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Article

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Posted Date: October 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11171006/v1>

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Additional Declarations: No competing interests reported.

Applications of Machine Learning and Geospatial Technology to Assessing Urban Flood Susceptibility: A Case Study of Wadi Hanifa, West of Riyadh City

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Abstract

Recurring urban flooding in large urban areas with drainage basins is one of the most serious crises requiring study due to its grave risks to life and property. The urban development of Riyadh is affected by the frequent flooding of the Wadi Hanifa basin which covers the western and central parts of the city. The city has been impacted by numerous flash floods leading to the inundation of large areas. This study presents an integrated methodology based on machine learning (ML), geographic information systems (GIS), and remote sensing (RS) for flood susceptibility mapping (FSM). The methodology relies on five data sources: Landsat 8 (OLI/TIRS) satellite, Sentinel-1 SAR VH, SRTM DEM, CHIRPS Rainfall, and OpenStreetMap (OSM), in addition to fieldwork. A random forest algorithm (RF) was employed with historical flood maps being generated in Google Earth Engine (GEE) to train the random forest model in the Google Colab environment. The model results demonstrated the impact of drainage density, land use Land cover, and rainfall on urban flooding susceptibility. The model exhibited high discriminatory power with an area under the curve (AUC) of 0.90 and an overall accuracy of 0.90. The resulting flood susceptibility map indicates that 6.1% of the basin areas show very high flood susceptibility, 14.2% high susceptibility, and 25.6% moderate. The results also show that the neighborhoods of Center Uraija, Uraija, Derab, Ukaz, Marwwah, Uraid, Twaeeq-Etaigah, and Hejrat Wadi Leban are highly susceptible to urban flooding. The flood-susceptibility maps are valuable tools for decision-makers as they offer critical insights into identifying priority areas that require effective flood-mitigation management in vulnerable regions.

Keywords: Urban Flood susceptibility; Machine Learning; Geographic Information System; Remote Sensing; Wadi Hanifa.

39 1. Introduction

40 Floods are among the most devastating natural disasters globally, causing significant loss of
41 life and property damage, especially in arid regions due to unusual rainfall events (Jonkman,
42 S.N., 2005; Yu, Q., et al., 2020; Tanoue, M., et al., 2021; Alharbi, T., 2024). Due to increased
43 urbanization, climate change, insufficient drainage systems, increased extreme rainfall and the
44 prevalence of impervious surfaces urban flooding—also known as urban deluge—is a rapidly
45 expanding problem in modern cities (D. Sowmya., et al., 2005; Park, K. & Choi, S, H., 2025). the
46 global urban area inundated by floods between 2000 and 2018 reached approximately 2.23
47 million km², affecting about 255 to 290 million people annually (Tellman et al., 2021).
48 Additionally, flooding accounts for almost 30% of yearly natural disaster damages (Rodriguez,
49 E. et al., 2021). Due to climate change, deforestation, sea level rise, and population growth, an
50 estimated two billion people will reside in flood-prone areas; this figure is predicted to double
51 or rise within two generations (Collins, T., 2004). the Sixth Assessment Report of the
52 Intergovernmental Panel on Climate Change (IPCC) indicated that an 1°C increase in global
53 temperature would have a clear impact on rainstorm intensity, increasing it by up to 7% (IPCC.,
54 2023). Statistics from the World Meteorological Organization also show that urban floods
55 caused an average annual economic loss of 40 billion US dollars over the past decade, affecting
56 more than 150 million people, with over 80% of these losses occurring in developing countries
57 (World Meteorological Organization, 2021). The consequences of urban flooding are severe,
58 encompassing loss of life, infrastructure and property damage, economic downturns, health
59 hazards, and environmental pollution worldwide (Youssef, A.M. et al., 2016; Ramkar, P. &
60 Yadav, S.M., 2021). The intensity and frequency of rainstorms have increased dramatically due
61 to human activity, rapid urbanization, and rising temperatures and Ledes to an increase in
62 impervious surfaces, which amplifies surface runoff and stresses sewage networks during
63 heavy rainfall events (Mahmoud, S.H. & Gan, T.Y., 2018; Daksiya, V. et al., 2021; Gupta, L. &
64 Dixit, J., 2023). This has made urban flood hazards worse and highlighted the necessity of
65 understanding city susceptibility to floods for successful damage mitigation efforts (Zhang et
66 al., 2025; Rogers et al., 2025; Tang et al., 2024; Yin et al., 2023). Concurrently, the massive and
67 rapid urbanization witnessed in certain regions of the world—including Riyadh City—has
68 substantially increased impervious surface areas. This weakens the soil's capacity to absorb
69 rainwater naturally, leading to increased runoff rates within watersheds and subsequently
70 creating severe problems due to this flow (Bai et al., 2025).

71 Urban flooding, while a natural occurrence, is significantly influenced by human activities.
72 Recent decades have seen dramatic changes in land use and cover (LULC), including the
73 reduction of green spaces and wetlands and the expansion of built-up areas, which have
74 exacerbated the severity of urban floods. (Boller, D. et al., 2019; Zhang, W. et al., 2018).
75 Substantial population growth in urban areas has worsened urban flooding, making it a
76 significant global challenge (Kumar, M. et al., 2023). Given that more than half of the world's
77 population resides in urban environments, high-density areas suffer from the Urban Heat
78 Island (UHI) effect and a relative rise in aerosol concentrations, leading to noticeable increases
79 in precipitation and consequently increasing flood risks (Sui, X. et al., 2024; Hirwa, H. et al.,
80 2023). By 2050, it is projected that 65% of the world's population will migrate to urban areas,
81 driving further commercial and economic growth, which may exacerbate urban flooding
82 (Dano, U.L. et al., 2019). Flood Risk Mapping (FRM) is essential for assessing and mitigating
83 flood risks caused by rainfall and dam overflows, aiming to minimize damage to human life
84 and property in flood-prone areas (Farhadi, H., & Najafzadeh, M., 2021). Three key factors

85 make mapping urban flood events difficult: the urban landscape is extremely complicated with
86 rivers at submeter resolutions; the flooding will be transient and shallow; and ponding will
87 cause the flooding area to be discontinuous (Tanim, A. H., et al., 2022).

88 Flood susceptibility concept refers to the probability of a specific area being exposed to
89 flooding, an inclination influenced by environmental, topographic, and climatic factors, as
90 previously mentioned (Miranda, F., et al., 2023; Khan, T.I., et al., 2026; Bouchikhi, S., et al.,
91 2026). Given the severity of urban flooding as outlined, it is of paramount importance to focus
92 on flood susceptibility mapping, particularly in dense urban zones where flooding can result in
93 massive losses of life and property (Hammond, M. J., et al., 2015; Shokouhifar, Y., et al., 2022).
94 Flood susceptibility mapping represents an effective strategy for flood prevention and
95 mitigation, as it helps identify the most vulnerable zones and their probability of inundation,
96 thereby providing an opportunity for early preventive intervention (Vojtek, M.; Vojteková, J.,
97 2019; Burgan, H. I., & Icaga, Y., 2019; Shokouhifar, Y., et al. 2022). Notably, mapping urban flood
98 susceptibility requires integrating geographical data sources—such as topographic maps,
99 satellite imagery, and Digital Elevation Models (DEMs)—with meteorological data and field
100 measurements, relying on software and algorithms that synthesize these datasets to output
101 results that help identify hazard zones and formulate preventative solutions (Al-Abadi, A.M.,
102 et al., 2016; Tariq, A., et al., 2022; Kaya, C. M., & Derin, L., 2023).

103 GIS has emerged as a widely adopted tool in flood hazard analysis due to its efficiency in
104 processing and analyzing spatial data, it plays a pivotal role in urban planning and
105 environmental management by providing a spatial dimension for data analysis, which
106 facilitates gaining more accurate and comprehensive insights (Alves, R.A., et al., 2024;
107 Elkhachy, I., 2015; Khoirunisa, N., et al., 2021). This methodology has proven its importance
108 in achieving a more comprehensive understanding of flood risks by accounting for the various
109 contributing factors (Alharbi, T., 2024). Multi-Criteria Decision Analysis (MCDA) is one of the
110 most prominent methods used to calculate urban flood susceptibility, helping decision-makers
111 select the optimal alternative when evaluating often competing and conflicting criteria
112 (Mardani, A. et al., 2015; Zavadskas, E. K. et al., 2014; Siahkamari, S., et al., 2018; Souissi, D.,
113 et al., 2020; Nachappa, T.G., et al, 2020; Ozkiper, O. et al., 2024). The Analytic Hierarchy Process
114 (AHP), proposed by (Saaty, T. L., 2004), is the most common technique in this field (Ahmed, F.,
115 & Kilic, K., 2019; Vaidya, O. S., & Kumar, S., 2006; Baalousha, H.M., et al., 2024; Mokhtari, E.,
116 et al., 2024; Sadek, M., & Li, X., 2019). It relies on expert opinions through pairwise
117 comparisons, then derives relative scales from comparison matrices, indicating the decision-
118 maker's preferences among different alternatives regarding the criteria, alongside the weights
119 of these criteria (Hammami, S., et al., 2019; Cikmaz, B., et al., 2022; Hosseini Sabzevari, S.A.,
120 et al., 2024). Both methods have contributed to the clear utilization of geographical inputs
121 toward a definitive formulation of hazard zones (Khoshkonesh, A. et al., 2024). Additionally,
122 Weighted Overlay Analysis (WOA) represents a powerful GIS technique that combines multiple
123 information layers to produce a composite result (Kyne, D., 2023; Chen, Y., et al., 2023). It
124 assigns specific weights to each data layer based on its relative importance, and then overlays
125 these weighted layers to produce a single integrated analysis (Merchán, L. et al., 2023). As time
126 progressed, the limitations of traditional statistical techniques in addressing flood
127 susceptibility assessments led to the extensive adoption of various machine learning (ML)
128 algorithms (Saha, A., et al., 2021). These algorithms have gained significant attention due to
129 their capacity to predict flood susceptibility and develop robust models tailored for this
130 purpose (Wang, Y., et al., 2021; Ganjirad, M., & Delavar, M. R., 2023). Commonly utilized ML
131 models in this domain include Random Forest (RF), Naive Bayes (NB), decision trees, Artificial

Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbor, and the index-of-entropy (Liu, S., et al., 2021; Pham, B. T., et al., 2021; Ghosh, A., et al., 2022; Islam, S., et al., 2022; Hasanuzzaman, M., et al., 2022; Sud, A., et al., 2023; Chakraborty, R., et al., 2023; Chowdhuri, I., et al., 2023). Each model brings unique advantages in effectively analyzing and forecasting potential flood risks, thereby improving the reliability of flood management strategies (Seydi, S.T., et al., 2022; Gharakhanlou, N. M. & Perez, L., 2023; Debnath, J., et al., 2024; Sun, J. Q., et al., 2026). Recent advancements in Artificial Intelligence (AI) and remote sensing technologies have transformed flood susceptibility assessments by enabling high-precision predictions and near real-time monitoring (Deng, W., Zhou, J., 2013; Soltani, K., et al., 2021; Maddodi, B.S., et al., 2026; Chang, D.L., et al., 2020). Despite advances in GIS, RS, geospatial datasets and machine learning, urban planning and flood control frequently depend on small datasets and conventional analysis (Danumah, J. H., et al., 2026; Zhao, G., et al., 2019; Dodangeh, E., et al., 2020). The GEE is a Cloud Computing Platform that facilitates the storage and processing of global time-series satellite images, aiding in analysis and decision-making (Gorelick, N., et al., 2017).

Riyadh City, the capital of the Kingdom of Saudi Arabia and its largest urban center, holds immense urban weight, to the extent that it has become the largest city in Western Asia in terms of area and population (Rahman, M.T, et al., 2016; Khraif, R., et al., 2018). The city's location atop the Najd Plateau and east of the Tuwaiq Mountains has clearly contributed to the volume of water the city receives, despite its location reflecting an arid desert climate characterized by high temperatures and scarce rainfall (Alghamdi, A.S., 2022; Alrasheedi, K.G., et al., 2023; Alharbi, T.; El-Sorogy, A.S., 2023). Riyadh's urban landscape has evolved tremendously, becoming one of the fastest-growing urban agglomerations, driven by the developmental boom witnessed by the Kingdom in general, and particularly over the past decade (Aina, Y.A., et al., 2019; Alotaibi, A., et al., 2022). Within half a century, Riyadh transformed from a small, walled old town into a modern city that has grown to over a hundred times its original size, spanning an area of 2,435 km² (ArRiyadh Development Authority (ADA), 2016; Alqahtany, 2014; Al-Qahtany, A. M., & Walker, G., 2015). The valley basin occupies about 55% of the city's total area, encompassing the western districts of the city alongside future urban expansion zones in the west and the slopes of the Tuwaiq Mountain. Riyadh's urban transformation comprises five stages: The first stage initiated by King Abdulaziz with the Murabba complex, followed by modern designs in the mid-1960s. The third stage featured the Dioxides urban master plan in the late 1960s. The fourth stage aligned with the oil boom in the mid-1970s and updates to the Riyadh Master Plan. The fifth stage involved urban growth management, starting in late 1989 under the Ministry of Municipal and Rural Affairs (Mubarak, F. A., 2004; Al-Hathloul, 2017; Altuwaijri, H., 2018; Amer, M., et al., 2021). The main objectives of the urban growth boundary project were: controlling haphazard urban sprawl by encouraging internal urban development, reducing the cost of providing infrastructure and facilities for new developments through improved coordination, and ensuring the sustainability of the natural environment surrounding the city through appropriate conservation measures (Sharif, H.O., et al., 2014; Nahiduzzaman, K.M., et al., 2015; Abdelkarim, A., et al., 2019).

The research's main goal is to locate and map Riyadh's Wadi Hanifa watershed's flood-prone zones. It uses an integrated framework that blends Earth observation data with machine learning methods. This work improves knowledge of urban flood dynamics, particularly in Riyadh, and provides a strong, data-driven basis for proactive urban planning and successful catastrophe risk reduction techniques.

2. Study Area

The study area is located in the western part of Riyadh City, specifically within the catchment basin of Wadi Hanifa. Wadi Hanifa is one of the valleys of the Najd Plateau, whose tributaries originate from the Tuwaiq Mountains west of Riyadh, sloping downwards with the general terrain towards the east and southeast, ultimately terminating at Wadi AS SAHBAA, north of Al-Kharj city. The valley extends west of Riyadh along a northwest-southeast axis with a length of up to 110 km, stretching between latitudes 24°23'19" and 24°57'40" N, and longitudes 45°59'06" and 46°53'53" E. The valley spans an area of 2,950 km² west of Riyadh City, running across the eastern slopes of the Tuwaiq Mountains. In certain sectors, the valley basin is characterized by fertile soil, which fostered agricultural activity in western Riyadh, historically serving as a center for human settlement in that region (Figure 1). The Wadi Hanifa basin consists of 2,392 streams and includes a group of important tributaries, such as Al-Baqrah, Namar, Laban, Mahdiah, Saffar, Mzair'ah, Al-Yusra, and Al-Ainiyah—all located in the western portion of the valley. Wadi Hanifa has long been a focal point for the Kingdom of Saudi Arabia due to its historical and environmental significance. An environmental rehabilitation program was established to transform the valley into a natural park, in addition to fostering other economic activities within its basin; this is likely what prompted this study to monitor the flood susceptibility of urban areas inside the basin. The Wadi Hanifa basin contains the western portion of Riyadh's urban footprint; within its basin boundaries lie approximately 132 residential districts out of the 207 districts that make up the entirety of Riyadh. About 114 residential districts are fully located within the basin boundaries, while roughly 18 districts are partially located within it.

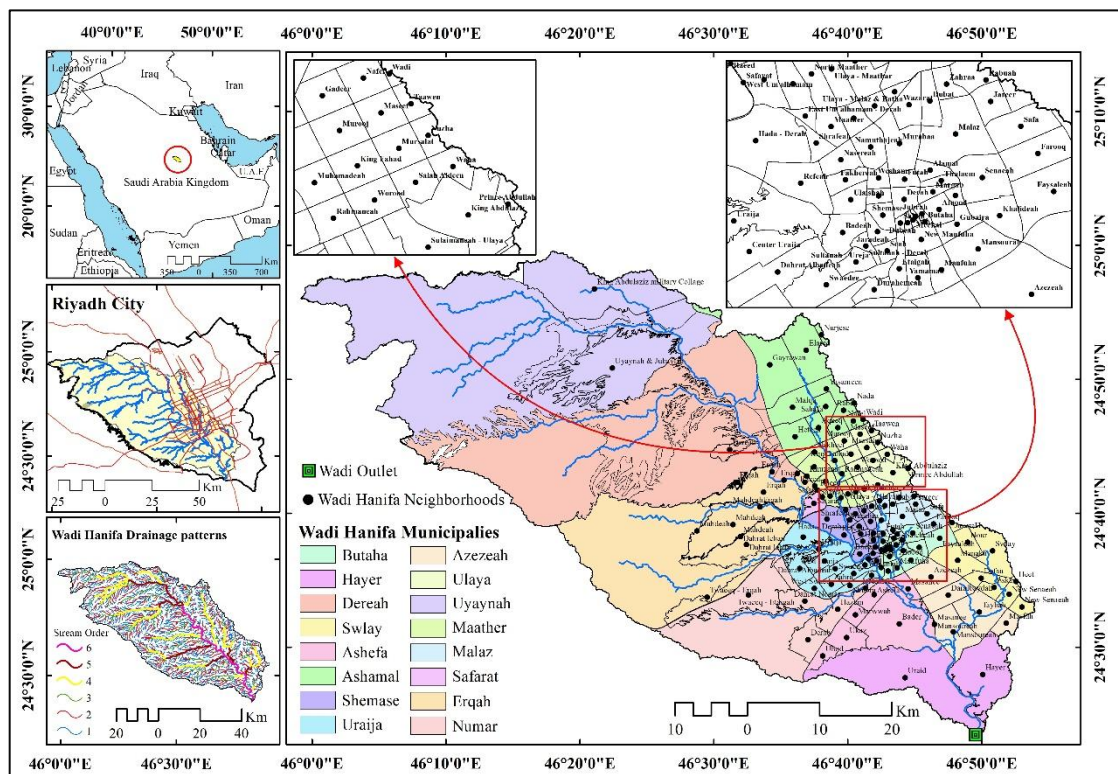


Figure 1. location map of The Study Area.

At the municipal level, around 14 of Riyadh's municipalities fall within the boundaries of Wadi Hanifa, with 8 municipalities entirely inside the basin and 6 partially within it. Furthermore, some of Riyadh's most densely populated districts lie within the basin's boundaries, such as Manfuha, Al-Marqab, Umm Salim, among others. In short, Wadi Hanifa served historically as one of the most vital hubs of human and cultural concentration in the Najd Plateau region, benefiting from the valley's waters that flowed strongly during floods. While that was the past, the districts within its basin—especially the western part—represent future expansion zones for the city's western sector. Therefore, it is of paramount importance to identify the potential exposure of these areas to urban floods in light of changing climatic conditions in general, and rainfall patterns in the region in particular.

3. Material and Methods

The study methodology focuses on mapping urban flood susceptibility in Wadi Hanifa through flood susceptibility modeling using influencing factors. The proposed method of Flood Susceptibility Modeling (FSM) involves five main steps: (1) Data collection and preparation from datasets like USGS, COPENICUS/S1, CHIRPS, and OSM; (2) Extraction of 12 flood susceptibility indicators; (3) Preparation of a flood inventory map and training dataset through change detection algorithms; (4) Implementation of the Flood Susceptibility Model (FSP) across six stages; and (5) Evaluation of model performance using a confusion matrix and four evaluation metrics (Table. 1) (Figure 2).

3.1. Data collection and data preparation

This study combined machine learning (ML), geographic information systems (GIS), and remote sensing (RS) to assess Urban Flood Susceptibility of the Wadi Hanifa Basin. It sought to determine flood-prone locations and assess flood-conditioning elements crucial for urban design in the face of increasing flood threats. Urban flood Susceptibility was evaluated using twelve indicators, which were obtained from multiple datasets and are as follows:

3.1.1. Landsat 8 (OLI/ TIRS) Satellite: In this study, the L8 satellite with OLI sensor, featuring nine spectral bands including panchromatic, visible, and near-infrared bands at a spatial resolution of 30 m, was utilized for flood risk mapping (Al-Abadi, A.M., et al., 2016; Ahmed, I.A., et al., 2022; Danso, S.Y., et al., 2024). The satellite data, accessible for analysis via Google Earth Engine (GEE) and downloadable from the USGS website, presents a challenge with cloud coverage. Consequently, images with less than 5% cloud cover were selected to enhance data accuracy as higher spatial resolution contributes to improved map quality and reliability of risk indices. Three indices are generated using Landsat 8 satellite images: LU, NDVI, and NDWI.

3.1.2. Sentinel-1 SAR VH: The COPENICUS/S1 collection's Sentinel-1 Synthetic Aperture Radar (SAR) images were used to analyze land surface features and identify flood-prone zones. These images, which have a spatial resolution of 10 m and vertical-horizontal (VH) polarization, are very useful for mapping floods, especially in regions that frequently observe cloud cover (Chini, M., et al., 2018; Vanama, V. S. K., & Rao, Y. S., 2019; Lin, Y. N., et al., 2019; Liu, W., et al., 2021; Pati, A.; Sahoo, B., 2022; Islam, M.T.; Meng, Q., 2022; Duwal, S., et al., 2023).

3.1.3. SRTM DEM: The SRTM DEM is an international initiative led by NASA and the NGA, utilizing a modified radar sensor aboard the Space Shuttle Endeavour during the STS-99 mission in February 2000. It offers a spatial resolution of 30 m and height accuracy of 16 m (Zhang, K., et al., 2019; Aldiansyah, S.; Wardani, F., 2023; Panfilova, T., et al.,

2024). The data, collected over a 10-day period from February 11 to 22, 2000, is freely accessible via GEE and the USGS website, <https://earthexplorer.usgs.gov/>. Digital elevation model data were used to derive the drainage network of the Wadi Hanifa basin, along with calculating hydrological and geomorphological indicators such as elevation, slope, aspect, curvature, Topographic Wetness, Topographic Roughness, Sedimentary Transport, and Stream Power.

Table 1. Flood Susceptibility Datasets used in the Study.

<i>Dataset</i>	<i>Data type</i>	<i>Data Source</i>	<i>Band Name</i>	<i>Resolution</i>	<i>Usage</i>
Multi Spectral Satellite Data	Landsat 8 (OLI/TIRS)	USGS	Band-1 Coastal/Aerosol	30	Produced a land use and land cover (LULC) map of the watershed. Estimate NDVI, NDBI.
			Band-2 Blue	30	
			Band-3 Green	30	
			Band-4 Red	30	
			Band-5 Near Infrared (NIR)	30	
			Band-6 Shortwave Infrared (SWIR) 1	30	
			Band-7 Shortwave Infrared (SWIR) 2	30	
			Band-8 Panchromatic	15	
			Band-9 Cirrus	30	
			Band-10 Thermal Infrared (TIRS)1	100	
			Band-11 Thermal Infrared (TIRS) 2	100	
Radar Satellite Data	Sentinel-1 SAR VH	COPERNICUS	SLC	10	utilized to map floods by detecting surface water, even when there is cloud cover.
Topographic Data	SRTM DEM	USGS	SRTM DEM	30	Derivation of the drainage network and calculations of hydrological and geomorphological indicators.
Rainfall Data	CHIRPS	CHIRPS	CHIRPS	5.0 Km	Provide comprehensive and reliable rainfall data sets, integrated with in-situ meteorological records, to assess historical flood events
Infrastructure Data	Road Network Data	Open Street Map (OSM)	Polyline Shapefile		assess exposure and accessibility during flood events.

3.1.4. CHIRPS Rainfall: CHIRPS was created in collaboration with scientists at the USGS Earth Resources Observation and Science (EROS) Center in order to deliver complete, reliable, up-to-date data sets for rainfall. CHIRPS database provides gridded precipitation datasets with a 0.05° spatial resolution over a span of more than 35 years (1981–2024) (Ren, H., et al., 2024). By integrating these datasets with in-situ meteorological records, high-resolution precipitation time series were reconstructed, vital for assessing historical flood events and seasonal rainfall variability.

3.1.5. OpenStreetMap (OSM): In order to identify the most vulnerable sectors and direct response planning, OpenStreetMap (OSM) was utilized to evaluate infrastructure exposure to flood susceptibility and accessibility of flooded areas.

Data processing and analysis were done using a variety of computer techniques. The creation of Python scripts for statistical analysis, machine learning, and data preprocessing—particularly for Random Forest model training—was made easier by Google Colab. By integrating multi-temporal data, Google Earth Engine (GEE) improved flood susceptibility mapping by providing access to satellite imagery and geographical analysis (Li, W., et al., 2022). Thematic maps and topographic and hydrological indicators were produced using the SRTM DEM using ArcGIS.

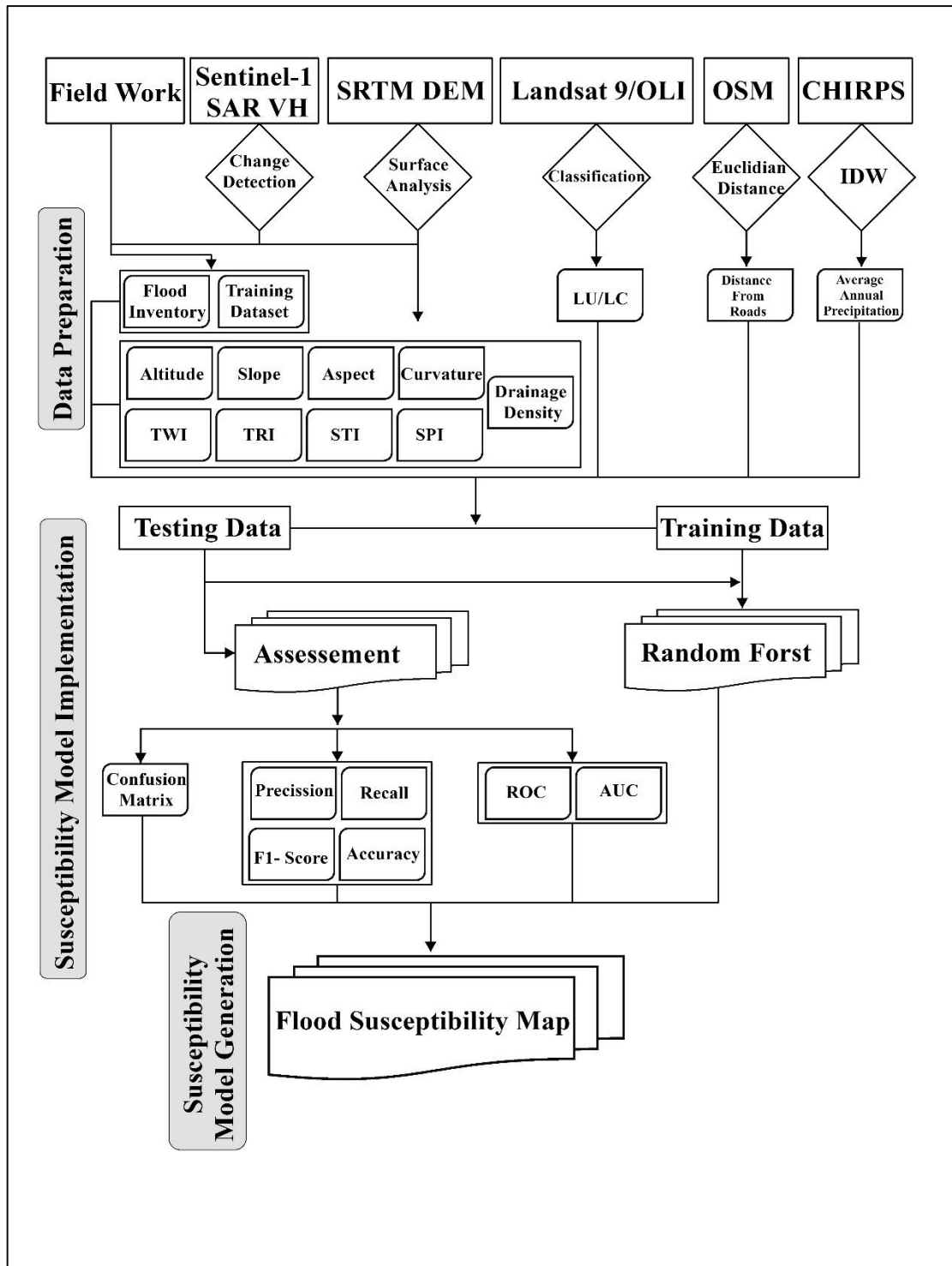


Figure 2. proposed methodology of the study.

3.2. Flood Susceptibility indicators extraction

Twelve indicators were used to assess urban flood susceptibility; these indicators were extracted using a variety of datasets and techniques, including the following: -

3.2.1. Altitude: The SRTM DEM model used to extract point elevation data in meters across the study area, ranging from 511 to 1063m. Higher elevation points are less vulnerable to flood risk compared to lower ones, with summits having lower risk than hillside locations. this map represents the terrain relative elevation of points and helps identify low-lying areas.

3.2.2. Slope: The slopes, which derived from the SRTM DEM, ranges from 0–100 percent and is critical for flood monitoring. In the case study, slope values were between 0–47.2%. Because steeper slopes enhance runoff velocity and decrease water accumulation while flatter places promote flood retention, this parameter is crucial for flood modeling.

3.2.3. Aspect: This index, which is based on the SRTM DEM, improves the precision of flood risk mapping by calculating pixel directions per degree. It uses slope direction and height to simulate the shape of the earth. it determines the direction of the slope, which has a major impact on patterns of water flow and accumulation.

3.2.4. Curvature: This index extracted using the Curvature Tool from SRTM DEM to find concave regions that are susceptible to water accumulation.

3.2.5. Topographic Wetness Index (TWI): This indicator is calculated based on the digital elevation model, which uses surface saturation potential analysis to identify regions that are vulnerable to water accumulation. The following equation is used to calculate it:

$$TWI = \ln \left(\frac{As}{\beta} \right) \quad (1)$$

where " β " is the tan slope and "As" is the flow accumulation.

3.2.6. Topographic Roughness Index (TRI): The Terrain Roughness Index gauges the irregularity of the terrain, which has an impact on floodwater dispersion and water flow resistance. It is computed using the following formula:

$$TRI = \left(\frac{Avg - Min}{Max - Min} \right) \quad (2)$$

where "Avg," "Min," and "Max" stand for the average, lowest, and highest altitude values inside a given neighborhood framework.

3.2.7. Sedimentary Transport Index (STI): this indicator evaluates the capacity of the streams to transport the sediment which effect greatly in drainage system efficiency and determine the basin's susceptible to erosion regions. This indicator can be estimate using the following formula: -

$$STI = \left(\frac{As}{22.13} \right)^{0.4} \times \left(\frac{\sin \beta}{0.0896} \right)^{1.3} \quad (3)$$

where " β " is the tan slope and "As" is the flow accumulation.

3.2.8. Stream Power Index (SPI): This indicator quantifies the potential energy for erosion and sediment transport in a watershed, combining flow accumulation and slope data to highlight areas with high erosive potential. This indicator can be estimate using the following formula:

$$SPI = \ln ((As + 0.001) \times \left(\frac{\beta}{100}\right) + 0.001) \quad (4)$$

where "β" is the tan slope, "As" is the flow accumulation, and the constant "0.001" avoids problems with a zero logarithm.

3.2.9. Land Use and Land Cover (LULC): Land Use and Land Cover data were derived from Landsat 8 satellite imagery, with over 98% of the area within the 166/43 scene and about 2% in the 165/43 scene. The Landsat 8 satellite image dated 3 April 2026 was used in the classification with a cloud cover of 7.85%. A random forest algorithm classified the images after mosaicking, precedes preprocessing that included color, radiometric, and spectral enhancements, along with atmospheric correction via the FLAASH application. Biophysical indices, such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-Up Index (NDBI) (Fu, S., et al., 2022; Wang, C., et al., 2023), were calculated to enhance segmentation accuracy based on the following Equations:

$$NDVI = \left(\frac{NIR - R}{NIR + R}\right) \quad (5)$$

$$NDBI = \left(\frac{SWIR - NIR}{SWIR + NIR}\right) \quad (6)$$

where SWIR stands for short infrared, NIR for near-infrared, and R for red. Vegetation values can be extracted using NDVI values ranging from +1 to -1. Values between 0.2 and +1 are classified as vegetation (Goward, S. N., et al., 1991; de Moraes, R.B.F.; Gonçalves, F.V., 2024; Zhu, X., et al., 2024).

3.2.10. Precipitation: The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) was used to extract precipitation in the study area. About the 161-point coverage of the Wadi Hanifa basin, data was processed using the IDW algorithm to generate rainfall maps. Vector data was managed in the WGS 1984 coordinate system, zone 39 north, with an output cell size of 250 meters, where pixels with no rain data were assigned a value of zero.

3.2.11. Drainage Density: The Wadi Hanifa basin's drainage network was taken from the SRTM DEM, and Arc GIS's Line Density algorithm was used to determine the surface water drainage pathways. Drainage Density is crucial to understand the watershed's capacity to evacuate flood water.

3.2.12. Distance to Roads: The Open Street Map (OSM) database is used to calculate the distance to roads using the Euclidean Distance Tool. This illustrates how the road system may serve as a conduit or a barrier for floodwater.

3.3. Flood inventory map preparation and training data-set

3.3.1. Inventory Map preparation

Sentinel-1 SAR data were processed by filtering and clipping to the relevant research area for model training. A binary raster was created through change detection analysis comparing pre- and post-flood mosaics, where flooded = 1, and non-flooded = 0, with a detection threshold set at 2.0. Water change detection utilized Sentinel-1 imagery through GEE code, comparing images from flood occurrence and non-flooded days. Data related to the floods that happened on July 22, 2021 (lower risk), February 12, 2017 (medium risk), December 10, 2022 (greater risk), and April 12, 2026 (highest risk) were included in this study. The flooded area included all of the sample data at the risk state. Based on the statistics, the places with the lowest risk level are those samples where floods did not occur.

3.3.2. Collection of Training Data

The quality and dependability of the final map are greatly impacted by the performance of the testing and training sets, so collecting sample data is crucial when mapping the flood risk. A dataset of 200 training points was randomly selected, comprising 100 flooded points (labeled 1) and 100 non-flooded points (labeled 0) (Figure 3). Random flood points were manually created based on field knowledge of flood-prone areas and compared with flood raster data from GEE. Non-flood points were established in areas not prone to flooding, considering location, slope, and elevation. To eliminate isolated misclassified flood pixels, Connectivity analysis was applied.

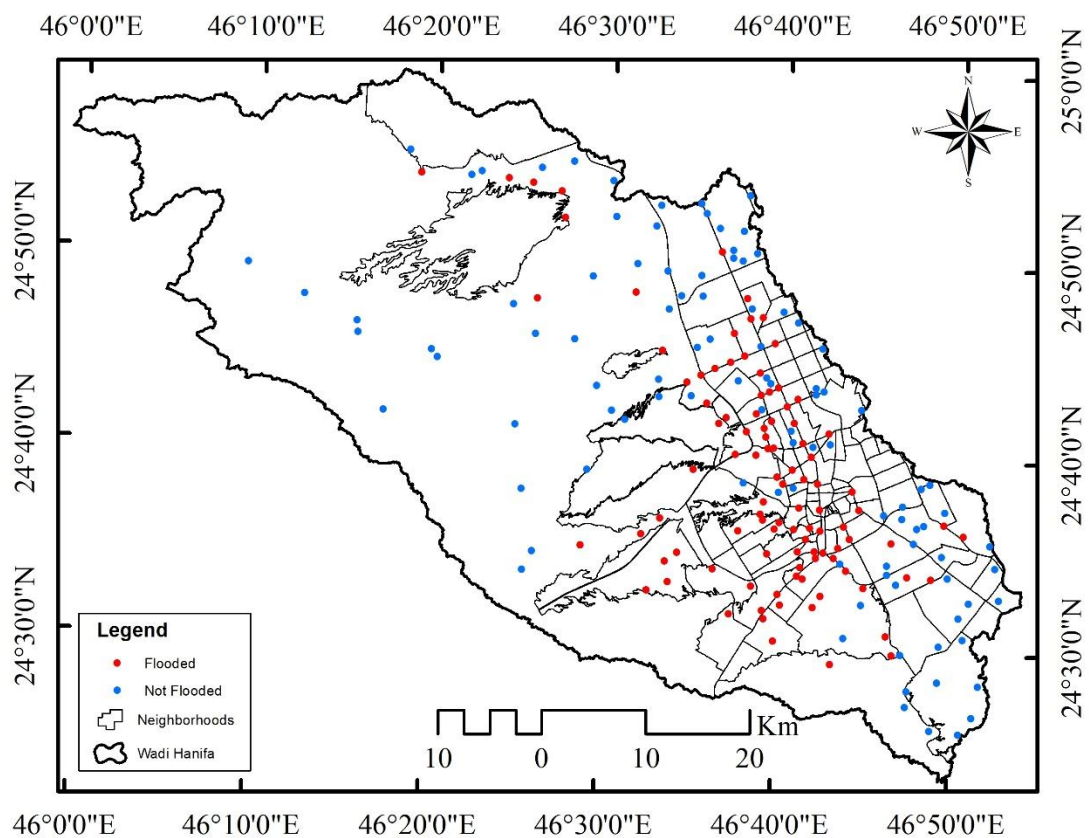


Figure 3. Model training data location map.

391

392 3.3.3. Flood Factor Extraction for Sampling Points

393 The values of the twelve flood conditioning factors were extracted at the 200 sampling points
394 during the data preparation stage. In order to assign the precise flood factor values to each
395 flooded and non-flooded location, the point dataset and the accompanying theme layers were
396 spatially intersected. Each sampling point is linked to an entire set of flood conditioning
397 variables in the feature matrix (organized attribute table) that is produced as a result of this
398 procedure. The Random Forest model is trained and validated using this processed dataset as
399 input.

400 3.4. Implementation of the (FSP) Model

401 Flood susceptibility mapping (FSM) is essential for preventing disasters, but it is still difficult in
402 areas with little data since hydrodynamic models need extensive geophysical inputs. The
403 dataset obtained from the extraction of flood conditioning factors was used for flood
404 susceptibility modeling. Variable definition, dataset partitioning, and model preparation for
405 training and validation are the main tasks of the workflow. Figure 3 provides an overview of
406 the overall scientific approach utilized to identify the flood-prone locations. The
407 implementation of the model went through six consecutive stages, which are as follows:

408 **3.4.1. Defining Variable:** The model was defined using training samples collected from
409 flood-prone and non-flood-prone locations in the study area, where those samples were
410 used as dependent variables and the sixteen variables were used as independent
411 variables.

412 **3.4.2. Partitioning Dataset:** In this step, the training sample groups that were randomly
413 collected were divided so that 75% of them amounting to 150 samples, were used as a
414 training group for the model while 25% of them amounting to 50 samples were
415 designated as test samples. This step aims to evaluate the model's performance.

416 **3.4.3. Selecting Model:** In this step, the Random Forest (RF) classifier was chosen because
417 of its resilience and effectiveness in handling intricate, non-linear geographic data.
418 Despite the training sample size's small size (200 points), it was judged adequate
419 because the sampling approach guaranteed representative coverage of the watershed's
420 varied hydrological and environmental conditions. The RF model is a renowned
421 supervised classification method that combines predictive trees. Each tree depends on
422 a random input vector and is equitably distributed among all trees in the forest. It is
423 widely utilized for classifying high-dimensional and multi-modal data (Breiman, L., 2001;
424 Wang,Z., et al., 2015; Yu,P.S., et al., 2017).

425 **3.4.4. Training and Validation:** After being trained on the training subset, the model was
426 assessed on the test subset. Overall Accuracy and the Receiver Operating Characteristic
427 (ROC) curve, whose area under the curve (AUC) enables evaluation of the model's
428 capacity to distinguish between flooded and non-flooded areas, were used to quantify
429 its performance.

430 **3.4.5. Prediction and Mapping:** To forecast flood susceptibility for every pixel in the
431 research region, the trained and verified Random Forest model was applied to the entire
432 watershed at a resolution of 30 m. The Flood Susceptibility Map (FSM), which offers a
433 continuous spatial representation of flood risk, was created using these probabilities.

434 **3.4.6. Exporting and Post-processing:** The results were exported in shapefile and
435 GeoTIFF formats, compatible with geographic information systems for spatial analysis.

Prediction results in GeoTIFF were integrated into ArcGIS for post-processing. For urban planning and disaster management, continuous probability values were reclassified into five categories: Very Low, Low, Medium, High, and Very High, using the natural break (Jenks) method to optimize value grouping.

3.5. Model Performance Evaluation

Several statistical indicators were used to evaluate the classification models' performance in order to determine the accuracy and dependability of the predictions. To gain a local and global assessment of the model's discriminative capability, these metrics are obtained from the confusion matrix and then enhanced by the study of the ROC curve and the area under the curve (AUC).

3.5.1. Confusion Matrix: The essential instrument for assessing classification models is the confusion matrix. It classifies events into four primary outcomes by comparing the model's predictions with observations in a contingency table (Table 2). Pixels that are accurately categorized as positive, or flood pixels (P), or negative, or non-flood pixels (N), in the machine learning method for flood susceptibility are known as True Positives (TP) or True Negatives (TN), respectively. Similarly, falsely recognized flood pixels and non-flood pixels are called False Positives (FP) and False Negatives (FN).

Table 2. Flood Susceptibility Confusion Matrix.

Observed values	Predicted Values		
		P	N
	P	TP	FN
	N	FP	TN

3.5.2. Evaluation Metrics: Four evaluation metrics are calculated from confusion matrix as following:

Precision or User Accuracy, which quantifies the ratio of correct positive predictions to the total positive predictions made by a model, represented by a specific equation:

$$Precision = \left(\frac{TP}{TP + FP} \right) \quad (7)$$

Recall or Producer Accuracy, which illustrates the model's capacity to accurately identify every instance that is truly positive, represented by the following equation:

$$Recall = \left(\frac{TP}{TP + FN} \right) \quad (8)$$

F1-score, which integrates recall and precision into a single statistic, offering a fair assessment of these two metrics and correlates to their harmonic mean. It is computed using the following formula:

$$F1 - Score = \left(\frac{2 (Precision \times Recall)}{Precision + Recall} \right) \quad (9)$$

Overall Accuracy (OA), which is the proportion of accurate forecasts to total observations. It is provided by the equation

$$Overall Accuracy = \left(\frac{TP+TN}{TP+TN+FN+FP} \right) \quad (10)$$

3.5.3. ROC & AUC: the Receiver Operating Characteristic (ROC) is a curve that shows a classifier technique's performance across all classes and illustrating how the True Positive Rate (TPR) and False Positive Rate (FPR) relate to one another at various categorization criteria. the x-axis represents the FPR and the y-axis represents the TPR. The TPR and FPR rates are obtained from the following Equations:

$$TPR = \left(\frac{TP}{TP+FN} \right) \quad (11)$$

$$FPR = \left(\frac{TN}{TN+FP} \right) \quad (12)$$

AUC is a statistical metric that may be used to summarize the ROC graph and evaluate a classifier model's ability to differentiate between classes. The computation of these parameters is:

$$AUC = \left(\frac{TP+TN}{P+N} \right) \quad (13)$$

where N is the number of non-flooded points and P is the number of flooded positive points.

4. Results

4.1. Flood susceptibility indicators

Twelve elements that affect urban floods were used in the study; these factors were taken from four major databases. From very low to very high, nine of these characteristics were categorized into five levels of susceptibility (Figure 4). The other three factors are an aspect map classified by cardinal and intermediate directions (north, south, east, west, northeast, northwest, southeast, southwest, and flat); a curvature map that distinguishes between concave, convex, and flat surfaces in order to ascertain how topography affects water accumulation and runoff; and a land use map that offers a comprehensive classification, differentiating between vegetation, bare soil, urban areas, and water bodies areas.

The Wadi Hanifa basin Altitude gradually from northwest to southeast, resulting in a network that primarily flows northwest to southeast. Low-lying areas (very high) comprise 18.5% of the basin's area and are the most susceptible to water accumulation and flooding, while higher-lying areas (very low) cover 13.7% and are also the least prone to flooding, as the higher elevations accelerate water movement and prevent accumulation.

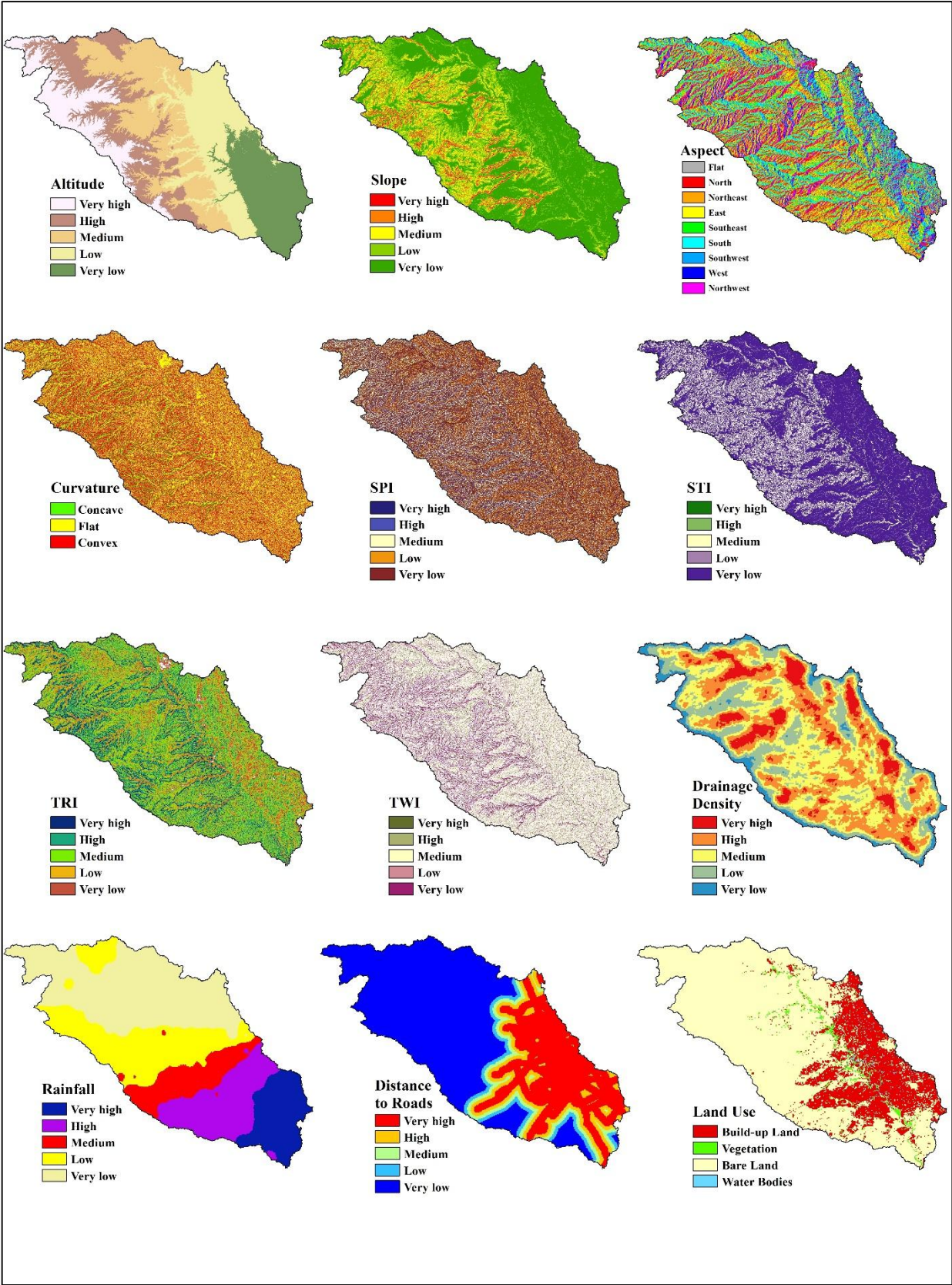


Figure 4. Flood susceptibility indicators map.

520

521 Slope affects urban flooding susceptibility. Water accumulation is lower in the high-slope
522 areas, which cover 2.5% of the basin's area, while it is higher in the low and flat slopes, which
523 cover 56.6%. Slopes are steeper in the western mountainous part of the basin including the
524 Tuwaiq Mountains, and gentler in the southeastern and eastern parts.

525 Aspect reflects the influence of both elevation and slopes. Certain slope patterns strongly
526 affect the flow and accumulation of surface water, particularly in flat areas or those sloping
527 southeast, east, and south, covering 1.7%, 15%, 16.1%, and 12.7%, respectively.

528 The curvature map consists of three categories: concave, convex, and flat, the curvature
529 exacerbates this risk. Flat areas covering about 12.1% provide limited natural drainage network
530 while concave areas covering 41.5% are potential water accumulation hotspots increasing the
531 risk of flooding.

532 The Stream Power Index (SPI) reflects the ability of drainage network to flow and carry
533 sediment, resulting in higher erosion rates and increased water velocity. Very High levels cover
534 about 3.1% of the basin and are concentrated within drainage network and their flow zones
535 as indicated by the blue color covering the western part of the basin. Areas where drainage
536 network are not present are Very Low levels covering 51.6% and appearing densely in the
537 eastern and southern parts of the basin.

538 The high Sedimentary Transport Index (STI) in the western areas indicates high sediment
539 movement, which can obstruct drainage channels, exacerbate flooding, and increase erosion
540 rates, covers 19.7% of the basin. The low levels in the eastern and southern parts of the basin
541 are influenced by the low slopes and fewer drainage network.

542 The low Topographic Roughness Index (TRI) in 11.1% of the basin indicates the flat topography
543 and the lack of natural obstacles affecting water movement in the eastern part. The western
544 part is characterized by high TRI values covering 12.1%, due to the influence of topographic
545 conditions, resulting in rough terrain and irregular surfaces, which in turn resist and disperse
546 floodwater flow.

547 The high Topographic Wetness Index (TWI) in the west reflects high saturation levels and
548 therefore a high probability of flooding, covering 18.2% of the area. Conversely, the lower-
549 lying areas in the east, covering 23.5%, have a lower probability of flooding.

550 Drainage density is high in the central and southern parts of the basin due to the extensive
551 network of canals, which efficiently drain floodwaters under normal conditions but lead to
552 water accumulation and flooding during peak rainfall. It is noted that 10.4% of the basin has a
553 high drainage density increasing the probability of flooding during peak rainfall. The lower-
554 lying areas covering 7.6% are located along the basin margins.

555 The rainfall map shows high precipitation rates during the study period (2000–2023)
556 particularly in the southern and eastern parts of the basin ranging between 123 mm and 172
557 mm. There were periods of high rainfall exceeding these averages highlighting the region's
558 susceptibility to heavy rainfall events. Spatial variations decrease across most of the basin with
559 concentration in the east and south thus exacerbating downstream flood risks. This increased
560 local rainfall combines with accumulated surface runoff from the upper northwest resulting in
561 a multiplier effect of flooding.

Roads are densely concentrated in the eastern part of the basin in areas of high drainage density. This increases flood risk and impedes the natural drainage system when roads intersect with them and acting as barriers or becoming waterways when running parallel to them especially at low levels. It is estimated that 55.1% of the basin has a high road density while 27.5% has a low density.

The land use land cover map clearly reflects its impact on flooding. Impermeable surfaces in built-up areas covering 23.5%, significantly reduce water infiltration, thus increasing the volume and velocity of surface runoff. Green spaces and bare soil covering 2.4% and 73.1% respectively, also mitigate flooding potential by facilitating water infiltration and impeding its advance.

4.2. Importance of Flood indicators

Analysis of the relative importance of flood indicators, based on a random forest model, reveals the specific contribution of each indicator to flood susceptibility within the Wadi Hanifa basin west of Riyadh (Figure 5). The analysis indicates that drainage density, land use, rainfall, and TRI are the four most significant factors in determining flood occurrence in the study area, accounting for 14.2%, 12.9%, 12.3%, and 10.3%, respectively.

Drainage density is the most influential factor in predicting flood susceptibility and thus reflects the crucial role of surface water networks. High drainage density indicates areas of concentrated water networks and consequently concentrated surface runoff especially during heavy rainfall. This leads to these channels reaching their maximum capacity resulting in backwater effects and overflow. Given the concentration of surface water networks in the middle and lower parts of the basin, which are linked to dense urban areas and activities, this finding highlights the urgent need to expand and maintain drainage infrastructure in these hydrologically densely networked areas.

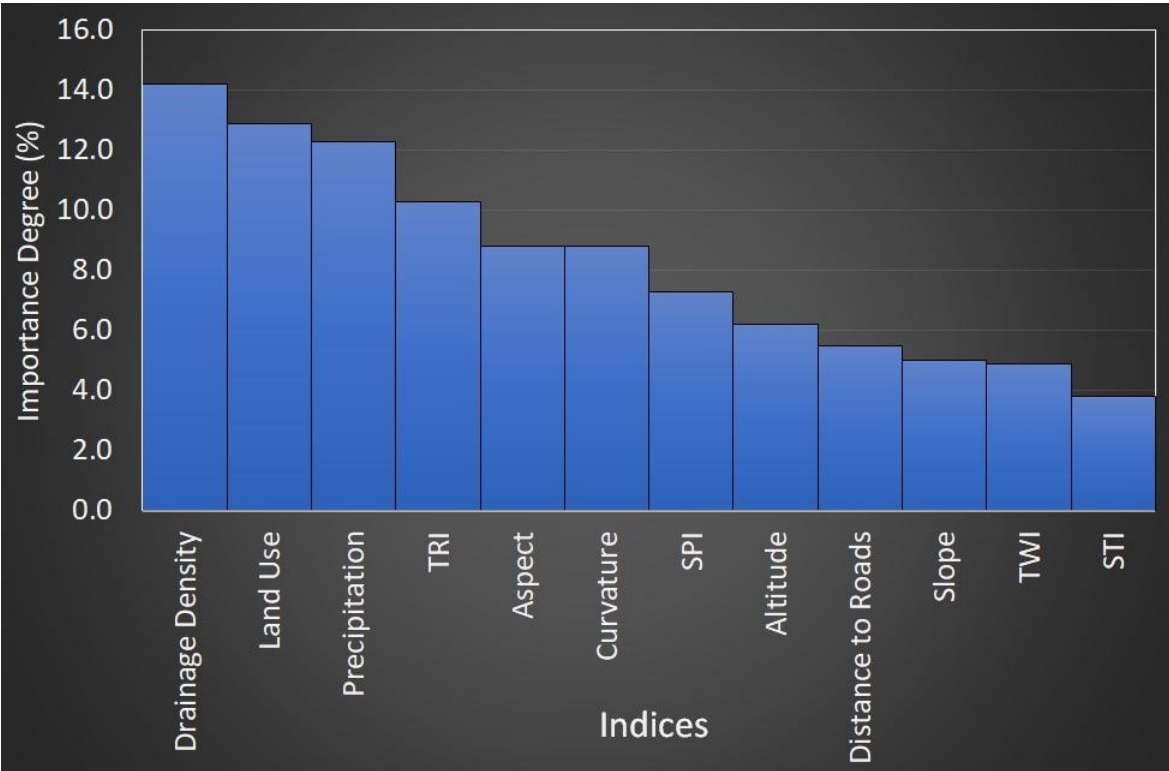


Figure 5. Flood susceptibility indicators Importance.

Land use ranks second in importance, highlighting the impact of impermeable water surfaces on flooding particularly in the central, southern, and eastern parts of the basin. This finding underscores the dangers of urban expansion in basins and reflects the importance of ensuring that buildings and structures are compatible with water flow conditions, so as not to impede the flow of water networks or contribute to their saturation and subsequent flooding. This result indicates the strong correlation between urbanization and flooding, thus necessitating the adoption of future urban development plans that do not negatively affect the dynamics of basins and surface water networks.

Rainfall is the third most important factor, highlighting the direct impact of rainfall intensity on flooding. Although the total annual rainfall in the region ranges between 123 and 173 mm, sudden flash floods are a defining characteristic. The region may experience prolonged periods without rain followed by sudden intense downpours that generate large quantities of surface runoff exceeding the capacity of surface water networks resulting in devastating floods. This underscores the need for flood management to prioritize rainwater capture and drainage along with land-use regulation to encourage infiltration and urban drainage particularly in the eastern and southern regions where rainfall-induced flooding is exacerbated by surface runoff from the northwest.

The TRI index ranks fourth in relative importance for flooding reflecting the impact of surface regularity on flooding within the basin especially in the western part. This results in a steady flow of water towards the central, eastern, and southern regions, which have impermeable surfaces and multiple runoff obstacles leading to significant flooding. This highlights the necessity of continuous dredging of the main wadi channel and the importance of a robust artificial drainage network capable of handling excess floodwater to prevent flooding.

Secondary factors, such as aspect, curvature, SPI, and altitude have a moderate impact on flood susceptibility, accounting for 8.8%, 8.8%, 7.3%, and 6.2%, respectively. These factors include three topographical factors that reflect the importance of surface shape and topography in flooding particularly aspect and curvature. Aspect influences the direction of surface water networks, concentrating water flow and thus increasing the likelihood of flooding. Curvature, on the other hand, contributes to water accumulation and concentration in specific areas further increasing flood risk and leading to land inundation in conjunction with other factors. The SPI index also reflects the strength of the water current and its erosive potential, increasing water speed and consequently contributing to flooding. Given the low topographical range of the basin, which is 525 meters with elevations ranging from 511 to 1036 meters, the altitude index plays a significant role in flood probability due to the gradual elevation gradient from northwest to east and southeast.

In contrast, variables such as Distance to Roads, Slope, TWI, and STI show a relatively smaller impact, at 5.5%, 5.0%, 4.9%, and 3.8%, respectively. While these factors contribute to local variations, their overall impact is diminished by other parameters. Although the Distance to Roads index is important because impermeable road surfaces impede natural water infiltration and direct surface runoff, its concentration within a limited area somewhat reduces its significance. Similarly, the low local variation in the Slope index also diminishes its importance as the basin is predominantly gently sloping (56.5%), which strongly influences flooding. The low weighting of TWI, despite its role in surface saturation potential, is likely due to its high values being concentrated in the western part of the basin, which does not spatially intersect with flooding sites. The same applies to the STI index, which reflects sediment transport capacity, erosion, and increased water velocity.

4.3. Random Forest Model Performance

4.3.1. Confusion Matrix Analysis

The Random Forest model's confusion matrix provides a comprehensive evaluation of the accuracy of its flood classification. It features a vertical axis representing actual values—0 indicating no flooding and 1 indicating flooding—and a horizontal axis depicting the predicted values based on the same coding. In the analysis involving 50 testing observations, the model successfully identified 24 actual flooded regions as flooded (True Positives) and accurately classified 21 non-flooded regions as not flooded (True Negatives). However, it misclassified one flooded area as not flooded (False Negative) and erroneously predicted four non-flooded areas as flooded (False Positives).

4.3.2. Performance Indicators

As shown in (Table 3), the performance measures highlight the classification model's efficacy through both class-specific and overall indicators. The model's precision for the "Not Flooded" class is 0.96, which indicates that 96% of the locations classified as not flooded are accurate. Nevertheless, an F1-score of 0.90 resulted from the recall score of 0.84, which shows that 16% of real non-flooded areas were mistakenly labeled as flooded. In contrast, the model achieves a high recall rate of 0.96 for the "Flooded" class, correctly recognizing 96% of flooded locations; however, the precision is somewhat lower at 0.86 because to false positives, resulting in an F1-score of 0.91. The model's overall accuracy is 0.90, meaning that out of 50 test samples, 90% of the predictions were accurate. Both weighted averages (precision = 0.94, recall = 0.87, F1-score = 0.91) and macro averages (precision = 0.91, recall = 0.90, F1-score = 0.91) show a robust and balanced performance across classes, demonstrating the model's strong predictive ability while taking the real distribution of observations into account.

Table 3. Flood Susceptibility Model Performance Metrics.

	precision	Recall	F1-score	Overall
Non-flooded	0.96	0.84	0.90	25
Flooded	0.86	0.96	0.91	25
Overall Accuracy			0.90	50
Macro Average	0.91	0.90	0.91	50
Weighted Average	0.94	0.87	0.91	50

4.3.3. ROC Analysis and AUC

The Random Forest model's Receiver Operating Characteristic (ROC) curve produced an Area Under the Curve (AUC) of 0.90. This outcome shows that the test dataset has a strong ability to distinguish between flooded and non-flooded classes. As seen in (Figure 6), the high AUC value highlights the model's dependability in precisely detecting flood-prone areas, displaying both high precision and minimum error.

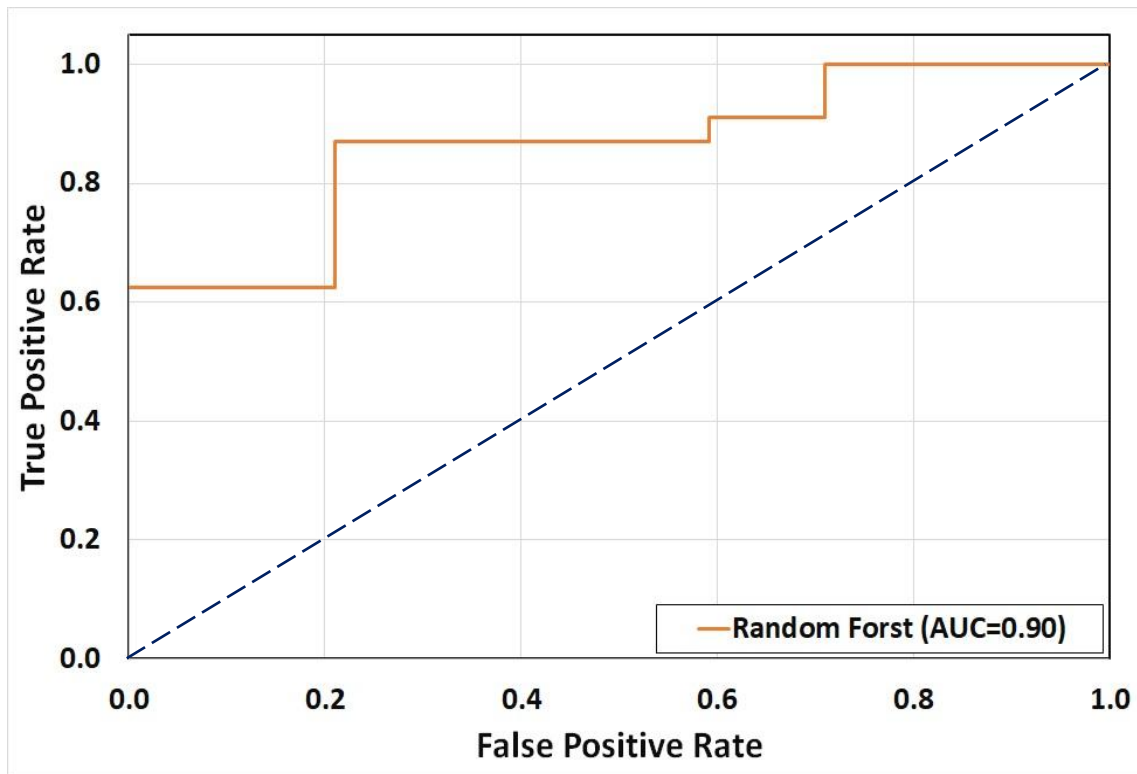


Figure 6. Random Forest model ROC-AUC curve.

4.4. Flood Susceptibility Map

The Wadi Hanifa watershed's final flood susceptibility map shows a varied spatial distribution of flood risk across different zones (Figure 8). The greatest percentage, 27.7%, is categorized as Very Low susceptibility, meaning that there is little risk to infrastructure components. On the other hand, places classified as Low susceptibility (26.4%) present a manageable danger, whilst areas classified as medium susceptibility (25.6%) require careful management and hydrological control because they are at a transitional risk level. Because high vulnerability zones (14.2%) are frequently associated with dense urban development and extensive drainage systems, they necessitate increased attention and the application of unique flood prevention and mitigation techniques. Because of their increased impermeable surfaces and decreased infiltration, these variables enhance the risk of flooding caused by runoff.

In addition, areas classified as Very High susceptibility, which account for 6.1% of the total area, require ongoing surveillance and prompt flood risk reduction measures to protect people and infrastructure. These crucial hotspots, which are shown in blue on the map, are mostly found in low-lying urban areas such Center Uraija, Uraija, Derab, Ukaz, Marwwah, Uraid, Twaeq-Etaigah, and Hejrat Wadi Leban, as well as close to important drainage routes. These locations are especially vulnerable to flash floods, possible infrastructure damage, and the possibility of having to relocate populations during extreme weather events due to their geographic location and fast urbanization. The necessity of customized flood management strategies based on vulnerability levels across various watershed areas is highlighted by this thorough investigation.

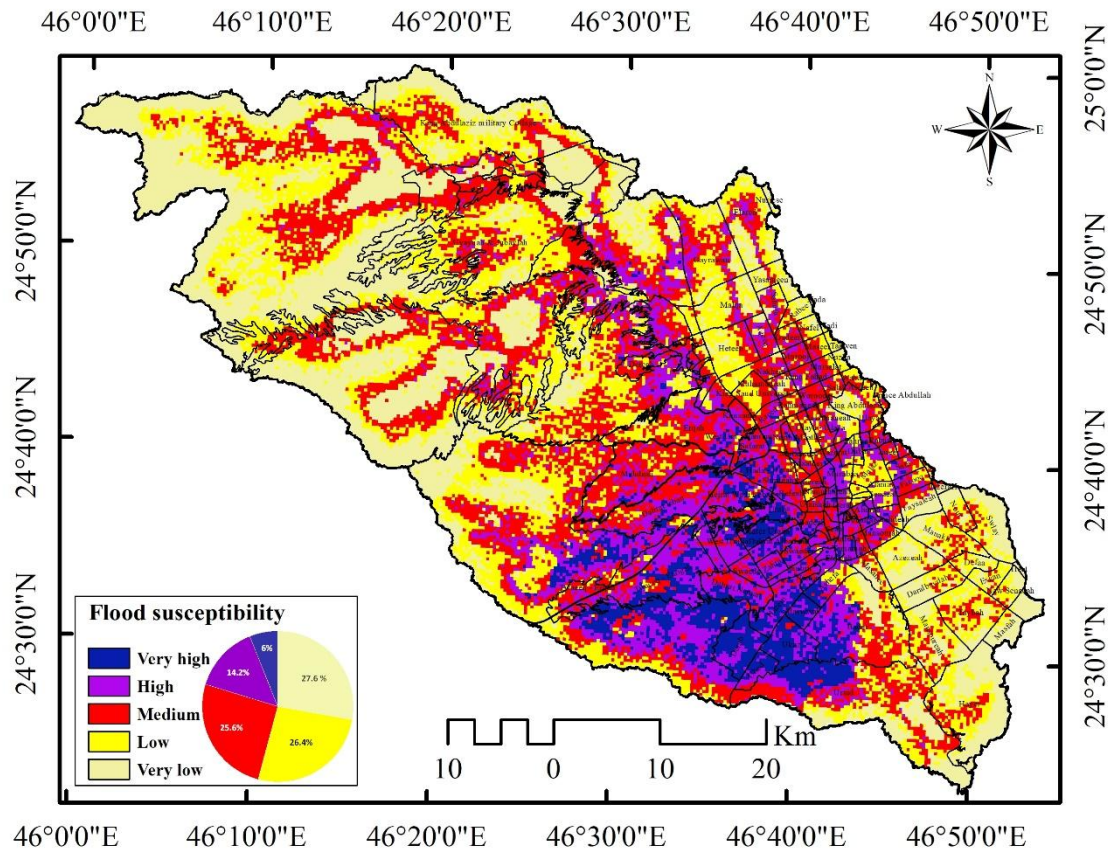


Figure 7. Wadi Hanifa Flood susceptibility map.

5. Discussion

This research explores a novel approach to assessing urban flood susceptibility by leveraging the capabilities of machine learning algorithms, geographic information systems (GIS), and remote sensing technologies (RS). Central to this methodology is the use of Google Earth Engine (GEE), identified as an advanced tool that facilitates the rapid and efficient generation of diverse parameters necessary for flood susceptibility analysis. The research is specifically applied to Riyadh, a major city in West Asia, where the Wadi Hanifa river system traverses the western and central regions, highlighting the study's relevance to rapidly urbanizing areas facing flood risks.

This study employed a combination of twelve carefully selected indicators, aligned with previous flood susceptibility analysis methodologies such as those of (Seydi, S.T., et al., 2022; Danumah, J. H., et al., 2026), which utilized machine learning algorithms to study flood susceptibility. These indicators were divided into three main categories: topographical (altitude, slope, aspect, and curvature), hydrological (rainfall, SPI, STI, TWI, TRI, and drainage density), and human (LU/LC and distance to roads). The quality of the input parameters has a direct impact on how reliable these classifications are. Previous studies highlight the significance of various indicators in assessing urban flooding. For instance, (Youssef, A.M., et al., 2016) utilized seven indicators for their investigation into urban flooding in Jeddah.

Similarly, (Hammami, S., et al., 2019) applied eight indicators in their research focused on northeastern Tunisia. Furthermore, (Sadek, M., & Li, X., 2019) employed five indicators to analyze flooding in Ras Gharib, Egypt. These studies collectively underscore the diverse methodologies adopted in urban flooding research across different geographical contexts.

The study examined urban flood susceptibility using five established data sources, from which twelve criteria were extracted. Initial processing of the data aimed to rectify errors that could compromise the accuracy of the outcomes. The algorithms implemented for data processing and result generation received positive evaluation; nonetheless, it is important to note potential error margins, especially concerning rainfall data sourced from CHRIPS (Climate Hazards Group InfraRed Precipitation with Station data). A significant limitation identified was the lack of a historical flood database for the specified study area. To counter this gap, the study adopted the use of Sentinel-1 radar imagery, reflecting methodologies previously utilized by researchers such as (Chini, M., et al., 2018; Vanama, V. S. K., & Rao, Y. S., 2019; Duwal, S., et al., 2023). This approach highlights the innovative efforts to leverage advanced imaging technology in unearthing historical flood data, providing a foundational framework for assessing flood risks in urban environments.

The study employed the random forest model to evaluate flood susceptibility achieving notable accuracy in distinguishing between flooded and non-flooded regions. The performance was quantified using the ROC curve and confusion matrix reflecting the model's robust ability to accurately locate flood zones with an impressive AUC value of 0.9. This indicates that the model effectively differentiates these areas based on critical analytical indicators supported by a well-structured training and validation dataset.

Despite its strong performance the AUC value of 0.9 is slightly lower than those reported in previous studies: (Danumah, J. H., et al., 2026) with 0.94, (Farhadi, H. & Najafzadeh, M., 2021) at 0.91, (Duwal, S., et al., 2023) with 0.91, and the notably high AUC of 0.9935 by (Gharakhanlou, N. M. & Perez, L., 2023). Conversely the model outperformed the findings of (Sun, J. Q., et al., 2026), who reported an AUC of 0.856, and (Debnath, J., et al., 2024) with an AUC of 0.893. The variances in AUC values can be associated with local environmental conditions and the specific predictive variables utilized which include drainage intensity, land use, and rainfall—identified as crucial elements impacting flooding events. The model demonstrated remarkable efficacy in identifying flooded areas evidenced by a low rate of false negatives recording only one out of 50 samples misclassified. A minor occurrence of false positives (four instances) indicates a slight overestimation of flood risk. Overall, the model showcases balanced performance metrics including accuracy, recall, and F1 scores, culminating in an overall accuracy rate of 0.90. The stability of these findings is further corroborated by the convergence of both overall and weighted average, reinforcing the reliability of the random forest model in flood susceptibility assessment.

Overall, the results are reliable and provide a strong scientific foundation for urban planning and disaster risk reduction strategies to the relevant Saudi Arabian Kingdom authorities. This study also highlights the importance of integrating historical data, advanced forecasting models, and mapping techniques to better advise flood control methods. The ongoing collection and integration of ground and satellite measurements, as well as the creation of predictive models, will gradually increase the accuracy of flood risk maps and reduce the damaging effects of floods on people and infrastructure.

6. Conclusion

This study conducted a comprehensive assessment of urban flood susceptibility in the Wadi Hanifa basin situated west of Riyadh. It employed an integrated methodology that combined machine learning algorithms (ML), geographic information systems (GIS), and remote sensing technologies (RS) to pinpoint areas at high risk of flooding. The creation of a flood susceptibility map is a significant outcome of this research serving as a critical tool for local authorities to identify flood-prone zones and implement effective mitigation strategies.

In total, five key data sources were utilized in this analysis: Landsat 8 (OLI/TIRS) satellite imagery, Sentinel-1 SAR VH data, the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), CHIRPS Rainfall data, and OpenStreetMap (OSM) information. Complementing the data analysis fieldwork was conducted to gather real-time data and validate the findings enhancing the reliability of the model's predictions.

The study specifically utilized a random forest model to evaluate urban flood susceptibility by focusing on twelve indicators categorized into three main groups: Topographic indicators included Altitude, slope, Aspect, and curvature; Hydrological Indicators like drainage density, Topographic Wetness Index (TWI), Topographic Roughness Index (TRI), Sedimentary Transport Index (STI), and Stream Power Index (SPI) were considered; Human Factors focused on land use/land cover and Distance to Roads.

The findings indicated that drainage density, land use/land cover patterns, and rainfall were the primary factors affecting flood susceptibility within the Wadi Hanifa basin. The application of the random forest model (RF) has critically advanced the understanding of the interplay between these factors and urban flood vulnerability providing essential insights for future urban planning and disaster preparedness initiatives.

Five main steps make up the study methodology: collecting and preparing data from sources; extracting 12 flood susceptibility indicators; using change detection algorithms to create a flood inventory map and training dataset; applying the (FSM) over six stages; and evaluating model performance using four evaluation metrics and a confusion matrix.

The application of the random forest algorithm in machine learning achieved high reliability with an area under the curve (AUC) of 0.9. Precision was 0.96 for unflooded areas and 0.86 for flooded areas while Recall reached 0.84 for unflooded and 0.96 for flooded areas. The F1-score was 0.90 for unflooded and 0.91 for flooded. Overall Accuracy was 0.9 indicating the model's effectiveness in identifying flood-prone areas in the basin. Strong alignment between the predicted significant-risk zones on the susceptibility map and the observed flood sites was demonstrated by the model's validation during the flood occurrence on April 12, 2026. The analysis indicates that 24 observed flood points occurred in regions categorized as High to Very High flood risk thereby validating the effectiveness of the risk assessment model. In contrast, only one flood occurrence was documented in areas classified as Low Risk further supporting the model's reliability concerning flood risk prediction.

The resulting flood susceptibility map indicates that 6.1% of the catchment areas show very high flood susceptibility, 14.2% show high susceptibility, and 25.6% show moderate flood susceptibility. The results also show that the neighborhoods of Center Uraiya, Uraiya, Derab, Ukaz, Marwwah, Uraid, Twaeeq-Etaigah, and Hejrat Wadi Leban are highly susceptibility to urban flooding.

The findings underscore the significant role of machine learning, Geographic Information Systems (GIS), and remote sensing applications in managing urban flood risks. There is an urgent need to improve infrastructure designs to effectively manage flood strength and concentration. Continuous flood monitoring is critical particularly in urban areas along with the activation of robust early warning systems aimed at mitigating the impact of floods thereby reducing loss of life and property. The study advocates for urban planners, real estate developers, civil authorities, and decision-makers to adopt a comprehensive methodology that guides development and urban growth away from flood-prone areas and contributing to an integrated and sustainable urban environment.

Funding: Ongoing Research funding program, (ORF-2026-1871), King Saud University, Riyadh, Saudi Arabia.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data supporting the findings of this study are available within the paper and its Supplementary Information.

Acknowledgments: The author extend their appreciation to the Researchers' Supporting Project number (ORF-2026-1871), King Saud University, Riyadh, Saudi Arabia.

Conflicts of Interest: The author declares no conflict of interest.

Abbreviations

ML	Machine Learning
KSA	Kingdom of Saudi Arabia
GIS	Geographic Information System
RS	Remote Sensing
FSM	Floods Susceptibility Map
RF	Random Forest
OSM	Open Street Map
CHIRPS	The Climate Hazards Center Infrared Precipitation with Stations
TWI	Topographic Wetness Index
TRI	Topographic Roughness Index
STI	Sedimentary Transport Index
SPI	Stream Power Index
LULC	Land Use and Land Cover

NDVI	Normalized Difference Vegetation Index
NDBI	Normalized Difference Built-Up Index
GEE	Google Earth Engine
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives
TPR	True Positive Rate
FPR	False Positive Rate

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