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Impact of climate-induced disasters on the sustainability of cities:

An urban resilience perspective on floods

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ABSTRACT

Climate change has intensified extreme rainfall and flood events, posing significant threats to urban sustainability. Floods, among the most catastrophic disasters, disrupt livelihoods and irreversibly damage economies, making disaster risk reduction critical for achieving safe, inclusive, and sustainable cities in line with the Sustainable Development Goals. Urban resilience, reflecting a city's ability to respond, recover, and maintain core functions during disasters, is challenging to assess due to complex urban system interactions and the non-linear nature of climate emergencies. This study examines resilience through land use changes as indicators of urban sustainability against flood disasters, using Colombo City, Sri Lanka, as a case study. The research evaluates urban flood resilience (UFR) based on ten natural, physical, and social parameters, integrating urban growth simulation, flood modeling, and geospatial assessments at a 30-meter resolution. Land use categories; waterbodies, wetlands, vegetation, and urban built-up areas; were analyzed alongside resilience classifications ranging from flood-susceptible to highly responsive. Results reveal that high-resilience areas are concentrated in vegetated high elevations and urban zones with effective drainage systems, while low-resilience areas are heavily populated floodplains and impervious city-center areas with limited greenery. Regression analysis confirms that impervious surfaces exacerbate flood risk, while vegetation and wetlands provide long-term resistance to extreme rainfall. The findings emphasize the need for green infrastructure-oriented drainage networks and sustainable urbanization to mitigate pluvial floods. Incorporating land use changes and socio-economic factors highlights the importance of disaster preparedness at the grassroots level for effective mitigation strategies. From an urban planning perspective, this approach aids in guiding future land use changes, prioritizing sustainable growth, and informing decision-makers on resource allocation to enhance flood resilience in cities.

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1. Introduction

The rapid growth of technology and innovation in the last century has improved the quality of life of the urban population. Most importantly, this has happened in cities where necessary infrastructure and services are available to facilitate creativity and human desires. Cities account for over 80% of the global Gross Domestic Product, are home to over 56% of the global population, and occupy only about 3% of the total land area globally [1,2]. The concentration of economic activities encouraged rural-to-urban migration, and the urban population is expected to reach over 68% by 2050, as about 7 of 10 people will live in cities [3].

Accumulating such a population in comparatively modest spatial entities can have economies of scale while increasing vulnerability to internal, external, and unforeseen threats. Since the competition for limited resources in the world is growing, pressure on natural resources and ecosystems can induce the risk of cities to natural hazards such as floods [4]. Climate change, urbanization, economic competition, and over-extraction of resources are some of the reasons for the unprecedented trend of hazards at high frequency and intensity [4,5]. Floods are one of the most catastrophic disasters cities face, affecting millions of populations and damaging economies in an irreversible way [6]. Many cities have invested in structural measures and adaptive strategies over the past to tackle the negative impacts of flood disasters on cities. Yet, the destruction and losses have continued consistently. In this context, disaster management in cities is paramount in promoting safe, inclusive, and sustainable human settlements, as identified by Sustainable Development Goals [7].

Scholars have recently focused on measuring the ability of cities to respond to flood disasters and manage the vulnerability to natural hazards from an urban resilience perspective [8–11]. However, the seminal work in the past decades shows a single focus or several aspects of vulnerability in flood resilience studies, including community, infrastructure, governance, or environmental features. Moreover, the primary focus was on conceptual frameworks, while limited attention to operational models or supported empirical evidence to measure the resilience of cities to natural hazards like floods [12–14].

However, cities are complex entities with interconnected networks and interdependencies on multiple spatial and temporal scales. According to [15], vaguely defined 'urban' definitions and limited understanding of trade-offs involved in resilience studies focused on cities

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have caused conceptual tensions and inconsistency in urban resilience research. This study conceptualized urban resilience as an integrated equilibrium between natural, human, and physical systems within cities. Application of an interdisciplinary framework to assess urban resilience at the micro spatial scale could reveal the location-specific hotspots ranging from vulnerable communities to critical infrastructure and essential services in a flood disaster. This framework is a novel approach to identifying resilience at the local level and simulating resilience change due to climate change and urbanization policy of cities, which can be useful for urban planners and disaster managers in climate resilience decision-making. The conceptual framework is shown in Figure 1.

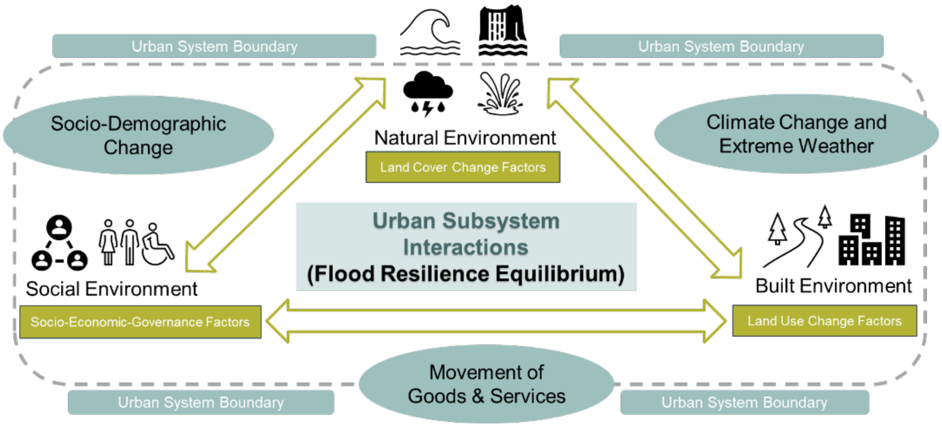

Figure 1. Conceptual framework of urban flood resilience and system interactions.

According to Figure 1, urban flood resilience is not a discrete phenomenon but an evolving dynamic process with multiple interactions. It is not only represented by the natural and physical elements of a city but also by the social layers of communities and their behavior patterns. The sustainability of a city is influenced by changes in nature, such as climate change and weather-related impacts. In the case of floods, the triggering factors could be extreme rainfall, limited impervious cover, limited drainage capacity, and so on [16,17].

However, the city's recoverability from floods depends on the level of impact on the built form and population. The socio-demographic changes over the years and the movement of resources within the city can affect the balance of city functions and the magnitude of the damage caused by floods. Therefore, the physical risks or flood inundation models alone cannot determine resilience, where socio-demographic factors will also play a crucial role. Hence, this framework incorporates a three-step analytical framework that can support mitigation and adaptation policies of a city to optimize resource allocation during natural disasters such as floods.

Sustainability can be broadly defined for an urban system based on its preparedness for future stresses such as floods. However, due to the dynamic nature of urban systems, it is challenging to model or assess the long-term impacts of existing cities. At the same time, priorities set by the Sendai Framework [18] highlight the importance of community resilience through risk identification and enhancing cities' preparedness through multiple strategic frameworks.

In this study, we quantify urban flood resilience through socio-demographic factors incorporating vulnerability and coping capacity as key city sustainability measures. The novelty of this framework is that this approach (Figure 1) complements the existing physical risk parameters while incorporating social environmental factors to denote the sustainability of cities.

Moreover, non-spatial social conditions can be represented in spatial strategy formulation to support decision-making bodies and merge conceptual frameworks into operational models using ground-level information. Applying this framework in Colombo City, Sri Lanka, shows that coastal cities with flood risk need integrated solutions to "Build Back Better" using multidisciplinary approaches for disaster management [19]

2. Methodes

2.1. Overview of analytical framework

This study follows three key steps to quantify flood resilience using the conceptual framework presented in Figure 1. The study formed three objectives to assess the flood resilience of cities. First, land use change assessment and simulation for multiple growth paradigms. In this step, the spatial simulation incorporates land use change based on previous and impervious areas in cities.

Machine Learning models are incorporated to assist in classifying land use under four categories: waterbodies, wetlands, vegetation, and built-up areas. The Cellular Automata model is used for simulation exercises in Python environments. Second, a flood model was developed to assess the runoff retention during a flood event. The Urban Flood Risk Mitigation (UFRM) model [20] gives useful spatial insights on runoff quantities to measure the impervious cover's impact on the spatial distribution of floods.

Inputs from land use change and actual rainfall scenarios assist the simulation of flood patterns within a city based on soil permeability and curve numbers. Third, the socio-demographic factors are incorporated into flood resilience assessment. In this final step, multiple social parameters were analyzed with flood impact using feature selection tools from Machine Learning models. Out of 28 variables selected from the literature, three social factors were selected, representing population, housing, and infrastructure accessibility. Once the parameters were set, flood vulnerability and coping capacity were spatially aggregated using 30-meter pixel resolution. Geospatial techniques are used to calculate urban flood resilience by incorporating normalized parameters in the ArcGIS Pro environment. The analytical framework used in this study is shown in Figure 2.

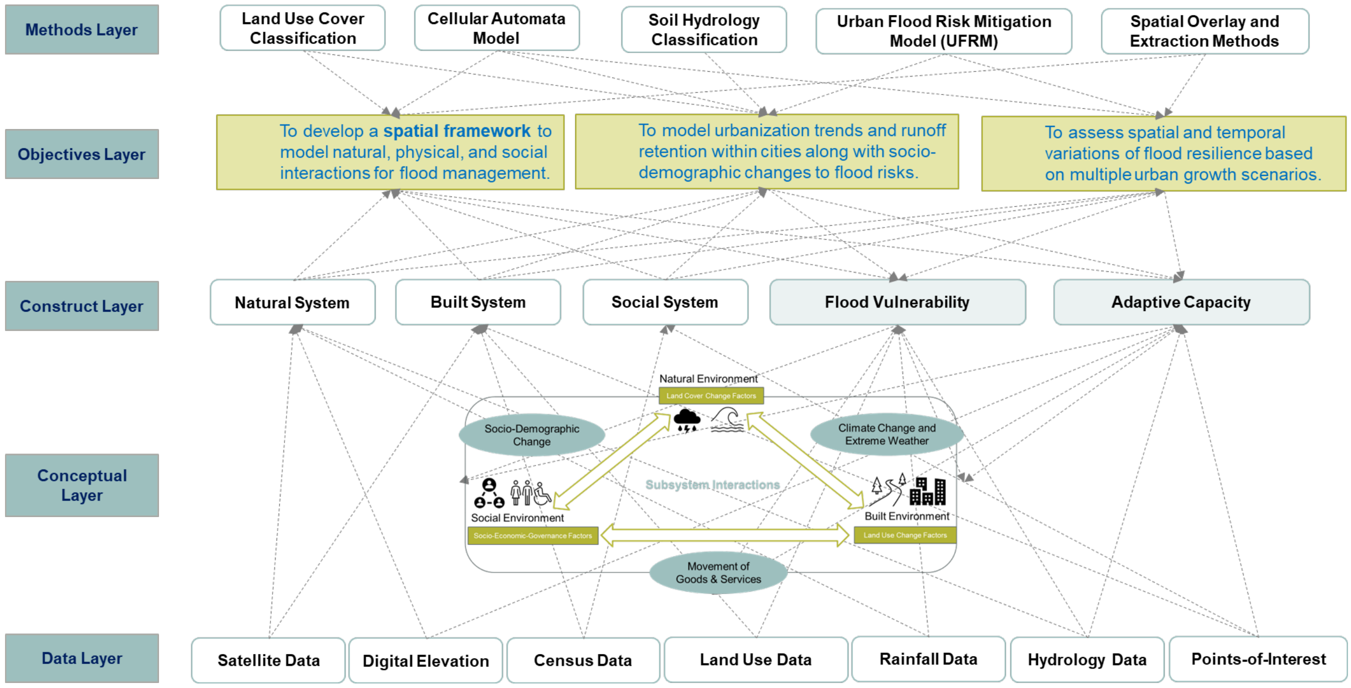

Figure 2. Analytical framework of urban flood resilience assessment.

2.2. Land use simulation and runoff retention assessment

In the first step, land use land cover classification is conducted using Machine Learning (ML) models. ML models show better accuracy and efficiency in land use classification compared with traditional methods of geospatial classification [21]. Landsat satellite images were obtained from the United States Geological Survey website for the period from 2000 to 2020 using world features with less than 20% cloud cover.

Once the image processing was completed using ArcGIS Pro software, the supervised image classification was conducted in a Python programming environment using the Anaconda 3 Jupyterlab software package. Multiple ML models were applied for classification and calibrated using hyperparametric optimization and confusion matrix. Accordingly, the Random Forest (RF) classification method gave the highest accuracy for the classified categories of waterbodies, wetlands, vegetation, and urban areas in the case study area.

Once the RF output is obtained, the next step is to complete the flood risk assessment for extreme rainfall conditions. For this, the Urban Flood Risk Mitigation (UFRM) model was used, which is a part of the Integrated Valuation of Ecosystem Services and Trade-Offs (InVEST) Model [17]. The UFRM model uses InVEST 3.13.0 workbench, an open-source software module, to calculate the runoff production using spatially explicit data sources to generate maps as outputs. Soil Conservation Service Curve Number (SCS-CN) or CN is a dimensionless parameter used to explain the runoff response of a watershed by using a hydrologic soil cover complex [22].

According to [22], soils are classified into four main groups based on the bare soil surface, maximum swelling capacity, temperature response, and water intake and transmission under maximum wetness conditions. The UFRM application generates the run-off retention of each sub-catchment based on the maximum rainfall and land cover characteristics.

Therefore, it gives the level of flood retention capacity using geomorphological characteristics and impervious cover on the city scale. Once the run-off retention is calculated, the resilience index is calculated based on natural, physical, and social parameters.

2.3. Social feature selection

Conventional flood resilience methods use physical risk or hydrology models through geospatial techniques to assess urban flood risk or resilience. In contrast, social vulnerabilities and non-spatial community-based factors are assessed separately. However, socio-demographic factors play a vital role in managing vulnerability or coping capacity of flood events [23–25]. This study used socio-ecological factors driven by community response to floods to determine long-term resilience.

Due to the vast literature on social factors, selecting important features for resilience assessment was challenging. However, with expert consultation and contextual factors, the social features were selected under three key categories: population, housing, and infrastructure. For the selection process, regression models were incorporated by adopting "Feature Selection" models in Python programming language.

Feature selection is one of the dimensionality reduction techniques used in ML models. In flood resilience studies, the availability of multiple socio-economic and demographic factors may lead to overfitting or underfitting of the ML model. Therefore, it is vital to select the factors that influence flood impact to improve the quality of the selected database.

This study used supervised feature selection methods involving filter-based and wrapper-based approaches. "Sci-kit Learn" – a free and open-source library for Python programming was applied in the analytical process, and the "Sweetviz" project was utilized for data visualization and exploratory data analysis [26,27].

The feature engineering process used the multicollinearity test and variance threshold measurement of all the socio-demographic variables before undertaking the regression analysis. Once the highly correlated features and features with low variance are removed, a model-based sequential feature selection process is employed. In this step, significant features based on the relative importance of the predictive feature are selected. The impact of floods on residential communities was selected as a dependent or predictive variable.

Linear regression and tree-based models such as "Random Forest and Extreme gradient Boosting" were used to select important features under three key categories. Once the social features were selected, they were combined with natural and physical features to conduct the flood resilience assessment.

2.4. Cellular automata model for land use projections

Cellular Automata (CA) is one of the commonly applied land use change models, which simulates complex systems and non-linear growth of urban areas effectively [28]. CA models are capable of simulating non-linear spatial interactions of complex ecosystems as against temporally explicit analytical models like system dynamics [29,30].

Moreover, CA models proved their effectiveness with simplicity in application, ability to generate complex patterns, and powerful spatial and temporal integration with Geographic Information Systems (GIS) [31,32].

CA model assumes that land use change emerges from the local interaction of spatial activities, which accounts for urban expansion from locally driven factors. The land use change modeling process use a two-dimensional lattice in which the simulation depends on the existing cell state, state of neighboring cells, discrete time step, and specific transition rules [30,33].

The CA algorithm is developed to simulate land use land cover changes using satellite images from 2020 to 2030. LANDSAT 7 ETM+ and LANDSAT 8 image data from the United States Geological Survey (USGS) with 30m resolution (8 bands) are used for the land use classification and pre-processing for CA modeling work.

The Cellular Automata framework used multiple parameters ranging from existing land use and land cover, population density, proximity to main roads, distance from the city center (CBD), slope, existing planning regulations, and natural constraints or conservation areas. Distance from roads is classified into 500m intervals, and areas closer to main roads with high accessibility are given high potential for urban growth and vice versa. Similarly, distance from the CBD is also taken to measure the non-uniform growth of urban areas.

CA model rules depict the existing growth patterns and key variations in the development trend. The existing built-up lands and waterbodies are exempted from elimination, while vegetation or open spaces are transformed into built-up forms based on threshold values and neighboring built-up counts. Moreover, restricted and conservation zone pixels are not eliminated while maintaining the consistency of unchanged pixels in the testing phase of the CA model.

Threshold values for multiple growth factors are obtained by trial and error to suit real-world conditions, and the calibration process is conducted by spatially subtracting the built-up pixels from post-simulation. Python programming language (Version 3.8) in Jupyter Notebook was used to run the CA modeling algorithm.

2.5. Case study: Colombo city and suburbs, Sri Lanka

Colombo City and its suburbs are located on the Western coast of the South Asian Island nation of Sri Lanka, which has experienced rapid urbanization in recent decades. Kelani River is the third largest river in the sense of annual discharge volume, having a catchment area of 2,292 km^2, which meets the Indian Ocean at the northern boundary of Colombo City [34]. Kelani River Lower Basin (KRLB) – mostly a flat terrain – where Colombo and its suburbs are located has been selected as the case study to test resilience assessment. The City of Colombo is prone to flooding and faced a major flood event in May 2016, which lasted over 6 days due to Monsoon rains (Figure 3).

Unprotected areas in the basin have critical infrastructure, population concentration, and well-connected wetland networks that face significant impacts during major flood events [35,36]. KRLB is prone to minor floods on an annual basis due to monsoonal rains. In contrast, major floods occurred in 2008, 2016, and 2024 due to multiple rainfall events in highlands and coastal cities, creating increased runoff to overflow of Kelani River. For analytical purposes, KRLB sub-basins were used for natural and physical factor modeling, while corresponding administration boundaries were used for social parameter estimates. The administrative boundaries of the study area and flood distribution are shown in Figure 4.

Figure 3. The flood damage occurred in May 2016 in Colombo city and the suburbs (Source: Sri Lanka Air Force, with permission).

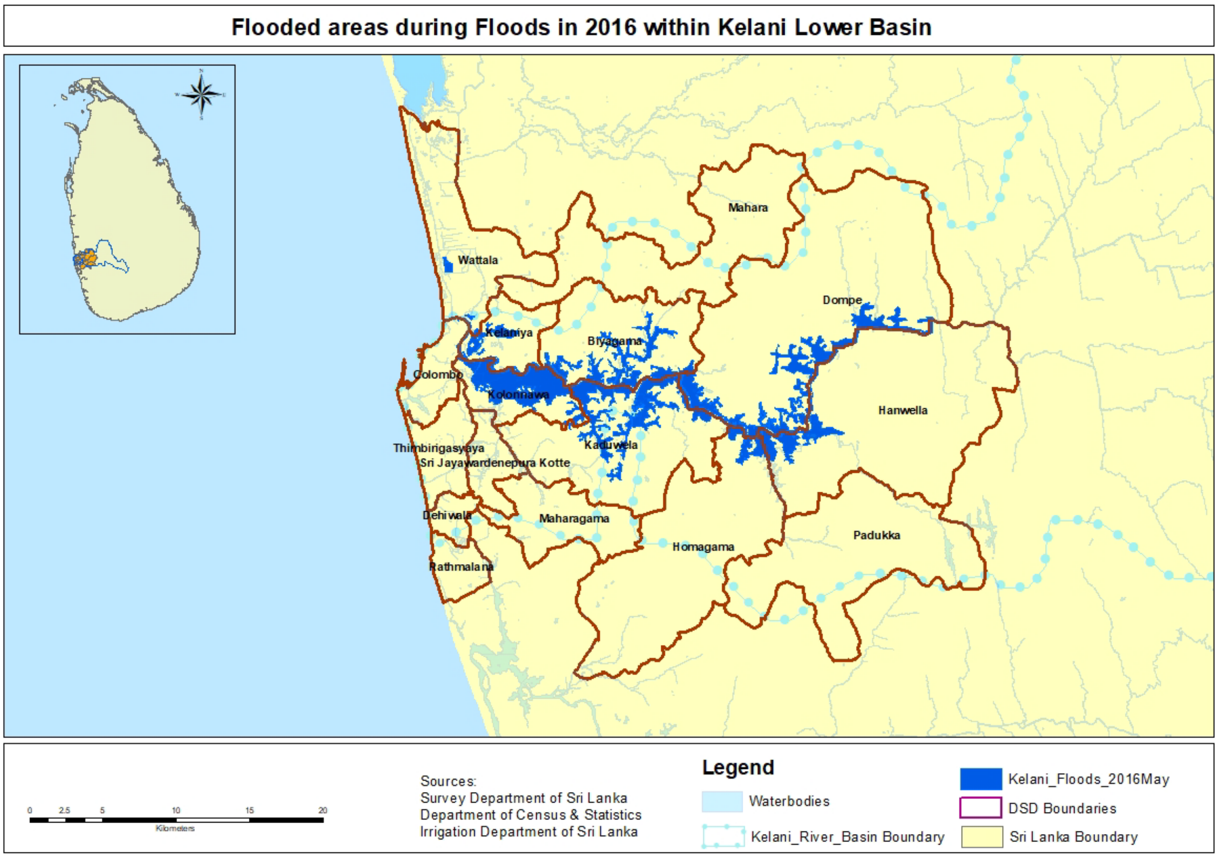

Figure 4. Flood distribution and case study boundary of Kelani River Lower Basin, Sri Lanka.

3. Results

3.1. Land use simulation and flood modeling

The processed satellite images from Landsat are classified into land use and cover types using supervised image classification techniques. Random Forest (RF) classification provided better accuracy than Decision Tree (DT) and Support Vector Machine (SVM) Techniques. Land use maps prepared for 2021 were validated with actual land use datasets provided by the Urban Development Authority (UDA) of Sri Lanka.

The accuracy levels of RF, DT, and SVM methods were 83.3%, 76.1%, and 77.8%, respectively. The confusion matrix prepared for each land use classification method is shown in Figure 5, and the classified land use map for 2001 and 2021 is shown in Figure 6 to compare the built area expansion.

According to Figure 6, the urban built-up area has increased from 6.35% to 27.5% in the last 20 years, while the vegetation area has reduced from 60.35% to 45.37% of the total land. The wetlands, which are a common feature in Colombo's landscape, have reduced from 32.42% to 27.49% during the period, showing disruptions to hydrology flow within the city. The waterbodies dominated by the Kelani River occupy about 1% of the total land area. It is visible that Colombo's city-centered urban growth expansion is a significant aspect of urban growth, and Kelani River has been at the center stage of this growth. However, according to UDA, Colombo's urbanization trajectory in the past few decades shows spontaneous growth with sprawling effects along main roads spiraling away to suburban areas.

KRLB and its floodplain are also impacted by this change in built-up areas. The flood modeling process revealed the change of run-off retention resulting from such land use change effects. The UFRM model used the soil's saturated hydraulic conductivity as the starting point of flood analysis. However, this model does not consider rainfall's spatial and temporal dynamics over the study area or other influencing factors like temperature. The maximum rainfall (250 mm) recorded during the last flood event (2016) was used for the model with varying geomorphological factors. 17 sub-basins within the study area were used with soil categories of sandy and clay as the input parameters. Soil condition-based Curve Numbers (CN) used for each land use category are shown in Table 1.

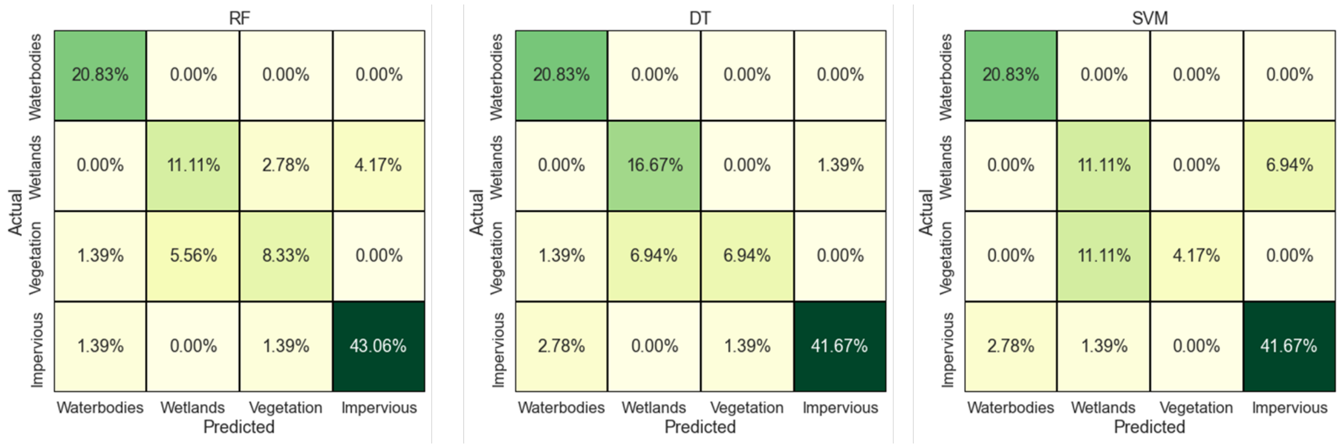

Figure 5. Confusion matrix generated for RF, DT, and SVM methods using Python programming methods

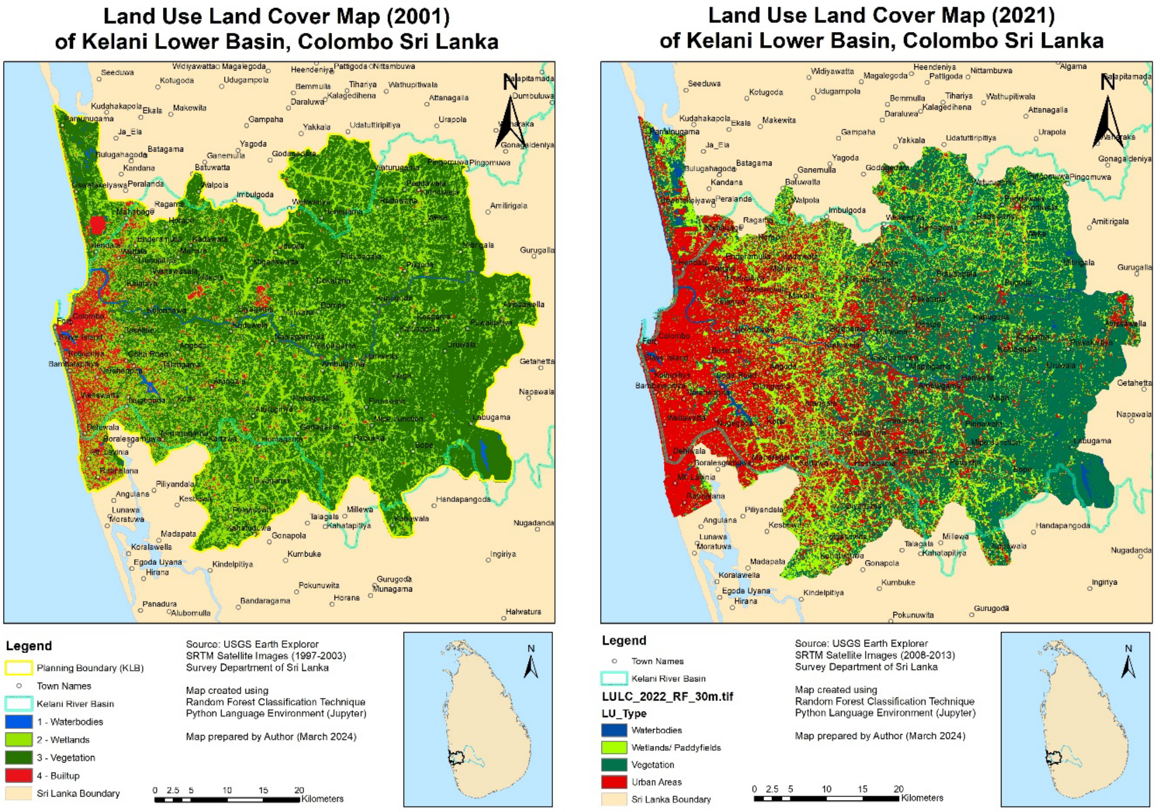

Figure 6. *Classified land use land cover map of the case study area from 2001 to 2021.*

Table 1: Curve number (CN) values used for land use land cover categories within the study area [37,38].

Code	2022 Land Use (%)	Land use Type	CN - A	CN - B	CN - C	CN - D
1	1.64	Waterbodies	100	100	100	100
2	25.49	Wetlands/ Paddy fields	39	61 65 92	74	80
3	45.37	Vegetation	43		76	82
4	27.50	Urban Areas	89		94	95

The UFRM model revealed the runoff retention during peak rainfall as an index relative to precipitation volume ranging from 0 to 32.9%. Accordingly, sub-watersheds closer to Colombo city show relatively high flood risks, while vegetation-rich hinterlands show lower flood risks with higher run-off retention capacity. Figure 7 shows the run-off retention in the study area on the sub-watershed basis and pixel-wise flood distribution during peak rainfall.

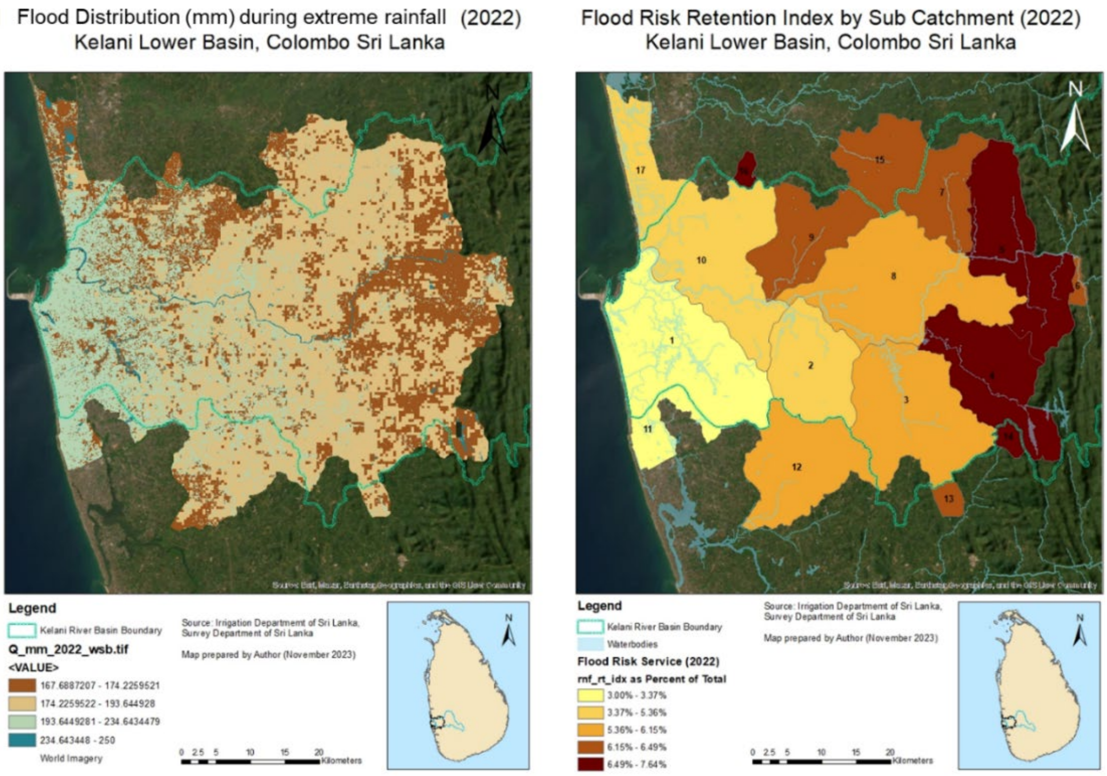

Figure 7. Potential flood distribution by pixels during an extreme rainfall (left) and run-off retention capacity by sub-basin level (right) for 2022 land use land cover distribution.

Figure 7 shows run-off retention values range from 0% (water) to 74.08% (vegetation) and proportionately varied based on land use types. The results were validated with actual flood data from the May 2016 floods using water level data from river gauges. However, floodwater discharge quantities slightly differed due to temporal rainfall variations and upstream water flow variations within the Kelani River during the 2016 floods.

Nevertheless, run-off retention and land use change results sufficiently explain the spatial distribution of floods; hence, they are used for spatial analysis.

3.2. Socio-demographic analysis

Social variables for the resilience assessment were selected from dimensionality reduction techniques. Grama Niladhari (GN) divisions were used as the smallest administration boundary for the data collection, and census data from government-published reports were obtained for analysis in 2001 and 2011.

Flood records were available for 569 GN divisions, and census data for 1734 GN divisions were collected from two districts from KRLB. Once the dataset was cleaned and preprocessed, a CSV file was generated for analysis in a Python environment. 24 parameters were selected under population, housing, and infrastructure categories, and the multicollinearity test screened 13 variables.

Figure 8 shows the multicollinearity test matrix developed using Google Colaboratory. The heatmap was generated using correlation among variables of over 10% or more. The selected variables for the regression test are shown in Table 2.

Selected 13 variables were used as independent variables (X), and flood records were used as dependent variables (y) for regression analysis. Random Forest Regression used 500 estimators with a depth of 10, and Extreme Gradient Boosting (XG Boost) was used afterward with 500 estimators and a depth of 5.

Three independent variables were selected based on the highest relative importance. Households with access to drinking water (0.3511), Total dependent population (0.1579), and houses with permanent structures (0.1078) were selected for the resilience analysis based on regression results. The feature importance results from Random Forest and XG Boost methods are illustrated in Figure 9.

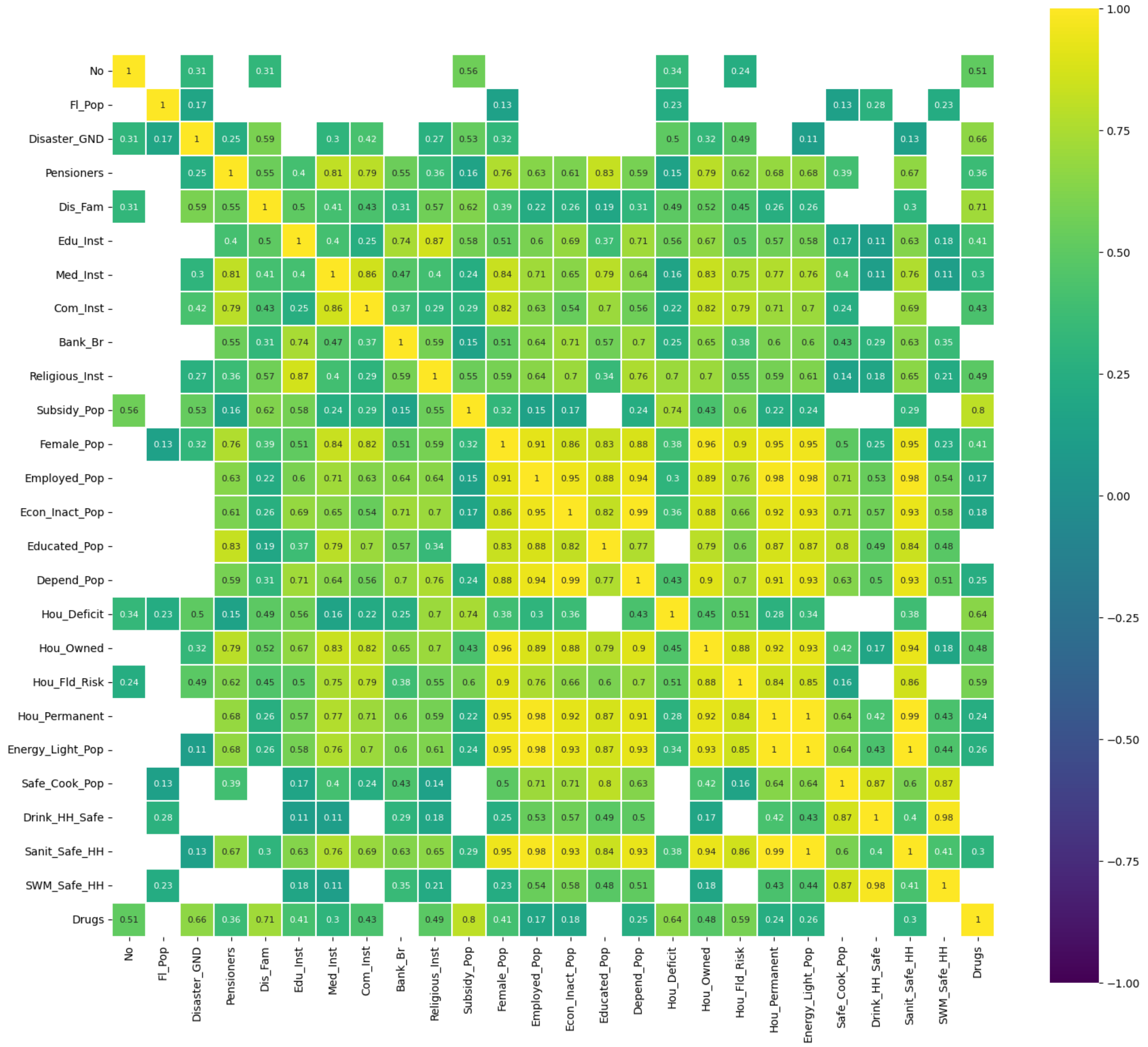

Figure 8. Correlation matrix developed for social variables where yellow color denotes high correlation and green color denotes low correlation among variables.

Table 2: Independent variables selected for regression analysis under key social dimensions.

Population parameters	Housing parameters	Infrastructure parameters
Total Female Population	Houses with a permanent structure	Access to a main power grid
Total Dependent Population	Houses with two or more floors	Access to pipe-borne water
Educated Population (Secondary)	Ownership of the houses	Availability of water-sealed toilets
Total employed population		Waste management service access

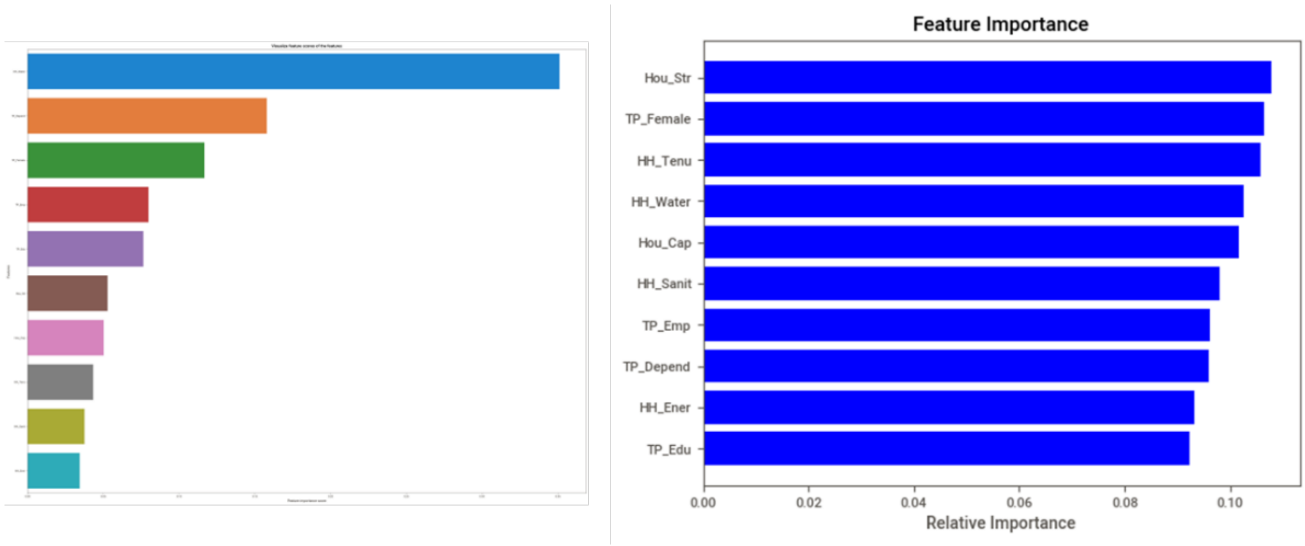

Figure 9. Relative importance values for multiple social variables in explaining the flood impact within KRLB.

3.3. Future land use projection

The Cellular Automata (CA) model used population data recorded from the census records from 2001 to 2011 and land use change data from satellite image processing. The distance from CBD was 5km to 45km from the center, while the distance buffer set for main roads was 500m to 5km. The threshold values were taken based on land use simulation based on actual classification up to 2021 and trial and error for assigned threshold values. Differences between classified images were computed by built-up pixel change, and a proportion of non-zero values was taken for accuracy assessment.

The land use land cover change simulation comprised from 1 to 4 depicting waterbodies to built-up areas similar to land use land cover classification. Figure 10 shows the results of the simulation pattern in the Python program, and Figure 11 shows the land use change map for 2031 based on existing urban sprawling effects.

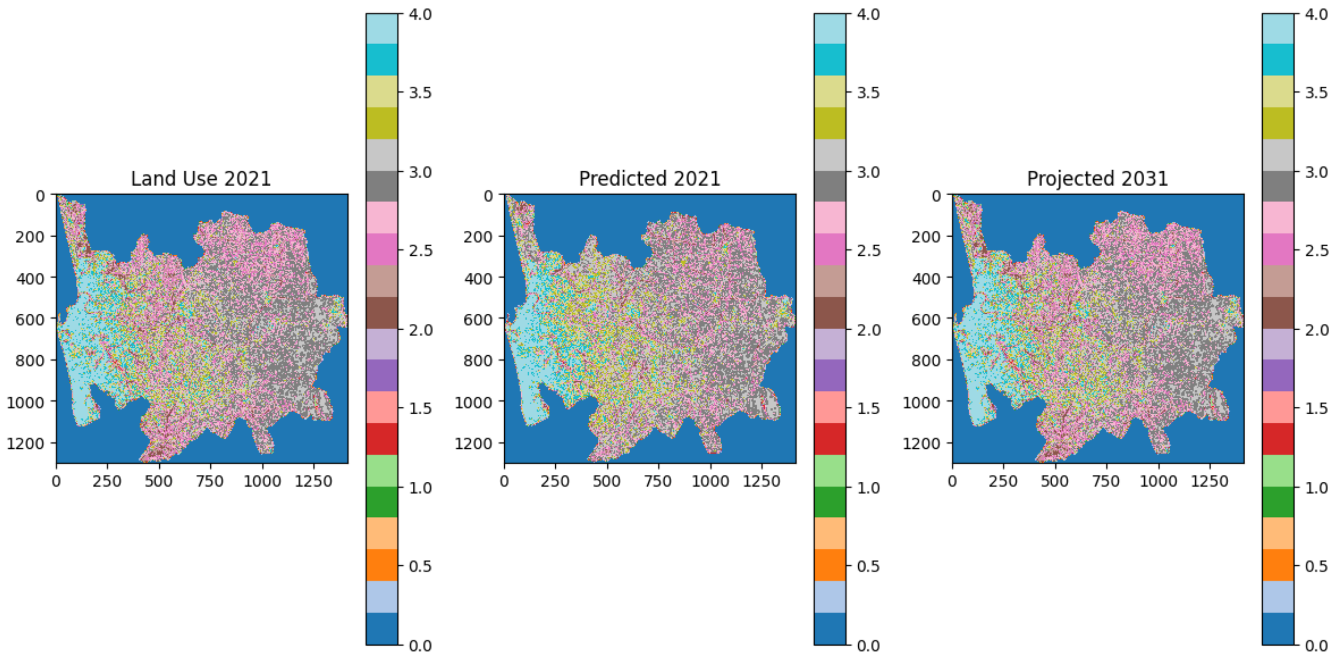

Figure 10. Visualization of land use and land cover maps using the CA model in Python.

The highest overall accuracy level of the CA model was 73.02%, and it achieved about a 3% increase in built-up areas in ten years with a 2% decrease in vegetation areas. According to Figure 11, the existing urbanization trend continues with restrictions on expansion to wetlands and water bodies. However, strict regulations are necessary to control the urban sprawl towards the floodplain of KRLB and wetland areas within Colombo City and its suburbs.

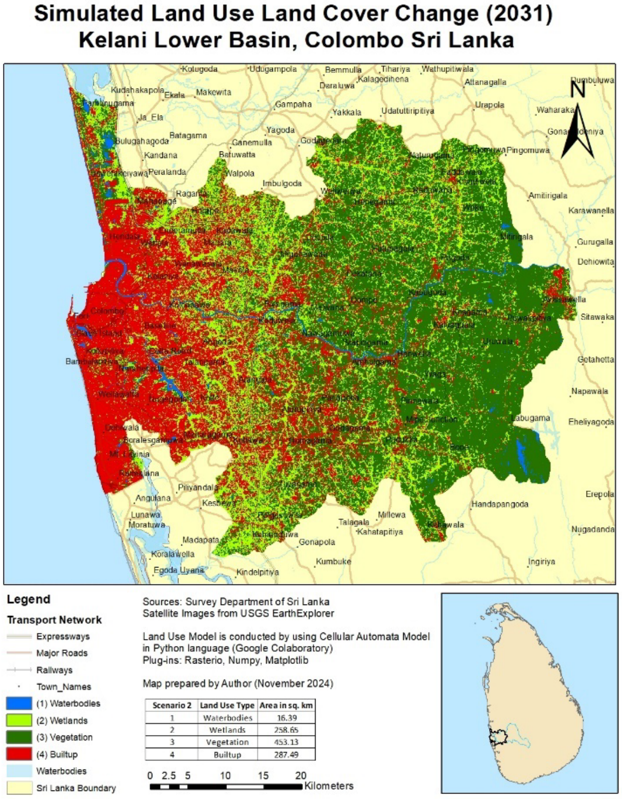

Figure 11. Simulated land use and land cover map of 2031 based on the CA model for Colombo City and suburbs.

Land use change from 2001 to 2031 is shown in Table 3, as urban growth can spur the built-up area growth unless spatial growth control strategies are not implemented. However, it is important to assess the resilience change for flood risk in the city in the face of land use, land cover change, and climate change impacts.

According to Table 3, it is clear that urbanization has a significant impact on land use change, with growth of over 300% in the study period. The population has significantly increased during the last 20 years, affecting the region's adaptive capacity and physical vulnerability. The resilience assessment incorporates both these factors in spatial analysis.

3.4. Urban Flood Resilience Assessment

Once the parameters were selected, the spatial distribution of each parameter was mapped for resilience index calculation. Based on the literature review, expert opinion, and dimensionality reduction techniques, ten parameters were selected for the resilience assessment, which was classified under natural, physical, and social environments in line with the conceptual framework presented in Figure 1.

The selected parameters for spatial analysis are shown in Table 4.

Table 3: Curve number (CN) values used for land use land cover categories within the study area [37,38] (The total study area is about 1,020 sq. km covering two districts around Kelani River Lower Basin).

Land use type	Share in (%) 2001	Share in (%) 2011	Share in (%) 2021	Share in (%) 2031	Growth over 30 years
Waterbodies	0.88	0.96	1.61	1.61	+ 82.96%
Wetlands	32.42	15.64	25.47	25.47	- 21.44%
Vegetation	60.35	60.80	45.42	44.61	- 26.08%
Built-up	6.35	22.61	27.49	28.31	+ 345.83%

Table 4: Parameters selected for the flood resilience calculation.

Natural Environment Variables	Physical Environment Variables	Social Environment Variables
Elevation or Slope	Building Footprint Density	Total Dependent Population
Waterbodies and Wetlands Density	Road Density	Density of Houses with Permanent Structures
Vegetation Cover Density	Flood Relief Locations Density	Households with Access to Safe Drinking Water

The non-spatial parameters were calculated based on the GN divisions (the smallest administration boundary) and converted into raster images at 30-meter resolution. Once the parameters were normalized using spatial analyst tools of ArcGIS Pro software, the 10 variables were resampled using the "Nearest Neighbor" method to match the pixel boundaries. The normalized maps are presented in Figure 12 and used for resilience assessment in the next step.

The parameters were categorized based on the influence on flood resilience and weighted using the Analytical Hierarchy Process. The parameters were pairwise compared using experts in the field, specifically from urban planning, disaster management, and academic disciplines. The consistency ratio was 0.08, indicating reasonable consistency levels among pairwise comparisons. The influence was measured positively and negatively based on adaptive capacity and risk-based vulnerability [39].

Permanent housing stock, access to safe drinking water, locations above 5 degrees elevation, vegetation cover, and availability of relief centers or points of interest for flood recovery are considered positive factors influencing the resilience to urban floods.

So, the remaining factors were considered as negatively influencing flood resilience. The parameters were spatially overlaid, and pixel values were reclassified based on the quartile range for weighted overlay in ArcGIS software. Raster images were given equal weights in the weighted overlay analysis with an evaluation scale of 1 to 10 by 1.

The final output comprised 30-meter resolution maps with values ranging from 1 to 4, with 1 being the least resilient and 4 being the highest resilient location. The urban flood resilience map for 2031 was simulated with population change as predicted by the government records and land use land cover maps generated from the Cellular Automata model.

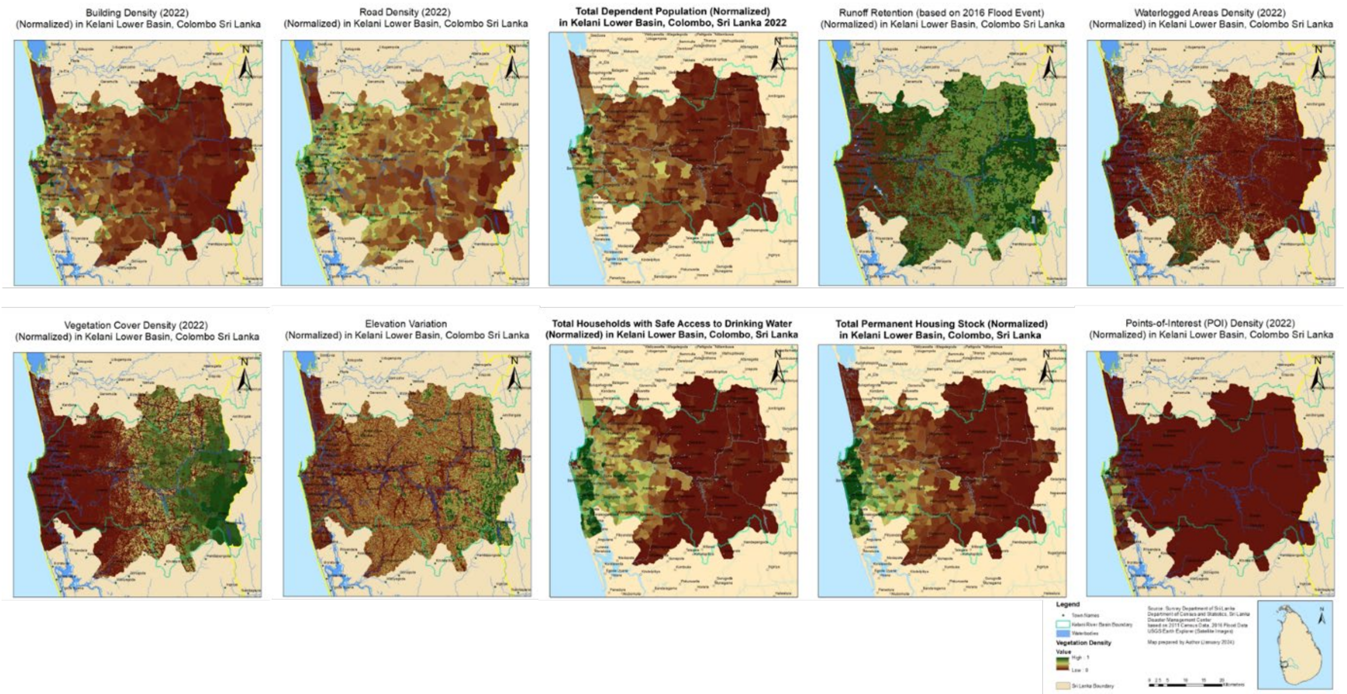

Figure 12. Normalized spatial representation of parameters for resilience calculation.

Figure 13 shows the resilience maps generated for 2021 and 2031 based on selected spatial parameters. Figure 13 revealed that the existing urbanization trend will move towards vegetation-rich suburban areas if the wetlands and waterbodies are preserved from 2021 to 2031. However, the highest resilience values (dark green) will decrease by about 4%, while the least resilience values (red) will increase by approximately 44% within the study area if this trend continues. The land area by resilience values is explained in Table 5.

Table 5: Share of land area (percentage) depicted by resilience values for 2021 and 2031.

Code	Color	Interpretation	2021 Land Area (%)	2031 Land Area (%)
1	Red	Low Resilience	5.86	8.43
2	Orange	Medium Resilience	33.46	33.56
3	Light Green	High Resilience	45.05	43.00
4	Dark Green	Very High Resilience	15.63	15.01

The resilience values are validated by using the spatial agreement index in ArcGIS software. Pixel values of resilience raster files were reclassified based on "resilience versus non-resilience" values, and zonal statistics of binary raster were computed for proportional agreement. Accordingly, 1,22,220 pixels were analyzed, and 82.48% spatial agreement was found among flood resilience pixels and hot spot Z score values. Figure 14 shows the results of the spatial agreement test plotted using a confusion matrix.

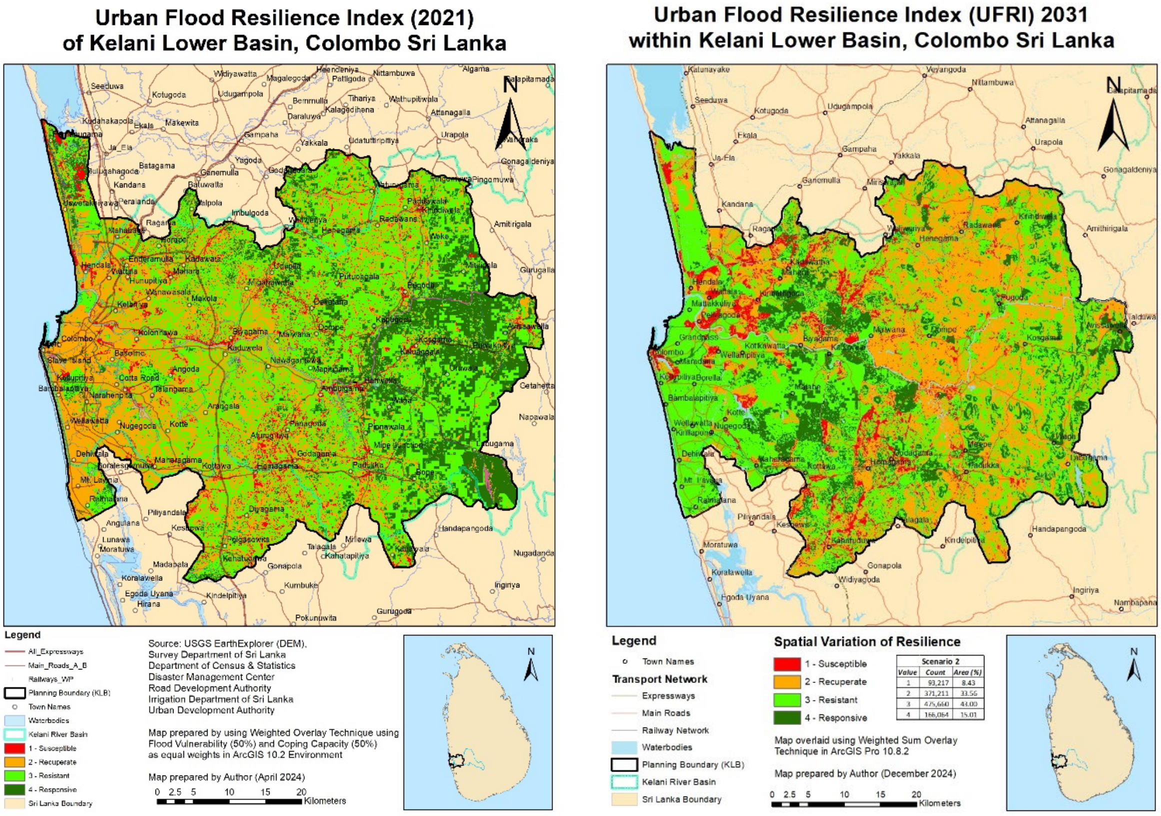

Figure 13. Urban flood resilience for 2021 and 2031 calculated for Kelani river lower basin, Colombo, Sri Lanka.

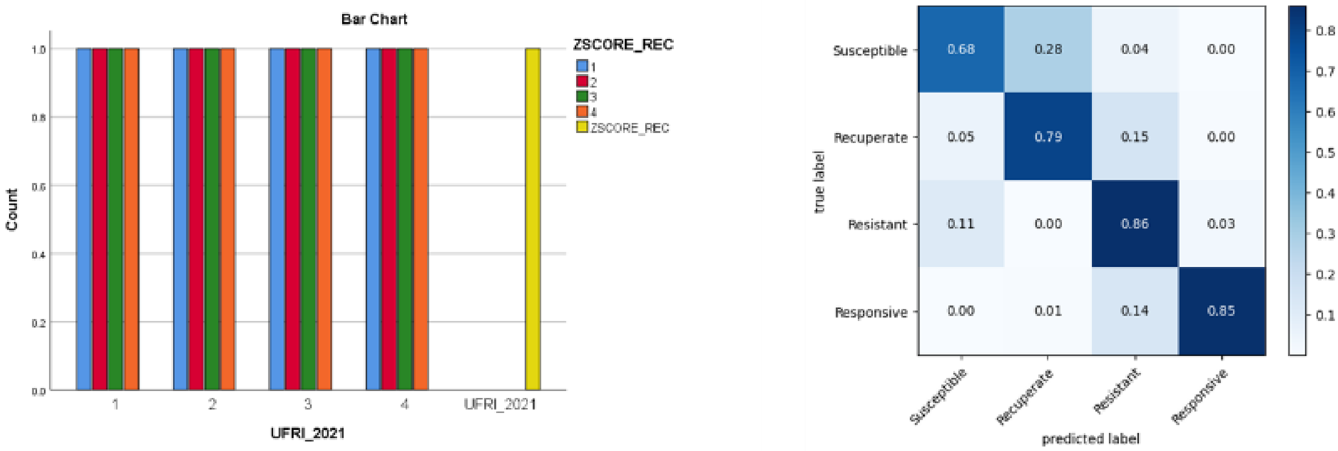

Figure 14. Spatial agreement of flood resilience pixels of 2021 resilience maps.

4. Discussion

This study used a multidisciplinary framework to measure urban flood resilience using natural, physical, and social environmental factors as key determinants of the sustainability of cities. In line with Sustainable Development Goal 11, this framework forms a bottom-up approach to monitor the existing mitigation and adaptation frameworks on the safety and inclusivity of the residents living in cities prone to natural disasters.

The analytical framework assists urban planners and disaster managers in strengthening the resilience strategy in two ways. First, it revealed that a small spatial scale (30-meter resolution) is ideal for identifying disaster hotspots and managing the risk levels through inclusive safety nets. For example, in Colombo, the local governments focus only on the flood-inundated areas and allocate resources based on the physical impacts. However, the damage from floods has moved beyond inundated areas causing supply chain disruptions, health, and epidemic risks, along with long-term economic impacts [19,35,40].

Therefore, hydrodynamic models and physical vulnerability models alone cannot capture such complexities in cities.

According to Figure 13, the least resilient regions (red colored) are the areas with the highest vulnerability in a flood event and need to analyze socio-economic conditions and demographic factors that can contribute to risks in a flood event. Secondly, the results show the impact of land use change beyond administrative boundaries. In the past, strategies for flood mitigation were oriented only on the south bank of the Kelani River (excluding the north bank, which is a different district boundary) and proposed solutions to manage floods in Colombo [41].

This has resulted in a significant spatial imbalance in resource allocation for flood mitigation and adaptation. As seen in Figure 13, the future risks cannot be targeted on a single spatial entity, while flood resilience must be managed in a holistic way. Moreover, existing infrastructure projects such as expressways, water supply, and power distribution projects need to be located in areas with higher resilience by incorporating the natural, built, and socio-economic factors contributing to flood resilience. Therefore, this framework assists the planning agencies in addressing the complexity of urban interactions and ensures a safe and inclusive spatial strategy for highly urbanizing cities like Colombo.

Land use change is one of the key determinants of urban growth, and city planners are responsible for orienting the growth to make it sustainable for future living. In Colombo, the urban built-up areas (including all impervious areas) have increased by over 300% in the last 20 years (Figure 6). Since growth is inevitable, land use plans must be robust enough to adapt to disaster risks and climate change impacts in the coming years. The simulated land use change map (Figure 11) and flood resilience map (Figure 13) reflect the non-linear impacts of land use on the flood resilience variation in the city.

Moreover, the Sri Lankan government has proposed structural mitigation measures to tackle the flood risk through a series of floodwater pumping stations and reservoir construction to manage runoff in Colombo and suburbs [41]. This framework can be used to assess the effectiveness of such projects in terms of the recovery capacity of the city and optimize such projects through validation. One of the challenges in the seminal work is that there are limited operational models to monitor and evaluate existing urban dynamics and changes due to the highly theoretical nature of resilience research.

However, this study used a novel framework (Figure 1) to combine different aspects of resilience along with urban system interactions to provide a holistic view of flood resilience. This study used urban planning professionals and disaster managers in Colombo City and its suburbs to validate the resilience results and obtain the representation of actual scenarios during recent flood events. Over 70% of decision-makers agreed upon the flood resilience results at the micro-scale and cross-checked with the development trends in the past 20 years to further validate the trends. Therefore, the results are statistically and physically validated using ground-level data and are useful for decision-makers to identify hotspots to improve flood preparedness in the future.

This framework can be modified to monitor the progress of existing flood management projects and simulate the proposed plans to assess potential resilience pathways for Colombo City and the suburbs. Using growth controls, urban planning professionals can optimize land use planning strategies to suit highly resilient conditions and minimize vulnerable hotspots in future plans. One of the challenges in set conditions of Cellular Automata simulation is its volatile nature.

Since waterbodies and wetlands were considered restricted, they can still be converted into built-up areas depending on the conditions. Therefore, ensuring sufficient infiltration space for urban runoff is a critical factor in achieving sustainability and flood resilience in the future. This study can be further improved by using spatial dynamics during flood events (big data analysis) to show the temporal variation of resilience from the start point to the end point of flood phenomena. Colombo has been named as a wetland city [42] due to its network of wetland environments, urban flood resilience in the face of development pressure is vital in achieving the city's future sustainability.

5. Conclusion

Floods are one of the destructive hazards causing multiple socio-economic and physical damages compared with any other disaster events that cities face today. Local governments use significant financial resources to mitigate floods and post-recovery of city functions. Urban planners and disaster managers commonly use physical vulnerability and short-term flood risks in cities to assess resilience. However, this study argues that cities need a novel perspective to understand the flood risks in relation to land use change and urban system interactions.

Conventional engineering solutions, let alone cannot solve complex problems associated with floods, as demographic and socio-political factors can dominate the recoverability and preparation for floods. This study used an interdisciplinary framework to assess the resilience at the micro-spatial scale in cities.

Quantifying urban flood resilience through natural, physical, and social parameters can assist decision-makers in identifying optimal land use strategies while improving flood preparedness for extreme events using coordination and collaboration. Applying the framework to Colombo City has proved that land use change has influenced urban resilience, and traditional command and control strategies may not be as effective as expected in disaster risk reduction.

Many studies used either social factors or physical risk factors to assess city vulnerability or resilience [43–47], which lacks the objectivity necessary to address the dynamic nature of cities. Even with novel technology, such models need justification from the conceptual basis while applied in multiple contextual environments to validate the consistency.

Therefore, this study proved a solid foundation to incorporate socio-demographic and ecological principles to quantify flood resilience, which can be applied in multiple urban contexts. However, the selection of desirable variables is important to reflect the ground realities of cities which can be unique in each context.

One of the challenges in disaster management in cities is identifying the long-term implications of urban growth strategy on disaster management. Urban growth strategy proposed by planners is a vital component to incorporate flood resilience, which can have long-term impacts on flood recovery.

Therefore, this framework is essential for planners to improve disaster preparedness and to simulate urbanization trends to increase resilience. Moreover, the spatial distribution of resilience can assist disaster managers in operating efficiently in flood-prone regions and incorporate spatial simulation data to mobilize resources in future disaster events.

This approach can be further improved by incorporating the stakeholder views on disaster resilience pathways and modeling behavioral patterns of the community during flood events to validate the results. Moreover, deep learning and agent-based models can be used to measure the performance of non-linear variables during disaster events to specify the critical parameters of flood resilience, which can be generalized into cities based on natural, physical, and social factors.

This approach provides a novel interdisciplinary focus to disaster resilience research which can be tested among coastal flood-vulnerable cities to simulate a sustainable urban future with effective disaster risk reduction strategies.

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