and bounce back from the effects of hazards. For example, Populations with low adaptive capacity and high sensitivity are more vulnerable. In contrast, those with greater adaptive capacity are better prepared to handle and recover from disasters, thereby reducing overall vulnerability. Factors like socio-economic conditions, location, infrastructure, health demographics, and institutional capacity also influence the vulnerability indices. Hence, vulnerability indicators can be integrated with forecast information to help identify potential hotspots for sector-specific interventions.

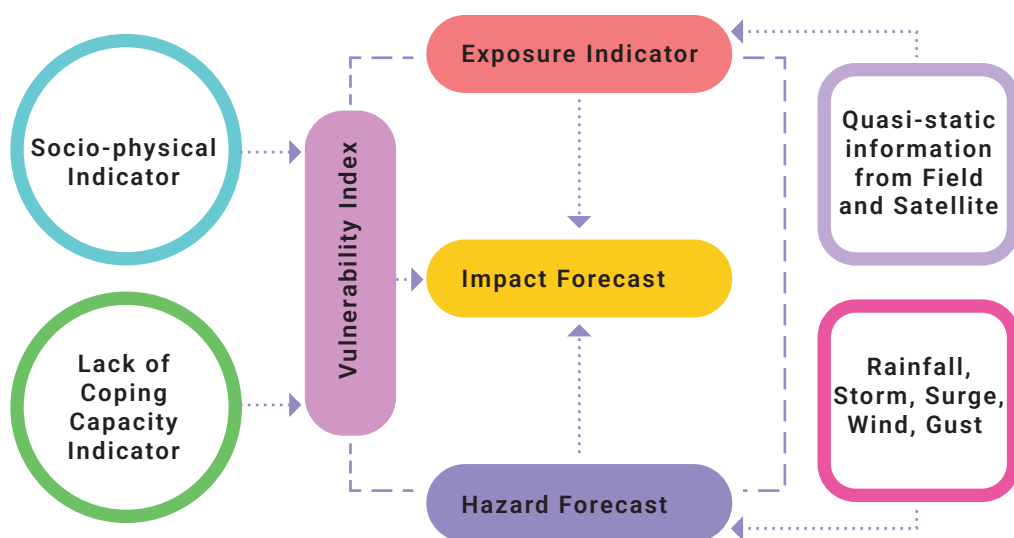


Fig. 1. Relationship between the key elements of an Impact Forecast Model



1.4 Impact

In general, Impact refers to the likelihood and severity of damage to individuals, their livelihoods, and property, resulting from their exposure and vulnerability in the event of a hazard (WMO, 2015). Impact can incorporate both adverse effects (such as economic losses) or positive effects (such as financial benefits). The effects can be economic, human, and environmental, which vary according to the scale of the disaster. The magnitude of impact may be lowered by improving response actions. Hence, understanding the effects and subsequent impacts is essential for customizing risk communication, navigating early interventions, and directing anticipatory action toward the most vulnerable populations. Since hazard forecasts differ from one area to another, the resulting impacts also vary from upazila to upazila. By predicting the area most likely to be highly impacted (for instance, through IF), relevant authorities can initiate early actions effectively to minimize harm and enhance preparedness. The mathematical Impact calculation in this Toolkit has been derived from INFORM (2022) and WMO (2015). Here, Impact is determined by multiplying the forecasted hazard with vulnerability and exposure. The relationship between all the variables are summarized in Figure 1.



1.5 Anticipatory Action

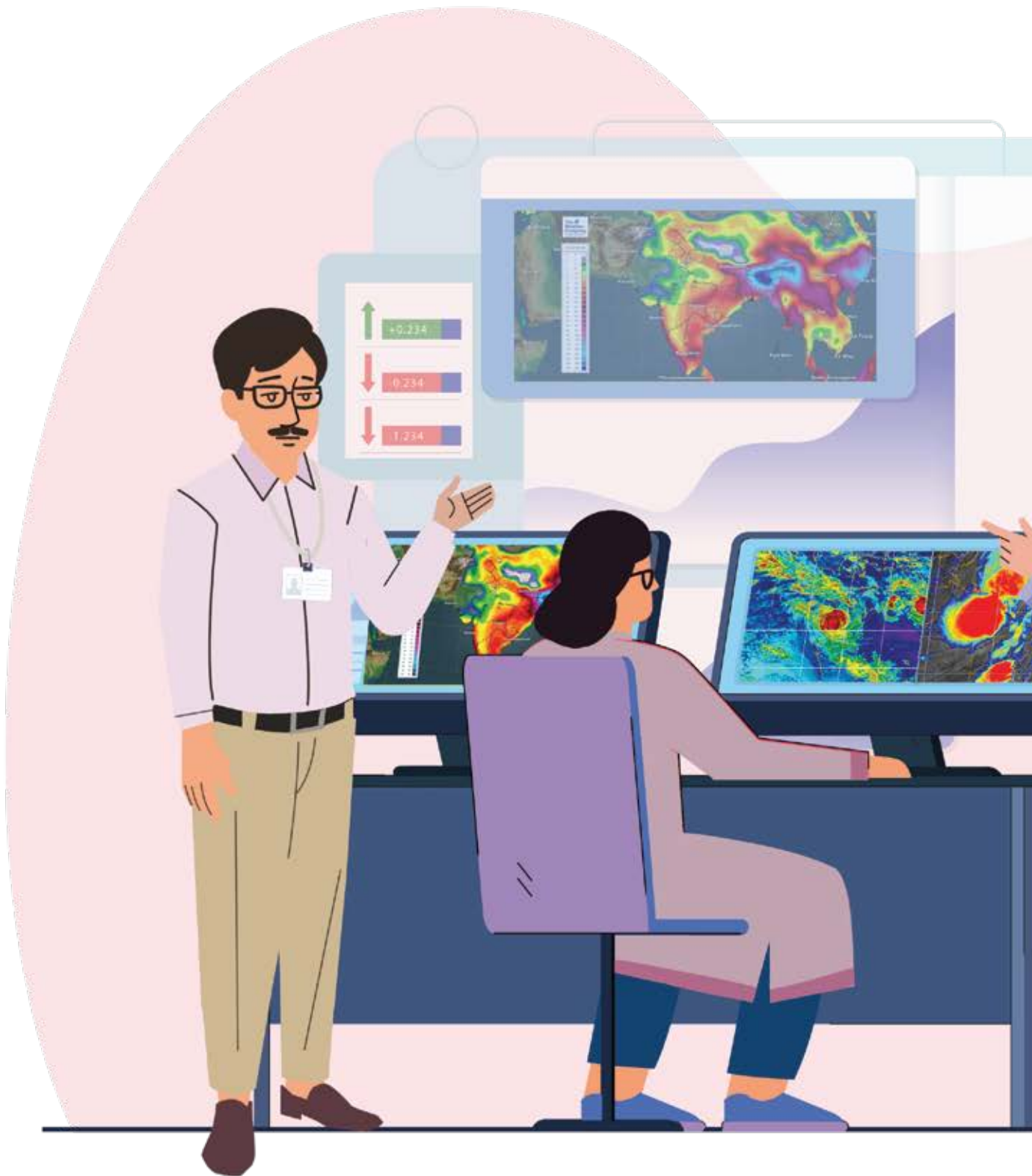
Anticipatory action involves measures taken to reduce the humanitarian impacts of a forecast hazard before it occurs, or before its most acute impacts are felt. The decision to act is based on a forecast, or collective risk analysis, of when, where and how the event will unfold (IFRC 2020). In general, it typically involves taking steps prior to the occurrence of a hazard to mitigate or lessen severe humanitarian effects. Successful execution of anticipatory action globally often involves considering pre-established triggers, taking pre-identified actions, and distributing pre-arranged funding (WMO, 2021). The consideration of pre-established triggers includes considering thresholds and decision-making criteria based on reliable forecasts. This approach enables the implementation of predetermined actions that effectively assist the most vulnerable communities during the trigger event and at the crisis's onset. Lastly, pre-arranged funds are allocated and disbursed based on the pre-established trigger linked to the pre-identified actions. Hence, the reliability of forecast plays a crucial role in mobilizing the resources during the time of crisis. Anticipatory actions are resource-intensive; therefore, the resources must be mobilized efficiently. As opposed to the conventional port-based forecasting, it is imperative to consider location-specific impact to facilitate sustainable and effective anticipatory actions.

Chapter

2



Chapter 2: Shifting the Paradigm: From Traditional to Impact Forecasting



Before delving into the specifics of location-specific Impact Forecasting, it is essential to establish a foundational understanding of the distinct approaches used in different meteorological forecasting. The forecasting approaches are described for better understanding.

2.1 Paradigm 1 - Traditional Forecasting

The first paradigm, also known as 'Traditional Forecasting,' mainly refers to information on meteorological characteristics such as the hazard's intensity, duration, and spatial extent. The traditional forecast information consists of atmospheric observations and expected conditions throughout the forecast period. These forecasts indicate the anticipated changes in observable atmospheric factors like wind, temperature, humidity, and precipitation. Forecasts can be presented in a deterministic or a probabilistic format. Importantly, traditional forecasts usually consider only the weather hazard and not its potential effects on society. Importantly, traditional forecasts usually consider only the weather hazard and not its potential impact on society and livelihood. pre-arranged funds are allocated and disbursed based on the pre-established trigger linked to the pre-identified actions. Hence, the reliability of forecast plays a crucial role in mobilizing the resources during the time of crisis. Anticipatory actions are resource-intensive; therefore, the resources must be mobilized efficiently. As opposed to the conventional port-based forecasting, it is imperative to consider location-specific impact to facilitate sustainable and effective anticipatory actions.





Example 1: Severe monsoon rainfall expected tomorrow, with anticipated wind gusts reaching 80 km/h



Example 2: Expect heat indices to rise above 40 degrees Celsius during peak afternoon hours tomorrow

Such forecasts describe what the weather will be. They sometimes include generalized statements about possible consequences or advice (e.g., “heavy rain may cause localized flooding; carry an umbrella”), but they remain largely hazard-centric. Traditional forecasting has undoubtedly been valuable and has saved lives by alerting communities to hazardous weather. However, it is understandable that providing hazard information alone, especially if it is generic, often does not give people or institutions enough guidance to reduce the social or economic consequences of that hazard. One major limitation is that generic warnings can impair early actions. Suppose a forecast is too broad (“a cyclone warning for an entire coastal region”) and does not clarify which areas will be most impacted or what the impacts might be. In that case, local disaster managers, officials,

and the public may not know how to act regarding it. They might delay preparations or under- or over-react, because they lack clarity on the expected impact in their specific area. For instance, if a disaster manager only knows a cyclone is coming but not that it will likely inundate certain villages, it will be hard to decide how many people to evacuate or which resources to mobilize. In short, traditional hazard-focused forecasts are necessary, but not sufficient – they set the stage for a needed paradigm shift toward forecasts that convey impacts, not just hazards.

2.2 Paradigm 2 - Impact-based Forecasting

Impact-based forecasting (IbF) represents an evolution of traditional forecasting. Under IbF, the forecast information goes beyond the hazard itself to include who and what might be affected and how. This approach integrates vulnerability information into the forecast, effectively translating weather data into expected consequences. In practice, IbF is often implemented by taking a specific hazard forecast and describing the potential impacts via warning messages. For example, weather warnings may mention expected effects on people, infrastructure, and services (often directed at both the public and disaster management agencies).



Example 1: Severe monsoon rainfall expected tomorrow, which may cause urban flooding and delays in transportation services



Example 2: Expect heat indices to rise above 40 degrees Celsius during peak afternoon hours tomorrow. This may lead to increased risk of heatstroke and dehydration amongst the elderly and outdoor workers

These warnings include the hazard forecast and its potential impact (flooding, health risks), thereby telling us what the weather will do, not just what it will be (Campbell et al., 2018). IbF usually relies on predefined rules or models that link certain hazard thresholds to likely impacts, based on historical experience or vulnerability data. For instance, forecasters might know that in City X, when rainfall exceeds 100 mm within 24 hours, specific neighborhoods are prone to flooding. As a result, a warning indicating that flooding is a probable impact would be issued. A key point in IbF is that impact thresholds are not one-size-fits-all. The level of rainfall that causes

floods in one city might not in another if, say, drainage conditions or terrain differ. Therefore, IbF requires understanding local vulnerability and exposure. The “threshold” for dangerous wind or rain can vary by location and over time, depending on how prepared or fragile a community is.

IbF typically does not fix a single trigger across the board; it aims to factor in the variability of vulnerability. For example, a resilient community exposed to 80 km/h winds might experience minor inconvenience in one place but devastating in another due to weaker infrastructures. By including potential impact warnings, IbF directly addresses the “so what?” question that a traditional forecast leaves to the user’s imagination. However, IbF in many countries is still an emerging practice and may sometimes rely on generalized impact statements. While, it represents a step in the right direction, but often the impact rules (e.g., “rain > X causes Y impact”) are static or based on expert judgment and might not account for all local nuances. Still, the move to impact-based messages has been shown to improve public responses to warnings, because people can better grasp what actions to take when they understand the likely outcomes.

2.3 Paradigm 3 - Impact Forecasting

Impact Forecasting (IF) builds upon IbF by formally and quantitatively integrating hazard, exposure, and vulnerability data to generate a direct forecast of impacts. In this paradigm, one does not just append impact statements to a hazard forecast; instead, one uses models or algorithms that take in hazard predictions (like wind speed, rainfall, and storm surge) along with datasets on exposure and vulnerability, and output metrics or maps of expected impact with advisories. Essentially, IF broadens the forecasting process from asking “What will the weather be?” to “What will the weather do?” (WMO, 2015).

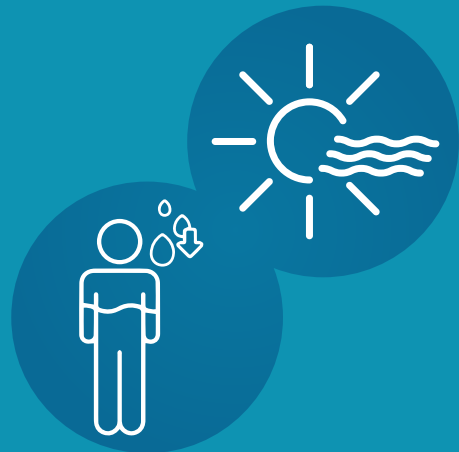
In practice, implementing IF requires detailed, localized data and close collaboration between meteorologists, disaster risk experts, and sector specialists. By incorporating local data (for example, exactly which villages are low-lying, where the elderly or disabled populations are concentrated, what the housing conditions are), IF can produce forecasts such as:

Example 1:

Expect severe monsoon rainfall in Sharankhola upazila tomorrow, likely causing urban flooding and transport delays in the south side. Residents should prepare for road closures and seek alternative routes.

**Example 2:**

Expect heat indices to rise above 40 degrees Celsius in Rajarkul union during peak afternoon hours tomorrow at Ramu Upazila. This may lead to increased risk of heatstroke and dehydration amongst the elderly and outdoor farmers located in that region.



These examples illustrate how IF gives specific, actionable information: exactly where and who will be affected and in what way. To achieve this, the approach behind IF must consider the local context. For instance, the forecast of heavy rain is combined with data on drainage or flood defenses in Sharankhola to predict flooding and travel disruption. The heatwave forecast is combined with demographic data about Rajarkul (perhaps knowing it has many senior citizens and laborers) to predict health impacts.

Because IF involves many data layers, it is more complex than traditional forecasting. It demands enhanced data sharing and coordination among agencies (meteorological agencies, local governments, disaster management offices, etc.). It may also involve more advanced statistical or machine-learning models to relate hazard inputs to impact outputs. The complexity is worthwhile because IF provides the most detailed and localized guidance for early action.

Paradigms 2 and 3 are excellent tools for stakeholders and decision-makers. By providing more relatable information, they help local authorities and communities respond more efficiently. Knowing the impacts of a weather event in advance enables immediate, appropriate actions to safeguard lives, livelihoods, and property. With climate change and other factors increasing the frequency of extreme weather (and the potential for multiple hazards occurring together), the need for localized impact information is greater than ever.

Figure 2 conceptually illustrates this progression (“Route to Impact forecasting”), highlighting how adding layers of vulnerability and exposure information to forecasts makes the warnings more actionable. Impact Forecasting, in particular, is a key enabler of anticipatory action because it directly links forecasts to expected outcomes, allowing for early, tailored interventions.

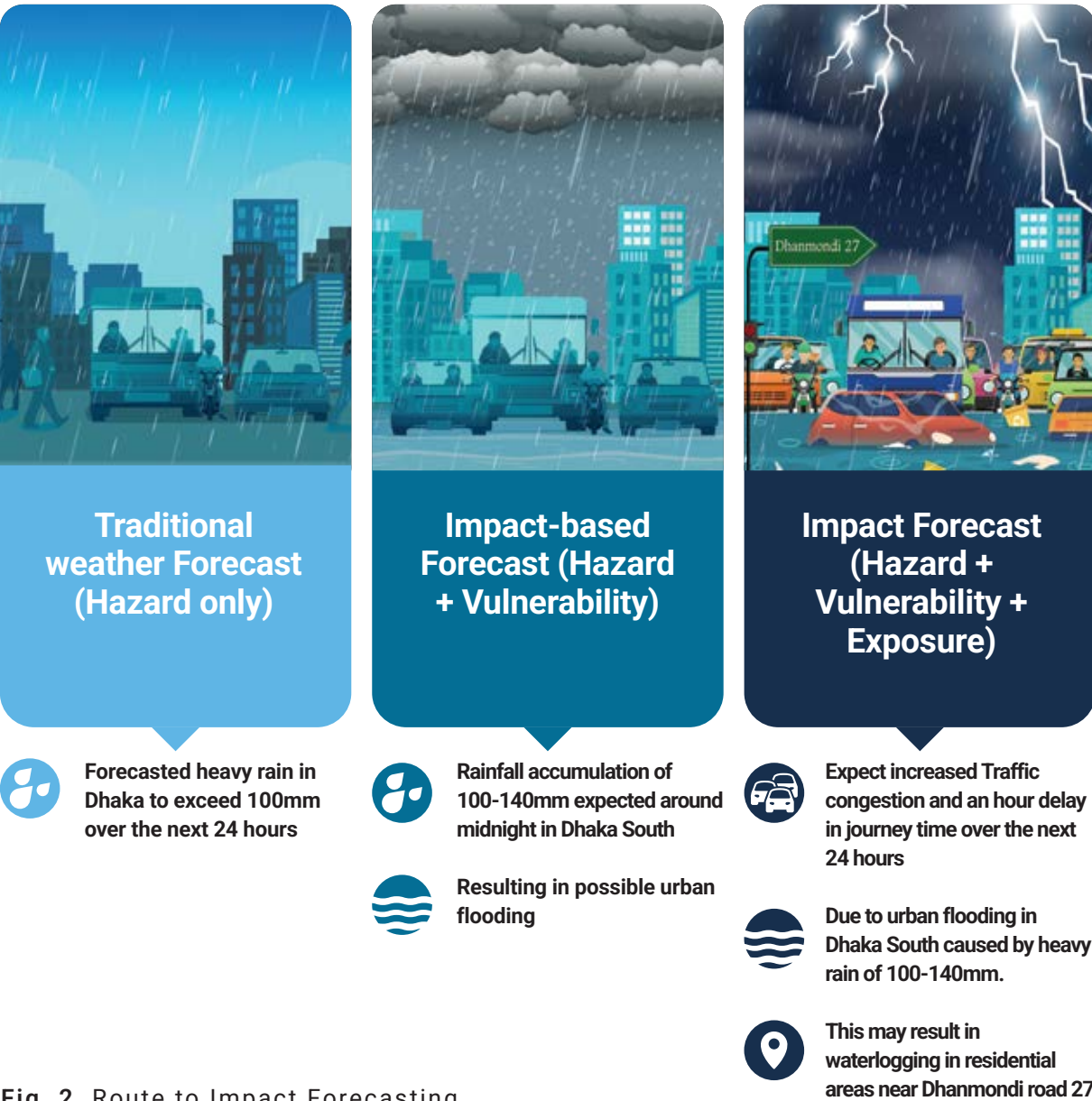


Fig. 2. Route to Impact Forecasting

2.4 Importance of Impact Forecasting in Anticipatory Action

Bangladesh’s existing cyclone forecasting system is predominantly port-based, providing limited location-specific information. By integrating higher-resolution, upazila-level (sub-district) forecasts, it becomes possible to address this shortfall and capture variations in wind speed, rainfall, and storm surges across different regions. Beyond the hazard itself, localized factors such as socio-economic vulnerabilities, exposure information such as infrastructure type or population density also shape the degree of impact at the district or upazila level.



Under the traditional system, large geographic areas often receive uniform forecasts, leading to a one-size-fits-all response that may neither match local needs nor be resource-efficient. This generic approach can erode public trust over time, as communities with markedly different risks and vulnerabilities are instructed to take similar precautions. Moreover, mobilizing extensive resources across vast areas is financially and logistically burdensome. In contrast, by integrating location-specific hazard forecasts with socio-economic and exposure data, decision-makers can generate robust impact scenarios that inform more precise, cost-effective AA.

To achieve this level of accuracy, strong collaboration among stakeholders—including government agencies, NGOs, and local communities—is vital. For instance, National Meteorological and Hydrological Services (NMHSs) alone may not have the breadth of socio-economic and sector-specific data needed for comprehensive impact forecasting. Effective partnerships can facilitate data sharing, technical support, and expertise, ensuring a more holistic response. Each step involved in Impact Forecasting is dynamic and requires extensive collaboration and data integration beyond standard hazard warnings.

Chapter



3



Chapter 3: Data and Methods

3.1 Method Overview

Given the increasing frequency and severity of cyclonic events, it is urgent to address the impacts caused by a cyclone's compound effects (destructive winds, heavy rainfall, and storm surges) on vulnerable coastal regions. In response to this need, RIMES has been developing a standardized Impact Forecasting toolkit for cyclones. The methodology presented in this toolkit builds upon RIMES's previous work on cyclone impact-based forecasting, incorporating improvements and more localized impact scenarios.

The aim of the toolkit is to utilize the most accurate available forecast products and available risk information to create impact scenarios at the district and sub-national (Upazila) level that can assist decision-makers in making informed choices about early actions (for example, deciding on evacuations or pre-positioning emergency resources). While the initial focus was on district-level impacts, the methodology has also been tested and demonstrated at the sub-national (Upazila) levels to showcase location-specific impacts. In doing so, it leverages vulnerability and other socio-economic data collected from local government sources, rather than relying solely on broader national indices.

Previously, RIMES's impact forecasting efforts utilized the INFORM Risk Index for baseline vulnerability and risk data. In this toolkit, however, a complementary approach has been introduced: incorporating new local, granular data to build on and enhance the previous methodology. In other words, instead of depending on INFORM's broader metrics alone, RIMES has incorporated actual different local socio-economic local from the demonstrated areas (through the STEP project, details are described later) and integrated it into the impact model. This allows the framework to reflect community-level realities more accurately.



The INFORM Risk Index is a global, open-source tool developed by the Joint Research Centre of the European Commission to assess disaster and crisis risks. It supports proactive disaster management and humanitarian planning. Bangladesh is highly vulnerable to hazards like cyclones, floods, storm surges, and droughts. The country uses INFORM's risk analysis to guide disaster risk reduction (DRR), anticipatory action, and resilience-building strategies. It aids policymakers, humanitarian organizations, and development planners in prioritizing interventions, allocating resources efficiently, and integrating disaster risk considerations into national and local policies. In addition to the national index, the INFORM Subnational Risk Index provides more localized risk assessments at the Upazila level, helping identify the more granular disparities in exposure, vulnerability, and coping capacity across upazilas, ensuring targeted and context-specific interventions. By leveraging INFORM risk insights, different stakeholders and organizations are using them to support the enhancement of disaster preparedness, minimize losses, and strengthen the resilience of vulnerable communities.

Thus, the Cyclone Impact Forecasting toolkit demonstrates a methodology that combines existing data (e.g., global/regional models and indices) with new location-specific data to generate impact scenarios for upazilas in coastal Bangladesh. It uses three fundamental data pillars – vulnerability, exposure, and hazard forecast (aligned with WMO 2015 and INFORM 2022 guidelines) – as the building blocks of the impact model. Local socio-economic data on vulnerability and lack of coping capacity were gathered via the STEP project and are interpreted in a case study within this toolkit. The following sections provide a step-by-step explanation of how to generate localized impact scenarios using these data and methods.

3.2 Case Study Area

The coastal regions of Bangladesh cover an area of 47,201 km² and are home to 35 million people, divided into the Eastern, Central, and Western zones (Hoque et al., 2021). For demonstration purposes, the districts of Bagerhat, Satkhira, Barguna, and Patuakhali have been selected as they fall within the working area of the STEP project. These districts are part of the Ganges tidal deltaic plain within the western coastal region of Bangladesh (22°–23° N latitude and 89°–90° E longitude). The residents of the western coast are highly

vulnerable to natural disasters due to their topography, socio-economic conditions and elevated poverty levels (Akter et al., 2019). The region experiences a humid climate with an annual rainfall of 1,940 mm. It is regularly impacted by severe tropical cyclones (i.e., Cyclone Remal (2024) and Cyclone Dana (2024)), which resulted in fatalities and notable damage to human property and the surroundings. The following figure demonstrates 4 of the 19 coastal districts and the selected upazilas and unions based on the project provision (Figure 3).

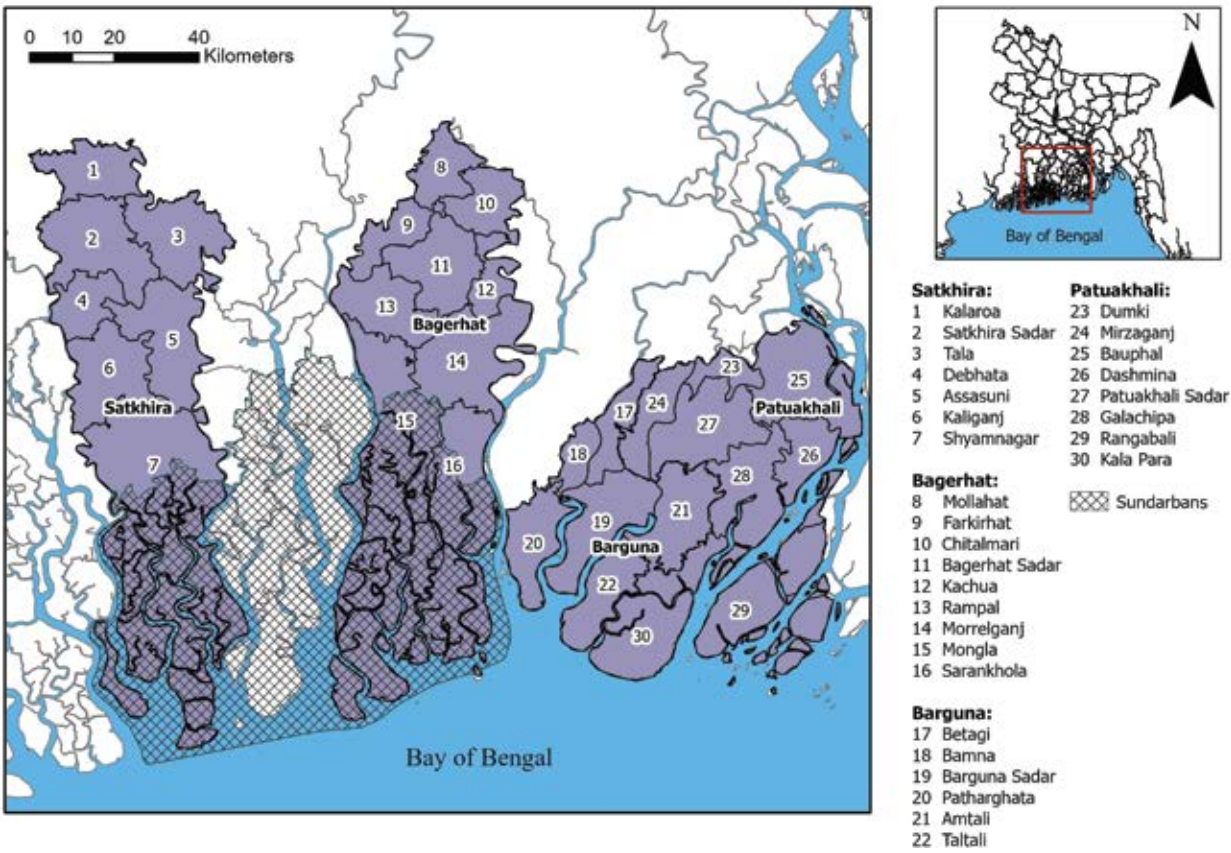


Fig. 3. The map depicts the geographical distribution of the selected study areas across Satkhira, Bagerhat, Barguna, and Patuakhali Districts in Bangladesh. The numbers represent the selected upazilas of the selected districts.

3.3 Data Synthesis

For creating a localized impact scenario, the study needed to collect data at granular level. Fine-resolution local data enables building a detailed vulnerability profile and improves the precision of the impact forecasts. This granular local data collection was conducted from local secondary sources with the help of STEP project members across the selected locations. Various local government offices and resources were consulted to gather the necessary information. Key data sources of these various secondary data included:



Local administrative offices: Union Parishad (council) offices, Upazila offices (such as Statistics, Agriculture, Fisheries, Livestock, Health, Project Implementation, ICT, Social Services), and the District Water Development Board. These offices provided data on local demographics, livelihoods, infrastructure, health facilities, and other local parameters relevant to vulnerability and coping capacity which is generally not available at national scale or not regularly updated on national database.



National surveys and census data: The Bangladesh Household Income and Expenditure Survey (HIES) 2016, and the Population and Housing Censuses (2011 Community Report for Bagerhat, and 2022 National Report). These provided standardized statistics on population, housing, and economic indicators at local levels where available.

Using these sources, a rich robust dataset of vulnerability indicators (e.g., poverty rates, number of households by structure type, literacy rates, access to services) and exposure indicators (e.g., population counts, infrastructure in hazard-prone areas) has been compiled for each upazila and even down to union level where possible.

This data collection effort was intensive but crucial: the quality and resolution of the input data directly affect the accuracy of the impact forecasting outputs. By combining institutional data and survey results, we ensured that the toolkit's analysis reflects on-the-ground realities in the project areas, rather than relying solely on broader indexes or assumptions. All collected data went through a cleaning and validation process (removing inconsistencies, filling gaps where feasible) to be ready for use in the modeling steps described in the next chapter.





Chapter

4



Chapter 4: Cyclone Impact Forecasting: A Step-by-Step Guide

This chapter outlines the step-by-step methodology used in the toolkit to forecast cyclone impacts. The process involves assessing vulnerability, using the hazard forecast, evaluating exposure, and finally computing the impact.

4.1 Addressing Vulnerability

As a first step, it was essential to identify the variables that make communities vulnerable during a cyclonic event. The framework for this cyclone impact toolkit was adapted from multiple peer-reviewed sources and best-practice frameworks. For instance, it drew certain elements from the INFORM subnational risk index for Bangladesh and from other frameworks associated with IbF and IF, and combined them to create a new method tailored to cyclone-specific vulnerability assessment

In this toolkit, a range of vulnerability indicators that significantly affect a community's capacity to cope during a cyclone (the full list is provided in Annex Table 1) were included. These indicators span various dimensions of vulnerability – such as poverty levels, housing strength, livelihood dependency on climate-sensitive sectors, population demographics

(children, elderly, disabled), infrastructure availability (like shelters, clean water, healthcare), and so on. The dataset also included indicators of “lack of coping capacity,” which often overlap with vulnerability (for example, low literacy or lack of access to communication can hinder effective response).

Once collected, the data for all vulnerability indicators were normalized to a common scale and then assigned weights through expert consultations. Normalization (detailed in the Annex under “Data Normalization”) converts indicators measured in different units (percentages, counts, indices) into unitless scores, typically ranging from 0 to 1 or 0 to 5, so that they can be compared and combined. Weight assignment was done via a multi-criteria analysis with input from experts, attributing a relative importance to each indicator. In this method,

weights ranged from 1 (least important or least vulnerable if that indicator is favorable) to 5 (most important or most vulnerable). For example, “poor households” might receive a high weightage if poverty is considered a critical factor in vulnerability, whereas “literacy rate” might receive a moderate weightage. The weights reflect the expert judgment (and assumptions) about which factors would most worsen cyclone impacts in the local context.

After normalization and assigning weightage, the next involved computing a composite vulnerability score for each area. This was done by multiplying each indicator’s normalized value by its weight and summing these products (the formula and steps are provided in Annex “Computing Vulnerability Score”). The result is a single numerical vulnerability score for each upazila/union. Afterwards, the scores were categorized into a Vulnerability Index with qualitative levels (for ease of interpretation). Specifically, the range of scores were divided into categories of Very Low, Low, Moderate, High, and Very High vulnerability. Using GIS software (ArcGIS Pro), the vulnerability maps were generated by coloring each area according to its category. These maps visually highlight which

locations are relatively more vulnerable to cyclone impacts (The steps involved in the process are summarized in Figure 4).

The vulnerability assessment – comprising the calculation of scores and the mapping – serves as the initial step in understanding where impacts could be worst. Highly vulnerable areas, especially if also highly exposed to the hazard, are likely to suffer greater impacts. This information is crucial on its own (for example, disaster managers might decide to strengthen preparedness in areas shown as highly vulnerable). Moreover, this vulnerability layer is a key input for later steps, where it will be combined with hazard and exposure data to compute impact forecasts.

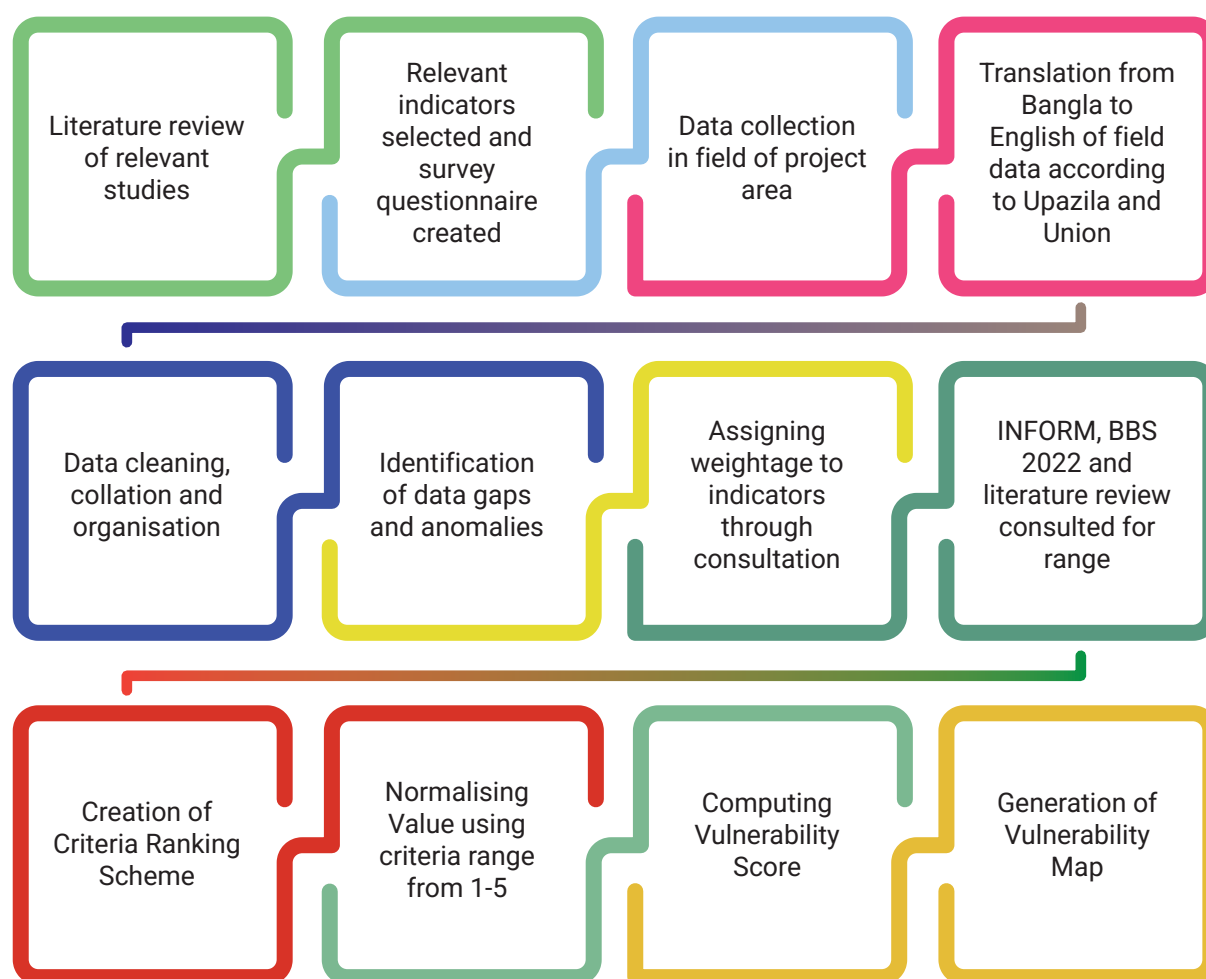


Fig. 4. Methodology of Vulnerability Assessment

4.2 Forecasted Hazard

This method's second component is the hazard forecast, i.e. the predicted intensity of the cyclone. In the context of cyclones, the hazard has multiple facets – primarily wind, rainfall, and storm surge. The forecasted hazard values refer to the expected magnitudes of these elements during the event, and they can vary significantly by location (for example, the south-east quadrant of a cyclone might bring heavier rain to one district while another district gets stronger winds). For this toolkit, forecast products from major modeling sources: the European Centre for Medium-Range Weather Forecasts (ECMWF) for wind and rain predictions, the Indian National Centre for Ocean Information Services (INCOIS) and BMD operated JMA's MRI model for storm surge modeling were used as regional inputs.

As mentioned earlier, forecast parameters can differ by location and by the specifics of each cyclone. Assigning weights to different hazard parameters (wind, rain, surge) is done on a per-cyclone basis, guided by expert knowledge of what the dominant threats are for that storm. For example, one cyclone might be particularly wet (huge rainfall but moderate winds), while another is a wind-heavy cyclone with less rain. Factors like the cyclone’s track, its landfall timing (high tide vs low tide), the season, and the local geography all influence which hazard component will have the greatest impact. Therefore, our toolkit does not use a fixed rule for weighting wind vs. rain vs. surge; instead, it allows forecasters to adjust weights based on their expert judgment for the scenario at hand.

To illustrate, in the case of Cyclone “Remal” (the case study in this toolkit¹), forecasters determined that wind and rainfall posed roughly equal threat levels, while storm surge, though significant, was slightly less of a threat compared to the other two. Accordingly, they assigned weights to the hazard components as follows: wind gust = 0.35, rainfall = 0.35, storm surge = 0.30. The Toolkit first normalized each parameter’s forecast values (ensuring, for example, that we consider relative wind speeds on a 0–1 scale, etc.), then applied these weights. The result was a single combined hazard score for each location – effectively an index representing the forecasted hazard severity for that area.



Forecast Hazard = (W1× Wind gust + W2 × Rainfall + W3 × Storm surge)

Where,

W1 is the weight for wind gust

W2 is the weight for rainfall

W3 is the weight for storm surge (refer to case study for details)

This weighted sum gave a forecast hazard score for each area, which was later used in the impact computation. In essence, these steps help condense multiple hazard dimensions into one measure,

¹ The details of this case study have been discussed later in this document

reflecting the expected overall hazard intensity. An area with extremely high wind and rain (even if storm surge is low) might get a very high hazard score, and vice versa.

By considering all relevant hazard aspects, it lowers the chance of overlooking a potential threat. For instance, a community behind a strong embankment might be safe from storm surge but still at risk from wind damage – the combined hazard score will still account for wind in that case. This approach also mirrors how forecasters think in practice, weighing different facets of a storm's behavior. It is an example of the toolkit's flexibility to accommodate expert input and adjust to the unique characteristics of each cyclone.

4.3 Exposure

The third component in impact forecasting is exposure, identifying who and what is in harm's way during the cyclone, and to what degree. It is essential to extract the relevant exposure indicators for the time and area of the disaster because even a severe hazard causes no impact if nothing is exposed to it. Exposure indicators can include any individuals, communities, infrastructure, or economic assets that could be affected by the cyclone. These indicators may be non-sector-specific (general exposure of the area) or sector-specific (focused on a particular sector like agriculture, health, etc.). A two-pronged approach to exposure was conducted for this toolkit: a general exposure analysis and a sector-specific analysis (focusing on agriculture).

General Exposure (Quasi-Static Data): Broad indicators that were available for all locations were inputted. Specifically, population data and road density were considered for overall exposure indicators. Here data were partly obtained from the INFORM subnational risk dataset for Bangladesh and other national sources. Population gives a sense of how many people are exposed, while road density serves as a proxy for how much infrastructure (and connectivity) is present and potentially at risk. Due to difficulties in obtaining very detailed local exposure data for every sector, the analysis limited the exposure assessment to these two indicators for the generic impact maps that are not sector-specific. In practice, population and infrastructure distribution can highlight areas that would face greater disruption or evacuation needs.

Sector-Specific Exposure (Agriculture): To enhance the analysis, the toolkit developed an exposure integration framework for the agricultural sector, recognizing that agriculture is a vital part of livelihoods in the coastal regions and highly vulnerable to cyclone

impacts. Here, in addition to road density (which is also relevant for agriculture, for transporting goods, accessing markets, etc.), vegetation health indicators as proxies for agricultural assets were included. In particular, it used two remote-sensing based indices: Fraction of Absorbed Photosynthetically Active Radiation (fAPAR) and Vegetation Condition Index (VCI). These indicators reflect crop and vegetation status, which in turn indicate the exposure of the agricultural sector – lush, extensive croplands mean a lot is at stake if a cyclone hits during the growing season. Both VCI and fAPAR data were sourced from the European Copernicus Sentinel-2 satellite imagery.

After computing the VCI and fAPAR, the data were exported to a CSV file and visualized in GEE for incorporation into the analysis and record-keeping. Using this satellite-based approach, the areas with the highest agricultural exposure before the cyclone were effectively mapped. If a specific upazila had a significantly high proportion of healthy crops (high VCI/fAPAR), it indicated that the cyclone could cause substantial crop damage in that area, categorizing the upazila as highly exposed in agricultural terms.

Finally, similar to the hazard components, a composite exposure score was created for each area. The exposure indicators were combined using appropriate weights: for the general overall exposure, Population and Road Density were weighted equally at 0.5 each; for agriculture-specific exposure, the weights applied were 0.35 for VCI, 0.30 for fAPAR, and 0.35 for Road Density. These weights were determined based on expert judgment, which suggested that road infrastructure and vegetation indicators are of roughly equal importance in capturing the agricultural impact scenario. The general formula for composite exposure follows the same structure as that for hazard.



Exposure = (W1 × Exposure 1 + W2 × Exposure 2 + Wn × Exposure n)

Where,

W1 is the weight for the 1st Exposed indicator

W2 is the weight for the 2nd Exposed indicator

Wn is the weight for nth Exposed indicator (refer to case study for details)

4.4 Impact Computation

With the vulnerability score, forecasted hazard value, and exposure value available for each area, the impact score can now be computed. Conceptually, as previously mentioned, impact is a function of all three components. In this toolkit, an approach was implemented where the impact score is proportional to the product of hazard, exposure, and vulnerability data. For each upazila/union:

- The normalized hazard score (from step 4.2) for that location was inputted.
- The composite exposure score (from step 4.3) for that location was inputted.
- The vulnerability score (from step 4.1) for that location was inputted.

$$I_m = V_s \left(\sum_{i=1}^3 H_i W_{\{ni\}} \right) \left(\sum_{j=1}^3 E_j W_{\{nj\}} \right)$$

Here, I_m is Impact Score of a selected area
 V_s is Vulnerability Score for a selected site
 H_i are the selected hazard forecast indicator values of a selected area
 E_i are the selected Exposure indicator values of a selected area
 W_{ni} = Weightage of respective hazard indicator
 W_{nj} = Weightage of respective exposure indicator

After computing a raw impact score for each area, normalization and categorization were performed similarly to the process used for vulnerability. The raw impact scores (which might be, say, on a 0 to X scale) were normalized to a 0–1 range and then divided into three distinct classes for easier communication: Low impact, Moderate impact, and High impact. In the classification scheme, Low Impact, Moderate Impact, and High Impact. In the classification scheme, scores above 0.7 were categorized as High Impact, scores between 0.3 and 0.7 as Moderate Impact, and scores below or equal to 0.3 as Low Impact. These thresholds were set based on the distribution of scores and aligned with known outcomes, though they can be adjusted for different contexts.

The categories were then mapped in ArcGIS Pro, using a traffic-light color scheme for clarity: red for High Impact areas (most severe expected impacts), orange for Moderate Impact, and green for Low Impact. This visual representation makes it easy for stakeholders to see at a glance which locations should be prioritized for emergency preparedness and response.

It is worth noting that while this toolkit used three categories here for simplicity, the underlying impact scores are continuous. Other studies can use a finer scale or different breakpoints if desired. Also, calibration and validation of these impact

scores against real outcomes are crucial (and are addressed in the case study and subsequent sections) to ensure that, for instance, “High impact (red)” truly corresponds to areas where major damage is likely.

The outcome of this process is an Impact Forecast Map, which serves as the primary output for stakeholders. In Chapter 5 (the case study), an example of such a map for Cyclone “Remal” is presented, along with guidance on how to interpret and act upon the map’s information.

INSTANT Portal

 Bangladesh

As the frequency of natural hazards increases, the need for accurate, timely, and relevant weather forecasts becomes ever more critical. While many meteorological agencies worldwide are refining their Numerical Weather Prediction (NWP) capabilities, forecasts often remain disconnected from the socio-economic data needed to produce robust Impact-based Forecasts (IbF) or Impact Forecasts (IF). A major challenge lies in accessing and combining these socio-economic indicators, typically collected by agencies outside of National Hydrometeorological Services (NHMSs), within a Decision Support System (DSS) that can integrate them seamlessly with weather forecast data and disseminate near-real-time impact forecasts to stakeholders.

To address this gap, the Regional Integrated Multi-Hazard Early Warning System (RIMES) developed the Integrated Forecast Dissemination Portal (INSTANT), available at instant.rimes.int. This semi-automated DSS provides five-day lead-time forecasts for key meteorological parameters—rainfall, temperature, wind speed, and humidity—along with real-time alerts for extreme weather events. By incorporating Impact Forecasting into the platform, INSTANT delivers timely, data-driven insights that enhance operational efficiency across sectors such as agriculture, transportation, and public safety. Drawing on data from the Bangladesh Meteorological Department and other reputable sources, INSTANT consolidates current and historical information to bolster resilience efforts.

Further enriching its functionality, INSTANT’s Special Bulletin section offers comprehensive reports on severe weather conditions, aiding humanitarian responses. Developed collaboratively by RIMES and various meteorological organizations, these bulletins provide critical, actionable information to reduce disaster-related losses and streamline decision-making.





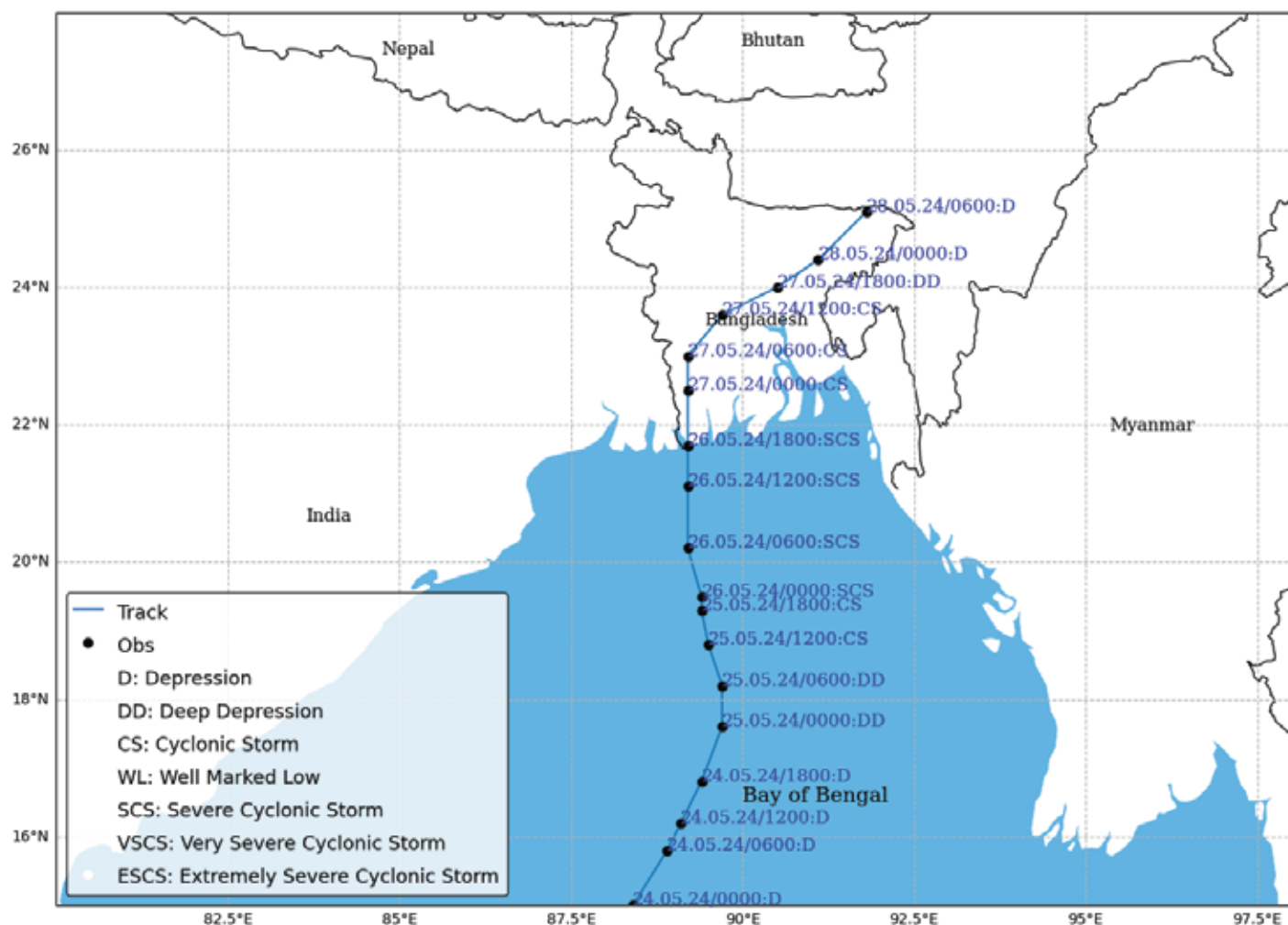
Case Study: Impact Computation of Cyclone “Remal”





Background

According to BMD, on May 21, 2024, an upper air cyclonic circulation developed in the southwest over the Bay of Bengal (BoB). By May 22, a low-pressure system (L) had formed over the southwest and westcentral area of the BoB. The conditions worsened, on May 24, it consolidated into a depression (D) over the central Bay of Bengal. On May 25, there was movement northwards, and the conditions intensified, developing into a deep depression (DD). The development continued and it escalated into a cyclonic storm known as "REMAL" around the north and adjoining east central area. During May 26, the



storm intensified into a severe cyclonic storm (SCS) and, with wind gusts of up to 135 kmph, moved across the shores of West Bengal and Bangladesh between Sagar Islands and Khepupara, close to Mongla, during the night of May 26. It turned into a cyclonic storm (CS) after weakening. The track for the cyclone, “Remal” has been depicted in Figure 5.

According to BMD, the cyclone struck the Sundarban Delta of West Bengal and Bangladesh on Sunday, May 26, as a powerful cyclonic storm. At the time of landfall, the storm's sustained winds ranged from 100 to 135 kilometers per hour in the coastal region. Remal resulted in the deaths of at least 84 individuals, with 65 casualties reported in

India and 19 in Bangladesh. The storm surge, along with wind speeds of up to 111 km/h and severe rainfall, caused 5-8 feet of flooding in coastal areas of Bangladesh. By June 2, the cyclone and ensuing flooding had caused widespread destruction in 19 districts, affecting nearly 4.6 million people (UNICEF, 2024; IFRC, 2024). By May 29, the cyclone had damaged embankments in a number of coastal communities, flooding roads and villages and disrupting access to the affected areas. On May 28, high winds damaged power lines, leaving over 3 million people without electricity in the impacted districts (ACAPS, 2024). Power outages caused by damaged roadways and electrical infrastructure, as well as delays in mobile and internet connections, hampered humanitarian workers' mobility and response efforts in the impacted districts (IFRC, 2024).

Fig. 5. Observed track of cyclone “REMAL” over the Bay of Bengal during 24.05.2024 to 28.05.2024.

Forecast Scenario during Landfall

In this case study, ECMWF forecast data was used to analyze the scenario at the time of Cyclone Remal's landfall, specifically looking at accumulated rainfall and peak wind gusts in the project area. Figure 6 shows the ECMWF forecast for total rainfall during Remal's passage, and Figure 7 shows the forecasted maximum wind gusts. These forecast maps help illustrate which areas were expected to get the worst of Remal's rain and wind.



Rainfall: According to the forecasts categories, virtually all upazilas in the study area were expected to receive heavy to very heavy rain during Remal's landfall. In BMD's meteorological terms, "Heavy" rain generally means 44–88 mm in 24 hours, and "Very Heavy" is >88 mm in 24 hours. The forecast indicated that the entirety of Satkhira District, all of Bagerhat District (except Chitalmari Upazila), all of Barguna, and parts of Patuakhali District would experience Very Heavy Rain (>88 mm) over the period of Remal's passing. Indeed, those areas were in the higher rainfall band (the southwest part of the storm). Chitalmari Upazila in Bagerhat, along with some northeastern upazilas of Patuakhali, were exposed to slightly lower rainfall but still within 44–88 mm range.



Wind: The forecast pinpointed Mongla Upazila (in Bagerhat District, near the coast and the Sundarbans) as facing the most extreme winds. Mongla was expected to see wind gusts exceeding 150 km/h, which makes sense as the cyclone's core passed very near Mongla. Following Mongla, other upazilas with severe wind exposure included Sarankhola (Bagerhat), Kaliganj and Shyamnagar (both in Satkhira) – each forecasted to receive gusts in the 120–150 km/h range. These upazilas are along or near the coast and were in the right-front quadrant of the cyclone where winds are strongest.

These forecast insights fed into our impact model: for example, Mongla's extremely high hazard values (for both wind and rain) combined with its vulnerability would likely yield a high impact score there, as the subsequent analysis will show.

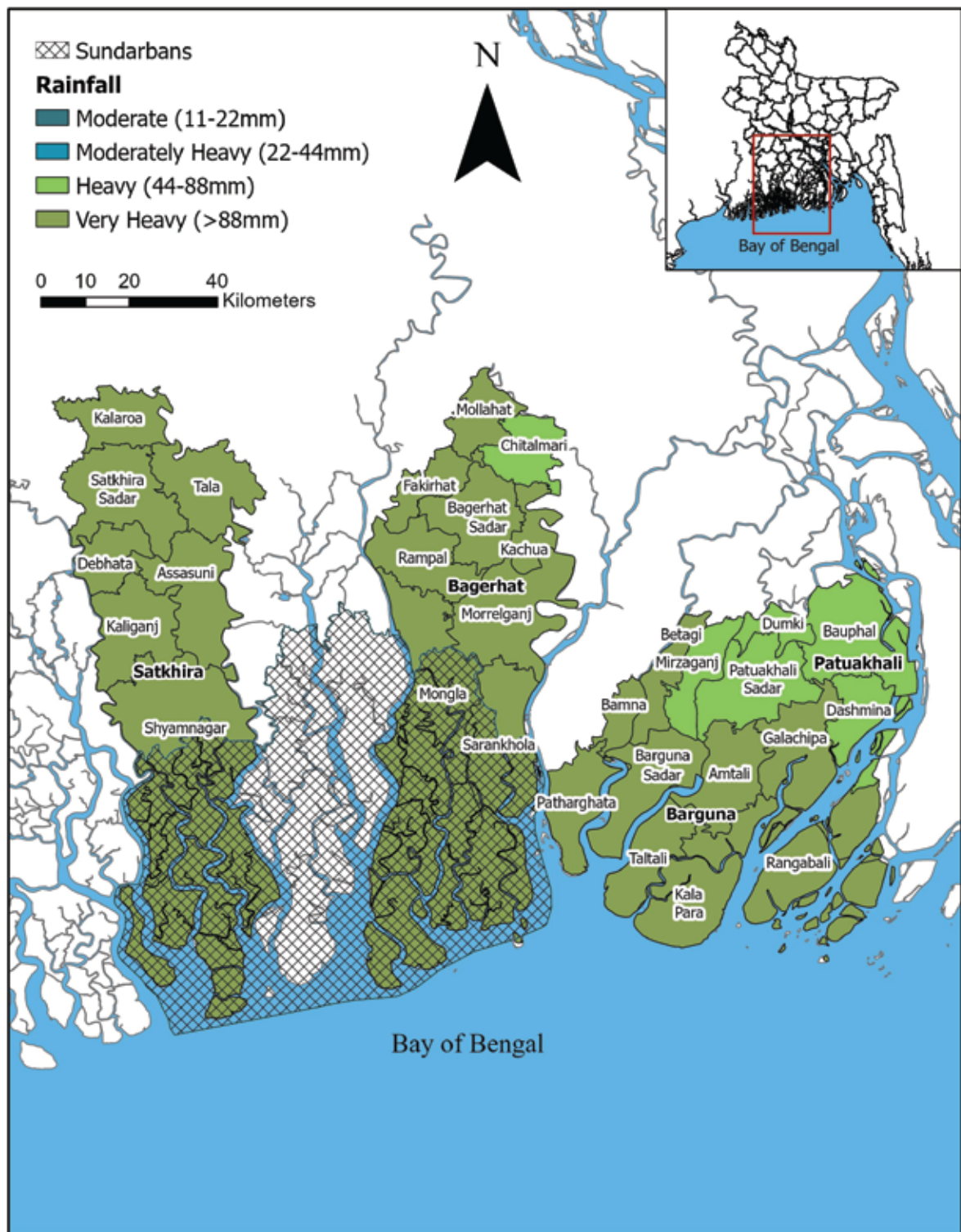


Fig. 6. ECMWF Daily Accumulated Rainfall Forecast during the passage of Cyclone “Remal” based on 00 UTC 26.05.2024 valid for 00 UTC 27.05.2024.

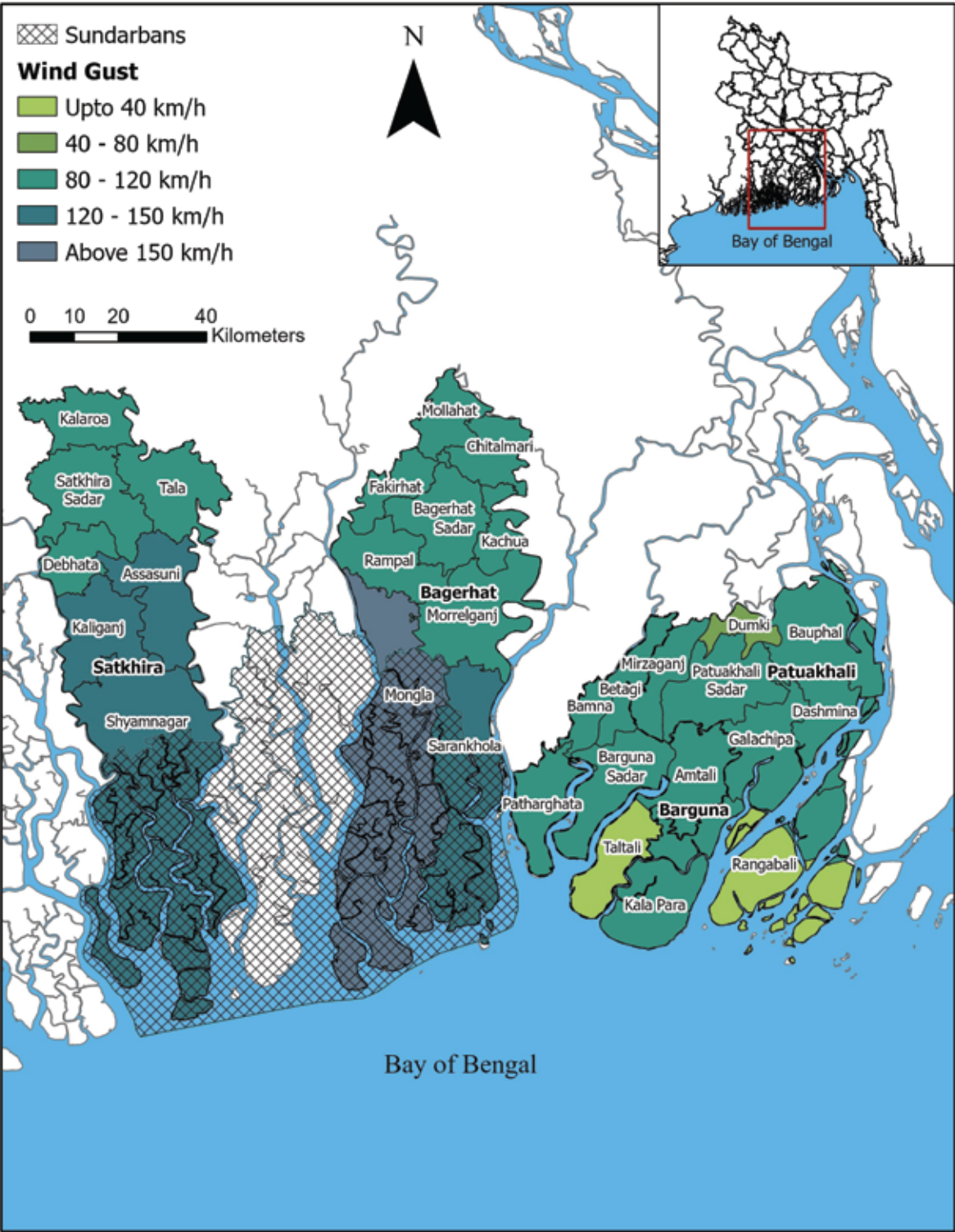


Fig. 7. ECMWF Wind Gust Forecast during the passage of Cyclone “Remal” based on 26.05.2024 valid for 26.05.2024.

Impact Scenario of the Case Study Area

Using the methodology from Chapter 4, impact scores for the upazilas in the STEP project area (within Satkhira, Bagerhat, Barguna, and Patuakhali) were computed. These scores were then classified into Low, Moderate, and High impact categories and outputted as a map. Figure 8 shows the overall generic impact map (overall impact), and Figure 9 shows the agriculture sector-specific impact map, both for the case study area during Cyclone Remal's passage.

On the overall impact map (Figure 8), areas categorized as High Impact (red), Moderate Impact (orange), and Low Impact (green) can be seen across the region. To produce this map, the analysis utilized the composite hazard (from wind + rain + surge) and general exposure (population + roads) together with the vulnerability score. As described earlier, for each upazila the impact score was calculated and then grouped into the three levels.

For creating a sector-specific impact map (Figure 9) focusing on agriculture, we incorporated additional exposure indicators relevant to the sector – namely fAPAR and VCI – alongside road density. These were standardized and weighted at 0.35, 0.35, and 0.3 respectively (summing to 1) in conjunction with the same vulnerability scores, to compute a separate impact score highlighting agricultural impact potential. Essentially, Figure 8 represents the “overall impact on any sector/assets,” while Figure 9 zeros in on agricultural impacts.

Identifying potentially high-impact areas is extremely useful for planning anticipatory actions, particularly when resources are limited and need prioritization. While we cannot stop a cyclone from forming, early warning and impact forecasting mechanisms allow us to reduce the impact on communities by acting beforehand. The impact maps give a data-driven basis for such action.

From Figure 8 (Overall Impact), it can be observed that certain upazilas were forecasted to be especially hard-hit by Cyclone Remal's combined effects. For example, Shyamnagar (Satkhira), Satkhira Sadar, Morrelganj (Bagerhat), and Amtali (Barguna) were highlighted in red as High Impact areas. These locations likely had the unfortunate mix of high hazard exposure (as seen in the forecast scenario) and high vulnerability (as per our data), leading to high impact scores. Shyamnagar and Satkhira Sadar in Satkhira District are both densely populated and low-lying, and they

experienced very strong winds and heavy rain; Morrelganj had very high vulnerability index (as we will see) plus significant hazard exposure; Amtali in Barguna faced the open coast. Thus, our model rightly flags them.

This overall impact information is useful as a general guide. However, impacts can vary by sector. For instance, an upazila might be severely impacted in terms of agriculture but not in terms of infrastructure, or vice versa. To address this, Figure 9 (Agriculture-specific Impact) was generated, which offers a more in-depth sectoral analysis. In Figure 9, the analysis essentially focused on answering the question, which areas will suffer the most in terms of crop/agricultural damage?

Comparing the two maps (overall vs agriculture focus) reveals:

- For Barguna and Patuakhali Districts, both maps show a similar impact level (both districts were largely orange, Moderate impact, with some red). This suggests that in those districts, the overall impact and agricultural impact were in line (likely because agriculture is a major exposure in those areas and was accounted for in the overall too).
- For Satkhira and Bagerhat Districts, differences emerge. For example, the agricultural impact map shows that Bagerhat has more high-impact areas relative to Satkhira. In contrast, the overall impact map shows Satkhira as equally or more impacted in general. In fact, our analysis found that Mongla Upazila (in Bagerhat), which was labeled as low impact on the general map, is identified as moderately impacted on the agriculture-specific map. The key reason behind this difference is because Mongla has the Sundarbans Forest (less human exposure) but significant vegetation; also, perhaps fewer people but still significant crop areas. Thus, while overall impacts on communities in Mongla might be lower (few people in the Sundarbans core and good sheltering by forests), the agricultural impact – in terms of ecosystem or any local agriculture – was not as low. Conversely, some areas that were high impact overall might not be as critical agriculturally if they are urban centers or have less cropland.
- The agriculture-specific map indicates that Bagerhat District's agricultural sector could be generally more affected than Satkhira's, which is interesting because the overall impact map might have suggested Satkhira was harder hit (perhaps due to more populated

areas). This could be because Bagerhat, especially in upazilas like Morrelganj and Rampal, has extensive agricultural land (rice paddies, shrimp farms, etc.) that were exposed, whereas Satkhira's worst impacts may have been flooding in populated areas rather than agricultural loss.

In summary, Figure 8 (overall impact) might guide general disaster response (where to send relief first, which areas to evacuate, etc.), while Figure 9 (sector-specific) can guide which sectors need particular support in which areas (for instance, where to focus interventions for farmers, such as distribution of emergency animal feed or seeds for replanting). Both perspectives are valuable and, as shown, they are complementary. Combining them, one sees that, for example, Morrelganj was highly impacted in both scenarios, meaning it is a clear hotspot for all kinds of damage (people and agriculture). Sarankhola might have experienced moderate overall impact, but its agricultural impact was high. This suggests that while human impact might have been relatively lower, significant crop losses occurred, indicating a need for agricultural recovery aid.

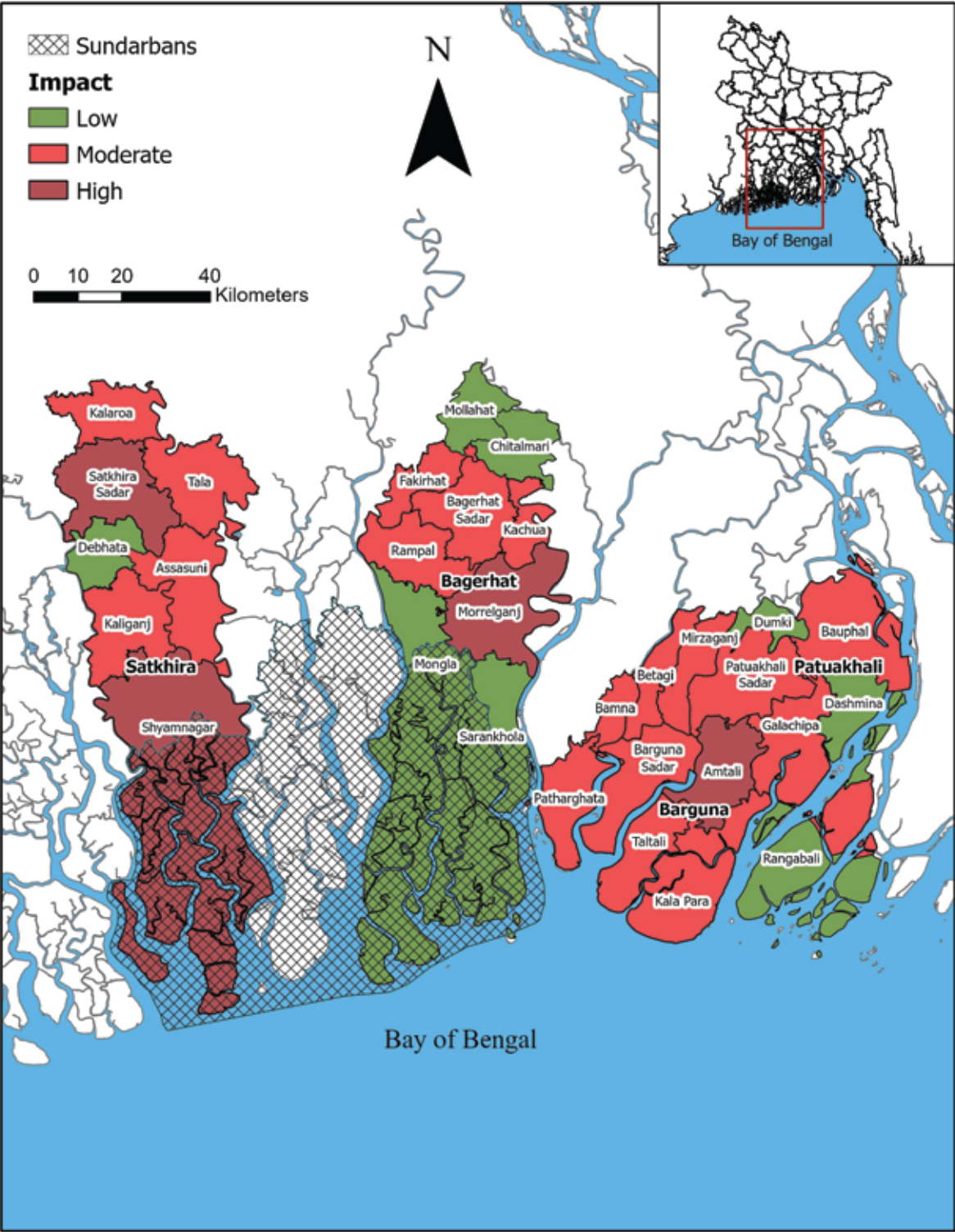


Fig. 8. Overall Impact Scenario of selected case study areas during the passage of cyclone, “Remal” based on 26.05.2024 considering ECMWF forecasted Wind Gust, Storm Surge, and Rainfall; Vulnerability and Exposure (Combined Road Density and Population) across Satkhira, Bagerhat, Barguna, and Patuakhali Districts.

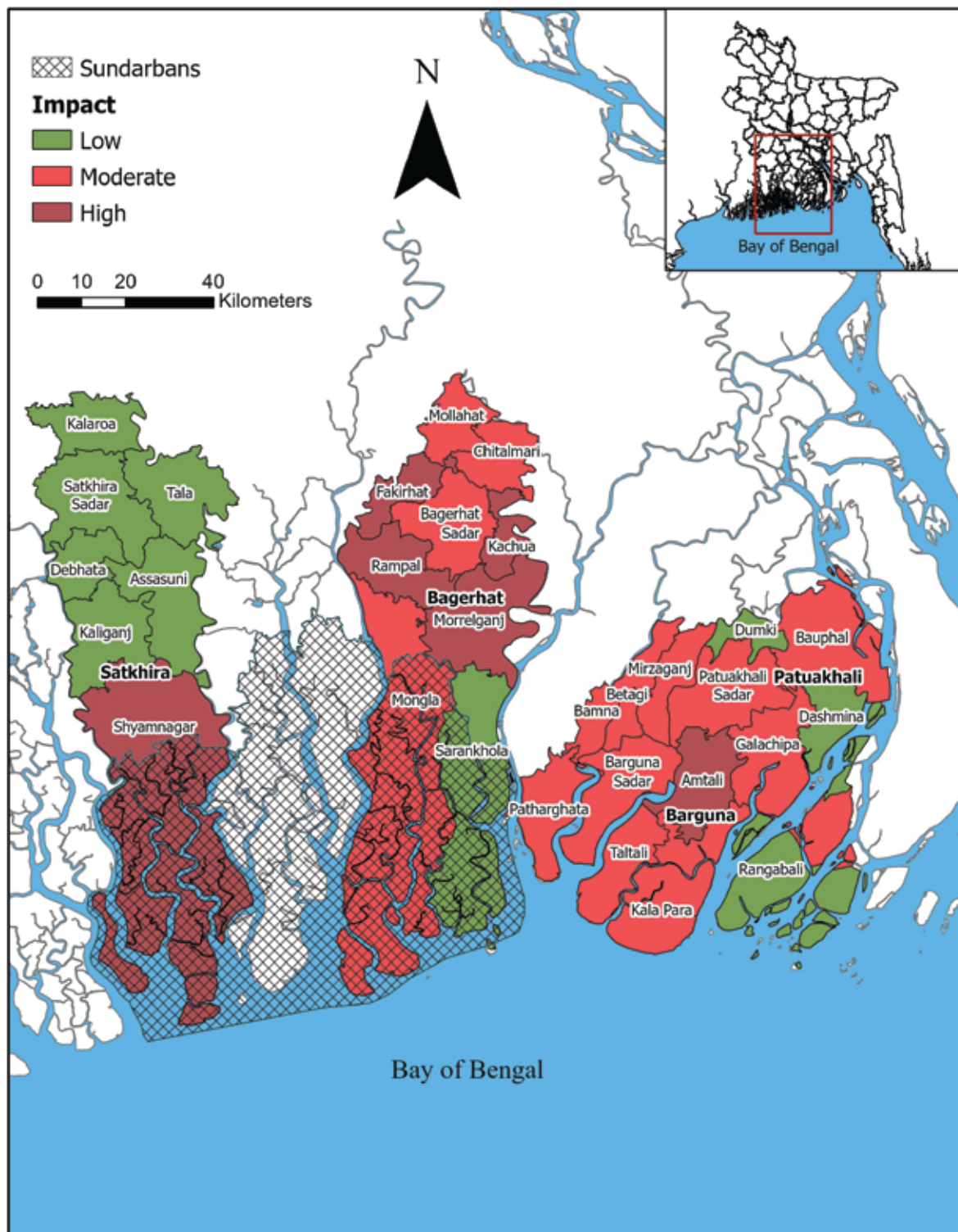


Fig. 9. Impact Scenario of selected case study areas during the passage of cyclone, “Remal” for the Agriculture sector based on 26.05.2024 considering ECMWF forecasted Wind Gust, Storm Surge, and Rainfall; Vulnerability and Exposure (Combined Road Density, VCI, and fAPAR) across Satkhira, Bagerhat, Barguna, and Patuakhali Districts.

Impact Interpretation

The results of the impact assessment are categorized into low, moderate, and high impact zones. It is important to interpret these categories correctly. The categorization simplifies a complex reality, and while it is very useful for communication and decision-making, one must remember that it's relative and based on our standardized scoring. It is challenging to capture every nuance of a dynamic disaster scenario in a simple numeric scale, but the categories aim to describe the most likely impact severity in a comparative sense.

An area categorized as “Low Impact” does not mean it is completely safe or that it will experience zero damage. It means that, relative to other areas, its overall impact is expected to be low. There might still be some damage or losses, but at a lower level. Perhaps only a few homes are damaged or only minor flooding occurs, etc. Some particularly vulnerable individuals in a “low impact” area could still suffer (for example, an isolated vulnerable household), even if on average the community fared well. Thus, low impact is a comparative term, not an absolute guarantee of safety.

Similarly, “Moderate Impact” indicates a level of impact higher than low-impact areas but lower than the worst-hit areas. Such a scenario might expect notable damage: more houses destroyed (though not as extensively as in high impact zones), services might be disrupted to some extent (maybe power outages for a day, some roads impassable), and financial losses are moderate in scale. It's a mid-range scenario – significant, but not catastrophic if proper response measures are in place.

“High Impact” areas are those likely to experience the most severe consequences. One can expect extensive damage to homes (including many houses severely damaged or destroyed), major disruptions to civil services (power, water, communications could be knocked out for a long period), significant economic losses, and possibly long-term recovery needs. Essentially, these are the communities that might be devastated and would require the most external aid and time to recover.

To formalize these interpretations based on the findings, the categories can be simplified as follows:



Low Impact

Minor damage and disruptions. There may be a few damaged houses (generally of lesser construction quality), little to no interruption of public services (e.g., roads mostly passable, power largely on), and relatively low economic losses. The community can cope mostly with local resources.



Medium Impact

Noticeable damage and disruptions. A number of houses suffer damage (more than in low impact areas, but not a majority as in high impact), public services experience moderate interruptions (power outages and road blockages that are resolved in days), and moderate financial loss occurs. External assistance might be needed, but the situation is manageable.



High Impact

Severe damage and major disruptions. Many homes are heavily damaged or destroyed. Critical infrastructure is compromised (long-term power loss, water supply contaminated, key roads/bridges down). There are significant losses of assets (livestock killed, crops destroyed, etc.), and possibly casualties. Recovery will require substantial support and time.

These interpretations align with how the toolkit categorized the numerical scores. For instance, recall previously how >0.7 was set as high impact. In our case study, that might correspond to something like: those areas had, say, $>70\%$ of assets at risk or similar, hence widespread losses. A low impact score (≤ 0.3) would correspond to scenarios where perhaps $\leq 30\%$ of assets might be affected. Again, these are relative cutoffs. Understanding these categories is crucial for action. Disaster managers looking at the map should know red zones (high) need urgent help and possibly full-scale emergency response; orange zones (moderate) need response too but perhaps not as much or they have more capacity to help themselves; green zones (low) should be monitored but can largely handle the situation with minimal assistance, barring any outliers.

Validation of the Impact Scenario at Different Level

Before developing the highly localized approach in this toolkit, RIMES initially produced cyclone impact scenarios at the district level (the administrative level above upazilas). In that approach, each of Bangladesh's 64 districts received an impact score using broader data (Figure 10). We carried that forward here for validation purposes. The district-level impact calculations used district-aggregated indicators: vulnerability and coping capacity data from INFORM, along with hazard inputs (rainfall, wind) from ECMWF and storm surge from BMD for Cyclone Remal. The methodology was essentially the same as described but applied at a coarser spatial resolution (districts instead of upazilas/unions).

The result was a normalized impact score for all districts on a 0 to 1 scale, where 0 would mean no impact and 1 the highest impact observed. These scores revealed a clear pattern: districts along or near the Bay of Bengal showed the greatest impact during Cyclone Remal, while inland districts had much lower scores (as expected, since the cyclone dissipated quickly after landfall). Notably, Bagerhat District emerged with one of the highest impact scores (essentially 1.0, as we normalized the maximum to 1), indicating it was the hardest hit in our model – which aligns with the fact that Remal's core passed through Bagerhat (Mongla, Sarankhola) and that Bagerhat has significant vulnerabilities (many low-lying areas, etc.).

To validate these district-level impact scores, we compared them with actual damage and loss data reported by the Department of Disaster Management (DDM) for the event. Specifically, we looked at metrics like the monetary value of losses and the number of houses damaged in each district, which were compiled in the aftermath (for example, DDM might report X million USD of damage in District A, Y houses destroyed, etc.). It was then checked whether higher impact score districts indeed had higher reported losses.

The analysis showed a strong positive correlation between our forecasted impact scores and the actual damage outcomes (Figure 11). For instance:

Bhola District had a normalized impact score of 0.37 according to the model. Data from the Disaster Management Division (DDM) indicated that Bhola incurred approximately USD 79 million in damage. When this loss figure is normalized relative to other districts, it also equates to around 0.37. This one-to-one alignment in Bhola’s case suggests our impact score (which predicted a moderate impact) was spot on in terms of real consequences.



Bagerhat District, which had the maximum impact score of 1.0 (the worst case), recorded the highest levels of destruction. For example, around 63,924 houses were damaged in Bagerhat the largest number among the affected districts. When normalized (taking Bagerhat’s count as 1.0), this matches the impact score ranking. In other words, Bagerhat being at the top in both forecast and reality further supports the reliability of the model.



Overall, statistically, the methodology found a significant positive correlation: as the forecasted impact score for a district increased, so did the actual losses report. This gives confidence that the methodology is capturing the key factors that determine the Cyclone’s severity. It also suggests that if used operationally, the impact forecasts could serve as a reasonable proxy for where damages will be high, even before reports come in crucial for directing emergency resources immediately.

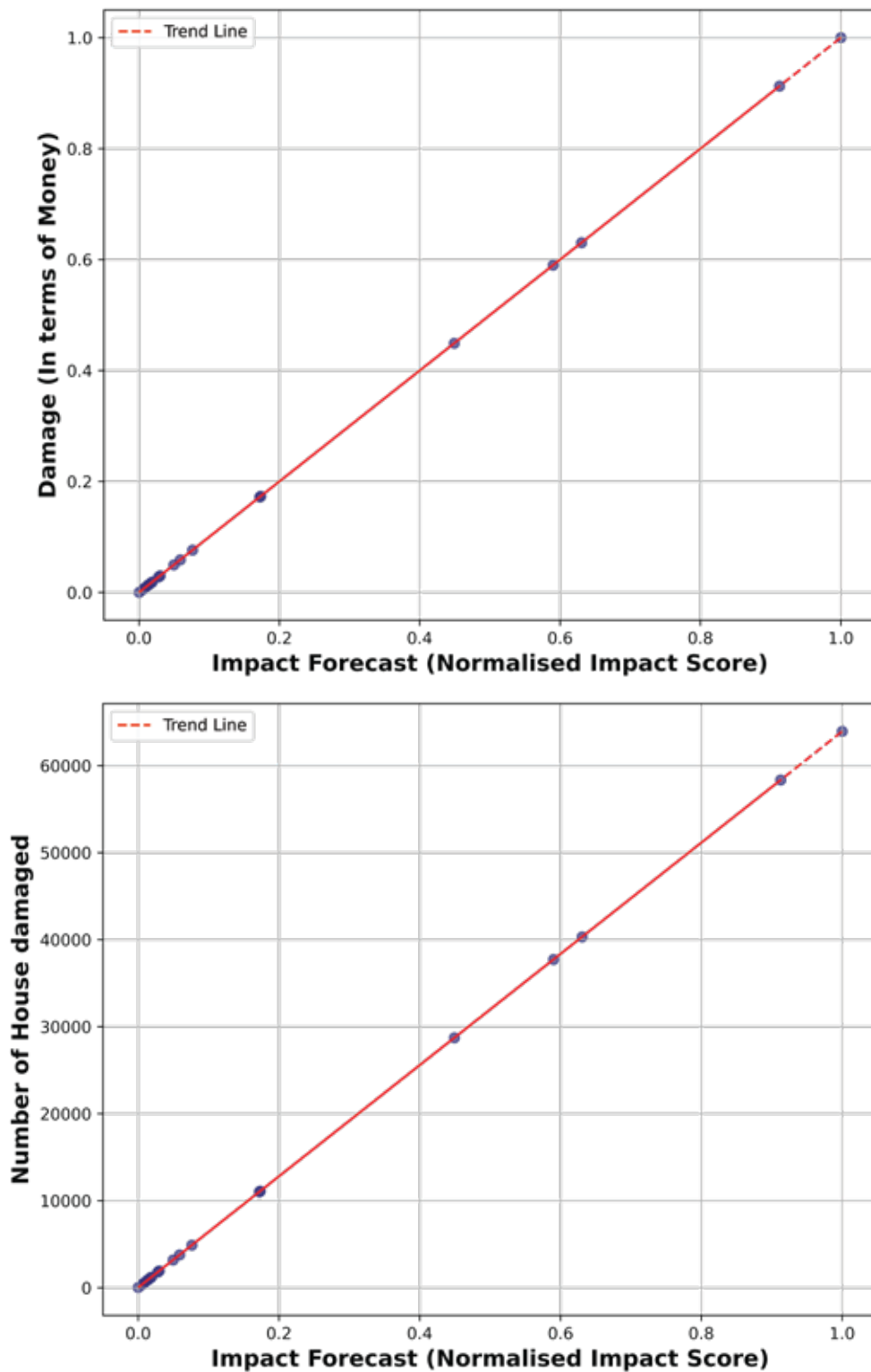


Fig. 11. Top: Relationship between Impact Forecast and Monetary damage, Bottom: Relationship between Impact Forecast and Number of Houses damaged (Source: DDM).

Impact Validation for the Study Area

While the district-level validation is encouraging, the aim of the toolkit is also to provide location-specific forecasts at sub-district (upazila/union) level. Validating at these finer levels is more challenging due to data limitations. The toolkit included both sector-specific and overall exposure data, plus granular vulnerability and hazard forecasts, to compute the impact for each upazila and some unions. The district analysis provides confidence that the general methodology is robust, as it proved to be “on the right track” when aggregated. The assumption is that adding more local data (as this methodology did) should only improve the accuracy. However, to rigorously validate sub-district results, this methodology ideally needs observed impact data at that same sub-district level.

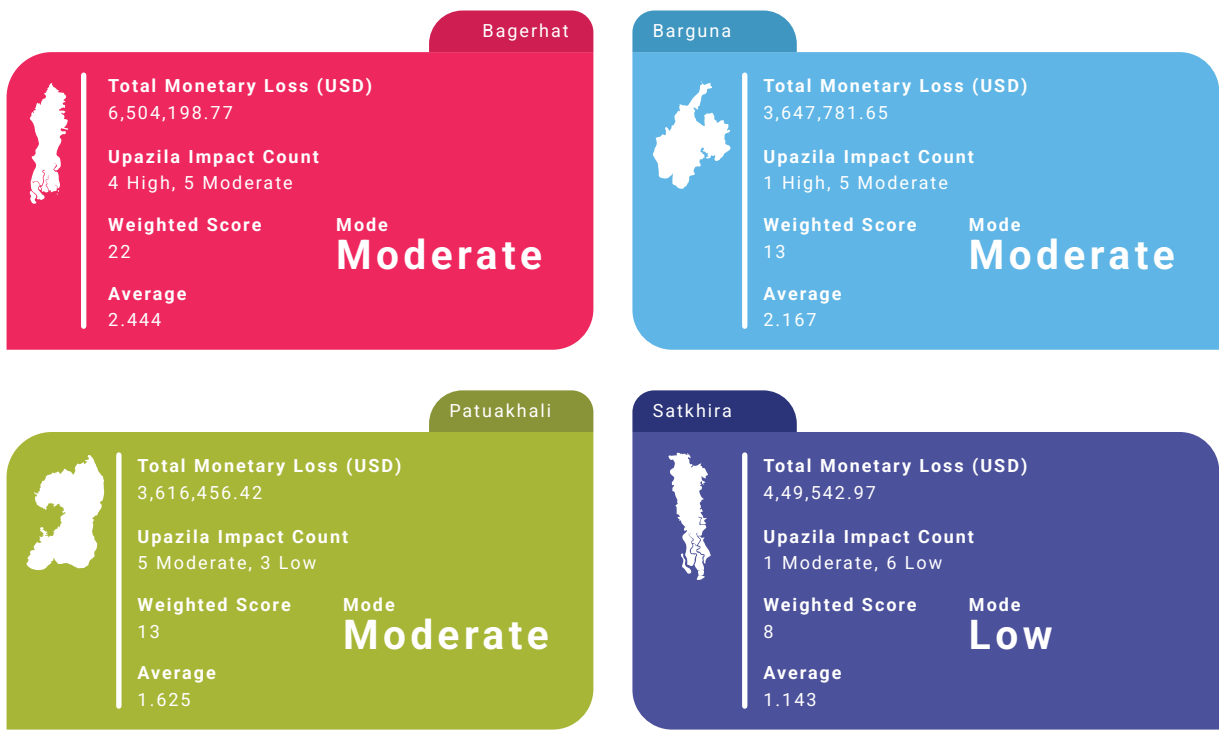
A key challenge faced was the limited availability of reference data at the upazila or union level. DDM and other agencies often report damages aggregated by district (and sometimes by broad region). Detailed, geo-referenced loss data (for example, exactly how many houses in each union/Upazila were damaged) are not always systematically collected or published. This is a common challenge in disaster analysis – the more local you go, the harder it is to get comprehensive data.

In the absence of full upazila-level damage datasets for all metrics, the methodology took two approaches for validation within the STEP project area:

- **Aggregated Upazila-to-District Comparison:** The results were upscaled from upazila to district level to compare with known district outcomes, as outlined in the previous section. This was achieved by analyzing the number of upazilas within each category (low, moderate, high) for each district to infer an overall district impact, and then comparing that with district losses. For example, in Satkhira District, six of the seven upazilas studied were categorized as low impact, and one as high impact. This allowed for the inference that Satkhira’s overall impact leaned low, with one trouble spot, which was consistent with DDM data showing that Satkhira had the lowest monetary damage (~USD 0.46 million). In Bagerhat District, many upazilas showed moderate to high impact. A “weighted score” was computed, assigning 2 points for each high-impact upazila and 1 point for each moderate (illustrative scoring). Bagerhat scored higher by this measure, aligning with its significantly larger damages (~USD 6.65 million). Barguna had mostly moderate impact upazilas, with one high impact, which slightly increased its score. Barguna’s losses

(~USD 3.73 million) were slightly higher than Patuakhali (~USD 3.70 million), which had no high impact upazilas, only moderate. This qualitative aggregation exercise indicated that the upazila-level forecasts, when aggregated to the district level, closely mirrored the actual district impact patterns.

The results of the cluster statistical analysis of the relevant dataset



- **Sector-Specific (Agriculture) Validation:** Some data on agricultural losses, such as crop area affected or yield reductions, was available from remote sensing data. These agricultural-focused impact scores were compared with the total agricultural losses reported by DDM for the cyclone. The inclusion of detailed local exposure data, such as VCI and fAPAR, proved to be valuable, as the sector-specific impact predictions showed a meaningful correlation with actual agricultural losses. In the case of Remal, statistical analysis showed strong relationships. For moderate-impact zones (in terms of agriculture), the Pearson correlation coefficient r was about 0.71, implying that over 50% of the variance in monetary loss could be explained by our impact metric. For high-impact agricultural zones, r was around 0.68, also corresponding to ~50% variance explained. Interestingly, in low-impact zones, a negative correlation ($r \sim -0.79$) was observed,

indicating that some areas classified as low impact still experienced notable losses. This could be due to local anomalies or limitations in how thresholds were set. It highlights that the "low" category might sometimes overlook issues if, for example, an area was generally low impact but one sector experienced significant damage. Furthermore, the overall impact correlation with losses was weaker than that of the sector-specific predictions. This is understandable: without local exposure data, the model remained more generic and could not account for, for example, an area with a high concentration of valuable crops. The incorporation of local data strengthened the correlation and improved prediction accuracy.

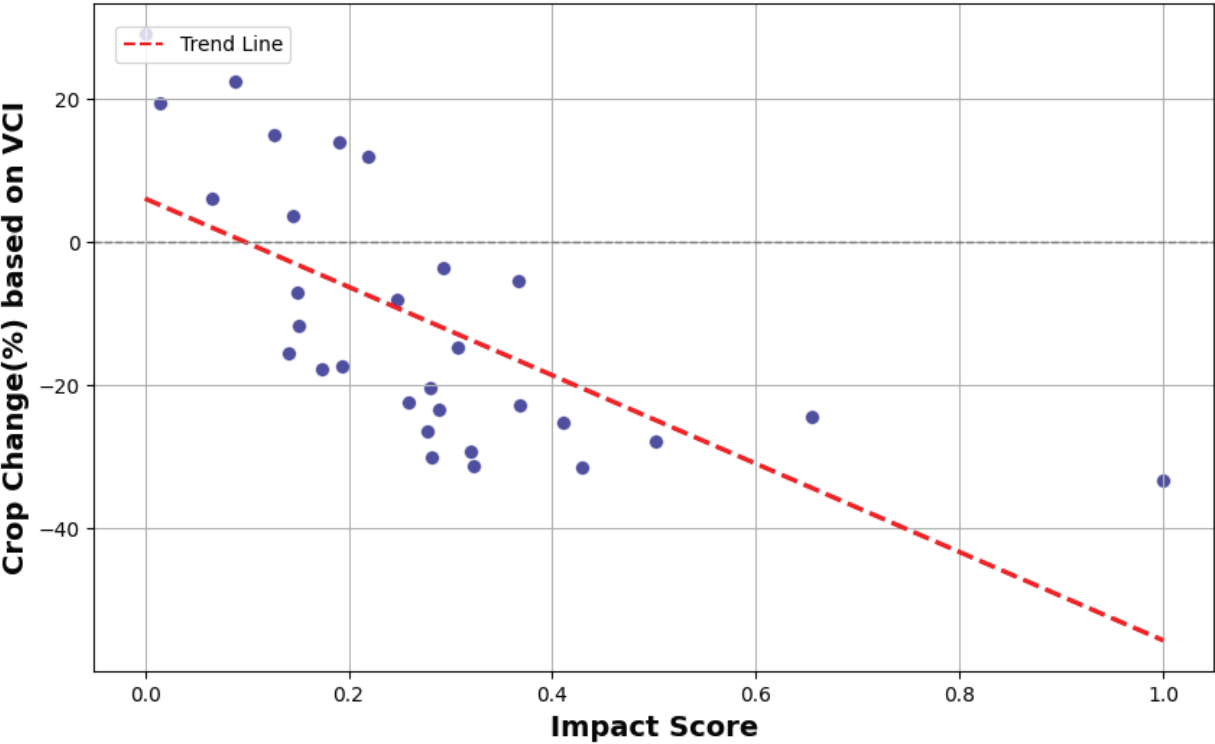


Fig. 12. Scatterplot showing the correlation between Impact score and crop change, trend line highlights the overall negative relationship, and black dots representing the different Upazilas.

- The relationship between impact scores and observed crop changes (using satellite-observed vegetation change as a proxy for crop damage) was further examined. A clear negative correlation was found: areas with higher impact scores tended to experience a greater decrease in vegetation (crop) health after the cyclone. The Pearson correlation coefficient (r) was -0.67, and Spearman's rank correlation coefficient (r) was -0.79 for the relationship between impact score and crop area change, both statistically significant with p -values on the order of 10^{-5} . An ANOVA test was also conducted, which revealed significant differences in vegetation loss across the low, moderate, and high impact categories ($F = 5.74$, $p \sim 0.008$).

In plain terms: our categories do correspond to real differences on the ground high impact areas lost a lot more crop cover than low impact areas, for example, validating that the impact categories mean something concrete.

That being said, these validations also highlight the limitations and areas for improvement:

1 Data Resolution: The methodology can only be fully validated where data exists. The discrepancies at “low impact” correlation likely reflect data gaps or threshold issues. It underscores a need for better data collection at local levels. Going forward, working with DDM and others to get detailed union-level damage data (perhaps through community reporting or drones, etc.) would help refine and validate the model further.

2 Category Thresholds: The moderate and high categories performed well; the low category was somewhat less predictive in terms of absolute losses. This might mean our threshold of 0.3 for low vs moderate could be tweaked, or that some “low” areas had one specific problem that caused more loss than expected. It's also possible that some losses in low-impact zones were due to freak incidents (e.g., a cyclone hitting a village where polder were weak and not reported). Adjusting categories or adding a finer gradation (maybe a “very low” vs “low”) might capture those nuances. However, adding more categories can also confuse stakeholders.

3 Over-simplification: By reducing impact to three classes, the process inevitably oversimplify some complexities. For example, a “moderate” impact area might have had mostly low impacts, but one neighborhood got wiped out; the average is moderate, but that nuance is lost in categorization. Stakeholders on the ground might be aware of such anomalies, so it's important we communicate that impact forecasts are guides, not gospel. This is why local knowledge should complement model outputs.





For future improvements, we suggest:



Higher-resolution data: Incorporate more detailed datasets such as building structural information, infrastructure network data, socioeconomic data at the village level, etc., which could improve model accuracy. Also, near-real-time exposure data (like current crop prices, or evacuation status of population) could further refine predictions on the fly.



Dynamic thresholds: Rather than static cut-offs like 0.3 and 0.7, the methodology could explore dynamic threshold setting based on context or using clustering algorithms to determine natural groupings in the impact results. Machine learning could potentially classify impact levels using more complex patterns in the data.



Context-specific calibration: Each cyclone has unique features; future study might calibrate the impact model differently for a slow-moving rain-heavy cyclone versus a fast, dry cyclone, etc. Impact categories should remain flexible and possibly scenario-specific. For instance, “high impact” in a densely populated district could mean something different than “high impact” in a sparsely populated one in absolute terms.

In conclusion, the validation shows that the toolkit’s impact predictions closely mirrored actual outcomes, especially when looking at larger scales or sector trends, which is promising. At the hyper-local level, the model performs well overall but will benefit from ongoing refinement and more data. This iterative process of applying the model, validating with real events, and then improving it, will gradually increase its reliability. Nonetheless, even in its current form, the toolkit provides a credible basis for early action decisions, as demonstrated by how well it correlated with Cyclone Remal’s observed impacts.

Experience from the Ground: Cyclone Remal (2024)

Cyclone-prone coastal regions in southwestern Bangladesh regularly experience severe disruptions to livelihoods, agriculture, and infrastructure. Traditionally, disaster response in these communities has focused on post-event relief, which often leaves them vulnerable to repeat events year after year. Recognizing the need for a more proactive approach, the impact forecasting toolkit described in this document was co-developed and applied in the field to help stakeholders anticipate and mitigate cyclone-related damages before they occur.

By combining local, sector-specific data with correlation analyses and detailed exposure indicators, the toolkit demonstrates how to produce reliable impact forecasts that inform early actions, optimize resource allocation, and ultimately enhance community resilience.

A practical example of this approach in action is the “Strengthening Forecast-Based Early Actions in Cyclone-Prone Coastal Regions in Bangladesh” (STEP) project. This ECHO-supported initiative, in collaboration with the Department of Disaster Management (DDM) and other partners, operationalized the insights from impact forecasting

to protect vulnerable communities. STEP worked with local disaster management committees to establish evidence-based triggers for anticipatory interventions. When forecasts (like those for Cyclone Remal) indicated high risk, these triggers activated predefined actions – essentially bringing the plans outlined by the toolkit to life.

Through this integrated, forecast-driven strategy, communities were able to mobilize resources and safeguard critical assets well in advance of landfall. For instance, farmers harvested crops early or moved them to safe storage, fishermen secured or moved boats to sheltered areas, households reinforced their homes or evacuated livestock, and emergency committees positioned relief goods at strategic points – all before the cyclone hit. The case study below details how Cyclone Remal’s projected impacts were addressed on the ground, highlighting the effectiveness of timely, data-driven actions in preserving lives and livelihoods.

With the issued special bulletin from BMD and technical support from RIMES, local committees under STEP took prompt action based on the forecasts issued for Cyclone Remal. They coordinated closely with the

national agencies: DDM, the Cyclone Preparedness Programme (CPP), and local government units. As early as a few days before landfall, when BMD's forecasts (augmented by our impact modeling) warned of Remal's potential severity, STEP activated readiness measures and Anticipatory Action (AA) triggers. Warnings were disseminated widely in communities, alerting people not just that a cyclone was coming, but what impacts to expect (e.g., which areas might flood, which crops might be ruined). This information came from the impact-based forecasts. Consequently, volunteers helped at-risk households tie down their roofs, farmers in flood-prone pockets raised their tubewell platforms and took other protective steps, and fishing communities hauled boats inland beyond surge reach.

After the cyclone, a rapid assessment was conducted (between June 27 and July 15, 2024) across four project districts: Patuakhali, Barguna, Bagerhat, and Satkhira. The goal was to evaluate the effectiveness of these anticipatory interventions. The findings were striking and affirmed the value of acting early:



Early Warning Reach:

58% of households in the project area reported receiving cyclone forecasts or warnings 2–3 days before landfall, compared to only 36% in nearby areas without the project's interventions. This indicates a much greater penetration of early warning, likely due to the project's communication efforts. People knew the cyclone was coming with a couple of days' notice, enabling them to prepare.



Reduced Damage

Incidence: Despite Cyclone Remal's force, only 49% of households in the project area were affected by some form of damage, compared to 92% of households in the control areas (areas not covered by the anticipatory actions). In other words, early actions nearly halved the proportion of families experiencing damage. This is a powerful testament to prevention: things like clearing drainage channels beforehand, pre-positioning boats for rescue, and reinforcing houses clearly paid off.



Asset Protection (FbF vs non-FbF): Some

communities received forecast-based financing

(FbF) support – essentially cash or materials given in advance to help them act (like money to buy ropes, fuel for evacuation, etc.). Those households were able to save 90% of their assets on average. But what's even more interesting is that even households without direct FbF support managed to save 91% of their assets. How? Likely because they still benefited from early warnings and guidance (even if they did not get cash, they knew to move their belongings to safety, etc.). This suggests that while cash helps, dissemination of impact forecasts and advisory can empower people to take effective measures on their own too.



Return on Investment:

The interventions under the project showed a remarkable return on

investment of 15:1. This means for every 1 United States Dollar (USD) spent on early action, about 15 USD of losses were averted. Interestingly, households outside the project who heeded the forecasts (for instance, those who heard the warnings on the radio and took action independently) saw a similar benefit – roughly USD 16 saved per USD 1 spent on their own actions, essentially equivalent to the project areas. This demonstrates that anticipatory actions are highly cost-effective. It is far cheaper to prevent damage than to repair it afterward.

Looking at specific sectors of losses in the project vs control areas reinforces the benefit of early action:

- **Agriculture:** In study areas, households had average agricultural losses of around USD 63, whereas in control areas it was around USD 87. That is about a 28% reduction in crop loss due to early harvesting or protection measures.
- **Livestock:** Project area households faced damage around USD 242 in livestock value on average, versus USD 252 in control. This is a smaller difference (~4% reduction), suggesting that even outside project areas people managed to protect livestock fairly well (perhaps because moving cattle is a standard practice now). Still, every bit helps.
- **Housing:** A dramatic difference was observed for the most vulnerable housing category, kutcha houses (made of mud/clay and straw, very flimsy). In project areas, households living in kutcha houses saved about USD 795 each, whereas in control

areas they saved only around USD 1.50. This implies that in control areas, essentially those houses were wiped out (almost nothing saved), while in project areas substantial value was preserved likely through actions like strengthening houses or evacuating belongings. This huge difference underscores how anticipatory actions (like reinforcing houses with extra struts or moving valuables out of kutchra houses into a cyclone shelter) prevented total loss in extremely vulnerable homes.



Photo: Volunteers disseminating Early Warning Information before Cyclone Remal
(Credit: STEP Consortium).

These outcomes underscore the value of deploying anticipatory actions guided by impact forecasts. Even without lavish resources or direct payouts to everyone, the combination of early interventions and accurate forecasts helped communities safeguard their assets and livelihoods. This is a real-world validation that forecast-based early action can significantly reduce cyclone impacts. It's worth noting that the STEP project was a concentrated effort, scaling this approach nationwide would require institutionalizing such localized impact forecast and early action protocols. However, the success stories from Remal, families who did not lose their main source of income (be it a boat, a cow, or a field of crops) because they acted early, spread a powerful message. It creates buy-in at the community level for future forecasts and early actions, thereby creating a virtuous cycle of trust and responsiveness.

In conclusion, Cyclone Remal (2024) provided a proof of concept for the application of impact-based forecasting in anticipatory action in coastal Bangladesh. The toolkit's information was applied on the ground through STEP, and it translated into tangible reduction in harm. This example can be used to advocate for further adoption of such toolkits and the scaling up of forecast-based financing and action programs. The experience from the ground demonstrated that timely, well-communicated forecasts empower communities: they shift from passively awaiting disaster to actively preparing for it. Forecasts, when combined with local knowledge and resources, become a tool not just for warning, but for doing – enabling people to take charge of their own safety and resilience.



Photo: Wind Gust from Cyclone Remal tore off the tin roof, leaving the house damaged (Credit: STEP Consortium).

Challenges and Way Forward

Implementing an effective and accurate impact-based forecasting is not without challenges. Reflecting on our toolkit's development and application, several limitations and areas for improvement have been identified:

- **Data Availability and Granularity:** One of the foremost challenges is accessing localized, union-level data, especially for hazard forecasts and certain vulnerability indicators. This toolkit attempted to use very granular data, but in many regions such detailed data either do not exist or are hard to obtain in real time. For example, while we might get union-level population or perhaps poverty data from the census, getting union-level projected storm surge values or union-level health capacity data is tough. The finer the granularity, the more data gaps and anomalies were encountered. In some cases we had to make do with upazila-level proxies or even district-level data for certain indicators in union calculations. Moving forward, investing in ground data collection and incorporating community-sourced data could help fill these gaps. Additionally, improving data sharing mechanisms among agencies can help – often data exists but is siloed.
- **Real-Time Exposure Data:** The exposure assessment would be stronger if the methodology had more up-to-date exposure information. For instance, knowing how many people are currently in harm's way (perhaps via mobile data or evacuation reports), or current asset locations, would refine impact forecasts. However, such real-time data are limited, particularly for sector-specific details (like which health facilities are operational, where livestock are kept at that moment, etc.). In the case of livestock, for example, the analysis assumed livestock are at the household location, but in reality, some might have been moved – if this information was available, exposure dataset could be adjusted. Incorporating technology like IoT sensors or crowdsourcing (e.g., getting farmers to report in an app if they moved animals) could one day feed into the system.
- **Remote Sensing Constraints:** While remote sensing was leveraged (e.g., Sentinel-2 for vegetation), there are limitations in data resolution and coverage. High-resolution satellites (that could see small features like individual homes or embankment cracks) might not pass frequently or may be costly. Also, heavy cloud cover after a cyclone can obscure imagery when we need it most (to assess impacts or get final readings for analysis). This was partly mitigated by using advanced filtering and GEE computations, but in some cases data was indeed scant right after

the cyclone (due to clouds). The toolkit resorted to using pre-event imagery for baseline and then the first clear post-event images for validation, but missing the immediate aftermath snapshot is a challenge. In the future, combining satellite data with UAV (drone) imagery for local validation could help, or using radar satellites (which penetrate clouds) for flood mapping.

- **Categorization and Thresholds:** The toolkit currently categorizes impact into three levels based on set thresholds (e.g. ≤ 0.3 , $0.3-0.7$, >0.7 in our normalized scale for cyclone Remal). These thresholds were chosen somewhat arbitrarily and then justified by correlation, but as mentioned, they might not capture all nuances. Using broad categories simplifies communication but can oversimplify data. For example, an upazila with an impact score of 0.29 vs one with 0.31 are nearly the same in reality, but one gets labeled low and the other moderate, which might affect response prioritization. This could lead to overlooking some areas that are borderline. Also, fixed thresholds may not apply equally to all contexts – a score of 0.5 in a very urban district might mean widespread moderate damage, whereas 0.5 in a rural district might mean fewer people affected but a large area of crops destroyed. Access to more detailed damage data (e.g., actual losses at upazila/union level) from past events will help refine these thresholds to be more empirically grounded. This can calibrate the category cut-offs so that, say, “high impact” truly corresponds to above a certain monetary loss or casualty rate observed historically.
- **Validity of “Low Impact” classification:** The validation computations showed that the model struggled a bit with the low impact category (some low-impact classified areas had unusual losses). This difference is likely due to comparing different scales of data (district losses vs upazila impacts) or perhaps that a few low-impact outliers skewed things. It is noted that similar issues have been observed in other IBF efforts (Purnama et al., 2023), where low-impact forecasts did not always align with outcomes. This indicates that the methodology should improve the accuracy of the “low” end of the spectrum. Possibly, low-impact areas might still suffer specific sectoral hits (like maybe one village had a breach in polder recently, which did not included in the vulnerability information yet). One solution is to integrate some probabilistic thinking e.g., even low-impact areas have a small chance of severe outcomes. Communicating that uncertainty is key so that “low impact” doesn’t breed complacency. Another approach is doing more localized validation for low categories: maybe use household-level survey data to see if low-impact upazilas still had pockets of problems. If patterns are identified, such as a recurring factor that was not included in the model, adjustments can be made to incorporate this factor and improve the model's accuracy.

In light of these challenges, several way forward actions can be recommended:



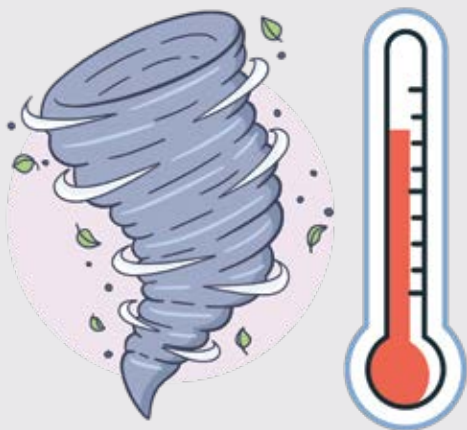
Enhance Data Integration: Work with national databases (like the upcoming digital census data, or an integrated disaster data platform) to ingest more local detail. Strengthen partnerships with institutions (like universities or local governments) to get socio-economic data at finer scales. Perhaps develop community-based data collection for vulnerability indicators where official data are missing (e.g., a community volunteer network that reports the status of local infrastructure annually).

Refine Impact Model with Machine Learning: The methodology may incorporate machine learning approaches to handle complex interactions of factors and to adjust impact categorization dynamically. For example, a machine learning model could be trained on past cyclone impact data to predict categories directly, possibly capturing nonlinear effects or combinations of indicators that our linear model might miss.



Improve Forecasting Tools: Continue improving the hazard models for local scales. For instance, downscale storm surge models to union levels where possible with inundation scenarios and incorporate high-resolution weather models (like BMD’s WRF model outputs). The better the hazard detail, the more pinpoint the impact can be.





Dynamic/Adaptive Classification:

Instead of fixed thresholds, the system could determine thresholds on the fly based on clustering of impact scores or using impact predictions in absolute terms (like expected \$\$ losses). Alternatively, inclusion of more granular rating (like a 5-point scale akin to how hurricanes are rated) if that conveys nuance better, though that might complicate user interpretation.



Local Verification & Feedback

Loops: After each event, collect as much local feedback as possible: Did the analysis miss any major impact area? Did it over-warn someplace that ended up fine? Such feedback from field personnel will help tweak the model. Essentially, treat each disaster as a live test of the system, then refine.



Capacity Building and Awareness: Challenges are not only technical – they are also about ensuring end-users know how to use this information. Continuous training for local officials on interpreting impact forecasts, and drills on anticipatory action based on them, will maximize the benefits even as we work on perfecting the system.

In conclusion, while the approach has proven effective, continuous improvement is needed to handle its current limitations. By addressing data gaps, refining methodologies, and incorporating more advanced techniques, we can enhance both the accuracy and the trust in impact forecasts. Importantly, securing access to detailed validation data at local levels (union/upazila damage reports, perhaps through DDM's future systems) is crucial for fine-tuning the model. This will allow us to quantify precisely how much better the localized approach performs and where it needs adjustment.

The ultimate goal is to integrate this impact forecasting model seamlessly into the national early warning system, making it a routine part of forecasting and response planning. With improvements, it can become a robust tool that dynamically guides decisions – for example, automatically triggering early action protocols when certain impact thresholds are forecast. As climate change likely increases the intensity of cyclones, having a fine-tuned impact forecasting and anticipatory action framework will be invaluable for Bangladesh and other cyclone-prone regions. The challenges we face are surmountable with collaborative effort, and the way forward is clear: better data, better models, and better integration lead to better outcomes for communities at risk.

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ANNEXES

The vulnerability scenario was assessed based on two dimensions: limited coping capacity and vulnerability dataset. This dataset was subsequently divided into categories, components, sub-components, and, ultimately, specific indicators.

Table 1

Cyclone Vulnerability Indicators

Dimension	Category	Component	Sub-Component	Indicator	Weight
Vulnerability	Poverty and Development	Poverty	Poor People	Poor People	4.5
			Extremely Poor People	Extremely Poor People	5
			Unsustainable Livelihood Household	Population dependent on Agriculture	4
				Number of Day Laborers (Non-agricultural and agri)	3
				Population involved in Fisheries	4.5
				Animal Husbandry	3
	Other Vulnerable Group	Other Vulnerability	Women Headed Households	Female headed Households	2.5
			House Structure	Non-Permanent Housing Structure	5
			Elderly Population	Dependent Population	3.5
			Population (age <15)		
			Population with Disability	Population with Disability	4.5
	Social-Economics Vulnerability	Economical Dependency	Unemployment Rate	Unemployment Rate	1.5
Lack of Coping Capacity	Natural	Epidemic	Population (age <5)	Children under 5 years	3.5
	Infrastructure	Communication	Adult Literacy Rate	Lack of Literacy Rate	2
				Lack of Female Literacy Rate	2
			Internet Users	Individuals without access to Internet	3.5
			Mobile Phone Users	Individuals without Mobile Phone	4
		DRR	Cyclone Shelter	Number of Cyclone Shelters (currently operational)	5
		Access to health care	Community Clinic and Health Center Density	Number of community clinics/health centers (currently operational)	3
		Access to water	Fresh Water	Lack of Fresh water access	4
		Embankment	Embankment Condition	Current condition of dam (non-fragile, fragile, absent)	4
	Institutional	Preparedness and Response	CPP volunteer	Number of Cyclone Preparedness Programme (CPP) Volunteer	5
			Early Warning	Disaster Prone HH Received Early Warning	3.5

Data Normalization

The dataset for vulnerable indicators was used to calculate hazard-specific vulnerability assessment. Indicator values measured on different scales and units were converted to unitless values on a common scale through normalization (Sarkar et al., 2024). Normalized values ranged between 0 and 5, and based on the categorized criteria range, the study depicted different states of vulnerability. To evaluate the criteria range comprehensively, the study employed the following formula for all indicators:

$$X_p=\frac{X_{max}-X_{min}}{X_n}$$

where, X_p is the class interval
 X_{max} is the maximum value of that indicator for all locations;
 X_{min} is the minimum value of that indicator for all locations;
 X_n is the total number of classifications

The obtained class interval was used to classify the indicator into five different range. The classification was made based on equal intervals. The categorized range was then used to assign thresholds to the selected indicators in excel to normalize the data for all upazila and union (Sarkar, 2024).

Weightage

The weight given to a particular component, category, or indicator alters based on the situation. The weight of an indicator will vary depending on the hazard, location, and time, as hazards are dynamic. As a result, the significance of specific indicators outweighs others, and their corresponding importance should be reflected in their weight. Through expert consultation (a type of multi-criteria analysis), the values were assessed on a scale ranging from 1 to 5, with 1 being least vulnerable and 5 being most (refer to Table 1). The reflected weights can vary as it is an assumption and not static. The score will be different from time to time depending on the situation and can change based on future data and event. The following steps show how to calculate a Vulnerability score from these respected values.

Computing Vulnerability Score

Step 1

$$W_{Ni} = \sum_{i=1}^m W_i * I_i$$

Here, W_{Ni} = Indicator value

I_i = Normalized value of any indicator

W_i = Weightage of respective indicator

Multiply the assigned weight with that of the normalized value of the indicator. Let us assign this value as 'W_{Ni}'.

Step 2 Repeat this step for all the indicator values for the selected sites

Step 3 Calculating Vulnerability Score

$$V_s = \frac{\text{Sum}(W_{Ni})}{\text{Sum}(W)}$$

Here, V_s is Vulnerability Score for a selected site

W is the weight of the selected indicator

W_{Ni} is calculated score of Indicator value

In a similar manner, all vulnerability scores were calculated for each of the selected upazilas and unions. The vulnerability scores were then used to calculate the Vulnerability Index and thereby form the Vulnerability Map.

Vulnerability Index

The Vulnerability Index has been calculated using ArcGIS PRO. To assess the cumulative vulnerability index for all case study districts (Bagerhat, Satkhira, Barguna, and Patuakhali), the vulnerability score for all the upazilas was needed (Figure 13). For further explanation, let us examine Bagerhat District (Table 2). The obtained vulnerability score was divided into five groups (very low, low, moderate, high and very high). The calculated Vulnerability Index was assigned a color based on the corresponding index; Very Low = Dark Green, Low = Green, Moderate = Light Green, High = Orange, and Very High = Red.

Table 2

Vulnerability Score and Index for Bagerhat District

District	Upazila	Vulnerability score	Vulnerability Index
Bagerhat District	Sarankhola Upazila	2.667	Very Low
	Rampal Upazila	3.149	High
	Morrelganj Upazila	3.435	Very High
	Mongla Upazila	2.665	Very Low
	Chitalmari Upazila	2.919	Moderate
	Bagerhat Sadar Upazila	2.627	Very Low
	Mollahat Upazila	3.186	High
	Kochua Upazila	2.522	Very Low
	Fakirhat Upazila	2.863	Low

In order to generate a vulnerability map for Bagerhat District, the vulnerability scores for all upazilas under that particular district was needed. The results revealed that Morrelganj Upazila fell into very high vulnerability zones, Rampal Upazila and Mollahat Upazila in high vulnerability zone, while, Chitalmari Upazila was classified in Moderate (Figure 14). On the other hand, Fakirhat Upazila was at low risk of vulnerability while Sarankhola Upazila, Mongla Upazila, Bagerhat Sadar Upazila, and Kochua Upazila were the least vulnerable. In the same manner the vulnerability index for all the unions under Bagerhat District was also assessed (Figure 15).

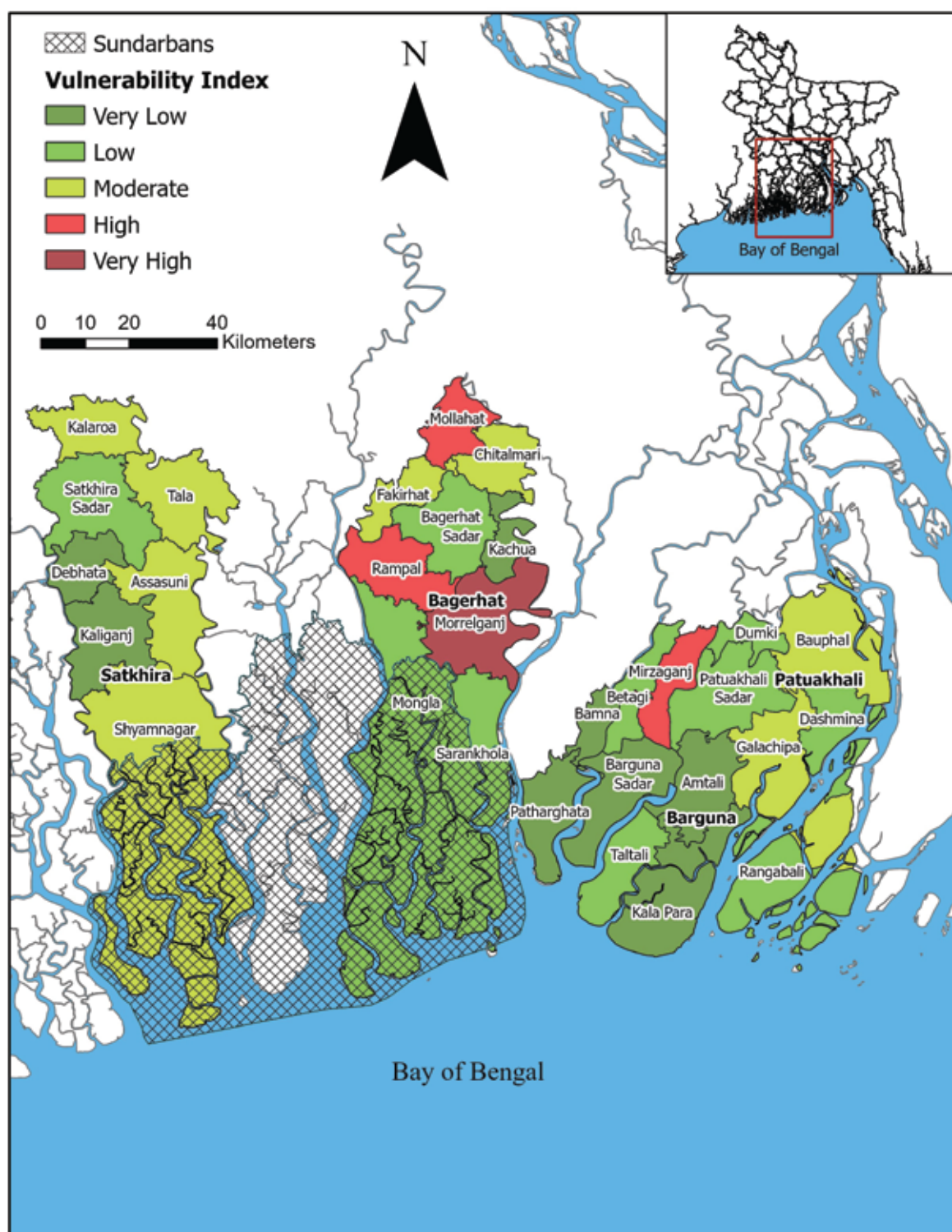


Fig. 13. The vulnerability map has been graphically generated depicting the vulnerability index of all Upazilas in Satkhira, Bagerhat, Barguna, and Patuakhali District. For comparison, the vulnerability index has been classified into very low (dark green), low (green), moderate (light green), high (orange), and very high (red) for all districts cumulatively.

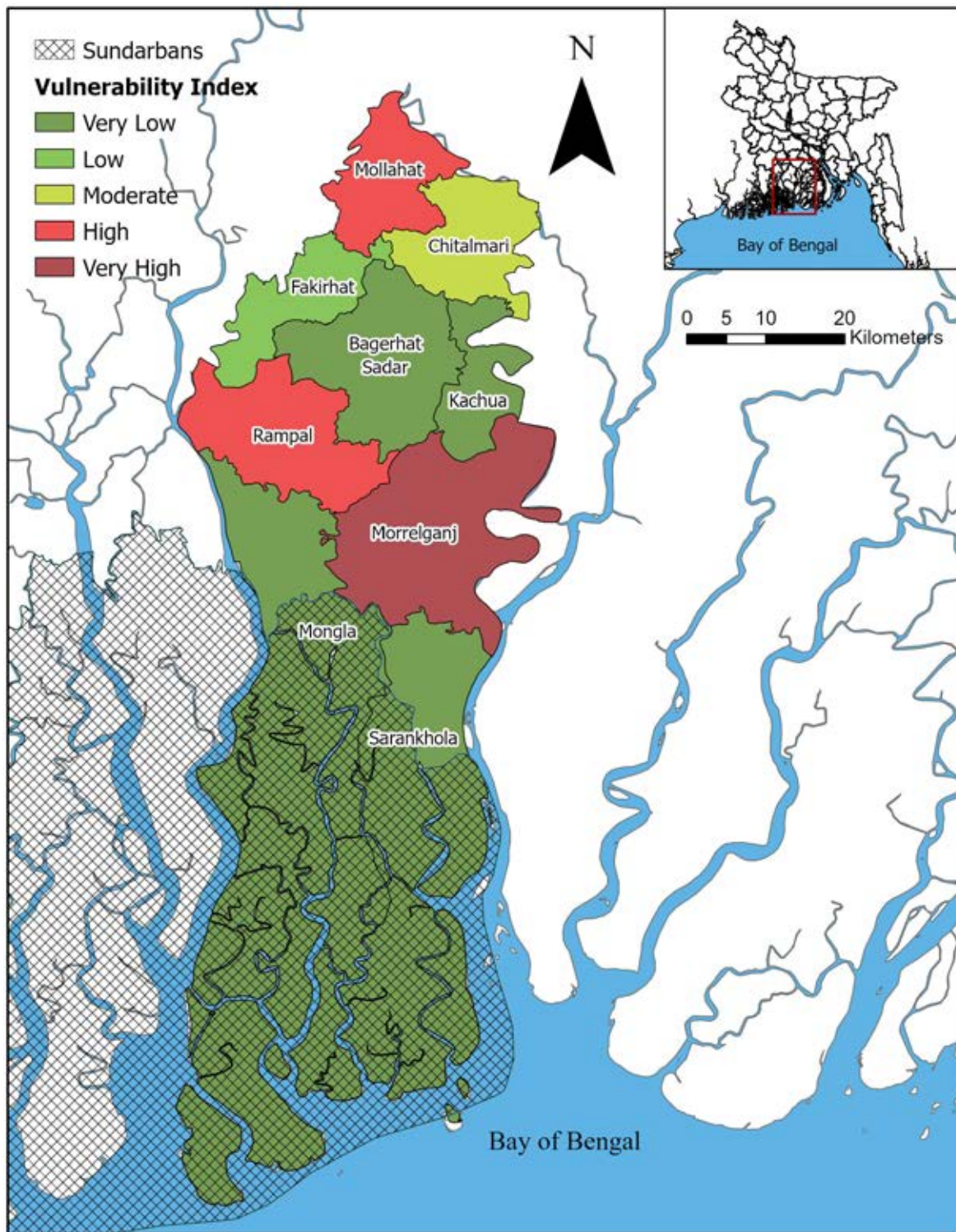


Fig. 14. The vulnerability map has been graphically generated depicting the vulnerability index of all upazilas in Bagerhat District. For comparison, the vulnerability index has been classified into very low (dark green), low (green), moderate (light green), high (orange), and very high (red).

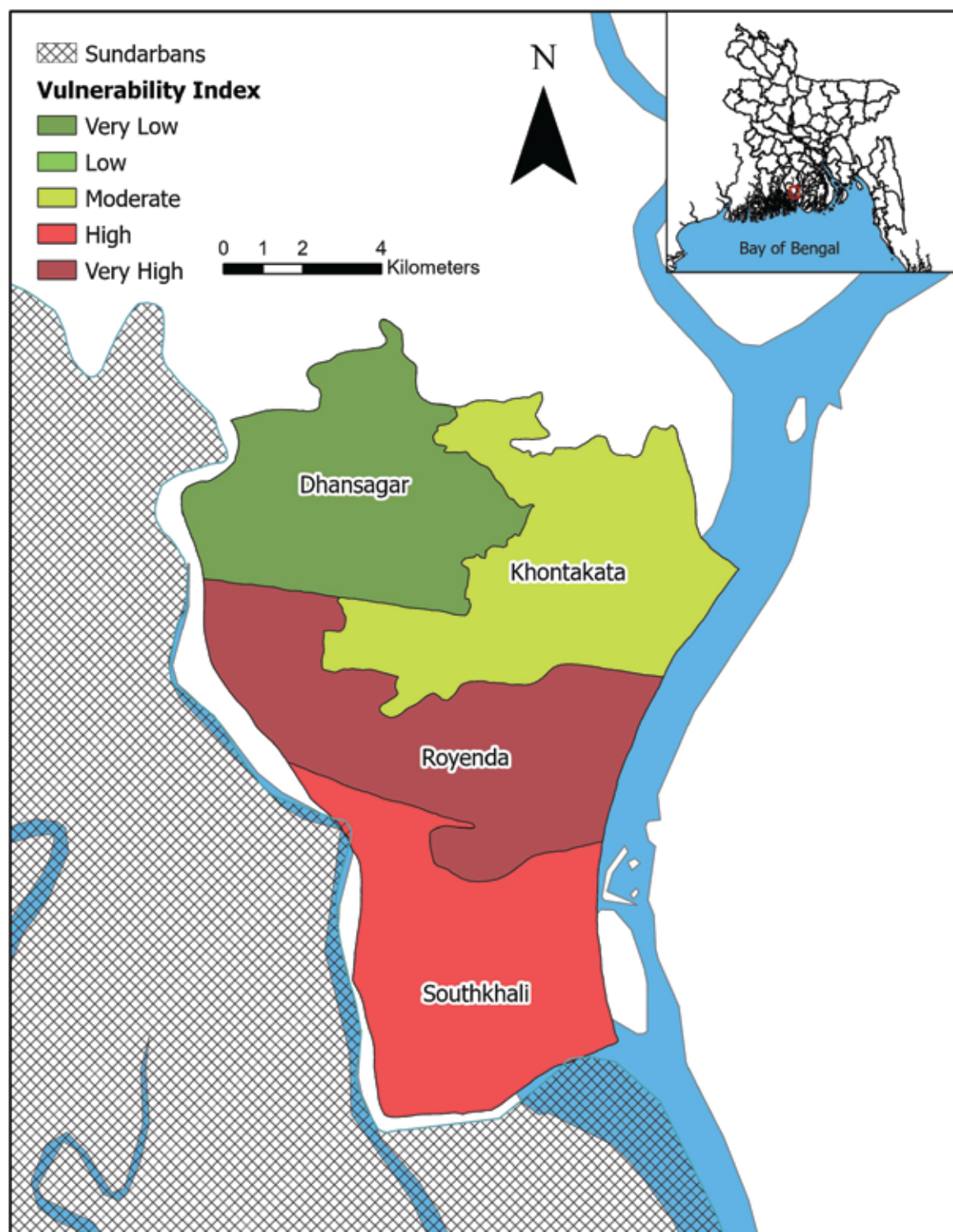
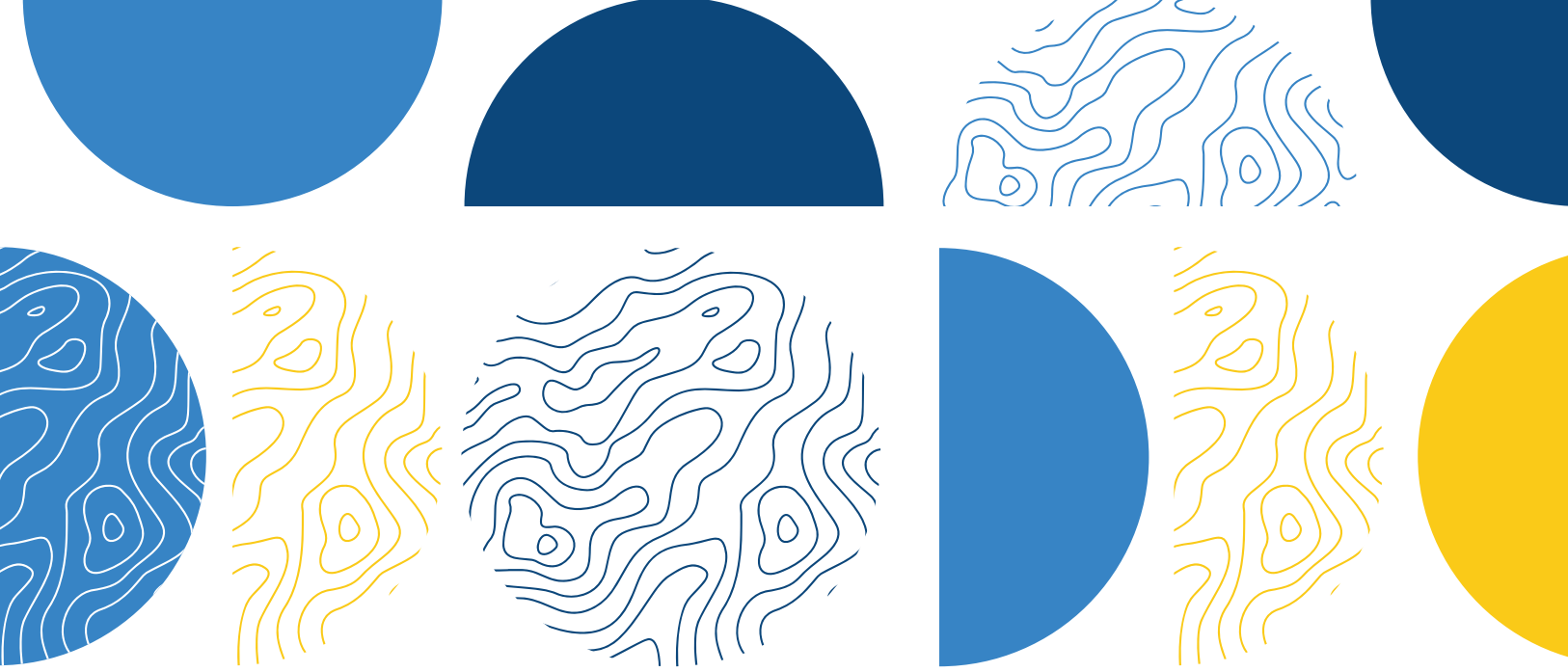


Fig. 15. The vulnerability map has been graphically generated depicting the vulnerability index of for all the Unions in Sarankhola Upazila, Bagerhat District.







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