

Floods, Rivers, And Night-Time Lights: Analysing human presence and vulnerability in the Indus - Ganga Basin

Ekta Aggarwal

This thesis is submitted to Imperial College London for the degree of
Doctor of Philosophy

Imperial College London
Department of Earth Science & Engineering
Royal School of Mines
South Kensington
SW7 2BP

IMPERIAL

Declarations

Declaration of originality

I declare that this thesis, submitted for the degree of Doctor of Philosophy at Imperial College London and Associateship of the Royal School of Mines, is original research that has been completed by me, and carried out under the supervision of Prof Sanjeev Gupta and Dr Alexander C. Whittaker. All published and unpublished material used in this thesis has been appropriately referenced. None of this work has previously been submitted to Imperial College London or any other academic institution for a degree or diploma, or for any other qualification.

Ekta Aggarwal

Date – 20th October 2024

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This thesis is dedicated to my father

Anil Aggarwal

who was witnessing my PhD journey from heaven. I miss you!

ABSTRACT

Since the dawn of human civilisation, rivers have profoundly shaped both landscape evolution and population dynamics. Rivers have historically attracted human settlements due to their accessibility for navigation, trade, and resources. However, with urbanization and population growth, particularly near rivers, flood hazards have intensified, leading to significant human and economic losses. This thesis focuses on flood risks in the Indus-Ganga Basin, the world's most populous river basin, which frequently experiences severe floods. Traditional flood risk assessments often use outdated datasets that may not capture the dynamic nature of human presence and infrastructure. To address these limitations, this study incorporates novel data from night-time lights (NTL), a proxy for human activity and settlement, in flood exposure and risk assessments.

The thesis applies a remote sensing and GIS-based approach to integrate NTL data, analysing spatial patterns of human activity and their interactions with landscape factors and flood hazards. Three key components are explored: landscape drivers shaping human presence, the socio-economic impacts of floods, and the development of a comprehensive flood risk assessment framework.

I first investigate NTL data to examine the relationship between river geomorphology and human settlements in the Indus Basin. Results highlight how settlement patterns near rivers are shaped by geomorphological factors, influencing flood vulnerability. In my second project, the impact of the 2022 Indus floods is analysed through NTL, revealing significant declines in radiance, indicating disruptions to human activity. This novel approach captures flood impacts beyond the inundation zone, emphasising the compound effects on both urban and rural areas. Lastly, I introduce a flood risk assessment model for the Ganga Basin, combining flood hazard, exposure, and vulnerability indices. The study showcases the value of NTL data in assessing flood exposure and vulnerability, offering an innovative, dynamic, and cost-effective method to enhance flood risk understanding in vulnerable regions.

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CONTENTS

List of Figures

List of Table

Chapter 1: Introduction

1.1. Overview	1
1.1.1. Flooding and flood risk assessment	3
1.1.2. Night-time lights	5
1.1.3. Night-time lights based assessment of human activities and disaster impact..	7
1.2. Aims and Objectives	11
1.3. Study Area	13
1.4. Thesis outline and structure	15

Chapter 2: Investigating the Influence of River Geomorphology on Human Presence Using Night Light Data: A Case Study in the Indus Basin

2.1. Introduction	20
2.2. Study Area	22
2.3. Data	24
2.3.1. DMSP Night Light Data	24
2.3.2. SRTM DEM	27
2.3.3. LandScan Global Population Data	27
2.4. Methods.....	28
2.4.1. Processing of the DMSP Night Lights (2000–2013).....	28
2.4.2. Extraction of the Indus Watershed and Major River Tributaries	30

2.4.3. Processing of the LandScan Global Population Data	30
2.4.4. Presence or Absence of Night Lights across the Basin and Buffer Zones	30
2.4.5. Night Lights Intensity Distribution with Relation to River Channel Pattern...	32
2.5. Results	35
2.5.1. How Well Do Night Light Data Serve as a Proxy for Human Activity?	35
2.5.2. Relation between Night Light Distribution and Proximity to Rivers	37
2.5.3. How Does the Intensity of Night Lights Vary in Proximity to Rivers?	38
2.5.4. Channel Pattern Influence on Human Presence	43
2.6. Discussion	45
2.6.1. What Do Night Lights Reveal about Human Presence and Activity in the Indus Basin?	45
2.6.2. What Is the Relation between Geomorphological Parameters and Night Lights Distribution?	46
2.6.3. Implications	49
2.7. Conclusions.....	51

Chapter 3: Differential impact beyond floodwater: An insight into 2022 Indus Floods using Black Marble Night-time lights

3.1. Introduction	54
3.2. 2022 Indus Floods in Pakistan.....	57
3.3. Data	58
3.3.1. NASA Black Marble Nighttime Lights (NTL)	58
3.3.2. GHS Settlement Model Layers (GHS-SMOD) data	59

3.3.3. GDP: Gross Domestic Product	62
3.3.4. Sentinel-1 SAR	63
3.4. Methods.....	65
3.4.1. Processing daily Black Marble NTL	66
3.4.2. Creating Weekly Rasters & Time-Series Analysis	67
3.4.3. Creating NTL-derived Spatial Impact Maps	68
3.4.4. Extraction of water-inundated areas using SAR in Google Earth engine	69
3.5. Results	71
3.5.1. Impact of the 2022 Indus floods on human activity	71
3.5.2. NTL derived spatial flood impact beyond water inundation	78
3.5.3. Differential impact of flooding and recovery on Rural-Urban communities ..	81
3.6. Discussion	84
3.6.1. Compound impact and recovery due to 2022 Indus floods	84
3.6.2. Differential impact on urban and rural communities	87
3.6.3. Conclusions.....	88

Chapter 4: Increasing flood risk in the Ganga Basin (India): A perspective from the night-time lights

4.1. Introduction	92
4.2. Study Area	98
4.3. Data and Methods	99
4.3.1. Datasets	101
4.3.2. Analytical Hierarchy Process (AHP) Framework	104

4.3.3. Defining factors that contribute to flood hazard	108
4.3.4. Mapping Yearly Exposure to flood hazard.....	112
4.3.5. Extracting Vulnerability to flood hazard	113
4.3.6. Flood Risk Index (FRI)	114
4.3.7. Data Validation	115
4.4. Results.....	120
4.4.1. Flood Conditioning Factors	120
4.4.2. Flood Hazard Assessment	126
4.4.3. Flood Exposure Index (FEI)	127
4.4.4. Flood Vulnerability Index (FVI)	129
4.4.5. Flood Risk Map	130
4.4.6. Validation	132
4.5. Discussion	134
4.5.1. Comprehensive approach for identifying and predicting flood risk	134
4.6. Conclusion	139

Chapter 5: Discussion

5.1. General Synthesis.....	143
5.1.1. Aim 1: Studying the role or influence of river geomorphology in the Indus Basin on human presence using night lights.....	143
5.1.2. Aim 2: Developing a methodology or framework for studying the impact of floods beyond water inundation	145

5.1.3. Aim 3: Creating a holistic approach to understanding flood risk using geospatial multi-criteria analysis	147
5.2. Cross-cutting themes	149
5.2.1. Temporal and spatial constraints on NTL- opportunities and challenges	150
5.2.2. Utility of NTL data and improvement over conventional approaches	153
5.2.3. A holistic approach to understanding flood risk	155
5.3. Future Work	156
5.3.1. Machine Learning for Predicting Risk	156
5.3.2. Spatial scale refinement of the impact maps	157
5.3.3. Fieldwork and collaboration with policymakers	158
Chapter 6: Conclusion.....	161
<i>Supplementary.....</i>	<i>165</i>
<i>References.....</i>	<i>173</i>

LIST OF FIGURES

- Figure 1.1:** ESRI world imagery showing the topography of the Indus and Indian-Ganga Basin. The green areas show higher elevation mountains whereas brown show lower elevation plains. The inset in the top-right corner shows the location of the basin within Asia..... 15
- Figure 2.1:** ESRI world imagery showing the Indus basin, Indus River (dark blue), and its major tributaries (blue). The red dots are the major cities/urban centres in the study area. The Indus River and its major tributaries, Satluj, Chenab, Ravi, Beas, Jhelum, Soham, Shyok, Kabul, Kurram, Tochi, Gumal, Kundar, and Zhob, are represented in the figure. The inset in the top-right of the figure shows the location of the study area within Asia.....23
- Figure 2.2:** Distribution of the DMSP-night lights across the Indian subcontinent in the year 2013. White areas correspond to high-intensity areas, while black areas correspond to the absence of night lights (Image and data processing by NOAA’s National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency).....27
- Figure 2.3:** Distribution of DMSP night light data over the Indus basin for the years (A) 2000, (B) 2007, and (C) 2013 over the same colour scale. The lighter yellow pixels represent higher-intensity areas, usually towns, cities, or urban centres, and the dark pixels represent the absence of night light or lower-intensity night light areas. Legend numbers denote the number range of the intensity of the pixels represented by the Digital Number (DN).....29
- Figure 2.4:** Average distribution of the DMSP night lights from 2000 to 2013 in the Indus Basin (black boundary). The darker red pixels represent higher-intensity areas and the lighter colour pixels represent lower-intensity night light areas or areas with an absence of night light. The black dots are the major cities/urban centres in the area. The Indus River and its major tributaries, Satluj, Chenab, Ravi, Beas, Jhelum, Soham, Shyok, Kabul, Kurram, Tochi, Gumal, Kundar, and Zhob, are represented in the figure.....29
- Figure 2.5:** Single-thread channel pattern of the Indus River; (B) multi-thread channel pattern of the Indus River. Source—ESRI, Maxar Technologies 2022.....32
- Figure 2.6:** Scatter plot between Landsat population and the sum of lights for the years 2000–2013. The blue circles represent individual data points for each year, with the

corresponding year labelled along the x-axis. The dashed red line indicates the regression line, with the shaded regions showing the upper and lower bounds of the 95% confidence interval. The correlation coefficient (0.66) suggests a moderate positive relationship, and the R^2 value (0.43) indicates that 43% of the variation in the sum of lights can be explained by the Landsat population. The graph is divided into coloured regions corresponding to different time periods collected between 2000 and 2003 by F14 and F15, in the blue region between 2004 and 2007 by F15 and F16, in the green region between 2008 and 2009 by F16, and in the yellow region between 2010 and 2013 by F18.....36

Figure 2.7: (A) Bar plot of the geographical area of the basin (teal green), 0–5 km (turquoise), 5–10 km (orange), 10–15 km (gold), and 15–20 km (grey) buffer zones. (B) Bar plot of the DMSP night lights derived lit pixels area in the basin, 0–5 km, 5–10 km, 10–15 km, and 15–20 km buffer zones. (C) Bar plot of the enhancement factor (E_{f-bz}) of the basin and the four buffer zones, denoting the normal occurrence of lit pixels independent of the geographical area of each buffer zone.....37

Figure 2.8: Frequency plots of lit pixels as a function of the intensity of the lit pixels (represented by digital number, DN) for the Indus Basin and the four buffer zones. The red line in the plots represents the mean of the distribution. (A) Frequency distribution plot of the lit pixels in the basin (teal green). (B) Frequency distribution plot of the lit pixels within the 0–5 km buffer zone (turquoise). (C) Frequency distribution plot of the lit pixels within the 5–10 km buffer zone (orange). (D) Frequency distribution plot of the lit pixels within the 10–15 km buffer zone (gold). (E) Frequency distribution plot of the lit pixels within the 15–20 km buffer zone (grey).....40

Figure 2.9: Cumulative distribution plot of the basin and four buffer zones. The medians of the basin, 5 km buffer zone, 10 km buffer zone, 15 km buffer zone, and 20 km buffer zone are 6.39, 5.63, 7.15, 7.73, and 7.89, respectively. Thus, 50% of the lit pixels across the basin and four buffer zones have an intensity below 10.....42

Figure 2.10: Correlation plot between the DMSP night light-derived mean intensity of lit pixels and the count of the lit pixels in the four buffer zones: 0–5 km, 5–10 km, 10–15 km, and 15–20 km. The red dashed line shows the polynomial regression relationship between the mean intensity and the count of the night light pixels.....42

Figure 2.11: (A–C) Bar plots for the multi-thread channels. The figure represents the geographical area, DMSP night lights-derived lit pixels, and enhancement factor of the multi-thread channel and its four buffer zones: 0–5 km, 5–10 km, 10–15 km, and 15–20

km. (D–F) Histogram plots for the single-thread channels. The figure represents the geographical area, DMSP night lights-derived lit pixels, and enhancement factor of the single-thread channel and its four buffer zones: 0–5 km, 5–10 km, 10–15 km, and 15–20 km.....43

Figure 3.1: (A) ESRI world imagery showing the downstream floodplains of the Indus Basin. The inset in the top-right of the figure shows the location of the study area within Asia; (B) Sentinel-2 False colour composite (FCC) image showing water inundation (dark navy blue colour) on 31st August 2022 accessed via Sentinel Hub EO Browser and accessed on 8th April 2023..... 57

Figure 3.2: Reclassification of GHS-SMOD categories (A) Distribution of pixels into 8 types of categories for the degree of urbanisation; (B) Reclassified settlement model layer consisting of 8 categories into 5 categories. 60

Figure 3.3: A schematic flowchart showing the detailed methodology explaining the pre-processing of daily raster data and creating weekly raster data. The processed good-quality daily and weekly rasters are used for time-series analysis and identifying impact areas. 65

Figure 3.4: Cumulative distribution of weekly NTL raster for May 2022. The blue line denotes the cumulative plot for the 18th week of 2022. Similarly, orange, green and red lines show the cumulative distribution curve for the 19th, 20th and 21st week respectively. 69

Figure 3.5: Water inundation maps from May to October 2022, derived from Sentinel-1 SAR data using Google Earth Engine. The blue areas show the water-inundated areas derived from the SAR data and the blue line is the Indus river. (A) Distribution of flooded pixels for the 18th week of the year (WOY) in 2022 (May); (B) Distribution of flooded pixels for the 23rd WOY in 2022 (June); (C) Distribution of flooded pixels for the 28th WOY in 2022 (July); (D) Distribution of flooded pixels for the 34th WOY in 2022 (August); (E) Distribution of flooded pixels for the 36th WOY in 2022 (September); (F) Distribution of flooded pixels for the 40^h WOY in 2022 (October). 70

Figure 3.6: Weekly total radiance (blue) and total rainfall (green) in 2022, along with the period of Indus floods (highlighted in the light orange shaded region). The radiance is measured in $\text{nW}\cdot\text{cm}^2\cdot\text{sr}^{-1}$, while the rainfall is in millimetres. The data points corresponding to missing values are indicated by dashed lines (No Data). Notable peaks

in rainfall coincide with the flood events observed during the summer months of July and August, as shown in the shaded region.....73

Figure 3.7: (A) The figure shows daily detrending NTL radiance data from Jan 2021 to December 2022. The solid blue lines represent the 7 days moving detrended average radiance in units of nanowatts per square centimetre per steradian($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$). The light blue band is the standard deviation of the radiance values. The red dashed lines show the RMSE of $\pm 2.23 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$; (B) The figure shows the weekly detrending of the NTL data from January 1st week 2021 to December last week 2022. The brown-shaded area highlights the decrease and recovery weeks between May to September 2022. The solid blue lines represent the total radiance in units of nanowatts per square centimetre per steradian ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$). The red dashed lines show the RMSE of $\pm 1.61 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ 75

Figure 3.8: Spatial distribution of the night-time lights during different weeks of 2022 of the flooding period. The bright yellow pixels are high-intensity radiance values that signify lit pixels and dark pixels represent the absence of lit pixels; (A) Distribution of lit pixels for the 18th WOY 2022 (May 2022); (B) Distribution of lit pixels for the 23rd WOY 2022 (June 2022); (C) Distribution of lit pixels for the 34th WOY 2022 (August 2022). August. The missing data corresponds to the large cloud cover; (D) Distribution of lit pixels for the 36th WOY 2022 (September 2022); (E) Distribution of lit pixels for the 40^h WOY 2022 (October 2022).....77

Figure 3.9: The figure depicts the relative decline in lit infrastructure during the 2022 floods across the study area in the Indus basin from June to October 2022 (A-D). The overlaid blue areas highlight water inundation derived from ESA's Sentinel-1 SAR data. The water inundated layer derived from the SAR data corresponds to the same WOY as the NTL data. Green pixels represent a 40-60% decline, red indicates 60-80%, and black signifies the most severe decline of 80-100%. Differential impact of flooding and recovery on Rural-Urban communities.....80

Figure 3.10: The figure quantifies the impact of the 2022 floods. (A) Area affected and economic damage in the urban centres. The green line represents areas with a 40-60% decline in night-time light radiance, signifying both the impacted area and the associated economic decline. The red and black lines depict similar results for 60-80% and 80-100% decline in radiance, respectively, indicating zones of progressively greater flood impact and economic decline. The grey shaded area are the standard deviation. (B) The area

affected and economic value decline in the rural areas. The red and black lines depict both areas impacted and associated economic decline for 60-80% and 80-100% reduction in radiance, respectively, indicating zones of progressively greater flood impact and economic decline. The grey shaded area are the standard deviation. 83

Figure 3.11: A schematic plot of the change in the radiance and the recovery from the flooding over the weekly detrended radiance data. The red line shows the trend of the weekly detrended radiance and the blue line shows the average detrended radiance. The red band shows the flooding period over two months from July'22 to August'22 due to surplus rainfall in the region. The figure illustrates the night-time light response to the 2022 rainfall-induced flooding episodes as five phases – Phase 1, Phase 2, Phase 3, Phase 4 and Phase 5. 86

Figure 4.1: ESRI world imagery showing the Ganga Basin (dark red boundary), Ganga River and its major tributaries in dark blue in India. The other streams are light blue. The inset in the top-right of the figure shows the location of the study area within Asia. 98

Figure 4.2: Flow chart illustrating the methodology for this work. 100

Figure 4.3: The figure illustrates eight potential flood hazard parameters, which are (a) elevation, (b) slope, (c) flow accumulation, (d) drainage density, (e) distance to the river, (f) distance from the confluence, (g) rainfall and (h) geomorphology. The colour scheme of blue to red is adopted to indicate the potential occurrence of floods. The blue area shows a low potential for the occurrence of floods compared to the red region which shows a high potential for flood hazard.....111

Figure 4.4: Distribution of average night-time lights indicating exposure from 2013-2023. The dark areas show the absence of night-time lights and the bright areas are where high human activity-related artificial lights are captured.....113

Figure 4.5: Vulnerability index of the districts in the Ganga Basin from the Climate Vulnerability Assessment Report- DST 2020, Government of India.....114

Figure 4.6: ArcGIS Model builder showing the workflow for the processing of the 2016 risk map.....119

Figure 4.7: Schematic diagram explaining the four components of the confusion matrix i.e., True Positives, False Positives, True Negative and True Negatives. 119

Figure 4.8: Flood Hazard Index (FHI) map for 2022 of the Ganga Basin produced after the AHP analysis. Continuous data ranging from 1.9 to 46% are classified into 5 categories: Very Low, Low, Moderate, High and Very High FHI. In the figure the blue areas have low FHI values, indicating less potential for flood occurrence or flood hazard, and red areas have higher flood hazard values, suggesting higher susceptibility to floods. 126

Figure 4.9: Flood Exposure Index (FEI) map for 2022 across the Ganga Basin produced after the AHP. The FEI is categorized into 5 classes based on the unique values of weights derived, which are: Very Low (4%), Low (6%), Moderate (14%), High (27%) and Very High (49%). 128

Figure 4.10: Flood Vulnerability Index (FVI) map for 2022 across the Ganga Basin produced after the AHP analysis. The FVI is categorized into 5 classes based on the unique values of weights derived, which are: Very Low (4%), Low (6%), Moderate (14%), High (27%) and Very High (49%). 130

Figure 4.11: (a) Normalised Flood risk index map of the Ganga Basin for 2022, highlighting areas of moderate to high risk. Yellow indicates moderate risk (3-10%), orange represents high risk (10-30%), and brown denotes very high risk (30-100%). (b), (c), and (d) provide zoomed-in views of specific geographic regions. 132

Figure 4.12: ROC curve (maroon colour) plotted between the false positive rate and the true positive rates at different risk threshold values. The AUC is the value of the area under the curve of the 2016 flood risk map. 133

Figure 4.13: (a) The spatial distribution of increasing flood risk trend within the Ganga Basin in India over the past 10 years. Each pixel represents the average percentage point change in FRI per year, enabling us to identify areas of significantly increasing flood risk. The blue areas represent regions with a lower rate of flood risk increase ca. 1 point change/per year, while the red areas indicate regions with a higher flood risk trend ca. 5 point change/ per year. The white areas are where there is no flood risk; (b) shows a focused view of the trend within the state of Bihar; (c) highlights the trend near the foothills of the Himalayas; (d) zooms in on the trend in the state of West Bengal; (e) provides a detailed view of the trend over the state of Madhya Pradesh within the basin. 137

Supplementary Figure 1: Flood Hazard Index plots from 2013 to 2023. Continuous data ranging from 1.9 to ca. 46% classified into 5 categories of Very Low, Low, Moderate, High and Very High FHI. In the figure the blue areas have low FHI values, indicating less potential for flood occurrence or flood hazard, and red areas have higher flood hazard values, suggesting higher susceptibility to floods.....	165
Supplementary Figure 2: FEI plots from 2013-2023 across the Ganga Basin produced after the AHP. The FEI is categorized into 5 classes based on the unique values of weights derived, which are: Very Low (4%), Low (6%), Moderate (14%), High (27%) and Very High (49%).....	166
Supplementary Figure 3: Normalised flood risk index (FRI) map of the Ganga Basin. The FRI are shown in three categories- Yellow indicates moderate risk (3-10%), orange represents high risk (10-30%), and brown denotes very high risk (30-100%).....	167

LIST OF TABLES

Table 1.1: Comparison of the DMSP-OLS and VIIRS-derived Black Marble data (Elvidge et al., 1999; Román et al., 2018)	7
Table 2.1: Geographical and DMSP night light-derived area for different proximity zones of the rivers in the Indus Basin.	32
Table 2.2: Geographical and DMSP night lights-derived area for four proximity zones of the single-thread channel of the Indus River.	34
Table 2.3: Geographical and DMSP-Night lights derived area for 4 proximity zones of the multi-thread channel of the Indus River.	34
Table 2.4: Descriptive statistics of the night light data for the basin and the four buffer zones.	39
Table 3.1: GHS-SMOD data categories and their description.....	61
Table 3.2: Reclassified classes of the GHS-SMOD data.....	61
Table 3.3: Descriptive Statistics of the NTL pixels from May to November cloud-free composites within the cloud mask (derived from the august composite).....	77
Table 4.1: List of datasets used in the study and their sources.....	101
Table 4.2: Relative importance scale (1–9) developed by Saaty (1980,1990).....	105
Table 4.3: Random consistency index (RCI) based on by Saaty (1980,1990).....	106
Table 4.4: Flood Hazard Index (where RW- relative weight).....	124
Supplementary Table 1: Level 1 pairwise comparison for the flood hazard parameters.....	168
Supplementary Table 2: Level 2 hierarchy elevation	168
Supplementary Table 3: Level 2 hierarchy slope	169
Supplementary Table 4: Level 2 hierarchy for rainfall.....	169

Supplementary Table 5: Level 2 hierarchy for distance to the river	169
Supplementary Table 6: Level 2 hierarchy for the distance to the confluence points....	170
Supplementary Table 7: Level 2 hierarchy for the drainage density	170
Supplementary Table 8: Level 2 hierarchy for flow accumulation	171
Supplementary Table 9: Level 2 hierarchy for geomorphology	171
Supplementary Table 10: Level 1 Hierarchy of Exposure using night time lights.	172
Supplementary Table 11: Level 1 Hierarchy of Vulnerability Index from the Climate Vulnerability Report	172

Chapter 1: Introduction

1.1.Overview

Since the beginning of human civilisation, rivers have influenced landscape evolution and population dynamics (Singh et al., 2017). From ancient times, early humans have settled near rivers for navigation, trade, and availability of water supply and resources. Over historical time, some of these small towns have developed into megacities with a large population and an increase in urbanisation. (Grimm et al., 2008). According to a study by Kummu et al. (2011), more than 50% of the world's population lives within a proximity of 3km from freshwater, whereas 10% lives in areas more than 10km away from freshwater. The global population has doubled in the last 50 years, particularly in high-hazard-prone areas (Jongman et al., 2012). The high concentration of people near the rivers is because of access to fresh water, symbolic significance, aesthetics, annual flooding for agricultural purposes, and other reasons (McCool et al., 2008; Nikula, 2008).

Such population growth has modified/alterd the streams, rivers, flood channels, canals, and other hydrological systems, leading to the loss of lives and resources due to floods (Grimm et al., 2008; Di Baldassarre et al., 2013). Climate change causes changes in the intensity, frequency, spatial range and duration of weather and climate extremes and can lead to unprecedented extremes (Fazel-Rastgar, 2020). At the same time, rainfall patterns and intensities may shift under climate change, which could influence the flood hazard (Milly et al., 2022; Kundzewicz et al., 2013; IPCC, 2013; Rojas et al., 2013; Jongman et al., 2014). However, over time, these areas have become more susceptible to the catastrophic effects of flooding because of the rapid increase in the human population and anthropogenic activities on a global scale (Kummu et al., 2011; Ceola et al., 2015). The increasingly high economic and human losses associated with flooding make it

important to understand the associated risks with such extreme events or natural disasters. When assessing flood risk, we need to understand the role of flood hazard, exposure and vulnerability. These hazard and exposure elements can only partly explain spatiotemporal patterns in flood risk because of the importance of vulnerability (Jongman et al., 2015).

Floods are caused by a complex interplay between hydrology, climate, and human management and are among the most significant climate-related disasters (IPCC, 2023). As per the Emergency Events Database (EM-DAT), a hazard is termed as a disaster when either of the following is true – ten or more people are reported killed; 100 or more people are reported affected; a state of emergency is declared, or international assistance is called for (UNDRR, 2019). According to the database, in the last 50 years, the frequency of flood disasters has increased from 25.8 in the 1970s to 153.9 per year on average since 2011 (CRED, 2021; Vestby et al., 2024). As per the Global Flood Database, 3054 flood events were reported worldwide during 2000-2018, and the majority were concentrated in Southeast Asia (Tellman et al., 2021). For instance, the Indus flooding in Pakistan in 2022 killed ca. 1500 people and impacted > 33 million people in the region (Qamer et al. 2023). Thus, it is important to understand how the human settlements or presence are shaped in correspondence to the terrain or landscape to assess flood hazards and further flood risk assessment over time.

In this PhD thesis, I focus on the Indus-Ganga Basin (or the Indo-Gangetic Basin) in Asia, which is the world's most populous basin and poses a significant threat to people and resources because of the frequent flooding (United Nations 2015). The available literature offers insight into drivers of flooding or flood damage using conventional and old datasets, although key knowledge gaps remain (Chen et al., 2021; Jamshed et al., 2021; Lin et al., 2019; Martinis et al., 2022; Merz et al., 2021; Mishra and Sinha, 2020a; Otto et al., 2023; Roy et al., 2021; Vegad et al., 2024). Central among these is the need for an up-to-date dataset representing human presence and infrastructure to assess flood exposure.

Thus, to address this drawback, we use a novel data set called nightlights or night-time lights having distinct luminosity captured during the night which represents human presence like settlements, industries, etc (Andries et al., 2023; Bharti and Tatem, 2018; Ceola et al., 2014; Cole et al., 2017; Elvidge et al., 2013, 2017; Hsu et al., 2021; Levin, 2017; Levin et al., 2020; McCord and Rodriguez-Heredia, 2022; Román et al., 2018; Stokes and Román, 2022). I use this particular data because the light intensity of affected human settlements, industrial, commercial, and public areas is reduced compared to the pre-disaster conditions. This is because, during flooding, impacts happen both within and beyond inundation areas. That includes damages to residential buildings, displacement and fatalities, and interruptions in the industry, manufacturing, service, and public sectors (Afroze, 2023; Ceola et al., 2014, 2014; Elshorbagy et al., 2017; Enenkel et al., 2020; Fang et al., 2021; Gillespie et al., 2014; Hu et al., 2024; Levin, 2023; Levin and Phinn, 2022; Wang et al., 2018; Zhang et al., 2023). Further, the flood impact also differs depending on the societal structures and vulnerability to cope with floods.

Thus, in this study, we incorporate night-time lights by adopting a holistic remote sensing and GIS-based approach to understand flood risk. That includes investigating the dynamics of landscape shaping human presence (activities), conditions inducing floods, the consequential socio-economic flood impacts representing both direct and indirect impacts, and identifying flood risk areas. The study of such spatial patterns is important to strengthen the understanding of flood impacts beyond water inundation and minimising flood risk.

1.1.1. Flooding and flood risk assessment

An increase in the frequency of floods has particularly been noticed in South Asia in recent decades (Nanditha et al., 2023; Otto et al., 2023; Roy et al., 2021; Tellman et al., 2021; Tiwari et al., 2024; UNDRR, 2020). However, the Asian and Sub-Saharan African countries, in particular, have also had increased flood exposure between 2000-2015 (Tellman et al., 2021; Qamer et al., 2023; Nanditha et al., 2023; Chen et al., 2024). South

Asian countries are affected by the summer monsoon season, usually between July and September, impacting their livelihood markedly compared to other parts of the world because of higher exposure and vulnerability (Qamer et al., 2023; Almazroui et al., 2020). The higher frequency of flood events in South Asia is estimated to have affected ca. 1 billion people in the past 20 years, according to the EM-DAT data (Nanditha et al., 2023; Delforge et al., 2023). These large basins in South and Southeast Asia (Indus, Ganges-Brahmaputra and Mekong) had the largest absolute numbers of people exposed to flooding (17.0–19.9 million, 107.8–134.9 million and 20.2–32.8 million, respectively) and increased proportions of the population exposed to inundation of 36%, 26% and 11%, respectively (Tellman et al., 2021). Anthropogenic climate change, along with increasing human exposure and land use changes, have been the primary drivers for the increase in global flood exposure (Jongman et al., 2012; Tanoue et al., 2016).

The occurrence of disastrous flood events has increasingly led to research initiatives focusing on flood vulnerability, exposure, and post-disaster assessment. Many global studies considered the affected GDP, population, and physical assets damaged by flooding (IPCC, 2012; Jongman et al., 2015; Tellman et al., 2021; Winsemius et al., 2013). Thus, remote sensing can be a powerful tool and a cost-efficient way to analyse the spatial extent of flooding and its impact on human population and infrastructure. Conventionally, mapping flood-affected areas using satellite images usually includes mapping water-inundated areas using optical, radar images or both and mapping the infrastructure damage using optical images (Levin and Phinn, 2022; Joyce et al., 2009; Martinis et al., 2022). Synthetic Aperture Radar (SAR) is usually acceptable data for flood detection as it is independent of external energy sources like the sun and is not affected by cloud cover (Giustarini et al., 2013; Tanguy et al., 2017). For instance, the SAR data from the recent European Space Agency (ESA) Sentinel-1 has a period of 12 days over the world, except Europe, which has a revisit of 6 days. On the other hand, other studies like Tellman et al. (2021) used optical data from the Moderate-resolution imaging

spectroradiometer (MODIS) sensor from the NASA Terra/Aqua satellites to map the global flood extent from 2000 to 2018 and estimate the population. However, the lack of cloud-free data availability and MODIS's limited ability to map urban floods always limit mapping flood damage.

However, such satellite data captures impact *within* the water-inundated areas. But, flood impact can happen within or beyond inundation areas (Jongman et al., 2012; Jonkman et al., 2008; Merz et al., 2010; Smith & Ward, 1998). The impact within the inundated area is due to the physical contact with flood water, while the impacts outside of the inundation area may be due to a cut of supply (e.g., electricity, production material, potable water, etc). Moreover, areas and populations impacted by flooding extend well beyond water-inundated areas. Further, there has been a limited focus on studying the indirect or the compound impact of floods, the recovery of communities and how it varies among different socio-economic communities. Thus, in my research, I use a novel dataset called night-time lights or nightlights as a proxy for human presence to understand the impacts of floods.

1.1.2. Night-time lights

Remote sensing of night-time light series data provides a unique perspective into human activities and has been previously utilised for demographic, economic, and environmental purposes (Bennie et al., 2014; Chand et al., 2009; Chen & Nordhaus, 2011; Elvidge et al., 1997, 2009; Small, 2004). Stable night lights are cloud-free digital products, signifying the presence of lights and distinct luminosity. The data captures human signal-artificial signals at night, providing an understanding between the human systems and the environment, and multiple data products have been released (Ceola et al., 2016; Mård et al., 2018; Fang et al., 2018; Zhong et al., 2018). There are various sensors and platforms like the Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS) and the Visible and Infrared Imaging Suite (VIIRS) from which remote sensing of night lights in the visible range has been performed (Elvidge et al.,

1997; Elvidge et al., 2017). Importantly, recent efforts toward analysing the applications of night light data have indicated their enhanced value in determining human exposure and vulnerability to natural hazards compared to traditional approaches. Night-time light (NTL) or the night lights data has proven effective in disaster monitoring, risk assessment and reduction, humanitarian response, preparedness, resilience, and sustainable development (Levin, 2023; Levin and Phinn, 2022; Wang et al., 2018; Zhao et al., 2018). I use two artificial night-light data products in this study, DMSP/OLS and Black Marble night-time lights.

1. DMSP-OLS v4:

These are free digital products by the National Geophysical Data Center from the National Oceanic and Atmospheric Administration (NOAA) collected under the Defense Meteorological Satellite Program (DMSP) from 1992 to 2013 using the Operational Linescan System (OLS). These are annual cloud-free composites from sites that are cities, towns, and gas flares, excluding the sunlit and moonlit data observations from ephemeral sources like fires. The data is expressed in terms of average annual intensity denoted by Digital Number (DN). The digital number (DN) values are from 0 to 63 (Elvidge et al., 1999). The spatial resolution is roughly 1 km at the equator. The nightlight values are expressed as a range from 0 to 63, where 0 represents complete darkness (no detectable light), and 63 indicates highly saturated brightness, which often corresponds to urban or brightly lit areas. Table 1.1 lists the specifications of the data, and it is further discussed in the subsequent Chapter 2.

2. NASA Black Marble Data Product:

NASA Black Marble night-time lights product suite (VNP46) produced at NASA's Land Science Investigator-led Processing Systems (Land SIPS) is a product of the Visible Infrared Imaging Radiometer Suite (VIIRS) Day-Night Bands (DNB) available from January 2012 at daily/monthly/yearly frequency (Román et al., 2018). The product suite, available globally on daily, monthly, and annual composite scales,

corrects extraneous sources of noise in night-time light (NTL) radiance signals (Román et al., 2018). In this study, I use the daily and annual data products, which are the VNP46A2 and VNP46A4 (Román et al., 2018). The data has a spatial resolution of 15 arc seconds (ca. 500m resolution) and is provided in the Hierarchical Data Format Earth Observing System (HDF-EOS) format (Román et al., 2018). The NTL radiance is measured in nanowatts per centimetre square per steradian ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$) units having a valid range of 0-65534. Table 1.1 lists the specifications of the data, and it is discussed further in Chapter 3 and Chapter 4, where I show the applicability of both the daily and annual datasets.

Table 1.1: Comparison of the DMSP-OLS and VIIRS-derived Black Marble data (Elvidge et al., 1999; Román et al., 2018)

Variable	DMSP-OLS	VIIRS derived Black Marble
Builder/Operator	U.S. Air Force	NASA
Data Range	0-63	0-65535
Units	Digital Number (DN) values representing visible band radiance	Radiance values in nanowatts per square centimetre per steradian ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$)
Spatial Resolution	30-arc seconds (approx. 1 km at the equator)	15 arc seconds (approx.. 500 m at the equator)
Orbit	Sun-synchronous polar orbit	Sun-synchronous polar orbit
Swath	Approx. 3000 km	Approx. 3060 km
Night-time Overpass	Varies due to orbital drift; initially around 19:30 local time	Approximately 01:30 local time
Spectral resolution	Single band (visible and near-infrared)	Panchromatic band sensitive to 0.5–0.9 μm wavelengths
Quantisation	6-bit	14-bit
Saturation	Occurs in brightly lit areas, limiting detection in urban centres	Improved dynamic range reduces saturation issues
Temporal availability	Annual composites	Daily, monthly, and annual products

The terms radiance and intensity are used in the thesis. Radiance, luminosity, and intensity are fundamental concepts in the study of night-time light emissions and remote sensing. Radiance refers to the amount of electromagnetic radiation emitted, reflected, or transmitted by a surface in a given direction per unit area and solid angle. It is expressed

in SI units of watts per square metre per steradian ($\text{W}/\text{m}^2/\text{sr}$) (Petty, 2006). In the context of night-time light (NTL) data, radiance is typically measured in nanowatts per square centimetre per steradian ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$) to capture the faint emissions from artificial lighting sources detected by satellite sensors (Elvidge et al., 1997). **Intensity**, often used interchangeably with radiance in informal contexts, specifically refers to the power per unit solid angle, measured in watts per steradian (W/sr). However, in satellite-based night-time light analysis, radiance is the primary metric used to assess variations in artificial illumination across different regions and periods. Luminosity describes the total amount of light energy emitted by a source per unit of time, typically measured in **lumens (lm)**, and is more relevant in astronomical or perceptual studies rather than remote sensing applications (Petty, 2006).

1.1.3. Night-time lights-based assessment of human activities and disaster impact

In the past 20 years, the DMSP-OLS, VIIRS, and Black Marble night light data have increasingly been explored for demographic, economic, and environmental purposes (Elvidge et al., 1997; Chand et al., 2009; Elvidge et al., 2009; Chen and Nordhaus, 2011; Bennie et al., 2014). Over this period, these data products have been used as a proxy for human activities and have been used to study the relationship between human landscape and response to natural disasters.

The use of night-time light (NTL) data has become a valuable tool in understanding the intricate relationship between human settlements and natural hazards, particularly floods. Ceola et al. (2014) pioneered this approach by employing NTL as a proxy to assess human exposure to floods on a global scale. By integrating night lights with river networks, the study was able to identify areas prone to flooding, offering a novel perspective on how human populations are distributed about flood risks. This methodology has since inspired further research, such as that of Gómez et al. (2015), who explored the temporal variations in the spatial distribution of exposure to hydrometeorological hazards along the Samala River in Guatemala, again using NTL

data. The ability of night lights to track changes in human settlement patterns over time proved invaluable in revealing how communities adjust to flood risks.

Expanding this global lens, Ceola et al. (2015) quantified the growth and spatial distribution of urban settlements near rivers, underscoring the persistent attraction of riverside locations despite their inherent risks. In a related study, Ceola et al. (2016) analysed human activity along the Eastern Alpine river network, demonstrating a marked increase in human presence near rivers from 1992 to 2013, based on DMSP night-time light data. These findings highlight not only the historical significance of rivers as centres of human activity but also the rising human footprint along vulnerable watercourses over time.

Fang et al. (2018) took this a step further by exploring how geomorphic features of rivers influence human settlement patterns on a global scale. Using night light data, the study identified a distinct tendency for human settlements to cluster downstream across six continents, suggesting a long-standing relationship between rivers, trade, and transport infrastructure. This global pattern illustrates the strategic importance of riverine environments while also highlighting the vulnerability of these clustered settlements to floods and other water-related hazards. Similarly, Masrur et al. (2018) applied multi-temporal satellite NTL data to assess human presence and flood exposure in Bangladesh. His study revealed emerging hotspots of population growth and flood exposure near rivers, underscoring the critical need for proactive flood management in regions with rapidly expanding riverside communities.

Night-time light data has thus emerged as a powerful tool for understanding human-environment interactions, particularly in the context of flood risk. Mård et al. (2018) argued that NTL data can be used to study the relationship between catastrophic flood events, flood protection measures, and long-term changes in human proximity to rivers. This approach offers insights that traditional demographic data often overlook. For example, Zhong et al. (2018) investigated the spatial evolution of urban areas in the

Yangtze River Economic Belt from 1992 to 2013 using DMSP night light data, which provided a more real-time reflection of human activity at a broad spatial scale. Thus, the availability of higher temporal frequency of annual datasets and large-scale perspectives enabled a more dynamic understanding of how urbanisation unfolds near major rivers, as compared to more static census data (Fang et al., 2021).

The utility of NTL data has been further employed to map and quantify the impact of various natural disasters by detecting damage and power outages (Zhao et al., 2018). It has been used to assess the impact of earthquakes, hurricanes, and floods, including big disasters like the 2023 Turkey earthquake (Levin, 2023), the 2022 floods in Queensland, Australia (Levin & Phinn, 2022), and Hurricanes Sandy and Maria (Wang et al., 2018). These studies demonstrate the versatility of NTL data in capturing the immediate aftermath of disasters, highlighting its potential for rapid response and recovery planning.

In the realm of disaster response, Gao et al. (2020) developed a night-time light change model to monitor the real-time impacts of disasters, with a specific focus on Hurricane Maria. The model, later applied in other contexts by Román et al. (2019) and Zhang et al. (2023), underscores the potential of NTL data to enhance post-disaster response and recovery efforts by providing near real-time insights into the extent and severity of impacts.

Together, these studies illustrate the growing importance of night-time light data in disaster risk management and environmental monitoring. By providing detailed, real-time information on human activity patterns and settlement dynamics, NTL data offers a unique lens through which researchers and policymakers can better understand the evolving relationship between humans and their environment, especially in the face of increasing flood risks and other natural hazards.

1.2. Aims and Objectives

Despite significant progress in understanding flood hazards, flood modelling, and risk assessment, several critical knowledge gaps remain unresolved, particularly in how human settlements interact with flood risks. Below are the three research gaps that I have identified:

1. **Influence of Geomorphology on Human Settlements:** While many studies treat rivers as homogenous features, there is a lack of understanding of how the heterogeneous behaviour of river systems—shaped by geomorphology—affects human settlement patterns. Rivers vary in their physical characteristics, such as their shape, gradient, and flow regimes, which can influence where and how people settle along their banks. Understanding these nuances is crucial for accurately assessing future flood risks. As rivers are often studied in a simplified manner, the impact of these geomorphic variations on human populations remains underexplored, leaving an important gap in predicting settlement vulnerability and flood exposure.
2. **Indirect Impacts of Floods Beyond Water Boundaries:** Most studies on flood impacts tend to focus exclusively on the areas directly inundated by floodwaters. This narrow approach often overlooks the indirect impacts of floods, which can extend well beyond the immediate water boundaries. These indirect effects, such as damage to infrastructure, supply chains, and livelihoods in areas not directly flooded, represent a significant but understudied aspect of flood risk. A more comprehensive understanding of both direct and indirect impacts is essential to fully grasp the broader consequences of flooding on communities and to improve flood preparedness and recovery strategies.
3. **Data Availability for Monitoring Human Settlements and Response to Floods:** A major challenge in flood risk assessment is the limited availability of high-

resolution temporal and spatial data on human populations and settlements. Such data are critical for monitoring how people respond to floods, particularly in differentiating the reactions of urban and rural populations. Currently, the use of night-time light data and other satellite-based proxies holds promise for tracking human presence and settlement changes over time. However, there remains a gap in fully utilising the latest open-source satellite datasets to capture these dynamics in real-time. Bridging this gap would improve our ability to monitor human settlements' responses to floods and to anticipate future risks, especially in rapidly urbanising or rural areas.

Addressing these gaps is essential for enhancing our understanding of flood risks and the resilience of human settlements, especially in the face of increasing flood hazards driven by climate change. Thus, I have identified the following three key research aims and their respective objectives that I shall address in my thesis:

- 1. To study the role and influence of river geomorphology in the Indus Basin on human presence using night lights. The key objectives for Aim 1 are:**
 - a. Test the hypothesis that the night-time lights signifying human activities are higher near the major rivers compared to the basin as a whole and its quantification.
 - b. Understand the role of channel pattern bank stability on the presence of humans, i.e., whether human presence is higher near single-thread or meandering river channel reaches than near braided or multi-thread channels.
- 2. Develop and apply a methodology for studying the impact of floods beyond water inundation using night light data. This would give an understanding of the impact and recovery in space and time and for different socio-economic classes. The key objectives of Aim 2 are:**

- a. Utilise daily NASA Black Marble night-time lights to create good-quality (i.e., having maximum data coverage) weekly night-time light raster data.
- b. Estimate the temporal impact on human activities of the Indus floods (Pakistan) in 2022.
- c. Calculate the spatial impact of the floods using night-time light data.
- d. Understand the difference in the impact and recovery for urban centres and rural areas.

3. Creating a holistic approach to understanding flood risk using geospatial multi-criteria analysis. The key objectives of Aim 3 are:

- a. Use hydro-geomorphic factors to identify flood hazards in the Ganga Basin (India) using a GIS-based Analytical Hierarch Process (AHP).
- b. Utilise the annual Black Marble night-time lights data to derive the temporal flood exposure from 2013-2023.
- c. Derive temporal flood risk maps of the Ganga Basin from 2013-2023 and identify flood risk trends.
- d. Validate the flood risk model with the impact-based data from the Emergency Events Database EMDAT and Geocoded Disasters GDIS dataset.

1.3.Study Area

The Indus and Ganga Basins are two of the most densely populated basins in the world, having a population of ca. 267 million and ca. 581 million in 2017, respectively (Dharpure et al., 2020). The drainage of the Indus Basin is spread over India, Pakistan, Afghanistan and China, whereas the Ganga Basin is spread over India, Nepal, Pakistan, Bhutan and Bangladesh. The Great Northern Plains (i.e. Indo-Gangetic plains) is situated south of the Himalayas, which is one of the most fluvial systems in the world (Banerjee and Kumar,

2018). The complex topography of the area results in altitude-driven climatic variability ranging from semi-tropical to semi-arctic in the Himalayas (Bahadur, 1993).

The Indus Basin has an area of $>1,100,000 \text{ km}^2$. The major tributaries of the basin are Sutlej, Ravi, Chenab, and Jhelum, as shown in Figure 1.1. The trunk river originates in western Tibet at an elevation $>6700 \text{ m}$, initially flowing northwest and then southwest through Pakistan and finally draining into the Arabian Sea. In this thesis, I also focus on the Indian part of the Ganga basin, which is the largest river system in India (Figure 1.1). The basin covers an area of ca. $860,000 \text{ km}^2$, which is $> 26\%$ of the total geographic area of India. (Tripathi and Mohanty, 2024). The river originates from the Gangotri Glacier in the Himalayas at an elevation of nearly 7010 m and traverses a length of about 2550 km before it flows eastwards into the Bay of Bengal (Figure 1.1). Along its way, the Ganga is joined by several tributaries, the major ones being- Chambal, Yamuna, Ghaghara, Kosi, etc.

The climate of both the basins is influenced by the East Asian and Indian summer monsoon systems, as well as the Westerlies (Dharpure et al., 2020). The basin receives rainfall during the southwest monsoon between June to October. The streamflow in the upper Indus basin is glacier-dominated, i.e., 41% , and the rest is snowmelt (22%) and rainfall runoff (27%). However, the streamflow for Upper Ganga is rainfall runoff, contributing around 66% (Shreshtha et al., 2015). Further details on the study area will be discussed in the following research chapter.

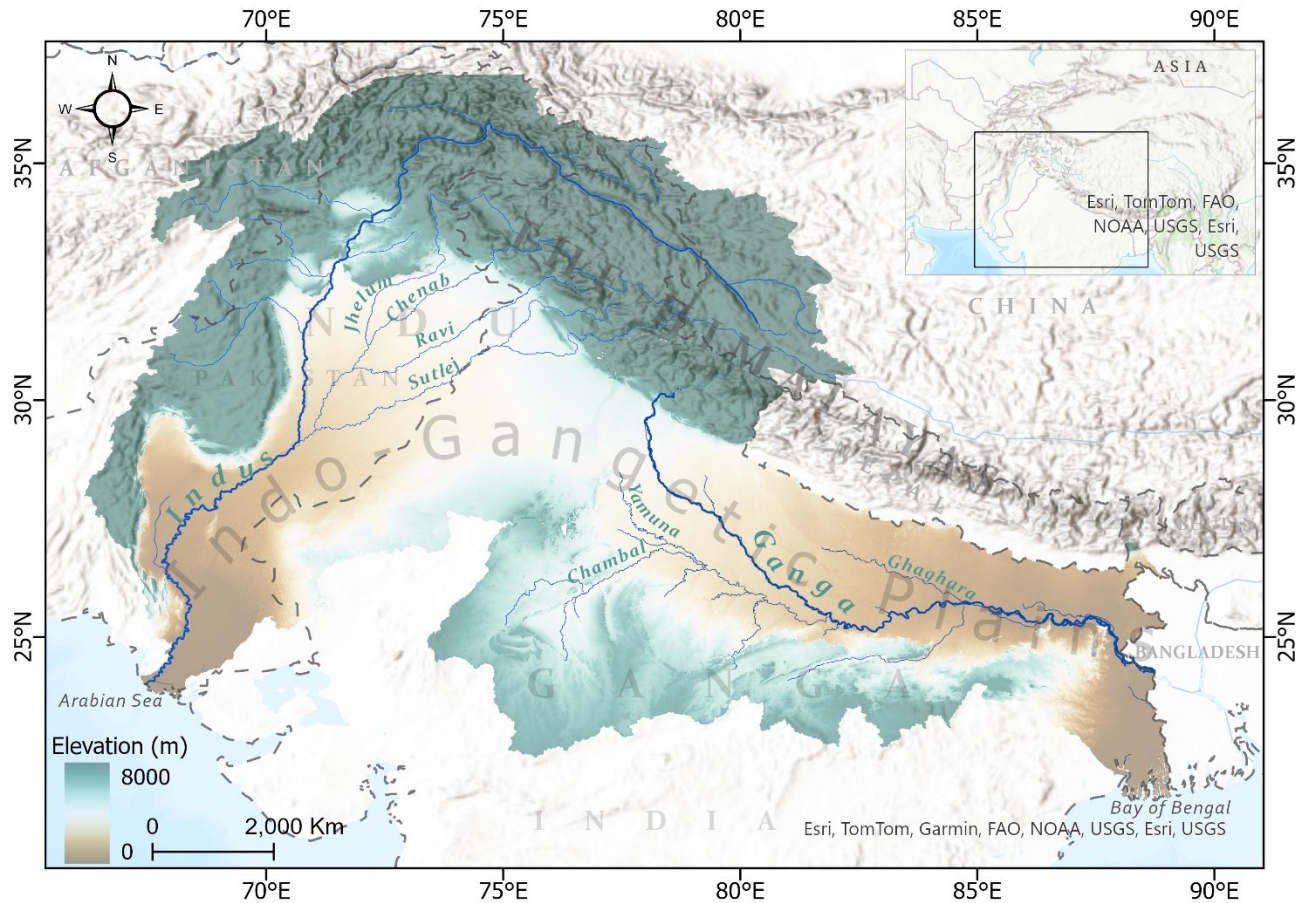


Figure 1.1: ESRI world imagery showing the topography of the Indus and Indian-Ganga Basin. The green areas show higher elevation mountains whereas brown show lower elevation plains. The inset in the top-right corner shows the location of the basin within Asia.

1.4. Thesis outline and structure

The thesis provides a detailed insight into the use of night-light data for understanding the presence of human activities or human presence, the impact of floods on human-lit infrastructure and assessing flood risk. This is accomplished in six chapters, with the introduction and conclusion as the first and the final chapters, respectively. Three technical chapters address specific scientific objectives. A brief description of each chapter is presented below:

Chapter 1: Introduction. This chapter focuses on the motivation behind the study. The chapter covers a general introduction to the thesis, a broad literature review of satellite-

based flood monitoring techniques, conventional population datasets, and night-time light data. Based on this, gaps in knowledge are identified and organised into key research questions and objectives to be addressed in this thesis.

Chapter 2: *Investigating the influence of river geomorphology on human presence using night light data: A case study in the Indus Basin*. This chapter focuses on addressing the role of river geomorphology in terms of channel patterns and distance to the Indus River in shaping or distribution of human presence within the Indus basin using nightlights. Here, I use the DMSP stable night light data from 2000 to 2013 as a proxy for human presence and activities to quantify the statistical relationships. I test two hypotheses. First, if there is an increased human presence near the river in floodplains due to water availability and soil fertility. Secondly, I evaluate whether human presence is higher near single-thread channels because of the documented stability of the channel bank compared to multi-thread channels. A version of this chapter has already been published in *Remote Sensing*: Aggarwal, E., Whittaker, A.C. and Gupta, S., 2024. *Investigating the Influence of River Geomorphology on Human Presence Using Night Light Data: A Case Study in the Indus Basin*. *Remote Sensing*, 16(7), p.1272.

Chapter 3: *Differential impact beyond floodwater: An insight into 2022 Indus Floods using Black Marble Night-time lights*. This chapter utilises the novel NASA Black Marble night-time lights satellite data to understand the 'real-time' impacts of the Indus floods in 2022 compared to traditional SAR flood monitoring. Here, I show the time series and spatial analysis of the affected region over a period of five months. I also investigate the recovery time for the flood-impacted areas and the exposure for different socio-economic communities in the floodplains. The study highlights the importance of assessing the indirect impacts beyond the flood-inundated water, which can potentially be assessed from the nightlights, highlighting the cascading and compounding hazards along with the main flooding event. A manuscript of this chapter is being prepared in short form for Nature NPJ Natural Hazards journal.

Chapter 4: *Increasing flood risk in the Ganga Basin (India): A perspective from the night-time lights*. This chapter addresses the complex interplay between flood hazards, exposure, and vulnerability to understand flood risk. The study delves into flood risk within India's Ganga Basin, focusing on the flood-inducing factors, vulnerability, and exposure through the application of the Analytical Hierarchy Process (AHP), which is a Multi-Criteria Decision Making (MCDM) model. The study aims to capture the dynamic nature of flood risk, driven by hydro-geomorphic controls, expanding human activities and population growth, and variations in flood resilience. The accuracy of the flood risk maps is validated using the historical flood-impacted data from the EM-DAT and GDIS databases. A manuscript version of this chapter will be submitted to NHESS.

Chapter 5: *Discussion*. This chapter presents a general synthesis of the thesis and cross-cutting themes. The chapter highlights the summary of the main research aims of the PhD. The research highlights significant implications for flood management, offering insights for developing risk mitigation strategies that transcend administrative boundaries.

Chapter 6: *Conclusion*. The thesis finishes with a conclusion section that summarises the key outcomes of this piece of research.

Lastly, I would like to mention that because of the collaborative nature of science and to acknowledge the diverse contributions made by supervisors, co-authors and collaborators, I have chosen to use the pronoun 'we' instead of 'I' in the research chapters. At the end of each chapter, I outline the specific roles that each person has contributed in the contribution section.

Chapter 2: Investigating the Influence of River Geomorphology on Human Presence Using Night Light Data: A Case Study in the Indus Basin¹

Abstract

Human settlements have historically thrived near rivers due to enhanced navigation and trade and the availability of water supply and resources. The use of night light data, representing economic activities, provides a novel approach to studying the interactions between human activity and rivers over time. Here, we use the Defense Meteorological Satellite Program (DMSP) stable night light data from 2000 to 2013 as a proxy for human presence and activities to quantify the statistical relationships between night light presence and intensity in the Indus Basin, Asia. We test how these data are affected by proximity to trunk channels and by channel type (single/multi-thread) in the study area. We find that night light presence is enhanced by 26% within a 0 to 5 km proximity range of the Indus River and its tributaries relative to the basin as a whole. We interpret this to represent increased human presence and activity within this zone. However, the mean intensity is lower near the river and higher away from the river, signifying denser settlements, such as towns and cities, which are preferentially located away from the Indus and its tributaries. Moreover, the enhancement of lit pixels signifying human presence and activities is increased by 18% near single-thread sections of the Indus River, compared to segments of the Indus displaying multi-thread morphologies. We suggest that this is due to the enhanced stability of single-threaded channels relative to mobile multi-threaded channel reaches. This study demonstrates how night lights are an important tool in studying the relationship between human presence and river dynamics in large catchments such as the Indus, and we suggest that these data will have an important role in assessing differential flood spatial and social vulnerability at a regional scale.

¹ A version of this chapter has been published in *Remote Sensing*: Aggarwal, E., Whittaker, A.C. and Gupta, S., 2024. Investigating the Influence of River Geomorphology on Human Presence Using Night Light Data: A Case Study in the Indus Basin. *Remote Sensing*, 16(7), p.1272.

2.1. Introduction

Since the beginning of human civilisation, rivers have influenced landscape evolution and population dynamics (Singh et al., 2017). From ancient times, early humans have settled in the proximity of rivers for navigation, trade, and availability of water supply and resources. However, over time, these areas have become more susceptible to the catastrophic effects of flooding because of the rapid increase in the human population and anthropogenic activities on a global scale that have impacted the environment (Kummu et al., 2011; Ceola et al., 2015). Thus, an in-depth understanding of the role of geomorphology in shaping human settlements through time is required. The Indus Basin is one of the world's largest and most populous basins. However, the river system in this basin poses a significant threat due to urbanisation and related human activities (United Nations 2015). This study aims to explore the influence of terrain and geo-morphology on human presence to understand the vulnerability of humans to natural hazards like floods.

The analysis of satellite images is an effective and cost-efficient way to investigate the spatial patterns of the populations of a landscape in a basin at a relatively recent timescale. Traditionally, human presence has been analysed using optical data, such as NASA-provided LANDSAT and MODIS data (Ceola et al., 2015). However, conventional processing and multispectral classification make it hard to identify or extract urban areas from the bare soil (Xu, 2007). Thus, as an alternative, we use the Defense Meteorological Satellite Program (DMSP) stable night light data as a proxy for human presence (see also Section 2.3.1) (NOAA 2017). Stable night lights are cloud-free digital products, signifying the presence of lights and distinct luminosity. In the past 20 years, the DMSP-OLS night light data have increasingly been explored for demographic, economic, and environmental purposes (Bennie et al., 2014; Chand et al., 2009; Chen and Nordhaus, 2011; Elvidge et al., 1997; Elvidge et al., 2009). Importantly, recent efforts toward analysing the applications of night light data have indicated their enhanced value in

determining human exposure and vulnerability to natural hazards compared to traditional approaches.

For instance, Ceola et al. (2014) provided night lights as a proxy for the assessment of human exposure to floods by associating them with the river network and identifying flood-subjected areas worldwide. Ceola et al. (2016) also studied the overall human signatures from the DMSP night light data along the Eastern Alpine network. The research showed an overall increase in human presence along the rivers in the area from 1992 to 2013 (Ceola et al., 2016). Following this approach, Gómez et al. (2015) used night lights to investigate the temporal variation of the spatial distribution of the exposure to hydrometeorological hazards in the Samala River in Guatemala. Ceola et al. (2015) also quantified the temporal evolution and spatial distribution of urban settlements in the proximity of streams and rivers at a global scale. Mård et al. (2018) used stable night lights to understand human-environment interactions by studying the relationship between catastrophic flood events, flood protection levels, and long-term changes in human proximity to rivers. Additionally, Fang et al. (2018) explored the river's geomorphic structure and human settlement patterns at a global scale using night lights and identified the preferential downstream clustering of settlements across six continents, suggestive of distributions related to trade and transport purposes in the studied river basins. Recently, Masrur et al. (2018) demonstrated the assessment of the human presence and flood exposure in proximity to rivers in Bangladesh using the multi-temporal satellite night-time light (NTL). Their study showed emerging hotspots of night lights and populations near the rivers that were under flood-exposure risk. Zhong et al. (2018) studied the spatial pattern evolution of the urban built-up area of the Yangtze River Economic Belt from 1992 to 2013 based on the DMSP night light data.

Most previous research using night light data in this context has been on a global scale. The research has been limited to the scale of individual catchments and as a function of different geomorphic parameters. The novelty in our contribution, therefore, lies in

characterising the detailed relationship between river patterns, terrain, and human presence, using the Indus Basin as a well-constrained natural laboratory. This study demonstrates the value of night light data in quantifying human presence within river basins and their geomorphic parameters. Thus, we use an unconventional dataset, the DMSP night light data, compared to the traditional/conventional satellite images along with the LandScan population data and the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), to study the relationship of human presence with respect to different geomorphic parameters. We test two hypotheses. Our first hypothesis is that there is a higher human presence near the river in floodplains due to water availability and soil fertility. Thus, we test and evaluate the prediction that both night light presence and intensity should be higher near the major tributaries of the Indus catchment compared to the basin as a whole. Secondly, we hypothesise that human presence is also affected by the channel-pattern type, i.e., single-thread or multi-thread channel types. Given the documented stability of the channel banks for different channel patterns (Schumm, 1981), we evaluate whether human presence is higher near single-thread or meandering river channel reaches than near braided or multi-thread channels. This study is one of a kind as it explores the application of night light data to study the differential signal of human response to river channel patterns.

2.2. Study Area

The Indus Basin is one of the major river basins of the world, having a drainage area of >1,100,000 km² (Figure 2.1). The basin is shared by four countries, with Pakistan occupying 47% of the basin and India occupying nearly 39%. China and Afghanistan occupy approximately 8% and 6% of the area of the basin, respectively (Food and Agriculture Organization, UN 2011). Several tributaries transport the snowmelt, glacier melt, rainwater, and runoff from the Himalayas, Hindu Kush, and Karakoram mountain areas. The major tributaries of the Indus are the Kabul, Kurram, Jhelum, Ravi, Beas,

Sutlej, and Chenab. The Indus River starts in western Tibet at an elevation of >6700 m, initially flowing northwest and then southwest through Pakistan and finally draining into the Arabian Sea. It has a total length of 3180 km (Sharma et al., 2017). In the Upper Indus Basin, which is upstream of Tarbela Dam in Pakistan (Karim and Veizer, 2000), the river flows as alternating meandering single-channel reaches and reaches with multi-channel patterns in an initial length of 1125 km (Sharma et al., 2017).

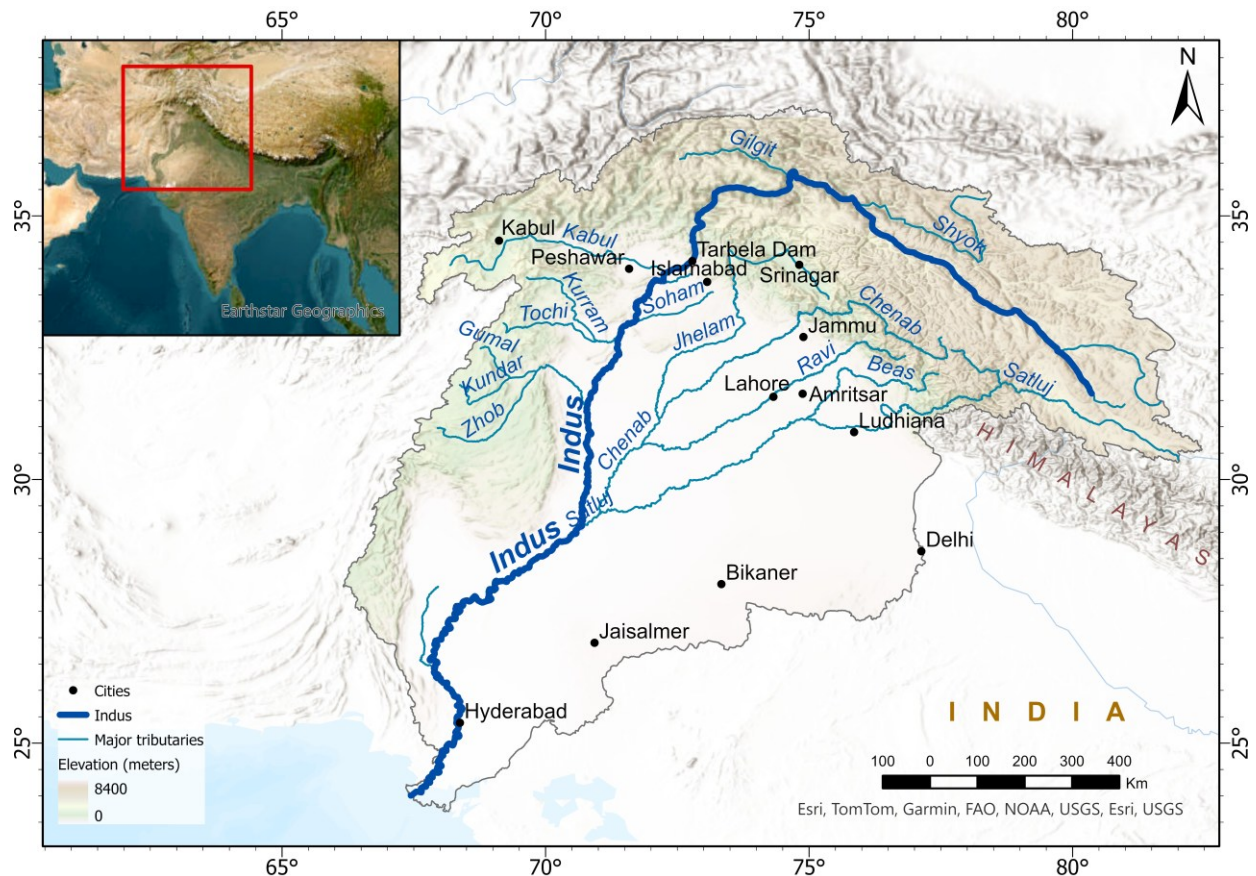


Figure 2.1: ESRI world imagery showing the Indus basin, Indus River (dark blue), and its major tributaries (blue). The red dots are the major cities/urban centres in the study area. The Indus River and its major tributaries, Satluj, Chenab, Ravi, Beas, Jhelum, Soham, Shyok, Kabul, Kurram, Tochi, Gumal, Kunder, and Zhob, are represented in the figure. The inset in the top-right of the figure shows the location of the study area within Asia.

The Indus Basin climate varies from alpine in the northern mountain highlands to semi-arid to temperate subhumid in the plains. The annual precipitation in the mountainous areas of the basin is around 2000 mm and between 100 and 500 mm in the lowlands or plains (Food and Agriculture Organization, UN 2011). The basin receives maximum

rainfall during the monsoon period from July to September, which is the primary reason for the flooding (Kumar et al., 2011). The average rainfall over the lower plains is 125 mm and 500 mm upstream (Kumar et al., 2011). According to UN Food and Agriculture Organization AQUASTAT data, the population of the Indus Basin is around 300 million (Food and Agriculture Organization, UN 2011). The inhabitants of the basin are dependent on agriculture irrigation, industrial requirements, hydroelectric power, flood control, recharging of aquifers, transportation, fisheries, and domestic human consumption (Adeel and Wirsing, 2000).

2.3. Data

2.3.1. DMSP Night Light Data

The night-time light time series (DMSP-OLS v4) are open-access digital products by the National Geophysical Data Center from the National Oceanic and Atmospheric Administration (NOAA) collected under the Defense Meteorological Satellite Program (DMSP) from 1992 to 2013 using the Operational Linescan System (OLS) (NOAA, 2013). These are sun-synchronous, near-polar orbit satellites. Each satellite completes an orbit in roughly 101 minutes, resulting in approximately 14.1 to 14.4 orbits per day. This configuration allows the satellites to pass over the same regions at consistent local solar times daily (NOAA, 2013). The DMSP-OLS night light data are collected by six satellites: F10, F12, F14, F15, F16, and F18. The DMSP stable night light data have undergone the following corrections: sunlit observations are excluded using solar elevation angle criteria, glare is removed based on the same parameter, moonlit data are omitted through calculations of lunar illuminance, cloud-covered observations are excluded using cloud identification from the OLS thermal band data, and auroral lighting features in the northern hemisphere are excluded on an orbit-by-orbit basis through visual inspection (Elvidge et al., 1997).

The Operational Linescan System (OLS) sensor acquires global daytime and night-time images in two spectral bands: the thermal infrared band (TIR) from 10.5 to 13.4 μm and the visible and near-infrared band (VNIR) from 0.4 to 1.10 μm . The data are expressed in terms of average annual intensity denoted by Digital Number (DN) (DMSP data collected by the US Air Force Weather Agency). The digital number (DN) values in the visible band range from 0 to 63, whereas zero signifies the absence of lights and distinct luminosity (Figure 2.2). The OLS night light data represent a grid of 30 arc seconds spanning from -180 to 180 degrees longitude and from -65 to 75 degrees latitude. The spatial resolution is roughly 1 km at the equator. In years when two satellites were collecting data, two composites were produced. For example, in 1994 and from 1997 to 2007, two satellites simultaneously acquired two distinct sets of night light data. To obtain a unique night light value for each pixel in a year, the average luminosity pixel value can be calculated from the two overlapping satellite data for each year.

The program started in the mid-1960s and originally aimed to gather the global cloud cover day and night data. However, the usage of night lights remained limited within the remote sensing community until the 1990s because of the unavailability of data in digital form (Levin et al., 2020). In 1992, the NOAA National Geophysical Data Center established a digital archive of the DMSP data, and now the data have usability for studying human presence and settlement dynamics. Earlier work established a relationship between the “stable lights” data and measures of the population, regardless of economic development (Elvidge et al., 1997). Imhoff (1997) studied the correlation between the urban extent using the DMSP-OLS night lights and the population using census data.

Despite the advantages of the DMSP-OLS night light data, there are some limitations associated with it, including relatively low spatial resolution (Huang et al., 2014); some inconsistency in the DMSP sensors due to the absence of onboard calibration (Li and Zhou, 2017); light saturation in urban core areas and the blooming effect, which is the

overestimation of night light values over the transition areas between urban and rural areas (Zhao et al., 2019). The average DN values are weaker in developing countries, and thus, the threshold methods are not always valid (Mård et al., 2018). Hence, the influence of these effects can be minimised by studying the trends in night lights over the long term rather than measuring absolute values or focusing on individual years (Stathakis et al., 2015).

As mentioned before, the data often saturate the bright cores of urban areas due to its six-bit quantisation and limited dynamic range. However, the dataset was calibrated for radiance due to a lack of intensity information by the Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines (Elvidge et al., 1999). The calibration process combines fixed-gain images from the DMSP satellite, which records night-time lights at different brightness levels, to create a dataset with a wide dynamic range that captures both bright and dim lights. These images are then blended with an operational stable light product to recover detail in less illuminated areas. The merging process uses the highest gain image as a reference and applies weighting factors to other images. Additionally, to account for differences in sensor sensitivity between satellites, inter-satellite calibration is performed using pre-flight sensor calibration data, with the "F16 gain 55" as the reference sensor (Elvidge et al., 1999). These calibrated data products are downloaded from <https://eogdata.mines.edu/products/dmsp> (the data was accessed on 17 December 2021).

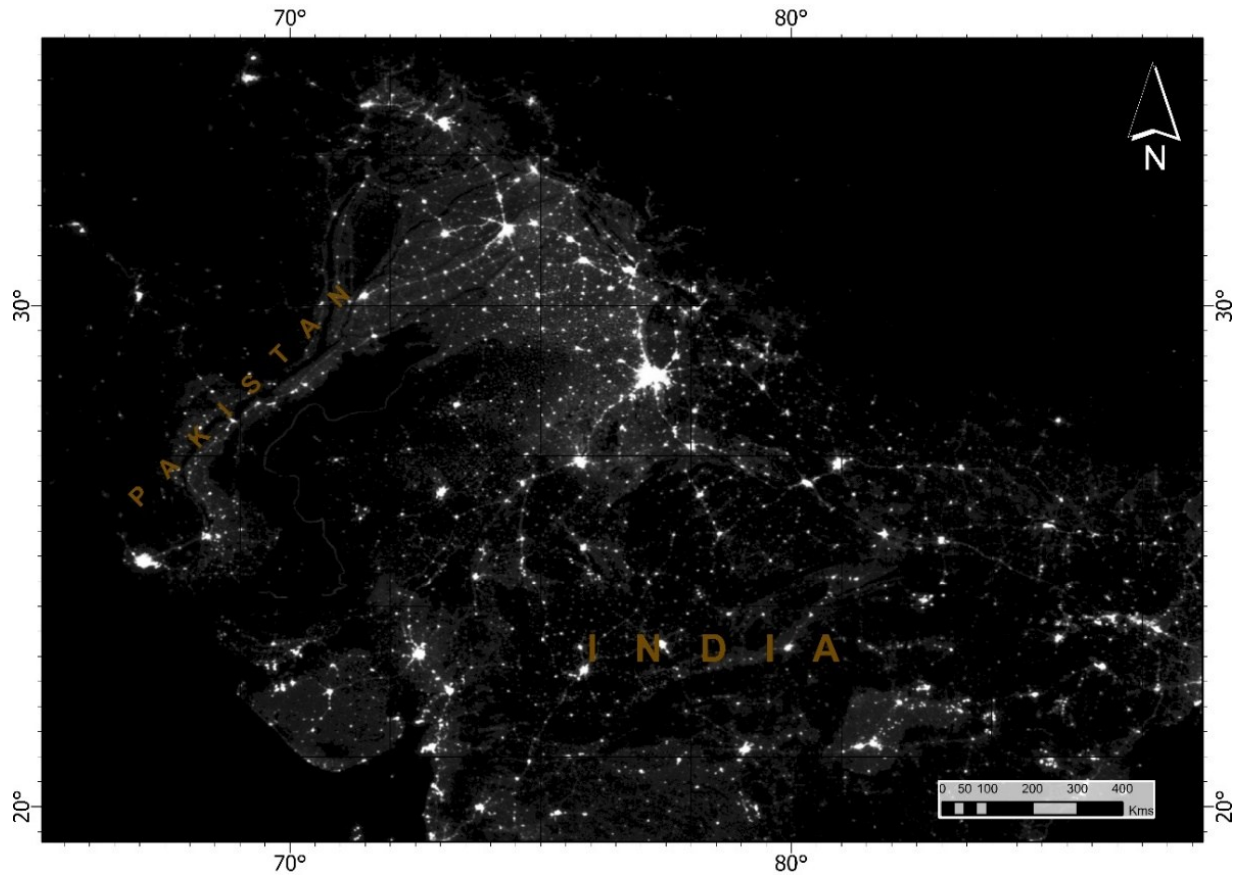


Figure 2.2: Distribution of the DMSP-night lights across the Indian subcontinent in the year 2013. White areas correspond to high-intensity areas, while black areas correspond to the absence of night lights (Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency).

2.3.2. SRTM DEM

The NASA Shuttle Radar Topography Mission (SRTM) data set obtained the near-global digital elevation model (DEM) of the Earth using radar interferometry. For this study, we used the SRTMGL3 data product having a spatial resolution of 3 arc seconds, which is ~90 meters near the equator. It was downloaded from <https://appeeers.earthdatacloud.nasa.gov/> (accessed on 20 November 2021) in the GeoTIFF format for further processing.

2.3.3. LandScan Global Population Data

In our study, to validate the night lights as a proxy for the population in the study area, we used the LandScan data. They are considered to have high spatial accuracy and

estimated errors compared to other open-source global population data like WorldPop, Global Human Settlement Layer Population Grid (GHS-POP), and Gridded Population of the World (GPW) in an area of rapidly changing population (Yin et al., 2021). LandScan Global is a worldwide database that integrates geographic information systems (GIS), remote sensing technology, and machine learning to estimate the ambient population at a 30 arc-second resolution (Dobson et al., 2000). The data from 2000 to 2013 were downloaded from <https://landscan.ornl.gov/> (accessed on 8 January 2022).

2.4. Methods

2.4.1. Processing of the DMSP Night Lights (2000–2013)

We used the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) stable night light data in the Indus Basin from 2000 to 2013 to study human presence in the basin. Yearly global calibrated night lights were downloaded in GeoTIFF format for the period from 2000 to 2013. From 2000 to 2009, two simultaneous satellites operated and gathered data. Thus, to obtain the unique values of a particular year, the average of the two satellite datasets was computed in ArcGIS.

The DMSP-OLS rasters for 14 years were cropped for the Indus Basin and projected into the WGS Albers 1984 projection for calculation purposes. Figure 2.3 represents the distribution of night lights over the Indus Basin for the years 2000, 2007, and 2013. To obtain the average distribution of night lights for further statistical analysis, the mean of the annual datasets was computed per pixel over the time in the basin in RStudio. Figure 2.4 shows the average distribution of night lights from 2000 to 2013 over the Indus Basin.

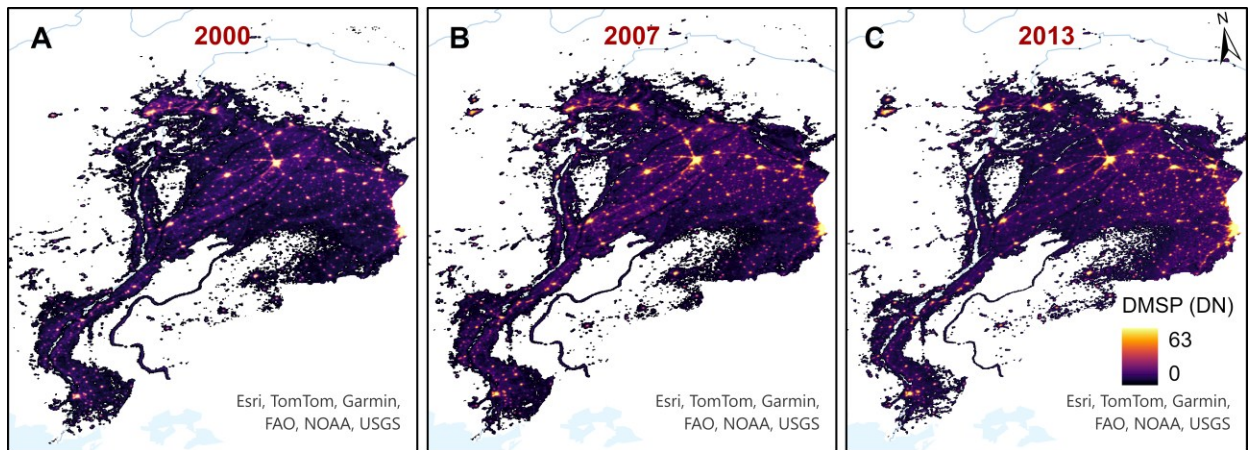


Figure 2.3: Distribution of DMSP night light data over the Indus basin for the years (A) 2000, (B) 2007, and (C) 2013 over the same colour scale. The lighter yellow pixels represent higher-intensity areas, usually towns, cities, or urban centres, and the dark pixels represent the absence of night light or lower-intensity night light areas. Legend numbers denote the number range of the intensity of the pixels represented by the Digital Number (DN).

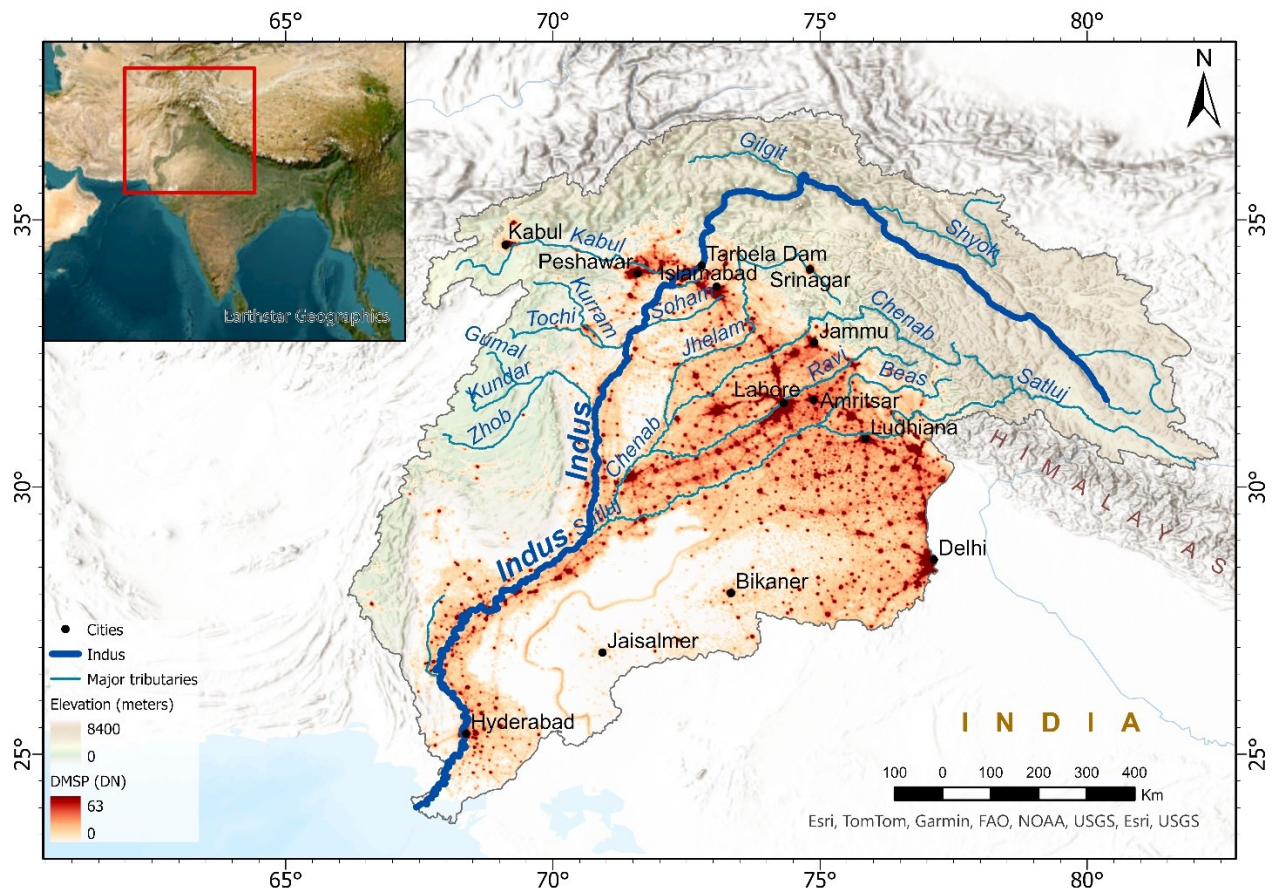


Figure 2.4: Average distribution of the DMSP night lights from 2000 to 2013 in the Indus Basin (black boundary). The darker red pixels represent higher-intensity areas, and the lighter colour pixels represent lower-intensity night light areas or areas with an absence of night light. The black dots are the major cities/urban centres in the area. The Indus River and its major tributaries, Satluj, Chenab, Ravi, Beas, Jhelum, Soham, Shyok, Kabul, Kurram, Tochi, Gumal, Kundar, and Zhob, are represented in the figure.

2.4.2. Extraction of the Indus Watershed and Major River Tributaries

The basin boundary was extracted from the SRTM Digital Elevation Model (DEM) using the D8 algorithm in ArcGIS. Using the DEM as an input, the flow direction, flow accumulation, and channel network were extracted using the ArcHydro tools in ArcGIS. Thus, the Indus River, its major tributaries, and the catchment were delineated to understand the distribution of the night lights as a proxy for human presence with respect to the rivers in the basin. This study considers higher-order streams (six and above) only, as these are the major watercourses in the region.

2.4.3. Processing of the LandScan Global Population Data

In this study, we use night lights as a proxy for human presence. The night lights include informal human settlements, for instance, industrial setups, workplaces, highways, etc., where a residing population is absent but which are representative of anthropogenic activities. Thus, to establish the extent to which night light data can be used as a direct proxy for the human population, we used the LandScan Global data and reprojected it into the WGS Alber 1984 projection using ArcGIS Pro. The raster data for 14 years were clipped to the basin boundary, and the total population for each year was calculated. The population derived from the LandScan data was related to the sum of lights from the night light dataset. Such a correlation between the night lights and the population density would specifically show the extent to which night lights record the human population as well as indicate human presence in the study area.

2.4.4. Presence or Absence of Night Lights across the Basin and Buffer Zones

We started with an evaluation of the basics of night light distribution as a proxy of human presence with respect to the catchment, as earlier studies have focused on very large-scale studies rather than considering the local terrain. Consequently, to understand the role of the proximity of the rivers in human presence and to test our hypothesis of preferential settlements and human activity near the river, four “buffer zones” of 5 km

each were established for the Indus River and its major tributaries. We define buffer zones as areas within specific distances from the river channel. Four buffer zones, at 0–5 km, 5–10 km, 10–15 km, and 15–20 km (as measured from the major water course), were extracted using the buffer tool in the Geoprocessing toolbox in ArcGIS Pro.

To investigate the distribution of lit pixels in the basin and buffer zones, their geographical area and the area of the lit pixels were calculated in km² for each zone. Additionally, the area percentage (%) for the catchment area of the Indus was calculated (Table 2.1). Because the absolute area of each zone varied, the occurrence of lit pixel frequency was normalised by the spatial extent of each zone. This enabled us to determine whether the occurrence of lit pixels simply mirrored the area distribution of the different buffer zones or if some zones, for instance, those close to rivers, were associated with an enhanced probability of occurrence of lit pixels. We describe this ratio as an Enhancement Factor, $Ef\text{-}bz$, which we obtained by dividing the percentage of lit pixels in a zone by the percentage of lit pixels across the basin as a whole (Equation 2.1). The enhancement factor indicates the occurrence of lit pixels independent of the geographical area of each buffer zone.

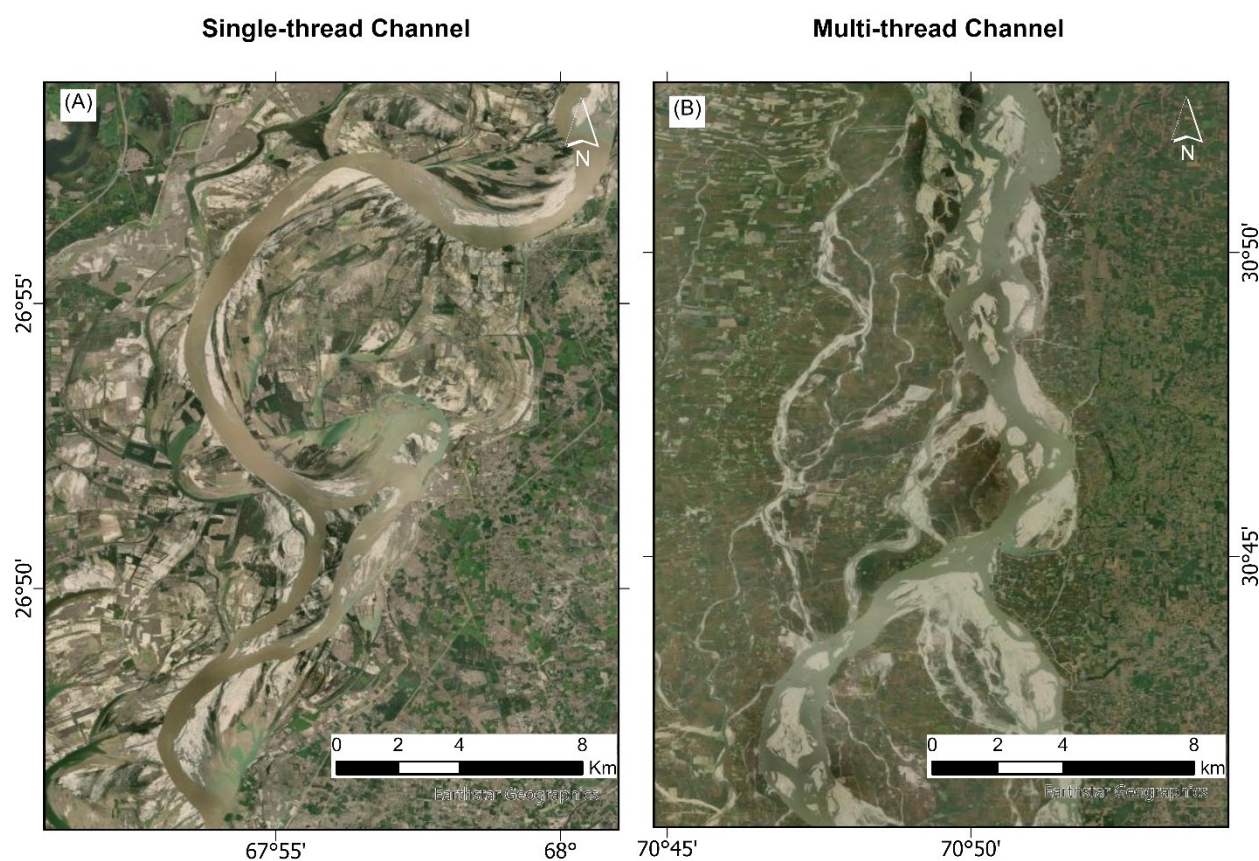
$$\text{Enhancement factor, } Ef\text{-}bz = Lbz/Lb \quad \dots\dots\dots (2.1)$$

Where, $Ef\text{-}bz$ is the enhancement factor for the respective buffer zone, Lbz is the percentage of lit pixels for the respective buffer zone, and Lb is the percentage of the lit pixels across the basin.

Table 2.1: Geographical and DMSP night light-derived area for different proximity zones of the rivers in the Indus Basin.

	Geographical Area (km ²)	Geographical Area Percentage w.r.t Basin (%)	Number of Lit Pixels (N)	Area Percentage of Lit Pixels w.r.t Basin (%)	Area of Lit Pixels (km ²)	Percentage of Lit Pixels w.r.t Geographical Area (%)	Enhancement Factor (E _{f-bz})
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Basin	1,168,436	100	560,906	100	533,211.30	45.63	1.00
0–5 km	112,657	9.64	68,352	12.19	64,977.12	57.68	1.26
5–10 km	104,533	8.95	55,692	9.93	52,942.21	50.65	1.11
10–15 km	99,004	8.47	48,884	8.72	46,470.35	46.94	1.03
15–20 km	92,233	7.89	43,778	7.80	41,616.46	45.12	0.99

2.4.5. Night Lights Intensity Distribution with Relation to River Channel Pattern

**Figure 2.5:** Single-thread channel pattern of the Indus River; (B) multi-thread channel pattern of the Indus River. Source—ESRI, Maxar Technologies 2022.

To explore the influence of channel patterns on human presence in the Indus Basin, the distribution of lit pixels adjacent to the Indus River was calculated in relation to channel-

pattern type—single-thread versus multi-channel patterns. Single-thread and multi-thread reaches of the Indus River were identified through visual inspection on Google Earth Pro between 2000 and 2013 (Figure 2.5A, 2.5B). The first-order channel-pattern type was recognised based on detailed observation from Google Earth imagery, including the number of styles of channel threads. Multi-thread river segments had multiple channel bars separated by channels, whereas single-thread channel segments had a single channel with a sinuous planform typically characterised by high sinuosity (Zhou and Wang, 2015). Due to the area of the basin, the distribution of night lights across the pattern type of only the Indus River was studied for this analysis; we did not consider local variations in the planform over short distances (<500 m). The points of change in the predominant pattern type of the Indus River were identified on Google Earth Pro. Four buffer zones of 0–5 km, 5–10 km, 10–15 km, and 15–20 km were created for each pattern type using the buffer tool in the Geoprocessing toolbox in ArcGIS Pro.

To understand the distribution of night lights across the two channel-pattern types, the geographical area and the lit pixel area were calculated within each buffer zone for each channel pattern. Table 2.2 represents the geographical and night light occupied area percentages for each buffer zone for the single-thread channel. The total area represents the area occupied within the 20 km vicinity of the single-thread channel from its centre line. Similarly, geographical and night light-lit areas were calculated for the buffers for the multi-thread channel (Table 2.3). Further, the enhancement factor for single-thread and multi-thread channels ($Ef-s$ and $Ef-m$) were computed by dividing the percentage of lit pixels in each class of channel-pattern type by the percentage of lit pixels of the total area of the respective channel-pattern type (Equations 2.2 and 2.3). This enabled a normalised relation between the presence of lit pixels and the distance from the river for different channel-pattern types to be analysed (Tables 2.2 and 2.3).

$$\text{Enhancement factor, } Ef-s = Lbz-s/Ls \quad \dots\dots\dots(2.2)$$

$$\text{Enhancement factor, } Ef-m = Lbz-m/Lm \quad \dots\dots\dots(2.3)$$

where E_{f-s} is the enhancement factor for the respective buffer zone of the single-thread channel, L_{bz-s} is the percentage of lit pixels for the respective buffer zone of the single-thread channel, L_s is the total percentage of the lit pixels across all the buffer zones within the single-thread channel, E_{f-m} is the enhancement factor for the respective buffer zone of the multi-thread channel, L_{bz-m} is the percentage of lit pixels for the respective buffer zone of the multi-thread channel, and L_m is the total percentage of the lit pixels across all the buffer zones within the single-thread channel.

Table 2.2: Geographical and DMSP night lights-derived area for four proximity zones of the single-thread channel of the Indus River.

	Geographical Area (km ²)	Geographical Area Percentage w.r.t Basin (%)	Number of Lit Pixels (N)	Area Percentage of Lit Pixels w.r.t Basin (%)	Area of Lit Pixels (km ²)	Percentage of Lit Pixels w.r.t Geographical Area (%)	Enhancement Factor (E_{f-s})
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0–5 km	21,995.42	27.01	10,544	32.00	10,023.39	45.57	1.18
5–10 km	20,248.08	24.86	8174	24.81	7770.41	38.38	1.00
10–15 km	19,678.50	24.16	7129	21.64	6777.01	34.44	0.90
15–20 km	19,517.19	23.97	7102	21.55	6751.34	34.59	0.90
Total	81,439.19	100	32,949	100	31,322.14	38.46	1.00

Table 2.3: Geographical and DMSP-Night lights derived area for four proximity zones of the multi-thread channel of the Indus River.

	Geographical Area (km ²)	Geographical Area Percentage w.r.t basin (%)	Number of Lit Pixels (N)	Area Percentage of Lit Pixels w.r.t Basin (%)	Area of Lit Pixels (km ²)	Percentage of Lit Pixels w.r.t Geographical Area (%)	Enhancement Factor (E_{f-m})
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0–5 km	6392.98	26.21	5399	24.10	5132.42	80.28	0.92
5–10 km	6037.94	24.76	5933	26.48	5640.06	93.41	1.07
10–15 km	5950.71	24.40	5743	25.63	5459.44	91.74	1.05
15–20 km	6005.78	24.63	5328	23.78	5064.93	84.33	0.97
Total	24,387.40	100	22,403	100	21,296.85	87.33	1.00

2.5. Results

2.5.1. How Well Do Night Light Data Serve as a Proxy for Human Activity?

To establish how well night light data approximate human presence and activity in our study area, we compared the sum of lights derived from night light data with population density data from the Indus Basin derived from the LandScan Global population dataset. The sum of lights is the summation of the lit pixel values over the study area. This enables us to evaluate the extent to which night light data serves as a reasonable proxy for human presence and activity. We note that the sum of lights represents data captured from four different satellite sensors—F14, F15, F16, and F18—capturing the night light data between 2000 and 2013 (Figure 2.6: red, blue, green, and yellow colours, respectively).

Figure 2.6 shows an overall positive correlation between summed night lights and population over 14 years. The linear correlation coefficient (R) is 0.655, indicating a moderate positive relationship and the coefficient of determination (R^2) is 0.429, suggesting that 43% of the variation in the sum of lights can be explained by the Landscan population. The red-dashed regression line represents this linear relationship, with the shaded regions showing the upper and lower bounds of the 95% confidence intervals. All data points lie within these bounds, with a few outliers from the regression line, which is further discussed in Section 2.6.1.

To assess the statistical significance of the observed relationship, we computed the p-value, which was 0.011. The p-value is a statistical measure that helps determine the strength of evidence against the null hypothesis, assuming the null hypothesis is true. As the p-value was 0.11, it provides evidence against the null hypothesis of the variables not being dependent, as there is less than a 5% probability that the null is correct (and the results are random). Therefore, we reject the null hypothesis and accept the alternative hypothesis of the variables being dependent. Thus, our results suggest that

the night light data provide a good proxy for human presence in the study area (red-dash line, Figure 2.6).

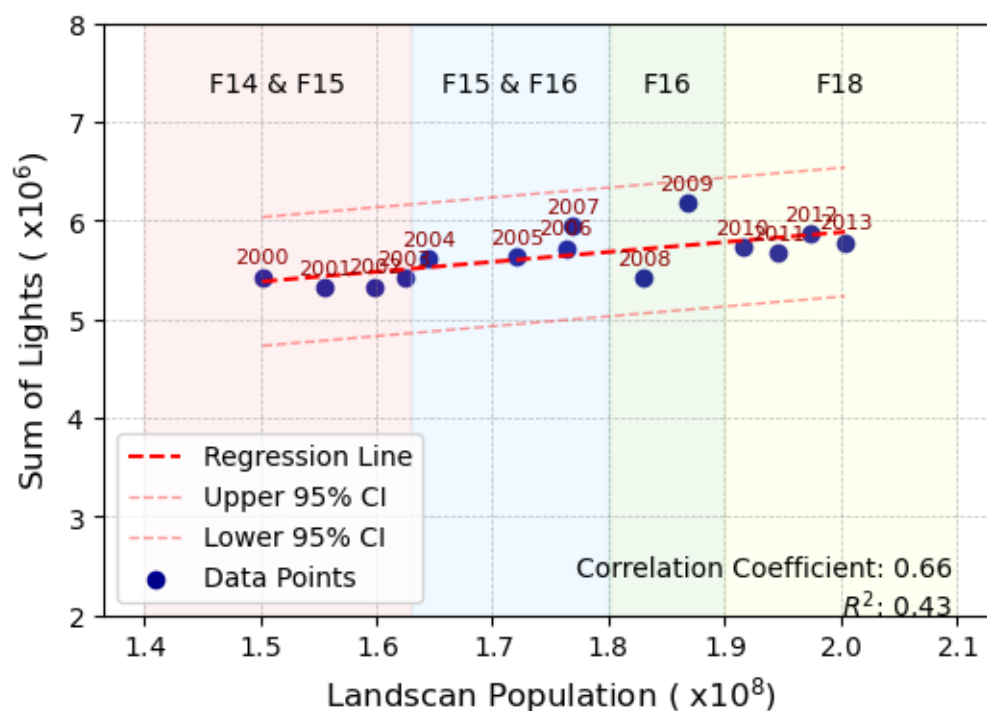


Figure 2.6: Scatter plot between Landscan population and the sum of lights for the years 2000–2013. The blue circles represent individual data points for each year, with the corresponding year labelled along the x-axis. The dashed red line indicates the regression line, with the shaded regions showing the upper and lower bounds of the 95% confidence interval. The correlation coefficient (0.66) suggests a moderate positive relationship, and the R^2 value (0.43) indicates that 43% of the variation in the sum of lights can be explained by the Landscan population. The graph is divided into coloured regions corresponding to different time periods collected between 2000 and 2003 by F14 and F15, in the blue region between 2004 and 2007 by F15 and F16, in the green region between 2008 and 2009 by F16, and in the yellow region between 2010 and 2013 by F18.

2.5.2. Relation between Night Light Distribution and Proximity to Rivers

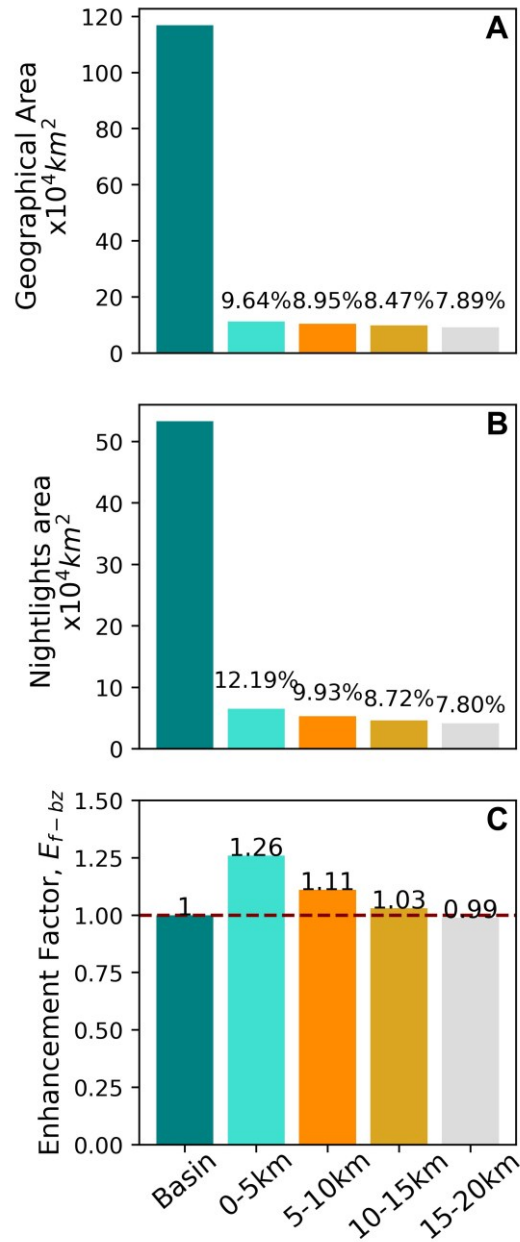


Figure 2.7: (A) Bar plot of the geographical area of the basin (teal green), 0–5 km (turquoise), 5–10 km (orange), 10–15 km (gold), and 15–20 km (grey) buffer zones. (B) Bar plot of the DMSR night lights derived lit pixels area in the basin, 0–5 km, 5–10 km, 10–15 km, and 15–20 km buffer zones. (C) Bar plot of the enhancement factor (E_{f-bz}) of the basin and the four buffer zones, denoting the normal occurrence of lit pixels independent of the geographical area of each buffer zone.

To investigate the proximity of human presence to the main rivers in the Indus Basin, we examined the relation between the occurrence of lit pixels and distance to rivers. In Figure 2.7, we compare the spatial distribution of lit pixels in each of the four buffer zones

progressively moving outwards from the river centreline with the geographical area covered by each of the buffer zones. The buffer zone geographical area percentages, with respect to the basin area, were 9.64%, 8.95%, 8.47%, and 7.89% for the 0–5 km, 5–10 km, 10–15 km, and 15–20 km buffer zones, respectively (Figure 2.7A). Figure 2.7B shows the area (in km²) of lit pixels across these different buffer zones. Around 533,200 km² of the Indus Basin is occupied with night lights, equivalent to 46% of the area of the basin, indicating extensive human presence across the basin. The percentage areas of the lit pixels, with respect to the total lit pixels area of the basin across the four buffer zones, are 12.19%, 9.93%, 8.72%, and 7.80% for the 0–5 km, 5–10 km, 10–15 km, and 15–20 km buffer zones, respectively. The lit pixels area is higher within the 0–5 km river network buffer, signifying a larger number of lit pixels in proximity to the river.

To characterise the degree of enhancement of lit pixels independent of the geographical area of the buffer zone, an enhancement factor, Ef_{bz} , was calculated, as described in Equation (2.1). Figure 2.7C shows that the number of lit pixels is enhanced by 26% (a factor of $Ef_{bz} = 1.26$) within 5 km of the river network in the Indus Basin, compared to the data set as a whole. Moreover, the number of lit pixels is enhanced by 11% and 3% within the 5–10 km and 10–15 km buffer zones, respectively. However, the distribution of night lights in the 15–20 km zone is approximately the same as in the whole basin ($Ef_{bz} = 0.99$). Consequently, our data suggest that, at more than 15 km away from the Indus and its major tributaries, the human presence or activity recorded in the night light data is not statistically different from that of the basin as a whole. Figure 2.7C also demonstrates that human presence is significantly enhanced near major rivers in the basin, with a particularly high concentration within 5 km of the drainages analysed.

2.5.3. How Does the Intensity of Night Lights Vary in Proximity to Rivers?

Figure 2.7C demonstrates a statistically significant increase in the occurrence of lit pixels in proximity to rivers in the Indus Basin. We now turn to an exploration of whether the intensity of these lit pixels captured in the data set behaves similarly. The relationship

between the intensity of the lit pixels and the occurrence of lit pixels is explored by a comparison of the frequency distribution of the lit pixel digital number (DN) across the basin and the four buffer zones of 0–5 km, 5–10 km, 10–15 km, and 15–20 km. DN is a proxy for night light intensity. Figure 2.8 shows histograms plotting the frequency of the occurrence of DN values in the overall Indus Basin and the various designated buffer zones outward of the river centrelines. These plots represent the variation in the frequency of the intensity of night lights across the buffer zones. Importantly, the histograms in Figure 2.8 indicate that the distribution of intensities (DN value) within the basin and the buffer zones identified for this study are not the same shape as the frequency of lit pixels differs.

Table 2.4: Descriptive statistics of the night light data for the basin and the four buffer zones.

	Count	Area (km sq.)	Min	Max	Mean	Std. Dev.	Sum	Median
Basin	560,906	533,211.30	0	62.64	8.01	8.05	4,491,618.90	6.39
5 km	68,352	64,977.12	0	62.64	7.22	7.63	493,725.20	5.63
10 km	55,692	52,942.21	0	62.64	9.10	8.95	506,808.10	7.15
15 km	48,884	46,470.35	0	62.64	9.60	8.92	469,529.80	7.73
20 km	43,778	41,616.46	0	62.55	9.66	8.89	422,969.80	7.89

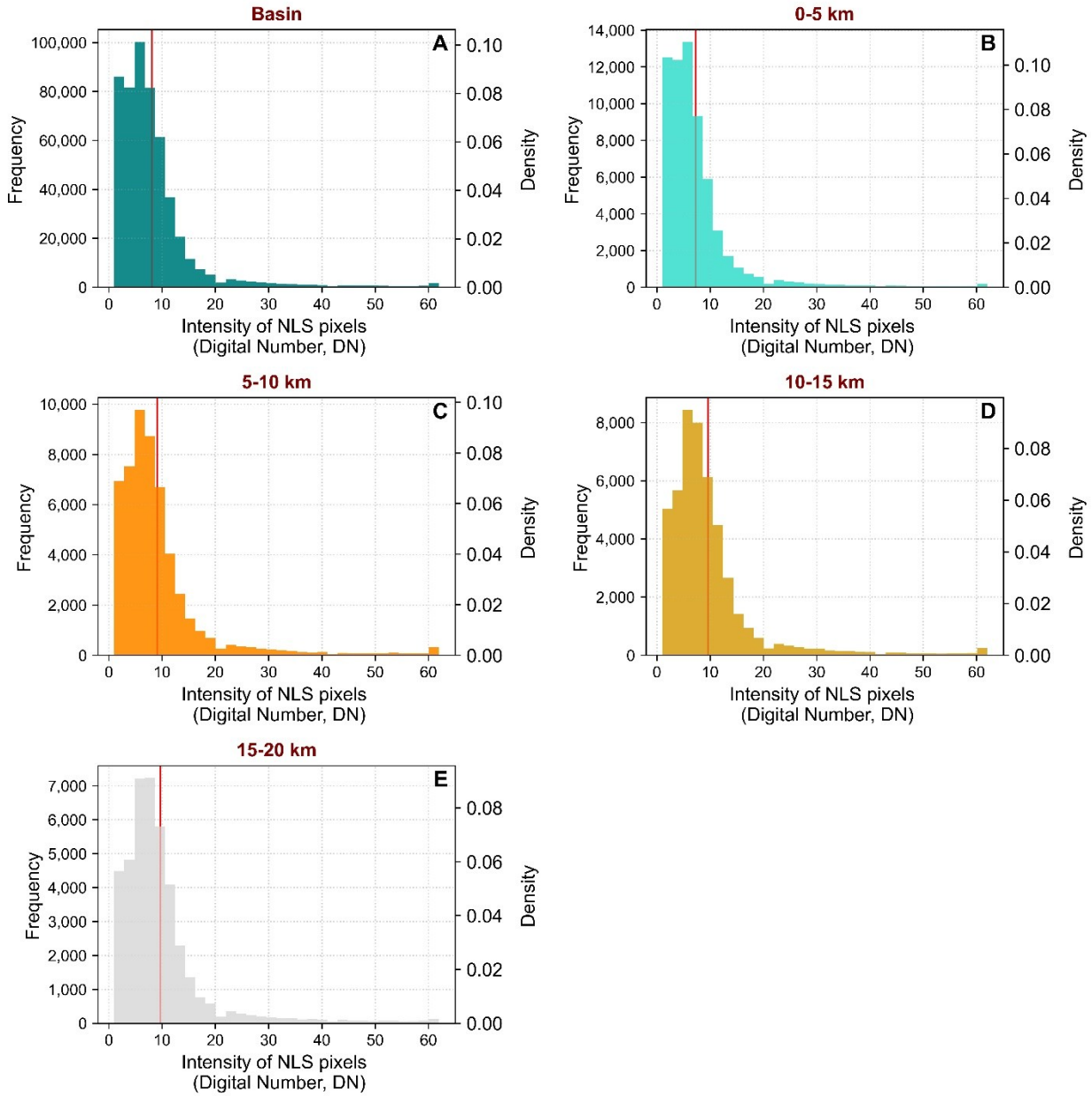


Figure 2.8: Frequency plots of lit pixels as a function of the intensity of the lit pixels (represented by digital number, DN) for the Indus Basin and the four buffer zones. The red line in the plots represents the mean of the distribution. (A) Frequency distribution plot of the lit pixels in the basin (teal green). (B) Frequency distribution plot of the lit pixels within the 0–5 km buffer zone (turquoise). (C) Frequency distribution plot of the lit pixels within the 5–10 km buffer zone (orange). (D) Frequency distribution plot of the lit pixels within the 10–15 km buffer zone (gold). (E) Frequency distribution plot of the lit pixels within the 15–20 km buffer zone (grey).

Descriptive statistics for the lit pixels in the buffer zones were calculated in Table 2.4. The mean DN of the basin is 8.0, and the median is 6.4. Figure 2.9 shows the cumulative frequency of the lit pixels as a function of DN intensity in the night light data. The median

intensity (DN) of lit pixels over the 5 km buffer zone closest to the major rivers is 5.6; this increases to 7.15 in the 5–10 km zone, 7.7 in the 10–15 km, and 7.9 in the 15–20 km buffer zone, values which are greater than the median for the basin (=6.4) as a whole. Thus, all five distributions are offset from each other. To further test the statistical significance of the varying night light distribution, two sample KS-tests were computed. The KS test is a non-parametric test that compares the cumulative distributions of two samples to determine if they come from the same distribution. The test allowed us to reject the null hypothesis that these distributions were similar at a 95% confidence level, showing that night light intensity was greater further from the river.

To understand the relationship between the distance to the river and the mean intensity of night lights, the mean intensity (DN) of the lit pixels was plotted against the count of lit pixels across each buffer zone (Figure 2.10). We recover a quadratic relationship that shows that, as the distance from the river increases, the number of lit pixels decreases, whereas the mean intensity (DN) increases. For instance, in the 0–5 km buffer zone, the mean intensity was 7.2, and the total number of lit pixels was 68,000 compared to in the 15–20 km buffer zone, where the mean intensity was 9.7, and the total number of lit pixels was 44,000. This variation in intensity and count of lit pixels is important, as it clearly shows that, while the number of lit pixels near the Indus and its tributaries is enhanced relative to the basin as a whole, the intensity of lit pixels is greatest in the zone that is 10–20 km away from the river. We hypothesise, based on this observation, that the relation between intensity and night light presence may be an important parameter in understanding settlement density in proximity to rivers, and we return to this idea in the discussion.

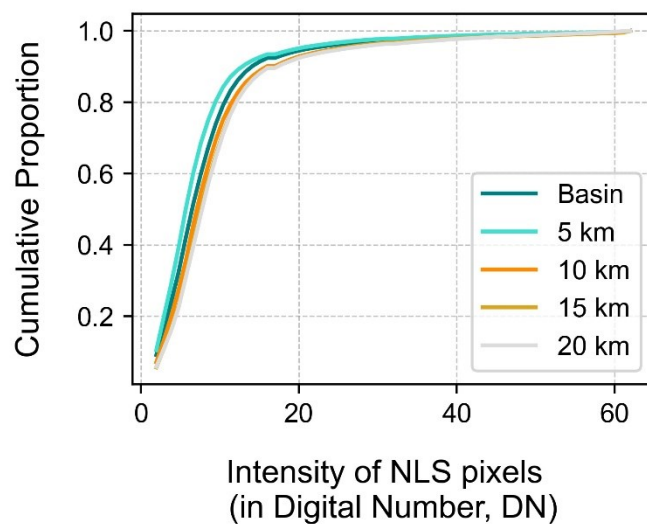


Figure 2.9: Cumulative distribution plot of the basin and four buffer zones. The medians of the basin, 5 km buffer zone, 10 km buffer zone, 15 km buffer zone, and 20 km buffer zone are 6.39, 5.63, 7.15, 7.73, and 7.89, respectively. Thus, 50% of the lit pixels across the basin and four buffer zones have an intensity below 10.

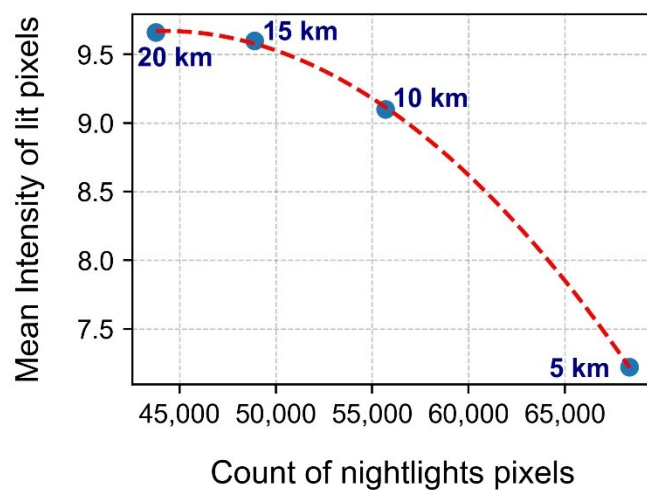


Figure 2.10: Correlation plot between the DMSP night light-derived mean intensity of lit pixels and the count of the lit pixels in the four buffer zones: 0–5 km, 5–10 km, 10–15 km, and 15–20 km. The red dashed line shows the polynomial regression relationship between the mean intensity and the count of the night light pixels.

2.5.4. Channel Pattern Influence on Human Presence

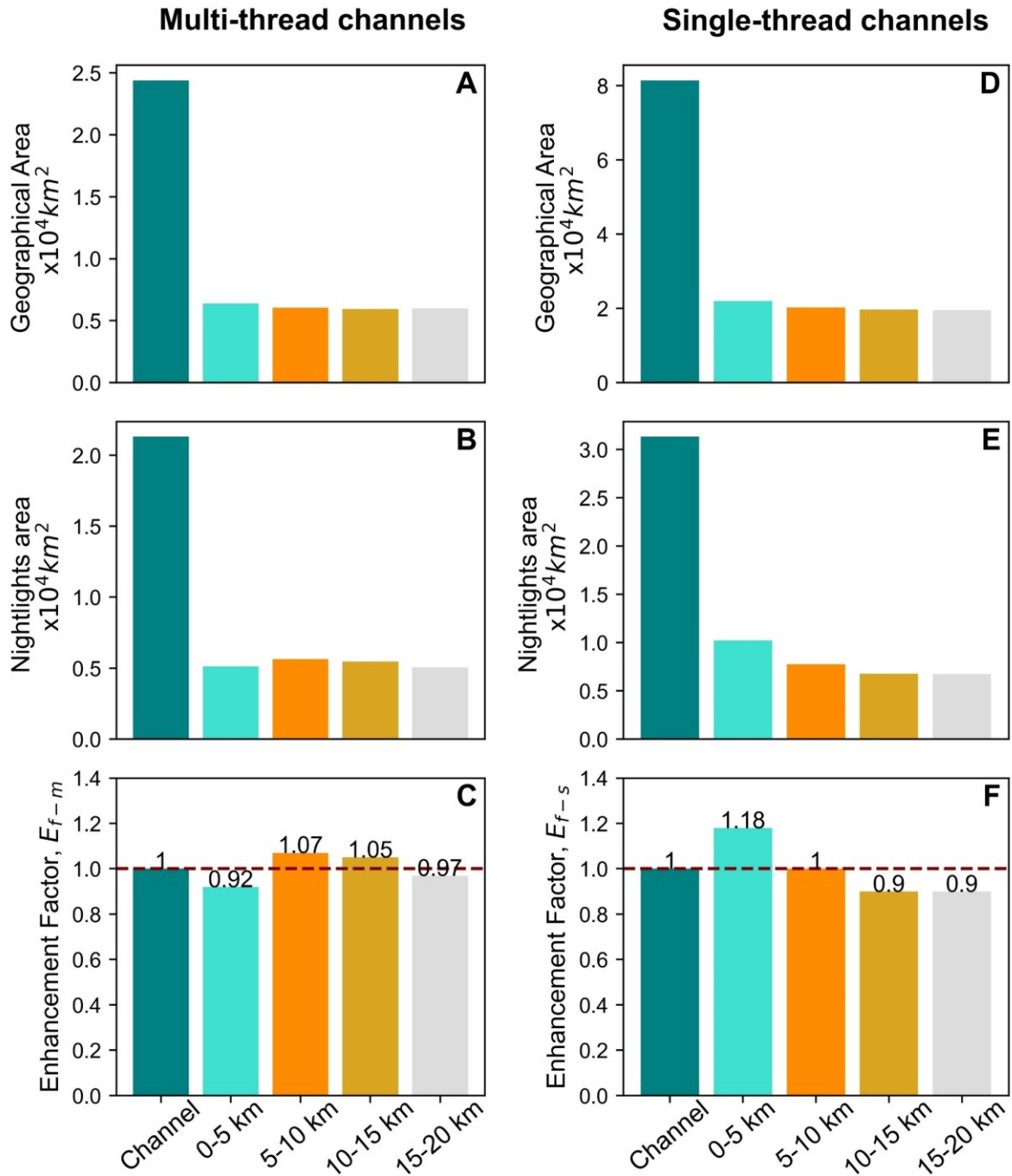


Figure 2.11: (A–C) Bar plots for the multi-thread channels. The figure represents the geographical area, DMSP night lights-derived lit pixels, and enhancement factor of the multi-thread channel and its four buffer zones: 0–5 km, 5–10 km, 10–15 km, and 15–20 km. (D–F) Histogram plots for the single-thread channels. The figure represents the geographical area, DMSP night lights-derived lit pixels, and enhancement factor of the single-thread channel and its four buffer zones: 0–5 km, 5–10 km, 10–15 km, and 15–20 km.

To evaluate the hypothesis that human presence as indicated by night light data is also influenced by the planform river channel pattern, we used a conceptual framework to illustrate and focus on the planform of the trunk channel of the Indus River in the basin. To do this, we calculated enhancement factors for each buffer zone comparing across the single-thread and multi-thread channels of the Indus River (Figure 2.11). We investigated the relationship between the occurrence of lit pixels, distance to the river, and the channel-pattern type by calculating the geographical area for each channel pattern (Figure 2.11A, 2.11D) and the area of lit pixels in each buffer zone (Figure 2.11B, 2.11E).

For the multi-thread channel zones, the geographical area mapped was $\sim 24,400 \text{ km}^2$ (Figure 2.11A). The areas of the lit pixels in the multi-thread channels across the four buffer zones were ca. 5100 km^2 , 5600 km^2 , 5500 km^2 , and 5100 km^2 for the 0–5 km, 5–10 km, 10–15 km, and 15–20 km buffer zones, respectively (Figure 2.11B). The lit-pixel area is higher across the 5–10 km river network buffer, signifying a larger number of lit pixels. When the spatial occurrence of night lights in each class is normalised independently of the geographical area (Figure 2.11C), we find an enhancement of lit pixels (Ef-m) by 7% in the 5–10 km zone for the multi-thread channels. Whereas, for the 0–5 km buffer zone, the lit-pixel occurrence is reduced by 8% relative to the multi-thread river channel area. However, at a distance of more than 10 km from the river, lit pixels are within 5% of what we observe across the basin.

For single-thread channels, the total area of the buffer zones is ca. $81,400 \text{ km}^2$ (Figure 2.11D). The areas of lit pixels across the single-thread channel buffer zones are $10,000 \text{ km}^2$, 7800 km^2 , 6800 km^2 , and 6700 km^2 for the 0–5 km, 5–10 km, 10–15 km, and 15–20 km zones. To understand the occurrence of lit pixels independent of the geographical area, an enhancement factor of 1.18 was computed for the 0–5 km zone (Figure 2.11F), representing an 18% enhancement of lit pixels near the single-thread channel of the Indus River. For the 5–10 km zone, the lit pixels occurrence is the same as that of the total area of the single-thread channel. Whereas, for distances more than 10 km from the river, the

enhancement factor, $Ef-s$, is 0.9, signifying a decrease of 10% of the lit pixel presence relative to the basin as a whole.

The variation in night light distribution across the buffer zones of multi-thread and single-thread channels is interpreted to be representative of the preferential human presence in these two different geomorphic settings. We hypothesise that this is related to the differing channel dynamics and mobility of braided versus single-thread channels, and we return to this in the discussion below. Thus, our analysis indicates that the combination of channel type and proximity to the river plays an important factor in determining the human presence in alluvial basins.

2.6. Discussion

2.6.1. What Do Night Lights Reveal about Human Presence and Activity in the Indus Basin?

In this study, we investigated the application of DMSP night light data from 2000 to 2013 across the Indus Basin to characterise human presence and activity as a function of proximity to rivers and the geomorphic style of the river. We demonstrated that night lights serve as a useful proxy for human presence and activity in the Indus Basin. The DMSP-night light distribution shows a moderate correlation ($R = 0.655$) with the population derived from the LandScan Global population dataset. The correlation is not strong (i.e., 1) because nightlights can signify human activity, not just population. Night lights can serve as a proxy for human activity; however, they do not exclusively reflect population. Instead, night lights capture the signatures of a wide variety of human activities across different areas, such as urban centres, industrial zones, streets, and residential areas (Zhao et al., 2019). As a result, regions with similar population sizes may exhibit varying levels of night-time brightness depending on the nature and intensity of human activities, thereby weakening the direct association between population and night light intensity. Additionally, discrepancies in satellite data acquisition—such as

variations in sensor calibration, sensor degradation, and differences in instrument settings over the period from 2000 to 2013—may further contribute to the observed moderate correlation (Levin et al., 2020). Despite these potential sources of variability, the data points remain within the 95% confidence interval of the regression line.

From our analysis, we find that around 92% of the distribution of the night lights across the Indus Basin is concentrated within the plains of the basin with an elevation of less than or equal to 800 meters. This demonstrates preferential settlement within the plains regions. The availability of census data in developing nations can be a limitation in estimating population. However, recent advancements in night lights have enabled spatial correlation with population density in developing nations, even with limited census data (Kabanda, 2022). Thus, our approach at the basin scale enables us to understand how hydrological and geomorphic processes can reflect human settlement patterns within a specific river catchment and how these can be quantified using night light data.

2.6.2. What Is the Relation between Geomorphological Parameters and Night Lights Distribution?

To explain how geomorphology plays a driving role in the distribution of night lights signifying human activities, we analysed the normalised night light distribution within each buffer of the basin and the channel patterns as well. Based on our first hypothesis, that preferential human presence occurs in proximity to rivers, we show that night light luminosity is enhanced by 26% within the 0 to 5 km buffer zone adjacent to a river and by 11% in the 5 to 10 km buffer zone. This finding suggests that human presence and activity are concentrated in proximity to major rivers in the basin. This signature of enhanced human presence and activity is not detectable in the night lights luminosity data set beyond 15 km distance from the centreline of the major rivers studied. Our findings are consistent with previous independent findings from the literature from other parts of the world, which have inferred that people prefer settlement locations

closer to rivers (Kummu et al., 2011; Fang et al., 2018; Cao et al., 2023). Masrur et al. (2022) and Ceola et al. (2015) studied human presence and activity in near proximity to a river network consisting of all stream orders streams. The stream network for their analyses was extracted from the HydroSHED data, which incorporates streams of all orders (Ceola et al., 2015; Masrur et al., 2022). However, as a fact, lower-order streams do not practically cause floods (Mård et al., 2018). Thus, our study aimed to assess human presence near the vicinity of higher-order streams of the major rivers in the basin, which are likely to cause large-scale flooding.

However, when we study the relation between intensity and the number of lit pixels, we observe greater pixel intensities and a concomitant reduction in the percentage of lit pixels within the 15–20 km buffer zone compared to the 0–5 km buffer zone. We interpret this to indicate that denser settlements (with higher intensity luminosity), such as towns and cities, are preferentially located away from the Indus River and its tributaries in the basin. Historically, it may be the case that large settlements like towns and cities developed away from close proximity to rivers where they were less susceptible to river flooding. A similar independent study in China by Cao (2023) provides further evidence of high population density away from the river in the basins having relatively large plains area percentage. Similarly, Fang and Jawitz (2019) found that people living in regions constituting plains in the US preferred to live away from the rivers. This implies that the presence of the river is a driver of the density of lit pixels and the spatial distribution of the lit pixels in our night light data set, signifying varying human activities and presence. Thus, such an approach could help in the estimation of flood exposure near the river at a regional scale, in contrast to the global approaches that do not account for geomorphic variation in rivers within the basin (Kummu et al., 2011; Ceola et al., 2015; Fang et al., 2018).

To further demonstrate the relation between human activity and the channel patterns of the Indus River, we tested our second hypothesis, which posits that human presence is

enhanced in proximity to single-thread sinuous river channels compared to multi-thread channels of the Indus River. Multi-thread or braiding rivers are the most dynamic or rapidly changing river patterns due to their continuously shifting channels compared to single-thread channels having stable banks. Since rivers such as the Indus do not have a single planform type, we tried to correlate the distribution of human presence as derived from night light data with different channel patterns. We analysed the night light distribution in the Indus River's single-thread and multi-thread channel buffer zones. Due to the difference in the geomorphic setting of the channel pattern, the enhancement factor (Ef-bz) varies within different buffer zones. Thus, in support of our null hypothesis, we observe an 18% enhancement of lit pixels, signifying human presence and activity, within the 0–5 km zone of the single-thread channel, compared to the multi-thread channels. We interpret this as representing small urban centres or towns located near single-thread reaches of the channel. This is possibly due to the relative stability of the channel banks, as stable channels (single-thread channels) tend to migrate in an organised manner on their floodplains, having a single set of bars on alternate sides, whereas unstable channels (multi-thread channels) are in continuous movement and migration across their floodplains (Eaton et al., 2010). Thus, mobile braided or multi-thread river channels are laterally shifting, making them less suitable for riverside human settlements compared to single-thread channels, which are less mobile and are more suitable for human settlements (Macklin and Lewin, 2015).

However, within the 5–15 km buffer zone of the Indus River, multi-thread channels tend to have higher enhancement compared to single-thread channels. The repeated inundation, in the case of multi-thread mobile channels, tends to make the plains cultivable, but the valley-margin building sites or terraces having river incision might be preferred sites for settlements (Macklin and Lewin, 2015). Beyond 15 km, the distributions of lit pixels are similar to those of the whole basin. Thus, an important finding emerging from this study is the importance of channel type and proximity to the

river in determining the human presence in an area, as well as night lights as a tool to study this relationship.

2.6.3. Implications

The interplay between human presence, channel patterns, and distance to rivers can improve how we try to assess flood risk and vulnerability in a given region. While Earth scientists possess an increasingly comprehensive knowledge of river geomorphology and dynamics, our understanding of how geomorphological features influence human settlement patterns adjacent to river systems remains incomplete. In an endeavour to bridge this knowledge gap, our study aimed to elucidate the roles of channel-pattern type and proximity to rivers in determining where humans are present in a landscape.

This study presents a novel approach to the assessment of human presence near rivers by utilising night light data, building on previous studies that were either constrained by political boundaries or global-scale analyses that lacked specific regional detail (Ceola et al., 2015; Fang et al., 2018). The study shows the usefulness of the remotely sensed night light dataset in providing a proxy for human presence near the rivers. Moreover, the study considered major rivers or higher-order streams of the basin for human presence in proximity to the rivers. Nevertheless, there are a few limitations that need to be considered. The data-driven methodology employed in this study uses the DMSP NTL data instead of the recent VIIRS data because the DMSP data have been available since 1992, compared to the VIIRS data availability from 2012. Since we wished to study the influence of rivers on human presence at the earliest time possible using night light data, we chose the DMSP NTL due to its data availability since 2000. Additionally, both datasets cannot be compared directly due to differences in satellite sensor parameters, spatial resolution, spectral response characteristics, and the presence of pronounced “saturation effects” in the DMSP-OLS data. Thus, to maintain the data consistency, we used the DMSP NTL data. Further, this study incorporates data spanning the period from 2000 to 2013, primarily due to the availability of both the Landsat Population and DMSP

NLS datasets. Additionally, the temporal frequency of the DMSP NLS data is yearly, compared to the recent version of the night lights products, like VIIRS and the Black Marble product suite, which are available daily or monthly. The data used in this study provide a coarser resolution compared to recent versions of night light data, which might not be suitable for understanding human presence at a micro or lower administrative level.

Though this study is based on the Indus Basin, it provides a framework that can be used to identify the different socio-economic classes of people exposed to flood risk within the floodplains of the river. The occurrence of extreme flood events can lead to loss of life and infrastructure. As floodplains of the basin are prone to frequent flooding, this approach of studying human presence using earth observation data, specifically night lights, can be used to identify spatial vulnerability as well as social vulnerability to floods. For instance, floods often cause interruptions in electricity, thus affecting the distribution of lights during the disaster period (Levin, 2023). Recent data with daily temporal frequency, like the VIIRS/DNB sensor or the NASA Black-marble product, can be used to evaluate the effects of floods in real time (Zhao et al., 2018).

This remote sensing study has implications for policymakers involved in assessing flood vulnerability and risk to human society at the basin scale, enabling the implementation of effective mitigation measures in high-risk areas. In the long run, such information can help planners develop land-use plans and building codes that take into account differential channel patterns and distance from the river for flooding, reducing vulnerability to people and infrastructure and ensuring developments that are less susceptible to flooding. By examining the influence of varying channel patterns on anthropogenic activities and settlements, this research sheds light on the complex interactions between natural river processes and human presence, enabling more informed flood management strategies.

2.7. Conclusions

To date, most research using night light data in the context of human presence near rivers has been on a global scale. Compared to prior studies, the novelty of our contribution lies in the detailed relationship between the river patterns, proximity to the rivers, and human presence/activities, using the Indus Basin as a detailed case study. We used remotely-sensed DMSP-derived night lights to quantify statistically the enhancement of lit pixels, which are a proxy for human presence and human activities with river systems, offering a unique perspective on the influence of channel patterns and proximity to the river on humans. We establish that anthropogenic presence is enhanced by ca. 26% from the night light data within a 0 to 5 km proximity range of the Indus River and its tributaries relative to the basin as a whole. Additionally, away from the river, the mean intensity is higher, and the number of lit pixels is lower compared to areas in close proximity to the river centreline. These data are interpreted to signify denser settlements, like towns and cities, which are preferentially located away from the Indus and its tributaries due to lower susceptibility to flooding. Moreover, our study identified an enhanced human presence near single-thread channels of the Indus River of around 18%, compared to multi-thread channels, likely because of the stable channel banks and lower channel mobility associated with single-thread channels. The seasonal inundation within the close reaches of multi-threaded channels makes them less preferred sites for settlements, but valley margins or terraces further away from the river channels are preferred sites for settlements. Thus, we observe that the enhancement beyond 5 km was greater for the multi-thread channels. Our study provides new insight into understanding the dynamics of geomorphology in natural hazards using night lights as a proxy for human presence. In future work, it would be important to explore their role in evaluating flood risk spatially and in understanding the differential social vulnerability at a regional scale. We propose that this might provide a unique perspective

on landscape dynamics for identifying flood-prone areas and vulnerable communities, which could assist in devising mitigation measures.

Authors Contribution:

Authors: Ekta Aggarwal (E.A.); Alexander C. Whittaker (A.C.W.); Sanjeev Gupta (S.G.) (Sequence written as per the published research paper)

Conceptualisation, E.A., A.C.W. and S.G.; methodology, E.A. and A.C.W.; software, E.A.; validation, E.A., A.C.W. and S.G.; formal analysis, E.A.; investigation, E.A.; data curation, E.A.; writing—original draft preparation, E.A.; writing—review and editing, A.C.W. and S.G.; visualisation, E.A.; supervision, A.C.W. and S.G.; project administration, A.C.W.; funding acquisition, A.C.W. and S.G.

Chapter 3: Differential impact beyond floodwater: An insight into 2022 Indus Floods using Black Marble Night-time lights

Abstract

Major flood events cause adverse impacts on human populations, infrastructure, and resources. The occurrence of flood events has led to much research on flood vulnerability, exposure, and post-disaster assessment. However, there has been a limited focus on studying the recovery of societies and how this varies among different socio-economic communities. Satellite datasets are an effective and cost-efficient way to analyse the spatial extent of flooding and its impact on anthropogenic activity in floodplains. In our work, we provide a high-resolution temporal and spatial analysis of the NASA Black Marble night-time lights (NTL) for the 2022 Indus River flood in Pakistan, providing a proxy for the impact on lit infrastructure for real-time monitoring. We also investigate the recovery time for the flood-impacted areas and the exposure for different socio-economic communities in the floodplains. In our study, we observed that the area was affected for approximately 16 weeks before the recovery set into a similar level of pre-precipitation. The key observation in assessing the spatial impact of the NTL and the flood-inundated waters from the radar data highlighted the importance of assessing the indirect impacts beyond the flood-inundated water. This shows the impact due to cascading and compounding hazards along with the main flooding event. The study also demonstrates the potential of the Black Marble NTL in assessing the impact and recovery for different socio-economic communities.

3.1. Introduction

Floods, caused by a complex interplay between hydrology, climate, and human management, are among the most significant climate-related disasters (IPCC, 2023). At the same time, the frequency of extreme weather events has increased in many areas around the globe in recent years primarily in South Asia (Qamer et al., 2023; Nanditha et al., 2023; Chen et al., 2024). In particular, Asia and sub-Saharan African countries have experienced increased flood exposure between 2000-2015 (Tellman et al., 2021). Large basins in south and southeast Asia (Indus, Ganges-Brahmaputra and Mekong) had the largest absolute numbers of people exposed (17.0–19.9 million, 107.8–134.9 million and 20.2–32.8 million, respectively) and increased proportions of the population exposed to inundation of 36%, 26% and 11%, respectively (Tellman et al., 2021). In particular, South Asian countries are affected by the summer monsoon season, usually between July and September, which impacts the livelihood of their population compared to other parts of the world because of higher exposure and vulnerability (Qamer et al., 2023; Almazroui et al., 2020). The higher frequency of flood events in South Asia is estimated to have affected ca. 1 billion people in the past 20 years according to the EM-DAT data (Nanditha et al., 2023; Delforge et al., 2023).

The 2022 flooding in the Indus River (Pakistan), shown in Figure 3.1B, killed ca. 1500 people but is estimated to have impacted > 33 million people in the region with economic losses of ca. \$30 billion (Qamer et al., 2023; Otto et al., 2023; Nanditha et al., 2023). The severity of the floods was due to a combination of factors - heavy rainfall, glacial-melt contribution, and the formation of the intense low-pressure system developed over the mainland from May to June 2022 due to the prolonged intense summer heatwave (Nanditha et al., 2023; Otto et al., 2023). The repeated occurrence of floods in Pakistan has also been an increasing problem in the last 15 years, with three other large-scale events having occurred in 2010, 2011, and 2012 on the Indus River (Kumar et al., 2011; Qamer et al., 2023). The frequency and magnitude of the floods have been on the rise,

underscoring the growing impact of extreme weather conditions in the region (Yuan et al., 2023).

The occurrence of such disastrous flood events has in recent years led to research initiatives focusing on flood vulnerability, exposure, and post-disaster assessment. Many global studies considered the affected GDP, population, and physical assets damaged by flooding (IPCC, 2012; Jongman et al., 2015; Tellman et al., 2021; Winsemius et al., 2013). However, flood impact can also occur both within or beyond inundated areas (Johnmen et al., 2012; Jongman et al., 2008; Merz et al., 2010; Smith & Ward, 1998). The impact within the inundated area is due to the physical contact with flood water, while impacts beyond the inundated area are due to flood-related cessation of supply (e.g., electricity, production material). However, there has been a limited focus on studying the indirect or the compound impact of floods, the recovery of communities and how it varies among different socio-economic communities. Remote sensing is a powerful tool and a cost-efficient way to analyse the spatial extent of flooding and its impact on anthropogenic activity. Conventionally mapping flooding using satellite images usually includes mapping water-inundated areas using optical, radar images or both, and mapping the infrastructure damage using optical images (Levin and Phinn, 2022; Joyce et al., 2009; Martinis et al., 2022). However, the temporal frequency and availability of cloud-free data always hinder satellite data regarding damage and recovery assessment. Moreover, areas and populations impacted by flooding extend well beyond water-inundated areas. Here, we leverage NASA's Black Marble Night-time Lights (NTL) to constrain the impact and recovery of human activities from the 2022 Indus floods. NTL data are widely used to characterise the real-time distribution of human activity at a large scale and with better temporal frequency compared to traditional statistics and census data (Fang et al., 2021). NTL data (like VIIRS, DMSP, and Black Marble Product) have proven effective in disaster monitoring, risk assessment and reduction, humanitarian response, preparedness, resilience, and sustainable development. For instance, NTL data has been used to map

and quantify impacted areas by detecting damage and power outages arising from earthquakes, hurricanes, and floods and, more specifically, to assess the 2023 Turkey earthquake, 2022 floods in Queensland in Australia and Hurricane Sandy and Maria (Levin, 2023; Levin and Phinn, 2022; Wang et al., 2018; Zhao et al., 2018). Further, to study the post-disaster response, a night-time light change model has been developed by Gao (2020), showcasing the potential of the data to improve real-time disaster impact monitoring in the case of Hurricane Maria (Román et al., 2019; Zhang et al., 2023). When a flood happens, impacts, including damage to residential buildings, displacement and fatalities of people, and interruptions to the industry, manufacturing, service, and public sectors, will happen within and beyond the inundation areas. Consequently, the light intensity of affected human settlements, industrial, commercial, and public areas should be reduced compared to the pre-flood conditions (Enkel et al., 2020).

Here, we use the daily NTL data to study the impact of flooding on the radiance, signifying human activity, which we define as the artificial lights from the settlements, industries, etc. We use this particular data because the light intensity from human settlements in industrial, commercial, and public areas is affected during the disaster (Enkel et al., 2012). We target the downstream floodplains of the Indus Basin as the Indus River collects and carries large volumes to the south to flood-prone regions that are densely populated, and frequent flooding over this area has been historically documented (Figure 3.1A & 3.1B) (Qasim et al., 2015). Our approach transcends conventional flood monitoring by offering high-resolution spatiotemporal insights into the human response to these events. We use ESA Sentinel-1 SAR data to map the spatial extent of water-inundated areas, and we analyse daily NTL data to capture, for the first time, how the flood influences the NTL radiance values during the flooding and recovery period, including for different socio-economic communities living in the flood-affected region. Our work establishes Black Marble NTL as a powerful, rapid and cost-effective

tool for quantifying flood impact and exposure both during and after an event, revealing a footprint distinct from the flood-inundated area itself.

3.2. 2022 Indus Floods in Pakistan

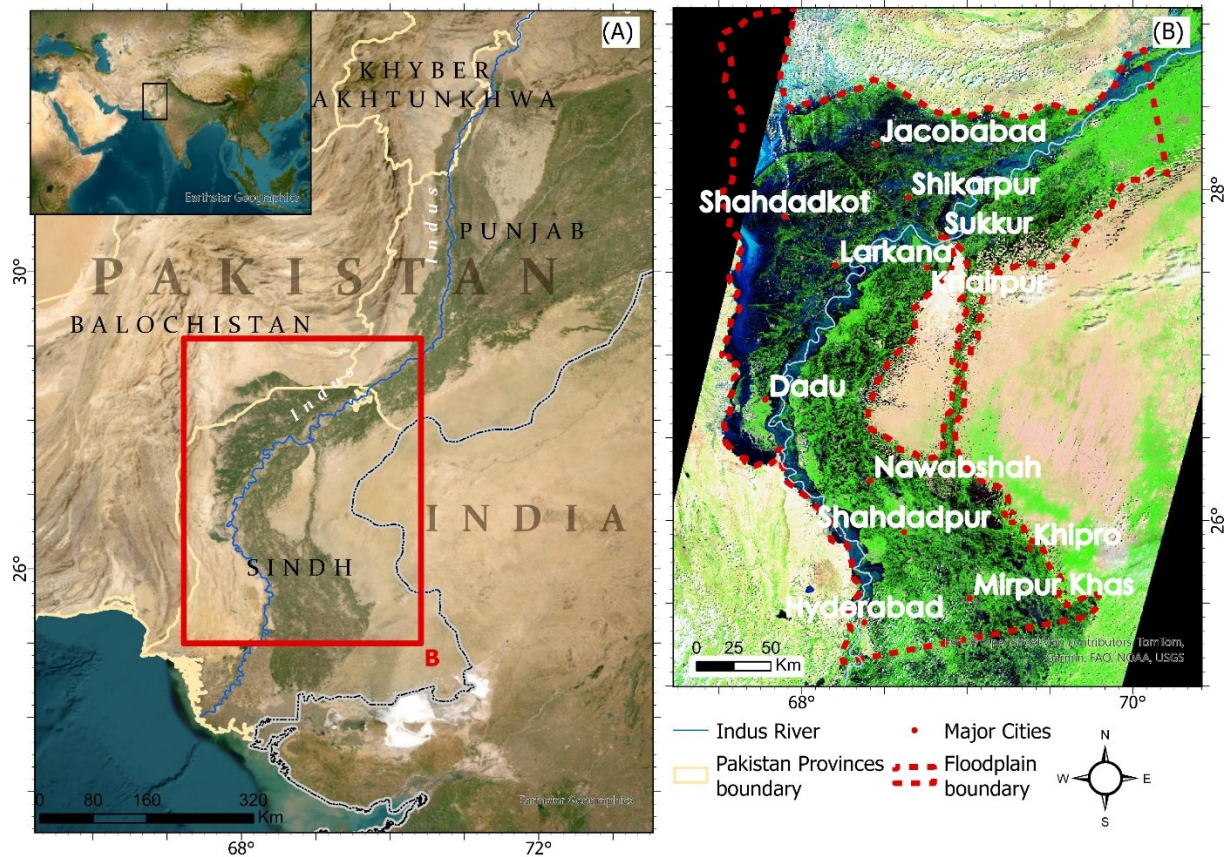


Figure 3.1: (A) ESRI world imagery showing the downstream floodplains of the Indus Basin. The inset in the top-right of the figure shows the location of the study area within Asia; (B) Sentinel-2 False colour composite (FCC) image showing water inundation (dark navy blue colour) on 31st August 2022 accessed via Sentinel Hub EO Browser and accessed on 8th April 2023.

In August 2022, an unprecedented flash flood occurred in the history of Pakistan's Indus River due to higher-than-average monsoon rainfall in Balochistan, Sindh, and southwest Punjab provinces, as evidenced in Figures 3.1A & 3.1B (Nanditha et al., 2023; Qamer et al., 2023; Wang et al., 2024; Shreshtha 2024). The rain-induced flooding commenced in July, and by mid-August, one-third of Sindh province was submerged by the floods, as shown in Figure 3.1B. According to the Pakistan Meteorological Department, July and

August experienced a surplus of rainfall, with 180% and 243% excess, respectively (PMD, 2022). The flood-affected area encountered intense precipitation from August 16th to 24th in Sindh and Balochistan provinces. In Pakistan's Sindh region, rainfall was +307% and +726% above average in July and August 2022, while Balochistan experienced +450% and +590% above average precipitation in July and August 2022 respectively (PMD, 2022). Satellite-derived estimates of rainfall indicated exceptionally high monthly rainfall (~1000 mm) in Sindh Province, nearly eight times its average rainfall in August 2022 (Nanditha et al., 2023). The highest two-day extreme precipitation occurred on August 17–18, 2022, and the highest daily rainfall (92 mm) was recorded on August 18th. The extreme daily precipitation surpassed the 99.9th percentile of rainy days based on the 2001–2021 long-term mean (Nanditha et al., 2023). As per the study by Roth (2023) using the Sentinel-1 SAR data, the catastrophic Pakistan Floods of 2022 increased from the beginning of the 18th of August 2022, grew until the 30th August 2022 and decreased afterwards.

3.3. Data

3.3.1. NASA Black Marble Night-time Lights (NTL)

NASA Black Marble night-time lights product suite (VNP46) produced at NASA's Land Science Investigator-led Processing Systems (Land SIPS) is a product of the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Bands (DNB) available from January 2012 at daily/monthly/yearly frequency (Román et al., 2018). The product suite, available globally on daily, monthly, and annual composite scales, corrects extraneous sources of noise in night-time light (NTL) radiance signals (Román et al., 2018). The data adopts a novel "Turning off the moon" approach.

Thus, to estimate daily night-time lights and other intrinsic surface optical properties, Black Marble data combines the cloud-free, atmospheric-, terrain-, vegetation-, snow-, lunar-, and stray light-corrected night-time VIIRS DNB radiances, daytime DNB surface

reflectance, bidirectional reflectance distribution function (BRDF)/Albedo, and Lunar irradiance (Román et al., 2018). The VNP46 product suite has four products: a daily at-sensor top of atmosphere (TOA) night-time lights (NTL) product (VNP46A1), a daily moonlight-adjusted night-time lights product (VNP46A2), a monthly moonlight-adjusted night-time lights product (VNP46A3), and a yearly moonlight adjusted night-time lights product (VNP46A4) (Román et al., 2018)

In this study, we use the VNP46A2 product, which represents daily moonlight and atmosphere-corrected radiance data. The data has a spatial resolution of 15 arc seconds (~500m at the equator) and is provided in the Hierarchical Data Format Earth Observing System (HDF-EOS) format (Román et al., 2018). The product has seven bands: BRDF-corrected NTL, Gap-filled BRDF-corrected NTL, lunar irradiance, mandatory quality flag, latest high-quality retrieval (number of days), snow flag, and cloud mask flag. For our analysis, we used the 'DNB_BRDF_Corrected NTL' and the 'Mandatory_Quality_Flag' layers. The NTL radiance is measured in $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ units having a valid range of 0-65534, and the fill value for no data is 65535. The quality flag layer gives information about the quality of the NTL pixel retrieved at the time of acquisition. The quality pixel values are unitless and range from 00-02, where 255 is the fill value for no data. 00 and 01 values of the quality pixels denote high quality having persistent night-time lights and ephemeral night-time lights. 02 are the poor-quality pixels denoting outliers, potential cloud contamination, or other issues (Román et al., 2018). Black Marble data thus provides accurate time series detection for monitoring short-term changes in the radiance of the lit infrastructure signifying human activities (Wang et al., 2018).

3.3.2. GHS Settlement Model Layers (GHS-SMOD) data

To study the exposure for different socio-economic communities in the floodplains, we used the Global Human Settlement (GHS) Model layers (GHS-SMOD) 'GHS-SMOD_GLOBE_R2023A' data, giving us an overview of the rural-urban settlement type.

The GHS-SMOD data is a derivative product of the GHS-POP and the GHS_BUILT-S 2023 data released within the GHSL Data Package 2023 (GHS P2023). The data is a 2023 release of the 2020 Epoch, which provides an improved product of the ‘degree of urbanisation’ framework. The data classifies settlements based on built-up area, population, and the cell cluster population size in the pixel (Schiavina, M. et al., 2023). The GHS-SMOD 2023 release 2020 Epoch data is available at a spatial resolution of 1 km and Mollweide coordinate system. The data has eight categories and divides the typologies into eight settlement classes, assigned as 30, 23, 22, 21, 13, 12, 11, and 10 (Figure 3.2A).

Table 3.1 lists the classes and descriptions of the typologies (Schiavina, M. et al., 2023). For our study, the data has been resampled to 5 classes, and the explanation for each category is mentioned in Table 3.2. For further analysis, the data is clipped to the area of interest, resampled to NTL resolution, and reprojected to Equal Area projection (Figure 3.2B).

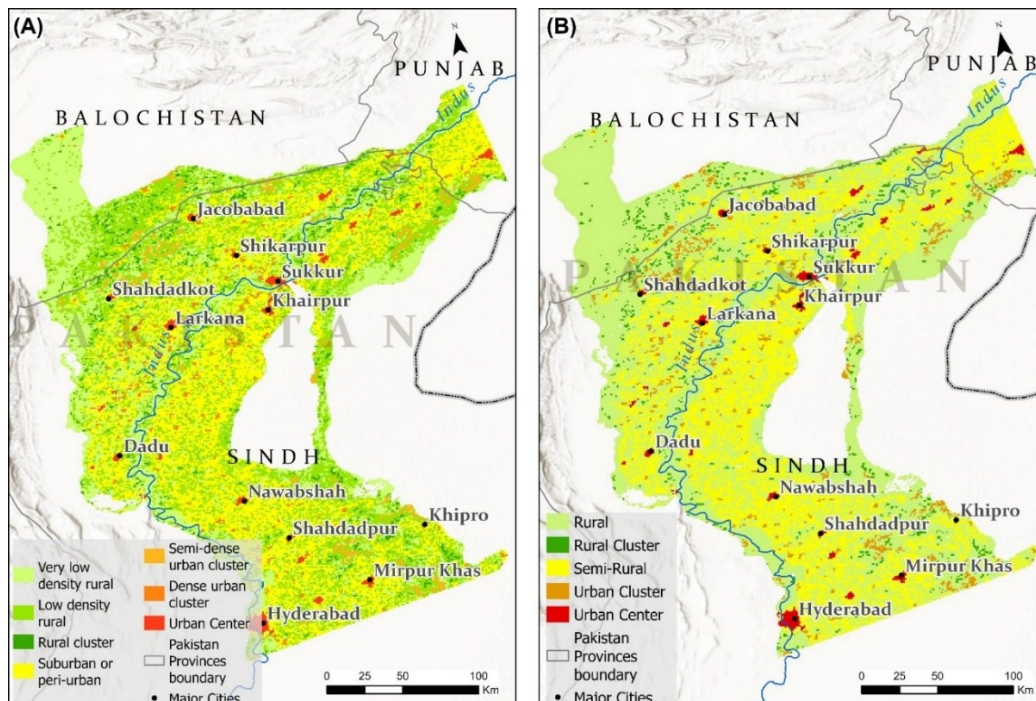


Figure 3.2: Reclassification of GHS-SMOD categories (A) Distribution of pixels into eight types of categories for the degree of urbanisation; (B) Reclassified settlement model layer consisting of 8 categories into five categories.

Table 3.1: GHS-SMOD data categories and their description.

Class		Description
30	Urban Centre	An urban centre consists of contiguous grid cells (4-connectivity cluster) with a density of at least 1,500 inhabitants per km ² of permanent land and has at least 50,000 inhabitants in the cluster with smoothed boundaries (3-by-3 conditional majority filtering) and <15 km ² holes filled
23	Dense Urban Cluster	A Dense Urban cluster consists of contiguous grid cells (4-connectivity cluster) with a density of at least 1,500 inhabitants per square km of permanent land or with a built-up surface share on permanent land greater than 0.5 and has at least 5,000 inhabitants in the cluster
22	Semi-dense Urban cluster	A Semi-dense Urban Cluster consists of contiguous grid cells (4-connectivity cluster) with a density of at least 300 inhabitants per square km of permanent land, a built-up surface share on permanent land greater than 0.03, at least 5,000 inhabitants in the cluster, and at least 3-km away from other “Urban Clusters”
21	Suburban or Peri-Urban grid cells	These are all the other cells that belong to the Urban domain but are not part of an “Urban Centre”, “Dense Urban Cluster” or a semi-dense “Urban Cluster”
13	Rural-cluster	A Rural Cluster consists of contiguous cells (4-connectivity cluster) with a density of at least 300 inhabitants per square km of permanent land and has at least 500 and less than 5,000 inhabitants in the cluster
12	Low-density rural grid cells	Rural grid cells with a density of at least 50 inhabitants per square km are not part of a “Rural Cluster”
11	Very low-density rural grid cells	These are cells with a density of less than 50 inhabitants per square km and are not water grid cells
10	Water grid cells	These are all the cells with more than 0.5 share covered by permanent surface water not populated nor built

Table 3.2: Reclassified classes of the GHS-SMOD data

New Resampled Classes	Original Classes of the GHS-SMOD 2023 data
Urban Centre	Urban Centre (Class 30)
Urban Cluster	Dense Urban Cluster (Class 23) & Semi-dense Urban cluster (Class 22)
Semi-Rural	Peri-Urban grid cells (Class 21)
Rural Cluster	Rural Cluster (Class 13)
Rural	Low-density rural grid cells (Class 12) & Very low-density rural grid cells (Class 11)

3.3.3. GDP: Gross Domestic Product

A country's economic activities are usually expressed as Gross Domestic Product (GDP), which is important, amongst others, for analysing inequalities within a country (McCord and Rodriguez-Heredia, 2022). It is also considered an important parameter for economic decision-making because 18 of the 231 unique UN Sustainable Development Goals (SDGs) indicators are based on GDP (McCord and Rodriguez-Heredia, 2022). Thus, to understand the economic damage due to the flood, we consider the Gross Domestic Product (GDP) within our approach. Previous research has studied the relationship between the GDP and the night-time light radiance as a tool for development and economic activities within a country (Yu et al., 2023). In our study, we used the Purchasing Power per Parity (PPP) and the population density to estimate the GDP. We calculated GDP per pixel, which is defined as a product of Purchasing Power per Parity (PPP) per pixel and the population density per pixel. The PPP vector data for Pakistan is provided by ESRI ArcGIS online, and the data source is Michael Bauer Research GmbH. The data gives information about the PPP for 2022 in Pakistan at the multiscale level of Country, Province, and District. The PPP is provided at the lowest administrative level, i.e., at the district level, in vector format. The data is converted to a raster for further analysis.

The other data that we use in the calculation of the GDP is the GHS-POP R2023A data for the year 2020. The GHS-POP raster data gives information about the population per cell, and it estimates the population from 1975 to 2020 at 5 years temporal frequency derived from the global census data harmonised by CIESIN GPWv4.11 data (Schiavina, M. et al., 2023). The 2020 GHS_POP data has a spatial resolution of 100m projected in the Mollweide coordination system. Both the rasters are multiplied in ArcGIS Pro to derive the GDP per pixel, which we use as a data set for this study and projected to equal-area projection. Lastly, the derived GDP per pixel data, representative of economic wealth, is

calculated for different GHSL-SMOD classes (discussed in section 3.3.2) representing rural-urban classes using zonal statistics.

3.3.4. Sentinel-1 SAR

The Sentinel-1 SAR data has been used by researchers to map flooded areas as it provides cloud-free imageries all day (Giustarini et al., 2013; Tanguy et al., 2017; Roth et al., 2023). To retrieve the flooded areas from the satellite data, the Copernicus Emergency Management Service (CEMS) the GFM service relies exclusively on Sentinel-1 observations and provides results fully automatically in near-real-time (NRT) for each satellite observation (Salamon et al., 2021). In this study, we use the C-band Synthetic Aperture Radar (SAR) images from Sentinel-1B for mapping the progressive water-inundated areas from May 2022 to October 2022. The data was accessed from the Google Earth Engine (GEE). The Level-1 Ground Range Detected (GRD) images at 10m spatial resolution were processed using the 'COPERNICUS/S1_GRD' collection on GEE. Various studies have developed enhanced techniques for automatic floodwater detection over large areas using SAR and estimating the impact of the 2022 floods (Chen et al., 2024; Nanditha et al., 2023; Qamer et al., 2023; Roth et al., 2023; Wang et al., 2024). However, our aim in using the SAR data is to derive the SAR-based flood maps and overlay them with the NTL-derived impact maps to assess the “real-time” impact.

3.3.5. Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS)

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a 35+ year quasi-global rainfall data set. The data spans 50°S-50°N (and all longitudes) and ranges from 1981 to the present. CHIRPS incorporates the climatology, CHPclim, 0.05° resolution satellite imagery, and in-situ station data to create gridded rainfall time series (Funk et al., 2015). The latest version, 2.0 (V2.0) of this precipitation data measured in mm, is available for 1981–2024 at 0.05° spatial resolution and at daily, pentad, and monthly time scales. For studying the impact of the rainfall on the radiance from NTL, I

used the daily data for the year 2022 accessed using Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY#description). This was further used to calculate weekly total rainfall (mm), which is discussed in section 3.5.1.

3.4. Methods

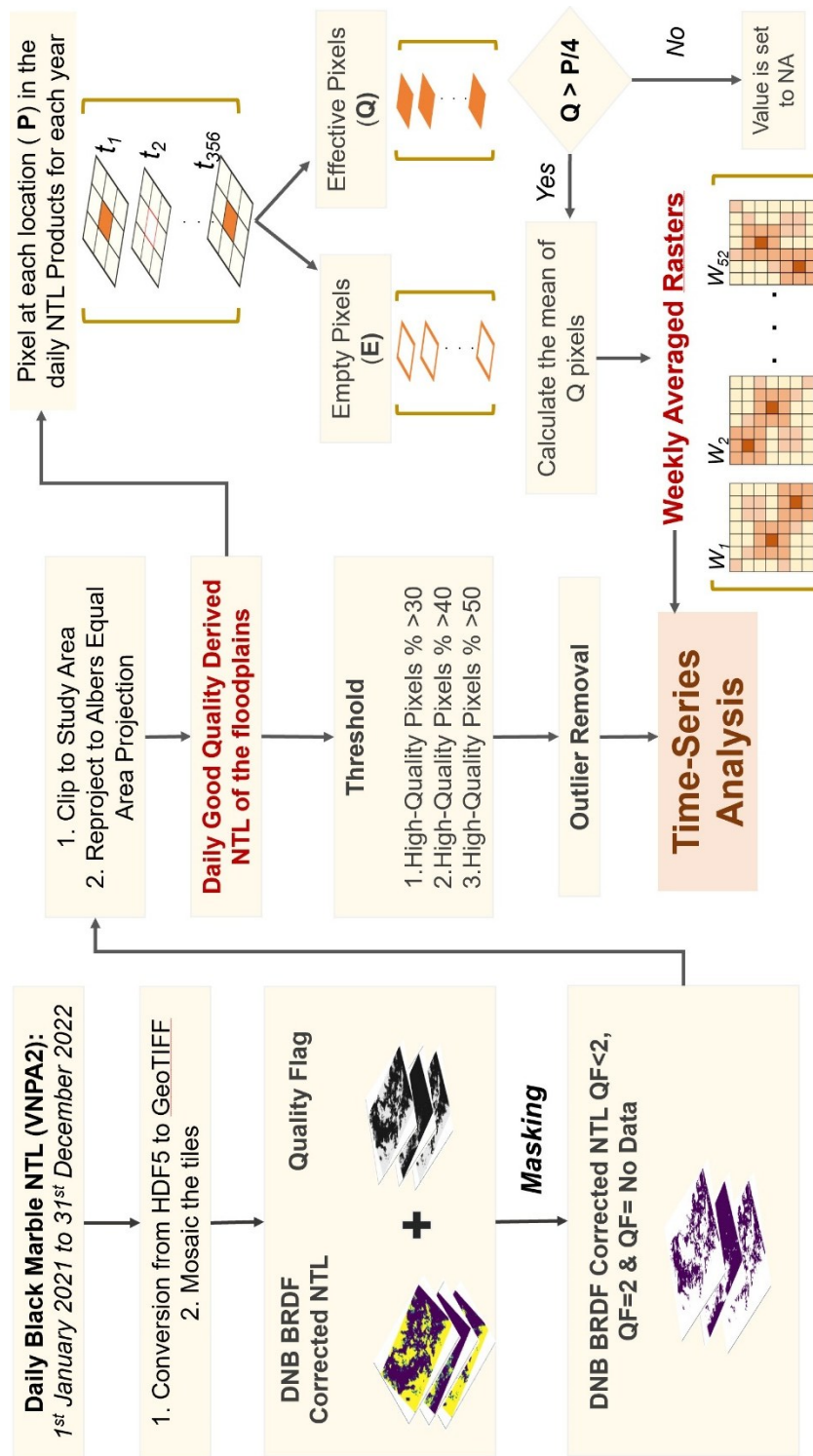


Figure 3.3: A schematic flowchart showing the detailed methodology explaining the pre-processing of daily raster data and creating weekly raster data. The processed good-quality daily and weekly rasters are used for time-series analysis and identifying impact areas.

3.4.1. Processing daily Black Marble NTL

The VNP46A2 daily data provides moonlight-adjusted and atmospheric-corrected night-time lights. Figure 3.3 shows a schematic flowchart of the daily NTL processing. The data was downloaded from the NASA Level 1 and Atmosphere Archive and Distribution System Distributed Active Archive Center (LAADS DAAC). The NTL tiles over the study area h24v06 and h25v06 were downloaded from 1st January 2021 to 31st December 2022 (accessed in January 2023). After preprocessing the images, daily high-quality derived NTL rasters were used for weekly raster creation and time-series analysis. The daily rasters generated were further used to prepare weekly data by setting up a minimum number of two-layer thresholds per pixel. Further descriptive statistics and detrending were calculated for time-series analysis.

However, no data was available for the study area from July 26th to August 10th, 2022, as the data files were not accessible on the server at the time of download. The data downloaded was in HDF5 format, consisting of 7 layers. The DNB_BRDF_Corrected-NTL and Mandatory_Quality_flag layers were extracted in GeoTiff format using a Python script. We do not use gap-filled data because, for the study of short-term disaster assessment, the gap-filled data is populated with historical values and cannot give true signals about change detection (Wang et al., 2022). The daily NTL and quality flags GeoTIFF files were respectively mosaiced using a Python script. Further, we used high-quality pixels of the QA flag layer to create a consistent nightlight time series and weekly raster (Stokes and Román, 2022). Thus, we filtered high-quality (QA flag 0 or 1) daily NTL radiance pixels within the mosaic NTL files. Low-quality or no data pixels representing potential outliers due to auroras, incorrect snow flags, or cloud contamination were not considered in the calculation of our study. Further, the rasters representing daily high-quality NTL pixel observations were clipped to the study area of lower Indus floodplains and reprojected into an equal area projection for further calculations.

3.4.2. Creating Weekly Rasters & Time-Series Analysis

Figure 3.3 shows the schematic methodology workflow of creating weekly rasters from the daily NTL raster. To understand the impact and recovery of the flooding, both daily and weekly NTL datasets were used for time series analysis. For the daily data time-series analysis, due to cloud coverage and the availability of no data radiance (pixels signifying poor quality or no data retrieval) in the generated good-quality daily NTL data, we set up a threshold and removed outliers (Wang et al., 2022). Thus, a threshold of 30% was set, which means that for the time-series analysis, only dates with a minimum 30% area of high-quality NTL pixels were considered for the analysis. A higher threshold would mean losing out on all the relevant data. Descriptive statistics like the mean and sum of lights (SOL) were calculated for daily raster data over two years from 1st January 2021 to 31st December 2022.

For creating weekly rasters, we used the generated good-quality daily NTL data. The pixel at the same location (P) for all the dates in each week is divided into effective pixels (non-NA values, having value ≥ 0 defined as Q) or Empty pixels (NA values, defined as E) (Xu et al., 2021). Thus, while stacking weekly layers, if we have $Q > P/4$ in a week, we calculate the average of the effective pixels, and if $Q < P/4$, we set the pixel value to NA. The process is iterated over for all pixel locations in the study area and all the weeks of the year 2021 and 2022. All the processing for daily NTL raster data was done using Python. Descriptive statistics like the mean and sum of lights (SOL) were calculated for weekly data over two years, from 1st January 2021 to 31st December 2022.

However, to remove the long-term trends from the average radiance and the total radiance for two years, we performed detrending of the average radiance, which is discussed in the result section 3.5.1. This is typically performed by linear regression as night light data typically shows increased radiance over time. This will enable us to study the temporal patterns and recovery from the flooding event in the context of 2 years' worth of evolving nightlight data (Hsu et al., 2021).

3.4.3. Creating NTL-derived Spatial Impact Maps

To study the spatial impact of flooding, we created NTL-derived impact maps, which depicted the percent decline in NTL radiance per pixel relative to May. The percent decline in radiance is calculated per pixel, which is defined as the ratio of the NTL radiance of a pixel in a respective week to the NTL radiance of a pixel in the 18th week of the year (WOY) 2022 (May).

While all May weeks exhibited statistically similar pixel value distributions (as confirmed by the Kolmogorov-Smirnov (KS) test), the 18th WOY in 2022 (May) serves as the optimal reference point (Figure 3.4). The KS test is a non-parametric test that compares the cumulative distributions of two samples to determine if they come from the same distribution. The first reason is that the 18th week has the least cloud cover and bad quality pixels (<1%) compared to other May weeks, ensuring the most accurate representation of the pre-flood landscape. Secondly, the T-tests, which assess whether the means of the two groups are significantly different from each other, indicate no statistically significant differences between the 18th week and any other week in May. Lastly, its median pixel value (D50) falls within the range observed in other May weeks, further highlighting its representativeness of the pre-flood conditions.

To analyse the spatiotemporal effects, we generated the NTL-derived impact maps for the 23rd WOY in 2022 (June), the 34th WOY in 2022 (August), the 36th WOY in 2022 (September) and the 40th WOY in 2022 (October) respectively. The percentage decline in the radiance (%) during these weeks was calculated relative to the 18th WOY in 2022 (May), as explained earlier.

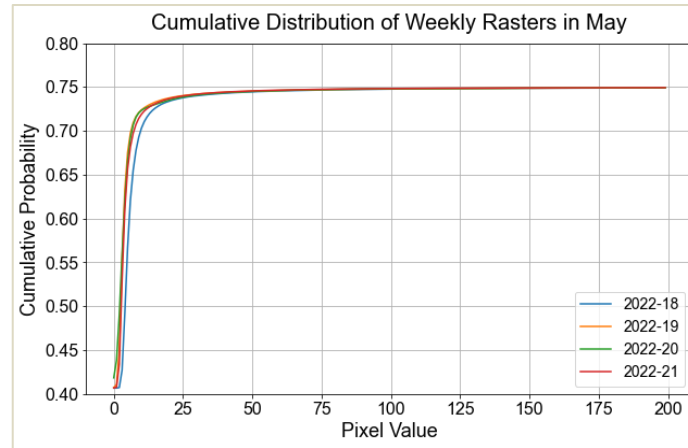


Figure 3.4: Cumulative distribution of weekly NTL raster for May 2022. The blue line denotes the cumulative plot for the 18th week of 2022. Similarly, orange, green and red lines show the cumulative distribution curve for the 19th, 20th and 21st week, respectively.

3.4.4. Extraction of water-inundated areas using SAR in Google Earth engine

The Sentinel-1 GRD archive called ‘Image Collection’ available on GEE has undergone pre-processing, which included the application of orbit-file, ARD border noise removal, thermal noise removal, radiometric calibration, terrain correction and conversion of backscatter coefficient into decibels. These images are further filtered based on instrument mode, polarisation, pass direction, and spatial resolution in GEE. The images were occupied for the same weeks as the NTL-derived impact maps for the area of interest, i.e. Sentinel-1 radar data are not affected by the time of the day and cloud cover, thus making it easier for extraction of the water-inundated areas during flooding. We used the Vertical-Horizontal (VH) polarisation SAR data to calculate the water-inundated areas (Nanditha et al., 2023). Based on visual inspection, a threshold of -22 was chosen. Due to the specular reflection of the C-band, water areas have lower or darker backscattering signals compared to non-water areas or rough surfaces, which appear to be brighter (Westerhoff et al., 2013).

Also, the method does not incorporate permanent water bodies, which were masked out using the ‘JRC/GSW1_0/GlobalSurfaceWater’ collection on GEE. The steep slope pixels were removed using the slope and connectivity information, reducing the noise of the

image (Nanditha et al., 2023). Analysis of the flood images was performed by applying a backscatter threshold, which was processed to extract the water-inundated areas at different times.

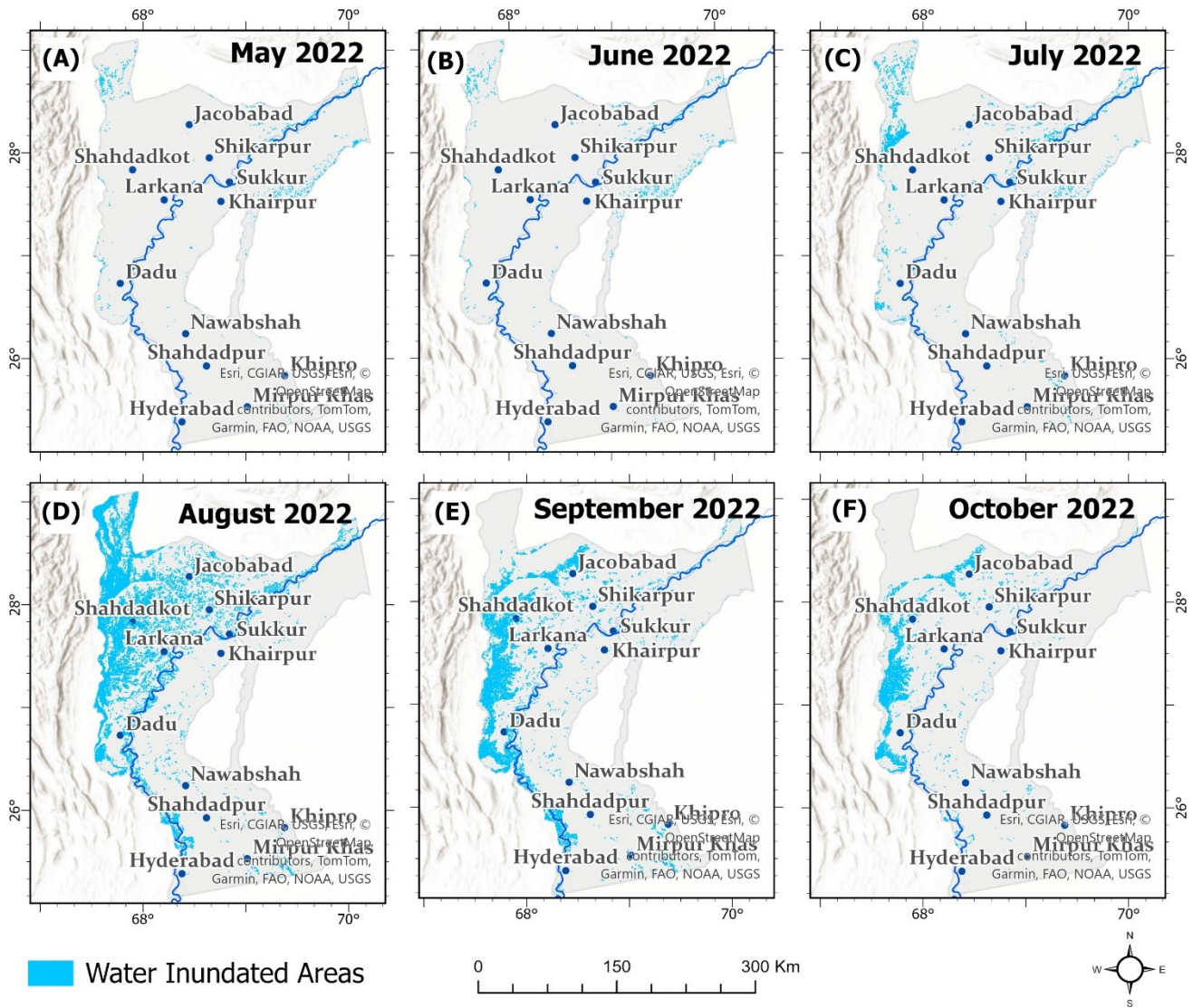


Figure 3.5: Water inundation maps from May to October 2022, derived from Sentinel-1 SAR data using Google Earth Engine. The blue areas show the water-inundated areas derived from the SAR data, and the blue line is the Indus River. **(A)** Distribution of flooded pixels for the 18th week of the year (WOY) in 2022 (May); **(B)** Distribution of flooded pixels for the 23rd WOY in 2022 (June); **(C)** Distribution of flooded pixels for the 28th WOY in 2022 (July); **(D)** Distribution of flooded pixels for the 34th WOY in 2022 (August); **(E)** Distribution of flooded pixels for the 36th WOY in 2022 (September); **(F)** Distribution of flooded pixels for the 40^h WOY in 2022 (October).

3.5. Results

3.5.1. Impact of the 2022 Indus floods on human activity

To investigate the impact of the 2022 Pakistan Indus floods on human activity signifying lit infrastructure, we conducted a spatio-temporal analysis of the night-time lights across the study area encompassing both the flood period and pre- and post-flood periods. Figure 3.5 highlights the spatial coverage of the inundated areas from May 2022 to October 2022 derived from SAR. The months of May and June 2022 show minor inundations in the northeast and northwest of the region, possibly driven by localised precipitation (Figure 3.5A and 3.5B). This represents the baseline pre-monsoon conditions of the basin, with very little inundation associated with the main trunk channel of the Indus River, mainly concentrated in the upstream northeast part of the basin. The month of July sees increasing coverage of the inundated areas in the northwest and along the main channel in the central and northwest parts of the basin (Figure 3.5C). This inundation was driven by increasing precipitations associated with the intensifying southwest monsoons over the Indian subcontinent. The month of August represents the peak flooding in the basin, with heavily inundated areas to the west of the channel (Figure 3.5D). While most of the basin shows the impact of the flood, the most significant inundation is concentrated in the central, midstream portion near Shahdabkot and Larkana and the northwest part of the basin. Downstream of Dadu, major inundation is along the channel. We observe some recession in flood waters in September (Figure 3.5E). The northwest part of the basin has no inundation. Major inundated areas are concentrated towards the west of Shahdabkot and north of Jacobabad. Inundation along the channel continues, with an increase in inundated areas in the downstream portion compared to August. Finally, we see a further reduction in inundated areas in October, with most inundated areas lying close to the western margin of the basin (Figure 3.5F). Inundation along the channel also appears to have substantially reduced.

However, to understand the response of the night-time lights to rainfall and flooding, we analysed the night-time light radiance in the area over time. Figure 3.6 shows the weekly sum of lights (total radiance) expressed in nanowatts per square centimetre per steradian ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$) units derived from the Black Marble NTL and the average weekly rainfall from the CHIRPS data across the study area from January to December 2022. The average weekly rainfall is the total rainfall for each week averaged over the geographic area.

We observe that the total radiance from the 1st week of the year (WOY) in 2022 (i.e., in January) to the 18th WOY in 2022 (i.e., in May) ranges between $1.5\times 10^6 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ to $3.0\times 10^6 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$. However, beyond the 18th WOY, the total radiance drops markedly from $3.0\times 10^6 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ in the 18th WOY in 2022 to a minimum of $0.5\times 10^6 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ in the 33rd WOY in 2022 (i.e., in August) before the total radiance starts increasing. During the 15 weeks from the 18th WOY to the 33rd WOY, the total radiance decreased by 80-85% over the area. This period corresponds to the increase in weekly average rainfall from ca 5 mm to over 60 mm, then again reducing it in the 33rd week. The onset of extreme rainfall and the impact of the Indus flooding event, which lasted from July to August 2022, as reported by PMD (2022), suggests that the impact of the floods can be detected in NTL data. After the 34th WOY in 2022, the total radiance slowly increases from $1.5\times 10^6 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ to approximately $2.5\times 10^6 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ by the end of December 2022.

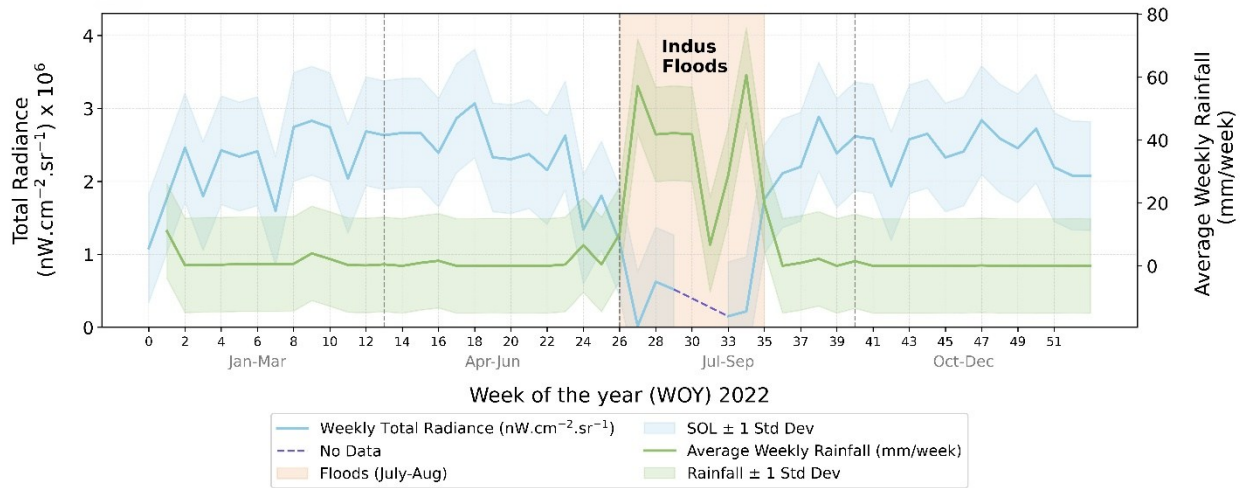


Figure 3.6: Weekly total radiance (blue) and total rainfall (green) in 2022, along with the period of Indus floods (highlighted in the light orange shaded region). The radiance is measured in $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$, while the rainfall is in millimetres. The data points corresponding to missing values are indicated by dashed lines (No Data). Notable peaks in rainfall coincide with the flood events observed during the summer months of July and August, as shown in the shaded region.

However, to understand if the distinct decline in the total radiance from 18th WOY to 33rd WOY in 2022 could partially be explained by seasonality or can unambiguously be linked to the impact of the flooding event, we detrended on daily and weekly NTL data over 2 years for both 2021 and 2022 (Figure 3.7A & 3.7B) as discussed in the methods section 3.4.2. Detrending of NTL aimed at removing long-term trends from the total radiance of the night-time lights to quantify flood impact and recovery timescales as appropriate.

Figure 3.7A shows the daily detrended average radiance from January 2021 to December 2022. This plot has repeated episodes of increase and decrease in the average radiance between -4 to $+4$ $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ after trend removal. The light blue envelope around the data curve shows a normal standard deviation, and the daily average data's root mean square error (RMSE) is ± 2.23 $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$. The average radiance is broadly stable from January 2021 to June 2022, with peaks a and b in the graph of timescales 3-4 correlated to Ramadan and Diwali festivals in the Sindh region. However, from June 2022, the data shows a major and long duration deviation in the average radiance for ca. three months until late August 2022 before it slowly starts to increase. This strongly contrasts with the

NTL radiance patterns for the year 2021. These patterns lead us to interpret the longer-duration decline to represent the impact of the Indus flooding event on lit infrastructure across the study area. This plot has a minimum of 30% coverage of the good-quality NTL pixels for each day. Because daily data is impacted by varying cloud coverage and satellite fluctuations, as discussed in section 3.3.1, to analyse the radiance trend due to flooding, we consider the weekly average detrended radiance (Figure 3.7B), which acts to filter the short-term noise in the daily data.

We observe that the weekly average detrended radiance from the 1st week of 2021(2021-00) to the 18th week of 2022 (2022-18) ranges between -3 to +3 nW·cm⁻²·sr⁻¹. The average detrended radiance drops after the 18th week of 2022 (2022-18), i.e., in May'22, with a maximum decline in the radiance of ca 8 nW·cm⁻²·sr⁻¹ before week 32 of 2022 (2022-32), i.e., in August'22. The maximum decline in the weekly average radiance corresponds to the period of major flooding in the area, as highlighted in Figure 3.7B (Chen et al., 2024; Nanditha et al., 2023; Otto et al., 2023). Given the RMSE of ± 1.61 , this 400% decline in radiance is statistically significant and illustrates the impact of the flood event on night light radiance and, thus, human activity during the period. Following the flooding period, i.e., weeks from September 2022 (2022-34) onwards, we observe the initial rapid recovery of the average radiance for 1-2 weeks until 2022-36, followed by a slow recovery in the radiance towards the end of the year 2022. Thus, the nightlight data acts as a powerful tool to allow us to quantify the impact, duration and recovery timescale of the flood event. Further evidence that the decline in the radiance was not due to cloud cover or unavailability of data is discussed further.

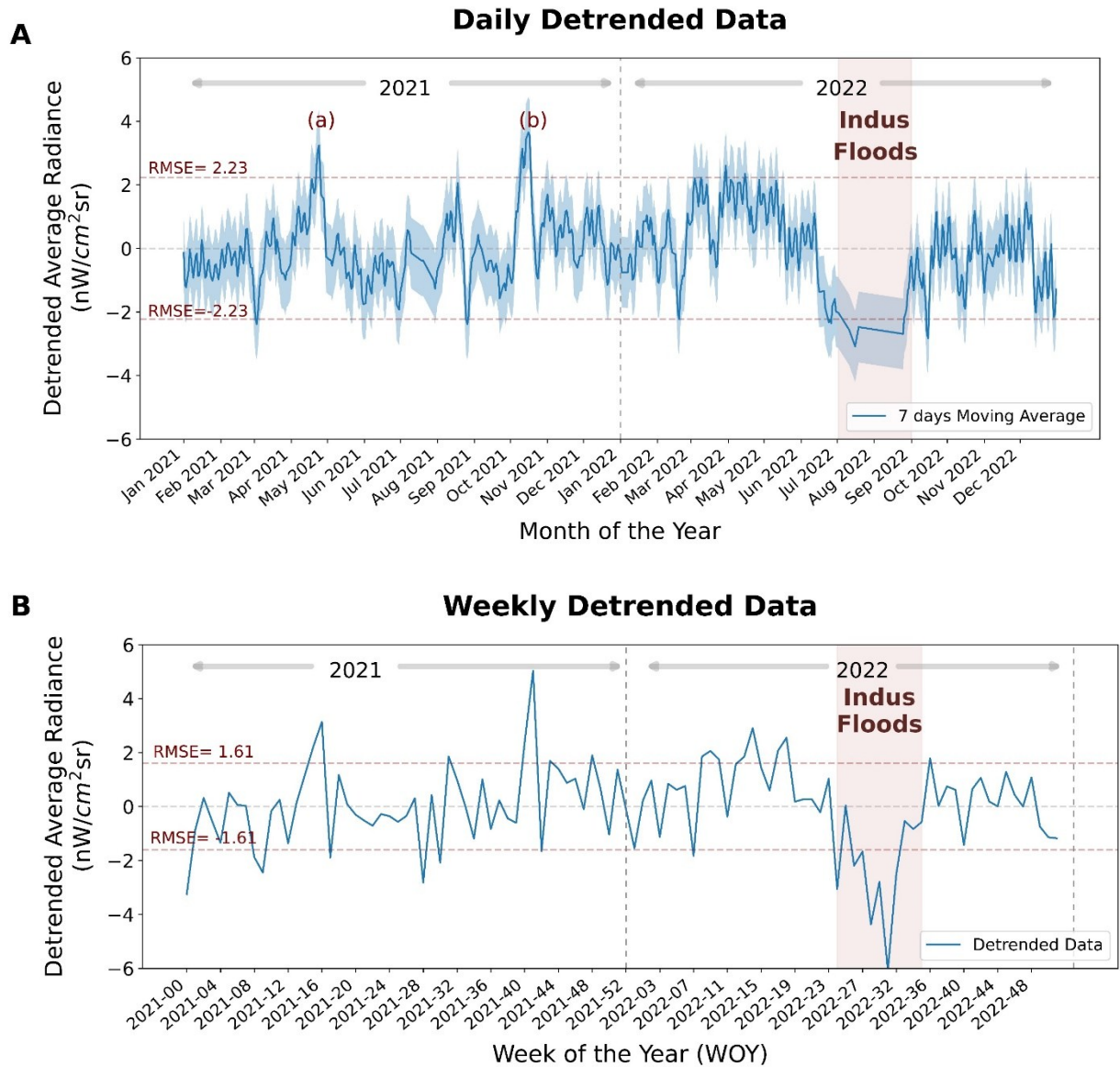


Figure 3.7: (A) The figure shows daily detrending NTL radiance data from Jan 2021 to December 2022. The solid blue lines represent the 7 days moving detrended average radiance in units of nanowatts per square centimetre per steradian ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$). The light blue band is the standard deviation of the radiance values. The red dashed lines show the RMSE of $\pm 2.23 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$; **(B)** The figure shows the weekly detrending of the NTL data from January 1st week 2021 to December last week 2022. The brown-shaded area highlights the decrease and recovery weeks between May and September 2022. The solid blue lines represent the total radiance in units of nanowatts per square centimetre per steradian ($\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$). The red dashed lines show the RMSE of $\pm 1.61 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$.

To explore the spatial extent of the direct and associated impacts of the floods on human activity, we analysed cloud-free weekly NTL composites from May to October 2022 (Figure 3.8). This data shows the distribution of lit pixels across the study area over 5

months from May 2022 to October 2022. At a 30-arcsecond (~500m) resolution, each pixel reflects the local radiance intensity. In Figure 3.8A, we observe a well-lit landscape during May (corresponding to the 18th week of 2022) before the decline in the radiance, as seen in Figure 3.7B. High-intensity radiance is recorded around major cities such as Jacobabad, Shirkarpur, Sukkur, and Larkana in the north of the area and Hyderabad, Nawabshah, and Mirpur Khas in the south. The total radiance was $3.1 \times 10^6 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$, with the average radiance being around $9.8 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$. In June (corresponding to the 23rd week of 2022), however, a distinct reduction in the spatial extent of lit pixels is observed (Figure 3.8B). This dimming intensifies further by August (Figure 3.8C). However, we do not get complete good-quality NTL coverage within August because of the high cloud cover. Beyond August, the NTL radiance within the area remains low up to the 36th week of 2022 (September), as seen in Figure 3.8D, where the total radiance is $2.2 \times 10^6 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ and the average radiance is $7 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$. In October 2022, we observed that the total radiance increased to $2.5 \times 10^6 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ and the average radiance was $8.3 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ (Figure 3.8E). These spatial images vividly illustrate how the flood event impacted human activity and infrastructure spatially, reflected in the altered NTL patterns. Such patterns can help us to identify areas and the duration of the impact of the water inundation during the flooding event.

To eliminate the possibility that the observed decline in radiance was influenced by cloud cover (visible as white patches in Figure 3.8C), we applied a cloud mask to all the cloud-free composites and analysed changes in total radiance within the masked area. As shown in Table 3.3, the total radiance within the masked region decreased from approximately $609,460 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ in the 18th week of 2022 (May) to $448,220 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ in the 36th week (September). If the decline continued into August, the data suggest a gradual recovery in radiance from September onward, as indicated by the spatial NTL maps in Figure 3.8.

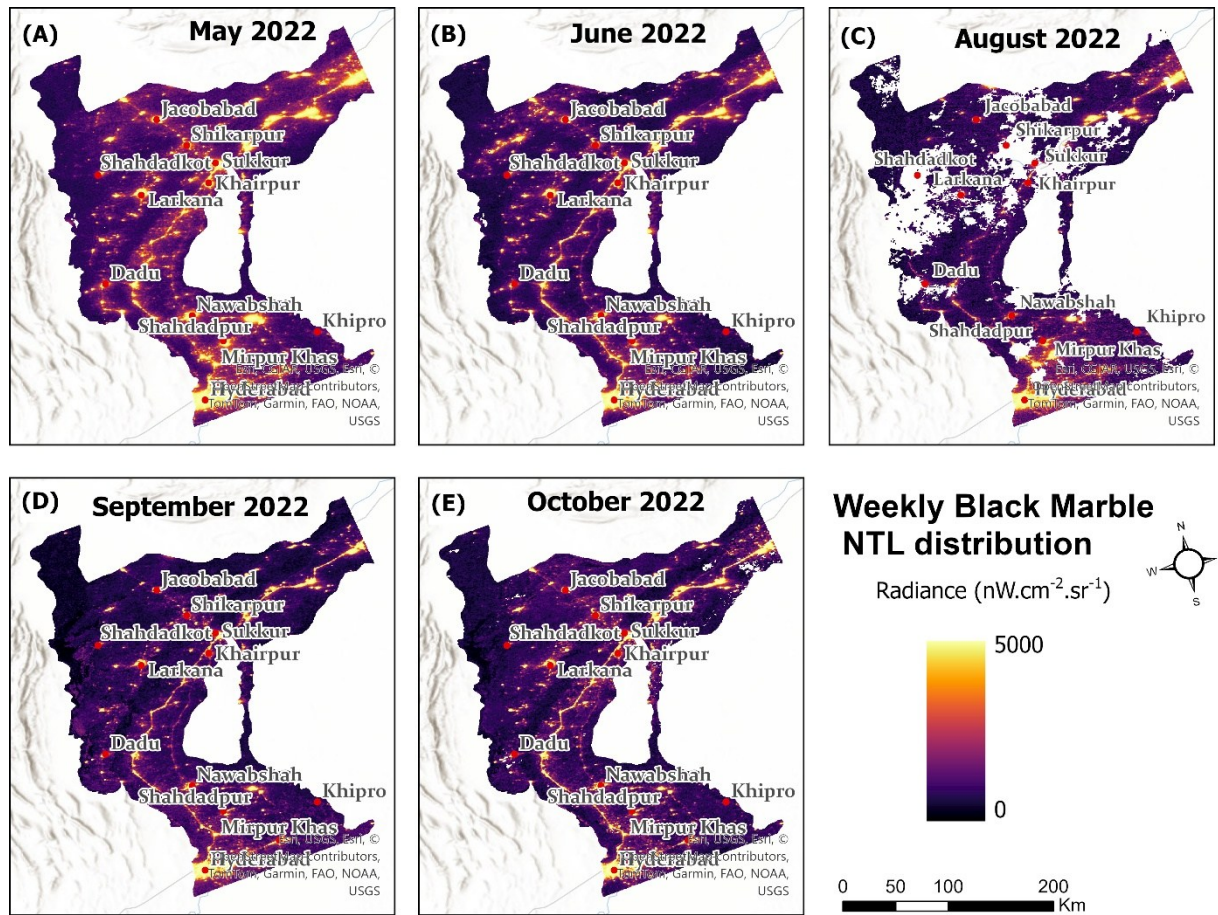


Figure 3.8: Spatial distribution of the night-time lights during different weeks of 2022 of the flooding period. The bright yellow pixels are high-intensity radiance values that signify lit pixels, and dark pixels represent the absence of lit pixels; **(A)** Distribution of lit pixels for the 18th WOY 2022 (May 2022); **(B)** Distribution of lit pixels for the 23rd WOY 2022 (June 2022); **(C)** Distribution of lit pixels for the 34th WOY 2022 (August 2022). August. The missing data corresponds to the large cloud cover; **(D)** Distribution of lit pixels for the 36th WOY 2022 (September 2022); **(E)** Distribution of lit pixels for the 40th WOY 2022 (October 2022).

Table 3.3: Descriptive Statistics of the NTL pixels from May to November cloud-free composites within the cloud mask (derived from the August composite)

Month	WOY	Mean	Sum	Min	Max	Std Dev
May	2022-18	0.892593	609466	0	2892	10
June	2022-23	0.808739	552205	0	5119	15
August	2022-34	0	0	0	0	0
September	2022-36	0.656296	448224	0	3900	12
October	2022-40	0.803781	548754	0	4120	15
November	2022-47	0.829722	566604	0	4279	13

3.5.2. NTL derived spatial flood impact beyond water inundation

To understand the spatial impact of flooding on human activity, we examined the spatial variation in NTL radiance across the study area. To do this, we calculated the % decline in NTL radiance relative to May 2022. The 18th WOY in 2022 as the reference allows for a robust and reliable comparison with subsequent weeks, enabling a clear understanding of how NTL radiance patterns record the impact of flooding (section 3.4.3). Note we only considered the areas with a minimum decline in the radiance of 40% overall as point variation in the radiance of less than this value had less significance of change in the radiance.

These data give a unique opportunity to quantify flood impacts on human activity beyond the inundated areas. Figure 3.9 illustrates the relative decline in lit infrastructure during the 2022 floods across the study area in the Indus basin from June to October 2022 (A-D). Green pixels represent a 40-60% decline relative to May 2022, red indicates 60-80%, and black signifies the most severe decline of 80-100%. The overlaid blue areas highlight flood water inundation derived from Sentinel-1 SAR data, offering us a visual narrative of the flood's consequences.

In Figure 3.9A, before the onset of major flooding in July 2022, we observed only small localised zones in the northwestern part of the study area experiencing inundation (shown in blue). Nevertheless, areas beyond this show a 40-60% decline in NTL radiance. With the onset of major flooding in July, we observe that the water-inundated areas derived from Sentinel-1 in Figure 3.9B during August are mostly concentrated in the northwest and western parts of the area. During this period, we observe extensive NTL decline spatially at the peak of flooding, signifying an impact on the lit infrastructure. Beyond the inundated regions, we observe a scattered band of 40-60% decline surrounding the Indus River. Moreover, towns and major cities like Jacobabad, Larkana, Khairpur, and Nawabshah witnessed a significant 60-80% and 80-100% drop in radiance.

As the floodwaters receded in September 2022 (Figure 3.9C), the distribution of NTL decline started to shift. The area of high-impact (60-100% decline in radiance) shrunk, while regions with a 40-60% decline became more spatially dispersed. Further, in October 2022 (Figure 3.9D), the spatial distribution of the NTL-derived impacted pixels had reduced. The trend of increase in the NTL-derived impacted pixels, followed by a decrease, mirrors the receding floodwaters. This underscores the link between the event and NTL changes, showcasing a gradual recovery as the flooding receded.

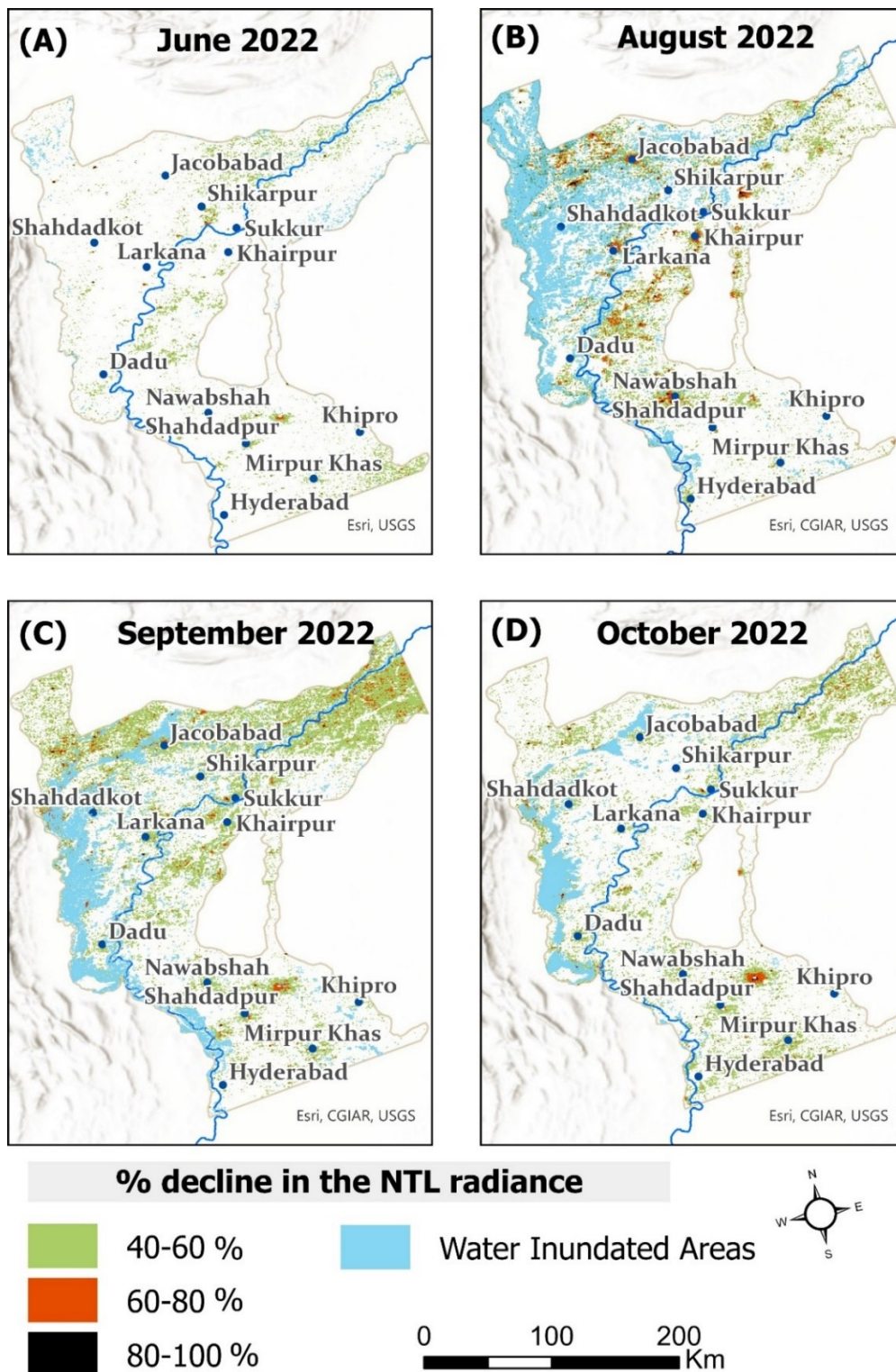


Figure 3.9: The figure depicts the relative decline in lit infrastructure during the 2022 floods across the study area in the Indus basin from June to October 2022 (A-D). The overlaid blue areas highlight water inundation derived from ESA's Sentinel-1 SAR data. The water-inundated layer derived from the SAR data corresponds to the same WOY as the NTL data. Green pixels represent a 40-60% decline, red indicates 60-80%, and black signifies the most severe decline of 80-100%. Differential impact of flooding and recovery on Rural-Urban communities

3.5.3. Differential impact of flooding and recovery on Rural-Urban communities

To characterise the differential impact of the 2022 floods on rural and urban communities within the study area and to document their recovery, we combined the NTL-derived impacted data, settlement type (GHS-SMOD) and economic data (GDP). These data have been discussed in section 3.3. Thus, to derive the spatial and economic impact for different communities, we superimposed our NTL-derived temporal impact with the GHS SMOD and the GDP spatial data. Figure 3.10 shows the area impacted due to the floods derived from the NTL-derived impact data and the equivalent economic damage for each month for both urban centres and rural areas.

To illustrate differential exposure here, we focus on two important categories:- Urban Centres and Rural classes. Figure 3.10A shows in urban centres, the areas that experienced an 80-100% decline in radiance due to the impact of flooding (i.e., extremely significant impact, black lines) increased from 0 to ca. 10km² from June to August 2022 and reduced from September 2022 to pre-flood values. These areas show the number of pixels that are marked as an 80-100% decline in radiance to pre-flood values in one month - suggesting that the very worst impacts were mitigated within one month because, by September'22, few pixels have such a marked decline. By contrast, for urban centres, the areas that showed a 60-80% and 40-60% decline in radiance were mitigated within 3 months and more than three months, respectively.

For rural districts which experienced a decline in the radiance of 60-80%, the area exposed to flood impacts is up to 600 km² in August 2022 (Figure 3.10B). The recovery for the rural areas is similar to the urban centres, i.e., the areas that showed an 80-100% decline in radiance recover to pre-flood values in one month, and the period increases to three months for areas that showed a 60-80% decline in the radiance, similar to the urban centres areas.

Our analysis of the area exposed to flood impact enables us to also analyse the wealth of populations affected by flooding. We can use our values of the area exposed to flood

impact derived from NTL radiance to estimate the economic damage cost due to floods by calculating the area-associated GDP. Interestingly, our analysis also indicates the economic status of those affected by the floods by associating the GDP with the NTL-derived impacts. Since we estimated GDP using Purchasing Power per Parity (PPP) and the population density (discussed in section 3.3.3), the represented economic damage in Figures 3.10A & 3.10B which is representative of the wealth of the population affected and not specifically the infrastructure damage that occurred during the floods. We observe that, as per our analysis, urban centres show the highest economic impact, reaching approximately 4 million USD in terms of the total GDP PPP multiplied by population, while rural areas represent less than 1 million USD when expressed by the same metric. However, despite exceeding urban centres in flood-exposed areas by 15 times, the rural economic status impact remains less than 25% of those in urban centres. This analysis highlights the diverse impact of floods on both rural and urban communities. While both experience economic and infrastructural consequences, the thresholds for visible impact and recovery rates differ significantly. We observe that both the area exposed and the economic loss follow the same trend along the categories of the NTL decline radiance relative to May 2022.

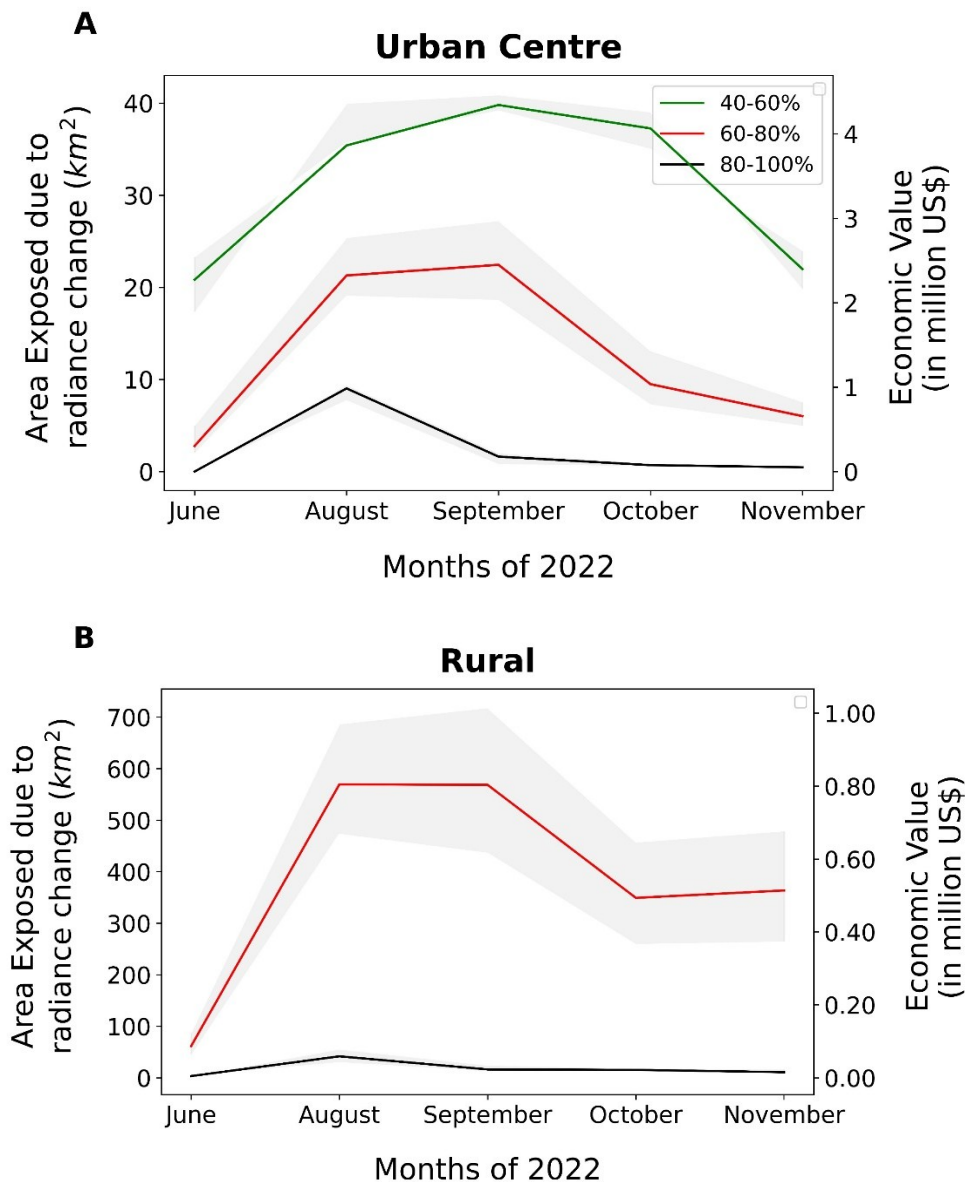


Figure 3.10: The figure quantifies the impact of the 2022 floods. (A) Area affected and economic damage in the urban centres. The green line represents areas with a 40-60% decline in night-time light radiance, signifying both the impacted area and the associated economic decline. The red and black lines depict similar results for 60-80% and 80-100% decline in radiance, respectively, indicating zones of progressively greater flood impact and economic decline. The grey shaded area is the standard deviation. (B) The area was affected, and economic value declined in the rural areas. The red and black lines depict both areas impacted and associated economic decline for 60-80% and 80-100% reduction in radiance, respectively, indicating zones of progressively greater flood impact and economic decline. The grey shaded area is the standard deviation.

3.6. Discussion

3.6.1. Compound impact and recovery due to 2022 Indus floods

The 2022 flooding event was unprecedented and led to a disastrous impact on both infrastructure and population (Chen et al., 2024; Dunstone et al., 2023; Nanditha et al., 2023; Otto et al., 2023; Waseem and Rana, 2023). The Pakistan floods were driven mainly by precipitation during the summer monsoon between June and September 2022. The above-normal rainfall in July and August 2022, compounded by exceptional heat-induced glacier melt, led to an extreme disaster impact (Nanditha et al., 2023; Qamer et al., 2023; Vestby et al., 2024). To date, most studies related to the flooding in Pakistan in 2022 have related to the drivers of the flooding event (Chen et al., 2024; Dunstone et al., 2023; Nanditha et al., 2023; Otto et al., 2023). In addition, several studies have focused on mapping population exposure using SAR satellite images and WorldPop population data (Akhtar et al., 2023). These works have largely considered direct exposure to floods. However, this does not capture the full impact of such disasters- because indirect impacts are not considered. The indirect impacts are not due to the physical contact with flood water but result, for example, from the reduced performance of infrastructure or the occurrence of secondary disasters triggered by primary disasters (Afroze, 2023; Arrighi et al., 2021).

In this study, we used the NTL as a signature for human activity with lit infrastructure to quantify the spatial and temporal impact of the flooding event both spatially and temporally. The decline in the radiance we observed in Figure 3.7B was due to the onset of the summer monsoon, followed by the above-normal rainfall in July and August 2022, leading to the catastrophic flooding event. The detrended weekly NTL data can be used to assess the disaster recovery timeline precisely and to examine the response of human activities to the event (Gao et al., 2020; Román et al., 2019; Afroze, 2023). The impacts of artificial lights as a proxy for human activity include compounding and cascading hazards like power lines being destroyed, water logging areas, extreme temperatures

and wind storms, leading to forced displacements (Vestby et al., 2024). The application of NTL to assess the impact and recovery from a disaster lays out the potential to map the exposure to lit infrastructure represented by the dimming of the lights. We find that the impact goes well beyond the extent of water-inundated areas. For instance, cities like Nawabshah, Larkana, Khairpur, and Jacobabad witnessed a significant 60-100% drop in radiance in August 2022, likely due to the cascading and compound effects of the floods, such as those caused by disruptions in electricity infrastructure. The combined analysis of NTL radiance decline and flood inundation maps provides valuable insights beyond the geomorphic impact of the floods.

Post-disaster recovery is based on Haas's Disaster framework, where the community experiences four post-disaster stages in a predictable manner, which are Emergency Stage, Restoration Stage, Reconstruction-1 and Reconstruction-2 stage, each of which varies in duration and resilience (Gao et al., 2020; Hass et al., 1977). In an ideal framework, the first stage is the emergency stage, which is usually a short period (several weeks) showing a sudden increase in the artificial light intensity; the second stage is the restoration or the recovery stage, which is about one month to six months, where emergency measures are gradually withdrawn leading to a gradual decrease in the intensity of artificial lights; the third stage is the reconstruction-1 where reconstruction work takes place and the artificial lights increase, followed by the last stage as the reconstruction-2 or development stage which depends on the previous stage and leads to intensity decline (Gao et al., 2020; Hass et al., 1977).

Figure 3.11 illustrates how the Black Marble NTL data shows a sudden decline and increase in the average radiance from T2 to T3, i.e., 2022-18 WOY (in May) until the 2022-36 WOY (in September), for 18 weeks. This depicts a strong radiance signal response as a result of the above-normal rainfall-induced floods in July and August 2022 in the region. The night-time light response to the 2022 rainfall-induced flooding episodes can be categorised into five phases.

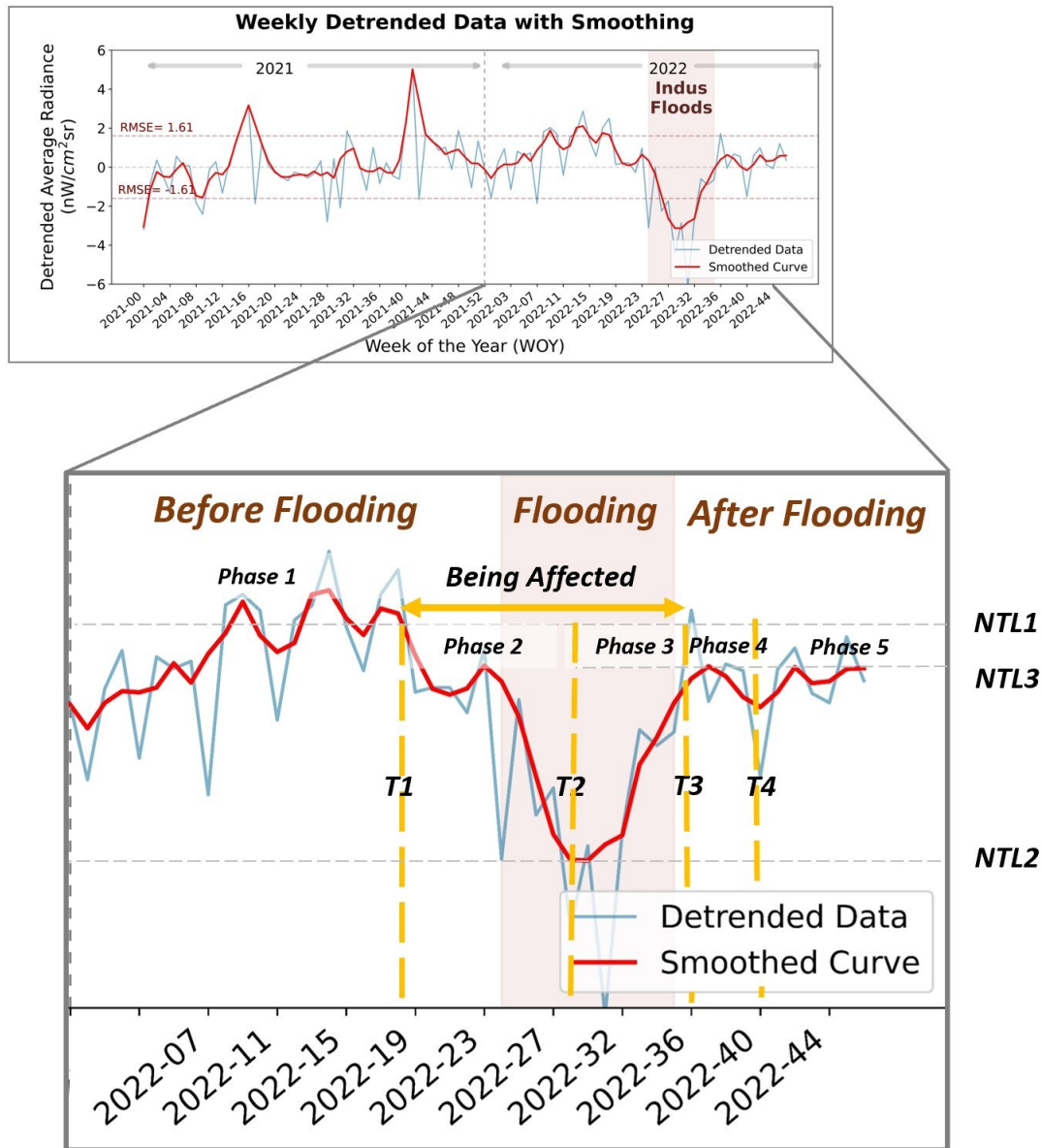


Figure 3.11: A schematic plot of the change in the radiance and the recovery from the flooding over the weekly detrended radiance data. The red line shows the trend of the weekly detrended radiance, and the blue line shows the average detrended radiance. The red band shows the flooding period over two months, from July'22 to August'22, due to surplus rainfall in the region. The figure illustrates the night-time light response to the 2022 rainfall-induced flooding episodes in five phases – Phase 1, Phase 2, Phase 3, Phase 4 and Phase 5.

Phase 1 is before week T1 (2022-18 WOY), which is the pre-disaster or before the radiance starts decreasing. Phase 2 is between T1 and T2 (i.e., from 2022-18 to 2022-28), where radiance decreased from ca $2 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ to $-3 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ in 10 weeks. This decline rate of $0.5 \text{ nW} \cdot \text{cm}^{-2} \cdot \text{sr}^{-1}$ per week in Phase 2 was followed by Phase 3 of the recovery rate of

ca. $0.4 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ per week between T2 and T3 (i.e., from 2022-28 to 2022-36) over 8 weeks. We associate the end of phase 2 and early phase 3 as the emergency stage (stage 1 of Haas's disaster recovery), where there was a sudden increase in the average intensity. This was followed by Phase 4, which was the Restoration stage (stage 2 of Haas's disaster recovery), which showed a sudden decline in the radiance, lastly leading to Phase 5, which is the reconstruction-1 stage (stage 3 of Haas's disaster recovery), where there is a slow increase in the average radiance until the end of the year. Thus, the NTL-derived data highlights the multi-dimensional and non-linear processes involved with the recovery process (Gao et al., 2020). It reveals the effects, both direct and indirect, on lit infrastructure, signifying human activities which are not typically captured using traditional flood monitoring techniques using Sentinel-1 SAR, especially over Pakistan, as it does not have high coverage compared to Europe (Ruth et al., 2023).

3.6.2. Differential impact on urban and rural communities

To understand the impact on the rural and urban communities, we investigated the relation between the NTL-detected spatial flood impact and socio-economic data derived from the settlement-type data (GHSL SMOD). Extreme flood events such as the Pakistan floods of 2022 can lead to changes in societal processes, disrupt rural-urban linkages and affect rural vulnerabilities both directly and indirectly (Jamshed et al., 2021; Wang et al., 2024). Although many studies quantify the flood impacts, they do not take into consideration the separate vulnerabilities of the urban and rural communities. For example, considering their relatively lower socioeconomic and physical development, rural communities are highly vulnerable to natural disasters like floods. Thus, to understand the impacts of the 2022 Indus floods, we quantified the varying impacts for rural and urban centres. First, we estimated that the maximum area exposed to the 2022 Indus floods was significantly higher for the rural areas than the urban areas by a factor of 15 (Figure 3.10). The primary reason for the higher exposure within rural areas is that the majority of the population of the country lives in rural regions, depends on

agriculture and has comparatively fewer resources devoted to disaster mitigation (Dasgupta et al., 2014; Jamshed et al., 2021). The impacts of flooding on rural communities in Pakistan are usually- damage to house structures, household belongings, harvested crops, standing crops and livestock (Jamshed et al., 2021). However, due to the high economic status of those associated with the urban centres, the economic damage was exponentially higher than in the rural areas.

In both urban and rural areas, regions with a significant impact, where night-time light (NTL) declined by 80-100%, exhibited a recovery within approximately one month. In contrast, areas experiencing a 60-80% reduction in radiance required up to three months to return to pre-flood levels (Figure 3.10). This aligns with the observation discussed earlier, where areas affected immediately after disasters undergo a sharp increase in the emergency stage, followed by a slower recovery stage. Specifically, pixels with an 80-100% radiance reduction during the floods may transition to a 60-80% reduction post-flood, thereby prolonging the recovery process. For instance, a 40-60% radiance reduction might extend the recovery period to three months, compared to one month for an 80-100% reduction. Ultimately, the rate of decline and recovery is influenced by the system's resilience, which includes factors such as preparedness and emergency response strategies (Arrighi et al., 2021). Highly impacted areas tend to have more resilient systems, leading to faster post-disaster recovery, whereas less impacted areas often exhibit lower resilience, resulting in longer recovery times across both categories.

3.6.3. Conclusions

Recent years have seen an increase in the frequency of extreme flood events driven by climate change and the severity of the floods due to population growth, particularly in developing countries (Tellman et al., 2021). Our findings highlight the effectiveness of night-time light (NTL) data in mapping the real-time impact of floods on human activities. Specifically, our study demonstrates the potential of NASA's Black Marble night-time light data for the rapid assessment of the impact of the 2022 Indus Floods in

Pakistan. The data's temporal and spatial resolution provides valuable insights into flood exposure compared to traditional flood mapping methods. Weekly detrended data revealed a maximum radiance decline of 400% during the flooding period, indicating the significant impact of floods on human activity. The region experienced excessive rainfall for eight weeks from July to August 2022, but the reduction in radiance persisted for about 18 weeks, from the 18th week of the year (WOY) in 2022 (May 22) to the 36th WOY (September 2022). This period included 10 weeks of declining radiance, followed by a rapid recovery over eight weeks during the Emergency Stage. Spatially, the data also pinpointed areas with significant radiance declines during and after the floods, extending beyond the water inundation boundaries identified by SAR. These declines highlight the indirect impacts of flooding, such as destroyed power lines, waterlogged areas, and wind storms, leading to forced displacements. Moreover, our study found that rural communities were more severely affected than urban centres, although the financial status value of those affected was higher in urban areas. Additionally, we find that areas with an 80-100% decline in radiance mostly recovered in approximately one month, while areas with a 60-80% decline took up to three months to return to pre-flood levels. Our analysis provides a detailed assessment of the human impact of floods through the lens of lit infrastructure, offering a rapid, safe, and cost-effective approach to quantify flood impact and vulnerability at all administrative levels.

Authors Contribution:

Authors envisaged for the publication: Ekta Aggarwal (E.A.); Sanjeev Gupta (S.G.); Alexander C. Whittaker (A.C.W.); Phillipa J Mason (P.J.M.); Fritz Schlunegger (F.S.); Kartikeya S. Sangwan (K.S.S.); Ranjay Sreshtha (R.S.) (Authors sequence to be discussed)

Conceptualisation, E.A., A.C.W. and S.G.; methodology, E.A. and A.C.W.; software, E.A.; validation, E.A., A.C.W. and S.G.; formal analysis, E.A.; investigation, E.A.; data curation, E.A.; writing—original draft preparation, E.A.; writing—review and editing, A.C.W., S.G, F.S., K.S.S.; discussion - A.C.W., S.G, P.J.M., K.S.S., F.S., R.S.; visualisation, E.A.; supervision, A.C.W. and S.G.; project administration, A.C.W.; funding acquisition, A.C.W. and S.G.

Chapter 4: Increasing Flood Risk in the Ganga Basin (India): A Perspective from the night-time lights

Abstract

The changing climate, intense rainfall, and geomorphological conditions within the Ganga Basin have led to recurring flooding within the area in the recent past, causing severe loss of life and property. The occurrence of such flooding events has increased the need to understand the complex interplay between flood hazards, exposure, vulnerability, and risk. This study delves into flood risk within India's Ganga Basin, focusing on the flood-inducing factors, vulnerability, and exposure through the application of the Analytical Hierarchy Process (AHP), which is a Multi-Criteria Decision Making (MCDM) model. The novelty of the work is using NASA's Black Marble Night-time Lights as a proxy for human presence and economic activities compared to some conventional parameters for flood exposure, such as population count and household density, amongst others. The study aims to capture the dynamic nature of flood risk, driven by hydro-geomorphic controls, expanding human activities and population growth, and variations in flood resilience. The accuracy of the flood risk maps is validated using the historical flood-impacted data from the EM-DAT and GDIS databases, showing a satisfactory model accuracy of approximately 70%. The findings emphasise the role of increasing human exposure and changes in rainfall patterns as the key drivers for increasing flood risk over time. This research has significant implications for flood management, offering insights for developing risk mitigation strategies that transcend administrative boundaries by identifying areas of escalating flood risk.

4.1. Introduction

Floods are one of the most destructive natural hazards, causing loss of human life, property, infrastructure, lands and other irreversible damages (IPCC, 2023; Islam et al., 2023; Mishra and Sinha, 2020). As the United Nations Office for Disaster Risk Reduction (UNDRR) reports, the number of flood disasters as reported by the Emergency Events Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED) has increased to more than 3200 between 2000-2019 compared to less than 1400 events between 1980-1999, resulting in economic loss worth \$651 billion (USD) (Delforge et al., 2023; UNDRR, 2020). The increase in the number of events has been in part attributed to the escalation of extreme hydrological events driven by climate change and anthropogenic activities (Swarnkar et al., 2021; Tripathi and Mohanty, 2024). Moreover, the increase in the severity of the flood impact has been complemented by an increase in exposure to flood hazards over time. Floods have varying economic impacts on Low and Middle-Income Countries (LMICs) and High-Income Countries (HICs). In particular, Asian and sub-Saharan African countries have particularly had increased flood exposure between 2000-2015 due to an increase in population (Tellman et al., 2021). Large basins in south and southeast Asia (Indus, Ganges-Brahmaputra and Mekong) have some of the largest absolute numbers of people vulnerable to flooding worldwide (17.0–19.9 million, 107.8–134.9 million and 20.2–32.8 million, respectively) and the proportions of their populations exposed to inundation increased by 36%, 26% and 11%, respectively (Tellman et al., 2021). The increasingly high economic and human losses associated with flooding make it important to understand the associated risks with extreme events or natural disasters.

Here we analyse the increasing flood risk in the northern part of India, one of the world's most populous regions is fed by three major rivers – Indus, Ganga and Brahmaputra- and is strongly influenced by the summer monsoon (Immerzeel et al., 2009). These three river basins have a population of over 700 million people, 60% of whom live in the Ganga

Basin (Nepal and Shrestha, 2015). The Indian summer monsoon between June and September contributes about 80% of the rainfall in the Ganga Basin (Maurya et al., 2024). Extreme precipitation during the monsoon leads to events such as floods, resulting in significant impacts and extensive devastation to both human lives and livelihoods. Notably, the floods in Uttarakhand (2013), Jammu & Kashmir (2014), Tamil Nadu (2015), Bihar (2016), Gujarat (2017), and Kerala (2018) were among the most devastating events in the past decade, leading to significant socioeconomic disruption, loss of biodiversity, and human lives in India (Mishra and Shah, 2018; Ray et al., 2019; Upadhyay et al., 2020; Swarnkar et al., 2021a, 2021b; Swarnkar and Mujumdar, 2023).

When we study flood risk, the three terms- hazard, exposure and vulnerability are often confused, leading to different meanings for different users. It is important to understand the role of vulnerability and exposure when assessing flood risk. According to the IPCC (2012) report, flood risk is defined as a product of hazard, exposure and vulnerability based on the common framework adopted by the United Nations. The definitions of the three risk components by UNDRR are as follows:

1. *“Hazard is defined as the potential occurrence of a natural or human-induced physical event or trend or physical impact that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources*
2. *“Exposure is defined as the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected”*
3. *“Vulnerability is defined as the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt”.*

In this study, we constrain all three components separately to assess the long-term flood risk within the basin. This combines both natural and anthropogenic factors, giving more accurate information about flood risk.

A general overview of different techniques for mapping flood-prone areas is broadly categorised into physical, numerical and empirical approaches (Liu et al., 2024; Mukhtar et al., 2024; Teng et al., 2017). A physical model approach predicts floods through a rigorous mathematical treatment based on physical mechanisms, including hydrological parameters, river geomorphic parameters, and topography by which floods occur (Teng et al., 2017). A numerical modelling approach is typically based on numerical solutions to solve flow equations in 1-, 2-, and 3-D dimensions and is sometimes referred to as a hydrodynamic model. An empirical model approach consists of the multi-criteria decision-making method (MCDM), which uses prior knowledge to predict floods by assuming subjective weights of different factors for potential flood factors, statistical methods for flood analysis and prediction, and machine learning and AI models.

Over time, there has been an evolution of different methodologies for understanding flood risk management. Integration of hydrological models, monitoring river gauge data, satellite imagery and remote sensing technologies for forecasting floods, flood susceptibility mapping and flood inundation mapping have gained popularity. Such methods gather information on precipitation, river flow, soil moisture, and snowpack, reliable weather forecasts, and advanced meteorological models, which can be used to predict the amount, intensity, and duration of rainfall in a particular region, aiding in flood predictions (Islam et al., 2023; Munawar et al., 2022). Analysing flood risk can be a complex and challenging task, mainly due to limitations in data availability. To date, there are no universal criteria that specify which type of model should be used in which situation, as each model has pros and cons (Khosravi et al., 2018). However, de Brito and Evers (2016) reviewed almost 128 papers regarding the MCDM model and found that the Analytic Hierarchy Process (AHP) is the most widespread MCDM method for flood

susceptibility modelling. Thus, the AHP method, with the integration of remote sensing and GIS, provides a powerful tool for integrating multiple information, preparing flood impact maps, and providing more accurate insights on flood risk.

The Analytical Hierarchy Process (AHP) developed by Saaty (1980) is one of the widely known approaches for flood susceptibility mapping (Sinha et al., 2008; Chakraborty and Mukhopadhyay, 2019; Ghosh and Kar, 2018; Grozavu, 2017; Huang et al., 2011; Mishra and Sinha, 2020). This approach uses pairwise comparisons to assess the extent to which one factor within the model is more important than the other, thereby producing a weighting for each factor. Previous research related to flood risk assessment has been conducted in different areas in the Ganga Basin. For instance, Dwivedi (2022) assessed hydrometeorological risk in the upper reaches of the Ganga Basin using the MaxEnt Machine Learning model. The study included various parameters derived from a DEM and other sources, albeit without the incorporation of exposure and vulnerability estimates for the basin. Roy (2021) conducted a flood risk assessment in the active flood-prone regions of the foothills of the Himalayan range in the Ganga Basin using the Analytical Hierarchy Process (AHP). Their methodology included various hydrological parameters and flood vulnerability parameters to prepare flood risk assessment in the fan. Similarly, Mishra and Sinha (2020) and Ghosh and Kar (2018) used AHP to evaluate flood risk in parts of the Ganga basin based on hydrogeomorphic parameters and socio-economic vulnerability parameters such as population density, household density, female density, literacy, Land use Land cover (LULC), and road density.

However, these strategies for characterising regional flood risk have some limitations which are important for us to consider. They commonly do not consider the three risk components as separate entities, specifically ignoring the vulnerability and exposure aspects, which are often considered together due to the unavailability of high temporal exposure data. The exposure data usually used for assessing flood risk in the area is based on the last census data, which was back in 2011 (Government of India, 2011).

Secondly, in the case of the Ganga catchment, one of the most populous basins of the world, flood risk assessment is usually done in parts of the basin and not the basin as a whole. Lastly, the increasing exposure and vulnerability have resulted in a limited understanding of how risk has changed over time. Thus, in our study, we aim to incorporate factors like geomorphology, hydrogeomorphic parameters, human exposure and vulnerability of different societies to floods and combine them using GIS techniques to create a reliable decision-making tool for flood-risk assessment. Since this study is aimed at risk identification in the Ganga Basin, we take into account easy access to data when determining flood risk factors, that is, to avoid the actual data acquisition being too complicated or costly. The key novelty of the approach lies in using night-time lights (NTL) as a proxy for flood exposure within the basin, unlike the population data, and leveraging the temporal availability of the data. The NTL data can reflect the real-time distribution of human activities at a large scale and with better temporal frequency compared to traditional statistics and census data (Fang et al., 2021). It has been investigated as a proxy for human activities and has been used in various studies for different domains (Andries et al., 2023; Román et al., 2018; Wang et al., 2018). The data has also increasingly been explored to examine human exposure and presence near rivers, including those associated with floods (Aggarwal et al., 2024; Ceola et al., 2014; Elshorbagy et al., 2017).

This study aims to conduct a novel flood risk assessment for the Ganga Basin in India at a pixel level, motivated by the limitations of previous approaches and the emerging opportunities provided by night-time light (NTL) data. By utilising remote sensing datasets and Geographic Information System (GIS) techniques and integrating them with the Analytic Hierarchy Process (AHP) method, this research presents a detailed evaluation of flood risk. The assessment focuses on key components of flood risk, including hazard, exposure, and vulnerability, with a specific emphasis on using real-time exposure data from night-time lights.

One of the key contributions of this study is the development of annual flood risk maps for the Ganga Basin from 2013 to 2023. These maps provide a valuable tool for identifying areas where flood risk has been increasing over time, down to the pixel or cell level. This spatial and temporal analysis offers a clearer picture of evolving flood risks in the basin, revealing trends and highlighting regions that may require immediate attention.

By applying remote sensing, GIS techniques, and multi-criteria statistical analysis, this study offers a comprehensive framework for understanding and managing flood risk. The approach developed here is designed to assist a range of stakeholders, from local communities to policymakers, in creating more effective flood risk management strategies. The annual flood risk maps, in particular, are anticipated to inform these stakeholders by identifying areas with rising flood threats and guiding efforts to reduce the impacts of flooding. This, in turn, could help minimise loss of life, economic damage, and disruptions to society, making the findings of this research crucial for future flood management planning in the region.

4.2. Study Area

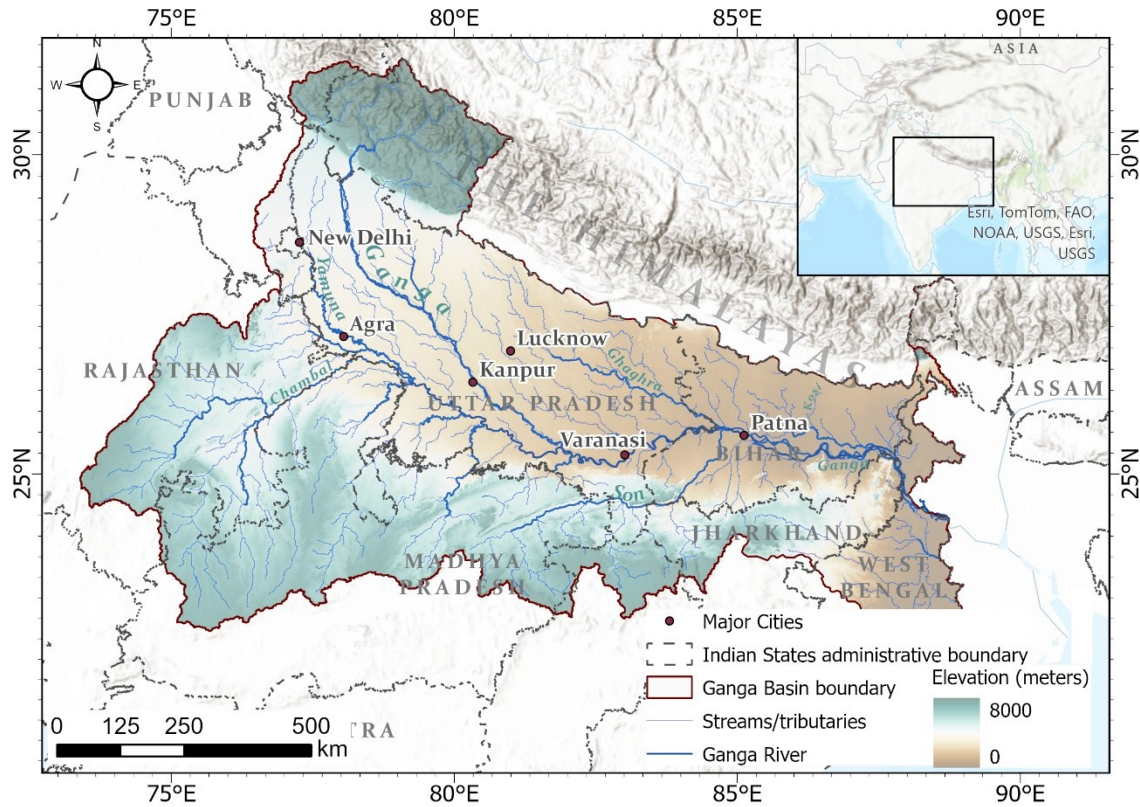


Figure 4.1: ESRI world imagery showing the Ganga Basin (dark red boundary), Ganga River and its major tributaries in dark blue in India. The other streams are light blue. The inset in the top-right of the figure shows the location of the study area within Asia.

The Ganga River basin is one of the largest in the world, extending across India, Bangladesh, Nepal and Tibet. In our study, we focus on the Indian part of the basin, which is the largest river system in India (Figure 4.1), covering an area of ca. 860,000 km² and draining into 11 states of the country - Uttarakhand, Uttar Pradesh, Haryana, Himachal Pradesh, Delhi, Bihar, Jharkhand, Rajasthan, Madhya Pradesh, Chhattisgarh and West Bengal (River Basin Atlas of India, 2012). The basin covers > 26% of the total geographic area of India (Tripathi and Mohanty, 2024) and extends between the latitude of 21°6'N to 31°21'N and the longitude of 73°2'E to 89°5'E. The Himalayas bound the basin to the north, and the primary river of the basin is the Ganga (or Ganges), which originates from the Gangotri Glacier in the Himalayas at an elevation of nearly 7010 m

and traverses a length of > 2500 km before it flows into the Bay of Bengal (Figure 4.1). Along its way, the Ganga is joined by several tributaries to form the most fertile alluvial plain in Northern India (River Basin Atlas of India, 2012). A few of the important tributaries include the Yamuna, Chambal, Kosi and Ghaghara. All the rivers in the basin are perennial and carry large runoff due to heavy rainfall, making it one of the most flood-prone regions in the world (Swarnkar et al., 2021b). The basin receives rainfall during the southwest monsoon between June to October. In the majority of the basin, the average rainfall is 70-80% of the total annual rainfall over three months from July to September. The annual average rainfall in the basin varies between 400 - 2000 mm, with approximately 179 and 152 rainy days in the upper and lower basins (River Basin Atlas of India, 2012). In the eastern part of the basin, such as areas of West Bengal and Bihar, the monsoon is longer, starting from early June to early October. The effect of the monsoon weakens from east to west.

4.3. Data and Methods

Flood risk assessment considers not only the hydrological extremes but includes complex processes characterised by a large number of physical hazards, vulnerability and exposure parameters. Consequently, both temporal and spatial resolutions are essential for comprehensive analysis. To develop variable risk maps for the Ganga Basin, we employed multiple datasets and adhered to a rigorous methodology to identify areas of prolonged risk. Figure 4.2 illustrates the workflow of the research. The first step was acquiring various data, which are listed in Table 4.1. The next step was processing and calculating normalised relative weights for each factor to compute flood hazard, exposure and vulnerability, respectively. This was followed by computing the flood risk, validating the data model and calculating the flood risk trend. Below, we outline these data sets and processing steps in further detail, which are shown diagrammatically in Figure 4.2.

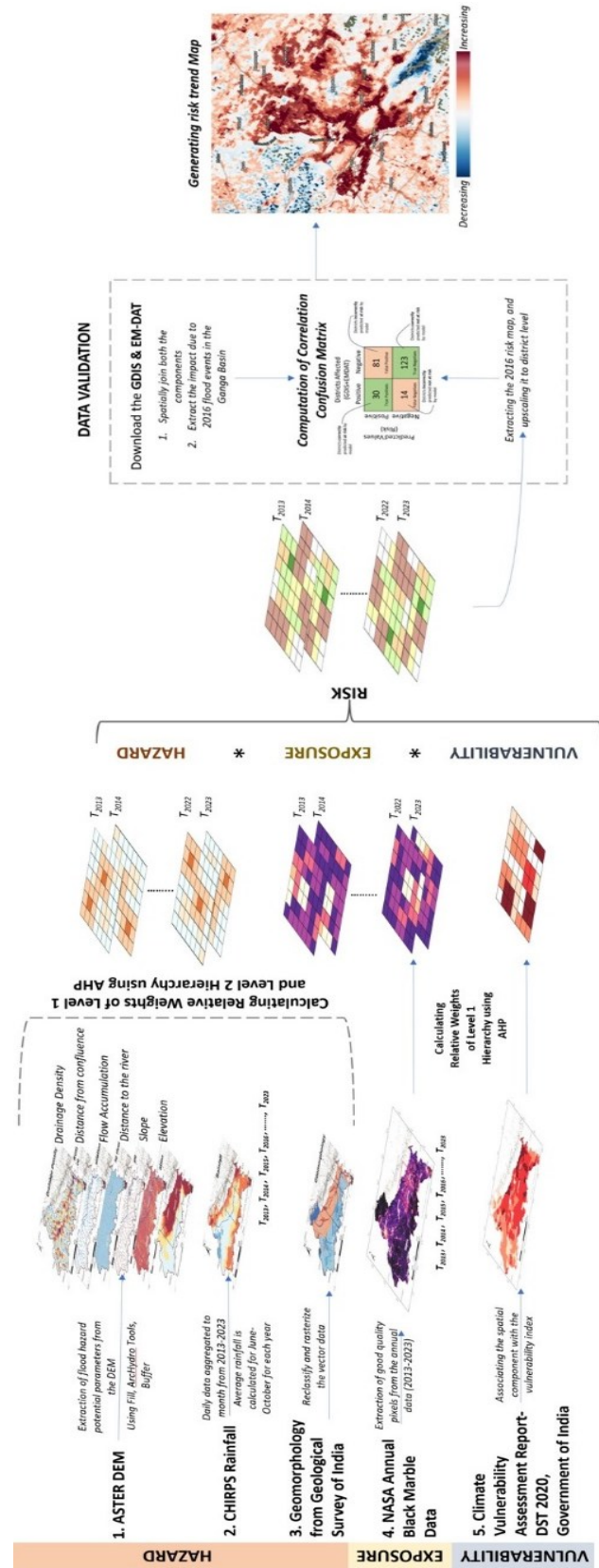


Figure 4.2: Flow chart illustrating the methodology for this work.

4.3.1. Datasets

Table 4.1: List of datasets used in the study and their sources

	Dataset	Source
1	Digital Elevation Model (DEM)	ASTER-GDEM (https://appears.earthdatacloud.nasa.gov/)
2	Rainfall	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) ((https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY#description)
3	Geomorphology	Geological Survey of India (https://bhukosh.gsi.gov.in/Bhukosh/Public)
4	Exposure	NASA Black Marble night-time lights annual product suite (VNP46) (https://ladsweb.modaps.eosdis.nasa.gov/search/order/2/VNP46A4--5000)
5	Vulnerability	Climate Vulnerability Assessment Report- DST 2020, Government of India (https://dst.gov.in/national-climate-vulnerability-assessment-identifies-eight-eastern-states-highly-vulnerable)
6	Historic Disaster Impact Database	EM-DAT (https://public.emdat.be/); GDIS (https://sedac.ciesin.columbia.edu/data/set/pend-gdis-1960-2018)

- 1 **Digital Elevation Model (DEM):** In our study, we used the free open source DEM, i.e., ASTER-GDEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model) Version 2. The spatial resolution of the data is 1 arc-second, approx. 30m spatial resolution (NASA/METI/AIST/Japan Spacesystems and U.S./Japan ASTER Science Team, 2019). The DEM was downloaded from the NASA Appears website (<https://appears.earthdatacloud.nasa.gov/>, accessed on 5th January 2024) in geotiff format. The DEM is further used for extraction of elevation, slope, drainage density, distance from the confluence, flow accumulation and distance to the river, which are further explained in section 4.3.3.

- 2 **CHIRPS Rainfall Data:** Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a 35+ year quasi-global rainfall data set. The data spans 50°S-50°N (and all longitudes) and ranges from 1981 to the present. CHIRPS incorporates the climatology, CHPclim, 0.05° resolution satellite imagery, and in-situ station data to create gridded rainfall time series (Funk et al., 2015). The latest version, 2.0 (V2.0) of this precipitation data measured in mm, is available for 1981–2024 at 0.05° spatial resolution and at daily, pentad, and monthly time scales. In our study, we used the daily data from 2013-2023 accessed using Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY#description, accessed on 21st Feb 2024).
- 3 **Geomorphology:** To assess the potential flood hazard, we used the geomorphology information provided by the Geological Survey of India, which can be accessed online on the Bhukosh server (<https://bhukosh.gsi.gov.in/Bhukosh/Public>). We use the Geomorphology 250k vector data, which provides spatial information on the floodplains, alluvial plains, hills and valleys, plateaus and pediment-peneplain complex.
- 4 **NASA Black Marble Annual Data Product:** NASA Black Marble night-time lights product suite (VNP46) produced at NASA's Land Science Investigator-led Processing Systems (Land SIPS) is a product of the Visible Infrared Imaging Radiometer Suite (VIIRS) Day-Night Bands (DNB) available from January 2012 at daily/monthly/yearly frequency (Román et al., 2018). The data captures human signal-artificial signals at night, providing an understanding between the human systems and the environment. The product suite, available globally on daily, monthly, and annual composite scales, corrects extraneous sources of noise in night-time light (NTL) radiance signals (Román et al., 2018). This study uses the VNP46A4 yearly product. The data has a spatial resolution of 15 arc seconds (approx. 500m) and is provided in the Hierarchical Data Format Earth Observing System (HDF-EOS) format (Román et al., 2018). The product has 28 layers. In our

analysis, we use the 'AllAngle_Composite_Snow_Free' and 'AllAngle_Composite_Snow_Free_Quality' bands. The NTL radiance is measured in $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ units having a valid range of 0-65534, and the fill value for no data is 65535. The quality flag layer gives information about the quality of the NTL pixel retrieved at the time of acquisition. The quality pixel values are unitless and range from 00-02, where 255 is the fill value for no data. 00 are values of high quality, 01 denotes pixels with bad quality, and 02 are gap-filled quality pixels (Román et al., 2018). The data is accessed via <https://ladsweb.modaps.eosdis.nasa.gov/search/order/2/VNP46A4--5000>, accessed on 20th September 2023).

- 5 **Climate Vulnerability Assessment Report- DST 2020:** For assessing the vulnerability, we used the report developed by the Department of Science and Technology, Government of India (<https://dst.gov.in/national-climate-vulnerability-assessment-identifies-eight-eastern-states-highly-vulnerable>, last access: 3rd March 2024). The report presents the vulnerability index for each district and state in the country. The vulnerability index is calculated using 14 indicators based on biophysical, socio-economic, and institution and infrastructure-related vulnerability indicators, each with an equal weight. The indicators capture both sensitivity and adaptive capacity (*Climate Vulnerability Assessment for Adaptation Planning in India Using a Common Framework*, 2020). The vulnerability data from the report has been previously used for assessing basin risks in India (Vegad et al., 2024).
- 6 **GDIS and EM-DAT:** EM-DAT is the International Emergency Event Database maintained by the Centre for Research on the Epidemiology of Disasters (CRED), containing data on the occurrence and impacts of over 26,000 mass disasters worldwide from 1900 to the present day (Delforge et al., 2023). The database is compiled from various sources, including UN agencies, non-governmental organisations, reinsurance companies, research institutes, and press agencies and

was downloaded from <https://public.emdat.be/>, accessed on 5th March 2024. It documents natural disasters as a single group, which contains five subgroups – geophysical, meteorological, hydrological, climatological, and biological – each of which further contains one or more types of specific natural disasters, and their physical impacts or risks – fatality, injured, affected, and damage are described (Delforge et al., 2023). Geocoded Disasters (GDIS) is an open-source extension to the Emergency Events Database (EM-DAT) that allows researchers, for the first time, to explore and make use of subnational, geocoded data on major disasters triggered by natural hazards (Rosvold and Buhaug, 2021). The GDIS dataset provides spatial geometry in the form of GIS polygons and centroid latitude and longitude coordinates for each administrative entity listed as a disaster location in the EM-DAT database. In total, GDIS contains spatial information on 39,953 locations for 9,924 unique disasters occurring worldwide between 1960 and 2018. The dataset facilitates connecting the EM-DAT database to other geographic data sources on the sub-national level to enable rigorous empirical analyses of disaster determinants and impacts downloaded from <https://sedac.ciesin.columbia.edu/data/set/pend-gdis-1960-2018>, accessed on 25th April 2024.

4.3.2. Analytical Hierarchy Process (AHP) Framework

When different thematic layers are combined on a GIS platform, a Multi-Criteria Decision Analysis or Multi-Criteria Decision Making can be used to make an evaluation based on several criteria and disagreeing evaluations (Sinha et al., 2008; Huang et al., 2011). One of the widely used MCDMs is the Analytical Hierarchy Process (AHP) developed by Saaty (1980), which incorporates both practical and subjective knowledge. The method involves decomposing the problem into a hierarchy and calculating the relative weight percentage in a GIS environment. The AHP model consists of four stages, namely (i) parameter hierarchy construction, (ii) pairwise comparison matrix, (iii) weight

normalisation, and (iv) consistency check (Ghosh and Kar, 2018; Mishra and Sinha, 2020; Roy et al., 2021). The first step is the selection of parameters for flood hazard, exposure and vulnerability assessment, respectively. This is usually based on the available literature and discussion among researchers. In this study, we include eight parameters for assessing flood hazard, namely- elevation, slope, flow accumulation, drainage density, distance to the river, distance from the confluence, rainfall and geomorphology as outlined in section 4.3, and we further return to the significance of these factors in the results below. For studying the exposure, we chose to use the radiance values from the night-time light data signifying activities and district vulnerability index from the Climate Vulnerability Assessment Report- DST 2020, Government of India, for calculating flood vulnerability in the catchment. The second step is developing the pairwise comparison matrix using the scale developed by Saaty 1980 at each decision level (Table 4.2). This scale utilises a basic sequence of absolute numbers from 1 to 9 for each pair to represent the individual preferences in the upper half of the matrix. In the lower half of the matrix, the pairing is assigned a rating equal to the reciprocal of the value of the corresponding pair in the upper matrix based on the decision maker's subjectivity, experience, and knowledge intuitively and naturally (Saaty, 2008). Following the construction of a pairwise comparison matrix, weights are calculated, and a consistency check is done.

Table 4.2: Relative importance scale (1–9) developed by Saaty (1980,1990)

Intensity of Importance	1	2	3	4	5	6	7	8	9	
Definition	Equal	Weak	Moderate	Moderate Plus	Strong	Strong Plus	Very Strong	Very very strong	Extreme	

Table 4.3: Random consistency index (RCI) based on Saaty (1980,1990)

No. of parameters selected	1	2	3	4	5	6	7	8	9	10
RCI Value	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

The following is the series of steps for the computation of the pairwise matrix:

Step 1: Give pairwise priorities ($X_{11}, X_{12}, \dots, X_{nn}$) based on Table 4.2 for each parameter ($P_1, P_2, \dots, P_n$) and sum the priorities for each column.

	P_1	P_2	P_n
P_1	X_{11}	X_{12}	X_{1n}
P_2	X_{21}	X_{22}	X_{2n}
P_n	X_{n1}	X_{n2}	X_{nn}
	S_1	S_2	S_n

Thus, the Sum of priorities (S_n) for the n^{th} Parameter (P_n) :

$$S_n = X_{1n} + X_{2n} + \dots + X_{nn} \quad \dots\dots\dots (4.1)$$

Step 2: Normalise each value by dividing each cell (X_{nn}) in Step 1 with the column total (S_n) computed from equation 4.1.

	P_1	P_2	P_n
P_1	X_{11}/S_1	X_{12}/S_2	X_{1n}/S_n
P_2	X_{21}/S_1	X_{22}/S_2	X_{2n}/S_n
P_n	X_{n1}/S_1	X_{n2}/S_2	X_{nn}/S_n

Step 3: Computing the relative weightage for each element (RW_n) by addition of row-wise priorities (Equation 4.2).

	P₁	P₂	P_n	
P₁	X_{11}/S_1	X_{12}/S_2	X_{1n}/S_n	RW₁
P₂	X_{21}/S_1	X_{22}/S_2	X_{2n}/S_n	RW₂
P_n	X_{n1}/S_1	X_{n2}/S_2	X_{nn}/S_n	RW_n

$$RW_n = (X_{n1}/S_1) + (X_{n2}/S_2) + \dots + (X_{nn}/S_n) \quad \dots\dots\dots (4.2)$$

Step 4: Calculating the Consistency Ratio (CR) to validate the AHP judgement

$$CR = CI/RI \quad \dots\dots\dots (4.3)$$

$$CI = (\lambda_{max} - n)/(n-1) \quad \dots\dots\dots (4.4)$$

where CI is the Consistency Index, RI is the Random Consistency Index based on Table 4.3, λ_{max} principle Eigenvalue and n indicates the total number of parameters selected for the study.

Thus, to compute the consistency ratio, we first derive the weighted sum (WS_n) for each row. To compute it, we multiply the relative weightage (equation 4.2) for each element computed in step 3 and the pairwise priorities derived in step 1.

	P₁	P₂	P_n	
P₁	$X_{11} * RW_1$	$X_{12} * RW_2$	$X_{1n} * RW_n$	WS₁
P₂	$X_{21} * RW_1$	$X_{22} * RW_2$	$X_{2n} * RW_n$	WS₂
P_n	$X_{n1} * RW_1$	$X_{n2} * RW_2$	$X_{nn} * RW_n$	WS_n

Second, λ_{max} is calculated based on the following computation:

$$\lambda_{max} = [(WS_1 * W_1) + (WS_2 * W_2) + \dots + (WS_n * W_n)]/n \quad \dots\dots\dots (4.5)$$

Lastly, the Consistency Index is computed based on equation 4.4. Lastly, the Consistency Ratio (CR) for each AHP judgment is calculated based on Equation 4.3.

4.3.3. Defining factors that contribute to flood hazard

AHP requires the identification of factors that contribute to the flood hazard. We defined factors for mapping flood-prone areas or flood hazards based on literature analysis and the characteristics of the study area. Previously, many researchers have undertaken flood hazard mapping using a combination of geomorphic morphometrics parameters, hydrological analysis, slope, aspect, type, curvature, precipitation index, rainfall, land use land cover (LULC), distance to roads, topographic roughness index (TRI), topographic wetness index (TWI), stream power index, sediment transport Index (STI) amongst others (Adnan et al., 2019; Kanani-Sadat et al., 2019; Towfiqul Islam et al., 2021). In our study, the key factors we used to map the flood hazard in the basin are – elevation, slope, flow accumulation, drainage density, distance to the river, distance from the confluence, rainfall and geomorphic setting, and are shown in Figure 4.3. The figure shows the potential occurrence of the floods with respect to each parameter. The reasoning behind the selection of the factors is further discussed in section 4.4.1.

The first dataset we used to derive potential flood hazard was the ASTER 30m DEM. We addressed the DEM sinkholes using the Spatial Analyst Tools -> Fill tool. With the DEM as the input, the slope was computed using the Slope function in ArcGIS Pro. Further, flow accumulation, drainage density and stream network were calculated using the ArcHydro Tools in the ArcGIS Pro. Our analysis focuses on the main river (Ganga) and its major tributaries, considering a minimum stream order of 5 for the analysis. To evaluate the proximity to the river, we created seven buffer zones at intervals of 0-500m, 500-1000m, 1000-1500m, 1500-2000m, 2000-2500m, 2500-3000m, and 3000-3500m using the buffer tool in the Geoprocessing toolbox in ArcGIS Pro. Similarly, the buffer zones for the confluence points were constructed at intervals of 0-500m, 500-1000m, 1000-1500m, 1500-2000m, and 2000-3000m respectively.

For rainfall analysis, we used the daily data CHIRPS raster data accessed via Google Earth Engine (GEE) to prepare the monthly average composite. Furthermore, monthly data from 2013 to 2023 was analysed, focussing on the monsoon months from June to October due to a higher frequency of flooding recorded during this period. This contrasts with other flood risk studies, which only consider average annual rainfall for risk analysis. Thus, we used this data to generate annual flood risk maps for each subsequent year. The exported monthly composite was clipped to the basin boundary. The monthly rainfall from June to October 2024 was averaged using a Python script.

The geomorphic setting of the basin was downloaded from the Bhukosh server (<https://bhukosh.gsi.gov.in/Bhukosh/Public>). The data was downloaded in a vector format and contains a breakdown of basin elements, including fluvial, structural, denudational and aeolian classes, as well as landforms such as hills, valleys, plateaus, and alluvial plains. The actual categories in the data are – FluOri- Active floodplain (i.e., Fluvial origin active floodplain), Fluori- Older floodplain, Fluori- Younger alluvial plain, Fluori - Older alluvial plain, Denori- Moderately dissected lower plateau (i.e., denudational origin), StrOri- Highly dissected hills and valleys (i.e., structural origin), Strori- Moderately dissected hills and valleys, Strori- Low dissected hills and valleys and StrOri- Pediment-Peneplain Complex respectively. The vector data categories were reclassified based on the geomorphology: active floodplains, older floodplains, younger alluvial plains, older alluvial plains, hills and valleys, plateaus and pediment-peneplain complexes. The data was also clipped to the basin boundary. Figure 4.3 shows the potential hazard parameters data that are used to prepare for the potential flood hazard. All the hazard parameters raster layers were resampled to the 500 m spatial resolution for further integration with other satellite datasets.

Supplementary Table 1 shows the relative weight for each parameter calculated based on the above AHP Procedure from Step 1 to Step 3 in Section 4.3.2. Further, for each parameter, a level 2 hierarchy was structured. Supplementary Table 2 to Supplementary

Table 9 shows the pairwise construction matrix and relative weights for sub-factors for elevation, slope, rainfall, distance to the river, distance to the confluence points, drainage density, flow accumulation, and geomorphology, respectively. The level 1 and level 2 hierarchy for calculating FHI was constructed based on a literature review and discussions on the understanding of the flood-prone areas, which is discussed in detail in section 4.4.1. Following the construction of a pairwise matrix and the calculation of relative weights at level 1 and level 2 hierarchy, based on Step 4 of section 4.3.2, the $\lambda_{\max}$ principle Eigenvalue, the consistency index (CI) and the consistency ratio (CR) were calculated for the hazard factors (Supplementary Table 1 to Supplementary Table 9). This was followed by normalising the relative weights by multiplying the relative weights (RW) of level 1 and level 2 hierarchy.

Finally, the flood Hazard Index (FHI) at each pixel location (i) is calculated based on the following equation:

$$FHI_i = (RW_E * E_i) + (RW_S * S_i) + (RW_R * R_i) + (RW_{DR} * DR_i) + (RW_{DC} * DC_i) + (RW_{DD} * DD_i) + (RW_{FA} * FA_i) + (RW_G * G_i) \quad \dots\dots\dots(4.6)$$

, where FHI is Flood Hazard Index at pixel i , RW are the relative weights calculated from Supplementary Table 1 for level 1 parameters, E_i is the elevation at pixel i , S_i is the slope at pixel i , R_i is the rainfall at pixel i , DR_i is the distance to the river at pixel i , DC_i is the distance to the confluence at pixel i , DD_i is the drainage density at pixel i , FA_i is flow accumulation at pixel i and G_i is geomorphology at pixel i .

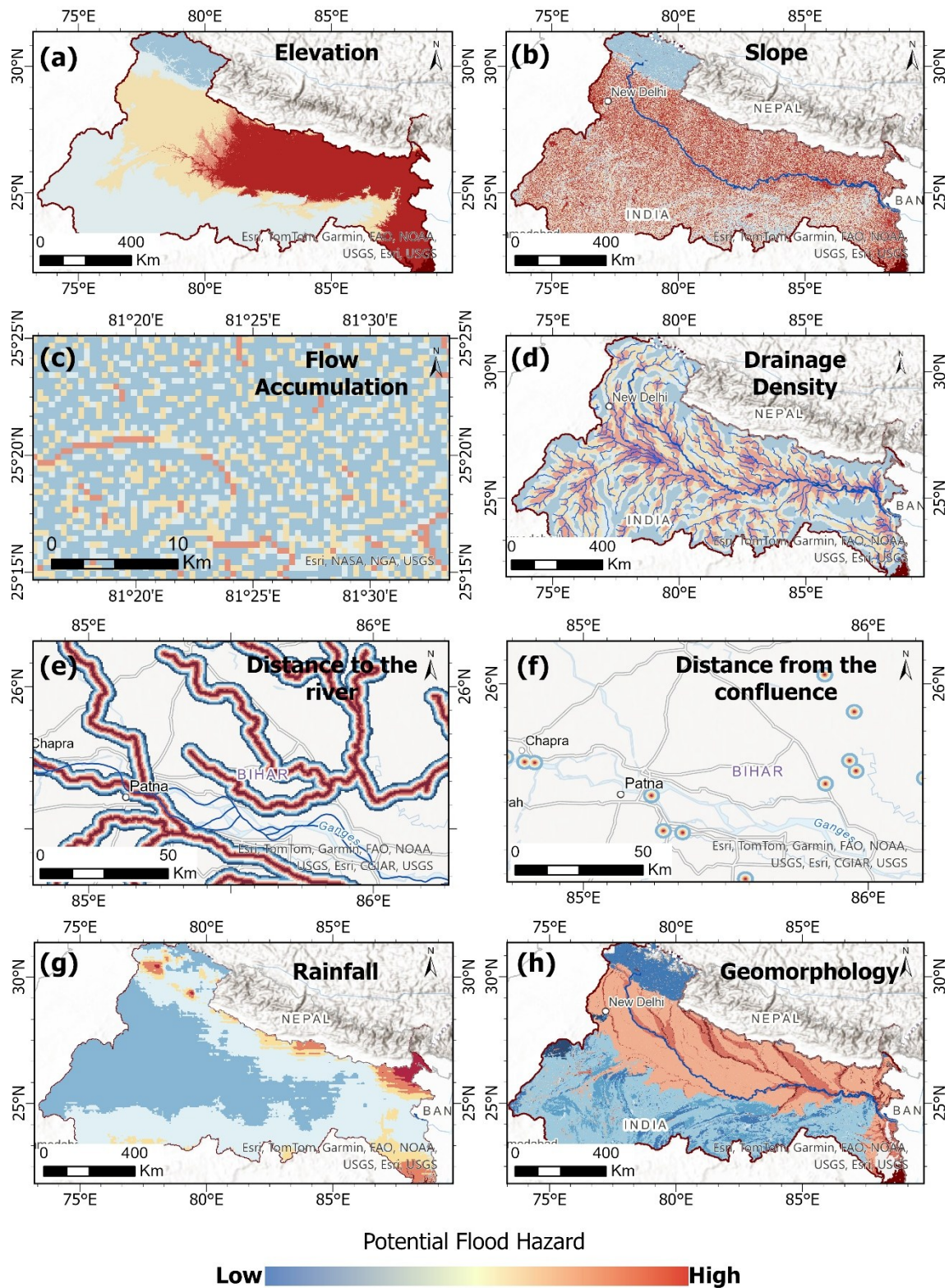


Figure 4.3: The figure illustrates eight potential flood hazard parameters, which are (a) elevation, (b) slope, (c) flow accumulation, (d) drainage density, (e) distance to the river, (f) distance from the confluence, (g) rainfall and (h) geomorphology. The colour scheme of blue to red is adopted to indicate the potential occurrence of floods. The blue area shows a low potential for the occurrence of floods compared to the red region, which shows a high potential for flood hazard.

4.3.4. Mapping Yearly Exposure to Flood Hazard

To characterise the exposure to flood hazard, we use satellite nightlight luminosity data as a proxy for the spatial and temporal distribution of human presence and activity, as has been described by numerous previous studies (Aggarwal et al., 2024; Andries et al., 2023; Ceola et al., 2014; Fang et al., 2021; Mård et al., 2018; Román et al., 2018). For this study, we used the annual NASA Black Marble nightlights dataset to map the yearly exposure to flood hazards from 2013 to 2023. The VNP46A3 annual data product was downloaded in the hdf format from the <https://ladsweb.modaps.eosdis.nasa.gov/search/order/4/VNP46A3--5000> (accessed on 20th September 2023). The tiles in the ROI used were h25v5, h25v6 and h26v6. The NTL and quality layers were extracted from the hdf file, converted to tiff format, and mosaiced using Python script. The good-quality pixels of the NTL were extracted and clipped to the basin boundary. Figure 4.4 shows the distribution of the night-time lights averaged for the period 2013 to 2023. Further, the intensity for the annual data was classified into five categories based on geometric classification (in ArcGIS), i.e., 0-10, 10-17, 17-34, 34-293 and $\geq 293 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$. Supplementary Table 10 shows the pairwise matrix table for the sub-factor and the relative weights that were computed. Based on Step 4 of section 4.3.2, the $\lambda_{\max}$ principle Eigenvalue, the consistency index (CI) and the consistency ratio (CR) were calculated to check the decision of the factors. The annual exposure rasters are reclassified to the calculated relative weights, which would represent the Flood Exposure Index (FEI) at each pixel.

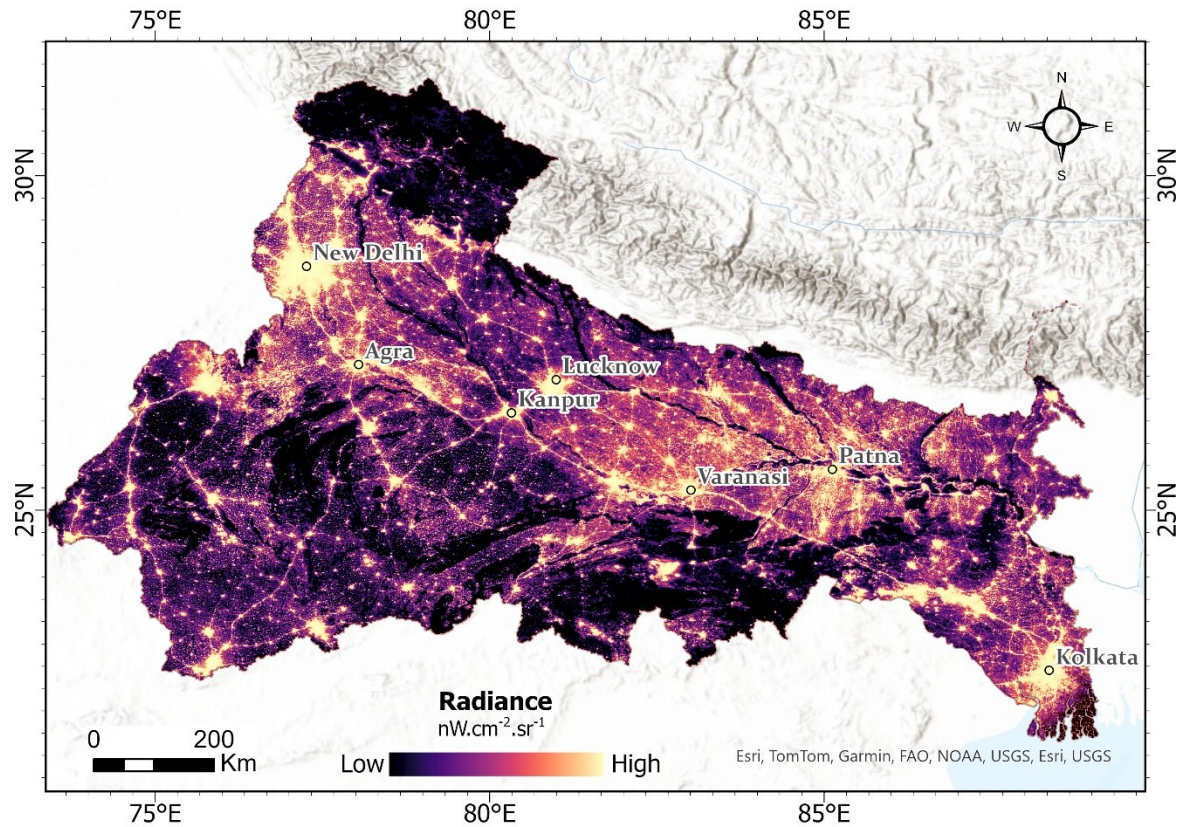


Figure 4.4: Distribution of average night-time lights indicating exposure from 2013-2023. The dark areas show the absence of night-time lights, and the bright areas are where high human activity-related artificial lights are captured.

4.3.5. Extracting Vulnerability to flood hazard

We characterise the vulnerability to flood hazards in the Ganga Basin using the vulnerability index derived from the DST vulnerability assessment report. The report provides the vulnerability index in tabular format at the district level. We incorporated these index values as attributes into the district shapefile for spatial analysis, which was then clipped to the Ganga basin boundary. Figure 4.5 shows the vulnerability index values for districts in the Ganga Basin from the Climate Vulnerability Assessment Report- DST 2020, Government of India; these range from 0.35 to 0.72 within the basin, with low values representing low vulnerability and high values representing higher vulnerability. The index values are divided into five categories- 0.35-0.425, 0.425-0.5, 0.5-0.575, 0.575-0.65 and 0.65-0.73 based on the index classification in the report. New Delhi territory is not included in the vulnerability assessment report because of high human

presence and activities. For further analysis for risk assessment, the spatial vulnerability vector data was converted into a raster format at a spatial resolution of 500m. Supplementary Table 11 shows the pairwise matrix table for the sub-factor and the computed relative weights. Based on Step 4 of section 4.3.2, the $\lambda_{\max}$ principle Eigenvalue, the consistency index (CI) and the consistency ratio (CR) were calculated to check the decision of the factors. Lastly, the vulnerability index raster is reclassified to the calculated relative weights, which would represent the Flood Vulnerability Index (FVI) at each pixel.

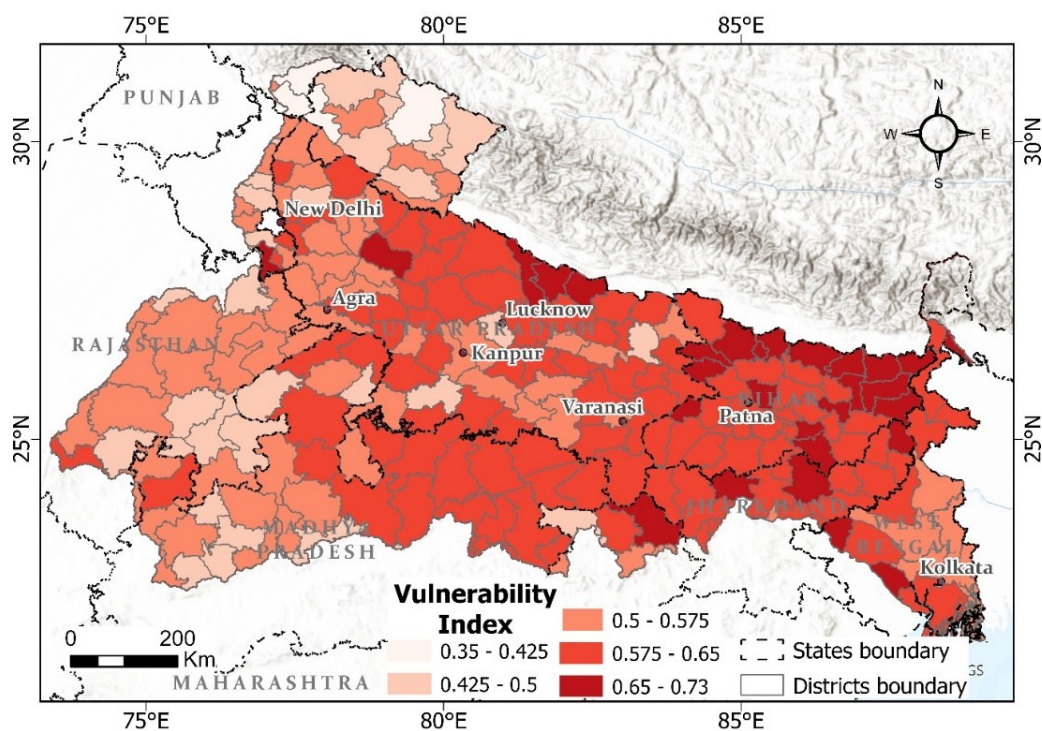


Figure 4.5: Vulnerability index of the districts in the Ganga Basin from the Climate Vulnerability Assessment Report- DST 2020, Government of India.

4.3.6. Flood Risk Index (FRI)

To compute the flood risk at the pixel or cell level for each year (t), we calculated the Flood Risk Index (FRI) as the product of the Flood Hazard Index (FHI), Flood Exposure Index (FEI) and Flood Vulnerability Index (FVI), as shown below:

$$FRI_t = FHI_t * FEI_t * FVI \quad \dots\dots\dots(4.7)$$

The FHI, FEI, and FVI represent the normalised relative weights of each parameter at each pixel obtained through AHP classification, as outlined in section 4.3.2. The FHI was determined using a two-level hierarchical structure, with normalised weights derived from Equation 4.6. Similarly, a Level 1 hierarchy was employed to compute the relative weights for FEI and FVI at each pixel, as discussed in sections 4.4.3 and 4.4.4, respectively.

The flood risk index for each year was then obtained by multiplying the corresponding FHI, FEI, and FVI rasters for each pixel from 2013 to 2023. These indices were classified into five risk levels. Figure 4.2 illustrates the process of multiplying these components. After generating the annual risk maps, we used the 10-year dataset to calculate the flood risk trend for each pixel. The trend raster was computed using linear regression, implemented through a Python script. This enabled us to calculate a percentage point change in FRI per year, enabling us to identify areas of significantly increasing flood risk.

4.3.7. Data Validation

To validate our risk maps, we compared them with an impact-based dataset using the ROC-AUC (Receiving Operating Characteristic-Area Under Curve) methodology. The ROC is the probability curve, and the AUC is the measure of the separability of different classes (Nam and D'Agostino, 2002). This popular method is used for quantitative validation (Das, 2020; Lin et al., 2019; Mukhtar et al., 2024; Roy et al., 2021; Saha and Agrawal, 2020). The ROC curve evaluates the effectiveness of a flood risk model by graphing the true positive rate against the false positive rate. The AUC value represents the model's capacity to distinguish between flood-risk districts and non-flood-risk districts, with higher values reflecting greater accuracy. This validation metric serves as evidence of the flood risk map's robustness, offering a quantitative assessment of its reliability in predicting and classifying flood risk within the studied area.

We used the AHP-derived flood risk map to compute the absolute risk index values for each district within the basin and the spatial impact flood inventory map at the district

level. In this method, a confusion matrix was computed stating the true positive, false positive, true negative, and false negative at different risk value thresholds. The definitions of the four values are described below:

1. True positives (TP): captures the number of districts at '*risk*' that are also predicted as '*impacted*' by floods in the EM-DAT/GDIS derived data.
2. False positives (FP): captures the number of districts '*not at risk*' that are predicted as '*impacted*' by floods in the EM-DAT/GDIS derived data.
3. True negatives (TN): captures the number of districts '*not at risk*' that are predicted as '*not impacted*' by floods in the EM-DAT/GDIS derived data.
4. False negatives (FN): captures the number of districts at '*risk*' that are also predicted as '*not impacted*' by floods in the EM-DAT/GDIS derived data.

For constructing the spatial impact flood inventory map, we utilised both GDIS and EM-DAT for validation. First, we downloaded the GDIS data from https://sedac.ciesin.columbia.edu/data/set/pend-gdis-1960-2018_ (accessed on 25th April 2024). The geodatabase data (.gdb) includes both spatial and attribute table components. The data was clipped to the Ganga basin boundary in ArcGIS Pro, giving spatial information at the administrative level for all disaster events, with each disaster assigned a unique disaster number. Next, EM-DAT data was downloaded from <https://public.emdat.be/portal> (accessed on 5th March 2024), which is a global repository of all disaster events. The downloaded data included flooding events in India from 2013 to 2023 and contained information on the total number of affected people linked to the unique disaster numbers also found in the GDIS data.

The two datasets (i.e., EM-DAT csv data & the GDIS shapefile) were merged based on the unique disaster number using a Python script, resulting in an updated GDIS shapefile that included the total number of people affected in its attribute table. Additional tools, such as Multipart to Singlepart and Pairwise Dissolve, were used for data processing and refinement. A new column, Area (km²), was added, representing the spatial polygon

area. This processed data repository consisted of all the flooding events from 2013 to 2018, providing information on the affected districts in a vector format, aligning with the common timeline of both data. For a case study, we chose the 2016 flooding event and created a new file giving information on the affected districts, polygon areas and the total number of people affected by a particular disaster. We chose the 2016 specific case study because of two primary reasons. First, the common availability of years between the GDIS and the risk map generated is between 2013 and 2018. Secondly, as per the Global Flood Database, the flood event triggered by heavy rains on 25th July 2016 had the highest exposed population of 18,456,496 million between 2013 and 2018 in the Ganga Basin (Tellman et al., 2021). Thus justifying our choice of the 2016 flood risk as a case study for validating the data. The major limitation of linking the spatial data with the affected population was that the number of people listed for each administrative level represented the total number of people affected in a particular disaster number. Thus, to address this issue, we normalised the number of people affected for each district based on the district area and used the 2016 event, consisting of 46 entries, to validate the risk maps.

Next, we converted the 2016 risk map to a vector format at the district level for two primary reasons: to reconcile the format discrepancy between the raster risk map and the vector impact data and, secondly, because the impact maps operate at a district-level spatial scale. For comparison, we calculated the zonal risk index for each district in the Ganga Basin, followed by the vectorisation of the data. This processing of the risk maps was done using ArcGIS Model Builder on ArcGIS Pro (Figure 4.6). Supplementary Table 10 lists the risk index and people affected by the floods in 2016 for each district in the Ganga Basin.

Lastly, for the construction of the confusion matrix and deriving the ROC-AUC curve, we computed the True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN) districts. Figure 4.7 shows the schematic illustration of the four

components computed between the districts predicted at risk by AHP and districts affected by the GDIS and EM-DAT database. We performed a spatial join between the 2016 district risk map and the EM-DAT/GDIS-derived 2016 flood impact district map and calculated the normalised number of people affected based on the area of the respective district. Figure 4.7 schematically illustrates the four components of the confusion matrix and their definitions.

Finally, to assess the effectiveness of our risk model using the ROC-AUC curve, the true positive rate (TPR) or sensitivity and the false positive rate (FPR) or 1-specificity are calculated, which are defined as –

$$\text{True Positive Rate (TPR) or Sensitivity} = TP/(TP+FN) \quad \dots\dots\dots (4.8)$$

$$\text{False Positive Rate (FPR) or 1-Specificity} = FP/(FP+TN) \quad \dots\dots\dots (4.9)$$

The ROC-AUC curve assesses the performance of a flood risk model by plotting the true positive rate along the y-axis against the false positive rate on the x-axis. An AUC value signifies the model's ability to discriminate between predicted risk districts and actual flood impact districts, with higher values indicating better accuracy. The quantitative-qualitative relationship between AUC and prediction accuracy, which ranges from 0 to 1, is as follows: Excellent (0.9–1), very good (0.8–0.9), good (0.7–0.8), moderate (0.6–0.7) and weak (0.5–0.6) (Yesilnacar and Topal, 2005).



Figure 4.6: ArcGIS Model builder showing the workflow for the processing of the 2016 risk map.

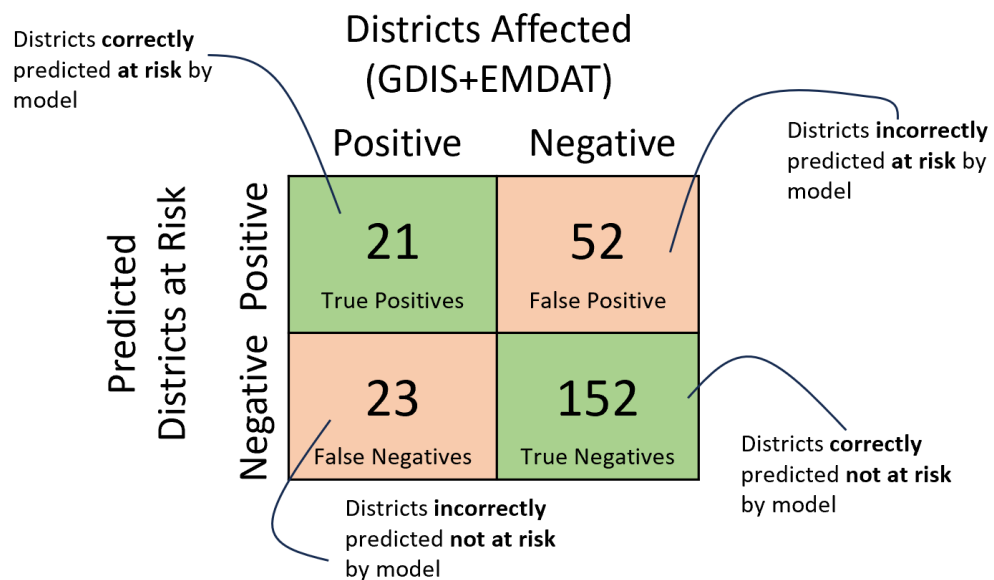


Figure 4.7: Schematic diagram explaining the four components of the confusion matrix, i.e., True Positives, False Positives, True Negatives and True Negatives.

4.4. Results

4.4.1. Flood Conditioning Factors

To generate comprehensive flood risk maps of the Ganga Basin, we first computed a Flood Hazard Index (FHI) by integrating eight hazard parameters, namely elevation, slope, flow accumulation, drainage density, distance to the river, distance from the confluence, rainfall and geomorphology using the AHP methodology (section 4.3.3). The choice of the parameters and level 1 priorities are based on the literature review and expert knowledge. The FHI represents the probability of the location suffering from a potential flood based on hydrological and geomorphic factors in the study region (Mishra and Sinha, 2020). Supplementary Table 1 shows the decision matrix of the chosen eight parameters (level 1 hierarchy) and their relative weights, showing a consistency ratio (CR) for all the decision matrix tables was satisfactory as $CR \leq 0.10$ and statistically validated our decision-making process. Similarly, a decision matrix for each parameter was constructed, and the relative of sub-factors were computed. Supplementary Table 2 to Supplementary Table 9 shows the consistency ratio (CR) for all the decision matrix tables was satisfactory as $CR \leq 0.10$ and statistically validated our decision-making process. A summary of the relative weights of both the levels of hierarchy and the derived normalised weight is shown in Table 4.4.

Elevation is the primary or the most important parameter for assessing potential flood hazard, having a level 1 relative weight (RW) of ca. 0.31 or 31% (Table 4.4). Elevation in the region ranges from 0-8000m, which has been categorised into five categories based on geometric classification - 0-115, 115-130, 130-250, 250-1,115 and 1,115-8,000 meters, respectively. This corresponds to the relative weights of ca. 49%, 27%, 14%, 6% and 4% respectively (Table 4.4). This is because the low-lying areas having a lower elevation are more prone to floods due to water inundation in the areas. Thus, the low elevation or flat areas tend to have a higher level 2 relative weightage of ca. 49% compared to higher elevation areas having a lower RW of ca. 4%.

Similarly, slope is the second most important criterion for flood hazard assessment, having a level RW of ca. 0.21 or 21%. In the study area, the slope is categorised into five zones geometric classification, i.e., 0°-1.5°, 1.5°-1.7°, 1.7°-3.2°, 3.2°-13° and 13°-90° respectively. This corresponds to the relative weights of ca. 49%, 27%, 14%, 6% and 4% respectively (Table 4.4). Extensive flat land with a very gentle slope suffers from prolonged inundation, whereas moderate to high slope provides an easy passage to pass away the flood water (Ghosh and Kar 2018). Besides, the topographic gradient has considerable influence over the infiltration rate (Das 2020). Therefore, a huge volume of water becomes sluggish near the sites of low-lying flat topography (Bui et al. 2019). Thus, a low geographic slope usually displays greater susceptibility to flood flat areas and tends to have a higher level 2 relative weightage of ca. 49% compared to steep areas having a lower RW of ca. 4%.

Next, the intensity of rainfall is an important parameter for assessing flood risk, having a level 1 RW of ca. 0.15 or 15%. In our study, rainfall is categorised into five classes of geometric classification - >350, 290-350, 260-290, 200-260, and 0-200 mm/month respectively. This corresponds to the relative weights of ca. 49%, 27%, 14%, 6% and 4% respectively (Table 4.4). The amount of rainfall is usually directly proportional to the intensity of flooding, especially during the summer monsoon, where major floods in the area are triggered by the rainfall, which generates high surface runoff. Also, high sediment flux from the catchment during rainfall events and limited accommodation space in the channel encourages siltation and, therefore, breaching and flooding (Mishra and Sinha, 2020). Thus, areas experiencing high rainfall have a higher level 2 relative weightage of ca. 49% compared to lower rainfall areas having a lower RW of ca. 4%.

As floods are frequent in areas closer to a river, distance to rivers is an important flood hazard factor having a level 1 RW of ca. 0.12 or 12%. In the study, we divided the distance from the major rivers of the basin into seven categories, primarily 0-500, 500-1000, 1000-1500, 1500-2000, 2000-2500, 2500-3000, and 3000-3500 meters respectively. This

corresponds to the relative weights of ca. 37%, 24%, 16%, 10%, 7%, 4% and 2% respectively. Distance from rivers is another significant factor that plays a vital role in determining flood conditions. According to several researchers, (Rahmati et al. 2016; Ghosh and Kar, 2018; Bui et al, 2019) flooding is typically expected in the areas near the river due to heavy runoff in the drainage system, mainly after intense rainfall, which results in the river exceeding the limit of stream capacity. Thus, areas in close proximity to the river of 0-500m have a higher level 2 relative weightage of ca. 37% compared to areas away from the river having a lower RW of ca. 2%

Similarly, areas near river confluences are often prone to flooding. In the study, we divided the distance from the confluence points into five categories- 0-500, 500-1000, 1000-1500, 1500-2000 and 2000-3000 meters respectively. This corresponds to the relative weights of ca. 49%, 27%, 14%, 6% and 4% respectively (Table 4.4). During the monsoon season, these rivers carry large volumes of water, leading to fluctuations in water levels and flow velocities. Additionally, the high sediment load, aggradation, and reduced conveyance capacity can become problematic, especially when a channel has to handle the combined flow of multiple tributaries, particularly during floods. This often results in the overtopping of riverbanks inundating nearby floodplains (Ghosh and Kar, 2018). Thus, areas within 0-500m of the confluence points have a higher level 2 relative weightage of ca. 49% compared to areas 2000-300m away from the confluence points, which has a lower RW of ca. 4%.

Next, watershed morphometric parameters that are important for assessing flood hazard and flood risk are drainage density and flow accumulation, having a level 1 RW of ca. 0.06 and 0.05, respectively. In the study, drainage density is classified into five categories using a geometric classification - 0-0.00002, 0.00002-0.000032, 0.000032-0.000052, 0.000052-0.000089, and 0.000089-0.000155 meters⁻¹ respectively. This corresponds to the relative weights of ca. 49%, 27%, 14%, 6% and 4% respectively (Table 4.4). According to Das and Pardeshi (2018), high drainage density indicates a great amount of surface

runoff. Higher drainage density demonstrates a higher length of drainage lines per unit area. Hence, the regions having a dense stream network generally show frequent flooding due to higher drainage density (Ogden et al., 2011; Das, 2020; Roy et al., 2021). Thus, areas having high drainage density of range $0.000089\text{--}0.000155\text{m}^{-1}$ have higher level 2 relative weightage of ca. 0.48 compared to low drainage density areas of range $0\text{--}0.00002\text{ m}^{-1}$ having a lower RW of ca. 0.04 (Table 4.3). Drainage density was followed by flow accumulation, which signifies total flow to a particular point within the catchment from upstream areas and thus, higher flow accumulation indicates a high possibility of flooding. It is classified into five categories in the study: geometric classification - 0-1, 1-2, 2-26, 26-314, and 314-3800, respectively. Naturally, more amount of accumulated flow leads to increased runoff in a low-elevated area, which contributes to more flooding. Thus, areas having a high accumulation of 314-3800 unit cells have a higher level 2 relative weightage of ca. 49% compared to areas having a low flow accumulation of 0-1 unit cells, which has a lower RW of ca. 4%.

The last parameter that is of importance is the geomorphology, having a level 1 RW of ca. 0.02 or 2%. It is important to highlight that the overall geomorphology of the Ganga basin does not influence or trigger the floods directly, but the presence of individual geomorphic features influences the potential of flooding and duration of inundation in a given region. Therefore, geomorphology has been ranked the lowest in the hierarchy in comparison to the other factors (Mishra and Sinha, 2020). In our study based on the geomorphic features in the basin, the layer is divided into ten categories, namely - active floodplains, older floodplains, alluvial plains, water bodies, coastal, anthropogenic terrain, pediment-peneplain, plateau, hills and valleys, and aeolian plane, which corresponding have relative weights of 29%, 21%, 14%, 10%, 9%, 7%, 4%, 3%, 2% and 1% respectively. Among all the geomorphic units, active floodplains are most prone to frequent flooding compared to older floodplains. Thus, active floodplain areas have

a higher level 2 relative weightage of ca. 29% compared to the aeolian plane having a lower RW of ca. 1%.

Table 4.4: Flood Hazard Index (where RW- relative weight)

Parameters		Level 1 RW	Categories	Level 2 RW	Flood Hazard Index (Level 1*2)	Percentage (%)
Elevation (in meters)	E	0.31	0-115	0.49	0.150389	15.04
			115-130	0.27	0.081937	8.19
			130-250	0.14	0.041752	4.18
			250-1,115	0.06	0.020483	2.05
			1,115-8,000	0.04	0.013643	1.36
Slope (in degrees)	S	0.21	0-1.5	0.49	0.10105	10.10
			1.5-1.7	0.27	0.055055	5.51
			1.7-3.2	0.14	0.028054	2.81
			3.2-13	0.06	0.013763	1.38
			13-90	0.04	0.009167	0.92
Rainfall (in mm/month)	R	0.15	>350	0.49	0.071491	7.15
			290-350	0.27	0.03895	3.90
			260-290	0.14	0.019848	1.98
			200-260	0.06	0.009737	0.97
			0-200	0.04	0.006485	0.65
Distance to the river (in meters)	DR	0.12	0-500	0.37	0.045778	4.58
			500-1000	0.24	0.029748	2.97
			1000-1500	0.16	0.019787	1.98
			1500-2000	0.10	0.013019	1.30
			2000-2500	0.07	0.008697	0.87
			2500-3000	0.04	0.005092	0.51
			3000-3500	0.02	0.002895	0.29
Distance from river confluence (in meters)	DC	0.08	0-500	0.49	0.040997	4.10
			500-1000	0.27	0.022336	2.23
			1000-1500	0.14	0.011382	1.14
			1500-2000	0.06	0.005584	0.56
			2000-3000	0.04	0.003719	0.37
Drainage Density	DD	0.06	0.000089-0.000155	0.49	0.0293	2.93
			0.000052-0.000089	0.27	0.015963	1.60

(in meters ⁻¹)			0.000032-0.000052	0.14	0.008134		0.81
			0.00002-0.000032	0.06	0.003991		0.40
			0-0.00002	0.04	0.002658		0.27
Flow Accumulation (unit cells)	FA	0.05	314-3800	0.49	0.022133		2.21
			26-314	0.27	0.012059		1.21
			2-26	0.14	0.006145		0.61
			1-2	0.06	0.003014		0.30
			0-1	0.04	0.002008		0.20
Geomorphology	G	0.02	Active floodplains	0.29	0.006895		0.69
			Older floodplains	0.21	0.005093		0.51
			Alluvial Plains	0.14	0.003331		0.33
			Water Bodies	0.10	0.002458		0.25
			Coastal	0.09	0.002037		0.20
			Anthropogenic Terrain	0.07	0.001575		0.16
			Pediment-Peneplain	0.04	0.000901		0.09
			Plateau	0.03	0.000626		0.06
			Hills and Valleys	0.02	0.000496		0.05
			Aeolian Plane	0.01	0.000346		0.03
							100.00

4.4.2. Flood Hazard Assessment

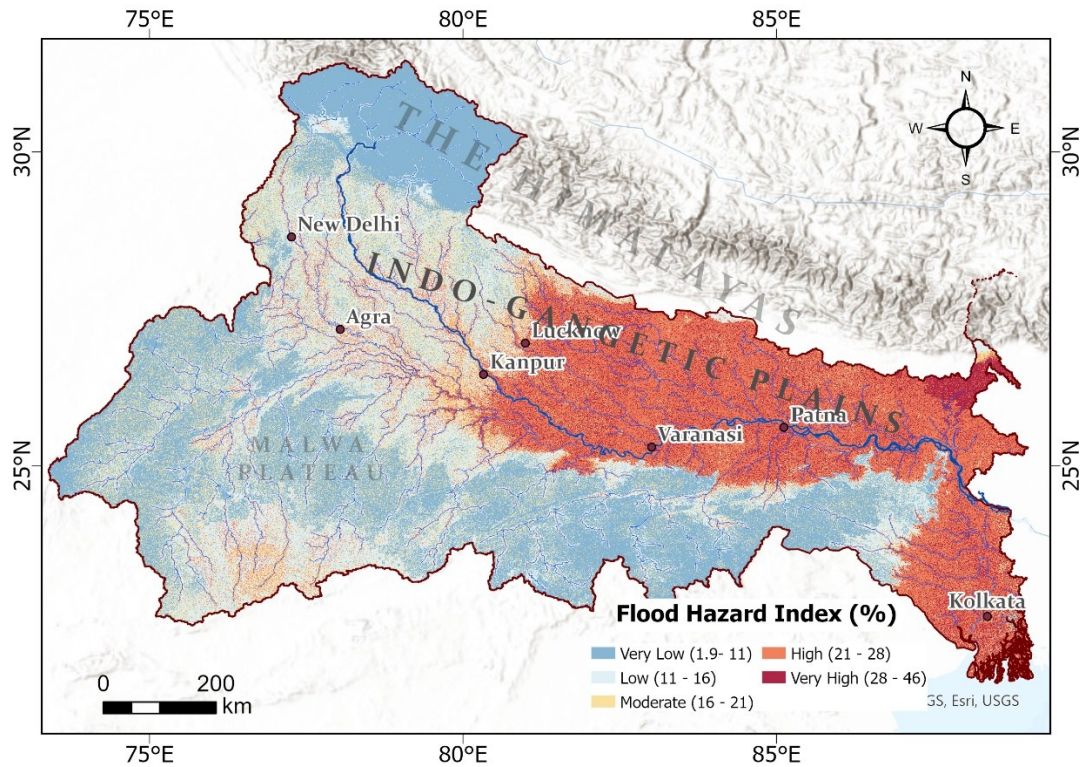


Figure 4.8: Flood Hazard Index (FHI) map for 2022 of the Ganga Basin produced after the AHP analysis. Continuous data ranging from 1.9 to 46% are classified into five categories: Very Low, Low, Moderate, High and Very High FHI. In the figure, the blue areas have low FHI values, indicating less potential for flood occurrence or flood hazard, and red areas have higher flood hazard values, suggesting higher susceptibility to floods.

To determine the flood hazard index (FHI), we integrated thematic layers related to flood factors. Using the relative weights (RWs) from both level 1 and level 2 hierarchies provided in Table 4.4, we calculated the FHI for each pixel (i) from Equation 6 for the years 2013 through 2023. Supplementary Figure 1 shows the derived FHI maps from 2013 to 2023. The analysis reveals that the FHI varies both spatially and temporally. The temporal variations in FHI are primarily influenced by annual rainfall, which is treated separately each year. For clarity and to illustrate the spatial distribution of flood-prone areas, Figure 4.8 displays the FHI map for 2022. This map shows FHI values ranging continuously from ca. 0.019 to 0.49 or 1.9% to approximately 46%, categorised into five levels: very low (1.9-11%), low (11-16%), moderate (16-21%), high (21-28%), and very high (28-46%). Figure 4.8 indicates that flood risk is particularly high in the Indo-

Gangetic plains, notably affecting major cities like Kanpur, Lucknow, Varanasi, Patna, and Kolkata. In contrast, mountainous and arid regions such as the Himalayas, Malwa Plateau, and the western part of the basin exhibit lower FHI values. This spatial variability is influenced by consistent topographic factors, including elevation, slope, distance to rivers, distance from confluences, drainage density, flow accumulation, and geomorphology, which remained constant throughout the analysis period.

4.4.3. Flood Exposure Index (FEI)

For assessing the exposure to flood hazard, the Flood Exposure Index (FEI) was determined across the Ganga basin, using the annual night-time lights data from 2013 to 2023 and applying the Analytical Hierarch Process (AHP) method as outlined in section 4.3.2. According to Supplementary Table 10, the radiance indicated by the night-time lights data ranges from 0 to 4000 $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ and were classified into five categories based on geometric classification, i.e., 0-10, 10-17, 17-34, 34-293 and ≥ 293 $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$. Based on the decision matrix table constructed through AHP, the derived relative weights (RW) for 0-10, 10-17, 17-34, 34-293 and ≥ 293 $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$ are ca. 0.04, 0.06, 0.14, 0.27 and 0.49 respectively. Our decision was statistically validated by the consistency index (CI) and the consistency ratio (CR), where the CR for the exposure decision matrix table was 0.051, which is below the acceptable threshold of 0.10, as shown in Supplementary Table 10. The calculated relative weights correspond to the Flood Exposure Index (%). Supplementary Figure 2 illustrates the derived flood exposure index (FEI) from 2013 to 2023 in the Ganga Basin. The brighter areas having higher intensity are indicative of high exposure compared to the dark areas, having lower exposure in non-inhabited places such as forests. For detailed visualisation, Figure 4.9 displays the FEI map for 2022. Figure 4.9(a) highlights that areas with a very high FEI (around 49%) correspond to regions with significant night-time lighting (radiance ≥ 293 $\text{nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$), suggesting a dense presence of infrastructure. Conversely, areas with a very low FEI

(around 4%) reflect minimal night-time lighting (radiance $0-10 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$), indicating sparse infrastructure.

The spatial distribution of FEI indicates that the highest exposure is concentrated in the plains of the Ganga Basin, particularly in regions stretching from New Delhi to Kolkata. This highlights the greater exposure of densely populated areas to flood events due to the presence of human activities reflected by artificial lights. Meanwhile, southern and western parts of the study area exhibit lower exposure levels. Figure 4.9(b) focuses on the northeastern part of the basin, particularly over the state of Bihar, where the FEI map reveals clusters of lit infrastructure near the Kosi and Ganga rivers, indicating higher flood exposure in these regions. These results demonstrate the higher importance of areas with large human presence compared to low-exposure areas for prioritising flood risk efforts.

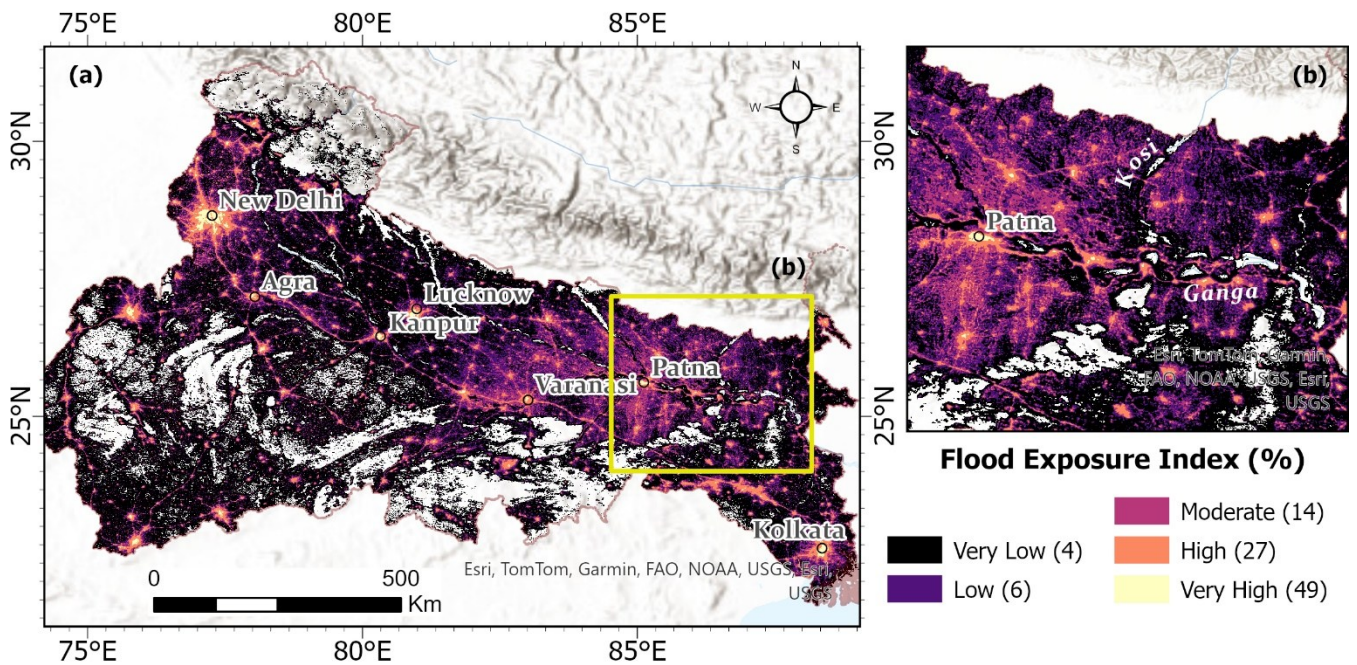


Figure 4.9: Flood Exposure Index (FEI) map for 2022 across the Ganga Basin produced after the AHP. The FEI is categorised into five classes based on the unique values of weights derived, which are Very Low (4%), Low (6%), Moderate (14%), High (27%) and Very High (49%).

4.4.4. Flood Vulnerability Index (FVI)

In this study, the Flood Vulnerability Index (FVI) for the Ganga basin was determined using the district-wise vulnerability index from the Climate Vulnerability Report 2020 and the Analytic Hierarchy Process (AHP) method. The continuous index was divided into five categories, ranging from low (0.35-0.425) to very high (0.65-0.73) based on the report classification, as outlined in Supplementary Table 11. The AHP method allowed us to derive the relative weights (RW) for each category, with Supplementary Table 11 providing a detailed decision matrix. The calculated RWs for the five categories were approximately 0.04, 0.06, 0.14, 0.27, and 0.49, respectively. This analysis showed that areas with higher vulnerability (0.65-0.73) exhibited a significantly larger RW of around 0.49, indicating that nearly 49% of the vulnerability can be attributed to the factors considered in this range. In contrast, areas with lower vulnerability values (0.35-0.425) were associated with a considerably smaller RW of approximately 0.04, reflecting a lower contribution to the overall FVI. After computing the decision matrix for the five vulnerability classes, we conducted a consistency check to ensure the robustness of the AHP model. The Consistency Index (CI) and Consistency Ratio (CR) were calculated for the decision matrix. The CR value for the exposure decision matrix was found to be 0.051, which is well within the acceptable threshold of 0.10, indicating a satisfactory level of consistency in the judgments made during the weighting process. This result underscores the validity of the AHP-derived weights and confirms that the classification scheme is statistically sound.

The higher RW for areas in the 0.65-0.73 range highlights the critical need for targeted flood mitigation efforts in these regions, as they are the most vulnerable based on the selected indicators. Similarly, areas in the lower vulnerability category, although less at risk, should still be monitored, given their susceptibility to changes in biophysical, socio-economic, and infrastructural conditions. Additionally, spatial mapping of the FVI across the basin reveals clear geographic patterns of vulnerability. The northwestern and central

regions of the Ganga basin show a higher concentration of districts falling into the high and very high vulnerability categories, while the southeastern and northern regions are generally associated with lower vulnerability. This spatial distribution suggests the focus of vulnerability in assessing flood risk within the basin. This should help to provide a clear framework for prioritising flood mitigation resources and policy interventions in the most at-risk areas within the basin.

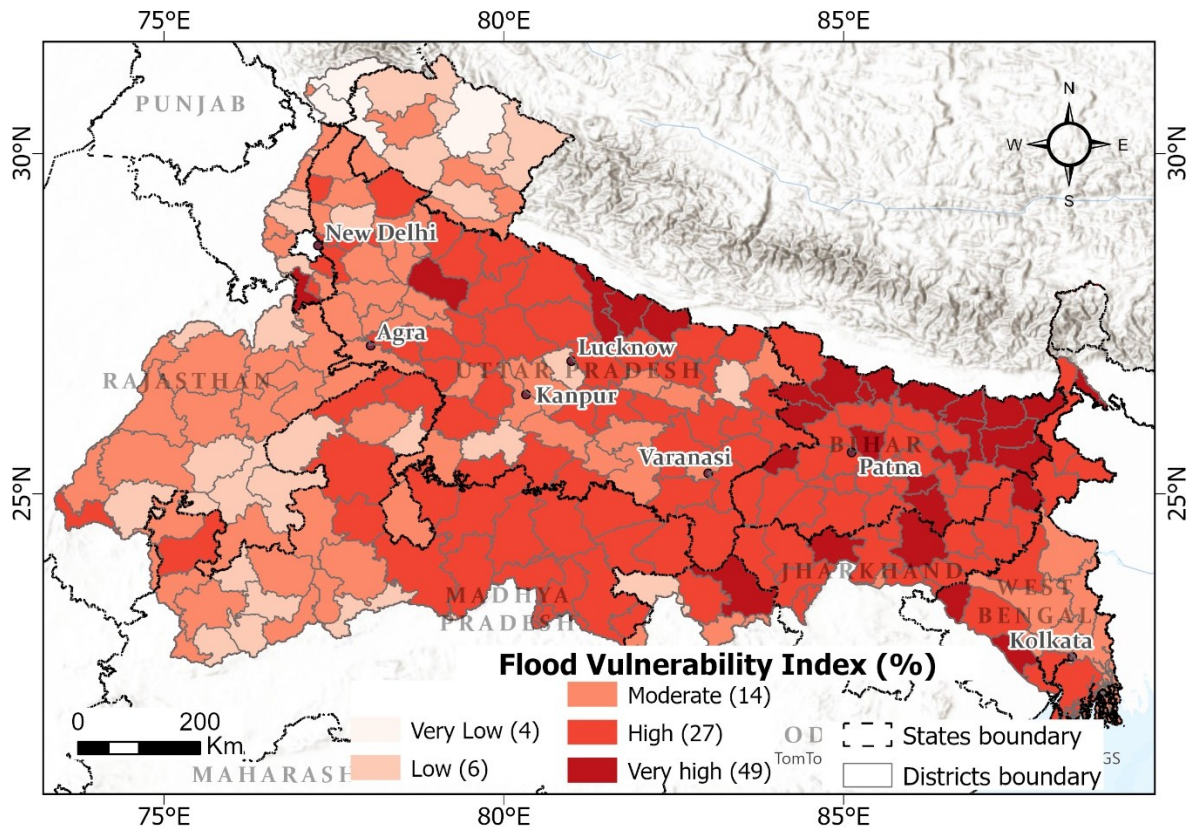


Figure 4.10: Flood Vulnerability Index (FVI) map for 2022 across the Ganga Basin produced after the AHP analysis. The FVI is categorised into five classes based on the unique values of weights derived, which are Very Low (4%), Low (6%), Moderate (14%), High (27%) and Very High (49%).

4.4.5. Flood Risk Map

The annual normalised Flood Risk Index (FRI) map of the Ganga Basin from 2013 to 2023 is calculated at each pixel using Equation 7, which combines the Flood Hazard Index (FHI), Flood Exposure Index (FEI), and Flood Vulnerability Index (FVI). The FRI values for this period range between 0 and 0.085. For better visualisation and discussion, these

original values are normalised to a maximum of 0.09 and expressed as percentages in Supplementary Figure 3. Based on geometric classification, the FRI percentages are divided into five categories: very low risk (0-1%), low risk (1-3%), moderate risk (3-10%), high risk (10-30%), and very high risk (30-100%). Very low and low-risk categories are not presented in the results as they have minimal or no significant contribution to overall flood risk. The maps demonstrate a temporal increase in flood risk distribution, with a noticeable concentration in the eastern part of the basin, particularly over eastern Uttar Pradesh, Bihar, and West Bengal.

To illustrate spatial variability, the flood risk map for 2022 is presented as an example in Figure 4.11. In Figure 4.11(a), the distribution of moderate to very high flood risk pixels across the Ganga Basin is shown, with a significant concentration towards the eastern region. Areas located farther from the river in the southwestern basin, including parts of Madhya Pradesh, Rajasthan, and the northern mountainous region, exhibit minimal to no flood risk. Figures 4.11(b)-(d) offer closer views of the flood risk in Bihar, Uttar Pradesh, and West Bengal. In Figure 4.11(b), a large portion of Bihar shows moderate flood risk, with the eastern areas experiencing high to very high risk. Similarly, Figure 4.11(c) highlights that the high-risk regions in Uttar Pradesh are situated away from major urban centres such as Lucknow and Kanpur, emphasising that flood risk is not solely determined by exposure but reflects the comprehensive methodology applied in this study. Figure 4.11(d) shows the high-risk areas in West Bengal, particularly in the northern and northwestern regions of the state. These findings provide a detailed understanding of flood risk at a higher spatial resolution, which is influenced by not one of the flood potential hazards, exposure or vulnerabilities but an amalgamation of all the aforementioned. However, we recognise the potential inconsistencies in the classification into five risk categories. Thus, we calculated flood risk trends at each raster pixel to identify areas with increasing flood risk trends, which will be discussed in section 4.5.1.

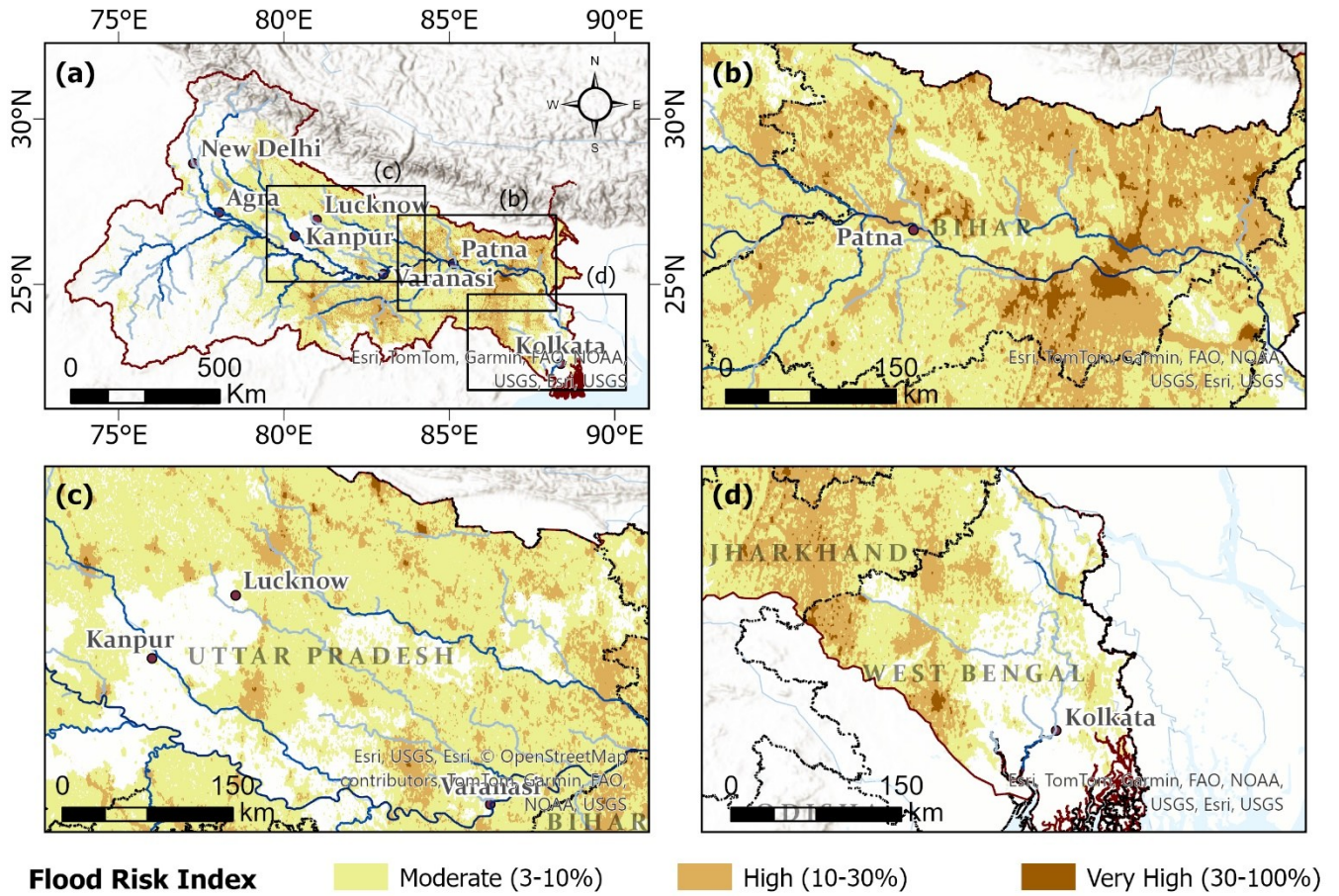


Figure 4.11: (a) Normalised Flood risk index map of the Ganga Basin for 2022, highlighting areas of moderate to high risk. Yellow indicates moderate risk (3-10%), orange represents high risk (10-30%), and brown denotes very high risk (30-100%). (b), (c), and (d) provide zoomed-in views of specific geographic regions.

4.4.6. Validation

Validating a model entails systematically comparing its outputs to real-world observations and gauging prediction accuracy in quantity and quality. For this study, the 2016 flood risk map was validated by comparing its output with the flood impact inventory developed for the basin using the EM-DAT and GDIS data using the ROC-AUC (Receiver Operating Characteristics-Area Under the Curve) method, which is previously discussed in section 4.3.7. We chose the 2016 specific case study because of 2 primary reasons. First, the common availability of years between the GDIS and the risk map generated is between 2013 and 2018. Secondly, according to the Global Flood Database, the flood event triggered by heavy rains on 25th July 2016 had the highest

exposed population of ca. 18.5 million people between 2013 and 2018 in the Ganga Basin (Tellman et al., 2021). Thus justifying our choice of the 2016 flood risk as a case example for validating the data.

The ROC-AUC curve assesses the performance of the flood risk model by plotting the true positive rate against the false positive rate. An AUC value signifies the model's ability to discriminate between actual flooded districts (derived from EMDAT and GDIS) and flood risk districts from the model, with higher values indicating better accuracy. This validation metric confirms the robustness of our flood risk map, providing a quantitative measure of its reliability in predicting and classifying flood risk in the studied region. In Figure 4.12 we observe that the ROC-AUC curve plotted between the true positive rate (TPR) and false positive rate (FPR) has an area under the curve (AUC) value of 0.69 (or 69%), which is satisfactory – very good range as per the classification Das, 2020; Lin et al., 2019; Mukhtar et al., 2024; Roy et al., 2021; Saha and Agrawal, 2020). The model can discriminate and predict accurately if the AUC value is closer to 1.

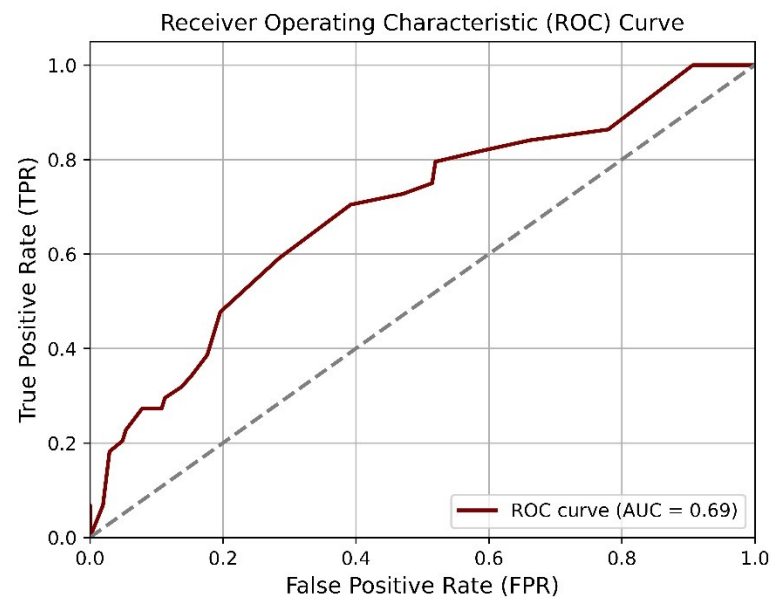


Figure 4.12: ROC curve (maroon colour) plotted between the false positive rate and the true positive rates at different risk threshold values. The AUC is the value of the area under the curve of the 2016 flood risk map.

4.5. Discussion

4.5.1. Comprehensive approach for identifying and predicting flood risk

Our study adopts a GIS-based Analytical Hierarchy Process (AHP) method to characterise flood risk in the Ganga Basin, India. The main objective was to integrate flood hazard, exposure, and vulnerability datasets while also demonstrating the utility of the night-time lights (NTL) data for assessing flood risk. Numerous studies have suggested that the increase in risk in recent years primarily due to the increase in exposure of assets and people in hazard-prone areas, with only minor increases in hazard itself over the last decade (IPCC, 2012; Blaikie et al., 2014; Kundzewicz et al., 2014; Munich Re, 2014; Visser et al., 2014; Jongman et al., 2015; GFDRR, 2016, de Ruiter et al., 2017; UNDRR, 2020). This growing risk is also linked to increased vulnerability, a critical factor in flood damage assessments (Connor and Hiroki, 2005; de Ruiter et al., 2017; Mishra and Sinha, 2020). Our study allows us to address the changing flood hazard and exposure over time within the Ganga Basin. Flood hazards in this basin are influenced by elevation, slope, flow accumulation, drainage density, proximity to rivers and confluences, rainfall, and geomorphology. The impact of these hazards is amplified by the exposure and vulnerability to floods in various areas. As discussed in section 4.4.2, the majority of flood hazard factors have remained constant over the past 10 years except for rainfall, which contributes to the temporal variation of flood hazard within the basin, as seen in Supplementary Figure 1.

Our flood risk map of the Ganga Basin, developed using an integrated hydro-geomorphological approach with AHP, outperforms traditional hydrological and hydraulic models as it combines the physical (geomorphological) criteria with hydro-meteorological data. This emphasises process-based understanding and overcomes the necessity of dense hydrological data as required by the hydraulic modelling of floods (Mishra and Sinha, 2020). Our hazard map reveals that the majority of high flood hazards in the basin are concentrated within the plains of the Ganga Basin and are majorly

influenced by the elevation (31%), slope (21%), rainfall (15%) and distance from the river (12%). Monsoonal precipitation was also identified as a key factor, making it integral to the flood hazard index. However, geomorphology had the least influence on the occurrence of identifying flood-prone areas, about 2%. Our model utilises multiple data like the DEM, night-lights, and vulnerability index, for understanding and predicting risk had an accuracy of ca.70%, which is satisfactory (Das, 2020; Lin et al., 2019; Mukhtar et al., 2024; Roy et al., 2021; Saha and Agrawal, 2020). Hazards that occur in areas with low vulnerability will not become disasters (Quarantelli, 1998; Birkmann et al., 2013). However, most hazards occur in low and middle-income countries (LMIC) with a high population density, poor infrastructure, and limited or no disaster preparedness plan (Mishra and Sinha, 2020). For instance, in Figure 4.8, the eastern part of the basin has a very high FHI, but it does not have a similar concentration of a very high FRI in Figure 4.11. This highlights that the high flood hazard index does not necessarily relate to high flood risk as well, highlighting the analysis of vulnerability and exposure to disasters, magnitude, and their impact (de Ruiter et al., 2017; Mishra and Sinha, 2020).

To gain an understanding of the distribution of flood risk and identify areas with persistent or increasing risk, we derived the trend of the flood risk from the flood risk maps from the last ten years, which is representative of percentage point change per year. Figure 4.13a shows maps that highlight areas of increasing flood risk (red colours), with a noticeable concentration in the eastern part of the basin, particularly in the state of Bihar, eastern parts of Uttar Pradesh, and Madhya Pradesh. Bihar has periodically experienced floods due to extreme rainfall-induced riverine flooding, as several rivers flow in this area. Some of the major flood events in the northern part of Bihar occurred in the years 1987, 1998, 2000, 2001, 2003, 2004, 2008, 2010, 2013, 2017, 2018 and 2020 (Tripathi et al., 2022). Figure 4.13b, for example, illustrates an increasing trend of flood risk near the confluence of the Ganga and Kosi rivers in Bihar. Moreover, areas along the current path of the Kosi River show a more pronounced trend compared to regions

farther from the river, particularly areas within and adjacent to the districts of Supaul, Saharsa, and Khagaria. This elevated risk could be attributed to the Kosi River's historical avulsions, having shifted its course westward by approximately 150 km over the past 200 years (Sinha, 2009; Mishra and Sinha, 2020). Additionally, the Himalayan foothill regions have experienced regular flooding, resulting in the loss of human lives and infrastructure damage (Roy et al., 2021). Occasional landslides in the upper catchment areas of the rivers trigger sudden water release, causing rivers to discharge massive volumes of water (Roy, 2011). Figure 4.13c displays a heightened flood risk trend near the foothill regions of the Himalayas, particularly around Jamunaha. As the country's population has grown, settlements have moved to the riverbanks, increasing the risk of erosion and flooding (Islam et al., 2023). Figure 4.13d shows that downstream areas of the Ganga River in West Bengal exhibit varied trends, with the northern part facing higher flood risk compared to the southern areas, where risk is either stable or decreasing. This is because the northern region possesses unique physiographic and orographic conditions influenced by the eastern Himalayas, where numerous streams converge at the foothills, forming large, braided rivers (Chakraborty and Mukhopadhyay, 2019). Finally, Figure 4.13e indicates that areas within and adjacent to the districts of Satna and Rewa have a higher risk trend compared to other parts of the Madhya Pradesh state. This is due to the variability of the southwest monsoon, which causes high rainfall in the eastern part of Madhya Pradesh and reduces towards the north and western parts (Tiwari et al., 2024).

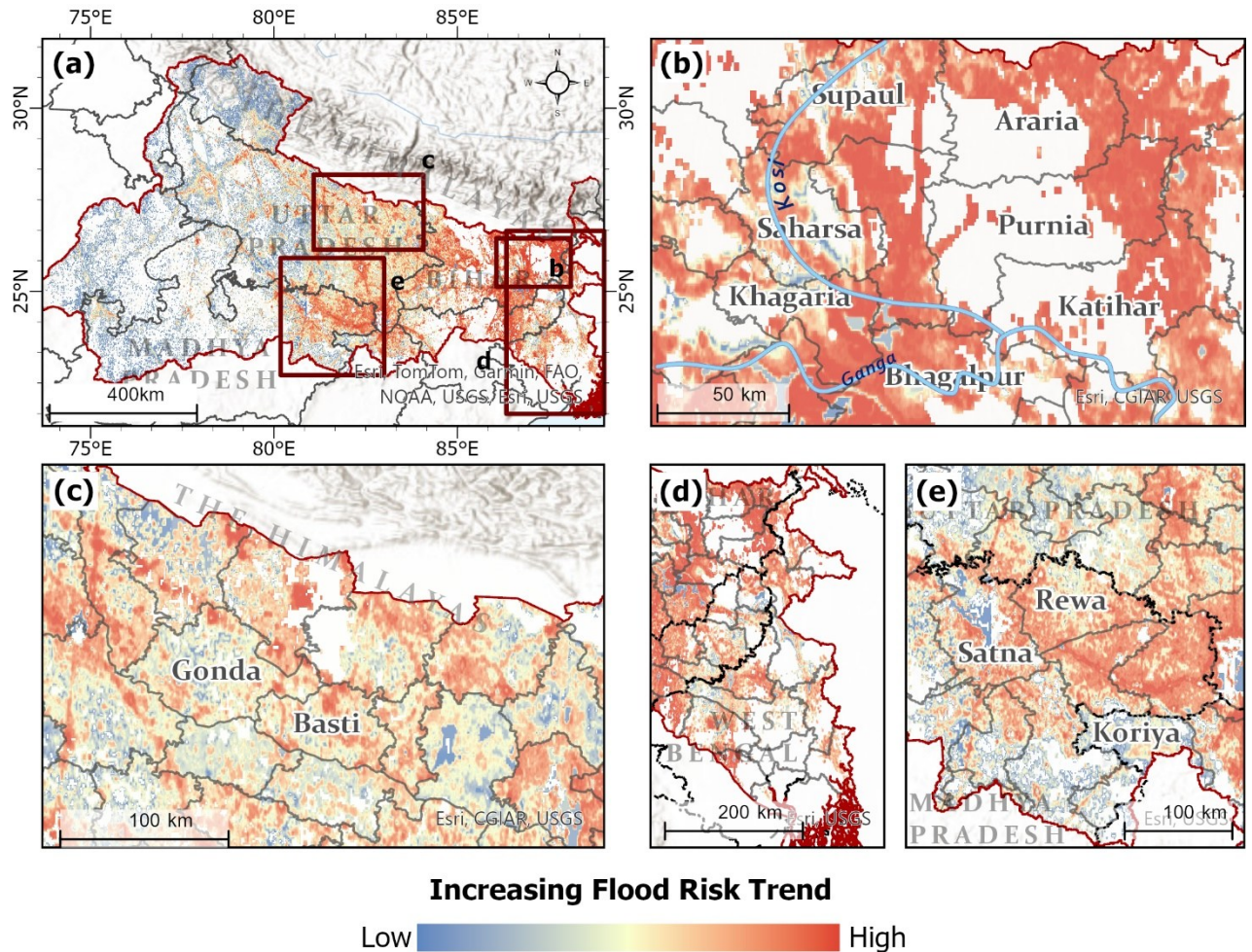


Figure 4.13: (a) The spatial distribution of increasing flood risk trend within the Ganga Basin in India over the past 10 years. Each pixel represents the average percentage point change in FRI per year, enabling us to identify areas of significantly increasing flood risk. The blue areas represent regions with a lower rate of flood risk increase, ca. 1 point change/per year, while the red areas indicate regions with a higher flood risk trend, ca. 5 points change/ per year. The white areas are where there is no flood risk; (b) shows a focused view of the trend within the state of Bihar; (c) highlights the trend near the foothills of the Himalayas; (d) zooms in on the trend in the state of West Bengal; (e) provides a detailed view of the trend over the state of Madhya Pradesh within the basin.

The occurrences of episodic flooding over time, especially during the summer monsoon, are a potential flood hazard which becomes a disaster if leading to human and resource loss (UNDRR, 2020). The cumulative reasons for the exponential loss in the area are the geomorphic factors, the exposed human population and the ability to cope with the floods. The key highlight of our work is leveraging the temporal and spatial resolution of night-time lights as a proxy for exposure to flood hazards. In general, the lack of data, especially up-to-date or recent datasets, provides a hindrance to robust estimation of

flood exposure and risk. As observed in Supplementary Figure 2, the distribution of lit pixels serving as a proxy for human exposure has increased over the last decade, and consequently, we suggest that flood models should make use of recent datasets such as this, representing population and human infrastructure. Compared with traditional statistical and census data, NTL can directly reflect the real-time distribution of human activities and address the issue of not being able to document human presence promptly using traditional methods (Fang et al., 2021).

Flood risk, which combines hazard, exposure, and vulnerability, is crucial for prioritising resources and interventions, as it reveals the spatial distribution of potential damage (Elshorbagy et al., 2017). Thus, the Analytical Hierarchy Process (AHP) framework integrated with the GIS datasets and, most importantly, human population proxy datasets aids in formulating and identifying flood risk areas. His study provides a high spatial resolution assessment of flood risk hotspots, which can serve as a valuable tool for guiding policy development aimed at mitigating potential flood damage. This kind of research can help contribute to informed disaster planning for government and non-governmental organisations. For urban planners and policymakers, these flood risk maps are crucial for making informed decisions regarding future land development or infrastructure projects, ensuring that these initiatives are strategically located to minimise long-term costs and risks. By considering a variety of interrelated factors, this approach fosters a more holistic and comprehensive understanding of flood risk, leading to better-informed, evidence-based decision-making. The novel part utilises the NTL data to give a holistic understanding of exposure at a better temporal approach.

For this approach to be of most value to stakeholders, it is important to address study limitations and areas for future refinement, as this is essential for ensuring transparency regarding potential weaknesses and constraints within the research methodology. By acknowledging these limitations, the credibility of the findings is strengthened, offering a more informed interpretation of the results. This also paves the way for refining future

research, contributing to a balanced and realistic assessment of the study's scope and implications. The AHP method relies on prior subjective knowledge and assumptions, leading to uncertainties, but its main advantage is that it does not require historical datasets. In contrast, machine learning (ML) models based on historical data are rapidly evolving, and they can improve model accuracy by incorporating multiple parameters for multidimensional analysis of the significance or weighting of different factors (Khosravi et al., 2019). The study assumes a constant vulnerability level over the past decade for simplification purposes, reasoning that vulnerability components wouldn't have changed significantly. However, given rising exposure, future work should account for variations in vulnerability over the decade. Night-time data was used to assess exposure, as it effectively captures the spatial distribution of human infrastructure. While useful for disaster assessment, its spatial resolution is limited to 500 meters, which is a limitation for neighbourhood-specific flood risk approaches. The validation process was based on disaster impact data repository from EM-DAT and GDIS data, two of the most comprehensive global disaster databases. While these sources are verified, data gaps stem from limited capacity and resources to fully document all events. Despite these limitations, we opted for this data due to the lack of alternative impact-based datasets, although they may have accuracy constraints and may not offer the most optimal validation framework. Additionally, using higher-resolution data could improve the precision and robustness of the study's findings.

4.6. Conclusion

Most previous research on flood risk has primarily relied on data, such as population or infrastructure, to estimate exposure to flood hazards, especially in developing regions where data availability is limited. The novelty of our work lies in using luminosity measurements derived from night-time light data as a proxy for mapping exposure to flood hazards within the Ganga Basin. Our study leverages the temporal frequency of

the data, which enables the characterisation of the spatial distribution of human activities at a large scale and with higher temporal resolution. Unlike previous studies that commonly used the terms hazard, exposure, and vulnerability interchangeably to assess the susceptibility of human populations to flood hazards, this research treats these components separately to better understand flood risk in one of the world's most densely populated basins—the Ganga Basin. In this basin, the Indian summer monsoon between June and September contributes about 80% of the yearly rainfall, affecting about 18 million people. This has caused increased frequency and magnitude of flooding as a major concern in recent years. In this research, through a comprehensive literature review, we identified the key factors of the flood and their relative weightings using the Analytical Hierarchy Process methodology. These factors influencing include elevation (31%), slope (21%), rainfall (15%), distance from the river (12%), distance from a confluence (8%), flow accumulation (6%), drainage density (5%) and geomorphology (2%). Using these data, the night-time lights and the vulnerability data from India's Climate vulnerability report, we computed the flood hazard index (FHI), flood exposure index (FEI) and flood vulnerability index (FVI) to characterise flood risk. Analysis of data from 2013 to 2023 enables us to assess how flood risk has evolved over the past decade. Our findings indicated certain areas had high FHI, meaning higher susceptibility to floods, but did not have high flood risk. Our analysis based on the flood risk trend reveals that there is a significant increase in flood risk trend in the eastern part of the basin, particularly areas in Bihar, eastern Madhya Pradesh, eastern Uttar Pradesh and the northern part of West Bengal, identifying high flood risk zones at the pixel or cell level. Conversely, a lower risk trend is observed in other parts of the basin, which can be attributed to variations in the southwest summer monsoon and expanding human exposure in certain areas. This research represents a first-of-its-kind effort to utilise night-time lights data to examine the temporal dynamics of flood risk, providing a novel approach for assessing and tracking increasing flood risk in the region. A better understanding of evolving hazards and exposure is crucial in areas having limited or

outdated population information, informing policymakers as it allows them to identify areas that are experiencing increasing flood risk.

Authors Contribution:

Authors envisaged for the publication: Ekta Aggarwal (E.A.); Marleen de Ruiter (M.R.); Alexander C. Whittaker (A.C.W.); Sanjeev Gupta (S.G.); Rajiv Sinha (R.S.); Kartikeya S. Sangwan (K.S.S.); Sophie Buijs (S.B.); Ranjay Sreshtha (R.S.) (Authors sequence to be discussed)

Conceptualisation, E.A., M.R. and A.C.W.; methodology, E.A.; software, E.A.; validation, E.A.; formal analysis, E.A.; investigation, E.A.; data curation, E.A.; writing—original draft preparation, E.A.; writing—review and editing, M.R., A.C.W., S.G; discussion - A.C.W., K.S.S. S.G, R.S., S.B., R.S.; visualisation, E.A.; supervision, M.R., and A.C.W.; project administration, A.C.W.; funding acquisition, A.C.W. and S.G.

Chapter 5: Discussion

5.1. General Synthesis

In this thesis, I aimed to investigate the landscape drivers shaping human presence near rivers, exposure to flood hazards and the consequential impacts to develop an approach for flood-risk assessment in the Indus-Ganga Basin. To achieve this, I exploited night-time lights data in combination with the other available open-source datasets like the Digital elevation model (DEM), GHSL-SMOD (Settlement type data), rainfall, geomorphology, Sentinel-SAR, and EM-DAT (international database for disaster). With these datasets, I explained the role of distance from the river channel and dynamic river patterns in influencing the human presence (Chapter 2), developed a methodology using daily night-time lights (NTL) data to assess the temporal and spatial compound impact of flooding, and to estimate recovery, focused on the 2022 Indus flood event (Chapter 3), and lastly provided a framework for a better understanding for flood-risk which I applied to the Ganga Basin (Chapter 4). Thus, the work presented in this thesis satisfies the key aims and objectives outlined in the Introduction (Section 1.2), which I shall discuss in this section.

5.1.1. Aim 1: Studying the role or influence of river geomorphology in the Indus Basin on human presence using night lights

The first aim of the thesis was to study the influence of river geomorphology in terms of distance to the river and river channel patterns on human presence. I addressed this aim in Chapter 2, where I used the average distribution of DMSP night-time lights from 2000-2013 as a proxy for human presence. First, to validate the DMSP data as a proxy for human activities, I correlated it with the annual LandScan population data, showing a moderate correlation of 0.655, demonstrating a useful proxy for the human activities

from cities, towns, industrial setups, streets, residential areas, etc. The correlation is not strong (i.e., 1) because nightlights can signify human activity, not just population. This helped to quantify statistically the enhancement of lit pixels with the river patterns and proximity to the rivers as a case study in the Indus Basin. The first objective of this aim was to test the hypothesis that the night-time lights signifying human activities are higher near the major rivers compared to the basin as a whole. One purpose of choosing high-order streams or the major rivers of the basin was that the higher-order streams are likely to cause large-scale flooding. The study shows that the nightlight luminosity is enhanced by 26% within the 0-5km buffer of the major rivers and about 11% within the 5-10km buffer zone relative to the 10-15km and 15-20km buffer zones. The findings are consistent with other research (Kummu et al., 2011; Fang et al., 2018; Cao et al., 2023), which showed preferential settlement locations near the river. However, an important observation was the inverse relationship between the mean intensity of nightlights and the spatial distribution of the lit pixels within the buffer zones. This implies that the denser settlements, like big towns and cities, are developed away from proximity to rivers, where they were less susceptible to river flooding (Figure 2.10).

Further, to test the second hypothesis that the channel pattern bank stability influences the presence of human settlements, I compared the nightlight distribution within the single-thread (meandering) river channel and the multi-thread (braided) channels. I identified the different channel pattern extent of the Indus River using Google Earth and computed the night-time light distribution for different channel patterns within the four proximity zones of 0-5km, 5-10km, 10-15km and 15-20km, respectively. I calculated that there is an 18% enhancement within the 0-5km of single-thread channels of the Indus River compared to multi-thread channels, as shown in Figure 2.11, because of the stable channel banks and lower channel mobility associated with single-thread channels. The seasonal inundation within the close reaches of multi-threaded channels makes them less preferred sites for settlements, but valley margins or terraces further away from the river

channels are preferred sites for settlements. However, beyond 5km, the enhancement is greater for the multi-thread channels compared to the single-thread channels (Figure 2.10). Such work provided an understanding of the dynamics of geomorphology in assessing or studying the impacts of natural hazards like floods and the application of a non-conventional dataset to estimate exposure.

5.1.2. Aim 2: Developing a methodology or framework for studying the impact of floods beyond water inundation

The second aim of this thesis was to investigate the spatial and temporal effects of the 2022 Indus floods in Pakistan, as discussed in Chapter 3. The floods, which occurred in August 2022, were the most severe in the country's history. The research aimed to develop a methodology for estimating the spatial and temporal impacts of extreme flooding using nightlight data, offering a more comprehensive understanding of the compound effects of floods. The first goal within this objective was to generate weekly Night-time Light (NTL) data from NASA's daily Black Marble NTL dataset. Figure 3.3 outlines the schematic methodology, which involved downloading daily NTL data for the study area for the years 2021 and 2022. Since cloud cover affected the daily data, high-quality lit pixels were filtered and used to create weekly rasters. Thresholding and outlier removal were applied to prepare the data for a time series analysis, which aimed to assess the temporal impact of the flooding—the second goal.

To achieve this, I calculated the weekly sum of radiance for 2022 (Figure 3.6), observing an 80-85% decline in radiance over 15 weeks, from the 18th week of 2022 (May) to the 33rd week (August). To better understand the significance of this decline, I detrended both the daily and weekly data over two years (Figure 3.7), favouring the weekly data due to fewer fluctuations. The weekly detrended data (Figure 3.7) provided critical insights into flood exposure, outperforming traditional flood mapping methods. It showed a maximum radiance decline of 400% during the flood, highlighting the considerable impact on human activities. While literature indicated heavy rainfall over

eight weeks from July to August 2022 (Nanditha et al., 2023; Qamer et al., 2023; Wang et al., 2024; Shreshtha, 2024), the reduction in radiance lasted for approximately 18 weeks, from the 18th to the 36th week of 2022. This period encompassed 10 weeks of declining radiance, followed by a rapid recovery during the eight-week Emergency Period.

In terms of spatial scale, Figure 3.8 shows the spatial distribution of the lit pixels from May to October 2022, showing a distinct reduction in the spatial extent of lit pixels and restoration from September onwards. These spatial images vividly illustrate how the flood event impacted human activity and infrastructure spatially, reflected in the altered NTL patterns. Such patterns can help to identify areas and the duration of the impact of the water inundation during the flooding event (the third objective of this aim). Thus, to pinpoint the impacted areas spatially, I calculated the change in the decline in radiance with respect to the 18th week of 2022 (in May), i.e., before the radiance started decreasing. I also computed the water inundation from May to September using Sentinel-SAR to check the overlap between the conventional flood monitoring using SAR and the impact derived from the NTL. The result showed NTL-derived impact extending beyond the water inundation boundaries identified by SAR. These declines highlight the indirect impacts of flooding, such as destroyed power lines, waterlogged areas, and wind storms, leading to forced displacements. This utility of the daily/weekly NTL provides a rapid assessment of the impact of the disaster on human activities by leveraging the temporal frequency of the data. This work is the first time that night-time lights have been used to monitor both the spatial and temporal impact of floods, providing insights into flood exposure compared to traditional flood mapping methods. The study stressed the potential of NASA's Black Marble night-time light data for the rapid assessment of the impact of the 2022 Indus Floods in Pakistan.

Further, to understand our fourth objective of difference in the impact and recovery for urban centres and rural areas, I used the GHSL SMOD data showing the settlement type (i.e., urban centre, urban cluster, semi-rural, rural cluster and rural areas) and the

economic dataset. The results in Figure 3.10 show that the rural communities were more severely affected in terms of area exposure than urban centres, although the financial status value of those affected was higher in urban areas. The primary reason for the higher exposure in rural areas is that the majority of the population depends on agriculture in rural regions and has comparatively fewer resources devoted to disaster mitigation. However, due to the high economic status of those associated with the urban centres, the financial decline was exponentially higher than in the rural areas. The data also provided insight into the recovery. Irrespective of the socio-economic conditions, the areas with an 80-100% decline in radiance mostly recovered in approximately one month, while areas with a 60-80% decline took up to three months to return to pre-flood levels. The analysis provided a detailed assessment of the human impact of floods through the lens of lit infrastructure, offering a rapid, safe, and cost-effective approach to quantify flood vulnerability at all administrative levels.

5.1.3. Aim 3: Creating a holistic approach to understanding flood risk using geospatial multi-criteria analysis

The third objective of this thesis was to develop an approach for assessing flood risk, building on the insights gained from the first aim, which focused on understanding potential flood hazards, and the second aim, which applied Night-time Light (NTL) data to measure flood exposure. Unlike some earlier studies that used the terms hazard, exposure, and vulnerability interchangeably to assess flood susceptibility, in this research, I treat these components separately to better understand flood risk in one of the world's most densely populated basins—the Ganga Basin. The first objective of this aim was to calculate the flood hazard index using a GIS approach. To achieve this, I conducted a comprehensive literature review to identify the key factors contributing to flooding and calculated their relative importance using the Analytical Hierarchy Process (AHP). The derived factors and their corresponding weights were as follows: elevation (31%), slope (21%), rainfall (15%), distance from the river (12%), distance from the

confluence (8%), flow accumulation (6%), drainage density (5%), and geomorphology (2%). These weighted factors were then used to generate annual flood hazard maps from 2013 to 2023. The resulting Flood Hazard Index represents an improvement over previously developed AHP-based flood susceptibility maps by incorporating monsoon-season precipitation and producing yearly flood hazard assessments over the decade from 2013 to 2023.

Building on the detailed methodology outlined in Chapter 3 for my second aim, I utilised annual night-time light (NTL) data to construct an exposure index at the pixel/cell level, addressing the second objective of this aim. The temporal resolution of the data allowed for real-time mapping of human activity on a large scale, as discussed in the previous two aims of this thesis. A key advantage of using annual data over 10 years is the incorporation of recent human proxy datasets, which provide more current insights compared to global population datasets that rely on older census data, such as India's 2011 census, in this case. This analysis highlights that the increasing flood severity over the past decade is also influenced by rising population and exposure levels.

My third objective was to construct an annual flood risk map from 2013 to 2023, which is discussed in Chapter 4. I computed them as a product of the flood hazard index (FHI), flood exposure index (FEI) and flood vulnerability index (FVI). This further was used to calculate the trend of increasing flood risk in the last decade. To validate my risk model, I used the 2016 flood risk map to check its output with the flood impact inventory EM-DAT and GDIS data using the ROC-AUC (Receiver Operating Characteristics-Area Under the Curve) method. The ROC-AUC curve plotted between the true positive rate (TPR) and false positive rate (FPR) has an area under the curve (AUC) ca. 0.70, which was satisfactory – a very good range as per the classification, as the closer the AUC value is to 1, better the model can predict.

The main finding indicated certain areas had high FHI, meaning higher susceptibility to floods, but did not have high flood risk. The analysis based on the flood risk trend

revealed a higher increase in flood risk trend in the eastern part of the basin, particularly areas in Bihar, eastern Madhya Pradesh, eastern Uttar Pradesh and the northern part of West Bengal, identifying high-flood risk zones at the pixel or cell level. Conversely, a lower risk trend is observed in other parts of the basin, which can be attributed to variations in the southwest summer monsoon and expanding human exposure in certain areas. This study represents the first instance of generating flood risk maps for the Indian Ganga Basin at a resolution of approximately 500 meters. These maps are based on two key factors contributing to the global rise in flood risk: changes in precipitation patterns driven by climate change and population growth, which intensifies the severity of flood impacts. To analyse the evolving flood risk over time and across different areas, I incorporated both precipitation data and night-time light (NTL) as indicators for potential flood hazard and exposure.

This thesis develops a comprehensive framework for assessing flood risk by integrating geomorphological factors, human settlement patterns, and flood exposure using night-time light (NTL) data. I used the NTL as a proxy for human activity, showing its relationship with the stability of river channels and its response to floods and studying flood risk. These findings offer a novel approach to flood risk assessment, improving on traditional methods and highlighting areas of growing vulnerability.

5.2. Cross-cutting themes

The three research chapters in this thesis are standalone studies, with each intended to address a specific research idea in its entirety. However, together, they address broader questions of utilising real-time and updated information for reflecting human activities for studying the role of fluvial landscape in shaping these settlements and further studying the consequential impacts of floods. In this section, I highlight a selection of key themes that emerge out of some or all the research chapters.

5.2.1. Temporal and spatial constraints on NTL- opportunities and challenges

The two NTL datasets used in the study are the DMSP and the VIIRS-derived Black Marble Product, which have been addressed in the previous chapters. We used the DMSP NTL data to study the influence of river morphology on human presence within the Indus Basin, as discussed in Chapter 2. The advantage of using the DMSP data is that the data temporally ranges from 1992 to 2013, which allowed me to study the human presence within the basin from the earliest time possible using the NTL approach. The DMSP data is in a yearly format and has a coarser resolution compared to the VIIRS Black Marble product suite, which is available daily or monthly. The data used in Chapter 2 provide a coarser resolution compared to recent versions of night light data, which might not be suitable for understanding human presence at a micro or lower administrative level.

The VIIRS/DNB sensor provides significant upgrades in terms of temporal and spatial resolution over the DMSP/OLS sensor (Levin et al., 2020). The former also provides better radiometrically calibrated data which does not have over-saturation in the urban areas, thus switching the generation of global NTL from the DMSP to the VIIRS sensor from 2013 onwards (Elvidge et al., 2013; Levin et al., 2020). However, the release of the novel NTL Product in 2019, i.e., NASA's Black Marble Product suite (VNP46A1) derived from the VIIRS provided cloud-free, atmospheric-, terrain-, vegetation-, snow-, and stray light corrected radiances for estimating daily night-time lights (Román et al., 2018). In Chapter 3 and Chapter 4, I used the daily and annual versions of the Black Marble NTL product for assessing the impact of 2022 floods within Pakistan and for flood-risk assessment within India. The application of NTL data has enabled the researchers to track the displaced population in conflict-affected areas, damage to the infrastructure following damage and identification of areas where people congregate (Román and Stokes, 2015).

Thus, numerous studies have utilised the DMSP/OLS and VIIRS/DNB sensors for the night-time lights data to identify the spatial and temporal patterns of the artificial lights

at regional, national and global levels but lack at street or neighbourhood levels due to a lack of fine spatial resolution (Levin et al., 2020). Although NASA currently offers the Black Marble HD product, which provides daily NTL data with 30m resolution, this product is currently limited to collaborators on funded projects. However, the tools to produce the HD products will be available through Google Earth Engine in the future, enabling researchers to generate higher-resolution damage degree maps using NTL with the Black Marble HD product (NASA, 2024).

The two key challenges of the NTL observation are the difference in the radiance between the day-time images and the nighttime images and the imaging direction (Levin et al., 2020). Levin (2020) compared the histograms of the radiance over Berlin from a Landsat daytime image and a VIIRS/DNB night-time image and observed that the radiance distribution was different and at night was about five orders of magnitudes lower than at daytime. This is because during the daytime, the sun, being the light source, illuminates the rooftops, treetops, grasslands and water areas equally, and the radiance depends on the albedo. However, during the night, the unlit or black areas are lit by natural sources and the streets are lit by lamps. The other challenge is the angular observation of the image taken from the DMSP or the VIIRS sensor. The two common situations in this case would be the blocking of artificial light by buildings, trees, or other objects, and, second radiation from vertical surfaces such as floodlit facades, light escaping windows, and illuminated signs. This, therefore, illustrates the major impact of the imaging direction on the radiance observed at night, which may provide structural and vertical information about urban areas. These considerations explain the fluctuations in the weekly average radiance observed in the study area for the year 2021-22 to study the flood impacts in Figure 3.6 and Section 3.3. However, for meteorological events like floods, cloud cover can significantly impact the reliability of detecting the impact (Zao et al., 2018). Thus, to address the utility of the data and to study the impact on the human activities of the 2022 floods, I created a weekly composite from May to October 2022, with

maximum data coverage and least cloud cover for a respective month (Figure 3.8). For each of the selected weeks, the coverage was >98%, except in August. Thus, monitoring of night-time lights is particularly well-suited to the assessment of impacts from major events over longer-time scales or for non-meteorological events (e.g. failed infrastructure, earthquakes) where cloud cover may be less prevalent (Zhao et al., 2018). Since the aim of my work was to understand the impact of human activities from the compound flooding event and recovery, the data was able to demonstrate the utility of NTL for monitoring the gradual impact of floods.

However, recent advancements in NTL remote sensing have focused on harmonising data from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) to create extended, consistent time series. This integration leverages the long historical record of DMSP-OLS, dating back to 1992, and the enhanced spatial and radiometric resolution of VIIRS, available since 2012. For instance, Li et al. (2020) developed a harmonised global NTL dataset spanning 1992 to 2018 by inter-calibrating DMSP-OLS observations and simulating DMSP-like data from VIIRS. This approach addressed discrepancies between the two sensors, resulting in a consistent time series suitable for analysing long-term trends in human activities and urbanisation. Building upon this, Chen et al. (2020) extended the NTL time series from 2000 to 2018 through a novel cross-sensor calibration method. They transformed DMSP-OLS data to be VIIRS-like, enhancing the continuity and comparability of NTL observations over time. These harmonised datasets are instrumental in facilitating comprehensive analyses of socio-economic development, urbanisation, and environmental changes over extended periods.

5.2.2. Utility of NTL data and improvement over conventional approaches

In recent decades, the world has been rapidly urbanising. As per the report by the United Nations (2014), about 54% of the global population lives in urban areas, a figure which is expected to increase by 70-90% by 2100. This forecast thus emphasises the need for reliable information which can directly reflect the real-time distribution of human activities and solve the problem of not being able to timely capture population mobility with traditional methods like census population count or the global gridded population dataset derived from the census (Fang et al., 2021). The night-time light remote sensing data is one such novel data that can identify areas lit up with artificial lights. Indeed, the data has been used for delineating urban extent and tracking electrification in rural areas as an indicator of economic activity being a proxy for the GDP (Elvidge et al., 2009; Min and Gaba, 2014; Zhu et al., 2019). The Indus Basin and the Ganga Basin belong to the Low and Middle-Income Countries (LMICs), where traditional census data were collected in 2011 and 2017 in India and Pakistan, respectively (Government of India, 2011; Pakistan Bureau of Statistics, 2017). In such scenarios, NTL can directly reflect the real-time distribution of human activities and solve the problem of not being able to timely capture population mobility with traditional methods. Meanwhile, compared with other real-time data like cellular signalling data with limited coverage, NTL can better reflect human activities at a large scale. Therefore, it is very suitable for the monitoring and assessment of emergencies such as natural disasters, especially in the context of the continuous emergence of new satellite platforms and higher spatial-temporal resolution data, such as VIIRS (Elvidge et al., 2017; Levin et al., 2020).

Conventional mapping of flooding using satellite images usually includes mapping water-inundated areas using optical, radar images or both, and mapping the infrastructure damage using optical images (Levin and Phinn 2022; Joyce et al. 2009; Martinis et al. 2022). Synthetic Aperture Radar (SAR) is usually acceptable data for flood detection as it is independent of external energy sources and is not affected by cloud

cover (Giustarini et al., 2013; Tanguy et al., 2017). On the other hand, other research uses optical data like Landsat or MODIS to map the flood extent and estimate the population exposure (Tellman et al., 2021). In Section 3.4.4, I used the SAR data to extract the extent of water inundation due to floods from May 2022 to October 2022, showing the increase and receding nature of flood water over the period of 6 months (Figure 3.5). Existing literature provides insights into the factors contributing to flooding and flood damage, primarily using conventional and outdated datasets. However, a major challenge remains in accurately estimating flood damage—such as human and resource losses—using real-time, up-to-date data.

To address this issue, I utilised NTL data, as the light intensity in affected human settlements, industrial areas, commercial zones, and public spaces diminishes compared to conditions before flooding (Enkel et al., 2012). Floods can lead to various impacts, including damage to homes, displacement of residents, fatalities, and disruptions in industrial, manufacturing, service, and public sectors, both within and outside inundated areas (Enkel et al., 2012). Outages may also arise from poorly maintained or damaged infrastructure, industrial accidents, or regional conflicts. Disruptions can range from a few hours for minor, isolated events to several days, weeks, or even months for significant or prolonged impacts, such as those caused by major hurricanes (Levin et al., 2020). Additionally, the effects of flooding can vary based on societal structures and the community's ability to cope with such disasters. Cole et al. (2017) and Zhao et al. (2018) used a ratio of pre- and post-disaster NTL radiance to measure the impact of the natural disaster. Similarly, in Figure 3.9, I show that the impact of the floods on human activities extended beyond the area of water inundation. Thus, the utilisation of NTL aids in the usage of recent data as a proxy of human activity, where the population datasets based on the census are outdated.

5.2.3. A holistic approach to understanding flood risk

Over time, human settlements have increasingly concentrated around water resources due to the availability of essential resources and transportation. However, as population growth and rapid industrialisation accelerate, these areas around water bodies have significantly expanded (Ceola et al., 2014; Fang et al., 2021; Tellman et al., 2021). This increased settlement has exposed a larger population to the risks of water-related disasters such as floods, tsunamis, and landslides (Kummu et al., 2011; Ceola et al., 2015; Fang et al., 2018; Fang et al., 2019). Therefore, understanding the landscape and terrain factors that influence or contribute to these disasters is crucial, as it helps in identifying potential hazards for future disaster events (United Nations, 2015; UNDRR, 2020). The increasingly high economic and human losses associated with flooding make it important to understand the associated risks with extreme events or natural disasters. When we talk about flood risk, the three terms- hazard, exposure and vulnerability are often confused, leading to different meanings and usage, but as per the IPCC (2012) report, the three should be collectively studied to identify risk. In my research, I show the role of fluvial landscapes like the distance from the river and river channel pattern in shaping human settlements or presence as a potential flood hazard in Chapter 2, However, with an increase in population, there has to be a growing need to understand the evolving exposure. Thus, in Chapter 4, I try to incorporate the understanding of utilising NTL as a proxy for human activities over time, the potential hydro-geomorphic flood hazard factors and the differential response to floods by the society, which I defined as three components of flood risk. This knowledge was applied to one of the largest basins in the world- Ganga, where about 107-135 million people live (Tellman et al., 2021). As per the UNDRR (2019) report, floods have the highest impact in Asia as the continent experienced >40% of all documented flooding events, with a total of 1.5 billion people affected, accounting for 95% of the people affected worldwide. However, a

hazard only becomes a disaster when human lives are lost and livelihoods are damaged or destroyed (UNDRR, 2019).

In chapter 4 of this study, I used the Analytical Hierarchy Process (AHP), which was a Multi-criteria decision model which involves assumptions and introduces uncertainties for complex interactions (Mukhtar et al., 2024). However, the AHP method, with the integration of remote sensing and GIS, provides a powerful tool for integrating multiple information, preparing flood impact maps, and providing more accurate insights on flood risk. Although many studies have shown that an increase in human population and climate change are the main factors for the occurrence of extreme floods leading to a disaster, it should also be noted that natural hydro-geomorphic factors such as elevation, slope, flow accumulation, distance to the rivers, drainage density, geomorphology, rainfall and distance from the confluence also provide the conditions for floods to occur and thus contributing to potential flood hazard.

This research represents a first-of-its-kind effort to utilise night-time lights data by providing a novel approach for assessing flood risk in the region. The study advocates a holistic approach to understanding flood risk that should include potential flood hazard factors, exposure and vulnerability.

5.3.Future Work

Based on the work presented in this thesis, I identify the following research questions that would be fruitful to address within the wider community using geospatial tools to study and mitigate natural disasters.

5.3.1. Machine Learning for Predicting Risk

Flood risk assessment is crucial for effective risk management, focusing on identifying areas that are highly susceptible to flooding during heavy rainfall events. Such identification is essential for guiding development planning, disaster prevention, and

mitigation efforts (Elshorbagy et al., 2017). In recent years, machine learning models (MLMs) have proven to be reliable tools for flood risk assessment, using intelligent algorithms to autonomously detect flood risk patterns. These models offer a more objective approach compared to traditional multi-criteria decision analysis (MCDA) and are less reliant on high-resolution data and extensive preprocessing (Ghosh and Das, 2020; Lin et al., 2020). A significant drawback of process-based models, such as the Analytical Hierarchy Process (AHP), includes the need for substantial input data, the dependence on expert-derived weights for input factors, and the pairwise comparison method, which introduces biases and subjectivity, reducing their general applicability. Additionally, these models have limited effectiveness at regional scales.

Machine learning (ML) has gained popularity in environmental and ecological modelling because it offers several advantages, such as handling data from multiple sources with different measurement scales requiring no prior statistical assumptions (Hong et al., 2016). As a result, MLMs support flood susceptibility mapping by identifying vulnerable areas through the integration of various flood-influencing factors, such as geological, hydrological, topographical, and morphological conditions (Chen et al., 2021). Commonly used MLMs for flood susceptibility studies include Decision Trees, Support Vector Machines, Artificial Neural Networks, Classification and Regression Trees, Adaptive Neuro-Fuzzy Inference Systems, and Random Forests (Chen et al., 2021; Tehrany et al., 2019; Safizadeh et al., 2018; Termeh et al., 2018; Zhao et al., 2018).

Despite the advancements in flood risk modelling using MLMs, several challenges remain. Notably, the effectiveness of flood susceptibility models is contingent upon the selection of appropriate flood-affecting factors, as not all factors contribute equally to flood risk. Furthermore, existing studies often focus on specific geographic areas, limiting their applicability to broader contexts. This lack of comprehensive analysis at various risk levels restricts the understanding of flood risk mechanisms and inhibits the effective identification of high-risk areas in different regions. In future work, it would be

helpful to understand the various flood conditioning and flood exposure factors responsible for the catastrophic impacts. The results of the flood risk in the Ganga basin from Chapter 4 can be further used to train the model for assessing flood risk at a larger spatial scale. This will enhance the predictive capabilities of machine learning applications in flood risk assessment and foster more informed decision-making in disaster management and urban planning.

5.3.2. Spatial scale refinement of the impact maps

Images of artificial lights at night directly observe human activity from space and, therefore, enable several remote sensing applications either unique to night light sensing (e.g. monitoring illegal fishing, remotely sensing lighting technologies) or strongly complementing other types of remote sensing (e.g. evaluating the impacts of armed conflicts and disasters and the recovery from them, quantifying temporary and seasonal changes in population, studying urban change). In section 5.2.1, I discussed that the NTL data used in the study are of a minimum spatial resolution of 500m, which was used to study the impact of the 2022 Indus floods and for studying varying exposure. The change in radiance maps currently does not give information about the type of land affected-like the building, industrial, roads or agricultural lands. Thus, combining the NTL-derived impact maps with another dataset, like the Open Street Map, settlement type, and land use land cover, will help to identify other details like damaged building infrastructure. This shall aid in fine-scaling the data and developing a comprehensive methodology incorporating multiple data for giving real-time damage information.

5.3.3. Fieldwork and collaboration with policymakers

In my research, I used geospatial data and tools to understand the controls of flood risk and identify areas having an increasing trend of flood risk within the Basin. While geospatial analysis provides valuable insights, addressing flood risk requires a holistic approach that extends beyond data interpretation. As a next step, it is essential to

integrate fieldwork to validate and refine the results derived from geospatial models. Ground validation through on-site investigation is crucial for improving the accuracy of flood risk assessments, as it enables the identification of local variables—such as infrastructure conditions—that may not be fully captured by remote sensing tools.

To support this field-based approach, building partnerships with local non-governmental organisations (NGOs) and academic institutions is essential. These partnerships can facilitate access to resources, logistical support, and specialised expertise needed for comprehensive fieldwork. Collaborating with these entities would enable a more thorough and community-centred evaluation of flood risk, fostering a deeper understanding of how social, economic, and environmental factors intersect to shape vulnerability. Moreover, community engagement through fieldwork is crucial for raising awareness about flood risks and empowering local populations to contribute to risk mitigation efforts. By involving local stakeholders in data collection and flood risk assessment, researchers and policymakers can ensure that the solutions developed are not only technically sound but also culturally appropriate and responsive to the needs of affected populations. In addition, I advocate for the increased use of night-time lights (NTL) data by policymakers to facilitate rapid disaster assessment. However, NTL and other geospatial techniques must be cross-validated through rigorous field studies to ensure that risk identification aligns with real-world conditions. A synergy between cutting-edge geospatial technologies and ground-level investigations will lead to more robust flood management strategies, ultimately helping to protect vulnerable communities and ecosystems within the Basin.

Chapter 6: Conclusion

This thesis contains three technical chapters that draw on the approach of investigating the landscape drivers shaping the human presence, the consequential flood impacts and building up an approach for flood-risk assessment in the Indus-Ganga Basin. The highlight of the study has been using the night-time lights (NTL) as a proxy for human presence or human activities in place of the traditional or conventional population data, providing information at higher temporal frequency. Here, I briefly summarise the key takeaways of the work and how it adds to the knowledge of the role of landscape in influencing human presence and the utility of night light data for studying flood exposure and vulnerability.

In Chapter 2, I demonstrate the use of night-time light data relationship between river geomorphology and human presence, using DMSP night-time lights as a proxy for human activity in the Indus Basin. Major findings include:

1. **Validation of Night-time Lights as a Proxy of Human Presence:** A moderate correlation (0.655) between DMSP lights and LandScan population data validated the use of nightlights to measure human activity.
2. **Proximity to Major Rivers:** Human activity, as indicated by nightlight intensity, was 26% higher within 0-5 km of major rivers and 11% higher in the 5-10 km range, reflecting settlements near rivers, though denser settlements were located further from the rivers.
3. **Channel Pattern Influence:** Single-thread (meandering) rivers saw an 18% higher human presence within 0-5 km due to stable banks, whereas multi-thread channels had higher nightlight intensities beyond 5 km due to flooding risks close to the river. This research emphasised how geomorphology affects settlement patterns and flood vulnerability.

In Chapter 3, I created a framework to assess the impact of floods using Night-time Light (NTL) data applied to the 2022 Indus floods. Key conclusions include:

1. **Temporal Decline in Radiance:** Weekly NTL data showed an 80-85% decline in radiance over 15 weeks during the 2022 floods, highlighting the extent of flood impact on human activity. This reduction lasted longer than the rainfall or flooding period, showing the compound effects of flooding.
2. **Spatial Impact Analysis:** The spatial extent of lit pixels declined significantly from May to October 2022, with the NTL-derived flood impact extending beyond water inundation boundaries detected by conventional SAR data, indicating additional disruptions such as power outages and infrastructure damage.
3. **Urban vs. Rural Impact:** Rural areas experienced greater exposure but quicker recovery than urban centres, although the economic losses were higher in cities. The framework offered a rapid, cost-effective way to assess flood vulnerability, especially in less accessible rural areas.

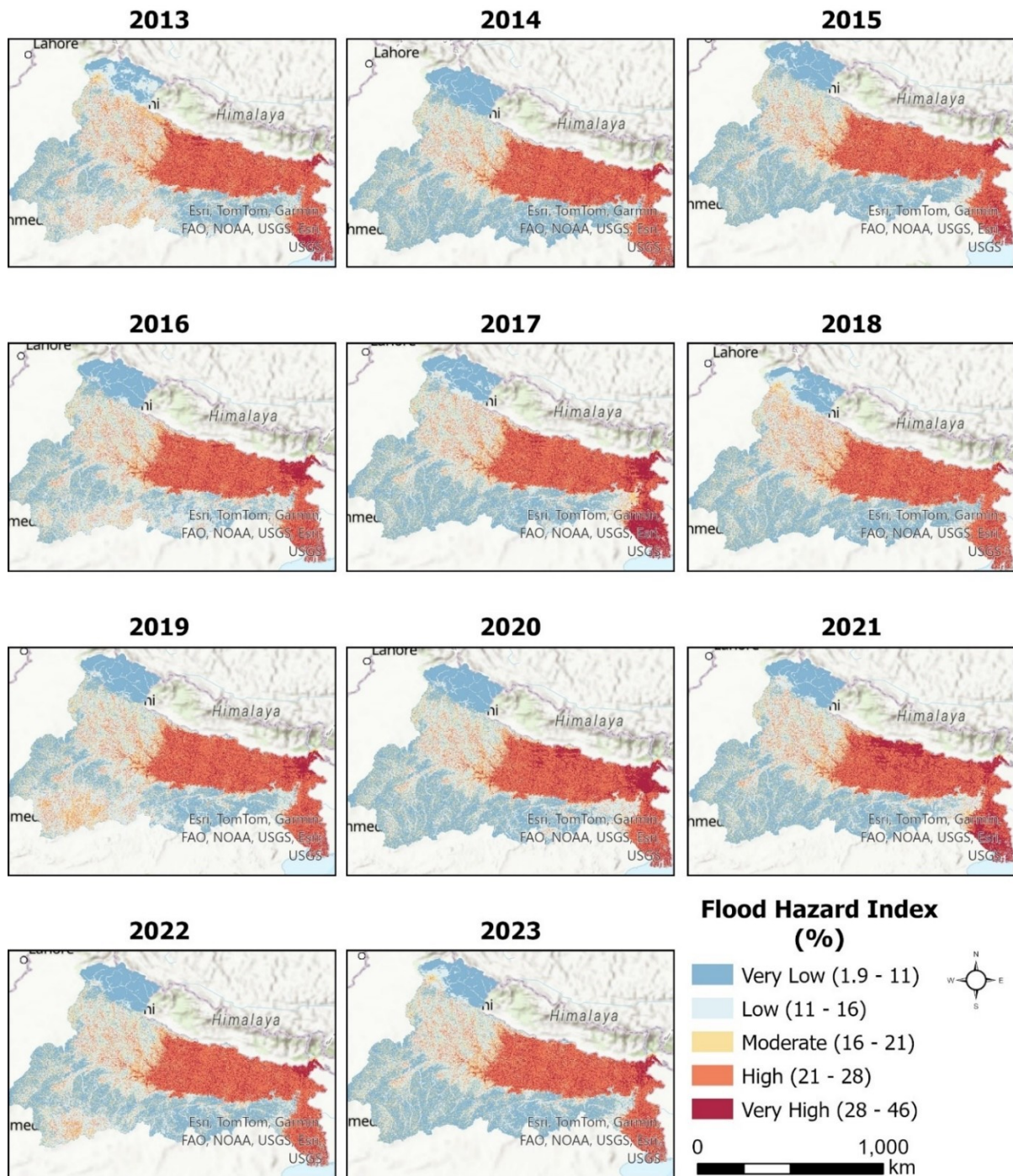
Lastly, in Chapter 4, I developed a comprehensive approach to flood risk assessment by combining flood hazard, exposure, and vulnerability components in the Ganga Basin. Major conclusions include:

1. **Flood Hazard Index (FHI):** Based on the hydro-geomorphic factors and their weights - The factors and their relative weights derived were - elevation (31%), slope (21%), rainfall (15%), distance from the river (12%), distance from the confluence (8%), flow accumulation (6%), drainage density (5%) and geomorphology (2%), the FHI was mapped annually from 2013 to 2023, identifying areas of high flood susceptibility.
2. **Flood Exposure Index (FEI):** Leveraging NTL data over the same period, the FEI captured real-time changes in human activity, complementing traditional flood exposure mapping methods.

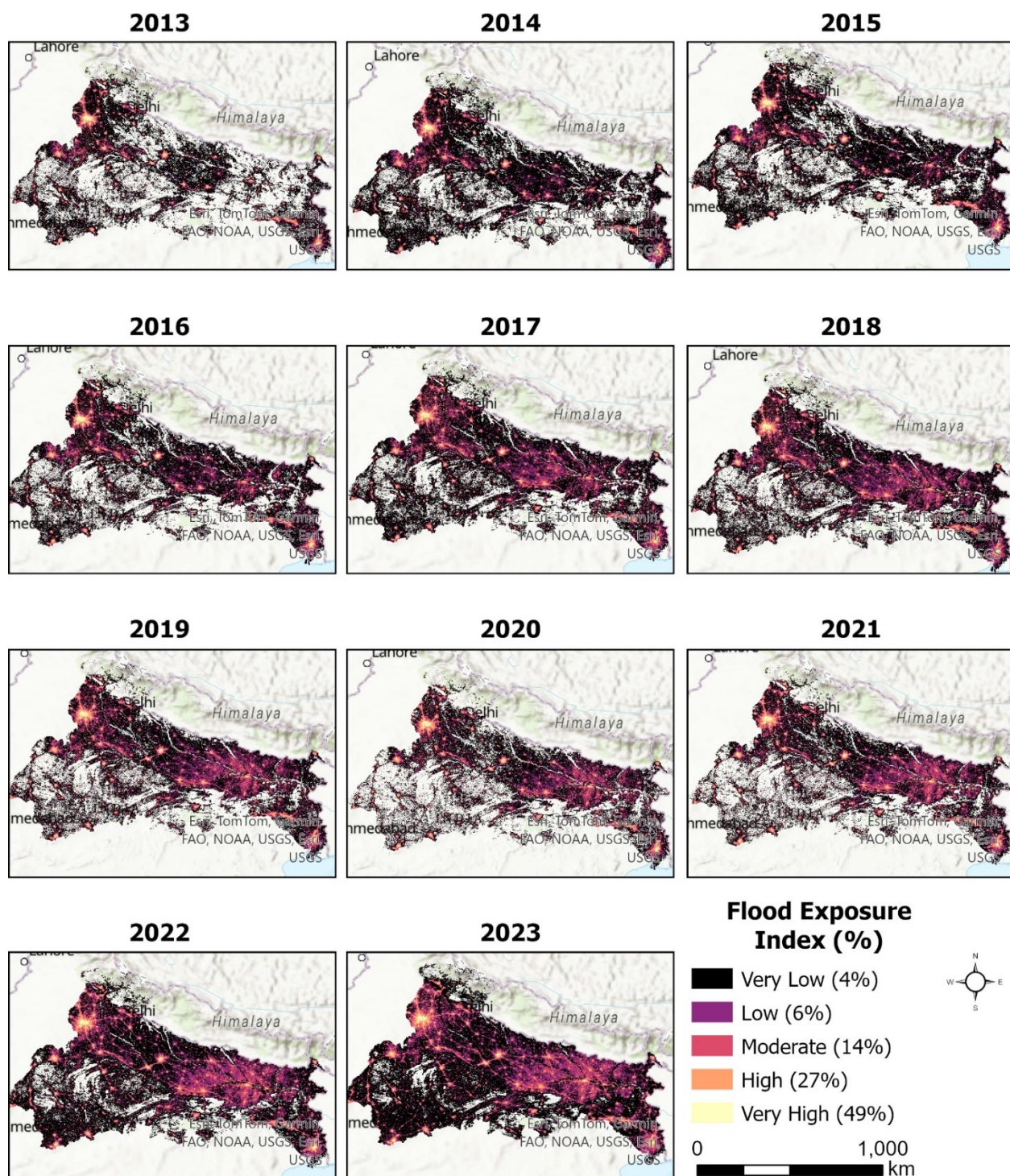
3. **Flood Risk Trends:** Combining FHI, FEI, and a vulnerability index (FVI) created annual flood risk maps. The research highlighted an increasing flood risk trend in the eastern Ganga Basin, while some high-hazard areas showed low flood risk due to lower exposure. A model validation using ROC-AUC yielded a satisfactory score of 0.69, showcasing the model's predictive accuracy. This study introduced an innovative approach for flood risk assessment and monitoring using NTL data.

Overall, the thesis showcases the utility of nightlight data in understanding the relationship between landscape and human presence and associated flood risk.

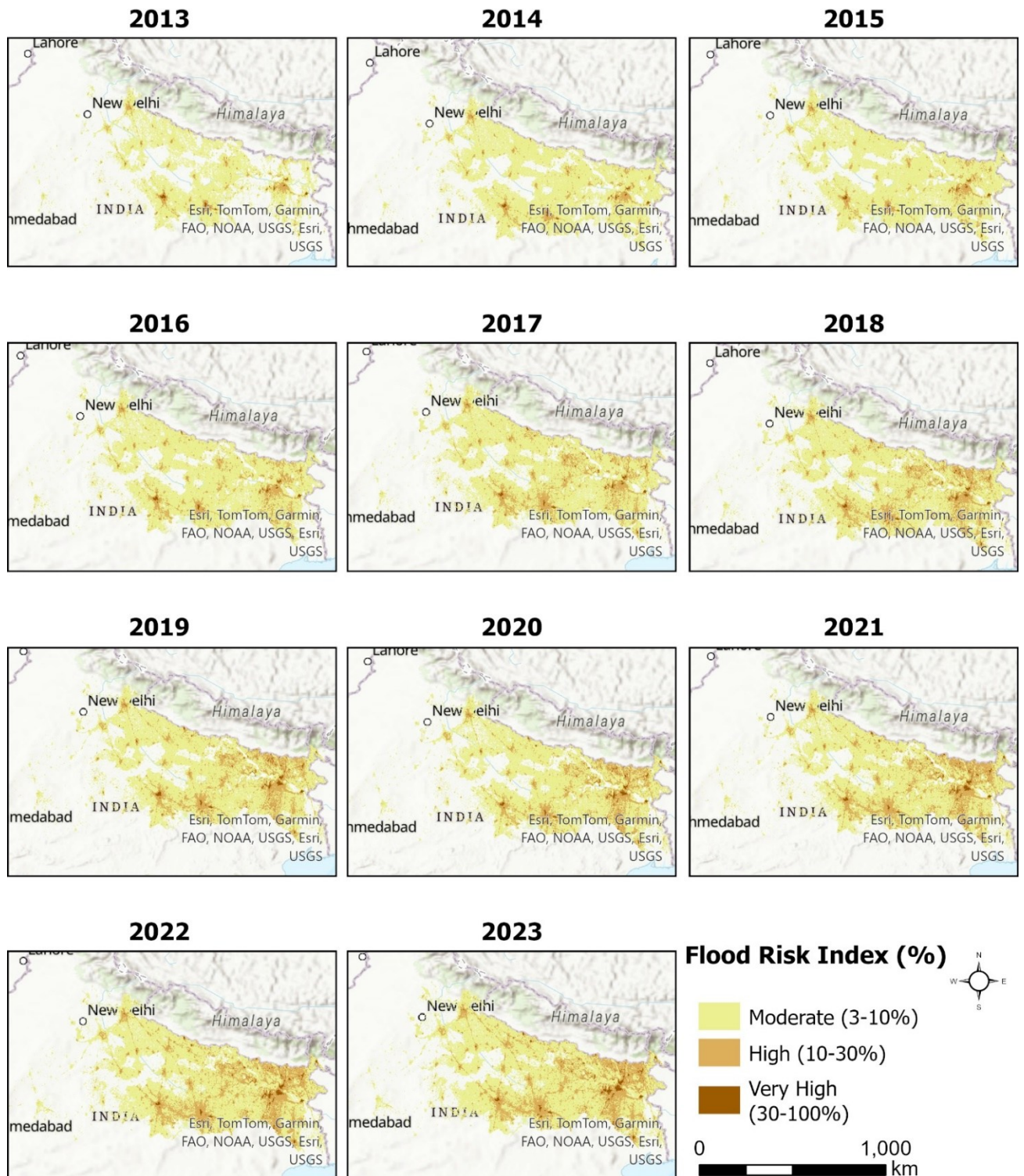
Supplementary



Supplementary Figure 1: Flood Hazard Index plots from 2013 to 2023. Continuous data ranging from 1.9 to ca. 46% are classified into five categories: Very Low, Low, Moderate, High and Very High FHI. In the figure, the blue areas have low FHI values, indicating less potential for flood occurrence or flood hazard, and red areas have higher flood hazard values, suggesting higher susceptibility to floods.



Supplementary Figure 2: FEI plots from 2013-2023 across the Ganga Basin produced after the AHP. The FEI is categorised into five classes based on the unique values of weights derived, which are Very Low (4%), Low (6%), Moderate (14%), High (27%) and Very High (49%).



Supplementary Figure 3: Normalised flood risk index (FRI) map of the Ganga Basin. The FRI are shown in three categories- Yellow indicates moderate risk (3-10%), orange represents high risk (10-30%), and brown denotes very high risk (30-100%).

Supplementary Table 1: Level 1 pairwise comparison for the flood hazard parameters

		E	S	R	DR	DC	DD	FA	G	RW (Relative Weights)
Elevation	E	1	2	3	3	4	5	6	7	0.31
Slope	S	1/2	1	2	2	3	4	5	6	0.21
Rainfall	R	1/3	1/2	1	2	2	3	4	5	0.15
Distance to the river	D R	1/3	1/2	1/2	1	2	3	4	5	0.12
Distance from river confluence	D C	1/4	1/3	1/2	1/2	1	2	2	5	0.08
Drainage Density	D D	1/5	1/4	1/3	1/3	1/2	1	2	4	0.06
Flow Accumulation	FA	1/7	1/5	1/4	1/4	1/2	1/2	1	4	0.05
Geomorphology	G	1/8	1/6	1/5	1/5	1/5	1/4	1/4	1	0.02
$\lambda_{\max} = 8.334$; C.I. = 0.047; RI = 1.41; CR = 0.033										

Supplementary Table 2: Level 2 hierarchy elevation

Elevation (in meters)							
		0-115	115-130	130-250	250-1,115	1,115-8,000	RW (Relative Weights)
0-115		1	3	5	6	7	0.49
115-130		1/3	1	3	5	6	0.27
130-250		1/5	1/3	1	3	4	0.14
250-1,115		1/6	1/5	1/3	1	2	0.06
1,115-8,000		1/7	1/6	1/4	1/2	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

Supplementary Table 3: Level 2 hierarchy slope

Slope (in degrees)							RW (Relative Weights)
		0-1.5	1.5-1.7	1.7-3.2	3.2-13	13-90	
0-1.5		1	3	5	6	7	0.49
1.5-1.7		1/3	1	3	5	6	0.27
1.7-3.2		1/5	1/3	1	3	4	0.14
3.2-13		1/6	1/5	1/3	1	2	0.06
13-90		1/7	1/6	1/4	½	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

Supplementary Table 4: Level 2 hierarchy for rainfall

Rainfall (in mm/month)							RW (Relative Weights)
		>350	290-350	260-290	200-260	0-200	
>350		1	3	5	6	7	0.49
290-350		1/3	1	3	5	6	0.27
260-290		1/5	1/3	1	3	4	0.14
200-260		1/6	1/5	1/3	1	2	0.06
0-200		1/7	1/6	1/4	1/2	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

Supplementary Table 5: Level 2 hierarchy for distance to the river

Distance to the river (in meters)									RW (Relative Weights)
		0-500	500-1000	1000-1500	1500-2000	2000-2500	2500-3000	3000-3500	
0-500		1	3	4	5	5	6	8	0.37
500-1000		1/3	1	3	4	5	6	7	0.24
1000-1500		1/4	1/3	1	3	4	5	7	0.16
1500-2000		1/5	1/4	1/3	1	3	4	6	0.10
2000-2500		1/5	1/5	1/4	1/3	1	3	5	0.07
2500-3000		1/6	1/6	1/5	1/4	1/3	1	3	0.04

3000-3500		1/8	1/7	1/7	1/6	1/5	1/3	1	0.02
$\lambda_{\max} = 7.743$; C.I. = 0.124; RI = 1.32; CR = 0.094									

Supplementary Table 6: Level 2 hierarchy for the distance to the confluence points

Distance to the confluence (in meters)							RW (Relative Weights)
		0-500	500-1000	1000-1500	1500-2000	2000-3000	
0-500		1	3	5	6	7	0.49
500-1000		1/3	1	3	5	6	0.27
1000-1500		1/5	1/3	1	3	4	0.14
1500-2000		1/6	1/5	1/3	1	2	0.06
2000-3000		1/7	1/6	1/4	1/2	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

Supplementary Table 7: Level 2 hierarchy for the drainage density

Drainage Density (in meter ⁻¹)							RW (Relative Weights)
		0.000089-0.000155	0.000052-0.000089	0.000032-0.000052	0.00002-0.000032	0-0.00002	
0.000089-0.000155		1	3	5	6	7	0.49
0.000052-0.000089		1/3	1	3	5	6	0.27
0.000032-0.000052		1/5	1/3	1	3	4	0.14
0.00002-0.000032		1/6	1/5	1/3	1	2	0.06
0-0.00002		1/7	1/6	1/4	1/2	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

Supplementary Table 8: Level 2 hierarchy for flow accumulation (unit cells)

Flow Accumulation							RW (Relative Weights)
		314-3800	26-324	2-26	1-2	0-1	
314-3800		1	3	5	6	7	0.49
26-314		1/3	1	3	5	6	0.27
2-26		1/5	1/3	1	3	4	0.14
1-2		1/6	1/5	1/3	1	2	0.06
0-1		1/7	1/6	1/4	1/2	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

Supplementary Table 9: Level 2 hierarchy for geomorphology

Geomorphology												RW (Relative Weights)
		AF	OF	AP	WB	C	AT	PP	P	HV	AOP	
Active floodplains	AF	1	3	4	5	5	6	6	7	8	8	0.29
older floodplains	OF	1/3	1	3	4	5	6	7	7	8	8	0.21
alluvial plains	AP	1/4	1/3	1	2	3	5	6	6	7	8	0.14
water bodies	WB	1/5	1/4	1/2	1	2	3	5	6	6	7	0.10
coastal	C	1/5	1/5	1/3	1/2	1	3	4	5	6	7	0.09
anthropogenic terrain	AT	1/6	1/6	1/5	1/3	1/3	1	3	5	6	7	0.07
pediment-peneplain	PP	1/6	1/7	1/6	1/5	1/4	1/3	1	2	3	5	0.04
plateau	P	1/7	1/7	1/6	1/6	1/5	1/5	1/2	1	2	3	0.03
hills and valleys	HV	1/8	1/8	1/7	1/6	1/6	1/6	1/3	1/2	1	3	0.02
aeolian plane	AOP	1/8	1/8	1/8	1/7	1/7	1/7	1/5	1/3	1/3	1	0.01
$\lambda_{\max} = 11.31$; C.I. = 0.146; RI = 1.49; CR = 0.098												

Supplementary Table 10: Level 1 Hierarchy of Exposure using night time lights.

Night-time Light Intensity							RW (Relative Weights)
		>=293	293-34	34-17	17-10	0-10	
>=293		1	3	5	6	7	0.49
34-293		1/3	1	3	5	6	0.27
17-34		1/5	1/3	1	3	4	0.14
10-17		1/6	1/5	1/3	1	2	0.06
0-10		1/7	1/6	1/4	1/2	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

Supplementary Table 11: Level 1 Hierarchy of Vulnerability Index from the Climate Vulnerability Report

Flood Vulnerability Index							RW (Relative Weights)
		0.65-0.73	0.575-0.65	0.5-0.575	0.425-0.5	0.35-0.425	
0.65-0.73		1	3	5	6	7	0.49
0.575-0.65		1/3	1	3	5	6	0.27
0.5-0.575		1/5	1/3	1	3	4	0.14
0.425-0.5		1/6	1/5	1/3	1	2	0.06
0.35-0.425		1/7	1/6	1/4	1/2	1	0.04
$\lambda_{\max} = 5.228$; C.I. = 0.057; RI = 1.12; CR = 0.051							

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