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ARTICLE

AI Based Urban Resilience Planning: Opportunities and Challenges

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ABSTRACT

Urban areas across the globe are confronting escalating flood risks, a crisis exacerbated by the effects of climate change, which necessitates precise hyper-localized risk assessments. This research introduces the application of the AI for resilient cities model for flood risk assessment, focusing specifically on the vulnerable area of Penthakata, located in the coastal city of Puri, Odisha. The hyper-local evaluation of associated flood risks is carried out, particularly at the building level. Leveraging cutting-edge geospatial technology, deep learning methodologies, and multi-parameter analysis, this study offers valuable insights into the flood vulnerabilities in the region. Additionally, the research emphasizes the integration of technology with community volunteers and local knowledge, highlighting the essential role of grassroots-level efforts in effective disaster management. The model is one of its kind combining advanced AI technology with community engagement, the study contributes to a holistic and localized approach to strengthen adaptive capacity in the face of increasing flood risks. The findings offer a compelling case for the adoption of hyperlocal risk assessments for urban and rural areas to be better informed of flood risks, prepared for potential disasters, and implement more effective mitigative measures. Ultimately, it aims to safeguard the lives and livelihoods of vulnerable communities of various regions, offering a model for spatial environmental and community resilience.

Keywords: Flood risk; Community; Hyperlocal assessment; Climate change; Disaster; Artificial Intelligence

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1. Introduction

Natural hazards have caused severe consequences to the natural, modified, and human systems, in the past. These consequences seem to increase with time due to both the higher intensity of the natural phenomena and higher value of elements at risk [1]. India is highly vulnerable to floods. Out of the total geographical area of 329 million hectares (mha), more than 40 mha is flood-prone [2]. With the increase in population and development activity, there has been a tendency to occupy the floodplains, which has resulted in damage of a more serious nature over the years [3]. Urban floods are the single most frequent disaster faced by the country [4]. Among the hydrological hazards, flood hazards have the most destructive impacts. The intent is to optimize emergency preparedness response and provide support on the ground [5]. The escalating frequency and intensity of extreme weather events, exacerbated by climate change, have outlined the imperative need for precise flood risk assessments. Floods in developing countries can destroy decades of infrastructure investments, severely impair economic development, and cause diseases and fatalities [6].

The hyper-local evaluation of associated flood risks is carried out, particularly at the building level. Traditionally, flood risk assessments have been conducted on a larger regional or sub-regional scale depending on the hydrological data, often encompassing vast geographical areas [7]. However, this approach can dilute variations in risk levels in an attempt to scale down the local area level and further at the building level, where factors like terrain, land use land cover, roof typology and building footprint/ plinth area can significantly impact on flood risks. While flood risk analysis has been a focal point of research, a noticeable gap persists in hyper-localised risk assessments scaled at individual buildings which would have direct implications at a local level response and community level strategies for risk reduction and response planning. The flood-generating parameters were researched for the development of the risk assessment [8]. Many methods can be used to incorporate the different parameters into Python scripts for flood risk assessment and management. With respect to the parameters, the Multi-Criteria Decision Analysis (MCDA) method was selected and the same has been increasingly used for combining, integrating, and evaluating flood risk-related factors [9]. One of the common MCDA techniques, the Analytic Hierarchy Process (AHP), was used to determine the flood risk. The assessment further utilises advanced geospatial techniques, machine learning, and multi-parameter analysis to assess flood risk at a granular level. The application of Artificial Intelligence (AI) holds the potential to enhance the need for effective strategic disaster risk management (DRM) through improved decision-making processes, that can safeguard impacts on communities and economies [10]. This study aims to identify the flood risk at high resolution and eventually at a building structure level depending on the dataset's availability, while establishing a community edge for effective outreach.

Communities are increasingly affected by challenges posed by naturally triggered disasters, including floods. In many regions, particularly those vulnerable to flooding like India, engaging communities becomes an essential component of disaster management [11]. The innovation in flood risk assessment goes beyond data and algorithms. It intertwines the power of technology with the strength of community involvement, creating a holistic approach to flood resilience. Recognising that communities residing in high-risk areas are often the most affected during flood events, it is essential to explore various approaches to community involvement through a multifaceted strategy that seeks to empower, educate, and mobilise communities at severe flood risk [12]. In the case of Odisha, which is considered as one of the major states to face catastrophic events such as cyclone, flood etc. bears heavy economical loss, which is estimated at approximately $696 million or Rs 420 crore. In a decade, it has struck Odisha more than 3 times on the coastal region of Puri district [13]. Taking this in account, an initiative is set out for an effective bottom-up framework in place for local-level disaster risk planning for various communities, governments, and stakeholders to not only respond to disasters but to proactively prepare and mitigate risks.

The current flood risk forecasting relies on data from two sources, the Central Water Commission (CWC), and the Indian Meteorological Department (IMD). However, a recurring challenge persists as these sources frequently deliver messages that lack or inadequately cover actionable insights at the ground level with a resolution that is relatable for impacted families and individuals. Consequently, a substantial gap emerges in terms of preparedness for potential flood events. To combat this issue effectively, it is imperative to focus on the development of innovative techniques capable of scrutinising flood risks at a hyper-local or granular level, thereby providing the essential data required for formulating robust urban resilience strategies. Additionally, the unpredictability of rain forecasts often leads to heavy disruptions and necessitates extensive rehabilitation efforts [14]. To minimise the impact of such events, it is essential to develop a short window or directional dispersal path. This approach requires building-level data and implementing the best-mitigating systems to identify resources at greater risk. Hyperlocal disaster risk assessment using AI-based geospatial technology models plays a crucial role in urban resilience planning, particularly safeguarding vulnerable communities [15]. By leveraging granular-level data, such as real-time weather conditions, socio-economic factors, and detailed topographical information, these advanced models can accurately predict and assess flood risks at a very local scale. This precision allows for tailored interventions and resource allocation, ensuring that the most at-risk populations receive timely support. Integrating such technology aligns with SDG 9 by promoting infrastructure growth to improve the local economy by predicting and assessing climate risks; SDG 11 by catering to diverse groups of communities within the settlement, helps in enhancing safety and inclusivity of urban environments; SDG 13 by building resilient city with climate mitigation strategies and adaptive capacity using technological interventions and SDG 17 by educating communities for capacity development and encouraging collaboration and partnerships with different level of stakeholders. This holistic approach not only mitigates the impact of disasters but also fosters a sustainable and resilient urban future [16]. Ultimately, this comprehensive approach aims to minimise the need for extensive rehabilitation efforts, thereby enhancing overall disaster preparedness and response mechanisms.

2. Study area

Penthakata, located at approximately 19°48'28.65" N latitude and 85°51'8.86" E longitude, is a densely populated locality in the coastal city of Puri, Odisha, India (see **Figure 1**). The history of this area reflects its transformation from a temporary fishing settlement in the 1950s, with families from Andhra Pradesh residing seasonally, into a mini township focused on the tourism and hotel industry. Over time, it has become a permanent residential colony, with certain areas designated as Ward No. 26 and Ward No. 32 by the Puri municipality.

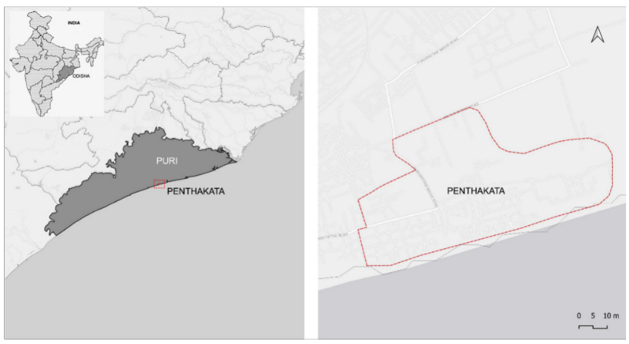

Figure 1. Penthakata Puri-Locational characterization.

The area features a mix of housing types, including slums, kutcha (temporary), semi-kutcha (semi-permanent), and pucca (permanent) houses. The buildings often showcase folk art on their frontages [17]. It is known for its vibrant atmosphere and its proximity to the sacred Jagannath Temple. However, Penthakata is also highly susceptible to flooding due to its geographical characteristics, including low-lying terrain and its adjacency to the Bay of Bengal.

The susceptibility to flooding in Penthakata has led to recurrent flooding events, causing significant economic losses for its residents. The area features a mix of building types, ranging from traditional structures to more multi-story buildings, highlighting the need for localised flood risk assessments tailored to the unique characteristics of the locality.

As urbanisation continues to reshape Penthakata, it is crucial to understand flood vulnerabilities at the building level. This understanding is essential for effective disaster management and resilience-building strategies specific to Penthakata. This research aims to utilise the ResSolv AI model to assess flood risk in a hyper-localised manner within Penthakata. This research identifies high-risk areas within the locality and provides insights into flood vulnerability, particularly in informal settlements.

3. Data collection

Different sources of data have been collected, processed, and integrated. Both digital image processing and GIS software have been used to carry out the technical analysis of these data. **Table 1** summarizes the different data types used in this study. The digital elevation model (DEM) from SRTM with 30 m resolution of the study area has been obtained from https://earthexplorer.usgs.gov/. The SRTM (DEM) data were acquired in 2016 and used to extract the hydrographic parameter and geo-morphological assessment with slope and elevation. The Landsat-8 OLI image with 30 m spatial resolution is available on the United States Geological Survey (USGS) Website (http://earthexplorer.usgs.gov). The Landsat bands are used to obtain land use land cover, vegetation cover, built-up area, and further primarily derived areas prone to landslide.

Table 1. Summary of the input datasets.

Input data type	Scale	Derived data	Derived data
Waterbodies	-	Waterbodies Polygon-lakes, ponds, water storage; Waterbodies Line-Rivers, streams, canals; Buffer distance from water bodies	Open street map
Ocean data	-	Ocean polygon	Natural earth
Digital Elevation Model (DEM)	30 m	Elevation, slope curvature, flow accumulation, topographic wetness index, landslide risk	SRTM
Road Data	-	Buffer distance from roads	Open street map
Landsat Data	30 m	Impervious surfaces, NDVI & NDBI	USGS earth explorer
Satellite Imagery	1–5m	Building Footprint, Building roof type	Base map

3.1 Water bodies

The major cause of flooding in the region is heavy rainfall in the catchment areas of rivers and poorly drained areas. When the level of water rises above the riverbanks or dams, the water starts to overflow. The water overflows into the areas adjoining to the rivers, and lakes, causing floods or deluge [18]. In addition, storm surge-related flooding is experienced in areas adjacent to the shoreline, and localised heavy rainfall also results in local inundation, particularly when the water bodies are already in high flows or water levels. Open street maps provide the dataset of waterbodies in the format of ponds, lakes, other water storages and flowing water like rivers and streams. This dataset can be easily procured from an open API. Water Bodies are used as an input on which further intermediate calculations are done.

3.2 Ocean data

When sea levels rise as rapidly as they have been, even a small increase can have devastating effects on coastal habitats farther inland, it can cause destructive erosion, wetland flooding, aquifer, and agricultural soil contamination with salt, and lost habitat for fish, birds, and plants [19]. Natural Earth Data is a public domain map data provider, it has a dataset that gives ocean polygons split into contiguous places, which helps to understand the ocean available data in the area of interest.

3.3 Digital Elevation Model

Digital Elevation Models (DEM) are important inputs for topography for the accurate modelling of floodplain hydrodynamics [20]. Floodplains have a key role as natural retarding pools which attenuate flood waves and suppress flood peaks. Digital Elevation Models help to know the topographical characteristics of the area of interest such as elevation, slope, topographic wetness index etc. All of these elevation modelling processes are mentioned in the methodology section.

3.4 Road dataset

A very important feature of road construction is drainage. Older roads may have less sophisticated drainage, but all have features to take the water away from the road surface. It is necessary to clean and maintain these drainage provisions so that they can work properly. Problems can occur even when drainage provisions are clean and well-maintained [21]. Flooded and waterlogged roads result when the amount of water arriving on the road is greater than the capacity of the drainage facilities that take it away. Since the road surface itself is impervious in nature water tends to flow instead of percolating. This flowing water finds its way into the nearby settlements. The process of defining distance from the road is defined in the proximity calculations.

3.5 Landsat 8 data

Landsat 8 dataset is available from USGS Earth Explorer at 30m resolution. The Landsat 8 dataset has been available from 2013 onwards for the entire globe. This dataset helps to calculate various indices such as NDVI (Normalized Difference Vegetation Index) to understand the vegetation status of AOI and NDBI (Normalized Difference Built-Up Index) to understand the built-up and impervious surfaces present. The Landsat calculations helps to understand the surface features and get used as one of the input parameters in the AHP process.

3.6 High-res dataset

For the process of building footprint extraction models which also include information on the roof type, the most important parameter is high-resolution Geo TIFF images which can be labelled by identifying roof types with the naked eye. High resolution satellite datasets are present for the regions where the project initially took place. The acquisition of these high-resolution images is also straightforward and gives the images falling under AOI shapefile/KML.

4. Materials and methods

4.1 Concept of risk assessment

A flood is a condition in which a landscape is submerged in water due to heavy rainfall, storm surge, high-tides or any other natural cause of water overloading; it causes devastation in lives, resources and economy on a vast scale [22]. Floods are considered one of the most frequent natural disasters, causing many fatalities and damage every year [23]. Floods are expected to become more frequent under future climate conditions [24]. Flood risk can be described as the probability of an occurrence of flood hazard leading to an associated loss, or negative impact on society [25]. The risk of the flood is determined not only by the nature of the hazard, exposure to and vulnerability of the population and property, but also by the adaptation, improvement and anticipation of the affected population and ecosystem, collectively called "resilience of the environment" (See equation 1). Flood risks have been managed traditionally by using grey infrastructures, such as drainage systems [26], river dikes, dunes, dams, and others [19].

$$R - f(H, E, V) \tag{1}$$

where, R is Risk, H is Hazard, E is Exposure and V is Vulnerability. Flood risk evaluation methods according to Samanta et al. (2019) [27] include Statistical methods relating extreme events to their frequency of occurrence using probability distribution functions based on long-term historical/projected records, Geographical Information System (GIS) combined with remote sensing (RS) techniques can analyse the hazard, exposure, and vulnerability in the output layer based on the data from the input layer (terrain, rainstorm etc.), Scenario-based inundation analysis of risk immediately before its occurrence, but is restricted in terms of scale and uses geomorphology, topography, and urban drainage system data. The most apt flood risk evaluation techniques adopted include multi-criteria analysis, mostly combined with the Analytic Hierarchy Process, and based on an indexing system. The approach utilized for evaluating the parameters chosen to assess flood risk in the Penthakata region is depicted in the following flowchart (See **Figure 2**).

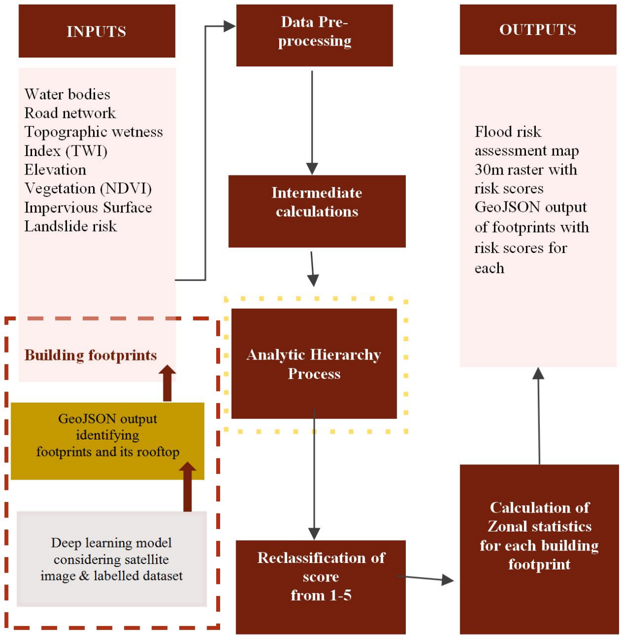

Figure 2. Flowchart of methodology.

4.2 Environmental factors

The environmental flood risk factors can be divided according to their temporally static or varying natures. The eight static factors identified in similar studies [28,29] are: waterbodies, road network, TWI, elevation, Vegetation, Impervious Surface and Topographic Wetness Index (TWI). The main temporally variable factor determining flood-susceptibility is precipitation recorded as daily time steps [30].

Water bodies

In this analysis, the water bodies input dataset is divided into two types: linear features comprising rivers, streams, and canals, and polygonal features including lakes, ponds, and water storage areas. These water bodies are associated with specific threshold values that determine their spatial significance within their surroundings. For linear water bodies, buffer zones are created at varying distances from the water's edge, with each buffer zone assigned a ranking based on predefined thresholds (See **Figure 3**). Similarly, for polygonal water bodies, buffers are established with distinct threshold values (See **Figure 4**).

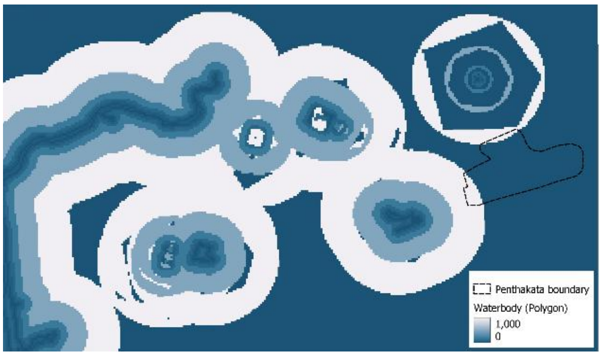

Figure 3. Buffer analysis for waterbody (polygon).

Figure 4. Buffer analysis for waterbody (line).

Ocean buffer

This input dataset involves creating concentric buffer zones around the ocean shapefile in QGIS (See **Figure 5**), treating it as a linear feature, to systematically evaluate its potential influence on flood vulnerability.

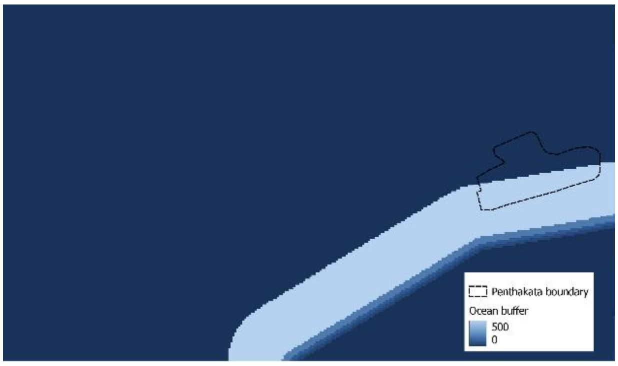

Figure 5. Proximity to ocean.

Road network

In the context of flood risk assessment, road network buffer analysis (See **Figure 6**) is a technique used to evaluate areas based on their proximity to road networks and their associated flood vulnerabilities. This analysis employs specific threshold values to categorize locations into different risk levels. Areas that are significantly distant from the roads and are at a lower risk of flooding associated with the road network.

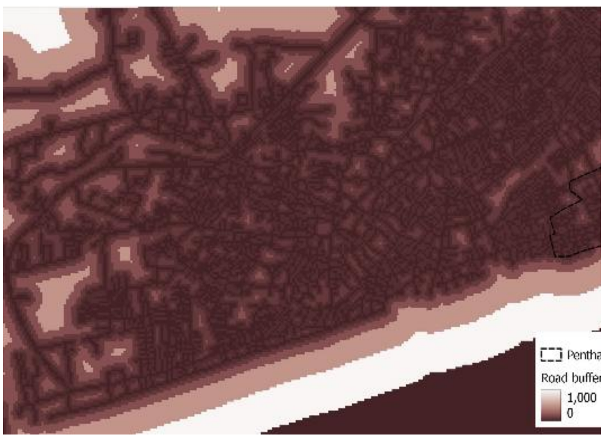

Figure 6. Proximity to road network.

Topographic wetness index

The topographic wetness index (TWI) relates upslope area as a measure of water flowing towards a certain point, to the local slope, which is a measure of subsurface lateral transmissivity [31]. TWI has gained widespread popularity for assessing wetness conditions, such as the position of shallow groundwater levels and soil moisture distribution. However, it's essential to note that TWI is a static measure and relies on the assumption that the local slope (tan(b)) adequately represents the effective hydraulic gradient downslope [26]. The topographic wetness index is defined as in (see equation 2):

$$TWI = \ln \frac{a}{\tan b} \tag{2}$$

where a is the local upslope area draining through a certain point per unit contour length.

For the calculation of flow accumulation, the D8 method was used. The D8 method assigns flow from a focal cell to one and only one of its 8 neighbouring cells. The chosen neighbour is the one accessed via the steepest slope. When such a neighbour does not exist, no flow direction is assigned. When two or more neighbours have the same slope, the chosen neighbour is the first one considered by the algorithm. This is a convergent, deterministic flow method. The accumulation values are gathered from the above calculations are then used with the slope in radiance to calculate the end output as TWI (See **Figure 7**). Since TWI does not have any specific unit it is referred to in numbers. Higher numbers represent higher risk in terms of waterlogging [32]. In the AHP-based flood risk analysis, TWI values are categorized into five ranks based on the range of standard deviation from the mean.

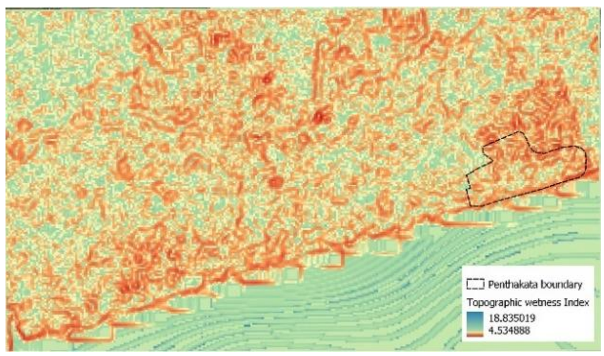

Figure 7. Topographic wetness index.

Elevation

The elevation input dataset derived from the Dem file was systematically divided into distinct elevation ranges (See **Figure 8**), each corresponding to a specific ranking for the flood risk assessment. The rank is based on the elevation range.

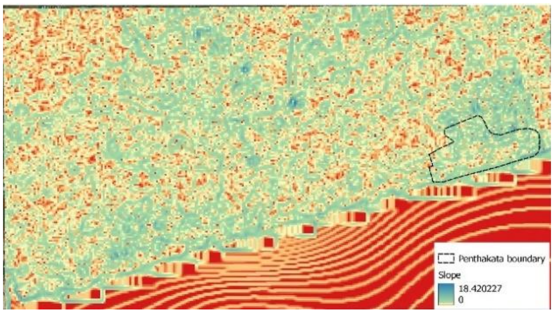

Figure 8. Elevation.

Vegetation (NDVI)

In recent decades, time-series data of the Normalized Difference Vegetation Index (NDVI) has gained substantial popularity as a valuable tool for tracking changes in vegetation patterns within terrestrial ecosystems. NDVI is calculated as a ratio difference between measured canopy reflectance in the red and near-infrared bands respectively [33]. The NDVI formula, expressed as $NDVI = \frac{(NIR - R)}{(NIR + R)}$, involves the near-infrared (NIR) and red (R) band from Landsat imagery. NIR represents the near-infrared band, while R stands for the red band. The formula quantifies the difference between these two spectral bands, enabling the inference of vegetation conditions. In the context of vegetation risk classification, specific threshold values have been established (see **Figure 9**) based on NDVI.

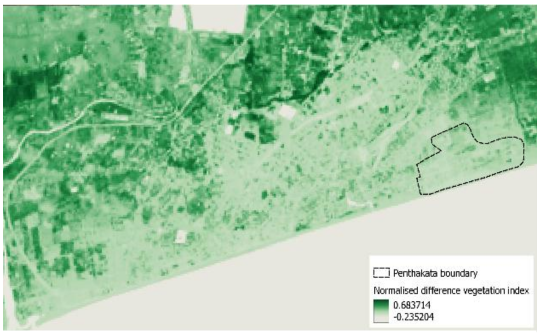

Figure 9. Normalized difference vegetation index.

Impervious surface

Impervious surfaces are surfaces covered by impervious materials and contain surfaces with low permeability, such as squares, pavements, roofs, and so on [34]. The extent and distribution of these impervious surfaces serve as indicators of a city's socio-economic development and urban infrastructure, reflecting how the city has evolved and grown over time. In urban planning, the extent of impervious surfaces is a key consideration. A higher percentage often correlates with an increased risk of urban flooding, prompting the need for better drainage systems and flood mitigation strategies to safeguard urban areas from flood hazards. Impervious surfaces are generally built-up areas excluding the parts of vegetation (See **Figure 9**), these can be also referred to as HARD surfaces. In this research, impervious surface is determined as follows:

$$Impervious\ surface = NDBI - NDVI$$

Where NDBI = Normalized Difference Built-up Index, NDVI = normalized difference vegetation index (see **Figure 10**).

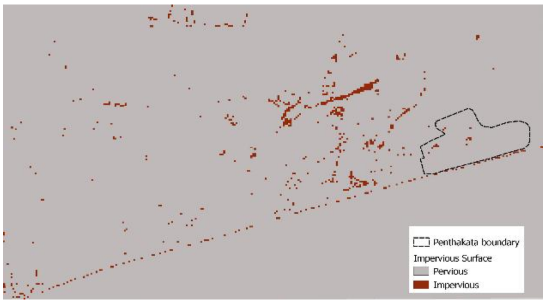

Figure 10. Impervious surfaces.

Landslide risk

Resilience AI has developed an evaluation matrix to understand the landslide risk at a place and is being utilised in the model. Using this evaluation matrix, the threshold values for the landslide input dataset are classified as the areas with landslide risk exceeding the mean plus 1.5 times the standard deviation is classified as having the highest risk (rank 5) (see **Figure 11**).

Figure 11. Landslide risk.

4.3 Building footprints and roof type classification

The proprietary high-resolution satellite used for the task of identifying building footprints and classifying building roof types was approached as a semantic segmentation problem. The objective was to extract structural information of different dwellings by creating identified polygons. The process involved several steps, starting with data collection and culminating in the application of a neural network-based model for accurate classification.

The acquired satellite imagery of 1m resolution, captured the intricate details required for accurate identification through image segmentation [35]. The approach to address this problem was to formulate it as multiclass semantic segmentation. More specifically, a Convolutional Neural Network (CNN)-based model was used to classify each pixel into one of the 8 possible classes: 7 dwelling types and the background class. The following are the rooftop classifications developed for the Puri Region:

(1) RCC
(2) CGI_Asb_1Slope
(3) CGI_Asb_2Slope
(4) CGI_Asb_4Slope
(5) Tile_2Slope
(6) Tile_4Slope
(7) Tarpaulin

The post-processing phase involved polygonising dwelling footprints from output maps, utilizing the Douglas-Peucker algorithm to preserve topology. This step enhanced the representation of dwellings for subsequent risk scoring.

Roof area

Built-up area refers to the portion of land that has been developed or covered with various man-made structures, including buildings, roads, parking lots, and other types of infrastructure. It is a measure of urbanization and land transformation within a given geographical area. The formula for calculating built-up area depends on the specific context and the data available. However, a common method for quantifying built-up areas in a GIS or remote sensing analysis is to use image classification techniques [36].

In the following assessment, the built-up areas/parcels are categorized into distinct rankings based on their size, reflecting the level of development within them [37].

4.4 Analytic hierarchy process

Multi-criteria programming, implemented through the application of the Analytic Hierarchy Process (AHP), serves as a valuable decision-making technique for addressing complex scenarios that involve the consideration of numerous variables and criteria when prioritizing and selecting alternatives or projects [38]. It provides a way to assess the degree of consistent judgment backed by a theoretical framework. The implementation of AHP commences with the systematic deconstruction of the problem at hand into a meticulously structured hierarchy of criteria (See **Figure 12**). This hierarchical framework is instrumental in rendering the elements more amenable to rigorous analysis and independent evaluation. The initial step in determining criteria weights involves establishing the preference order and assigning the degree of importance to each selected pair of criteria using a predefined scale. A pairwise comparison matrix is then constructed, where every criterion is assessed for its relative importance in comparison to the others. The following stage entails linear normalization of the pairwise comparison matrix: the sum of values in each column is calculated, and each element in the matrix is divided by this total. These comparative evaluations may draw upon empirical data associated with the alternatives or incorporate expert judgments, thus affording a channel for the assimilation of subjective information into the decision-making process. Subsequently, decision-makers are poised to methodically assess the available alternatives by conducting rigorous pairwise comparisons for each of the designated criteria.

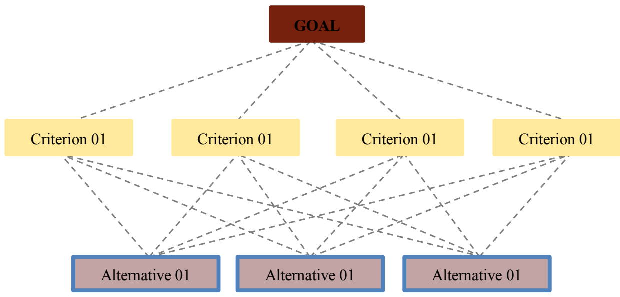

Figure 12. Analytic hierarchy process.

In the context of developing a flood risk assessment map for the Penthakata region, AHP was employed to analyse key parameters such as waterbodies, road network, elevation, vegetation, impervious surface, building typology, and Topographic Wetness Index (TWI). The AHP technique involved a systematic process wherein the criteria were prioritized, and the relative importance of each parameter was determined through pairwise comparisons. The Delphi technique was employed, ensuring a consensus-based and robust decision-making process. This comprehensive approach allowed for the integration of diverse factors, contributing to a more accurate and informed flood risk assessment map for the specified region.

5. Results and analysis

5.1 Flood risk assessment map

The flood risk map is generated by ResSolv tool developed by Resilience AI in collaboration with the not-for-profit organisation SEEDS. The model overlays each of the layers using the Delphi technique. The outcome of the flood risk assessment is an AI-driven disaster impact model specifically tailored for the Penthakata, Puri region in Odisha. This assessment meticulously categorizes buildings at an exceptionally granular, hyperlocal level, considering their unique vulnerabilities to flood risk. The risk assessments are divided into distinct score ranges, specifically 0 to 2, 2 to 3, and 3 to 4. Each range corresponds to a certain number of buildings categorized within, as 0, 3427, and 343, respectively. This comprehensive study encompassed an expansive area measuring 1.25 square kilometres, and within this vast expanse, it successfully identified and assessed 3,770 buildings with the help of high-definition satellite imagery. **Figure 13** shows the flood risk assessment results at a hyperlocal level after the U-Net algorithm run for Penthakata.

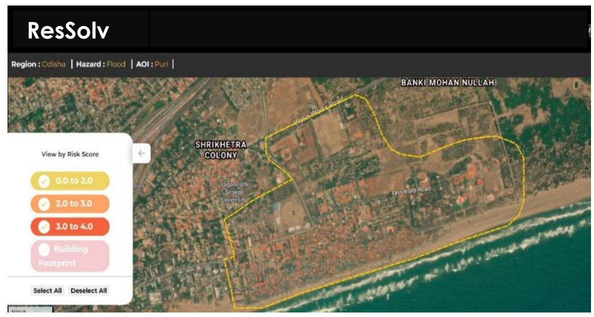

Figure 13. AI-based Flood vulnerability model results.

5.2 Community-driven ground truthing

The ground truthing process done in partnership with on ground partners involves a comprehensive assessment of various structural and non-structural parameters which engages the community at the grassroots level to validate the results obtained from the AI-based flood vulnerability model. In parallel, structural attributes are investigated, including architectural specifics like the number of building floors, the materials used for roofing and walls, as well as data pertaining to water levels during disaster events. Furthermore, non-structural factors, like power outages and toilet usability, are also part of the evaluation, along with post-disaster health concerns. The assessment extends to the identification of structural damage and the underlying causes, as well as the analysis of local risk factors and elements that help mitigate the impact of disasters. The process entails documenting temporary arrangements for sanitation, water, and food during disaster events. Lastly, visual documentation is facilitated through the inclusion of images portraying the surveyed properties and their immediate surroundings. The survey conducted at the household level following the flood in the Puri region provides valuable insights for the development of policies and interventions aimed at mitigating flood-related losses and enhancing disaster resilience.

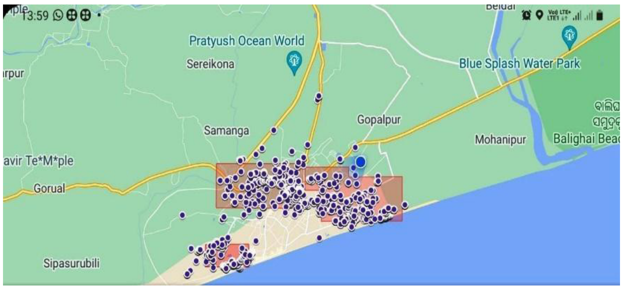

Figure 14. Ground truthing datapoints.

The study encompassed responses from a substantial number of 1676 households (see **Figure 14**). It is noteworthy that a significant portion of the respondents fall within the age range of 18–44 years, primarily comprising females. This demographic data underscores the importance of tailoring policies to address the specific needs and vulnerabilities of this age group and gender. Furthermore, the fact that 36% of respondents live within a mere 1 km of the nearest safe location highlights the urgency of establishing accessible evacuation routes and shelters. The identified causes of flooding are drainage blockages, low-lying areas, and proximity to the beach. Among the respondents, non-structural damages reported consist of issues like water seepage and minor damage to doors/windows. Remarkably, 12% of the respondents reported no damage to their homes. On the other hand, the structural damages identified a significant portion (47%) experienced substantial issues affecting their roofs, foundations, and walls, including roof collapses, or being blown away. Conversely, 15% of respondents reported no structural damage. The risks as reported by the respondents pertain to concerns like the presence of trees with shallow roots or weak trees, houses situated in low-lying areas, and the proximity of electrical poles. Hence, strategies can be formulated to address these specific aspects. By addressing these various facets, policymakers can contribute to the development of more resilient communities in the face of future flood events. One of the key aspects of this assessment is its engagement with the affected community and local individuals. This engagement serves a dual purpose: firstly, it validates the assessment conducted using AI models on the ground, enhancing the credibility of the collected data. Secondly, it underscores the essential integration of technology with community volunteers and local knowledge, emphasizing the paramount significance of grassroots-level efforts in the realm of disaster management. This holistic approach ensures that local expertise and insights are seamlessly integrated into disaster response strategies.

6. Conclusions

In conclusion, the integration of Geographic Information Systems (GIS) and multi-criteria analysis for flood risk mapping, as well as the utilization of advanced Artificial Intelligence (AI) and community engagement in hyper-localized flood risk assessments, represent significant advancements in disaster preparedness and urban planning. This method provides valuable information for water resource planners and decision-makers, enabling them to focus resources on areas that require more detailed assessment. It not only simplifies the process but also ensures reliability, making it applicable in data-scarce regions or situations demanding rapid risk assessment. The use of the Analytic Hierarchy Process (AHP) as a weighting criterion method empowers decision-makers to prioritize criteria according to their preferences, facilitating intelligent decision-making and tailored solutions to meet specific needs.

The flood risk maps produced in this research offer valuable insights for implementing essential mitigation measures, not only for insurance purposes but also for disaster response and effective land management. In addition to providing warnings, the model empowers both homeowners and governments to proactively reduce long-term risks. This can be achieved through the strategic reinforcement of buildings and infrastructure, ensuring a more resilient and secure environment. Furthermore, this approach can be easily extended to other jurisdictions to determine flood risk maps using indicators or criteria that are available. Ultimately, equips decision-makers with essential data for informed decision-making and underscores the importance of proactive measures to enhance the resilience of the region.

Author Contributions

Haripriya Kesavan made equal contributions to all stages of this research paper that involved: Literature review and research gap identification: Identified key research areas and established the foundation for the study; Developing the research aim and scope: Defined the research objectives and scope of the research; Data collection and collation: Contributed to gathering and organizing relevant data for analysis; Study area delineation & profiling: Basis the use case developed for the tool, she was involved in area delineation and locational characterization; Research methodology design: Helped establish the methodological framework for the research; Preliminary analysis of model outputs: Performed preliminary data analysis of the model-generated results; Ground truthing—community engagement and data validation: Played a key role in framing linkages & data analysis of the ground-truthing results that were conducted; Analysis of ground truth results: Contributed to analysing and interpreting the data collected from the community engagement.

Shradha Choudhary: Finalization of study area; Research methodology framework: Participated in refining the research methodology overview; Community-driven ground truthing: Provided assistance in the community engagement and data collection process for ground truthing; Developing the overall conclusion.

Sadaf Khan: Spatial data & data collection: Assisted in retrieving the source input data and generating flood risk maps; Pre-processing layers: Helped with delineating the study area; Building footprints and roof type classification: Contributed to processing spatial data related to building footprints and roof types.

Samhita R: Inputs on approach and methodology of the AI based model code development.

Anshu Sharma: Structuring of the paper and oversight of approach; Inputs on approach and methodology of the model development and application.

Conflict of Interest

Declaration of conflict of interest.

Data availability statement

The open source input data sets like waterbodies and road network data can be accessed on Open Street Map, Ocean data is downloaded from Natural Earth, Digital elevation model from SRTM, and Landsat imagery from USGS Earth explorer. Google satellite imagery has been used for building and roof top identification.

The building footprints layer and risk assessment output is proprietary and confidential to the organisation. Please refer to **Table 1** on summary of input datasets for more information.

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