



Assessing Flood Risk at the Catchment Scale by Integrating Hazard and Vulnerability with Climate Change Context

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ABSTRACT

Frequent flooding in the central part of the Hindu Kush region, Nepal, results in substantial damage to lives and property, particularly in the plains. This study explores the catchment-scale flood hazard and vulnerability, generating flood risks under climate change scenario. Flood model was developed using HEC-RAS 2D rain-on-grid approach and CMIP6 projected climate data for SSP245 and SSP585 scenarios was used. Flood hazard, vulnerability and risk maps were generated delineating potential inundation scenarios for both 50-year, and 100-year return periods, under present and future climate scenarios. Hazard maps revealed a probable increase in flooding under future climate scenarios. Vulnerability assessments also demonstrated an anticipated escalation in future. Cropland dominates the land-use type in the study area, with agriculture vulnerability increasing by 22.14% (SSP245) and 29.322% (SSP585). The number of inundated buildings increases from 2967 in the existing scenario to 4601 (SSP245) and 5274 (SSP585). Similarly, road vulnerability areas are increased by 28.06% (SSP245) and 37.86% (SSP585). The impact of flooding is higher in SSP585 scenario as compared to SSP245 scenario. The catchment level outcomes have diverse applications, particularly in decision-making for flood management, integrating risk maps for effective strategies, and providing valuable insights into shape climate change adaptation policies.

Keywords: Catchment scale, Climate change, Flood vulnerability, Flood risk, HEC-RAS 2D.

INTRODUCTION

Floods have become a widespread concern, affecting numerous regions across the globe, constituting one of the most severe natural hazards on the global scale. Over the past two decades, the consequences of floods have extended to affect over 1.65 billion people around the world (Budiyo et al., 2015; Duan et al., 2022). Nepal is susceptible to various water-related hazards, affecting

livelihoods of Terai-people every year, following the monsoon rains from June to September (Sharma et al., 2021). One such basin prone to flooding is the East Rapti river basin, emphasizing the necessity of evaluating the flood risk. In the past, the river has encountered repeated instances of significant flood intensity, primarily due to numerous temporary tributaries originating from the upstream mountains (Bruns et al., 2001). Climate change has substantial effects, particularly on water-

related hazards, including flooding. Understanding the characteristics of favorable climate conditions, rainfall patterns, basin shape and landform features is essential in grasping the mechanisms behind flood events, as extensive floods arise from the overall conditions of the basin and are often linked to specific precipitation patterns (Al-Qudah, 2011). The examination of climate change and its impact on flooding in South Asia reveals a significant shift in the dynamics, making it necessary to address the challenges posed by climatic shifts (Mirza, 2011). In Nepal, the expected rise in temperature is predicted to surpass the global average. By the 2080s, Nepal's temperature is estimated to rise by 1.2°C to 4.2°C, if the highest emission scenario is considered (WB & ADB, 2020). Therefore, assessing the impact of climate change on extreme precipitation and the resulting severe flow events is essential, as it is necessary in developing and enhancing adaptation and mitigation approaches (Lamichhane et al., 2024). Flood hazard mapping is essential for accurately estimating flood characteristics, like velocity, depth, and frequency. Recognizing the inevitability of flood-induced losses, flood hazard mapping is considered a highly effective approach for mitigation of such occurrences (Popa et al., 2019; Thapa et al., 2020). Numerous research efforts in Nepal have focused on mapping flood hazards, including Lothar Khola with the use of HEC RAS (Manandhar, 2010). Dangol (2017) focused on evaluating flood inundation in Balkhu Khola through steady-flow analysis. Dangol & Bormudoi (2017) conducted a flood analysis for the Bishnumati river.

To provide stakeholders and community with a comprehensive resource reference for flood risk management, flood vulnerability is coupled with flood hazard (Luu et al., 2020). Damage curves can be used for establishing relations between flooding and the elements at risk (Nasiri et al., 2016). Refining the accuracy of direct flood loss estimations and the incorporation of vulnerability curves into the analysis provide a valuable path for advancing multi-risk assessments (Englhardt et al., 2019). By examining the interaction between hazard and vulnerability, a more thorough understanding of risk dynamics is achieved (Banstola et al., 2019). Currently, prioritizing non-structural methods, like hazard and risk mapping, is considered more effective in reducing flood damage than structural approaches, mainly due to their positive

environmental and economic effects (Pandit & Bhattarai, 2023). Risk mapping conducted by Chidi et al. (2022) at Andheri Khola concluded that higher-risk zones are replacing low-risk areas with longer return periods. In Asian developing nations, data constraints highlight the need to improve flood-assessment methods. Quantitative analysis of flood risk amid climate change is crucial for crafting effective strategies to mitigate future damages (Shrestha et al., 2019). Flood-risk information is vital for crafting efficient flood-management strategies, aiding resource allocation and impact reduction. With the expected rise in extreme climate events in the Hindu Kush Himalayan region, proactive measures are essential for resilience (Sharma et al., 2021).

Changes in land use, land cover, and climatic behavior in the upstream part of river networks are expected to significantly increase the peak discharge of the basin (Lamichhane & Shakya, 2019). Lamichhane & Shakya (2019) integrated the impact of river run-off, and groundwater-table variation in a changing context, but lacking application in flood and associated risk assessment. Similarly, Thapa et al. (2020) conducted flood hazard mapping and vulnerability assessment at the catchment-scale, focusing on wattle and daub houses in Khado River by utilizing HECRAS-1D hydraulic modeling, flood vulnerability curves, and fragility functions. It was found that these settlements along the riverbanks would be severely affected by floods, even those with low return periods (e.g. 20 years). However, the changing future climatic behavior and the increasing frequency of flood magnitudes with the potential for natural devastation have not been adequately studied in terms of catchment level for vulnerability and risk assessment. Bhattarai et al. (2022) in a study of East Rapti watershed suggested that the hydrodynamic model is a great approach for conducting flood assessments under changing climate. The study used rainfall run-off data driven hydrologic and hydraulic modeling for flood analysis to study the impacts of flooding. However, an integrated risk map including hazard, and vulnerability parameters has not been included in the study and the paper suggested incorporating such multi-disciplinary dimensions for future flood assessment of the study area. Studies regarding the hydro-climatic projections resulting from climate change (Bhattarai et al., 2022; Dhaubanjari et al., 2020) have not answered the effects of these

projections on flood inundation at catchment scale. As a result, there is a gap in understanding the comprehensive implications of climate change on flood occurrences in the region. Integrated risk maps, considering both hazard and vulnerability parameters, are conspicuously absent in studies using hydro-dynamic models. This research gap emphasizes the urgent need for adaptive and proactive measures to address growing vulnerability and potential damages in the basin. In this regard, this study aims to assess the integrated flood risk under climate-change projections in various scenarios of East Rapti river basin. This includes the identification of flood inundation areas for assessing the flood hazard based on present and future climate-change contexts. This is followed by the assessment of vulnerability for multiple parameters and finally integrating the hazard and vulnerability to generate the flood risk for present and future climate scenarios.

MATERIALS AND METHODS

Study Area

The East Rapti river basin is in central Nepal, spanning across Makawanpur and Chitwan districts and extending from latitude $27^{\circ}21'23''\text{N}$ to $27^{\circ}47'00''\text{N}$ and longitude $84^{\circ}08'43''\text{E}$ to $85^{\circ}11'57''\text{E}$. The location map of East Rapti river basin is shown in Figure 1. The basin is prone to flooding, with 12 recorded floods in 2017 causing six fatalities and affecting 563 families, and six floods occurring between July 10 and 12 in 2019. Precipitation in the basin ranges from 150 mm in pre-monsoon, to 2000 mm in monsoon, 80 mm in post-monsoon, and 20 mm in winter annually (Karki et al., 2017). The area spans about 3200 square kilometers, with elevations varying from 2584 meters upstream to 124 meters downstream. International Centre for Integrated Mountain Development (ICIMOD)'s land classification data indicates that the basin is predominantly covered by forests, constituting 65.9% of the area, mainly attributed to the Chitwan National Park.

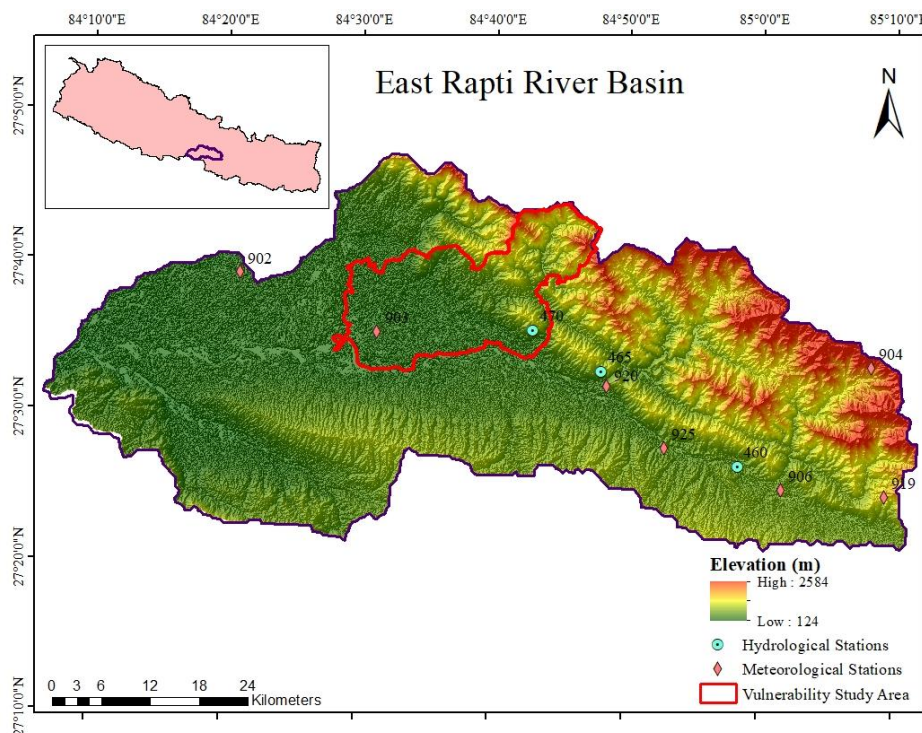


Figure (1): Location map of East Rapti river basin

Methodology

Model Setup, Calibration and Validation

In this study, the rain-on-grid modeling approach has been utilized to analyze flood hazards. Precipitation data

of seven meteorological stations used as an input dataset was obtained from the Department of Hydrology and Meteorology (DHM), Nepal along with the discharge data for Rajaiya (Station-460). Digital Elevation Model

(DEM) of 30x30m resolution was used. The data was processed by generating a Thiessen polygon of the study area, and the method was used to calculate the average precipitation data for analysis. The required dataset for modeling, including precipitation, DEM, and landuse was imported in the HEC RAS model. The optimal parameters required for the analysis were determined by conducting sensitivity analysis for different parameters, including mesh geometry, computational time step, governing equations and theta weighing factors. The

model was run multiple times until the ground result was obtained and then, the model was calibrated and validated.

After the computation, the value of Manning's roughness coefficient was adjusted according to the land classification. The result was then calibrated and validated by comparing simulated and observed discharges from the station Rajaiya along with the computation of NSE, PBIAS, R^2 and RSR values.

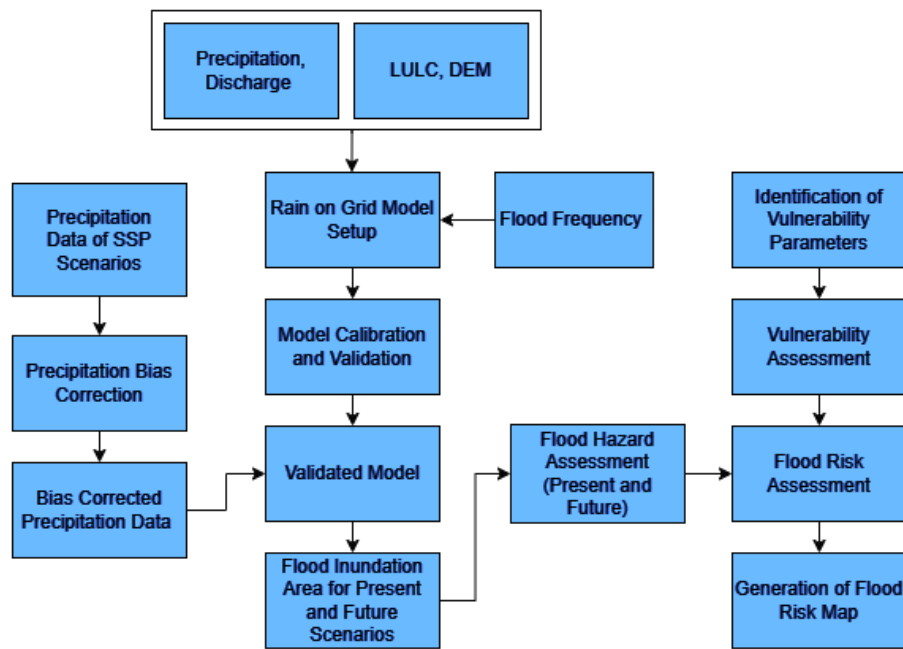


Figure (2): Methodological framework

NSE (Nash-Sutcliffe Efficiency), R^2 (Coefficient of Determination), Pbias (Percent Bias) and RSR (Root Mean Standard Deviation Ratio) (Moriassi et al., 2007) are commonly used as metrics for assessing the performance of hydrological or other models predicting continuous variables. NSE assesses how well a model's predictions match the observed values. It compares the squared differences between observed (O) and predicted (P) values to the squared differences between observed values and their means. An NSE value of 1 indicates a perfect match, while values less than 0 suggest that the model performs worse than a simple mean. R^2 quantifies the proportion of the variance in the observed data explained by the model. It is calculated by comparing the squared differences between observed and predicted values to the squared differences between observed values and their means. R^2 ranges from 0 to 1, where 1

signifies a perfect fit and 0 indicates that the model's performance is worse than predicting the mean. Percent bias measures the average tendency of the model to overpredict or underpredict compared to observed values. It calculates the percentage difference between observed and predicted values relative to their average. A Pbias of 0 indicates an unbiased model, while positive values suggest overprediction and negative values indicate underprediction. RSR assesses the goodness of fit by considering the ratio of the root mean square error to the standard deviation of observed values. RSR values closer to 0 indicate better model performance, with 0 representing a perfect match. Higher RSR values suggest that the model's performance is worse than predicting the mean.

Flood Hazard Assessment

The identification of factors contributing to flooding is essential for the preparation of hazard maps (Stefanidis & Stathis, 2013). Flood depth emerges as a key factor for assessing the damage extent and calculating the associated hazards. Flood hazard assessment typically focuses on the extent and depth of flooding, with flood depth as the most critical factor in this analysis (Islam & Sado, 2002).

Categorizing floods by severity, particularly depth, enhances understanding of varying impacts. This classification allows detailed analysis of risks and consequences associated with different inundation depths. This study categorizes flood hazards by depth: under 1 meter as Low, 1-2 meters as Moderate, 2-3 meters as Significant, and over 3 meters as Extreme. This classification, based on interviews with locals and previous studies in East Rapti river basin and other Nepalese regions, provides valuable insights into the perceived degree of hazard associated with each flood depth (Banstola et al., 2019; Bhattarai et al., 2022; Pandey & Dugar, 2019).

Climate-change Analysis

This study has used five Global Climate Models (GCMs) within the framework of CMIP6 (Coupled Model Intercomparison Project Phase 6). The choice of GCMs stems from a strategic consideration of their reliability and relevance, considering the accessibility of historical and future daily-rainfall data. The focus on both Shared Socio-economic Pathways (SSPs), SSP245 and SSP585 scenarios, further highlights the comprehensive nature of the investigation, providing an understanding of climate dynamics. In the South Asian context, their usage has been prevalent, adding depth to the rationale behind their selection. This particular approach aims to ensure that the chosen GCMs align with the study's objectives, enhancing the applicability of the climate projections utilized in this study (Mishra et al., 2020). The five GCMs used are ACCESS, EARTH, MIROC, MPI and MRI.

The CMIP6 scenarios were chosen, ranging from the most challenging SSP585 to the moderately challenging SSP245 trajectory, to encompass a spectrum of potential future conditions. SSP585 envisions a world with heightened fossil fuel usage and swift economic growth, resulting in elevated greenhouse gas emissions and a radiative forcing trend of about 8.5 watts per square

meter (W/m^2) by 2100. In SSP245, a future emerges with moderated greenhouse gas emissions, yielding a radiative forcing trajectory of around 4.5 watts per square meter (W/m^2) by 2100 (O'Neill et al., 2016). To enhance reliability and address potential errors in the models, bias correction using the RQUANT approach, which employs non-parametric quantile mapping with robust empirical quantiles, was applied. It estimates the quantile-quantile relationship between observed and model time series for regularly-spaced quantiles through local linear least-square regression. Subsequently, it performs quantile mapping by interpolating the empirical quantiles (Tong et al., 2021). If the model's biases are not addressed, the reliability of the dataset and the outcome will be weakened Aryal et al., 2022). The bias corrected precipitation data from all five GCMs was obtained. However, based on the statistical indicators, only the data from MIROC was selected for further analysis. The results are as shown in Figure 3. The bias-corrected precipitation data was then used for the calculation of future return period flood. The data generated was then used as input in the calibrated and validated model in HEC RAS in order to generate the future inundation maps.

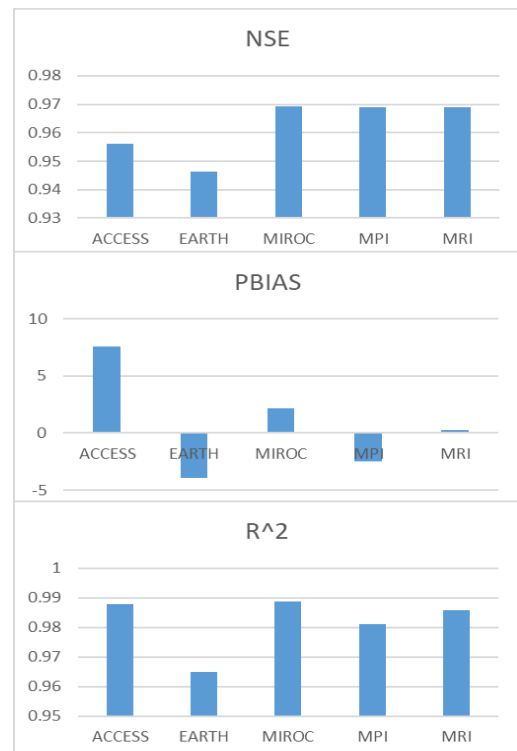


Figure (3): Statistical indicator values for different GCMs

Flood Vulnerability Assessment

In this study, buildings, roads, and agriculture have been selected as indicators for physical vulnerability. For social vulnerability, population density, healthcare, education, and disadvantaged groups have been chosen. For vulnerability assessment, a stretch of the basin, including Ratnanagar, Khairahani, and Rapti municipalities of Chitwan district was analyzed, considering the depth and extent of flooding. For physical vulnerability, existing depth damage curves adopted from the literature have been used. For social vulnerability, vulnerability scores were assigned to each indicator.

Physical Vulnerability

- **Buildings**

For building vulnerability assessment, QuickOSM was utilized combined with Google Earth Pro for the manual digitization of buildings. The buildings were then categorized based on typology, such as adobe, brick-cement masonry, and reinforced cement concrete (RCC) houses. This study employed well-developed curves for vulnerability assessment, using the curve developed by Englhardt et al. (2019) for adobe and brick cement masonry buildings. For RCC buildings, the curve developed by Dutta et al. (2003) was used.

- **Roads**

For assessing road vulnerability, data was extracted using QuickOSM in QGIS. The damage curves utilized for roads were adopted from Haque et al. (2023). These curves represent earthen and bituminous concrete roads, closely resembling the types observed in the study area.

- **Agriculture**

In agriculture vulnerability, emphasis was given to paddy crops. Depth damage curve developed by Shrestha et al. (2016) was used in this study. The curve has been used in multiple studies in Southeast Asia, and in Nepal for the study of Bagmati basin. The study mentions that the curves can be used for various other river basins as well for assessing the flood impacts. As per the interviews conducted, the occurrence of flooding is generally during the maturity stage of paddy crops and the damage occurs only when the flood continues for more than 3-4 days. Shrestha et al. (2021) considered similar values for the assessment of agriculture vulnerability. The damage curve used in this study has thus been chosen for the same stage.

Social Vulnerability

Social vulnerability is assessed on a ward level. The data for social vulnerability includes calculating the population density of all the wards in the municipalities by dividing the total population of the ward by the total area of that ward itself. The number of disadvantaged populations and educated populations in the wards was obtained from the Central Bureau of Statistics (CBS) and the number of health facilities was obtained from each municipality office. The social vulnerability scores were determined by assigning values to specific parameters: Population (0.5), Healthcare (0.2), Education (0.15), and Disadvantaged Group (0.15) according to the Atlas of Natural Hazards and Risks in Georgia (CENN, 2018).

Flood Risk Assessment

Risk is a function of hazard and vulnerability, and after their computation, risk maps are generated by multiplying them, focusing on the 100-year return period across all scenarios.

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability}.$$

RESULTS AND DISCUSSION

Model Setup, Calibration and Validation

The parameters subjected to sensitivity analysis include mesh geometry, computational time step, governing equations set, and theta weighing factors. The chosen parameters not only demonstrate a proper balance in accurately representing the hydraulic properties, but also ensure a reasonable computation time step for practical analysis. The constructed HEC RAS model underwent calibration and validation for the years 2006, 2007, 2009, 2010, 2011, 2012, 2018, and 2019. The values of statistical parameters obtained after calculation show that the model's performance is satisfactory, as recommended by Moriasi et al. (2007). The NSE ranges from 0.518 to 0.82 and from 0.688 to 0.925 for calibration and validation, respectively. Similarly, the values for R^2 range from 0.519 to 0.848 and from 0.806 to 0.926 for calibration and validation, respectively. Likewise, the Pbias values for calibration and validation range from -0.025 to 1.214 and from -0.087 to -3.493, respectively. Additionally, the values for RSR range from 0.424 to 0.693 and from 0.273 to 0.558 for calibration and validation, respectively. The validation phase's values show a better relation

compared to the calibration phase. However, all the numerical values for NSE, Pbias, R^2 and RSR obtained were found to be within the acceptable limits. The findings indicate a close alignment between the simulated and observed values, demonstrating minimal dispersion. This analysis instills confidence in the model's reliability and its capability to accurately represent the study region.

Climate-change Analysis

The bias-corrected precipitation data from the selected GCM (MIROC) served as input for assessing future return period flooding. Figure 4 illustrates a general increase in total annual precipitation in the future. Both dry and wet seasons in the study area are expected to be wetter compared to historical data. The range of annual projected precipitation spans from 2271.182 mm in historical scenario to 3310.49 mm in

SSP 245 and 3756.74 mm in SSP585, with SSP585 projecting higher rainfall than SSP245. The graph shows a rise in the peak annual precipitation levels when comparing future projections to historical data, suggesting a potential amplification in the intensity of upcoming floods. The trend of precipitation, found to be positive, shows a gradually increasing trend in SSP245 and SSP585 scenarios. The one-day annual maximum precipitation during the baseline period ranges from 37.240mm to 258.153mm, expanding to 50.26mm to 348.977mm for SSP245, and further expanding to 60.5523mm to 361.6374mm for SSP585. Notably, SSP585 signifies a higher magnitude of rainfall compared to SSP245. This observed upward trend in precipitation extremes highlights the urgency for comprehensive flood-risk management strategies, considering the evolving climate dynamics in the region.

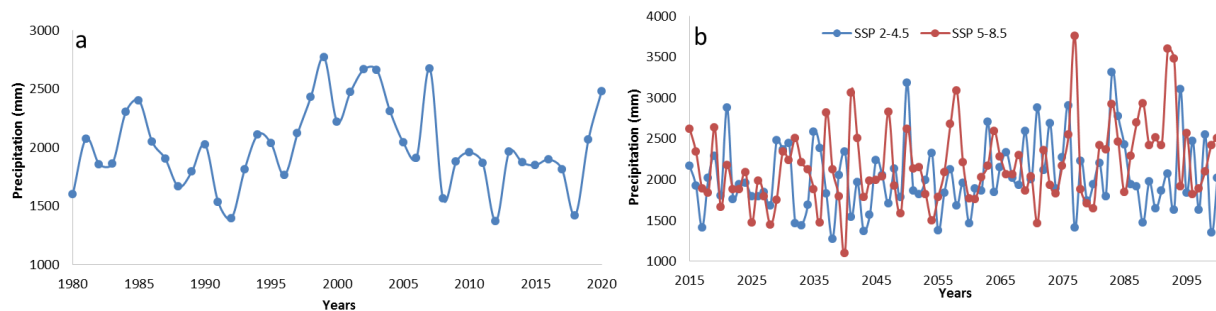


Figure (4) a) Historical annual total precipitation, b) Future annual total precipitation for SSP 2-4.5 and SSP 5-8.5 scenarios

Flood-hazard Assessment

The generated inundation map in HEC RAS was extracted for conducting flood-hazard assessments, where the depth of flooding is considered the primary evaluation criterion for determining hazards. For a 50-year return period, it is evident that the inundation area is highest in the low-flood hazard classification. In both SSP245 and SSP585 scenarios, the region of extreme flooding has increased. The total inundated area increases from 19.8% in the existing scenario to 25.3% and 27.4% in the future SSP245 and SSP585 scenarios. For a 100-year return period, in the present scenario, low and extreme floods cover 49.6% and 20.59%, respectively. In the future SSP585 scenario, the inundated area covered by low and extreme flood becomes almost equal at 36.07% and 32.14%, respectively. The total inundated areas have also

increased by more than 100 sq. km when comparing present and future scenarios. SSP585 scenario shows a significantly larger affected area compared to SSP245. The heightened severity in future flooding implies that the potential for damage from flooding may increase in the future.

Inundation area according to different landuse types is shown in Table 1. The study's findings on landuse indicate that cropland experiences the most substantial impact from floods across all return-period scenarios. Agriculture is the primary income source for most locals in the study area, and the effect of flooding on cropland has significant implications on their livelihoods. This emphasizes the critical importance of understanding and addressing the challenges posed by flood-related impacts on agricultural activities in the region. The change in the inundation area between future and

existing climate scenario is shown in Table 1. The change in percentage was found to be 17.4% and 23.6% for 50-year return period and 22.6% and 29.9% for 100-year return period for SSP245 and SSP585, respectively. The basin-scale flood hazard maps for existing and future scenarios for 50-year and 100-year return periods are shown in Figure 5. In the future climate scenario, areas with less than 1-meter depth decrease while those exceeding 3 meters increase for both return periods. Comparison shows more flooding in the 100-year than in the 50-year return period, with SSP585 indicating higher hazard than SSP245. The comparison of flood hazard maps of present and future climate scenarios is illustrated in Figure 6.

For a 50-year return period, the flood hazard change decreased by 0.13% and 0.17%, and increased by 31.79% and 39.39% for SSP245 and SSP585 scenarios, respectively, with the rest of the area remaining constant. Similarly, for a 100-year return period, the observed change decreased by 0.16% and 0.20%, and increased by 39.58% and 47.24% for SSP245 and SSP585 scenarios, respectively, with the rest of the area remaining constant (Table 2). This highlights a significant elevation in hazard levels when considering climate-change projections, emphasizing the crucial importance of comprehending, and addressing challenges posed by flood-related impacts.

Table 1. Percentage change in inundation area for land use

Land Use	Inundation Area (km ²)		Percent Change in Inundation Area from Present to Future Climate Scenarios			
	Existing Scenario		SSP 245		SSP585	
	50 years	100 years	50 years	100 years	50 years	100 years
Waterbody	15.01	15.31	10.9%	14.1%	14.3%	18.1%
Forest	157.51	161.58	15.2%	19.6%	20.0%	25.7%
Riverbed	42.02	42.92	11.9%	14.9%	15.8%	18.9%
Built up Area	6.97	7.19	16.7%	22.0%	23.1%	29.7%
Cropland	177.55	184.21	20.9%	27.7%	29.0%	37.1%
Bare Soil	0.015	0.015	0.0%	0.0%	0.0%	0.0%
Grassland	13.73	14.18	17.6%	20.9%	22.9%	25.9%
Other Wooded Land	23.64	24.56	19.2%	24.4%	26.4%	32.3%
Total	436.63	450.13	17.4%	22.6%	23.6%	29.9%

Table 2. Hazard area for various scenarios

Hazard Class	Area(km ²) for 100 YRP			Area(km ²) for 50 YRP		
	Present	SSP245	SSP585	Present	SSP245	SSP585
Low	223.60	217.34	211.01	222.49	221.85	219.58
Moderate	88.76	108.10	112.69	85.37	100.41	106.13
Significant	45.06	67.88	73.24	41.93	60.49	65.74
Extreme	92.70	158.8	188.01	86.83	129.97	148.19
Total	450.13	552.16	584.96	436.63	512.74	539.66

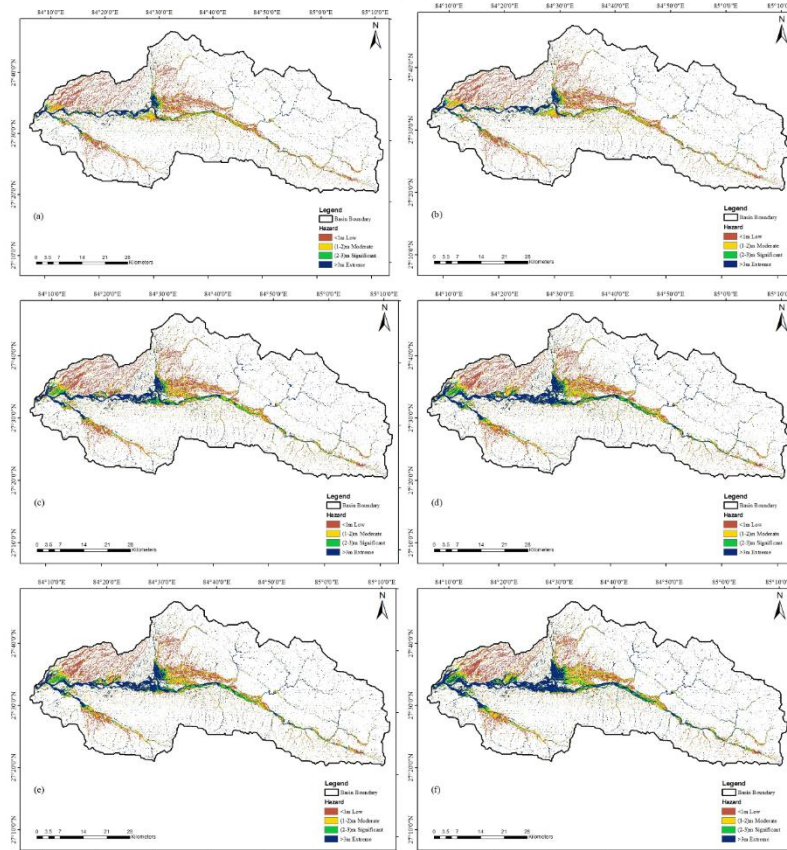


Figure (5): Hazard maps for (a) Present scenario 50YRP (b) Present scenario 100YRP (c) SSP245 scenario 50YRP (d) SSP245 scenario 100YRP (e) SSP585 scenario 50YRP and (f)SSP585 scenario 100YRP

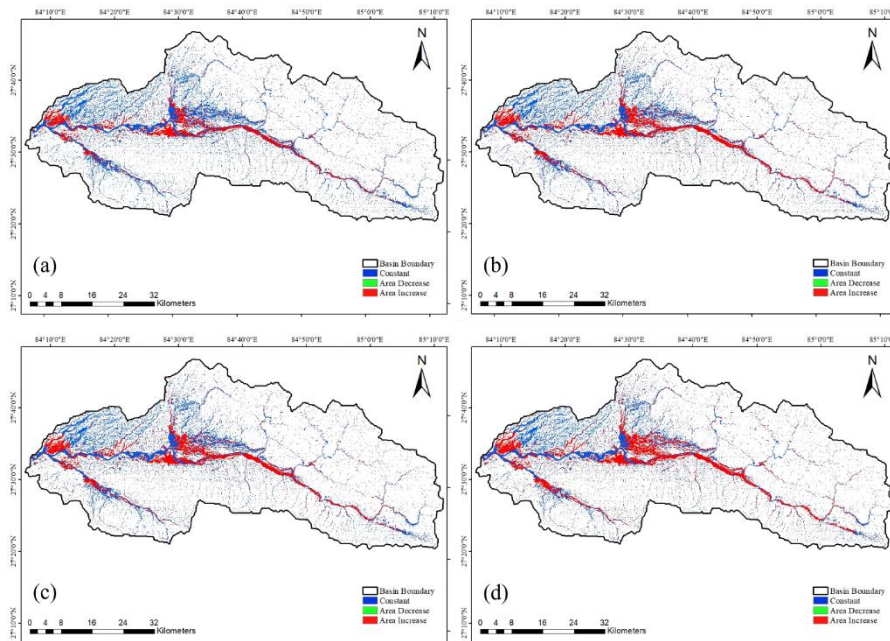


Figure (6): Comparison of change in area (a) Present 50YRP and SSP245 scenario 50YRP (b) Present 50YRP and SSP585 scenario 50YRP (c) Present 100YRP and SSP245 scenario 100YRP and (d) Present 100YRP and SSP585 scenario 100YRP

Flood Vulnerability Assessment

Physical Vulnerability

- **Buildings**

A total of 2967 buildings were inundated with the 100-year return period flood in the existing scenario (Table 3). Similarly, for the future SSP245 and SSP585

scenarios, the total number of inundated buildings increased to 4601 and 5274. This increase is attributed to the rise in precipitation and the corresponding expansion of the inundation area in different climate scenarios, potentially leading to such events in the river corridor.

Table 3. Building count in each hazard class

Hazard (Depth of Flood (m))	Building Count				Total	Building Typology		
	<1	1 to 2	2 to 3	> 3		Adobe	RCC	Brick Cement Mortar
Existing-100 YRP	2071	488	174	234	2967	466	2003	498
SSP245-100 YRP	2767	918	367	549	4601	1001	2750	850
SSP585-100 YRP	2852	1229	395	798	5274	1182	3093	999

Referring to the existing vulnerability curves employed in this study, it is apparent that adobe houses have the highest damage factor, followed by brick cement mortar houses, while RCC houses exhibit the least damage factor. Adobe houses experience damage of up to 90% at a 1-meter depth. According to a study by Maiti (2007), mud walls are susceptible to failure even when submerged one meter in water. Brick cement mortar buildings tend to incur a 50% damage rate at a 1-meter flood depth due to the reduced ability of unreinforced walls to withstand water pressure (Englhardt et al., 2019). RCC buildings show lower susceptibility, with an estimated 25% damage occurring at a 1-meter inundation depth, classifying them as more resilient to flooding. For an inundation depth of 2

meters, adobe houses get completely damaged, while brick masonry houses and RCC houses experience around 75% and 40% damage, respectively. These damage factors were used to calculate the vulnerability of buildings in the studied area stretch. The maps generated are illustrated in Figure 7 (a, b, c).

- **Roads**

Table 4 shows the total road damage area for a 100-year return period of present scenario and future SSP245 and SSP585 scenarios. The study reveals a significant rise in inundation levels, increasing by approximately 28.06% and 37.86% for SSP245 and SSP585, respectively, when comparing present to future 100-year return period scenarios.

Table 4. Road area damage in existing and future scenarios

Hazard	Road Damage Area(m ²)					
	Existing-100 YRP		SSP245-100 YRP		SSP585-100 YRP	
	Earthen	Bituminous Conc.	Earthen	Bituminous Conc.	Earthen	Bituminous Conc.
<1	343.97	666.52	317.42	709.95	313.45	694.07
1 to 2	518.69	817.33	739.57	1367.95	742.88	1607.20
2 to 3	513.73	533.42	702.84	1069.48	860.68	1367.95
>3	943.07	943.90	1864.64	1925.03	2311.36	2603.38
Total	2319.46	2961.17	3624.46	5072.41	4228.36	6272.60

- **Agriculture**

The study outcomes reveal significant variations in inundation levels when comparing the existing 100-year

return period scenario with future projections. There is an increase of around 22.14% and 29.322% for SSP245 and SSP585 scenarios respectively. (refer to Table 5).

These findings underscore the nature of flood patterns under different climate-change scenarios, emphasizing the significance of considering multiple projections for comprehensive assessment. Table 5 presents the damage area for agriculture, calculated using the damage factor obtained from the existing depth damage curve adopted from Shrestha et al. (2016). The damage area for the existing scenario's 100-year return period is 27.28 km².

Similarly, the damage areas for the 100-year return periods under the SSP245 and SSP585 scenarios are 35.90 km² and 39.54 km², respectively. These findings highlight the potential increase in the extent of damage due to flood events in future climate scenarios compared to the existing scenario. The maps for these scenarios are shown in Figure 7 (d, e, f).

Table 5. Agriculture inundation and damage in existing and future scenarios

Hazard	Agriculture Inundation Area (km ²)			Agriculture Damage Area (km ²)		
	Existing - 100 Years	SSP245 - 100 Years	SSP585 - 100 Years	Existing - 100 Years	SSP245 - 100 Years	SSP585 - 100 Years
<1	38.91	36.43	32.98	15.56	14.57	13.19
1 to 2	11.12	19.29	22.31	6.11	10.61	12.27
2 to 3	4.02	7.60	9.87	2.21	4.18	5.42
>3	6.15	11.88	15.72	3.38	6.53	8.65
Total	60.21	75.21	80.90	27.28	35.90	39.54

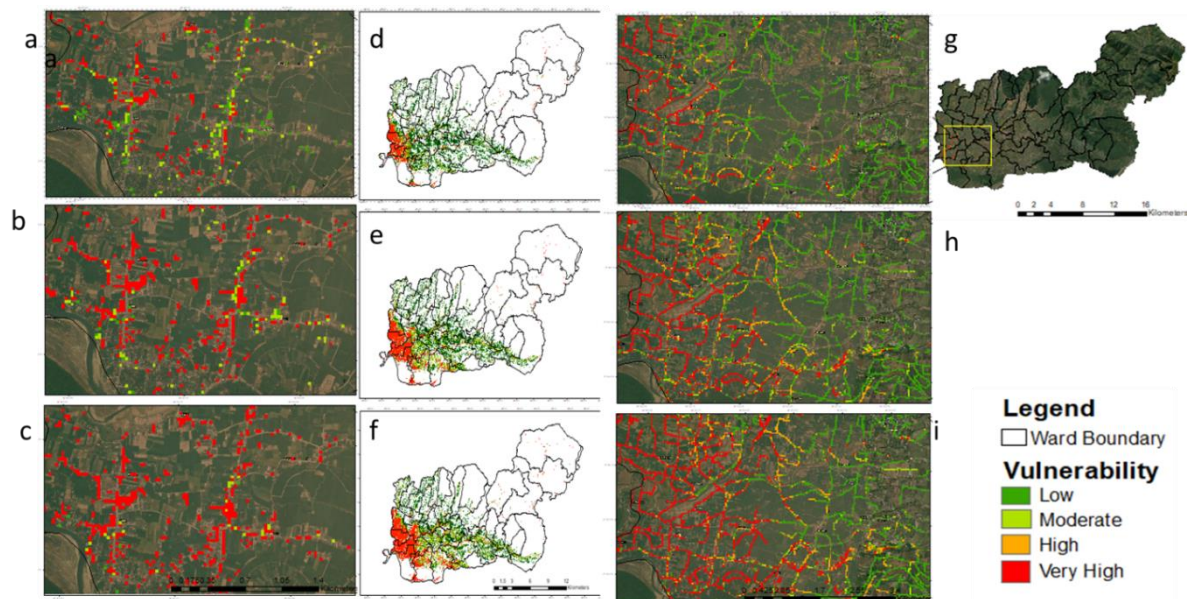


Figure (7): Building vulnerability for (a) Present scenario (b) SSP245 scenario and (c) SSP585 scenario, agriculture vulnerability for (d) Present scenario (e) SSP245 scenario and (f) SSP585 scenario and road vulnerability for (g) Present scenario (h) SSP245 scenario and (i) SSP585 scenario

Social Vulnerability

The social vulnerability map highlights that the wards in Ratnanagar municipality are situated in a more vulnerable zone compared to others (Figure 8). Flood inundation is also most pronounced in this region, coinciding with its high and growing population. In

Rapti municipality, which is at a higher elevation, vulnerability is minimal due to low population density. However, Ward 7 of Rapti and Ward 8 of Khairahani municipality exhibit very high vulnerability, attributed to higher population density.

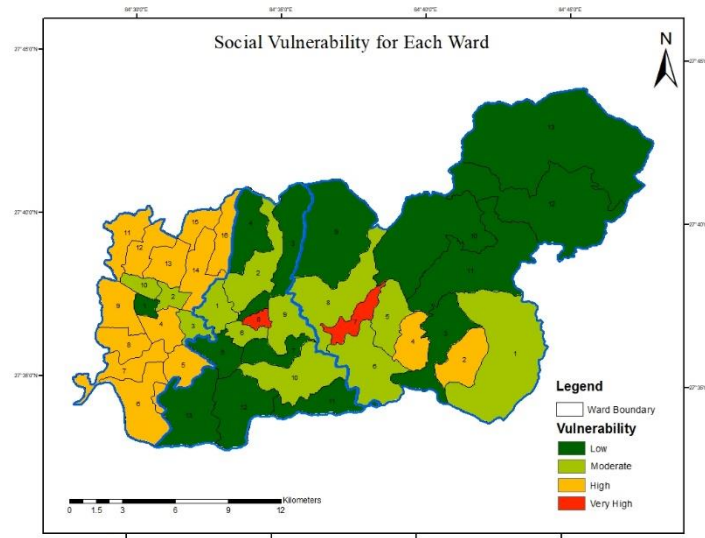


Figure (8): Social vulnerability for each ward

Flood-risk Assessment

Flood-risk assessment was conducted to generate risk maps for all parameters considered in this study. Among the areas investigated, Ratnanagar municipality exhibits the highest risk level. Wards 7, 8, and 9 in Ratnanagar municipality display the highest risk for all scenarios, with the area around Sauraha being particularly affected. In Khairahani municipality, the risk level is not as high as in Ratnanagar municipality, but some wards (10, 11, 12, 13) along the river channel exhibit moderate to high risk. In Rapti municipality, risk levels range from low to moderate in the lower regions and are almost nonexistent in the higher-elevation

wards.

The results indicate an approximately 22% and 29% change in risk from the existing 100-year return period scenario to the SSP245 and SSP585 scenarios, respectively, for agriculture (Figure 9 (d,e,f)). For road networks, the change is about 28% and 37%, respectively. The risk is notably higher in the future climate scenario for the 100-year return period compared to the present scenario (Figure 9 (g,h,i)). The area classified to be under a very high risk increases while the area under low risk decreases in future climate scenarios.

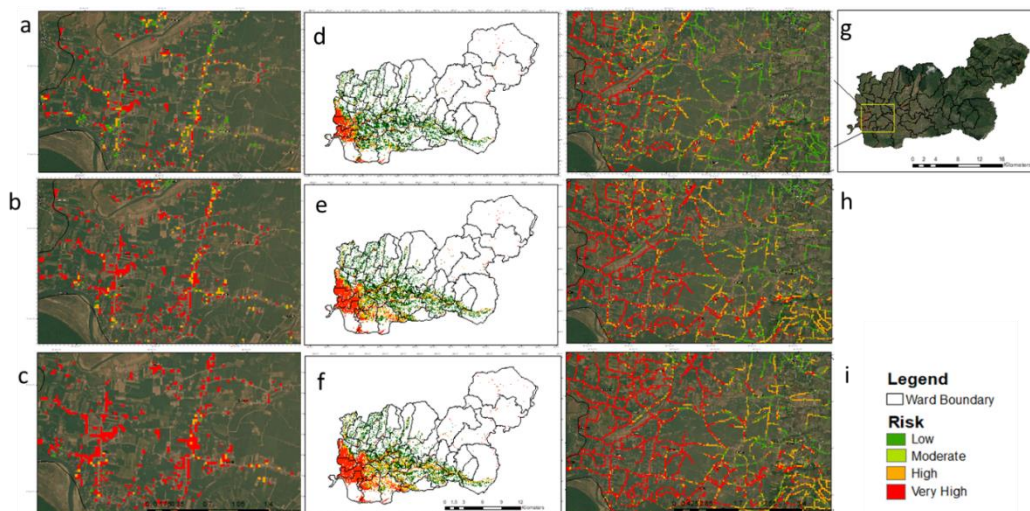


Figure (9): Building risk for (a) Present scenario (b) SSP245 Scenario and (c) SSP585 scenario, agriculture risk for (d) Present scenario (e) SSP245 scenario and (f) SSP585 scenario, and road risk for (g) Present scenario (h) SSP245 scenario and (i) SSP 5-8.5 scenario

Buildings, especially adobe houses, fall into high-risk zones due to their vulnerability even at 1-m inundation depth. People residing in these houses, being often from marginalized communities along riverbanks, face heightened vulnerability and risk. The risk for cropland, occupying the most significant area, is also at its highest value, with future scenarios indicating an increase compared to the existing 100-year return period scenario. This poses a substantial threat to most of the population dependent on agriculture for sustenance.

Social-risk maps reveal that areas with higher

population density are at greater risk as compared to other wards. Ratnanagar municipality exhibits the highest risk in both physical and social indicators (Figure 10). The level of risk significantly increases in future SSP scenarios, suggesting a potential intensification of flooding incidents. This highlights the critical need for proactive measures and comprehensive strategies to mitigate flood impacts and enhance the overall resilience. Addressing these challenges preemptively can help communities adapt to evolving flooding dynamics, ensuring long-term sustainability.

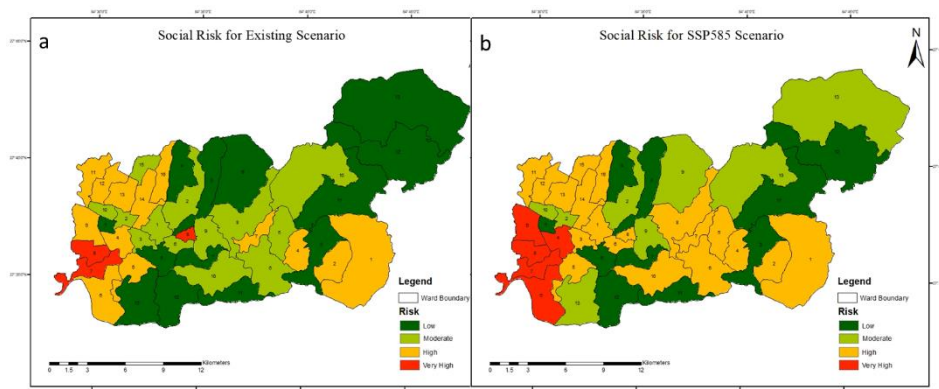


Figure (10): Social-risk map for a) Existing scenario, b) SSP585 scenario

CONCLUSIONS

This study assessed flood vulnerability and risk in the East Rapti river basin using CMIP6 climate-change projections. A flood model was developed using the HEC RAS 2D rain-on-grid approach for both current and future climate scenarios. This model was calibrated and validated to analyze flood-inundation areas. Hazard-map assessments for different scenarios indicate that future flooding is likely to increase. The findings indicate that the low-hazard class has seen minimal reduction, while there is a notable difference in the extent of hazard areas, particularly in the extreme hazard zone. For the 50-year return period, there is a 17.432% change in SSP245 and a 23.59% change in SSP585, while for the 100-year return period, the change is 22.66% in SSP245 and 29.95% in SSP585. SSP585 exhibits a greater extent of hazard compared to SSP245.

In the current scenario, 2967 buildings are inundated by a 100-year return period flood. For future SSP245 and SSP585 scenarios, the number of inundated buildings increases to 4601 and 5274, respectively.

Agricultural vulnerability increases by 22.14% in SSP245 and 29.322% in SSP585 for the 100-year return period compared to the existing scenario. Road vulnerability changes by approximately 28.06% in SSP245 and 37.86% in SSP585. The risk maps show that wards in Ratnanagar municipality, wards 6, 8, and 10 of Khairahani municipality, and wards 1, 2, 4, 5, 6, 7, and 8 of Rapti municipality are at the highest risk. The study indicates the possibility of flood risk being increased in future climate scenarios.

To enhance the robustness and comprehensiveness of flood evaluation, it can be recommended to incorporate a broader range of ensemble data and multiple GCMs by using self-generated depth damage curves. The outcomes of this study have various applications, particularly in informing flood management decision-making and integrating risk maps to develop effective strategies. The proposed methodology directly influences infrastructure planning and resilient design, providing valuable insights to promote sustainable development and mitigate the impacts of future floods, thereby shaping climate-change adaptation policies.

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