Assessment of flood intensity using probabilistic models: a study in the Atreyee and Punarbhaba river basins

Soumi Ghosh[1], Manua Banerjee[1], Asutosh Goswami[2]

[1] Department of Earth Sciences & Remote Sensing, JIS University, Agarpara, India

[2] Department of Geography, Rabindra Bharati University, Kolkata, India

Abstract

Flooding is a recurring and severe hydrological event in the Atreyee and Punarbhaba river basins that extend into some parts of Northern West Bengal, India, and adjacent Bangladesh. The area is susceptible to flooding during the monsoon months due to high rainfall along with shallow gradients and low river channel capacity. This study seeks to simulate flood behaviour in the Atreyee and Punarbhaba river basins with hydrological and hydrodynamic modelling analysis techniques. Rainfall-runoff modelling was conducted with the HEC-HMS modelling framework, and floodplain inundation mapping was conducted with the HEC - RAS 2D modelling framework, which integrated high resolution DEM and satellite-derived parameters. Model calibration and validation used observed discharge and water level from selected gauging stations. Inundation extent, depth and duration spatial analysis indicated that low-lying areas in Balurghat, Gangarampur and Thakurgaon are highly flood prone. The results highlight that both river basins have strong trans-boundary hydrologic linkages, and that upstream rainfall events significantly influence the flooding hazard downstream. The study highlights the need for real-time hydrologic forecasting, land use management, and trans-boundary collaboration for effective and sustainable flood risk mitigation. The simulation outcomes can support regional planners and disaster management authorities in developing early warning systems and adaptive flood risk management strategies.

Keywords: Atreyee River, Punarbhaba River, Flood Simulation, HEC-RAS, Hydrological Modelling, Remote Sensing, Floodplain Mapping.

1.0 Introduction

In the flood simulation domain, all tools and computational models are employed to emulate and forecast floodwater response in numerous contexts (Downer & Ogden, 2004; Bates et al., 2005; Abebe et al., 2010; Bates et al., 2010; Beven, 2012; Bhuiyan et al., 2015; Guo et al., 2021). It is critical in flood risk management, urban planning, emergency preparedness, and overall climate resilience strategies (Lindström et al., 1997; Horritt & Bates, 2002; Hunter et al., 2007; Neal et al., 2012; Sampson et al., 2015; Shirvani et al., 2020; Li et al., 2020). With climate change producing an unprecedented rate of extreme weather events, accurate flood simulation therefore has significantly increased importance. Flood simulations aid in understanding, analysing, and managing flood risk through modelling water flow and accumulation during flood events (Teng et al., 2017; Ugonna et al., 2019; Xu et al., 2024). Planners and policymakers would use such simulations to identify at-risk areas for flooding, design storm water drainage systems, assess flood protection measures, and make decisions around emergency preparedness. Focal scenarios of rainfall intensity, land cover change, or sea-level rise can also be projected using simulations to create better policies. Flood simulations help to identify at-risk flood areas thus providing opportunity for meaningful proactive interventions. Flood modeling contributes to preparedness for emergencies because it can provide inundation maps and risk assessment (Sanders, 2007; Schumann, et al., 2009; Tsubaki & Fujita, 2010; Fewtrell et al., 2011). Modeling contributes to policy development because it can produce reasonable future scenarios with both climate change and land-use changes as a consideration. Modeling is a critical aspect of modern flood risk management (Neal et al. 2009; Yamazaki et al., 2011; Zischg et al., 2017) when considering potential future flood scenarios that will factor into any approach to planning and policy development. By incorporating hydrological models in the land use planning processes and factoring climate scenarios, stakeholders could develop appropriate adaptive pathways to mitigate flood risks and enhance resilience. The present study could describe specific flood characteristics based on different indices in this study area. The general characteristics of the flood and runoff properties were changed due to the dam construction. In the case of trans-boundary rivers, this will affect the water allocation in the trans-boundary area. In simple terms, an estimate of flood probability refers to describing the likelihood of the occurrence (in any form) of a flood of a certain magnitude occurring at a location over a specific timeframe. The estimate of flood probability is one of the most important factors related to simulating flood characteristics and presents a platform for understanding, modelling, and predicting flood behaviour across different contexts and scenarios. In simulating scenarios, flood models utilise rainfall or discharge estimates that appear with some naming convention of 'probability-and-frequency' (a 10-year flood, 50-year flood, 100-year flood, etc). When estimating the probability of flood, it allows the flood modeller to simulate realistic flood events that are representative of statistically valid flood characteristics that reflect true and real risks rather than an arbitrary or extreme flood scenario. When estimating and predicting flooding risk scenarios there is an objective to match the simulated scenarios with observed return periods and therefore estimating a probability is helps provide assurance that the hydrologic model has been calibrated to accurately reproduce historical flood behaviour. Further, to simulate flood characteristics with known probability contexts supports associated engineering decisions/development strategies such as designing levees, culverts, and retention basins as an assurance that engineered structures/weirs can withstand flows above certain risk thresholds. The governments and stakeholders utilize flood simulations informed by probability to prioritize investments, implement mitigation measures, and assess long-term climate resilience policies. Estimating flood probability provides assurance that the flood simulation not only is technically sound, but that it is useful for real-world planning, associated risk assessment, and infrastructure resilience rendering it an essential component of flood risk management. Flood Probability has been estimated through five different indices: the flood density index, post dam construction moisture balance algorithm, the stress degree day index, the topographic behaviour of flood, and the vegetation influence on flood.

2.0 Materials and methods

2.1 Flood density index

The flood density index is developed from the data procured from the Google Earth Engine. For the present study, the use of microwave bands is considered to estimate the water depth for different seasons. During the pre-monsoon climate, the water table, groundwater, and surface water depths are prone to fluctuations. The uneven variability of very high water levels indicates significant depletion of water, and the soil moisture is reminded by a mild depletion. Dry spells and high evaporation rates are often exhibited during the pre-monsoon phase, which leads to exposed surfaces and dried out soil, neither of which is helpful to vegetative or agricultural settings. In the post-monsoon phase, it is the opposite condition (Fig. 1-bottom). With the arrival of monsoon rain showers, there is a substantial spike in water levels evident from the post-monsoon water depth maps-preceding monsoon rains are established heavy recharge to surface waters and groundwater bodies. These newfound heavy rainfalls were reflective of spatially widespread heavy rain. In this connection, it is also worth mentioning that the soil characteristics of this region play an important role in this conversion. Here, the soil has a reasonably good moisture retention capacity once it has received adequate rainfall. That means after a fairly long spell of heavy rainfall, the soil retains a good quantity of moisture, which makes moisture conditions competitive during the post-monsoon period, sustaining agricultural operations along with vegetation for a reasonable duration beyond the cessation of rainfall.

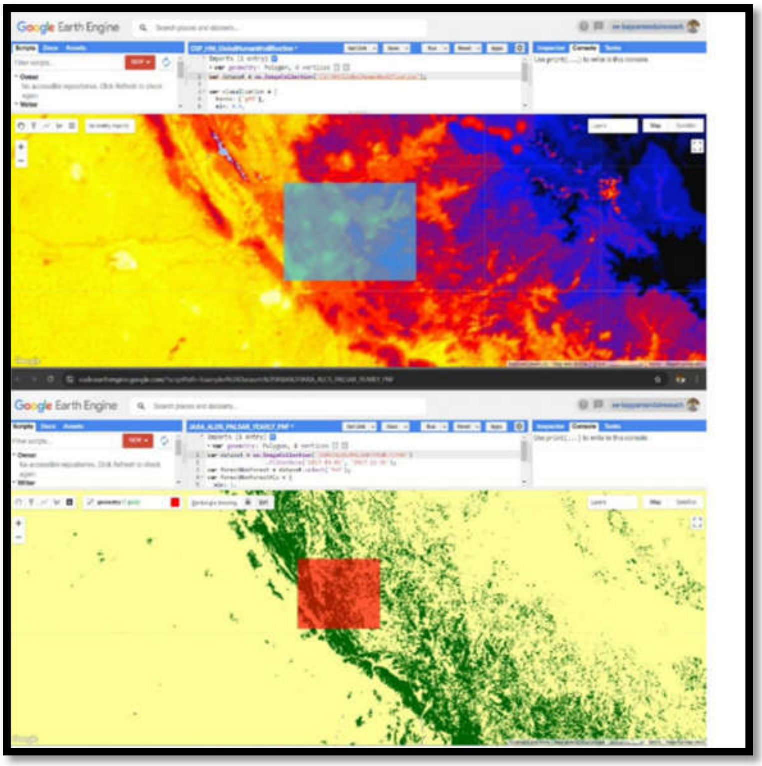

Fig. 1 Flood density index

2.2 Post dam construction moisture balance algorithm

The output reveals an image of Google Earth Engine (GEE), providing visualization of moisture balance data after dam construction, utilizing satellite datasets. The analysis seeks to discover any changes in moisture balance (precipitation minus evapotranspiration) that result after dam construction, which in general allows us to see water availability for use, agricultural viability, vegetation state, and regional climate. The contrast in surrounding areas seems to tell a different or localized moisture balance change due to dam related factors. The gradient change from brown to green suggests an opposite or opposing gradient to the northeast, downstream from the dam, which creates and better retains moisture due to positive factors. While there are better forms of visualizing, NDVI or land classification are tested here using a different base layer and the red AOI (area of interest) in the overlay. The red rectangle is on a location that is showing some green vegetation and therefore, suggests better post-dam moisture retention or availability leading to more vegetation. The dam has presumably improved moisture availability downstream. This can improve agriculture, vegetation, and lessen drought stress. Such changes are quite evident in the maps and representing a response to land cover, while acknowledging and incorporating increased moisture. The output from the Google Earth Engine is unmistakably showing the positive influence of dam construction on regional moisture balance. The methodology used here is using satellite data measured in space and time to analyze moisture balance throughout seasonal cycles. The data provide a snapshot of spatial patterns (changes happening across different areas) and also a snapshot of temporal dynamics (changes happening over time) to give a definitive understanding of how moisture availability is influenced by climatological events such as monsoon rain.

3.0 Results and discussions

3.1 Pre-monsoon moisture distribution

The map produced by the algorithm enables a varied and dispersed moisture distribution. The variation emphasizes the regional hierarchy of water availability, where some places receive little moisture, while others experience very high drying rates. This variation may imply that some areas have slightly better soil characteristics, vegetation cover, and landscape position for maintaining moisture, and that other areas experience compositional characteristics that have factors that fast track drying, such as high evaporation or low infiltration rates (Fig. 2-top). This demonstrates a precarious moisture balance during the pre-monsoon season, and especially with little rainfall, that there is loss of moisture at a rapid rate due to high temperatures. The variation occurs spatially across land parcels dependent upon various water holding characteristics, which can be determined by soil texture, land use, and elevation. Such disjunctive moisture distributions are indicators of ecological stress, as well reduced agronomic potential in dryland agriculture systems.

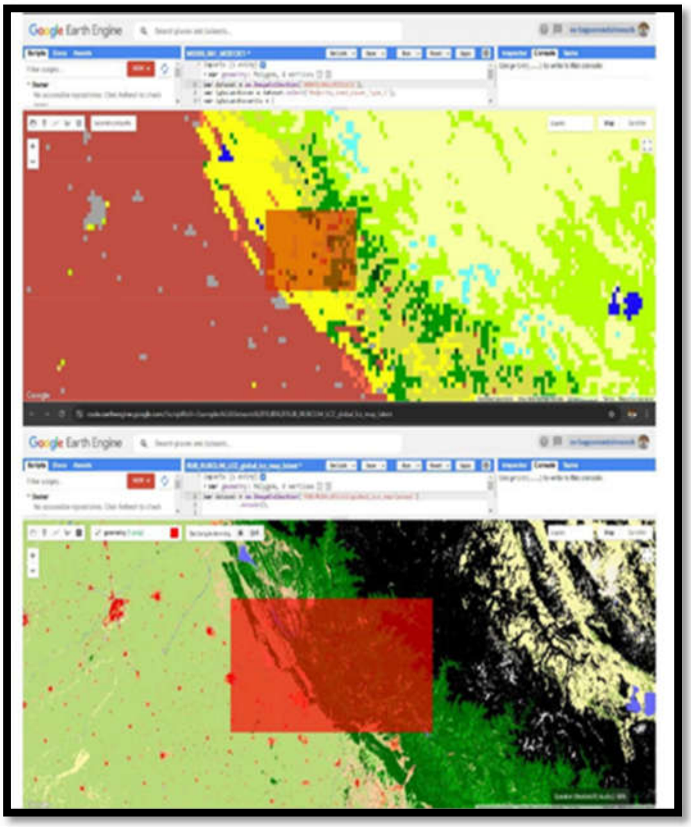

Fig. 2 Post dam construction moisture balance algorithm

3.2 Post-monsoon moisture accumulation

In this case, a reasonable assumption is made that the moisture map at post-monsoon indicates a relatively constant and stable moisture distribution pattern across the terrain (Fig. 2-bottom). This is primarily due to that the monsoon rains accumulated between these two months recharge the soil and groundwater systems quite well. The algorithm also implies that moisture balance ratio becomes healthier and more consolidated in post-monsoon phases, suggest soil across the region is saturated, or near saturation. Moisture is more uniformly balanced between them reducing the regional imbalance that was present during pre-monsoon. These bolstered moisture states of the area culminate into vegetation growth, agricultural productivity and groundwater recharge. Findings emphasize the significant role of rainfall intensification and soil types to consider. While rainfall is the primary water input, it is the characteristics of the soil on the water holding capacity which determine how long moisture is stored and becomes routinely available after a rain event. Soils with higher water holding capacity, (such as clay loams) store the moisture longer, sustaining post-monsoon water levels after the monsoon has practically ceased. The algorithm is utilizing spatio-temporal satellite data.

3.3 Topographic behaviour of flood

The pre-monsoon period is characterized by fairly light, intermittent rains and relatively little surface runoff and water pooling in depressions or hollows. Generally, these drier or semi-dry conditions limit the visibility of terrain relative to flood behaviour, as the volume of rainfall does not seem significant enough to initiate any substantial hydrological activity such as over-stream bankflow, pooling, or flash flooding. In most respects, the post-monsoon period is the polar opposite in the hydrodynamic behaviour of the landscape. Following the periods of intense monsoon rainfall, inland has generally become almost fully saturated with elevated water tables. For these events, floods are primarily topographically controlled, dependent on initiation, status, and spatial extent.

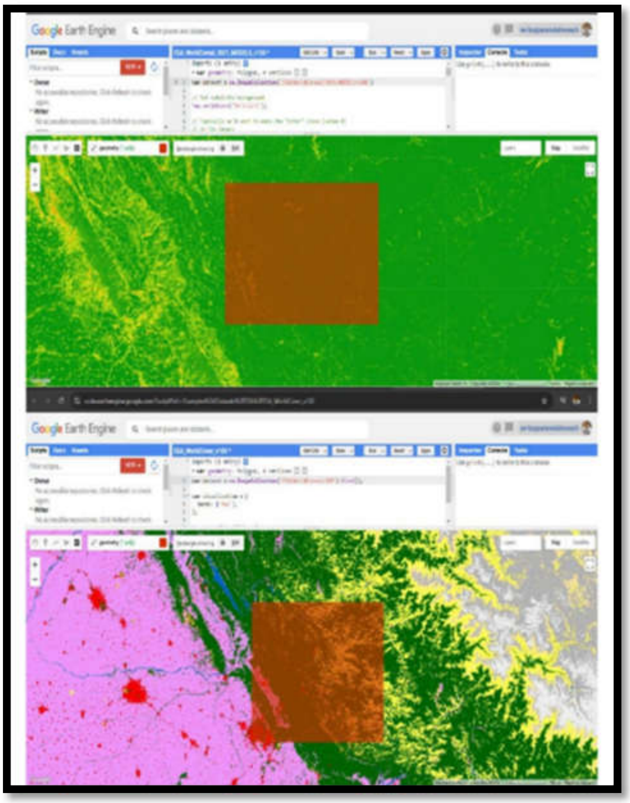

Fig. 3 Topographic behaviour of flood

All forms of landform have a separate impact on the overall event. High-hill locations are defined as runoff zones where runoff charges steep slopes, increasing the thickness of later floodwater downstream. Mid-slope areas act as either temporary channel flows or natural attenuation functions, depending on their vegetation cover and the infiltration capacity of the soil. Lowlands and floodplains are physiographically the lowest places on the land surface and function as natural catchment areas for water that drains from elevated places. Because of the low elevation, these areas are prone to flooding, waterlogging, and long durations of inundation, especially where drainage facilities are unknown or unable to handle the volume of water. In the post-monsoon period, even small depressions in the land surface, such as abandoned river channels, dry lakebeds, or shallow depressions, might be flood sites due to soil saturation and continued inflow of water (Fig. 3-bottom).

3.4 Stress degree day index

The Stress Degree Day Index (SDDI) is a numerical indicator of heat stress in plants, which is employed in agriculture and environmental science. It can be computed as:

$$SDDI = (Tc - Ta)$$

Where, Tc = Canopy temperature,

Ta = Ambient temperature.

This index represents the disparity between the canopy temperature and air temperature. The higher the SDDI, the more heat stress the plant undergoes, usually because of limited transpiration due to factors like water scarcity or high atmospheric demand. In the pre-monsoon months (typically March to May in South Asia) strong solar radiation causes high atmospheric temperatures and enhanced evapotranspiration. Precipitation is limited, and irrigation may not be sufficient to refill the moisture lost on the soil, therefore plants may go through soil moisture stress. Plants typically close their stomata in order to avoid water loss, and additionally, this reduces the transpiration of the plant. This can increase the canopy temperature above the ambient (Fig. 4-top). In the post-monsoon months, rainfall will refill the soil moisture and allow sufficient plant water uptake. Once there is sufficient moisture, plants will be able to maintain their stomata open, and the transpiration will assist in cooling the canopy and keeping canopy temperatures more similar to the ambient temperatures or even lower.

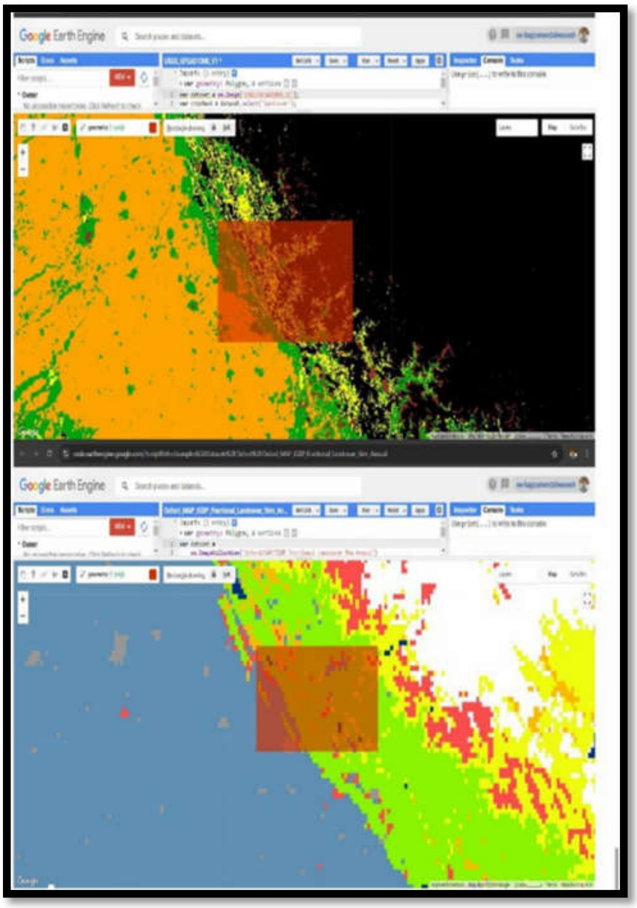

Fig. 4 Stress degree day index

The SDDI values were substantially lower in the post-monsoon period, as a result of decreased heat stress and enhanced relationship between canopy and air temperature (Fig. 4-bottom). The variation in SDDI on the pre-monsoon and post-monsoon basis indicates the considerable importance of environmental parameters such as solar radiation and soil moisture in plant physiological behaviour. SDDI monitoring provides an early warning of crop stress for irrigation scheduling and agricultural operational management to mitigate thermal and moisture stress-related crop yield loss.

3.5 Vegetation influence on flood

Vegetation typically performs a crucial function in regulating flood processes, in part through rainfall interception, increasing infiltration, root reinforcement of soils, and delaying surface runoff. However, in a landscape, the effectiveness of these processes is determined largely by the spatial aspects of vegetation itself. Typically, the pre-monsoon period is characterized by relatively dry soils, with low moisture content in soils over significant areas of vegetation and sparse vegetation. The vegetation is sparce in some areas, usually due the dry period and short-term moisture in soil. The vegetation is typically able to intercept any early showers and limit soil erosion. The initiation of some sites regrowing vegetation is allowing for hydraulic resistance against overland flow, during the very initial rains (Fig. 5). The spatial pattern of the vegetation can serve as a mechanism of flood mitigation in both the pre and post-monsoon periods. However, a slight variation in the strength of the vegetation over seasons, particularly where rainfall transition from anomalously low to anomalously high events, displays very little buffering capacity when rainfall goes beyond a threshold amount. This reinforces adding the more important consideration of man-made sitting dams, to augment natural flood controls. A merging of ecological infrastructure would set a companion cushion for flood resilience in a variable.

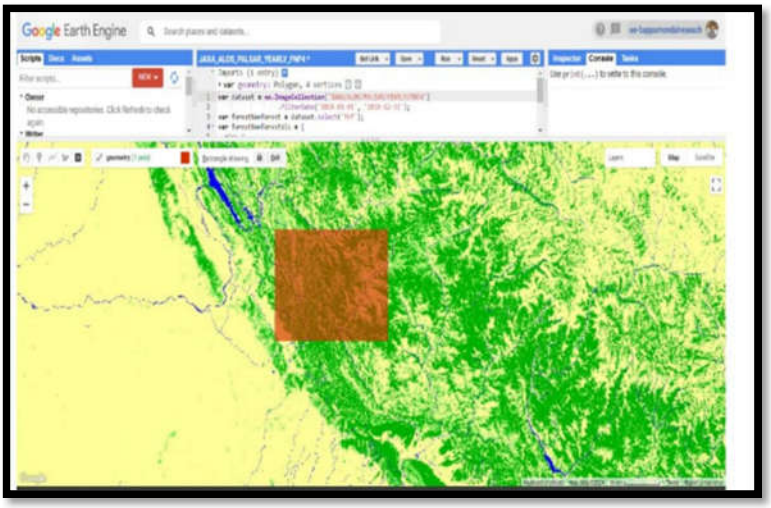

Fig. 5 Vegetation influence on flood

3.6 Flood simulating factors

Flooding simulations are significant for hydrologists for flood prediction, management and mitigation of flooding effects. Flood hydrology and flood simulation includes a topographic and weather distribution of parameters that impact the flood. Some topographic parameters of significance are slope, sediment transport index (STI), focal flow, stream power index (SPI), and flow accumulation. These parameters help characterize the terrain and water movement patterns relevant to flood dynamics. Slope accounts for the steepness of the terrain and is an important parameter of consideration in hydraulic studies. Slope directly impacts the speed of overland flow: the greater the slope the higher the flood discharge downstream. On the lower slope side, slower speed runoff promotes infiltration and as a result decreases flood intensity. Slope parameterization in flood simulation, identifies areas where there is relatively rapid flow and follow accordingly where erosion and flash flooding can form. The sediment transport index is a metric that provides a measure of sediment movement potential in the landscape and fundamentally represents a combination of the slope and contributing area sources. With floods, high values of STI represent the potential storm events where sediment erosion and sediment movement would be enhanced with overland flow. Focal flow identifies the density of water that is flowing toward a specific location in the landscape, and is generally derived from digital elevation models (DEMs). Focal flow also identifies the likely paths of water, and identifies locations that water is concentrating in runoff. This parameter is useful in modelling for flooding, as areas of focal flow indicate likely locations of water convergence, and may create flooding locations with or without joining an existing drainage network. High focal flow areas could also be related to a location for erosion or gullies. Stream power index describes erosive power of flowing water by incorporating slope and specific catchment area. It is a measure of sediment energy that can be made available to either mobilize or operate as sediment supply in channels. In flood simulations SPI can be applied to identify where water channels can flow strongly enough to create effective geomorphic change, ie. deepening or broadening channels. Also, SPI channels that could be considered unstable can likely be high risk factors during flooding which could also be a greater flood hazard downstream.Flow accumulation indicates the number of upstream cells that flow to a cell in a DEM. It reflects the amount of water that could be added to a point. Areas with high flow accumulation typically indicate channelized flow or depressions that would likely flow substantial amounts of water during a storm. Therefore, it's one of the principal conditions of possible flood areas. In conjunction with raindrop data and land use attributes, flow accumulation is able to predict the extent and intensity of flooding. In flood modelling, no one parameter is enough, instead slope, STI, focal flow, SPI, and flow accumulation are all parameters that together allow to model the complex conditions of flooding in a specific location. These are all parameters of relief and help compute the flow of water, movement of sediment, and the distribution of energy throughout the landscape and these are all factors that are central to modeling to determine where, when, and how flooding will occur.

4.0 Conclusion

The flood modeling of the Atreyee and Punarbhaba river systems provided key information on hydrologic performance, flood behavior, and spatial patterns of flooding in the transboundary floodplains of northern West Bengal and adjacent Bangladesh. Hydrologic and hydraulic modeling integrated with remote sensing and GIS, captured the temporal variability of runoff and the spatial extent of flooding. Both rivers responded to short-duration, intense monsoonal rain, which often led to concurrent flood peaks due to their relative geographic proximity and shared catchments. Low channel slopes, siltation, and encroachment of floodplains compounded flood extent and longevity. The flood scenarios demonstrate that regions around Balurghat, Gangarampur, and Thakurgaon are especially vulnerable to regular inundation, putting agriculture, infrastructure, and livelihoods at extreme risk. The model validation against observed data supports the use of the flood modeling as a reliable indication of what is possible, making the simulations suitable for planning practices for flood preparedness and response. The need for basin level, transboundary cooperation between India and Bangladesh is evident for effective sharing of data, joint water management, and sustainable flood mitigation practices.

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