

**Original Research Article**

## **Geospatial Approaches to Enhancing Urban Flood Resilience in Auckland, New Zealand: Implementation of Innovative Mitigation Strategies**

**Sai Meghana Annadi, Funmilayo Egun Rotimi\*,  
George Okyere Dokyi**

Built Environment Engineering Department, School of Future Environments,  
Auckland University of Technology, Auckland, New Zealand  
e-mail: [mnp3521@autuni.ac.nz](mailto:mnp3521@autuni.ac.nz), [funmi.rotimi@aut.ac.nz](mailto:funmi.rotimi@aut.ac.nz), [george.dokyi@aut.ac.nz](mailto:george.dokyi@aut.ac.nz)

Cite as: Annadi, S. M., Egun Rotimi, F., Dokyi, G., Geospatial Approaches to Enhancing Urban Flood Resilience in Auckland, New Zealand: Implementation of Innovative Mitigation Strategies, J.sustain. dev. energy water environ. syst., 13(4), 1130608, 2025, DOI: <https://doi.org/10.13044/j.sdewes.d13.0608>

### **ABSTRACT**

Flooding is a significant threat to urban resilience, particularly in rapidly urbanising coastal cities like Auckland, New Zealand, where urban growth and climate shifts increase flood risks. This study addresses the gap in integrating multi-criteria decision-making tools with the Geographic Information System to enhance flood resilience strategies. A novel combination of the Analytic Hierarchy Process and spatial analysis was used to develop a high-resolution flood susceptibility model, analysing seven key factors, including slope, land use, rainfall intensity, and drainage density. The results show that 16% of Auckland is highly susceptible to flooding, 63% moderately susceptible, and 21% at low risk. The model, validated against historical flood data, demonstrated 82.98% accuracy. These findings offer actionable insights for urban planners, enabling dynamic floodplain management and real-time decision support systems. This research provides a framework for sustainable urban planning and disaster mitigation, advancing both theoretical and practical approaches to flood resilience.

### **KEYWORDS**

*Urban Flooding, Climate Change, GIS, AHP, Flood Susceptibility, Spatial Analysis, Auckland.*

### **INTRODUCTION**

Floods are among the most common natural disasters worldwide, impacting many nations [1]. A flood occurs when large volumes of water inundate dry land [2]. Key causes include heavy rainfall, storms, river overflows, climate change, and poor urban planning [3]. Urban floods arise when unplanned development obstructs natural drainage systems, increasing flood risks [4]. While urbanisation is a significant factor, other contributors include deforestation, population growth, and rising sea levels driven by climate change [5], [6]. With flood vulnerability expected to increase [7], practical hazard assessment must consider meteorological, hydrological, and socioeconomic factors [8]. Flood risk evaluation involves four steps: assessing susceptibility, identifying areas, and estimating hazard intensity [9]. Advances in GIS, remote sensing, and hydraulic modelling have become essential tools for flood risk and hazard assessment [10]. Natural disasters significantly challenge many countries around the world; however, some nations bear a disproportionate share of these environmental threats [11].

---

\* Corresponding author

The Philippines is among the most vulnerable countries to natural calamities [12]. Because of the regular cyclones and typhoons, the nation is always at risk of flooding. Heavy rainfall is the leading cause of flooding, which is one of the most catastrophic natural disasters in Davao Oriental, Philippines [13]. In response to these challenges, government agencies continually seek tools and technologies to aid in disaster management [14]. Recently, they opted to leverage GIS technology, incorporating topographical data into a dedicated database to establish a GIS system [12]. By integrating multiple variables such as rainfall, slope, elevation, drainage density, soil type, distance to the main channel, and population density, the study identified flood-prone risk zones in the region [15]. A GIS-based flood risk assessment was conducted in Davao Oriental to evaluate the significance of each indicator. This analysis uses frameworks such as the analytic hierarchy process (AHP), weights by rank (WR), and ratio weighting (RW) [15]. The departments could determine natural hazard susceptibility by feeding in spatial inputs such as building sites and flooded regions and then integrating them with the present meteorological conditions. These actions assisted the agency in estimating the population that would be at risk of flooding and in planning rescue operations well in advance of any terrible occurrences [12]. The results are verified by comparing the flood-prone areas that the three approaches produce with the predicted flood map derived from ground truthing points from a field survey. Based on the comparative results, AHP is the best approach to evaluate flood hazards. According to the AHP flood-risk map, 95.99% (5,451.27 km<sup>2</sup>) of Davao Oriental in the Philippines is at low to moderate risk of flooding, and about 3.39% (192.52 km<sup>2</sup>) of the province, mainly in the coastal regions, falls within high and extremely high flood-risk zones. Given the current climate, 31 out of 183 barangays (towns) are at a high to very high risk of flooding. As a result, decision-makers need to take quick action to design mitigation techniques to prevent flooding in Davao Oriental in the future [15].

Thus, this study aims to bridge the existing gap in the integration of multi-criteria decision-making tools with Geographic Information Systems (GIS) to strengthen strategies for enhancing flood resilience.

## LITERATURE REVIEW

Flood susceptibility mapping is vital for disaster risk management, especially in urban areas. This section explores key methodologies, including GIS and MCDM approaches, with a focus on AHP as a widely used technique for flood risk assessment and mitigation.

### Flood susceptibility mapping method

An early warning system (EWS), as defined by the United Nations, is a climate change mitigation tool that leverages information technology for risk monitoring, alert communication, practical action, and risk awareness [16]. Auckland has implemented monitoring and warning systems as part of its EWS, but these efforts have yet to prevent flood impacts entirely. Flood susceptibility maps enhance the EWS by enabling authorities to analyse vulnerable areas and respond swiftly to warnings. Flood mapping and sensitivity analysis are crucial components, identifying flood-prone areas based on spatial factors [17]. This approach supports experts and communities in proactive flood prevention.

### Geographic Information System

GIS is a tool designed to store, manage, analyse, and visualise geographical data [18]. It enables the modelling and representation of spatial information, offering solutions to intricate planning and management challenges [19]. Each layer in a GIS represents data with specifics associated with specific locations and established relationships [20]. According to [21], GIS techniques are intended to offer an organised framework for effectively manipulating and analysing all information, which enables the timely identification of possible hazard zones. Recently, advancements in GIS and remote sensing have been incorporated into evaluating

geoenvironmental disasters. This integration has significantly progressed flood susceptibility mapping, flood hazard assessment, and flood management strategies [22].

### Multi-Criteria Decision Making approaches

The authors of [23] define Multi-Criteria Decision Making (MCDM) as a method for tackling complex decision problems involving multiple criteria. The process of ranking alternatives in an MCDM model involves three key steps: identifying relevant criteria and alternatives, assigning weights to criteria, and applying numerical measures to evaluate how alternatives impact these criteria [24]. Subsequently, numerical values are processed to generate a ranking score for each alternative [25]. The adoption of MCDM tools in flood risk management, as noted by [26], can offer substantial benefits. AHP stands out as the most widely used MCDM technique in flood hazard mapping due to its user-friendliness and versatility [27]. This current study on Flood Susceptibility Mapping for Auckland adopted an AHP approach based on GIS to identify the flood risk zones. Evidence suggests that GIS and AHP Multi-Criteria Decision Analysis (MCDA) is the most suitable method, as determined through an analysis of comparable articles published in high-impact journals [28].

### Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is a pairwise comparison method that uses multi-level hierarchies and priorities [29]. A key advantage of AHP is its ability to handle adaptive changes with minimal inconsistency using decidable data. Many researchers have applied AHP to develop weighted criteria for flood susceptibility mapping. For example, [30] used AHP to assign criteria weights, integrating them with GIS techniques like layer overlay and raster processing to produce a flood hazard map for the Philippines. Similarly, [31] applied AHP with nine factors and a weighted linear combination to analyse flood hazards and public preparedness in Abidjan, successfully identifying and mapping flood risk areas using GIS.

### Selection of factors for flood susceptibility analysis

The susceptibility analysis is to identify key factors that ensure reliable and accurate results. Drawing on a comprehensive literature review, this study integrates widely recognised factors that influence flood susceptibility, including proximity to slope [32], aspect [33], elevation [34], and Topographic Wetness Index (*TWI*) [35] other critical variables include rainfall [36] drainage density [37], Normalised Difference Vegetation Index (*NDVI*) [38] and land use and land cover (LULC). Together, these factors form the basis for an effective and comprehensive susceptibility mapping framework.

Therefore, the narrowed-down problem statement revolves around the challenge of leveraging GIS technologies to develop and implement robust flood mitigation measures specifically for urban environments. Several studies have explored flood risk in New Zealand, but there is a notable gap regarding a comprehensive GIS-based approach specifically focused on Auckland. The Northland region has been the focus of flood risk studies, with particular emphasis on using community-based flood maps to explain flood hazards, as highlighted in such published studies as [39], [40]. Their study lacks attention to technological tools like GIS, particularly for urban areas such as Auckland. Therefore, this research will evaluate the suitability of GIS techniques in mapping urban flood susceptibility, identify and assess areas at risk of flooding, and suggest innovative flood mitigation measures enabled by GIS technology.

## MATERIALS AND METHODS

This study applies geospatial methods to enhance urban flood resilience in Auckland, New Zealand. ArcGIS Pro software was used for its robust spatial analysis and data management capabilities, enabling detailed evaluation of flood-prone areas using data like topographic

maps, flood records, and rainfall patterns. Auckland was chosen as the case study due to its high flood susceptibility, which is driven by rapid urban development and changing land use.

The research method begins with evaluating GIS techniques for urban flood mapping, identifying flood-prone areas in Auckland, and suggesting innovative mitigation measures. Data collection is carried out, involving both spatial data (e.g., Digital Elevation Model – DEM, land use/land cover, *TWI*, and satellite data) and attribute data (e.g., rainfall, slope, and elevation profiles). These datasets are processed to generate thematic layers, including DEM, Elevation, slope, land use/land cover, *TWI*, *NDVI*, and rainfall maps. These thematic layers are then integrated and analysed using MCDA to create a flood susceptibility map. The process concludes with insights and recommendations based on the flood susceptibility map to improve urban flood resilience.

### Multi-Criteria Decision method

**Figure 1** outlines the application of MCDA analysis for flood risk mapping. It begins by integrating various data sources, including the DEM, satellite images, rainfall data, and land use/land cover (LULC) information. Each input is processed to extract relevant factors like elevation, *TWI*, slope, drainage density, land use, rainfall, and *NDVI*. These factors undergo reclassification to standardise their values for analysis. Finally, a weighted overlay of the reclassified data generates a flood risk map, aiding in flood susceptibility assessment.

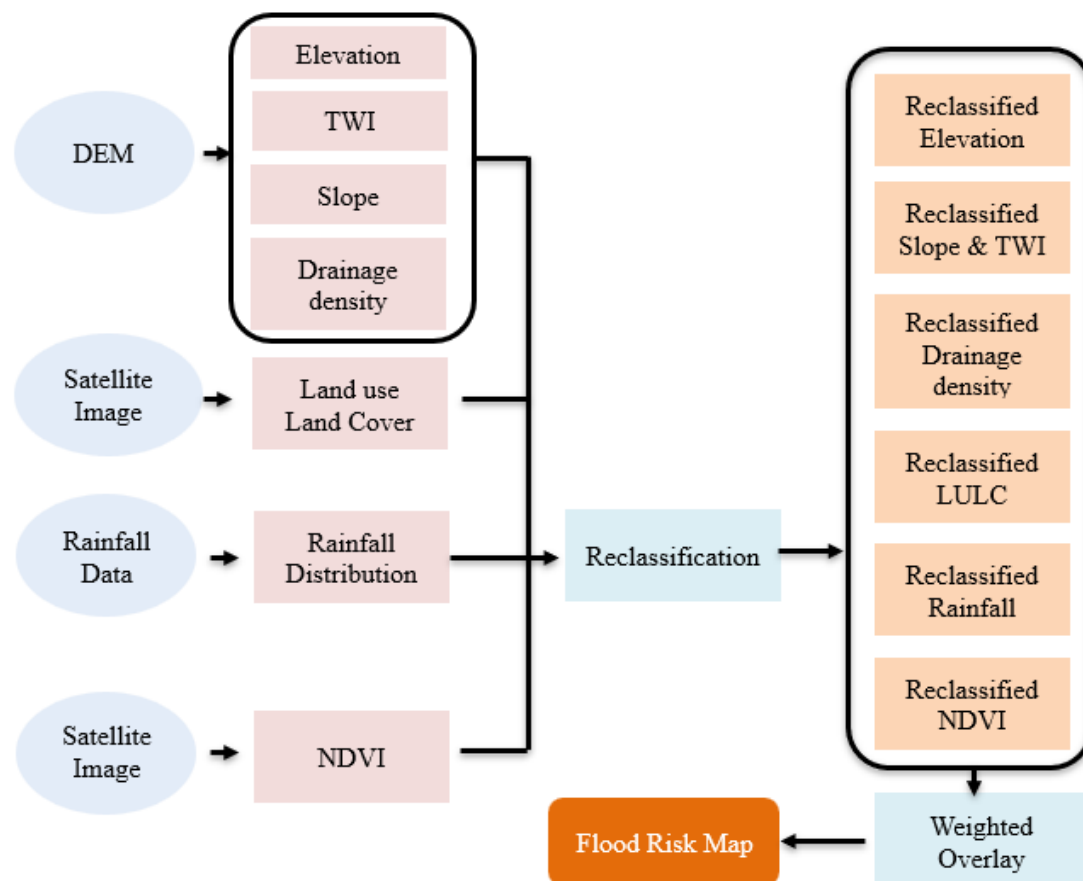


Figure 1. Multi-criteria decision making for flood risk mapping

### Case study context

Auckland, which is the focus of this study, lies in the northern part of New Zealand's North Island, between latitudes 36°45'–37°10' south and longitudes 174°30'–175°10' east, covering approximately 1,086 km<sup>2</sup>. Mount Eden, at 196 meters, is the highest point in central Auckland, as illustrated in **Figure 2**. The Tasman Sea borders Auckland to the west, the Hauraki Gulf and

Pacific Ocean to the east, the Waikato region to the south, and the Northland region to the north. The Tamaki River, in the east, connects through tributaries near urban Auckland. Auckland's geography features two principal harbours: Waitemata Harbour to the north and Manukau Harbour to the south, forming a distinctive isthmus. The Waitemata Harbour drainage basin is vital for water management. Urban areas consist of flat to rolling terrain, while surrounding regions are rugged with volcanic cones and ranges [41]. Around 80% of the region is urbanised or semi-urbanised, shaped by its unique volcanic and coastal landscapes [42].

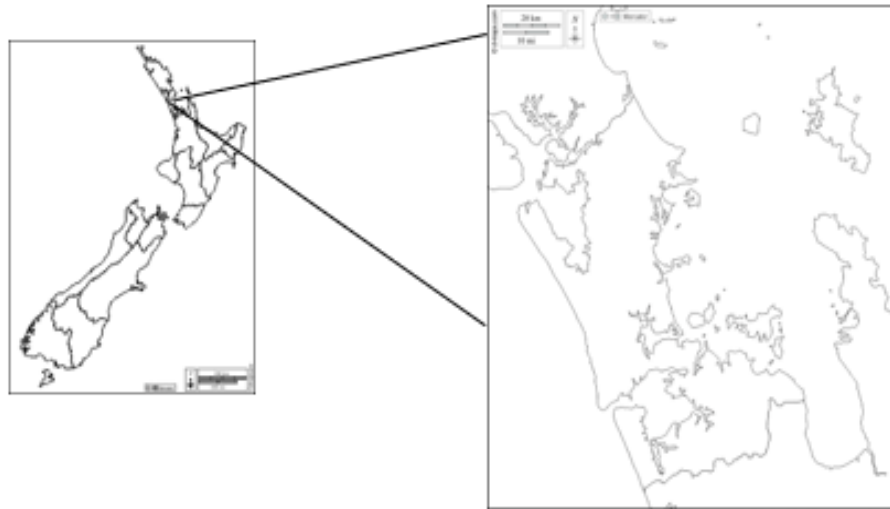


Figure 2. The map of New Zealand showing the location of Auckland [43]

The rate of temperature increase has accelerated in recent decades, as shown in **Figure 3**. While annual temperature fluctuations are evident, the overall pattern suggests a long-term warming trend. The steeper slopes of the trend lines for the more recent periods further confirm that temperature rise has intensified over time. Such a rise in temperature can significantly impact flood risks. Warmer air holds more moisture, leading to heavier and more intense rainfall, which increases the likelihood of flooding.

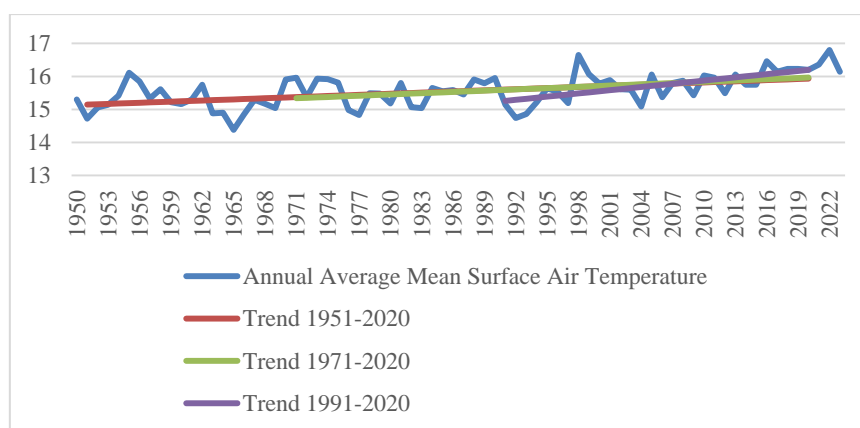


Figure 3. Average Mean Surface air temperature [°C] according to [44]

**Rainfall data.** **Figure 4** shows the annual precipitation of Auckland (1903–2023) graph, which indicates fluctuations in rainfall over the past century, with periods of both increasing and decreasing trends. While precipitation was highly variable in the early 20th century, the data suggest a gradual increase in recent decades, particularly after 2000. It could indicate a shift in rainfall patterns, which contributes to higher flood risks.

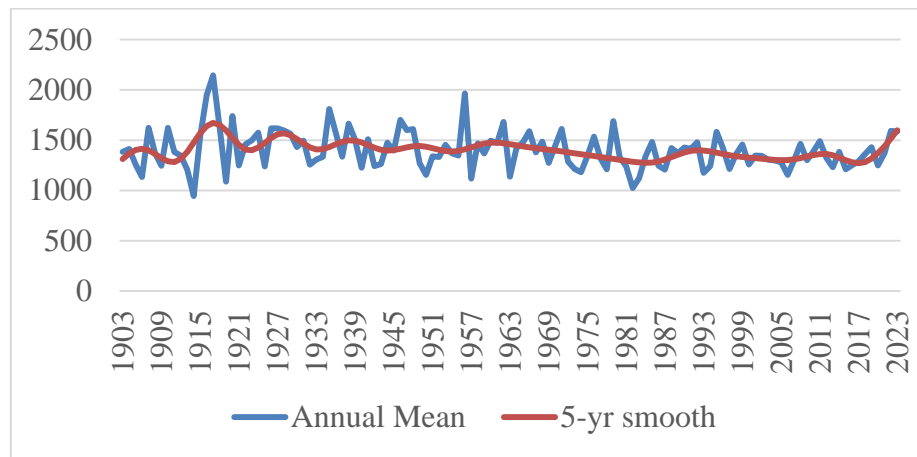


Figure 4. Annual precipitation [mm] of Auckland (1903–2023) [45]

**Table 1** shows the monthly precipitation data for 2019–2023 highlighting significant variations and extreme rainfall. The year 2023 experienced much higher rainfall, especially in January and February, compared to the previous years. These heavier rainfall amounts are essential for understanding recent floods and recognising climate trends that might affect future weather. By looking at these patterns, the study can identify times when heavy rainfall is more likely to cause flooding. The rainfall data presented in **Table 1** were collected from a single station, ensuring consistency in measurement and allowing for a focused analysis of precipitation trends over the study period. The station is located within the analysed area and provides comprehensive monthly precipitation records.

Table 1. Average rainfall data from a single station in the Auckland region [45]

Year/Month	Rainfall [mm]				
	2019	2020	2021	2022	2023
January	26.5	10.9	74.06	27.39	317.57
February	33.71	10.6	87.46	148.75	381.03
March	67.17	32.63	151.67	109.12	49.7
April	73.51	42.3	113.62	116.14	115.55
May	34.9	133.21	52.43	115.77	275.4
June	57.37	125.15	134.7	134.03	191.55
July	110.31	94.34	109.84	281.31	159.9
August	117.67	149.89	139.26	171.34	82.35
September	126.63	47.4	166.3	175.29	154.45
October	76.9	48.83	116.1	135.71	102.35
November	44.82	142.32	79.23	207.26	58.21
December	64.13	27.23	77.83	129.72	75.22

**Outline of Flooding Event.** January 27, 2023, and February 13 & 14, 2023, were the dates of the rainfall occurrences. Approximately 1.7 million people, or one-third of New Zealand's total population of 5.2 million, live in the Auckland region, which is the focus of this research. The country continues to recover from the billion-dollar destruction caused by rainstorm

disasters to property and infrastructure. Due to excessive rainfall, there were widespread catastrophic floods over the upper North Island of New Zealand starting on Friday, January 27, 2023. Urban flooding was the leading cause of these widespread, devastating floods. As the long weekend approached, Auckland was the most severely hit [46]. Because of the extreme weather, four people lost their lives [47].

A state of urgency was issued in Auckland; at least 5,000 properties in the city were assessed for potential damage from floods, with at least 77 of them receiving red stickers [47]. The terminal buildings of Auckland Airport were completely submerged in water, causing the airport to close temporarily. Flights that were cancelled or diverted affected tens of thousands of travellers [47]. Several areas of Auckland had to be evacuated due to flooding, and many people needed to be rescued due to the rapid intensification of the flooding. Floodwaters left lots of people trapped in their vehicles [47]. This research highlights the impacts of these rainfall events, which caused billions of dollars in damage and the need for effective flood resilience strategies. According to [46], the rainfall data for January 2023 indicate that Auckland experienced the highest-ever recorded rainfall with 478 mm, highlighting the severity of the weather conditions. Tauranga followed with 385 mm, while Hamilton recorded 235 mm [20]. In contrast, Wellington and Christchurch received significantly lower rainfall, with 116 mm and 26 mm, respectively [46]. These data underscore the exceptional and extreme rainfall events in Auckland compared to other locations.

### Geospatial data source and influencing factors

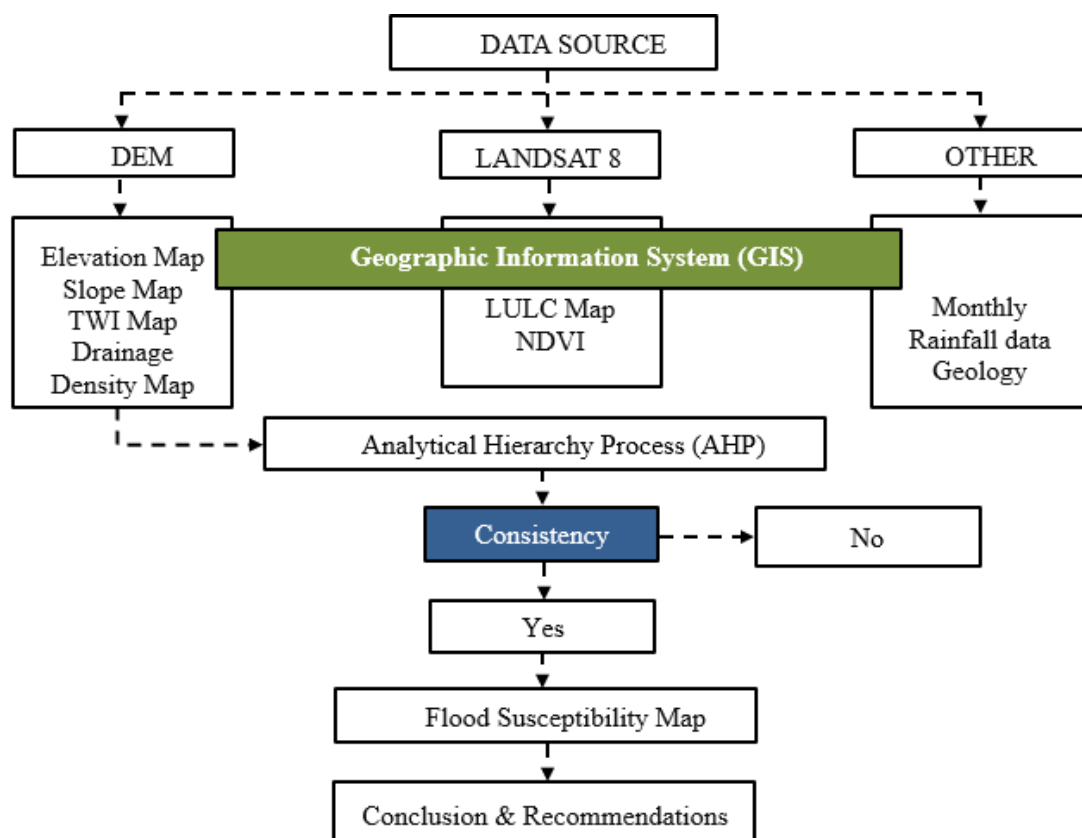


Figure 5. Method used to develop the flood susceptibility map for the Auckland region

The primary methodology of this study involves GIS-based multi-criteria decision analysis for flood susceptibility mapping. Creating a susceptibility map for the research area requires several multi-source geospatial datasets. Consequently, the influencing factors are collected

from various sources, including digital elevation model (DEM), Landsat 8 imagery, soil type, and rainfall data, as shown in **Figure 5**.

The spatial database for flood influencing factors comprises rainfall, geology, land use, topographic wetness index (*TWI*), drainage density, slope, normalised difference vegetation index (*NDVI*), and digital elevation model (DEM). Five of these factors can be extracted from the DEM using the spatial analyst tool in the ArcGIS Pro software, as explained in the flowchart shown in **Figure 6**.

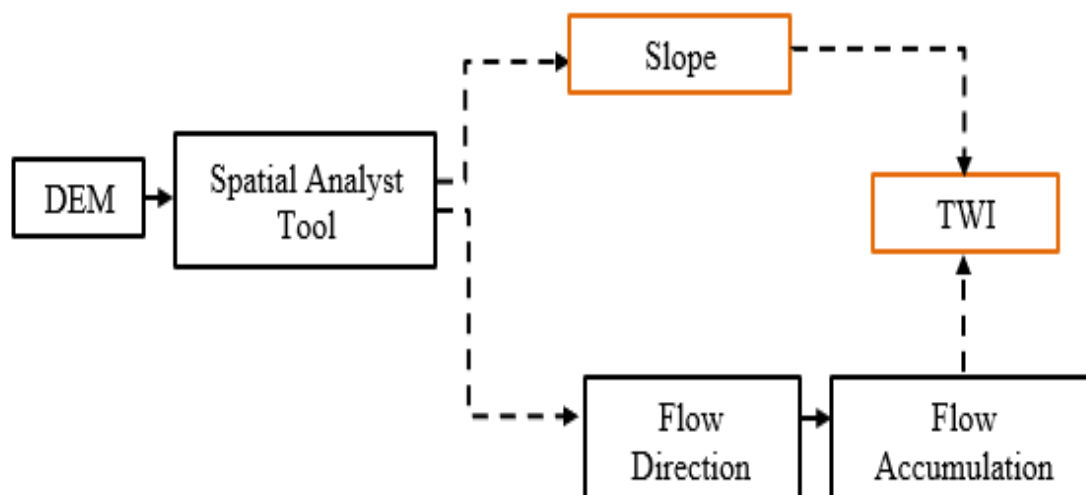


Figure 6. Flowchart for the data collection methodology using ArcGIS Pro

The slope map is generated directly from the DEM raster. To calculate *TWI*, flow direction and flow accumulation must be extracted and processed using the raster calculator in the spatial analyst tool. Using the same flow accumulation data, the spatial analyst tool also produces drainage density and distance from drainage.

## ANALYSIS AND PRESENTATION OF RESULTS

This study achieves its objectives by integrating the Analytic Hierarchy Process (AHP) with GIS to develop a flood susceptibility map for Auckland. Using ArcGIS Pro, parameter maps (e.g., Slope, Elevation, Rainfall, LULC, Drainage Density, *TWI*, and *NDVI*) are generated to analyse flood-influencing factors. A  $7 \times 7$  pairwise comparison matrix in AHP systematically evaluates these factors, assigning weights based on their significance. In addition, the calculated value of the consistency ratio (*CR*) ensures the reliability of the weighted criteria, simplifying complex decision-making.

### Elevation

Elevation significantly influences flood occurrence, as water flows rapidly from higher to lower elevations, making low-lying areas more prone to flash flooding. The elevation map of Auckland, presented in **Figure 7**, was generated using a Digital Elevation Model (DEM) sourced from the United States Geological Survey (USGS) and processed in ArcGIS. Elevation in Auckland ranges from  $-34$  to  $700$  meters, with higher elevations in inland hilly areas and lower elevations near coastlines and flatlands. These variations are critical for assessing flood risks, as low-lying areas are particularly vulnerable.

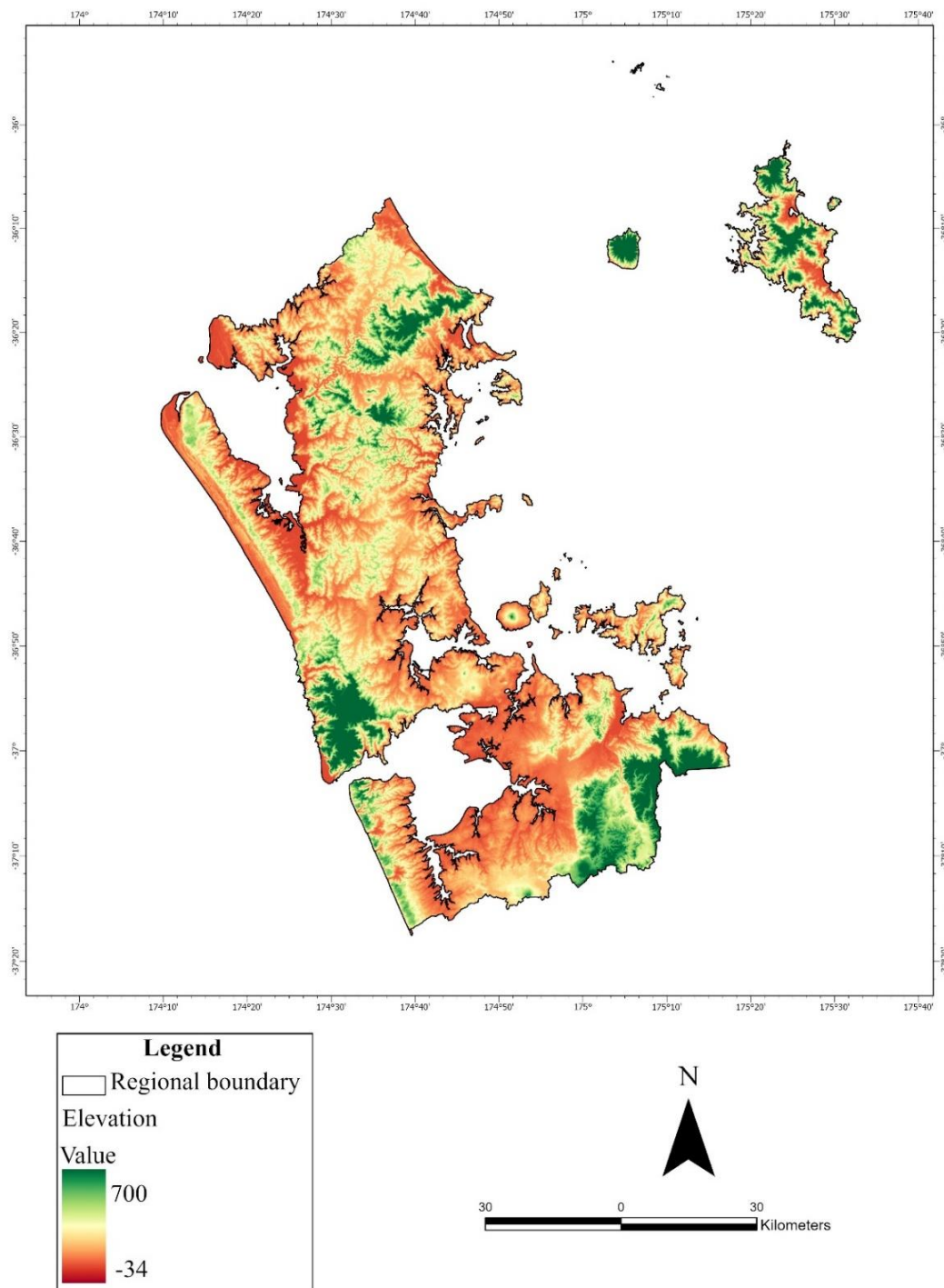


Figure 7. Elevation map of Auckland

## Slope

Flood risk increases in areas with lower slope values, as flatter terrain allows runoff to move quickly, heightening flood susceptibility. Conversely, steeper terrain slows runoff, reducing flood risk. The slope map of Auckland shown in [Figure 8](#), was created using a DEM and ArcGIS's spatial analyst tool. Slope values, measured in degrees, range from 0.001–4.418 (low) to 23.564–75.105 (high). Central and northern Auckland, with lower slope values highlighted in green, are more prone to flooding due to rapid runoff, while the western areas, with higher slopes, exhibit reduced flood risks.

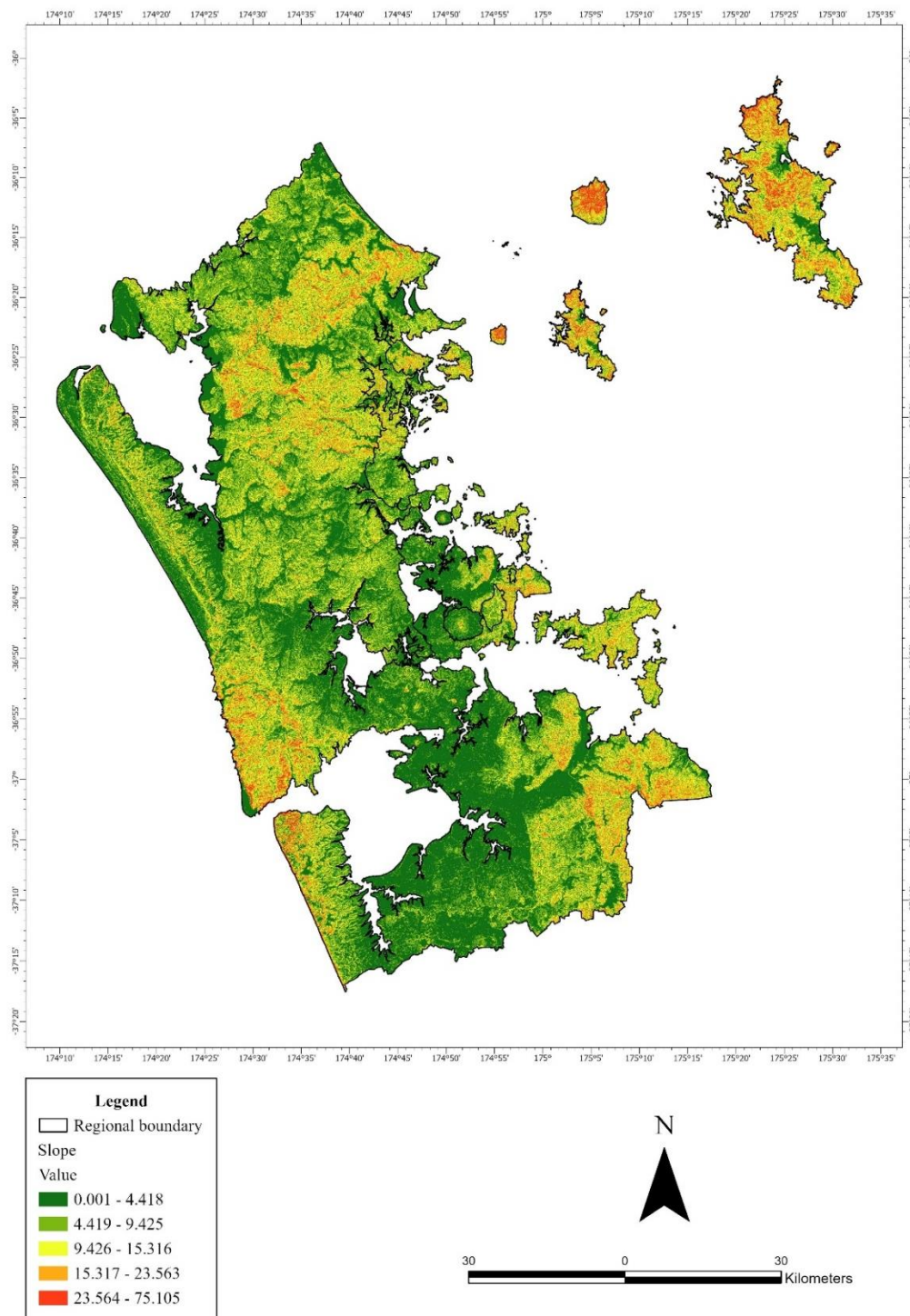


Figure 8. Slope map of Auckland

### Topographic Wetness Index

The Topographic Wetness Index (*TWI*) is a vital metric for identifying areas prone to wetland formation and high overland water flow potential. It helps assess flood susceptibility by highlighting zones likely to accumulate water. The *TWI* map is derived from slope and flow accumulation data and analysed using a Digital Elevation Model (DEM). Calculated with ArcGIS Pro's raster calculator, *TWI* values reflect topographical characteristics. In Auckland, as depicted in [Figure 9](#), *TWI* values range from  $-9.4$  to  $12.2$ . Lower values, shown in red,

indicate steeper slopes and smaller drainage areas, suggesting reduced runoff accumulation. Higher values, found in flatter regions or areas with larger drainage zones, signify greater water accumulation and flood risk.

$$TWI = \ln[As / (\tan\beta + C)] \quad (1)$$

Where  $As$  denotes the total area of upslope drainage,  $\tan\beta$  – local slope gradient, and  $C = 0.00$ .

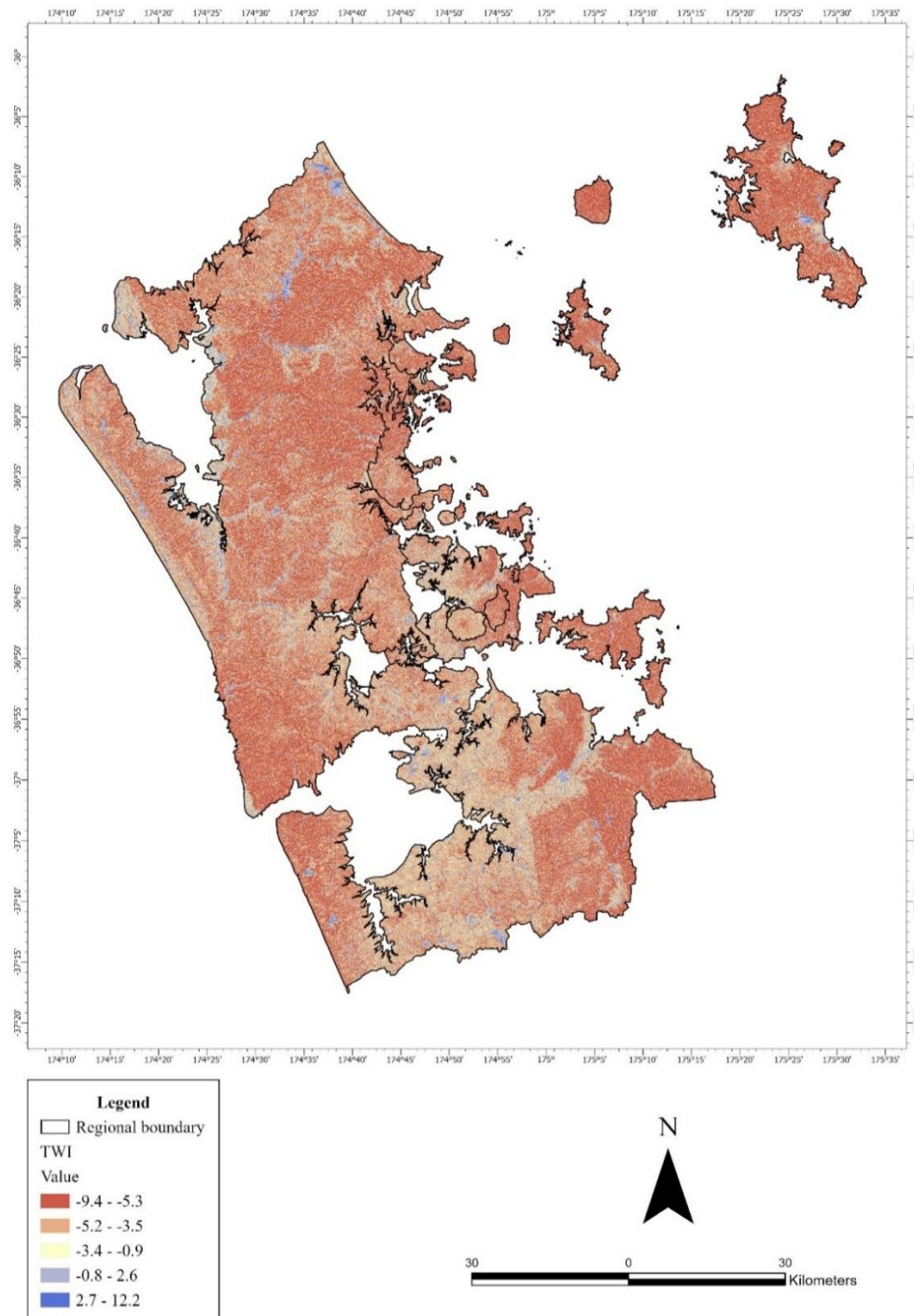


Figure 9. Topographic Wetness Index (TWI) map

## Drainage density

The drainage density map is calculated from flow accumulation, which can be derived from DEM data using the “line density” tool within the spatial analyst tools of ArcGIS Pro software. **Figure 10** presents the drainage density distribution for Auckland, with values ranging from the lowest (0.1–31.9) to the highest (127.7–159.6). The central and some southeastern parts of the region, where red and orange colours are prominent, are the areas most at risk. These areas have the highest drainage density values (127.7–159.6), indicating that they are more prone to the risks associated with high surface water runoff.

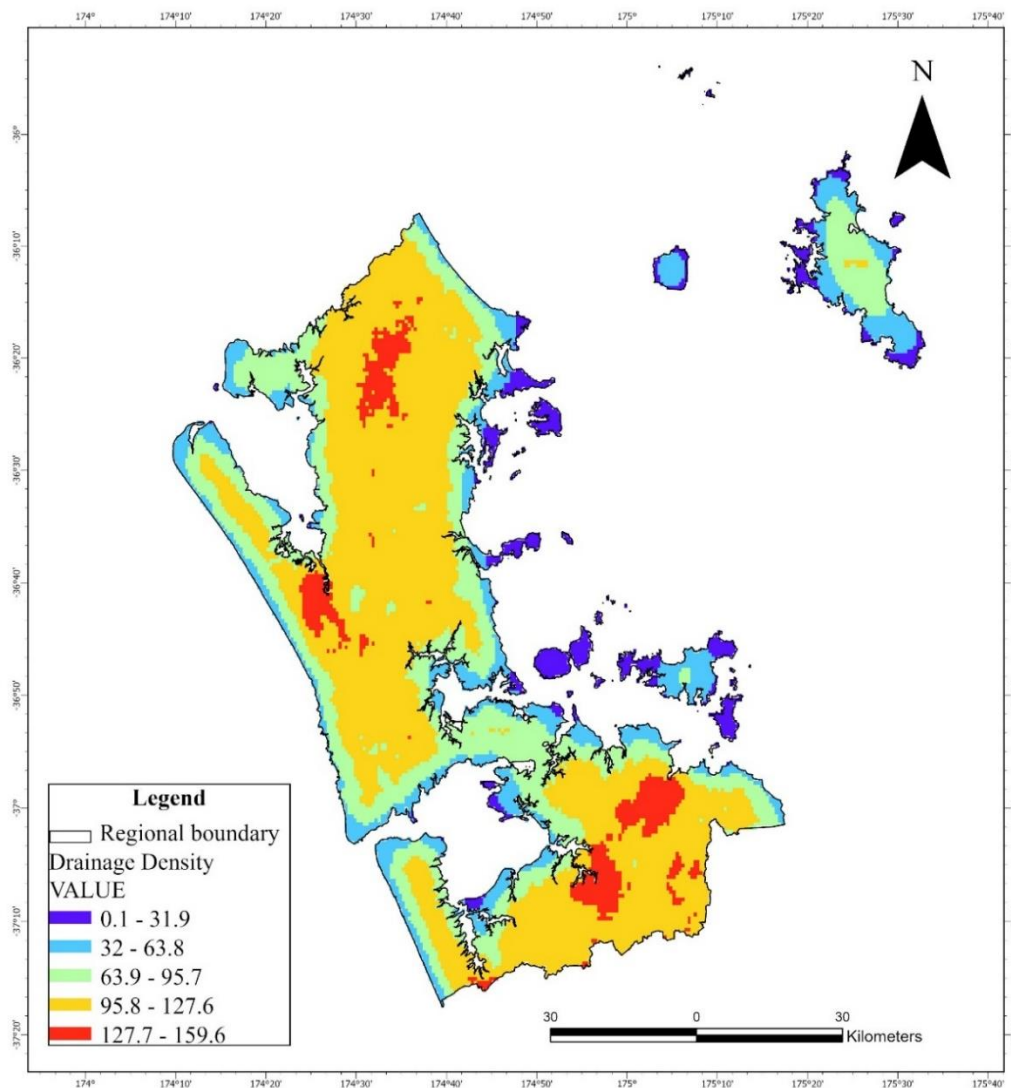


Figure 10. Drainage density map

## Rainfall

Rainfall is a primary driver of floods, as heavy rains can overwhelm river systems and lead to excess surface runoff when infiltration capacity is exceeded. Rainfall data for this study were obtained from the Climatic Research Unit (CRU). **Figure 11** shows the annual rainfall distribution across Auckland, with the northern areas receiving the least rainfall (34.92–150.18 mm). Moving south, rainfall increases, with the central region experiencing moderate levels (150.19–338.89 mm, shown in yellow and orange). The southern and southeastern areas receive the highest rainfall (415.8–503.79 mm), making them more prone to flooding due to

higher water availability. This rainfall gradient is critical for assessing flood risks and managing water resources.

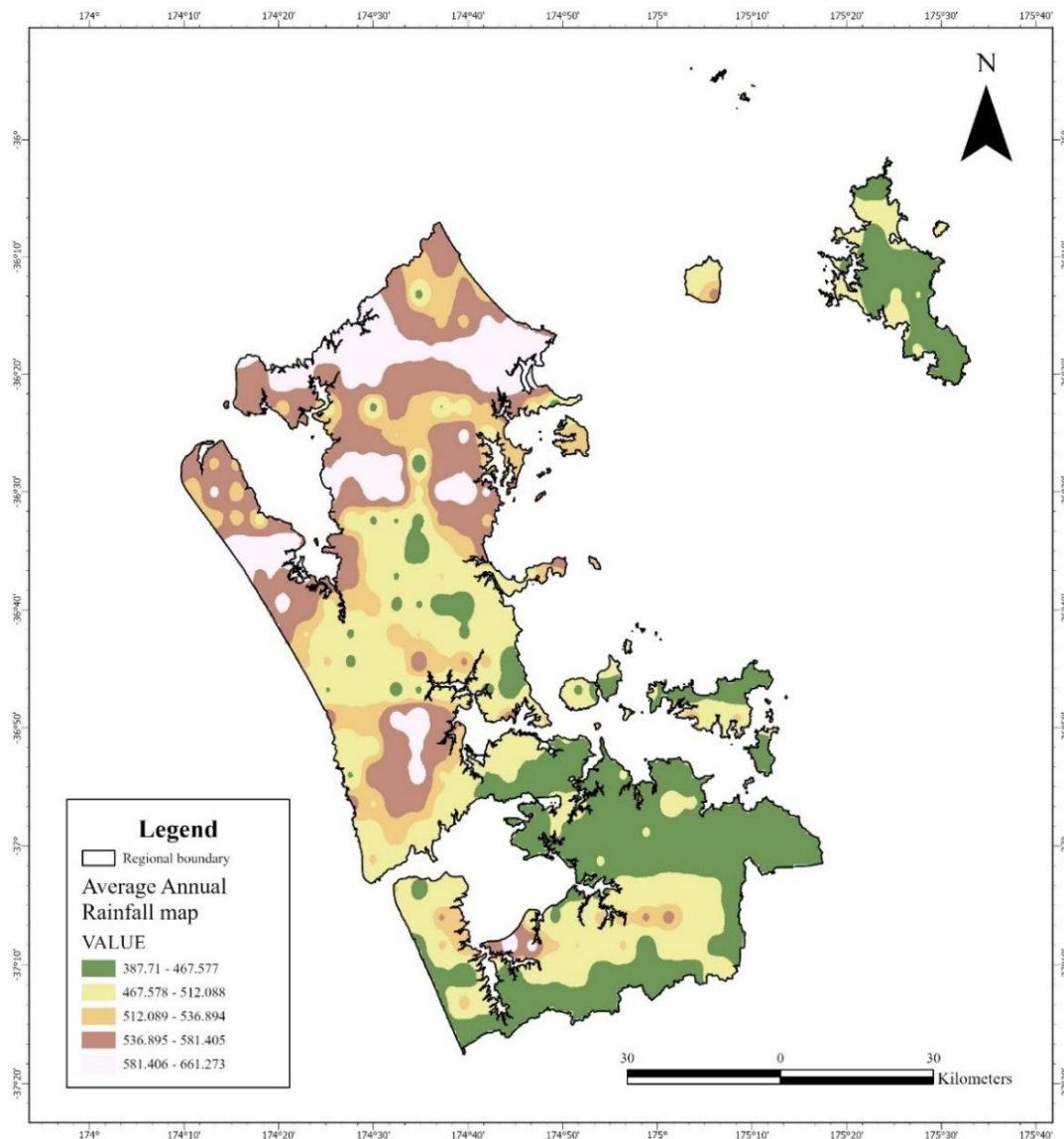


Figure 11. Rainfall map (2019–2023)

### Land use and land cover

Land use and land cover are critical in influencing soil stability and water infiltration, making them significant factors in flood susceptibility mapping. Areas with dense vegetation reduce surface runoff by slowing water movement from precipitation to the ground, promoting infiltration. Conversely, impervious surfaces such as concrete and asphalt limit water absorption, leading to an increase in surface runoff and elevating the risk of flooding. The LULC map shown in [Figure 12](#) was generated using 2023 Landsat 8 imagery acquired from the United States Geological Survey (USGS) website. From the LULC map obtained, 29% of Auckland consists of fallow land, 26% of forest, 22% of agricultural activities or cultivated, 13% of settlements and 1 % of water.

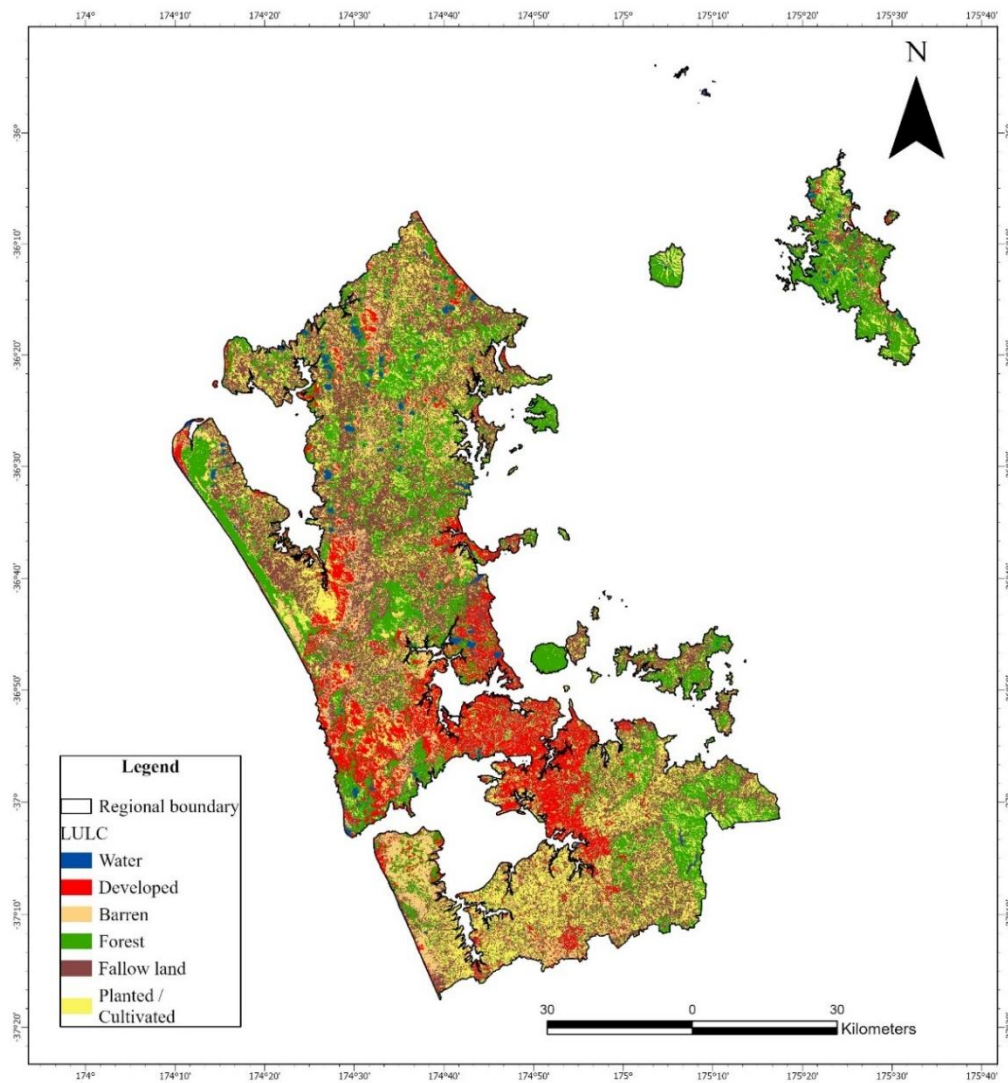


Figure 12. Land Use and Land Cover (LULC) Map

### Normalised Difference Vegetation Index

The Normalised Difference Vegetation Index (*NDVI*) is an essential tool for evaluating vegetation cover, which is crucial in reducing surface runoff and serving as a natural barrier against flooding. It is determined using the red (*R*) and near-infrared (*NIR*) bands from satellite data, such as Landsat 8, with values ranging between  $-1$  and  $+1$ . High *NDVI* values suggest lush, healthy vegetation, while low values point to sparse or minimal vegetation. The *NDVI* map of Auckland, shown in [Figure 13](#) and derived from Landsat 8 imagery, displays *NDVI* values ranging from  $-0.32$  to  $+1$ . The formula for this index is:

$$NDVI = (Band5 + Band4) / (Band5 - Band4) \quad (2)$$

Regions with lower *NDVI* values, shown in yellow and light orange, likely represent urbanised or developed areas with limited vegetation. Conversely, areas with higher *NDVI* values, illustrated in green and dark green, denote regions with thick vegetation, such as forests or parks, which play a key role in natural flood protection. This distribution highlights the

varying capacity of different areas within Auckland to withstand and mitigate the effects of flooding based on their vegetation cover.

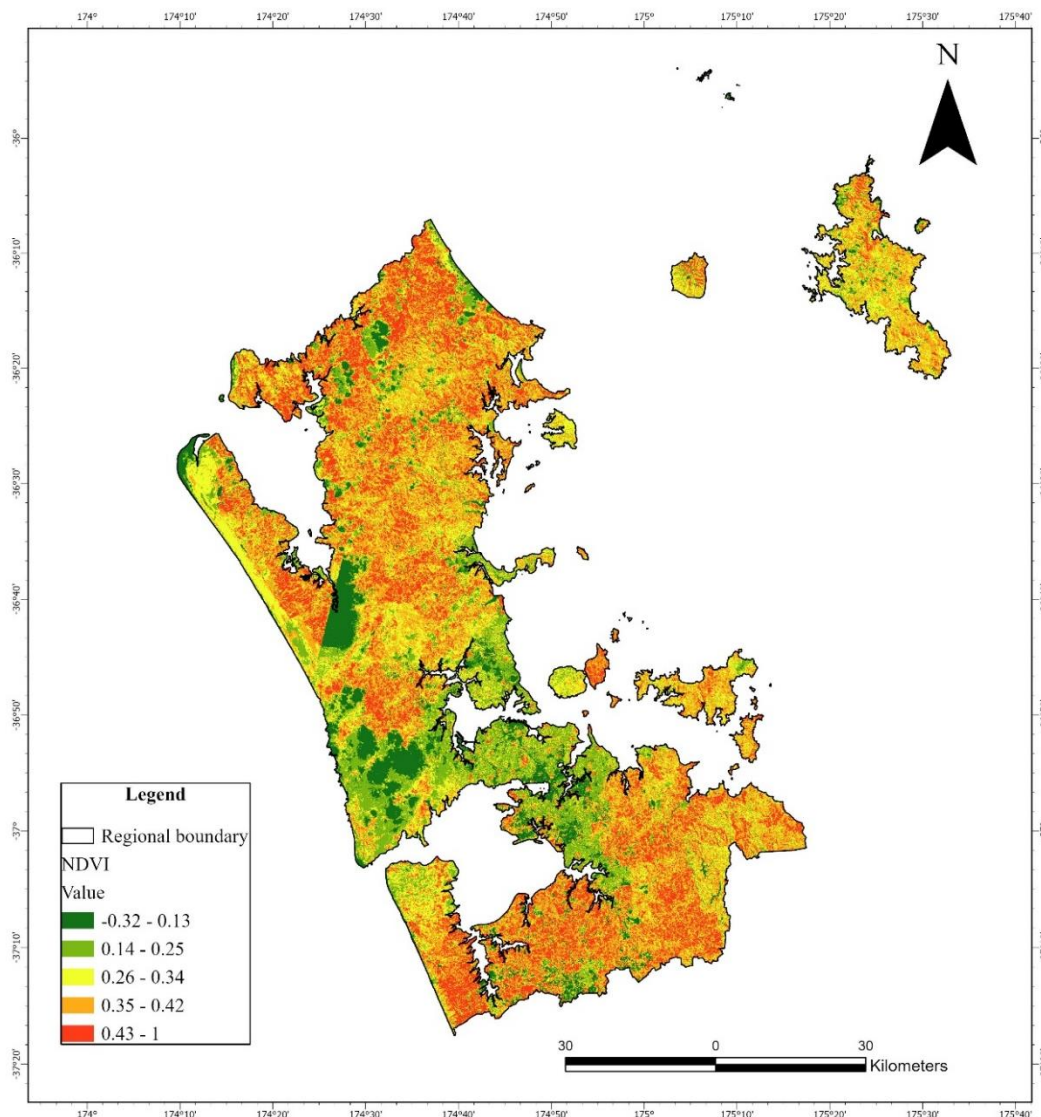


Figure 13. Normalised Difference Vegetation Index (NDVI) map

### Weight linear combination technique

The weighted linear combination (WLC) method assesses criterion relevance and assigns appropriate weights [48]. The Analytical Hierarchy Process (AHP) approach for WLC involves five key steps: (a) listing the unit factors; (b) organising these factors into a hierarchical structure; (c) assigning numerical values to the factors based on their importance; (d) generating a comparison matrix; and (e) calculating the normalised eigenvector to determine the weights of each factor. A combination of expert judgment and a literature review was used to assign numerical values, with the factors scored on a nine-point continuous scale [49] according to their relative importance, as shown in Table 2. The study employs the consistency ratio (CR) to evaluate the reliability of the pairwise comparison matrix. The procedure is initiated by calculating the Consistency Index (CI), using the following formula:

$$CI = (\lambda_{max} - n) / (n - 1) \quad (3)$$

Where  $\lambda_{max}$  is the principal eigenvalue of the matrix, and  $n$  is the number of criteria.

Next, the consistency ratio ( $CR$ ) is calculated to determine if the pairwise comparison matrix is consistent, using:

$$CR = CI / RI \quad (4)$$

In this formula,  $RI$  represents a random index value that depends on the size of the matrix [50]. A  $CR$  value of 0.10 or less is considered acceptable. However, a  $CR$  exceeding 0.10 indicates inconsistency in the assessments and implies the need for revisiting subjective judgments.

Table 2. Criteria weight of pairwise comparison matrix scale [51]

Intensity of importance <sup>a</sup>	Definition	Elevation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favour one element over another
5	Strong importance	Experience and judgment slightly favour one element over another
7	Very strong importance	One element is favoured very strongly over another; its dominance is demonstrated in practice
9	Extreme importance	The evidence favouring one element over another is of the highest possible order of affirmation

<sup>a</sup> The values of 2, 4, 6, and 8 can be used to express intermediate intensities

## DISCUSSION

The development of the flood susceptibility map is structured into two distinct phases. First, the weighted criteria are established through a pairwise comparison matrix within the AHP framework, ensuring a systematic evaluation of factor importance. Subsequently, these weights are applied using the weighted overlay method in Geographic Information Systems (GIS) to generate the final flood susceptibility map.

### Weight linear combination techniques

After assigning relative weights on a nine-point continuous scale following the method developed by [49], a comparison matrix was created where the diagonal elements are equal to 1. For example, the element corresponding to rainfall is of equal importance to itself, which means the diagonal element in the first row (for rainfall) is 1. Similarly, when elevation is compared with itself, the corresponding diagonal element will also be 1, and this pattern continues for all criteria. Next, the sum of the values in each column of the comparison matrix is calculated, as shown in Table 3. Following this, a normalised pairwise matrix is derived by dividing each element of the column by the sum of that column. The criteria weights are then determined by calculating the average of the elements in each row, i.e., by dividing the sum of

the row elements by the number of criteria. The criterion with the highest weight is considered the most significant in the overall calculation. From the criteria weights obtained, the three most influential factors in this analysis are *TWI*, Rainfall, and Elevation, collectively accounting for over 50% of the total weight [52], [53].

Table 3. Pairwise comparison matrix and final weights

<u>Matrix</u>	<i>TWI</i>	Elevation	Slope	Rainfall	LULC	<i>NDVI</i>	Drainage density	<u>Normalised principal eigenvector</u>
<i>TWI</i>	1	1	1	1	3	5	1	19.94%
Elevation	1	1	1	1	2	3	1	16.88%
Slope	1	1	1	1	3	1	1	15.86%
Rainfall	1	1	1	1	3	2	1	16.88%
LULC	1/3	1/2	1/3	1/3	1	1	1	7.73%
<i>NDVI</i>	1/5	1/3	1	1/2	1	1	1	8.89%
Drainage density	1	1	1	1	1	1	1	13.82%

Additionally, the consistency ratio (*CR*) was calculated to assess the consistency of the generated ratings. Using equations (3) and (4), the *CR* was found to be 0.05, which confirms the reliability of the assigned ratings. This value is deemed acceptable since it is below the threshold of 0.1. If the *CR* exceeds 0.1, it suggests that the evaluations may be too inconsistent to be considered dependable.

### Integration of GIS

After determining the criteria weights, the flood susceptibility map was created using the weighted overlay tool in ArcGIS Pro. To use this tool effectively, each raster parameter was first reclassified according to its susceptibility class ratings. Then, the cell values were multiplied by their corresponding percentage influence, and the resulting rasters were combined. This process led to the generation of the final flood susceptibility map, which was categorised into five risk levels: very high risk, high risk, moderate risk, low risk, and very low risk, as illustrated in Figure 14. Table 3 presents the areas of different flood susceptibility zones along with the percentage of each risk level.

The map from Figure 14 highlights that certain northern and northeastern parts of the region, along with some offshore islands, have higher flood risk, whereas central and southern areas of Auckland generally exhibit lower flood susceptibility. The south and central parts of Auckland show a predominance of low to very low flood susceptibility, marked in green on the map. These areas are likely covered with more vegetation and forested land, which helps absorb rainfall and reduces the risk of flooding.

Figure 15 presents a pie chart illustrating the spatial distribution of flood risk levels in Auckland, derived from the corresponding flood risk map. The results reveal that a substantial proportion of the area (63%) falls within the moderate risk category. Additionally, 21% of the area is classified as low risk, while 16% is designated as high risk. Notably, the analysis indicates that no regions fall under the very high or very low risk classifications.

These findings suggest that the majority of Auckland is currently exposed to a moderate level of flood risk. However, the potential intensification of urban development and deforestation activities poses a significant threat to this balance. Without the implementation of robust flood management and land-use planning strategies, there is a heightened likelihood that areas presently considered moderate or low risk could transition into higher risk categories over time. Therefore, proactive measures are critical to sustaining current risk levels and enhancing the city's resilience to future flood events.

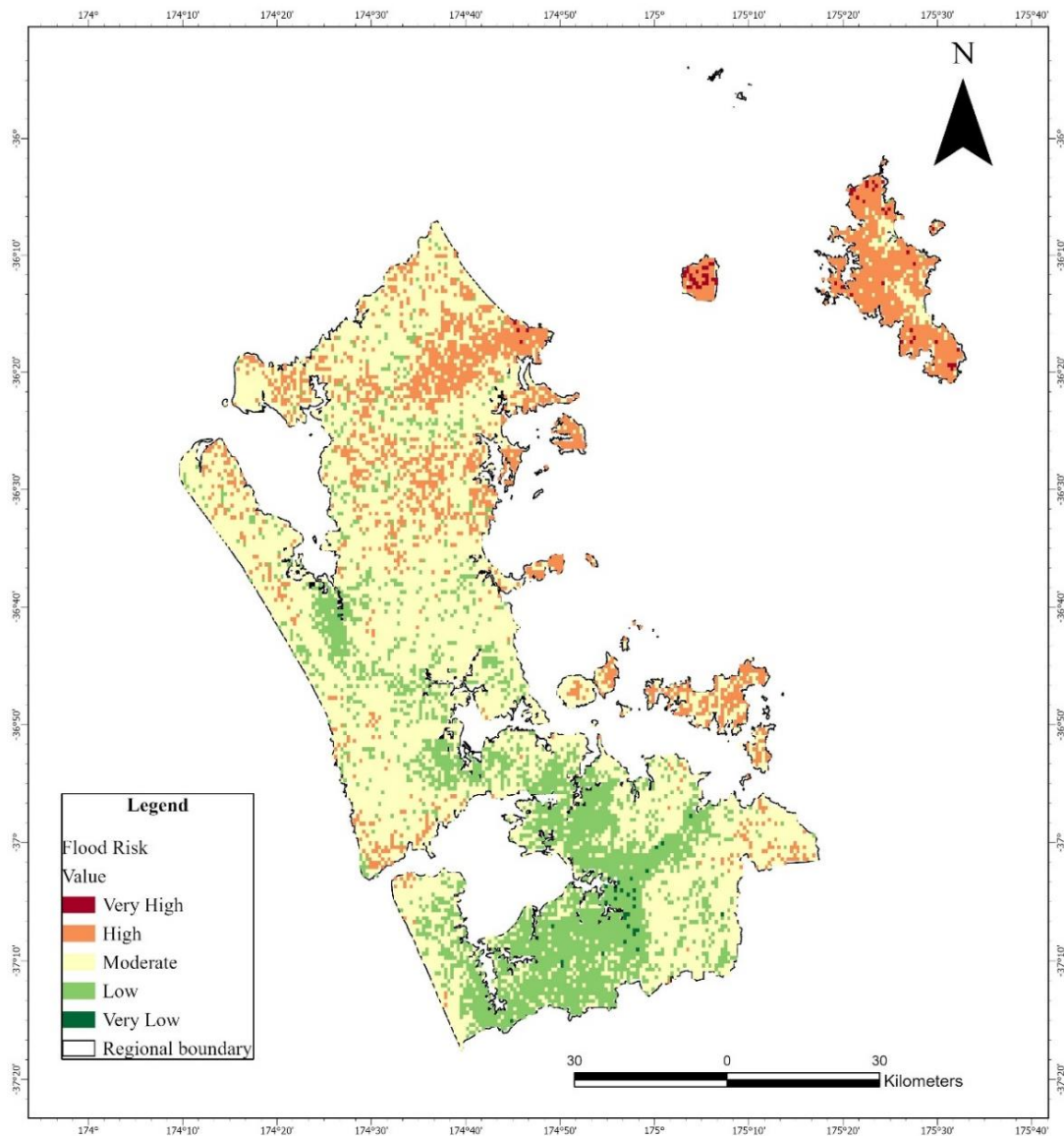


Figure 14. Flood susceptibility map

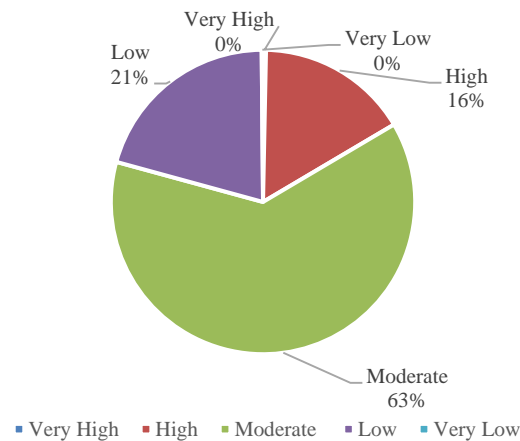


Figure 15. Percentages of flood susceptibility

Geographic Information Systems (GIS) is a powerful tool for capturing, analysing, and visualising spatial data, enabling efficient decision making in various fields, including environmental management and urban planning [54, 55]. GIS has been extensively used in the Philippines, one of the most disaster-prone countries, to assess and mitigate flood risks [15]. Due to frequent typhoons and heavy rainfall, government agencies have integrated GIS technology with topographical and meteorological data to develop flood-risk maps [14]. Studies in Davao Oriental have demonstrated the effectiveness of GIS-based flood risk assessment by incorporating multiple variables such as slope, elevation, drainage density, soil type, and population density [17]. Methods like the Analytic Hierarchy Process (AHP), Weights by Rank (WR), and Ratio Weighting (RW) have been used to classify flood-prone areas [17]. The results indicated that 95.99% of Davao Oriental falls within low to moderate flood risk zones, while coastal regions face higher susceptibility, necessitating urgent mitigation strategies [16]. Similarly, this study employs GIS-based spatial analysis to assess flood susceptibility in Auckland. The results highlight that northern and northeastern parts of the region, along with offshore islands, are at a higher risk of flooding, whereas central and southern Auckland exhibit lower susceptibility due to vegetation cover. These findings align with previous research emphasising the role of GIS in identifying flood-prone zones and supporting flood resilience planning [12], [56], [57].

### Validation process and results

The validation process assesses the accuracy of a flood susceptibility map by comparing its classified susceptibility zones with actual floodplain locations [58]. This ensures that the spatial prediction of flood-prone areas aligns with historical flood records, improving the reliability of flood risk assessment. The flood susceptibility map (raster) is classified into five susceptibility levels: Very Low (1), Low (2), Moderate (3), High (4), and Very High (5). The floodplain shapefile (vector) represents historically flooded areas based on Auckland Council data. Both datasets are loaded into ArcGIS Pro to ensure proper alignment and coordinate system consistency. The “Extract Values to Points” tool is used to sample flood susceptibility values at validation points. Each point is assigned a susceptibility class (1–5), allowing direct comparison with floodplain locations. A Spatial Join is performed to check whether high-susceptibility zones correspond to actual floodplain locations. The analysis examines how many of these points fall within the floodplain, indicating model accuracy.

The model's accuracy is determined using the formula:

$$\text{Validation Accuracy} = \left( \frac{\text{Correctly Predicted Floodplain points}}{\text{Total Floodplain points}} \right) \times 100\% \quad (5)$$

Where Correctly Predicted Floodplain points = 24,932 and Total Floodplain points = 30,047.

The model achieved an accuracy of 82.98%, indicating strong agreement between risk zones and actual flood-prone areas.

## CONCLUSION

The results of the research show that Auckland is vulnerable to floods, mainly due to its varied topography and urban development, which can exacerbate flood risks. The objective of this study was to create a flood susceptibility map for the Auckland region using GIS and the AHP (Analytic Hierarchy Process) technique. Seven influencing factors were used to generate the flood susceptibility map, and the final map was classified into five classes using a grading method. The results indicate that flood susceptibility in the Auckland region is predominantly moderate, with 63% of the urban area categorised under moderate risk. High-risk zones make up 16%, while 21% of the area is classified as low risk. These findings highlight the need for targeted flood mitigation strategies, particularly for the large portion of the area facing moderate risk and emphasise the importance of monitoring high-risk zones. Overall, this study demonstrates that the AHP method provides a reasonably accurate flood susceptibility assessment for the Auckland region. The study shows the efficacy of the AHP method in producing high-resolution spatial maps tailored to the specific criteria influencing flood risks. Such maps provide layered visual outputs, emphasising critical factors like terrain slope and proximity to drainage systems. This feature allows for better interpretation and actionable insights for present conditions and future challenges, aiding engineers and government officials in mitigating flood risks. The methodology used in this study could be applied to other regions, offering a robust tool for flood risk assessment.

## Implications of the research

This subsection outlines the recommended actions to enhance urban flood resilience in Auckland.

Short-term actions (0–2 years). The immediate priority is establishing foundational systems for real-time flood monitoring and response. A network of sensors would be installed across Auckland's flood-prone areas to monitor rainfall, river levels, and soil moisture. These data would feed into GIS platforms, forming a centralised flood monitoring system. By integrating the said data with GIS-based Decision Support Systems (DSS), dynamic flood scenarios and real-time risk assessments can be generated. Early warning protocols would also be developed, ensuring timely alerts for emergency services, authorities, and the public. Staff training programs would enhance technical proficiency in using GIS tools, interpreting flood maps, and operating DSS, creating a skilled workforce ready to manage flood emergencies.

Medium-term actions (2–5 years). The focus would shift to infrastructure upgrades and policy enhancements. High-risk areas would see improvements to stormwater drainage systems, embankments, and other critical assets. Nature-based solutions, such as wetland restoration and floodplain reclamation, would mitigate flood impacts naturally. GIS-based susceptibility maps would be updated to reflect urbanisation and climate changes, forming the basis for revised zoning regulations. Development in high-risk zones would be restricted, and new projects would incorporate flood-resilient designs. Community engagement programs would educate residents on flood preparedness through workshops, participatory mapping, and awareness campaigns, promoting resilient practices such as rainwater harvesting and permeable surfaces.

**Long-term actions (5+ years).** Dynamic floodplain management would be integrated into Auckland's urban development plans. GIS tools would help identify low-risk areas for growth and designate high-risk zones as green spaces or ecological buffers. Climate change adaptation would take centre stage, with GIS-based modelling evaluating impacts such as sea level rise and altered rainfall patterns. Adaptive land-use strategies, including buffer zones along rivers and coasts, would reduce vulnerability to extreme events. Infrastructure development would align with climate-resilient standards, using sustainable materials and designs. Regular updates and validation of GIS models would ensure their relevance, incorporating the latest environmental and urban data. Collaboration with academic institutions would foster innovation and improve model accuracy.

### Limitations of the research

While GIS technology provides capabilities for flood mitigation, this study acknowledges several limitations. The limitation of this study is that it used only open-source spatial datasets with different resolutions and scales. The elevation of the building is also not considered in this study. Additional building height information can provide detailed and accurate information about the risks of buildings. Building height can be obtained by fusing stereo images of high resolution, i.e., 5 cm, which can be generated through aerial photographs or from resolution satellite sensors; this high-resolution DEM can give more accurate results. In addition, this study does not provide a detailed analysis of the precipitation patterns, which have not been thoroughly examined. This limitation may affect the understanding of their specific impact on urban flooding dynamics.

### NOMENCLATURE

#### Abbreviations

AHP	Analytic Hierarchy Process
CRU	Climatic Research Unit
DEM	Digital Elevation Model
DSS	Decision Support System
EWS	Early Warning System
GIS	Geographic Information System
LULC	Land Use & Land Cover
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
NDVI	Normalised Difference Vegetation Index
RW	Ratio Weighting
TWI	Topographic Wetness Index
USGS	United States Geological Survey
WR	Weights by Ranks

### REFERENCES

1. C. Koem and S. Tantane, Flash flood hazard mapping based on AHP with GIS and satellite information in Kampong Speu Province, Cambodia, *Int J Disaster Resil Built Environ*, vol. 12, no. 5, p. 457-470 2020, <https://doi.org/10.1108/IJDRBE-09-2020-0099>.
2. Q. Sholihah, W. Kuncoro, S. Wahyuni, S. Suwandi, and E. Feditasari, "The analysis of the causes of flood disasters and their impacts in the perspective of environmental law," *IOP Conf Ser Earth Environ Sci*, vol. 437, p. 12056, 2020, <https://doi.org/10.1088/1755-1315/437/1/012056>.

3. S. Gössling, C. Neger, R. Steiger, and R. Bell, "Weather, climate change, and transport: a review," *Natural Hazards*, vol. 118, no. 2, pp. 1341–1360, 2023, <https://doi.org/10.1007/s11069-023-06054-2>.
4. "Floodsite," Flooding in urban areas (urban flooding). <http://www.floodsite.net/juniorfloodsite/html/en/student/thingstoknow/hydrology/urbanfloods.html>, [Accessed: 10-September-2024].
5. F. E. Rotimi, R. Kalatehjari, T. D. Moshood, and G. Dokyi, "NA Comprehensive Review of Bibliometric and Methodological Approaches in Flood Mitigation Studies: Current Trends and Future Directions," *Journal of Safety Science and Resilience*, 2025, doi: <https://doi.org/10.1016/j.jnlssr.2024.12.004>.
6. J. Dąbrowska et al., Between flood and drought: How cities are facing water surplus and scarcity," *J Environ Manage*, vol. 345, p. 118557, 2023, <https://doi.org/10.1016/j.jenvman.2023.118557>.
7. S. W. Chan, S. K. Abid, N. Sulaiman, U. Nazir, and K. Azam, "A systematic review of the flood vulnerability using geographic information system," *Heliyon*, vol. 8, no. 3, p. e09075, 2022, <https://doi.org/10.1016/j.heliyon.2022.e09075>.
8. A. Ali, R. Bajracharya, and H. Koirala, "A Review of Flood Risk Assessment," *International Journal of Environment, Agriculture and Biotechnology*, vol. 1, pp. 1065–1077, 2016, <https://doi.org/10.22161/ijeab/1.4.62>.
9. M. T. Anees et al., Flood Vulnerability, Risk, and Susceptibility Assessment: Flood Risk Management, in: *Decision Support Methods for Assessing Flood Risk and Vulnerability*, pp. 1-27. IGI Global, 2020. <https://doi.org/10.4018/978-1-5225-9771-1.ch001>.
10. W. A. Ayenew and H. A. Kebede, "GIS and remote sensing based flood risk assessment and mapping: The case of Dikala Watershed in Kobo Woreda Amhara Region, Ethiopia," *Environmental and Sustainability Indicators*, vol. 18, p. 100243, 2023, <https://doi.org/10.1016/j.indic.2023.100243>.
11. M. Zorn, Natural Disasters and Less Developed Countries," in *Nature, Tourism and Ethnicity as Drivers of (De)Marginalization: Insights to Marginality from Perspective of Sustainability and Development*, S. Pelc and M. Koderman, Eds., Springer International Publishing, Cham. 2018, pp. 59–78. [https://doi.org/10.1007/978-3-319-59002-8\\_4](https://doi.org/10.1007/978-3-319-59002-8_4).
12. R. Mina, "Philippines looks to improve disaster preparedness with geospatial tech," *Mongabay*, 2021. <https://news.mongabay.com/2021/03/philippines-looks-to-improve-disaster-preparedness-with-geospatial-tech/>, [Accessed: 20-September-2024].
13. G. D. C. Santos, "2020 tropical cyclones in the Philippines: A review," *Tropical Cyclone Research and Review*, vol. 10, no. 3, pp. 191–199, 2021, <https://doi.org/10.1016/j.tcrr.2021.09.003>.
14. C. V. P. Gianzon, Flood Risk Assessment in Philippines: Iloilo City Flood Risk Management Plan, in *Cross-Cultural Perspectives on Climate Change Adaptation: Adapting to Flood Risk*, K.-G. Kim and C. Atkin, Eds., Cham: Springer International Publishing, 2024, pp. 251–270. [https://doi.org/10.1007/978-3-031-50365-8\\_17](https://doi.org/10.1007/978-3-031-50365-8_17).
15. J. Cabrera and H. S. Lee, Flood-Prone Area Assessment Using GIS-Based Multi-Criteria Analysis: A Case Study in Davao Oriental, Philippines, *Water (Basel)*, vol. 11, p. 2203, 2019, <https://doi.org/10.3390/w11112203>.
16. R. Trogrlić, M. van den Homberg, M. Budimir, C. McQuistan, A. Sneddon, and B. Golding, "Early Warning Systems and Their Role in Disaster Risk Reduction," 2022, pp. 11–46. <https://doi.org/10.1007/978-3-030-98989-7>.
17. B. Pradhan, S. Lee, A. Dikshit, and H. Kim, "Spatial flood susceptibility mapping using an explainable artificial intelligence (XAI) model," *Geoscience Frontiers*, vol. 14, no. 6, p. 101625, 2023, <https://doi.org/10.1016/j.gsf.2023.101625>.
18. F. M. Howari and H. Ghrefat, "Chapter 4 - Geographic information system: spatial data structures, models, and case studies," in *Pollution Assessment for Sustainable Practices*

- in *Applied Sciences and Engineering*, A.-M. O. Mohamed, E. K. Paleologos, and F. M. Howari, Eds., Butterworth-Heinemann, 2021, pp. 165–198.  
<https://doi.org/10.1016/B978-0-12-809582-9.00004-9>.
19. A. Tsakiridi, “Applications of Geographic Information Systems (GIS) in Supply Chain Management: Systematic Literature Review,” *International Journal of Supply Chain Management*, 2021, <http://doi: 10.5281/zenodo.13908420>.
  20. R. Hanifah, R. R. Isnanto, and Y. Christyono, Simulasi Sistem Informasi Geografis (Sig)Pemantauan Posisi Kendaraan Via Sms Gateway (in Indonesian, Geographic Information System (GIS) Simulation: Vehicle Position Monitoring via SMS Gateway), *Doctoral dissertation*, Department of Electrical Engineering, Faculty of Engineering, Diponegoro University, Indonesia, 2010.
  21. J. Rocha, E. Gomes, I. Boavida-Portugal, C. Viana, L. Truong-Hong, and A. T. Phan, *GIS and Spatial Analysis*. IntechOpen, United Kingdom, 2023.
  22. D. U. L. Dano et al., “Geographic Information System and Remote Sensing Applications in Flood Hazards Management: A Review,” *Research Journal of Applied Sciences, Engineering and Technology*, vol. 3, 2011.
  23. H. Liao, Y. He, X. Wu, Z. Wu, and R. Bausys, Reimagining multi-criterion decision making by data-driven methods based on machine learning: A literature review, *Information Fusion*, vol. 100, p. 101970, 2023, <https://doi.org/10.1016/j.inffus.2023.101970>.
  24. H. Taherdoost and M. Madanchian, Multi-Criteria Decision Making (MCDM) Methods and Concepts, *Encyclopedia*, vol. 3, no. 1, pp. 77–87, 2023, <https://doi.org/10.3390/encyclopedia3010006>
  25. C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making: Methods and Applications - A State-of-the-Art Survey*, CRC Press, Taylor & Francis Group, London, 2011.
  26. M. M. de Brito and M. Evers, Multi-criteria decision-making for flood risk management: a survey of the current state of the art, *Natural Hazards and Earth System Sciences*, vol. 16, no. 4, pp. 1019–1033, Apr. 2016, <https://doi.org/10.5194/nhess-16-1019-2016>.
  27. S. H. Mahmoud and T. Y. Gan, “Multi-criteria approach to develop flood susceptibility maps in arid regions of Middle East,” *J Clean Prod*, vol. 196, pp. 216–229, 2018, <https://doi.org/10.1016/j.jclepro.2018.06.047>.
  28. S. K. Sahoo and S. Goswami, “A Comprehensive Review of Multiple Criteria Decision-Making (MCDM) Methods: Advancements, Applications, and Future Directions,” *Decision Making Advances*, vol. 1, pp. 25–48, 2023, <https://doi.org/10.31181/dma1120237>.
  29. I. Elkharchy, Flash Flood Hazard Mapping Using Satellite Images and GIS Tools: A case study of Najran City, Kingdom of Saudi Arabia (KSA), *The Egyptian Journal of Remote Sensing and Space Science*, vol. 18, no. 2, pp. 261–278, 2015, doi: <https://doi.org/10.1016/j.ejrs.2015.06.007>.
  30. G. P. Siddayao, S. E. Valdez, and P. L. Fernandez, Analytic Hierarchy Process (AHP) in Spatial Modeling for Floodplain Risk Assessment, *Int J Mach Learn Comput*, vol. 4, pp. 450–457, 2014. <https://doi.org/10.7763/IJMLC.2014.V4.453>
  31. S. Kittipongvises, A. Phetrak, P. Rattanapun, K. Brundiers, J. L. Buizer, and R. Melnick, “AHP-GIS analysis for flood hazard assessment of the communities nearby the world heritage site on Ayutthaya Island, Thailand,” *International Journal of Disaster Risk Reduction*, vol. 48, p. 101612, 2020, <https://doi.org/10.1016/j.ijdrr.2020.101612>.
  32. S. S. Band et al., “Flash Flood Susceptibility Modeling Using New Approaches of Hybrid and Ensemble Tree-Based Machine Learning Algorithms,” *Remote Sens (Basel)*, vol. 12, no. 21, p. 3568, 2020, <https://doi.org/10.3390/rs12213568>

33. H. Ha *et al.*, “Flash flood susceptibility prediction mapping for a road network using hybrid machine learning models, *Natural Hazards*, vol. 109, no. 1, pp. 1247–1270, 2021, <https://doi.org/10.1007/s11069-021-04877-5>
34. R. U. Zzaman, S. Nowreen, M. Billah, and A. S. Islam, “Flood hazard mapping of Sangu River basin in Bangladesh using multi-criteria analysis of hydro-geomorphological factors,” *J Flood Risk Manag*, vol. 14, no. 3, p. e12715, 2021, <https://doi.org/10.1111/jfr3.12715>
35. O. Rahmati, H. R. Pourghasemi, and H. Zeinivand, Flood susceptibility mapping using frequency ratio and weights-of-evidence models in the Golastan Province, Iran,” *Geocarto Int*, vol. 31, no. 1, pp. 42–70, 2016, <https://doi.org/10.1080/10106049.2015.1041559>
36. A. Tariq *et al.*, “Flash flood susceptibility assessment and zonation by integrating analytic hierarchy process and frequency ratio model with diverse spatial data,” *Water (Basel)*, vol. 14, no. 19, p. 3069, 2022, <https://doi.org/10.3390/w14193069>
37. G. S. Ogato, A. Bantider, K. Abebe, and D. Geneletti, Geographic information system (GIS)-Based multicriteria analysis of flooding hazard and risk in Ambo Town and its watershed, West shoa zone, oromia regional State, Ethiopia, *J Hydrol Reg Stud*, vol. 27, p. 100659, 2020, <https://doi.org/10.1016/j.ejrh.2019.100659>
38. M. N. Haque, S. Siddika, M. A. Sresto, M. M. Saroar, and K. R. Shabab, “Geo-spatial analysis for flash flood susceptibility mapping in the North-East Haor (Wetland) Region in Bangladesh,” *Earth Systems and Environment*, vol. 5, no. 2, pp. 365–384, 2021, <https://doi.org/10.1007/s41748-021-00221-w>
39. W. Auliagisni, S. Wilkinson, and M. Elkharraboutly, Using community-based flood maps to explain flood hazards in Northland, New Zealand, *Progress in Disaster Science*, vol. 14, p. 100229, 2022, doi: <https://doi.org/10.1016/j.pdisas.2022.100229>.
40. W. Auliagisni, S. Wilkinson, and M. Elkharraboutly, “Flood risk management in New Zealand: A case study of the Northland urban community,” *IOP Conf Ser Earth Environ Sci*, vol. 1101, p. 22035, 2022, <https://doi.org/10.1088/1755-1315/1101/2/022035>.
41. A. Council, “A brief history of Auckland’s urban form,” 2019, [Online]. Available: <https://knowledgeauckland.org.nz/media/1419/a-brief-history-of-aucklands-urban-form-2019-web.pdf>
42. S. Macready, S. Bickler, and R. Clough, Transforming Auckland’s landscape: the role of the entrepreneur, *Finding Our Recent Past: Historical Archaeology in New Zealand*, pp. 167–190, 2014.
43. W. of Atlas, “Map of New Zealand.” <https://www.worldatlas.com/maps/new-zealand> [Accessed: 6-October-2024]
44. World Bank Group, Climate Change Knowledge Portal, <https://climateknowledgeportal.worldbank.org/country/new-zealand/climate-data-historical> [Accessed: 11-September-2024]
45. World Weather Online, Auckland Annual Weather Averages, <https://www.worldweatheronline.com/auckland-weather-averages/nz.aspx> [Accessed: 11-September-2024]
46. NIWA, “Auckland suffers wettest month in history,” *National Institute of Water & Atmospheric Research*, 2023, <https://niwa.co.nz/news/auckland-suffers-wettest-month-history>. [Accessed: 6-September-2024]
47. NIWA, “Climate Summary January 2023,” 2023. [https://niwa.co.nz/sites/default/files/Climate\\_Summary\\_January\\_2023\\_NIWA.pdf](https://niwa.co.nz/sites/default/files/Climate_Summary_January_2023_NIWA.pdf) [Accessed: 20-October-2024]
48. M. Vojtek and J. Vojteková, Flood Susceptibility Mapping on a National Scale in Slovakia Using the Analytical Hierarchy Process, *Water (Basel)*, vol. 11, no. 2, p. 364, 2019, <https://www.mdpi.com/2073-4441/11/2/364> [Accessed: 12-October-2024]

49. R. W. Saaty, "The analytic hierarchy process—what it is and how it is used," *Mathematical Modelling*, vol. 9, no. 3, pp. 161–176, 1987, [https://doi.org/10.1016/0270-0255\(87\)90473-8](https://doi.org/10.1016/0270-0255(87)90473-8).
50. A. N. Matori, D. U. Lawal, K. W. Yusof, M. Hashim, and A.-L. B. Balogun, "Spatial Analytic Hierarchy Process Model for Flood Forecasting: An Integrated Approach," *IOP Conf Ser Earth Environ Sci*, vol. 20, p. 12029, 2014. <https://doi.org/10.1088/1755-1315/20/1/012029>
51. B. Cavallo and A. Ishizaka, "Evaluating scales for pairwise comparisons," *Ann Oper Res*, vol. 325, 2022, <https://doi.org/10.1007/s10479-022-04682-8>.
52. X. Shao Ma S. Xu C. & Xu Y, "Insight into the Characteristics and Triggers of Loess Landslides during the 2013 Heavy Rainfall Event in the Tianshui Area, China," *15*, no. 17, p. 4304, 2023, <https://doi.org/10.3390/rs15174304>.
53. P. Raja Shekar and A. Mathew, "Assessing groundwater potential zones and artificial recharge sites in the monsoon-fed Murredu river basin, India: An integrated approach using GIS, AHP, and Fuzzy-AHP," *Groundw Sustain Dev*, vol. 23, p. 100994, 2023, <https://doi.org/10.1016/j.gsd.2023.100994>.
54. O. Akindele, S. Ajayi, A. S. Oyegoke, H. A. Alaka, and T. Omotayo, Application of Geographic Information System (GIS) in construction: a systematic review, *Smart and Sustainable Built Environment*, vol. 14, no. 1, pp. 210–236, 2025, <https://doi.org/10.1108/SASBE-01-2023-0016>.
55. S. Sinjari and A. Kosovrasti, Geographic Information Systems (GIS) in Urban Planning, *European Journal of Interdisciplinary Studies*, vol. 1, p. 85, 2015, <https://doi.org/10.26417/ejis.v1i1.p85-92>.
56. F. Mukherjee and D. Singh, Detecting flood prone areas in Harris County: a GIS based analysis," *GeoJournal*, vol. 85, no. 3, pp. 647–663, 2020, <https://doi.org/10.1007/s10708-019-09984-2>.
57. M. O. Idrees, A. Yusuf, E. S. Mokhtar, and K. Yao, Urban flood susceptibility mapping in Ilorin, Nigeria, using GIS and multi-criteria decision analysis, *Model Earth Syst Environ*, vol. 8, no. 4, pp. 5779–5791, 2022, <https://doi.org/10.1007/s40808-022-01479-3>.
58. Auckland Council Open Data, "Flood Plains. <https://data-aucklandcouncil.opendata.arcgis.com/datasets/aucklandcouncil:flood-plains/explore> [Accessed: 10-October-2024]



Paper submitted: 08.01.2025  
Paper revised: 27.05.2025  
Paper accepted: 06.06.2025