

Geophysical Analysis Of Flood Susceptibility In Nyabarongo Lower Catchment, Rwanda

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Abstract: Floods have increasingly been observed as a recurring phenomenon and increasingly hazardous in the Nyabarongo Lower Catchment, Rwanda, which is characterized by fast-changing land use/land cover (LULC) together with topography and hydrology, all determining whether floods will occur or not. The current study sought to determine the impact of LULC changes in shaping flood susceptibility in the Nyabarongo Lower Catchment using Geographic Information Systems (GIS), Remote Sensing (RS) and the Analytical Hierarchy Process (AHP) under the Multi-Criteria Decision Analysis (MCDA) framework. Multitemporal Landsat images for the years 1990, 2000, 2010, 2020 and 2025 were classified into six LULC categories and were validated using stratified random sampling techniques that resulted in an overall average accuracy of 86.0% and Kappa coefficient of 0.83. There were ten factors considered during the evaluation of flood susceptibility in the study area and these include distance to river, topographic wetness index (TWI), elevation, slope, rainfall, drainage density, LULC, curvature, aspect and distance to road. Forest cover decreased by 68.4% from 1,099,311 ha in 1990 to 347,762 ha in 2025, wetlands by 91.1% while cropland increased by 180.3% and built-up land by 596%. FSI generated maps identified five susceptibility classes: very low (19.65%), low (27.79%), moderate (28.95%), high (14.92%) and very high (8.69%). 23.61% (approx. 71,188 ha) of the catchment area was found highly to very highly susceptible to flooding mostly along low-lying floodplains and riparian corridors. Spatial overlay analysis established a positive relationship between forest and wetland loss and the increase in the high susceptibility class with 67.2% of the remaining wetlands and waterbodies falling within high and very high susceptibility areas and more than 65% of new built-up area expansion between 2010 and 2020 falling within the moderate-to-very-high susceptibility class. The results illustrate the importance of anthropogenic land transformation over terrain alone as a major cause of increased flood risk in the catchment, and highlight the potential benefits of the application of multi-temporal LULC and GIS-AHP modeling in the evidence-based conservation of wetlands, river buffers and land use planning in Rwanda and similar East African catchments.

Keywords: *Analytic Hierarchy Process; Flood susceptibility; GIS; LULC; Multi-Criteria Decision Analysis*

1. Introduction

Floods have been one of the most destructive natural hazards throughout the world, making up roughly 40 percent of all documented natural hazards and having impacted more people over the last few decades than any other type of hazard [1]. Though intense rainfall as a result of climatic events constitutes a major cause of such natural hazards, there is increasing scientific evidence that anthropogenically induced LULC is becoming a more crucial factor in modifying hydrological behavior and increasing flood risk [2]. Population growth, economic development and urbanization across the world have transformed enormous tracts of forests, wetlands and grasslands into farmlands and built-up areas and have thus completely altered the behavior of catchments towards rainfall [3]. Deforestation reduces evapotranspiration and increases soil erodibility, urbanization

leads to huge amounts of impervious surfaces and thus restricts groundwater recharge, while agricultural activities lead to soil compaction [4]. Degradation of wetlands decreases natural storage, which moderates the peak flow of rain, thus increasing runoff quantity, decreasing the time between rainfall and peak flow, and increasing flood intensity [5]. There is ample proof globally in the recent years of how land use changes have led to increased vulnerability of people to flooding compared to the effect of climate change alone [6]. whereas floods have become a regular disaster due to intrusion into flood corridors because of land use planning [7]. The Geographic Information Systems (GIS) and Remote Sensing (RS) are valuable techniques that can help in assessing flood hazard due to the ability to provide continuous monitoring of changes in land cover, combining this data with topographical, hydrological and climatic factors [8]. Flood zones are usually determined using such factors as elevation, slope, drainage density, soil type, rainfall amount, land use, and proximity to rivers [9]. This kind of analysis is beneficial for risk reduction, sustainable watersheds and adaptation to climate change. In Sub-Saharan Africa, there is fast-growing urbanization taking place on flood-prone and environmentally sensitive areas [10]. Flood susceptibility has been exacerbated by greater rainfall variability in East Africa and the degradations in watershed conditions in the river basins of Kenya, Uganda, Tanzania, Ethiopia and Rwanda, whereby flooding has been found to be strongly correlated with deforestation, drainage of wetlands and floodplain development [11]. Research efforts that integrate land use/cover change assessments with terrain/hydrologic criteria through multi-criteria analysis have been proven to increase the accuracy of flood susceptibility mapping [9]. But few have been done in African watersheds. The river systems of Rwanda, among which are the Nyabarongo, Akanyaru and Mukungwa rivers, are experiencing floods due to the complex geography, high population densities and intensification of agricultural activities in the area. In the last decades, agricultural development, urban growth and degradation of wetlands have changed natural pathways of water and increased surface runoff in the Nyabarongo River Basin, accounting for a large part of Rwanda's territory and providing a living base for millions of Rwandans [12]. The Nyabarongo Lower Catchment is prone to flood hazards due to its lowland nature, floodplain landscapes and continuous development of agricultural and residential lands along rivers. Deforestation in the upstream region, drainage and transformation of wetlands into agricultural land, and urbanization of riparian zones in the downstream part have increased the hydrological connectivity of the watershed, thus intensifying the floods' magnitude and frequency [13]. Numerous studies have been conducted to evaluate the impact of precipitation changes and hydrological regime of Rwandan watersheds, but relatively few studies have considered the connection between LULC changes through time and flood vulnerability using the geographic information system (GIS)-based multi-criteria analysis approach [14]. This research fills in this gap by examining the effect of changes in land use/land cover on flood vulnerability in the Nyabarongo Lower Catchment utilizing an integrated GIS-AHP-MCDA framework. In particular, this research seeks to: (1) examine changes in land use/land cover in the catchment from 1990 to 2025; (2) develop and map flood vulnerability based on ten flood conditioning factors utilizing the Analytic Hierarchy Process; and (3) examine the relationship between land use/land cover change and flood vulnerability through overlay analysis. This evidence will be useful in informing sustainable land management and wetland conservation within the Nyabarongo Lower Catchment and similar catchments in East Africa.

2. Materials and Methods

2.1. Description of the Study Area

The Nyabarongo Lower Catchment comprises the downstream part of the greater Nyabarongo River Basin, which is the major tributary of the Nile in Rwanda, occupying an area of about 3,500 to 3,700 square kilometers (Figure 1). This catchment is distinguished by low elevations, mild slope gradients, presence of large wetlands and floodplains that facilitate the storage and slow flow of water during heavy rains, while the hydrology of the catchment is heavily impacted by activities upstream in the greater Nyabarongo River Basin. The catchment spans across a number of administrative districts, such as Burera, Gakenke, Gicumbi, Rulindo, Kamonyi, Muhanga, Gatsibo, Kayonza, Rwamagana, Gasabo, Kicukiro and Nyarugenge, all contributing their surface runoffs, which finally drain into the Nyabarongo River. In the last few decades, the changes in land cover due to increased agricultural activities and urbanization have significantly impacted the drainage of the area, increasing the risk of flooding in the floodplains due to wetland encroachment, poor enforcement of riparian buffer regulations and poor land management [14].

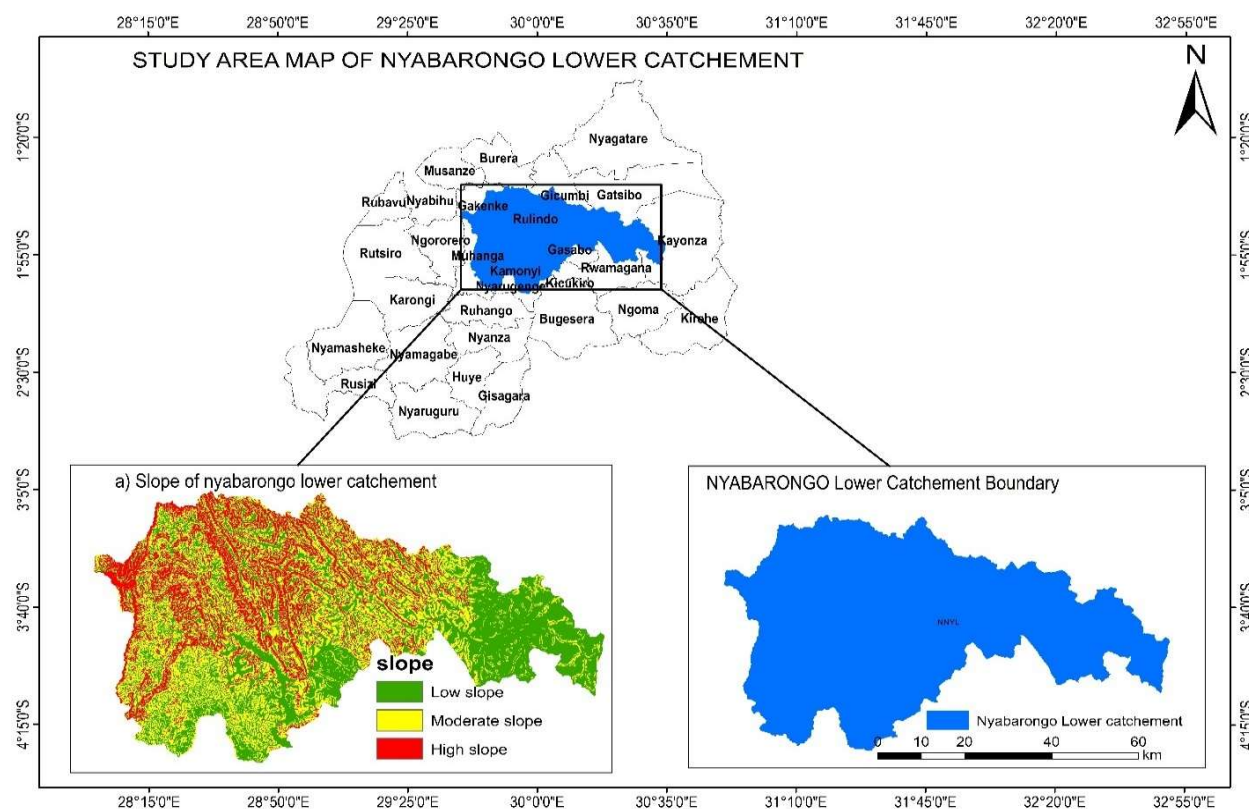


Figure 1. Location of the Nyabarongo Lower Catchment.

2.2. Research Design and Data Sources

The methodology involved the adoption of a quantitative research design based on geographic information system and remote sensing techniques owing to the fact that flood vulnerability is a spatial phenomenon that can be explained using physical and environmental parameters like elevation, slope, rainfall, land use and distance from rivers. Primary and secondary data were employed in the study. Primary data included field observation and verification carried out within the catchment area which helped in validating the physical characteristics of the selected locations (land use, settlement, agriculture, wetlands, distance from rivers, drainage and visible areas of floods). Secondary data included multitemporal satellite images from Landsat 7 ETM+ and Landsat 8 OLI/TIRS with 30 m spatial resolution in 1990, 2000, 2010, 2020 and 2025 to aid in LULC classification and change detection; 30 m Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) to calculate elevation, slope, aspect, curvature, flow accumulation and drainage density; and soil, rainfall, rivers/drains, roads and administrative boundary datasets from credible sources [[15]. [16]]

2.3. Data Processing and LULC Classification

The satellite imagery was subjected to geometric and atmospheric corrections, cloud and shadow masking, clipping to the extent of the study area and re-projection to a common coordinate reference system to reduce spatial and spectral variations before the classification process [17]. Classification process was done on each date of the image to produce the LULC map for the forest land, cropland, grassland, wetland, built-up/settlement and water body categories by selecting training samples for each class that would capture the spectral characteristics of the different classes. Change detection process was conducted through post-classification on successive dates (1990-2000, 2000-2010, 2010-2020 and 2020-2025) and the overall 1990-2025 period. The DEM data was processed through sink removal, flow direction, and flow accumulation to compute slope, elevation, curvature,

aspect, topographic wetness index (TWI) and drainage density that regulate the surface runoff accumulation. Accuracy of classification was carried out yearly by taking a stratified random sampling of 90 independent validation samples on each day, against confusion matrices that provide an accuracy score, producer's accuracy score, user's accuracy score, and the Kappa coefficient, which is commonly used to assess accuracy in remote sensing [18]

2.4. Flood Conditioning Factors and AHP-MCDA Modelling

Ten conditioning factors for floods were chosen due to their documented importance in influencing flood events from the literature and the field study: proximity to river, TWI, elevation, slope, rainfall, drainage density, LULC, curvature, aspect, and proximity to roads [19]. Each of these factors was reclassified in terms of their effect on generating runoff and water retention in a scale of 1-5 (1=very low, 5=very high). The relative weight of the ten factors was determined using Analytical Hierarchical Process (AHP), wherein each of the ten factors was paired up against one another on a scale of 1-9, as suggested by Saaty [20].. Pairwise comparison results were then validated using Consistency Ratio (CR) to ensure internal consistency of the data, CR values below 0.10 being acceptable [20]. The reclassified and weighted factors were then combined using weighted overlay analysis of ArcGIS software using the following formula:

$$FSI = (0.22 \times \text{Distance to River}) + (0.18 \times \text{TWI}) + (0.14 \times \text{Elevation}) + (0.12 \times \text{Slope}) + (0.10 \times \text{Rainfall}) + (0.09 \times \text{Drainage Density}) + (0.07 \times \text{LULC}) + (0.05 \times \text{Curvature}) + (0.02 \times \text{Aspect}) + (0.01 \times \text{Distance to Road})$$

The resultant continuous FSI was classified into five susceptibility classes based on Jenks natural break criteria: very low, low, moderate, high and very high. Validation of the FSI map was done using field observations and historical flood information gathered from the Ministry in Charge of Emergency Management (MINEMA). The spatial link between changes in LULC and FSI zones was further analyzed through intersect-based overlay analysis performed in ArcGIS by overlapping the classified LULC maps and the change detection maps for each time step against the FSI zones to determine the percentage of each land cover class and land cover change within each susceptibility zone [21]

3. Results and Discussion

3.1. Land Use and Land Cover Change, 1990-2025

The extent of forest cover dropped significantly from 1,099,311 ha (49.8% of catchment area) in 1990 to 347,762 ha (14.0%) in 2025 representing a reduction of 751,549 ha or 68.4% of the initial forest extent. Wetlands have reduced by 91.1%, from 263,482 ha in 1990 to 23,451 ha in 2025, while cropland increased by 180.3%, rising from 624,221 ha (33.2%) in 1990 to 1,749,862 ha (70.6%) in 2025 and built-up land increased nearly sixfold (by +596%), from 11,633 ha to 80,848 ha (Table 1). These changes reflect the similar LULC pattern that has been described in relation to the entire Nyabarongo River Basin over the period 1990-2020, where forest cover dropped from 58.2% to 17% and cropland increased from 32.2% to 71.4% of the total basin area with further increase predicted in cropland coverage.

➤ LULC Table

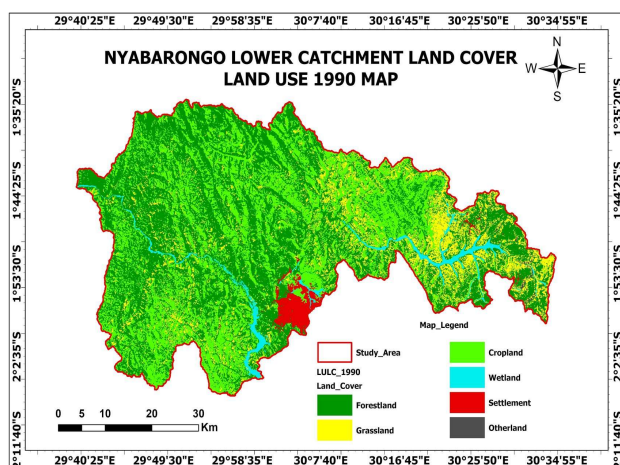
Table 1. LULC distribution in the Nyabarongo Lower Catchment, 1990-2025 (hectares).

LULC Class	Area 1990 (Ha)	Area 2000 (Ha)	Area 2010 (Ha)	Area 2020 (Ha)	Area 2025 (Ha)
Forestland	1099311.21	613330.7	739320.03	353786.34	347762.05
Cropland	624221.46	1753137.74	1116723.6	1781275.8	1749862.27
Built-up	11632.59	64869.31	20945.25	253940.13	80848.05
Grassland	534454.29	52028.32	399190.14	26452.23	244188.46
Wetland	263481.57	52148.74	257992.92	85350.53	23450.81
Waterbodies	3560.4	0	0	33604.56	33915.99
TOTAL	2536661.52	2535514.81	2534171.94	2534409.59	2480027.63

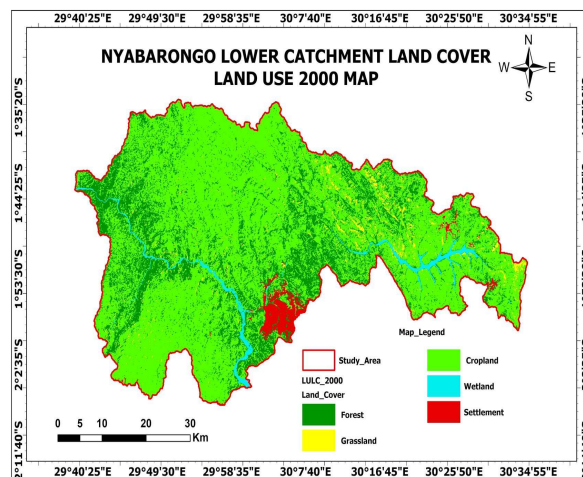
Nyabarongo Lower Catchment's LULC reveals drastic landscape modifications that occurred from 1990 to 2025 when natural cover was reduced as agriculture and built-up areas grew owing to demographic increases, farming activities, and urban sprawl. The percentage of forestlands fell to 68.4%, while wetlands dropped by 91.1%. This change resulted in less surface water absorption and the loss of natural flood defense capabilities. On the other hand, the extent of croplands almost tripled to 180%, whereas built-up lands rose by more than sixfold, to 596%.

➤ LULC Maps 1990 to 2025

Maps of Land Use and Land Cover (LULC) of the year 1990, 2000, 2010, 2020, and 2025 have been produced from multi-temporal Landsat imagery and GIS methods in order to analyze the spatiotemporal pattern of landscape transformation within Nyabarongo Lower Catchment. The LULC maps highlight the spatial extent and changes of the different LULC types, which include forestland, cropland, grassland, wetland, built-up areas, and water bodies. The maps show some level of variation in the spatial pattern of the LULC classes over a period of 35 years. In 1990, there existed a large area of natural vegetation and smaller portions of agricultural land and built-up areas. But in successive maps, there is a consistent reduction in the natural vegetation and wetland areas coupled with an expansion of the cropland and built-up areas. The agricultural land has been expanding into areas that had been covered by forests and wetlands whereas the built-up areas have been increasing around the urban and peri-urban areas. From the LULC map of the year 2025, it can be noted that cropland was the dominant land use type in the catchment area, taking up much of the area previously covered by natural ecosystems. The reduction in forest and wetlands implies that there has been considerable interference with the natural hydrological regime of the catchment, which might have resulted in high runoff and decreased infiltration.



a) 1990



b) 2000

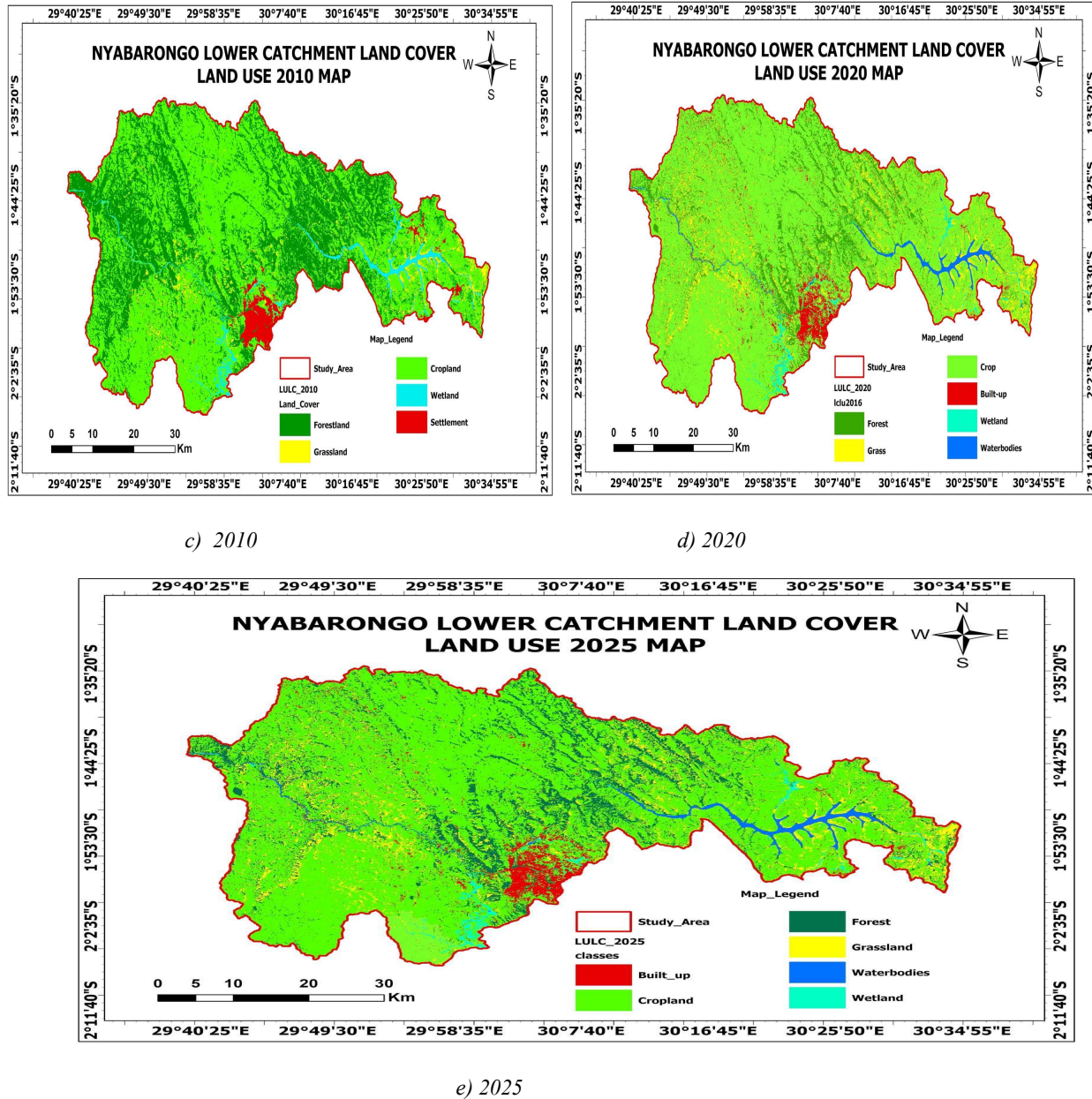


Figure 2. Classified Land Use/Land Cover maps of the Nyabarongo Lower Catchment

➤ LULC Change Table

The table below shows changes per decade in the LULC classes. The most significant net changes were observed in 1990-2000, where fast expansion of agriculture was associated with sharp declines in forests and grasslands, and 2010-2020, when there was fast development of built-up land and cropland at the expense of wetland and forest. 2000-2010 showed partial recovery in vegetation, whereas 2020-2025 was relatively stable. All these four periods indicate the

progressive shift of land use from natural state to anthropogenic one, implying gradual decline in the capacity of the catchment to intercept, infiltrate and store water.

Table 2. LULC change in the Nyabarongo Lower Catchment, 1990-2025 (hectares).

LULC Class	Change 1990-2000	Change 2000-2010	Change 2010-2020	Change 2020-2025	Change 1990-2025	% Change 1990-2025
Forestland	-485980.51	125989.33	-385533.69	-6024.29	-751549.16	-0.683654595
Cropland	1128916.28	-636414.14	664552.2	-31413.53	1125640.81	1.803271566
Built-up	53236.72	-43924.06	232994.88	-173092.08	69215.46	5.950133203
Grassland	-482425.97	347161.82	-372737.91	217736.23	-290265.83	-0.543106932
Wetland	-211332.83	205844.18	-172642.39	-61899.72	-240030.76	-0.910996393
Waterbodies	-3560.4	0	33604.56	311.43	30355.59	8.525893158

Note: From 1990 to 2025, the Nyabarongo Lower Catchment witnessed significant changes in the land cover due to human impact, as forest and wetlands were reduced by 68.4% and 91.1%, respectively, whereas the croplands and built-up area increased by 180.3% and 700% (from 11,632.59 ha to 80,848.05 ha), respectively. This clearly depicts the increasing pressure of agricultural activities and people's demand on nature. However, there was a pattern associated with the rate of change with time, where the rapid change occurred in agriculture and forest/grassland until the 1990s, vegetation regrowth occurred from 2000 to 2010, increase in built-up and agriculture until 2020.

➤ LULC Change map

Change detection maps for the periods 1990-2000, 2000-2010, 2010-2020, and 2020-2025 clearly demonstrate the transformation trends in the Nyabarongo Lower Catchment, where forests have mainly transformed into agricultural land, while wetlands have mainly transformed into built-up areas, especially along floodplains and rivers. The increase in agriculture is seen only in former natural vegetation areas, while the development of built-up areas takes place in the form of corridors and already developed built-up areas.

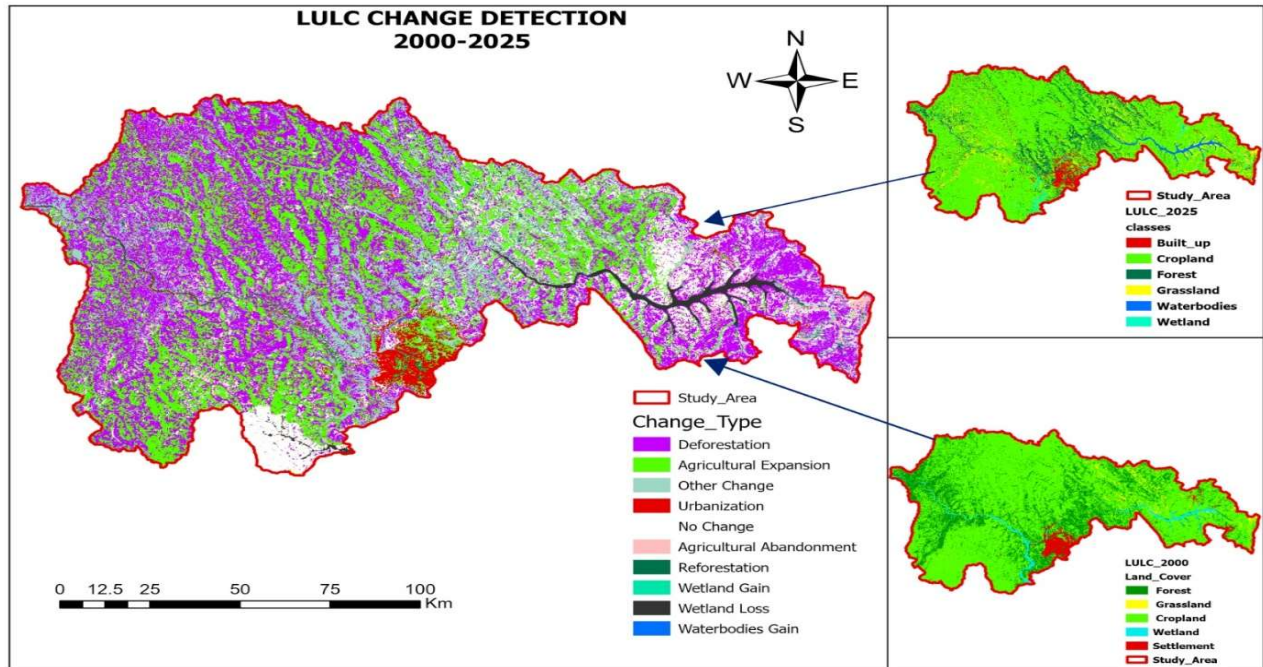


Figure 3. LULC change-detection maps from 2000 to 2025

3.1.1. Classification Accuracy Assessment

Classification reliability was assessed through confusion matrix analysis using 90 stratified validation points per year. Overall accuracy ranged from 82.22% (1990) to 87.78% (2000 and 2010), with Kappa coefficients between 0.787 and 0.848 (Table 3), exceeding the commonly accepted thresholds of 80% overall accuracy and 0.75 Kappa for reliable LULC classification [22]. The lower accuracy recorded for 1990 reflects the constraints of historical imagery quality and spectral overlap among classes, but remained within an acceptable range. The mean accuracy of 86.0% (Kappa = 0.83) across all five dates confirms that the classified LULC maps provide a reliable basis for change detection and for use as an input layer in the flood susceptibility model.

Table 3. Summary of LULC classification accuracy, 1990-2025.

Year	LULC Classes	Overall Accuracy	Kappa
1990	Forest, Cropland, Grassland, Wetland, Settlement, Other land	82.22%	0.787
2000	Forest, Cropland, Grassland, Wetland, Settlement	87.78%	0.847
2010	Forest, Cropland, Grassland, Wetland, Settlement	87.78%	0.848
2020	Forest, Cropland, Grassland, Wetland, Built-up, Waterbodies	85.56%	0.827
2025	Built-up, Cropland, Forest, Grassland, Waterbodies, Wetland	86.67%	0.84
Average	All five years with 90 validation points each	86.00%	0.83

3.2. Spatial Distribution of Flood Conditioning Factors

All the flood-conditioning factors displayed pronounced spatial variability in the catchment (Figure 5), thus clearly indicating the existence of a gradient of physical susceptibility, which is a major feature of the hydrologic system in the Nyabarongo Lower Catchment. The combination of low elevation, flat slope, high drainage density, high precipitation, high Topographic Wetness Index (TWI), and closeness to rivers occurred regularly in the floodplain in the eastern and central parts of the catchment, thus pointing to the high susceptibility to water retention, saturation, and flooding during rainfall events. Such low-lying areas, located at altitudes from 1,300 to 1,350 meters and having a flat slope of 0 to 2 degrees, are natural depressions where surface and subsurface water converge because of the presence of multiple flood-causing factors, including a high TWI of over 10, a high drainage density above 2.5 km/km², and proximity to the Nyabarongo River within 500 meters, as well as fine-textured soil with low infiltration rate and development of impervious surfaces due to road network and built-up land. In contrast, the high hills to the west and south with higher elevations over 1,500 meters above sea level, higher slope angles greater than 8 degrees, greater distance from drainage lines greater than 1,500 meters, coarser soil textures with higher permeability, and better drainage, exhibited less favorable conditions for flooding, even though they were important contributors of floodwater to downstream floodplains. This particular spatiotemporal configuration indicates that the occurrence of floods in this watershed is determined by the combination of several physical variables such as topography, hydrology, climate, and land cover rather than one single determinant [9]. This implies that the most vulnerable areas are those areas where there is a convergence of several environmental conditions that favor the occurrence of floods, thereby increasing vulnerability more than the combined effect of the individual environmental condition. Overlaying the patterns of change in LULC shows that manmade changes in land cover especially the degradation of forests and wetlands in these vulnerable areas have exacerbated the existing physical vulnerability.

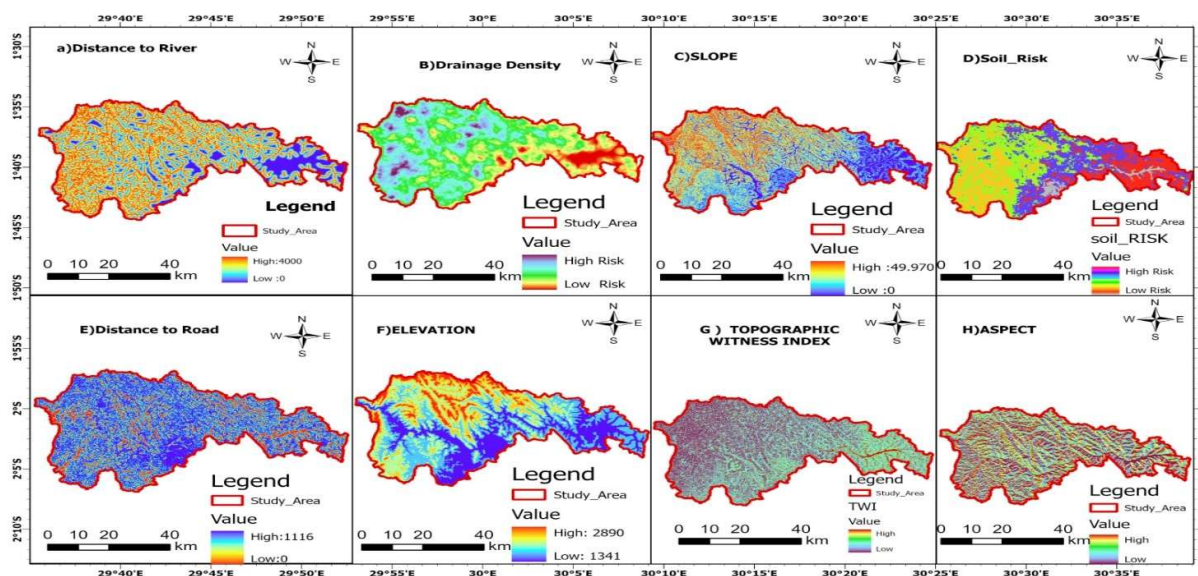


Figure 5. Spatial distribution of the flood-conditioning factors used in the AHP-MCDA model

3.3. AHP Pairwise Comparison and Factor Weighting

Pairwise comparison of the ten factors affecting floods using the Saaty scale of 1-9 (Table 4) led to obtaining weights of the factors which are summarized in Table 5. The weight of the distance from the river was the highest (22%) due to the fact that it is the best indicator of the extent of flooding, followed by TWI (18%), elevation (14%), slope (12%) and precipitation (10%). The weight of the drainage density, land cover/land use (LULC), curvature, aspect and distance from the road became progressively less (9%, 7%, 5%, 2% and 1%, respectively), which can be explained by the fact that they have an indirect effect on the process of runoff formation. The calculated Consistency Ratio of 2.92% is much below the recommended level of 10% by Saaty.

Table 4. AHP pairwise comparison matrix for the ten flood-conditioning factors.

Factor	Dist. River	TWI	Elevation	Slope	Rainfall	Drainage	LULC	Curvature	Aspect	Dist. Road
Dist. River	1	1	2	3	3	3	4	5	9	9
TWI	1	1	2	2	3	3	4	5	9	9
Elevation	1/2	1/2	1	1	2	2	3	4	7	9
Slope	1/3	1/2	1	1	1	2	2	3	7	9
Rainfall	1/3	1/3	1/2	1	1	1	2	3	5	9
Drainage	1/3	1/3	1/2	1/2	1	1	2	3	5	9
LULC	1/4	1/4	1/3	1/2	1/2	1/2	1	2	5	7
Curvature	1/5	1/5	1/4	1/3	1/3	1/3	1/2	1	4	5
Aspect	1/9	1/9	1/7	1/7	1/5	1/5	1/4	1/3	1	3
Dist. Road	1/9	1/9	1/9	1/9	1/9	1/9	1/7	1/5	1/3	1

Table 5. AHP factor weights, rank and justification.

Flood Conditioning Factor	Weight (%)	Rank	Justification
Distance to River	22%	1	Proximity to river channels is the strongest predictor of flood inundation extent
TWI	18%	2	Best hydrological indicator of water accumulation in low-lying terrain
Elevation	14%	3	Controls flow direction and determine flood-prone low-elevation zones
Slope	12%	4	Affects surface runoff velocity and flood peak timing during storm events
Rainfall	10%	5	Primary climatic driver of flood generation events in the catchment
Drainage Density	9%	6	Reflects stream network concentration and speed of runoff response
LULC 2020	7%	7	Land cover determines infiltration capacity and surface imperviousness
Curvature	5%	8	Terrain curvature influences flow convergence and divergence patterns
Aspect	2%	9	Slope orientation affects solar exposure, moisture retention, and evaporation

Flood Conditioning Factor	Weight (%)	Rank	Justification
Distance to Road	1%	10	Infrastructure proximity indicator for flood vulnerability assessment
TOTAL	100%		CR = 3.45% (less than 10% threshold- Consistent)

CR = 3.45% in the original 90-point pairwise judgement and 2.92% after refinement, both well below the 10% acceptable threshold (consistent).



Figure 6. Relative weights of the ten flood-conditioning factors derived from the AHP pairwise comparison.

3.4. Flood Susceptibility Index Map

The final overlay analysis, employing the AHP-weighted factor maps, led to the development of the continuous Flood Susceptibility Index which was further reclassified into five classes based on the natural break's method of Jenks (Figure 7, Table 6). The very low flood susceptibility zone constitutes approximately 59,300 hectares (19.65% of the catchment) while the low flood susceptibility zone occupies 83,900 hectares (27.79%). The moderate zone represents the biggest class covering 87,400 hectares (28.95%). High flood susceptibility zone and very high flood susceptibility zone constitute 14.92% and 8.69%, respectively, of the total catchment area. High and very high susceptibility classes occur mainly in the flat floodplains in the catchment with elevations of 1,300-1,350 m, slopes of 0-2°, TWI above 10 and river distance below 500 m. These areas were found to have historical waterlogging and flood incidences. The moderately susceptible class (elevation 1,350-1,450 m, slope 2-5°, distance to river 500-1,000 m) acts as a transitional class that is mostly stable during normal rainfall periods but is prone to flooding or is at risk when there is excessive rainfall or upper catchment destruction. The low and very low susceptibility zones (47.44% of the catchment area) are located in the elevated steep and well-drained parts of the west and south sides with elevations above 1,500 m and slopes above 8° where the effective natural drainage reduces the chances of flooding despite the fact that these areas are significant for runoff formation. The validation using historical records of flooding obtained from MINEMA and community reports revealed that 85% of the flooded places occurred within the high and very high susceptibility classes.

Table 6. Flood Susceptibility Index zones, Nyabarongo Lower Catchment.

Susceptibility Class	Area (ha)	Area (%)
Very Low	~59,300	19.65%
Low	~83,900	27.79%
Moderate	~87,400	28.95%
High	~45,030	14.92%
Very High	~26,225	8.69%
High + Very High (combined)	~71,188	23.61%

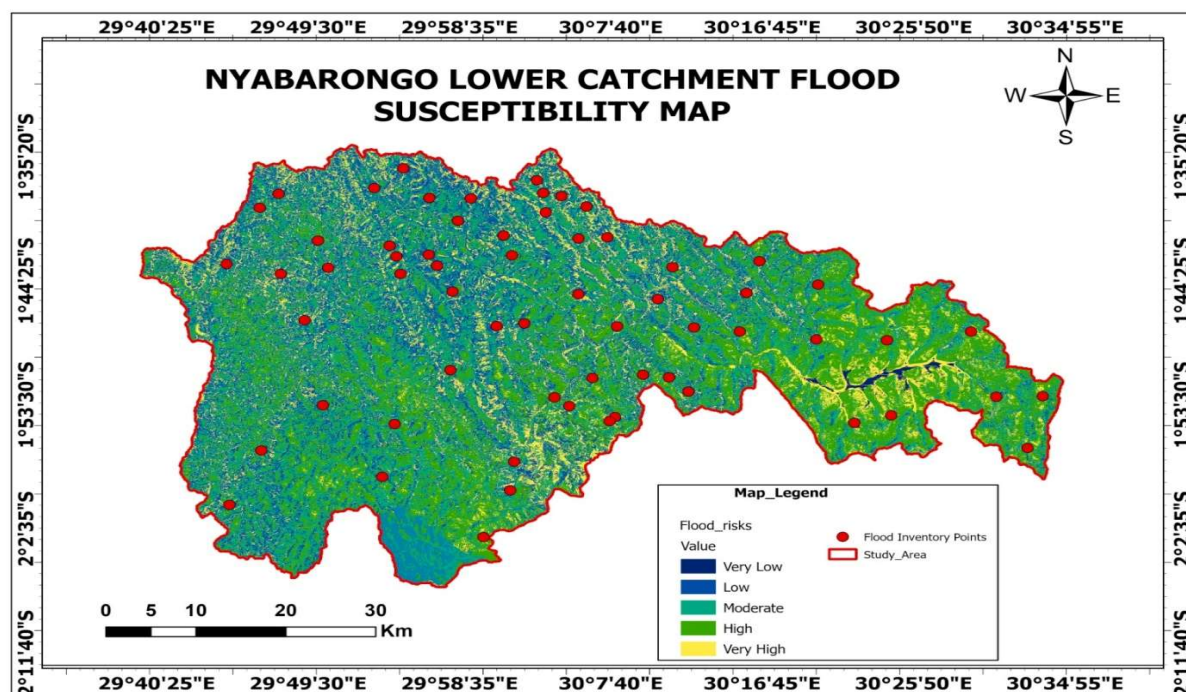


Figure 7. Flood Susceptibility Index (FSI) map of the Nyabarongo Lower Catchment

3.5. Integrated Overlay Analysis: LULC Change and Flood Susceptibility

The overlay analysis integrating the multi-temporal LULC maps with the FSI map and flood inventory/validation data showed a significant spatial relationship between land cover change and flood susceptibility. Wetlands and water bodies were highly represented in high and very high susceptibility classes (67.2%), and 91.1% of wetlands degraded between 1990 and 2025 were found in the areas of moderate to very high susceptibility, suggesting a considerable decrease in the flood mitigating capacity of the catchment. The built-up growth between 2010 and 2020 mostly took place (more than 65%) in the areas of moderate to high susceptibility, suggesting a trend of increasing urbanization in flood-prone lands due to population pressure and inadequate enforcement of land use regulations. Agricultural land use expansion between 1990 and 2025 was highly represented (53.3%) in

moderate to high susceptibility classes, since these lands are fertile and flat despite their vulnerability to floods. On the other hand, forests and grasslands were mostly found in low and very low susceptibility classes, but 68.4% of deforestation, which led to forest loss during 1990-2025, took place in moderate susceptibility class.

Overlying temporal analysis of the LULC change-detection maps on the FSI map reveals that changes from 1990 to 2000 were confined to low and very low susceptibility areas due to the encroachment of agricultural land in upland forest, with no significant impact on flood susceptibility. Changes during the years 2000-2010 include local restoration of forests and wetlands, resulting in more stable flood susceptibility. In contrast, changes in the years 2010-2020 involved large-scale transformation of wetlands and riparian forests within high and very high susceptibility zones, leading to increased flood vulnerability, whereas those in 2020-2025 witnessed more built-up land within very high susceptibility zones. The findings offer solid empirical evidence for the notion that LULC changes should not only be viewed as a factor but rather a driver of increased flood hazard in the Nyabarongo Lower Catchment. Reduction of forest cover by 68.4% and wetlands by 91.1% eliminates interception of rainwater, soil infiltration capability and water storage capacities, thereby reducing the delay in the occurrence of peak discharge after rainfall and increasing flood runoff as shown globally [23] and regionally in Rwanda [24]. The trend for human settlements and farming activities to occur in floodplains and wetlands, where their vulnerability to floods is evident, indicates a behavior where the benefits gained from these areas exceed the potential flood risk in the land use decisions [25]. Similarly, the continuing trend of reduction of wetlands and built-up development in high-susceptibility zones despite the existence of protection laws for wetlands and rivers in Rwanda suggests a failure in environmental governance enforcement [26].

The percentage area of the catchment considered highly to very highly flood-susceptible (23.61%) is largely similar to the percentages of river basin area being highly susceptible to floods observed in studies undertaken in Rwandan catchments at 18-25% [27]. With variation arising because of the use of relatively updated (2020-2025) LULC in this study [28]. The consistency ratio of 2.92% observed for AHP used in this study can be compared to the ratios obtained in other AHP based flood susceptibility studies [29]. There are certain limitations that need to be considered, first, the overlay technique can measure spatial susceptibility but cannot predict the depth, speed, or duration of flood which needs hydrodynamic modeling; second, 30-meter resolution of Landsat-derived LULC layers may not be able to capture the drainage systems and small patches of built-up areas; lastly, even though flood inventory is useful for validation, it may fail to capture some of the flood events. Despite these limitations, the use of the multi-temporal LULC analysis with GIS-AHP flood susceptibility modeling has shown that land use changes have greatly compromised the natural resistance of the flood hazard of the Nyabarongo Lower Catchment.

4. Conclusions

This study assessed the relationship between land use and land cover change and flood susceptibility in the Nyabarongo Lower Catchment, Rwanda, using an integrated GIS, Remote Sensing and AHP-MCDA approach. Between 1990 and 2025, the catchment experienced a 68.4% decline in forest cover and a 91.1% decline in wetland area, accompanied by a 180.3% expansion of cropland and a 596% increase in built-up land, with LULC classification accuracy averaging 86.0% (Kappa = 0.83) across the five study years. Weighted overlay of ten AHP-weighted flood-conditioning factors (Consistency Ratio = 2.92%) produced a Flood Susceptibility Index map showing that 23.61% of the catchment, approximately 71,188 ha, falls within high and very high susceptibility zones, concentrated in low-lying floodplains and riparian corridors. Spatial overlay analysis demonstrated that wetland loss, agricultural expansion and built-up growth have occurred disproportionately within these flood-prone zones, confirming that anthropogenic land transformation, rather than terrain conditions alone, is a principal driver of increasing flood hazard in the catchment. These findings carry direct implications for land use planning, wetland conservation and disaster risk management in the Nyabarongo Lower Catchment and in comparable East African river basins. The flood susceptibility map produced through this study offers a scientifically grounded, spatially explicit and replicable tool that can guide the protection of high-risk floodplains and wetlands from further conversion, support stricter enforcement of riparian buffer regulations, and inform district- and national-level zoning, infrastructure planning and early-warning system placement. Future research should extend this analysis using higher-resolution imagery (e.g., Sentinel-2), hydrodynamic flood models such as HEC-RAS or HEC-HMS to simulate flood depth and velocity, socio-economic vulnerability assessment, and climate change scenario analysis (RCP/SSP

pathways), and should test the transferability of the GIS-AHP approach to other Rwandan catchments such as the Akanyaru, Mukungwa, Sebeya and Nyabugogo.

5. Supplementary Information

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References

- [1] B. Merz, J. Hall, M. Disse, A. Schumann and et al, "Flood risk management in a changing world," *Nature Climate Change*, pp. 10, 331–338, 2020.
- [2] J. Ward, B. Jongman, F. Weiland, A. Bouwman, L. van Beek, M. Bierkens and et al, "Global projections of river flood risk in a warmer world," *Earth's Future*, vol. 3, p. 816–821, 2017.
- [3] D. V. Spracklen, S. R. Arnold, C. & Taylor and et al, "Forests as 'sponges' and 'pumps': Assessing the impact of deforestation on dry-season flows across the tropics," *Journal of Hydrology*, vol. 5025–15030, no. 109(38), pp. 574, 946-963, 2019.
- [4] C. J. A. Bradshaw, N. S. Sodhi, K. S. H. Peh, B. W. Brook and et al, "Global evidence that deforestation amplifies flood risk," *Global Change Biology*, pp. 13(11), 2379–2395, 2007.
- [5] B. R. Scanlon, R. C. Reedy, I. Jolly, M. Sophocleous, L. Zhang and et al, "Global land-use change and hydrological impacts," *Water Resources Research*, vol. 43, no. 3, pp. 3, 249–263, 2007.
- [6] B. Tellman, J. A. Sullivan, C. Kuhn, A. J. Kettner, C. S. Doyle, G. R. Brakenridge, T. A. Erickson, D. A. Slayback and e. al, "Satellite imaging reveals increased flood exposure from climate change and urbanization," *Nature*, pp. 596, 80–86, 2021.
- [7] K. Khosravi, E. Nohani, E. Maroufian and H. R. Pourghasemi, "Flood susceptibility mapping using AHP and GIS. Geomatics," *Natural Hazards and Risk*, vol. 83, no. 2, pp. 7(3), 1039–1061, 2016.
- [8] I. Wiekenkamp, J. A. Huisman, H. R. Bogen, A. Graf, H. S. Lin, C. Drüe, H. & Vereecken and e. al, "Changes in measured spatiotemporal patterns of hydrological response after partial deforestation in a headwater catchment," *Journal of Hydrology*, vol. 542, pp. 648-661, 2016.
- [9] M. S. Rahman, S. Saha and M. T. Rahman, "Urban expansion and flood risk assessment using GIS," *Sustainable Cities and Society*, vol. 50, p. 101687, 2019.
- [10] I. Douglas, K. Alam, M. Maghenda, Y. McDonnell, L. McLean, J. Campbell and et al, "Unjust waters: Climate change, flooding and the urban poor in Africa," *Environment and Urbanization*, vol. 20, no. 1, p. 187–205, 2008.

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- [11] F. Mugagga, V. Kakembo and M. & Buyinza, "Flood risk management in East Africa," *Natural Hazards*, vol. 64, p. 163–176, 2012.
- [12] A. Gasirabo, C. Xi, B. R. Hamad, U. D. Edovia and et al, "A CA–Markov-based simulation and prediction of LULC changes over the Nyabarongo River Basin, Rwanda. Land," *Land*, vol. 12, no. 9, 2023.
- [13] H. Hirwa, H. Ngwijabagabo, M. Minani, S. P. C. Tuyishime and I. Habimana, "Geospatial assessment of urban flood susceptibility using AHP-based multi-criteria technique: Case study of Musanze, Rwanda," *Rwanda Journal of Engineering, Science, Technology and Environment*, vol. 5, no. 1, 2023.
- [14] C. Mupenzi, G. Habiyaemye and L. Nahayo, *International Journal of Disaster Risk Reduction*, vol. 241, no. 101211, pp. 543-553, 2019.
- [15] P. A. Burrough, R. A. McDonnell, C. D. Lloyd and et al, "Principles of geographical information systems," *Oxford University Press*, 2015.
- [16] F. Karamage, C. Zhang, X. Fang, T. Liu, F. Ndayisaba, L. Nahayo, A. Kayiranga and J. B. Nsengiyumva, "Modeling Rainfall-Runoff Response to Land Use and Land Cover Change in Rwanda," *Water*, vol. 147, no. 2, p. 9, 2017.
- [17] S. K. Jenson, J. O. Domingue and et al, "Extracting topographic structure from digital elevation data for geographic information system analysis," *Photogrammetric Engineering and Remote Sensing*, vol. 54, no. 11, p. 1593–1600, 1988.
- [18] Congalton, "A review of assessing the accuracy of classifications of remotely sensed data.," *Remote Sens. Environ*, vol. 37, pp. 35-46, 1991.
- [19] M. Kaya, E. Sahin and V. Demir, "Parameters and methods used in flood susceptibility mapping: a review," *Natural Hazards*, vol. 116, pp. 345-372, 2023.
- [20] T. Saaty, "A scaling method for priorities in hierarchical structures," *Journal of Mathematical Psychology*, vol. 15, no. 3, p. 234–281, 1977.
- [21] J. Malczewski, "GIS and multicriteria decision analysis," John Wiley & Sons., 1999.
- [22] R. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sensing and Environment*, vol. 37, pp. 35-46, 1991.
- [23] T. Liu, C. Zhang, F. Karamage, C. Mupenzi and G. Habiyaemye, "Land cover change and its hydrological effects in the Nyabarongo catchment, Rwanda," *Science of the Total Environment*, p. 813, 2022.
- [24] L. Kulimushi, A. Elbeltagi, M. Mugabowindekwe, G. Rwanyiziri, R. Byizigiro, S. Pingale and S. Singh, "Erosion risk assessment through prioritization of sub-basins: implications for soil and water conservation in the Nyabarongo catchment," *Environmental Challenges*, p. 784, 2021.
- [25] S. Jacob, M. Carrier, S. Turcotte and P. Hamel, "Using the theory of planned behavior to predict the adoption of heat and flood adaptation behaviors by municipal authorities in the province of Quebec, Canada," *Sustainability*, vol. 9686, p. 13, 2021.
- [26] H. Mees, A. Crabbe and P. Driessen, "How to assess local climate adaptation policy? A framework for comparing policy instruments," *Journal of Environmental Policy & Planning*, vol. 18, pp. 221-241, 2016.
- [27] N. Hakizimana, G. Ishimwe, M. Ndagijimana, D. Ntwali and C. Mupenzi, "Land susceptibility to the stormwater runoff in

Nyabugogo river catchment area, Rwanda," *International Journal of Climate Research*, vol. 7, no. 1, pp. 9-23, 2023.

- [28] P. Kayastha, M. Dhital and F. De Smedt, "Application of GIS-based AHP for flood hazard mapping in mountainous river basins," *Natural Hazards*, vol. 105, pp. 1239-1260, 2021.
- [29] R. Pant, K. Bishwakarma and T. Bhatt, "Consistency evaluation and uncertainty reduction in AHP-based flood susceptibility mapping.," *Natural hazards*, vol. 112, pp. 145-165, 2022.
- [30] M. Kaya, E. Sahin and V. Demir, "Parameters and methods used in flood susceptibility mapping: a review.," *Natural Hazards*, vol. 116, pp. 345-372, 2023.
- [31] T. Saaty, "A scaling method for priorities in hierarchical structures....," *J. Math. Psychol*, vol. 1977, no. 15, pp. 234-281, 1977.