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Flood susceptibility modeling and hazard perception in Rwanda

Richard Mind'je[a,b,c,d], Lanhai Li[a,b,c,e,f,*], Amobichukwu Chukwudi Amanambu[a,c], Lamek Nahayo[a,c,d], Jean Baptiste Nsengiyumva[a,c], Aboubakar Gasirabo[a,c,d], Mapendo Mindje[g]

[a] *State Key Laboratory of Desert and Oasis Ecology Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, 818 South Beijing Road, Urumqi 830011, Xinjiang, China*
[b] *Ili Station for Watershed Ecosystem Research, Chinese Academy of Sciences, Urumqi 830011, Xinjiang, China*
[c] *University of Chinese Academy of Sciences, Beijing 100039, China*
[d] *University of Lay Adventists of Kigali (UNILAK), Faculty of Environmental Sciences, P.O Box 6392, Kigali, Rwanda*
[e] *CAS Research Center for Ecology and Environment of Central Asia, 818 South Beijing Road, Urumqi, Xinjiang 830011, China*
[f] *Xinjiang Regional Center of Resources and Environmental Science Instrument, CAS, Urumqi 830011, China*
[g] *University of Rwanda, College of Agriculture, Animal Sciences and Veterinary Medicine, P.O Box 117, Huye, Rwanda*

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ABSTRACT

Flooding is a deleterious phenomenon that induces detrimental impacts on humans, properties and environment. As a result, the knowledge of susceptible places and hazard perception is increasingly pertinent. This study mainly aims at identifying areas susceptible to flood through the application of logistic regression model using remote sensing data (RS) and Geographical Information System (GIS). A flood inventory was generated using 153 historical flood locations and a total of 10 predicting factors (elevation, slope, aspect, profile curvature, distance from rivers, distance from roads, the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Soil Index (NDSI), the Topographic Wetness Index (TWI) and rainfall) were utilized. Flood points were randomly subdivided into training (75%) for model building and testing (25%) points for validation through the Area Under Curve (AUC) approach. The results indicated that NDVI and rainfall are the most influencing variables for estimating flood risk as they showed a high positive relationship with flood occurrence in the study area. Testing datasets disclosed 79.8% of prediction rate using the AUC. Moreover, the results have been linked with community perception on flood and the outcome revealed that the government is perceived as responsible for all flood mitigation measures instead of being a shared responsibility. This perception may contribute to the increase in susceptibility. The results of this study will be essential for upcoming development projects from different organizations operating in many developing countries and would assist as a baseline for flood risk reduction and management especially for Rwanda.

1. Introduction

Floods are the most common and costly natural hazard with regards to human and economic loss worldwide [1]. It is estimated that more than one-third of the world's land area is flood-prone [2]. They are placed among serious disasters that occur as a result of heavy rainfall events causing an excessive overland flow greater than the capacity of natural or artificial movement system found in streams, canals, drainages, culverts, river basins and cities [3]. Hydrological disasters amount to 52% of natural catastrophes affecting about 140 million people with 20.4% deaths, and a total of 19.3% damages, culminating to $US 70.1 billion worldwide [4,5]. Also, according to the current statistics, the induced losses from floods cover 40% among all-natural disasters [6].

Floods incidence is a multifaceted and site-dependent event that has always interested researchers, fascinating them to analyze, investigate and better understand its processes. They have been known to be caused by both anthropogenic and natural factors such as environmental degradation, deforestation, intensified land use, and the increasing population [7,8]. The serious influences of floods on natural ecosystems and human activities have become an important factor to restrict sustainable development of societies and economies [6]. As evidenced by Termeh et al. [9], the damages caused by flood have doubled over the past decades with a very fast increase worldwide. Thus, the extent of impacts and the irreversible aspect of damages induced by floods make the execution of flood mitigation and control

* Corresponding author. State Key Laboratory of Desert and Oasis Ecology Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, 818 South Beijing Road, Urumqi 830011, Xinjiang, China.
E-mail address: lilh@ms.xjb.ac.cn (L. Li).

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measures a necessity [10]. The literature proved that the number of people vulnerable to devastating floods is expected to continuously double in the future unless adequate preventive steps are taken [11,12]. This trend calls for improvement in the management of flood, especially within developing countries where flood is becoming more disastrous and severe due to several reasons including high vulnerabilities, weak infrastructure, poor population mindset, low level of resilience and lack of strong and sustainable mitigation measures [13].

Human activities such as unplanned settlement development, uncontrolled construction of buildings and major land use changes influence the spatial and temporal pattern of the hazard. This is because informal settlements, as the term implies unplanned and uncontrolled settlements are usually not subject to land use restrictions, masterplan, rules, regulation or to enforcement of building codes or drainage codes [14]. Moreover, there are minimal or no infrastructure in these areas, in part because they have grown in an unplanned and uncontrolled manner, and in other part because municipal governments avoid making the kind of infrastructure investments in these settlements necessary to support the increasing population. These activities are exacerbated by environmental factors especially climate change in urban as well as rural areas [14]. There are several factors that contribute to floods, ranging from topographic, geomorphologic, drainage, structures, to climatic factors such as rainfall frequency, intensity and duration [15,16].

Generally, flood risk is defined as the result of the likelihood of flooding and its related possible damages over all flood events. These damages associated with an event describe flood risk levels [17]. Therefore, effective modeling to comprehend and mitigate flood risks is of great importance since it is increasingly becoming a common natural disaster. Similarly, one of the main solutions in future flood management and mitigation is the recognition of areas prone to flood using suitable approaches with good precision [18,19].

In recent years, Remote Sensing (RS) techniques and Geographic Information Systems (GIS) have been embedded in the evaluation of the geo-environmental hazards [20,21]. The purposes of using RS, as outlined by Refs. [2,22] in separate studies, include, but not limited to, a) investigating the susceptibility of the land and the vulnerability of the society, b) constructing hazard zoning maps and potential damage maps, c) monitoring potential hazards, and d) deal with emergency situations after a disaster. As confirmed by previous studies [6,8], flood susceptibility is a prerequisite for sustainable flood risk management, as it provides valuable information about the suitable measures for mitigation and adaptation.

The literature on flood studies avails a wide range of methods and techniques to be applied in natural hazards susceptibility modeling. These methods have been extensively used throughout the world including Artificial Neural Network (ANN) [23], Frequency Ratio (FR) [24], Support Vector Machine (SVM) [25], Random forest (RF) [26], Analytical hierarchy process (AHP) [27,28] etc. Additionally, other quantitative approaches such as Fuzzy Weight of Evidence (FWoE), data mining and Logistic Regression (LR) as proposed by Shafizadeh [29] have also been introduced in the flood susceptibility mapping and they have successfully proved to be promising approaches for flood susceptibility modeling.

Among these approaches, LR has been applied in different natural hazards modeling including flood, landslide [30–32] and has been of great importance in producing susceptibility maps as well as explaining the roles of effective casual factors across the globe [29]. However, its application has never been previously used in central and east African regions, which present a uniqueness to test and investigate the prediction capability of flood prone zones for mitigation and management. The geographical feature of any given area can make such an environment prone to flooding. This can be said to be true in Rwanda since its geographical features and climatic profile have made it prone to various hazards especially localized floods and landslides [33,34]. According to Asumadu [35], flood is the most recurrent environmental incident that constitutes the majority of disasters hitting many parts of Rwanda. As previously stated by Englhardt [36], urban floods should be distinguished from rural floods based on the extent of damages and geographical area covered. This is because urban floods occur in smaller geographical areas and such disasters record higher intensity of damages, whereas rural floods happen over a considerable large area accompanied by damages highly resulting from several reasons including weak construction materials, encroachment of fragile ecosystem and low capacity of its community to cope with the incident. Therefore, major flood events that have occurred within both areas of Rwanda resulted in infrastructural damages, fatalities and injuries, landslides, loss and damage to crops, and soil erosion with damages highly recorded in rural areas [37].

Although flooding is a serious hazard for Rwanda, insufficient attention has been paid to flood susceptibility prediction. In Rwanda, there have been recent studies about geo-environmental disaster management with significant emphasis on the description of hazards [33], awareness and capacity building [38], early alert and vulnerability [39]. Many of these studies were not conducted countrywide, but rather limited to district and province level using social and descriptive approaches with secondary data sources. Furthermore, these studies were conducted with a limited focus on flood predicting factors [39,40]. This outlines the limitation in these studies for susceptibility assessment while studies involving hazard mapping related to disaster risk have to be highlighted by a susceptibility assessment involving important predicting variables [26]. Existing studies that involved susceptibility modeling in the study area are only related to landslide [41,42]. Therefore, this present study seeks to address the spatial distribution of flood susceptibility and the main factors behind this distribution which influences have been left uncertain and critical high prone zones unknown. This will guide and inform decision/policy makers in the relocation process, land use planning and sustainable environmental management toward flood resilience building in the study area.

On the other hand, community perception of geo-environmental hazards has been a significant factor in determining how the society will evolve and deal with the incident [43]. Experience of the hazard, different historical background, and the lack of suitable information about the likelihood of a hazard incidence in a region may influence the way the community perceives the hazard and their associated effects in a different perspective, and shape the way effective mitigation actions can be adopted [43]. Nevertheless, the inability to appropriately perceive a hazard may make some regions susceptible and increase high risk of loss. For instance, the community may be more interested in living in a floodplain area based on the prospects found in the area, subsequently subject themselves to ineffective actions of flood risk management [44]. Once the perception of flood is low in a region, probably because flood events hardly occur, the community may lack preparedness and will be prone to likely disaster. In contrary, a community with good perception of the hazard, owing to their experience with changing severity, they tend to be better informed and well prepared [45]. Hence, the design of appropriate mitigation and adaptation measures will not progress from physical science knowledge alone, but in combination with an understanding of community knowledge, perception of the hazard and behavior when faced with hazards [46]. Therefore, understanding how individuals perceive the hazard can reveal the level of susceptibility.

From the above literature review, it was noted that little attention has been paid to the comparison of model results alongside community perception for flood susceptibility prediction especially for prone zones in central and east Africa. Thus, taking Rwanda as a case, this study comes to bridge the gap identified in the literature related to the nexus between modeling results and community perception on the hazard. Nonetheless, this study will thoroughly serve as a baseline for further flood modeling studies in order to overcome substantial impacts incurred by flood in the study area. The objectives of this study are therefore to: (1) determine factors mostly responsible for flood

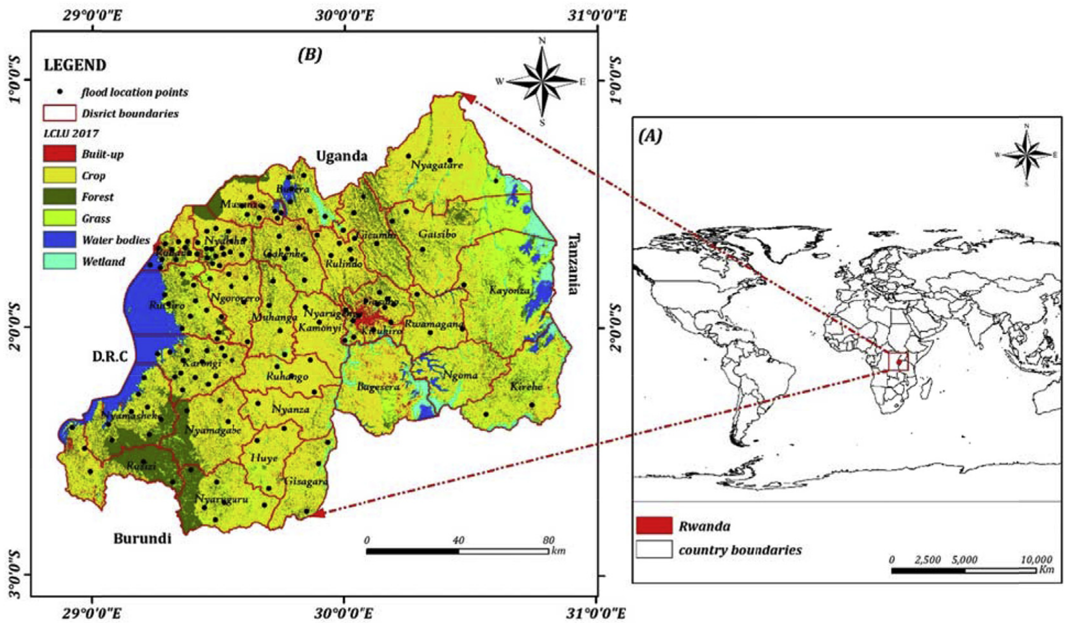


Fig. 1. Study area location and flood inventory (B) within the world map (A).

susceptibility in Rwanda; (2) identify both prone and the safest areas to floods; and (3) link community perception on flood hazard to the produced flood susceptibility.

2. Datasets and methods

2.1. The study area

This study focuses on the entire territory of Rwanda located in East Africa and bordered by Uganda to the north, Tanzania to the east, Burundi to the south and the Democratic Republic of Congo in the west (Fig. 1). It covers a total estimated area of 26,338 km^2 that is situated in the tropical belt geographically. The country is characterized by hilly and mountainous relief with a minimum elevation of about 921 m and its high elevation found in the northwest region (4501 m) above sea level. The relief feature contributes to the change in weather patterns and disaster incidence in different areas of the country [47].

In fact, the northwest and a part of south regions receive much rainfall resulting in more landslides and floods, while the eastern part of the country is the most vulnerable region to droughts due to low rainfall intensities [48]. The climate of the country is made up of four seasons; long dry (June–September), short dry (mid- December – mid-February), long rainy (late February – late May) and short rainy (late September – early December) [49]. Under ordinary conditions, much of the rainfall is expected to occur during the long rainy season. Generally, floods in Rwanda occur as a result of different factors such as climatic, topographic nature, environmental settings, fragile ecosystem and pressure on land. Thus, the increase in flood is mostly experienced for each rain year [35].

Flood affected people and properties situated in flood prone areas, and the recording system has shown agriculture to be the most affected sector across the country (Fig. 1). Consequently, mapping flood susceptibility will be significant and helpful to identify the zones under risks.

Table 1 below shows some of the main flood events that occurred in the last twenty years with their related impacts in different districts of the country which increased the attention in reducing the related impacts.

2.2. Datasets

Adequate recording of historical flood events over a period has a huge impact on the precise reliability of flood susceptibility mapping [51]. The success of this analysis was achieved using current information and detection of the historical flood extent data acquired from the Ministry of Disaster Management and Refugees (MIDIMAR) in the disaster loss inventory database (Desinventar database) containing records of flood events that happened from 2012 to 2017 countrywide. These events were mapped as flood inventory and used together with different conditioning factors for susceptibility modeling.

2.2.1. Flood inventory and conditioning factors

A data inventory was generated using 153 flood location points (Fig. 1). The x, y coordinates of each of flood sites were collected from MIDIMAR and upon field survey conducted by authors from February to October 2017. Generally, there are no rules of thumb for selecting the proportion of training and testing datasets [1]. Therefore, the generated inventory map was randomly split into a 75%–25% proportion for training (115 random points to run the model) and testing the susceptibility model (38 remaining points for validation step). The complete historical data concerning flood frequency and intensity were deficient for some flood-prone areas. Consequently, there might be some gaps in the existing flood database which may contribute to some degree of uncertainties. Generally, the effect of these uncertainties is considered not significant for the purpose of this study as it does not want to portray an exact event but to give a comprehensive understanding of the likely future scenarios for researchers and policymakers.

Furthermore, the physical attributes of the study locations can determine the characteristics of predicting factors to be used in any research. While only one variable may, to a large extent, contribute to flooding in a specific area, it may have no impact in another region [52]. The factors used in this study were selected after consulting different literature namely the national risk atlas of Rwanda, the national disaster management policy, the national risk management plan as well as the contingency plan for flood in Rwanda [50,53,54], expert's knowledge, study objectives, field investigation and observation, the study area context and indigenous knowledge.

To map flood susceptibility, a total of 10 conditioning factors were selected. These include: (1) elevation, (2) slope, (3) aspect, (4) profile

Table 1
Main disasters caused by floods in Rwanda (MIDIMAR [50]).

Year	Number of deaths	Affected people	Damages	Affected areas (District)
1988	48	21,678	1225 houses, 19 bridges, 7 roads cut off	Districts[15, 10, 25, 14, 20]
2000	0	1000	200 houses, roads, crops	Districts[25,3]
2001	12	3000	100 houses, 60 schools, crops	Districts[20, 25,10,15,7]
2002	69	20,000	NA	Districts[10,7,4,28]
2003	0	7016	NA	Districts[19,7,12]
2005	27	25,003	5000 houses, 3000 plantations	Districts[23,15,7]
2007	45	7310	1057 houses, 562 homeless families	Districts[25,18,7]
2008	15	3000	4000 ha crops, 500 homeless, bridges, roads	W-S-N
2009	NA	NA	infrastructures and crops destroyed	Districts[25,6,12]
2010	3	NA	1 industrial site, houses and crops	K
2011	1	NA	19 houses, 152 ha of land	Districts[18,2,19,22,30]
2012	26	NA	593 houses, 183 ha of land	Districts[1,2,7,15,25,28,4,12,20]
2013	15	64	201 houses, 411 ha of land	Districts[10,18,25,24,26,4,12,23,15]
2014	18		6 houses, 1110.5 ha of cropland	Districts[7,11,18,20,21,23,24,29]
2015	24	3425	34 houses, 206 ha of crops, water supply	Districts[1,14,10,15,17,25,26,27,28,29]
2016	54	2317	222 houses collapse, 448.2 ha of crops,	Districts[2,10,15,18,23,25,26,29]
2017	7	5850	640 homeless, 1036 ha of crops, farms	Districts[1,8,16,21,28,5,9,13,17,29]

District:[1] Bugesera, [2] Burera, [3] Gakenke, [4] Gasabo, [5] Gatsibo, [6] Gisagara, [7] Gicumbi, [8] Huye, [9] Kamonyi, [10] Karongi, [11] Kayonza, [12] Kicukiro, [13] Kirehe, [14] Muhanga, [15] Musanze, [16] Ngoma, [17] Ngororero, [18] Nyabihu, [19] Nyagatare, [20] Nyamagabe, [21] Nyamasheke, [22] Nyanza, [23] Nyarugenge, [24] Nyaruguru, [25] Rubavu, [26] Ruhango, [27] Rulindo, [28] Rusizi, [29] Rutsiro, [30] Rwamagana. **NA:** Not available, **W:** western province, **S:** southern province, **N:** Northern province, **K:** Kigali city.

Table 2
Flood predicting factors and their cell size.

Parameters	Sub classification	Resolution
Flood records area	Flood extent	Point coordinates
	Elevation (m)	30 m
	Slope angle (degree)	30 m
	Aspect	30 m
	Profile curvature	30 m
Flood predicting factors	Distance from rivers (m)	30 m
	Distance from roads (m)	30 m
	NDSI	30 m
	NDVI	30 m
	Mean annual rainfall (mm)	0.05°
	TWI	30 m

curvature, (5) distance from rivers, (6) distance from roads, (7) NDSI, (8) NDVI, (9) mean annual rainfall and (10) topographic Wetness Index (TWI) as shown in Table 2 (see Table 3).

In most cases, low elevation and plain areas might be more prone to floods. Therefore, to assess flood susceptibility, it is better to understand the topography and the derivative factors of the area [55]. To that, the Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM), with a resolution of 30 m provided by National Aeronautics and Space Administration (NASA) (http://www.dwtkns.com/srtm30m) was used to generate different factors (Fig. 2 a–f). The layers of distance from rivers (Fig. 2d) and distance from roads (Fig. 2e) were generated by applying the Euclidean distance tool of the Spatial Analyst tool in ArcMap 10.2. Additionally, this study used the profile curvature (Fig. 2f) as this affects the flow velocity of water draining the surface. It was therefore estimated by ArcMap using the spatial analyst tool.

Vegetation and soil are also important factors for flood susceptibility assessment [56]. Therefore, the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Soil Index (NDSI) were calculated using different bands from Landsat 8 OLI satellite images assembled by the United States Geological Survey (USGS) EROS data center. NDSI (Fig. 2h) is an empirical approach for improving soil information from vegetation and impermeable surface areas. It was computed to separate soil with other land cover types to a certain degree using band ratio method in ArcGIS (Raster calculator) whereby its high values indicate bare soil areas while the lower values depict different categories including vegetated area [57]. Additionally, NDVI (Fig. 2g) was also calculated to highlight the difference of the spectral responses of vegetation at the red and near infrared bands where low values correspond to barren areas of rock, sand, or snow while high values indicate temperate and tropical rainforests. They were then computed using equations (1) and (2) respectively.

$$NDSI = \frac{Band7 - Band3}{Band7 + Band3} \tag{1}$$

$$NDVI = \frac{Band5 - Band4}{Band5 + Band4} \tag{2}$$

Given the incompleteness of the gauged meteorological data in Rwanda, as confirmed by the Diagram of Station data against time delivered by the Rwandan Meteorological Agency (www.meteorwanda.gov.rw), we have been constrained to use the satellite-derived mean annual rainfall data. Previous studies [47,49] have echoed the lack of complete field datasets mainly because most of the meteorological infrastructure was devastated during the 1994 war and genocide. Nevertheless, the mean annual rainfall of the past 30 years (1986–2016) was derived from the datasets provided by the Climate Hazards Group Infrared Precipitation (CHIRPS) at 0.05° spatial resolution (Fig. 2i). However, gridded and modeled rainfall data is often unable to effectively capture climate variability compared to station data [58]. Lack of variability in modeled data may also cause some uncertainties when modeling flood susceptibility. Lastly, Topography is a first-order control on spatial variation of hydrological conditions influencing the spatial distribution of soil humidity and groundwater movement. Therefore, the Topographic Wetness Index (TWI) is usually used to measure topographic control on water processes [59]. In this study, TWI (Fig. 2j) was computed using the flow accumulation obtained from the flow direction extracted from DEM [60] where its high values refer to high potential of runoff generation while the low values correspond to lower runoff generation. All processes were done in the hydrological toolset from spatial analyst Tool of ArcGIS 10.2. TWI was obtained from equation (3) below:

$$TWI = \ln \frac{A_s}{\tan \alpha} \tag{3}$$

where A_s is the flow accumulation, and α is the slope (in degree).

Finally, all these factors were resampled to the same spatial resolution and transformed into a grid spatial database using GIS before running logistic regression model.

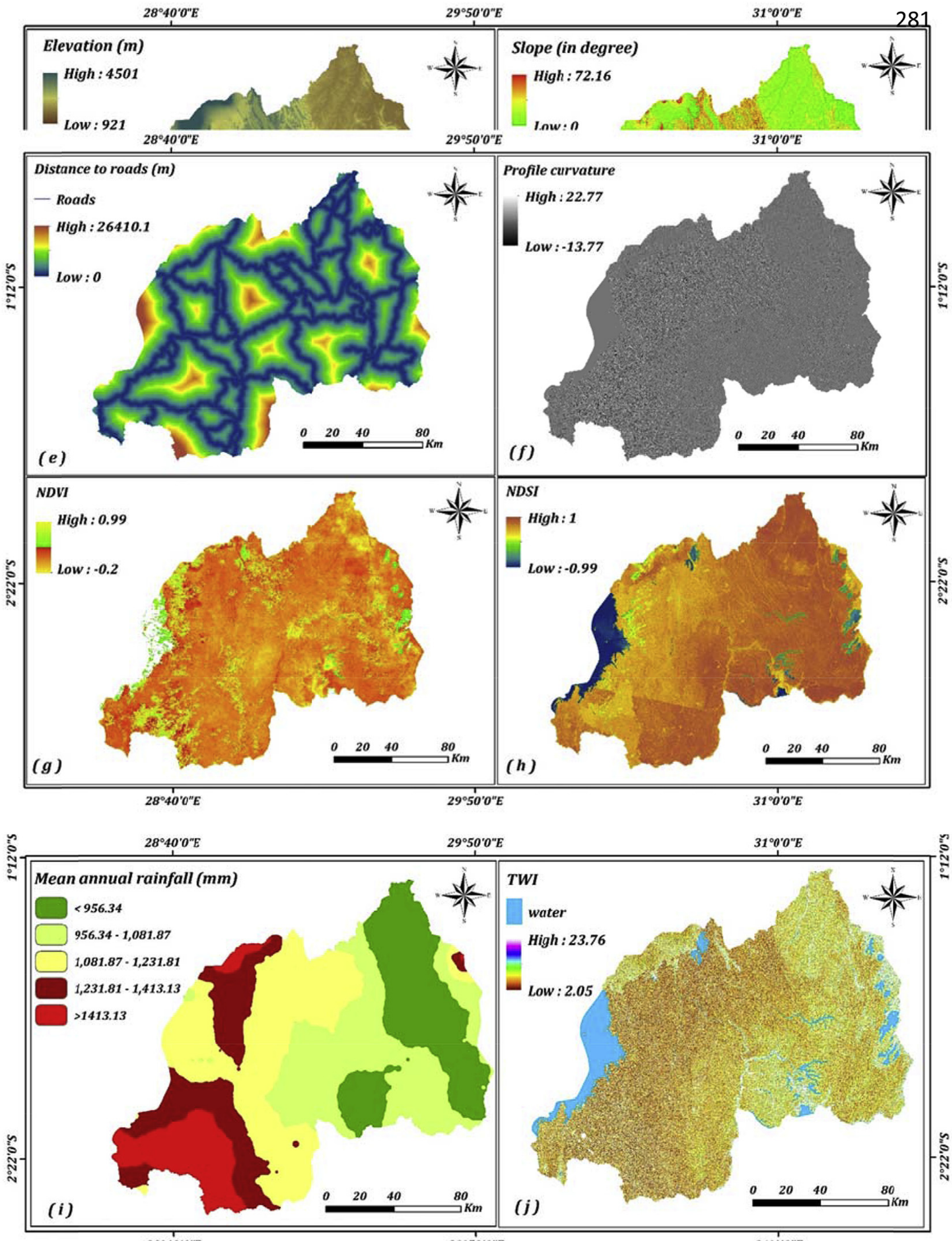


Fig. 2. Conditioning factors used to derive flood susceptibility map: (a) Elevation, (b) Slope, (c) Aspect, (d) Distance to rivers, (e) Distance to roads, (f) Profile curvature, (g) NDVI, (h) NDSI, (i) Mean annual rainfall, (j) TWI.

2.3. Logistic regression (LR)

Though various modeling approaches exist, the prediction and forecast of flood disasters are always a challenging and puzzling task [61]. It has therefore been noted that the choice and selection of suitable approaches to apply while studying susceptibility is often restricted to data availability, quantity and quality, study objectives and to the scope of the study. Also, models must be simple, easy and straightforward for planners to use in policy making [5]. Logistic regressions are simple powerful tools to support policy and decision makers using limited available data.

This method is most useful for understanding the influence of several independent variables on a single dichotomous outcome variable. And it produces good results based on one or more independent variables. These results make it easy to be interpreted through the coefficients that this model generates to predict flood occurrence in different regions [55]. Thus, for this study, LR has been selected to assess and predict flood occurrence in Rwanda and calculates the variations in the probability of an event occurring in a class. This is to find the best suitable model to describe the association between flood dependent variable (presence or absence of flood) and independent variables such as slope, aspects, and elevation, and then refereeing factors according to the highest numerical code.

In the current research, flood point is used as a dependent variable

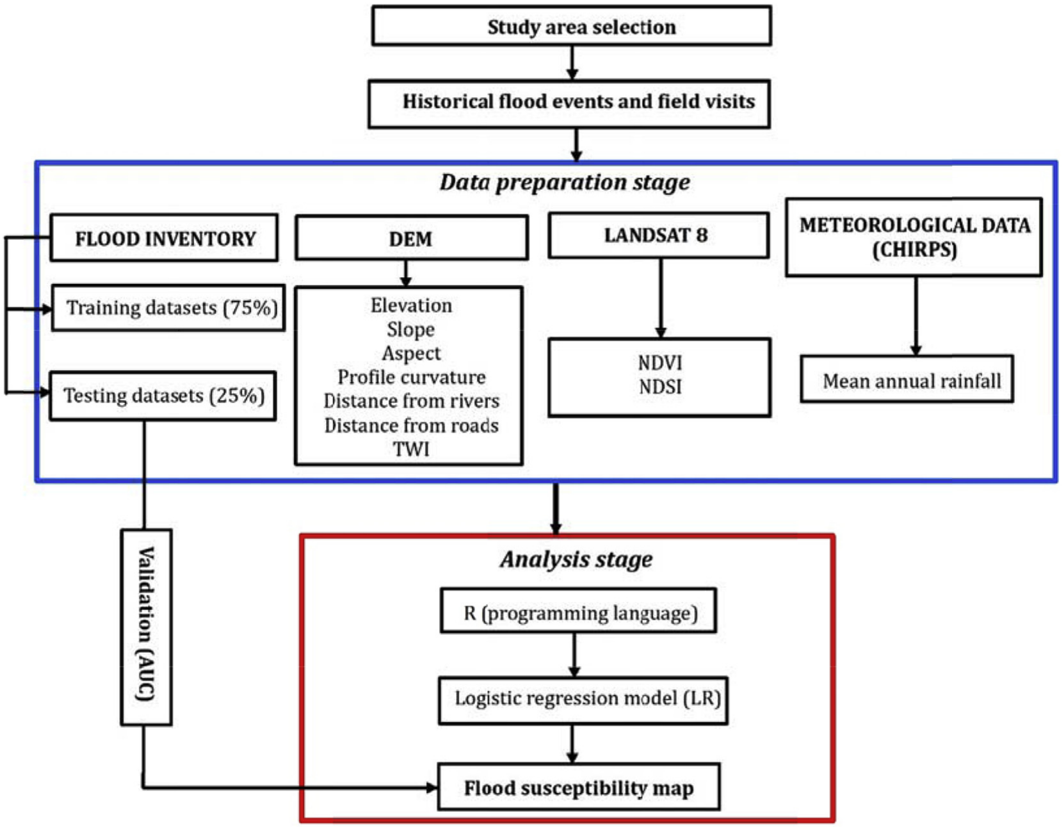


Fig. 3. Methodological flowchat of the susceptibility assessment.

representing the presence or absence of flooding. LR involves fitting an equation of the below form:

$$Z = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_nx_n \tag{4}$$

where Z represents the linear combination of the dependent variables (absence or presence of flood), and its values range from $-\infty$ to $+\infty$, b_0 is the intercept of the model, b_i (i = 0,1,2,3,4 …, n) represents the coefficients of the LR model, and x_i (i = 1,2,3 …., n) denotes the predicting factors [62]. To estimate the intercept and the coefficients of LR, the generated predicting factors were analyzed in R statistical environment then produced the LR model to finally map flood susceptibility (Fig. 3). The estimated probability of occurrence (p) represents any pixel that is susceptible to flooding, and can be denoted as the conditional probability in the LR model by the following expression:

$$p = ln\left(\frac{p}{1-p}\right) = \frac{1}{1+e^{-z}} \tag{5}$$

where p, a probability, ranges being between 0 and 1 and Z is the linear combination of dependent variables defined in equation (4). Finally, the Susceptibility Index (SI) that shows the possibility of flooded areas is calculated using equation (6).

$$SI = exp(z)/(1 + exp(z)) \tag{6}$$

A positive LR coefficient value signifies the presence of the factor in the area and increases the probability of flood occurrence, while the negative LR coefficient value indicates that the occurrence of flood is negatively related to that specific factor [51].

2.4. Perception of flood and mitigation

The SI is linked with the community perception on flood and mitigation. In this regard, a field investigation was conducted, and questionnaires designed by the authors of this manuscript were distributed in districts with frequent flood events based on flood occurrence rather than population size. The sampled areas were selected based on the past flood records with affected areas shown in Table 1. Eleven districts were therefore selected based on the frequency of occurrence within the five provinces that make Rwanda. In Western province (Nyabihu, Rubavu, Rusizi, Karongi and Rutsiro), Northern Province (Musanze, Rulindo, and Burera), southern province (Nyaruguru) Eastern province (Rwamagana) and finally in Kigali city (Gasabo) were part of the investigation. In general, the questionnaires were administered to 550 respondents such that in each selected district, 50 participants were randomly selected. This investigation was mostly conducted in rural areas because floods was mostly observed in these areas with different socio-economic factors such as poverty, lack of education and inadequate warning system.

The investigation aimed to assess the perception of the local community on flood and mitigation in relation to flood susceptibility map produced using logistic regression model. The questionnaire was divided into two categories: a) the first three questions were close-ended (Q1-Q3) to elicit the experience and concern of the community and b) the last two questions were multiple choice (Q4-Q5) focusing on their capacity and mitigation measures as illustrated in the below Table 3.

Table 3
Questions asked and choice.

Question	Choice
Q1. Have you ever experienced a flood?	yes/no
Q2. Do you think that your region is under risk of flooding?	yes/no
Q3. Do you believe that any action may be taken to mitigate the effects of flood?	yes/no
Q4. Who do you think is responsible to mitigate flood?	multiple choice
Q5. Which measures do you think can be used to mitigate the effects of flood?	multiple choice

Table 4
Coefficient of Logistic regression per factor.

Predicting Factors	Classes	α
	921–1546	
	1546–1839	
Elevation	1839–2202	0.0009533
	2202–2808	
	2808–4501	
	0–4.81	
	4.81–11.32	
Slope (degree)	11.32–18.67	−0.0225,357
	18.67–26.88	
	26.88–72.16	
	< −54.18	
	−54.18–129.16	
Aspect	129.16–205.57	0.002161
	205.57–281.97	
	> 281.97	
	−13.77– −0.55	
	−0.55– −0.22	
Profile curvature	−0.22–0.11	0.4898334
	0.11–0.55	
	0.55–22.77	
	0–1700.94	
	1700.94–4476.16	
Distance from rivers	4476.16–8773.29	−0.0001162
	8773.29–14,055.16	
	14,055.16–22,828.50	
	0–2485.65	
	2485.65–5592.71	
Distance from roads	5592.71–9217.63	−7.6264587
	9217.63–13,878.23	
	13,878–26,410.16	
	−0.2–0.18	
	0.18–0.43	
NDVI	0.43–0.59	0.5937508
	0.59–0.71	
	0.71–0.99	
	−0.99 – - 0.55	
	−0.55– −0.10	
NDSI	−0.10–0.19	0.0012,615
	0.19–0.32	
	0.32–1	
	2.05–4.61	
	4.61–6.40	
TWI	6.40–8.78	−0.0004931
	8.78–12.36	
	12.36–23.76	
	< 956.34	
	956.34–1081.87	
Mean annual rainfall	1081.87–1231.81	0.5159183
	1231.81–1413.13	
	> 1413.13	

3. Results and discussion

3.1. Flood susceptibility and responsible factors

The logistic regression model is beneficial for predicting the presence or absence of various hazards based on values of different predicting factors and the combination of flood inventory data from the area of study. It is imperative to make an effective modeling of flood susceptibility [9] so as to provide a good understanding of the factors predicting the hazard in the area being investigated.

ArcMap/ArcGIS and R software were used as analytical tools for spatial and statistical manipulations. The values obtained from R were applied in the function Z (equation (4)). These values are therefore displayed in Table 4 where alpha (α) constitutes the obtained coefficients of LR for all the predicting factors.

From the produced coefficients, NDVI, NDSI, rainfall, elevation, profile curvature, and aspect factors showed a positive relationship with flood incidence while TWI, distance from roads, distance from rivers and the slope have exhibited negative relationships (Table 4). Out of all these, NDVI and rainfall have shown the highest coefficients (0.5938 and 0.5159 respectively) while the distance from roads has the lowest (−7.6265). This expresses that NDVI and rainfall have a great impact on flood occurrence within the area as testified by the collected past flood locations through the inventory map where heavy rain zones and areas with positive NDVI values accounted for a big number of flood events. These results were in coherence with those of the previous studies [51,55,63] which used multivariate statistical approaches such as LR and other models for flood susceptibility and achieved a strong correlation between vegetation coverage (through NDVI and LCLU factors), amount of rainfall and flooding with the high LR coefficients among the used conditioning factors in their study areas. This led them to conclude that areas receiving higher rainfall amount with some vegetation are predicted as very highly susceptible to flooding which is the case in this study. Similarly to the results of this study, Shafapour [51] also found slope and TWI with negative relationship with flooding occurrence in his study.

To produce flood susceptibility map, the values obtained from R software were exported into ArcGIS software to build and simulate the model using equations (4)–(6). The derived susceptibility map (Fig. 4) was subdivided into five classes: very high, high, moderate, low, and very low susceptibility using natural breaks method. Moreover, the natural breaks have become the most widely applied method in classifying susceptibility map [10,64].

The model output (Fig. 4) has revealed the spatial distribution of flood susceptibility across Rwanda. It showed that the eastern province is the part of the country with low flood susceptibility while the urban area (Kigali) ranged from moderate to high susceptibility; the northern, western and southern provinces were found highly susceptible to floods. This situation can be justified by the topographic nature and the geomorphological aspect of the country in line with the considered conditioning factors (Fig. 2).

The results of the present flood susceptibility modeling is in accordance with previous studies [37,50] which concluded that the study area is prone and vulnerable to the recurrent flood hazard. Though it covers several water bodies with low elevation, the eastern part of Rwanda was modeled as low susceptible to flood. This could be attributed to its high rainfall deficit and late rainfall onsets (Fig. 2i) over a long period of time as confirmed by previous studies [37,65]. In the Northern part, the eroded soil from agricultural activities practiced on steep slopes eventually ends up in water channels, thus reducing the drainage capacity to accommodate peak runoff and sediments accumulation which accelerate the likelihood of flooding [66].

On the other hand, the western part is mostly dominated by ridges and plateaus including the Congo Nile with a topographic feature that is entirely hilly [67]. As a result, rain water originating from these ridges, flows towards the valleys which cannot effectively absorb and accommodate all the water owing to the increase in solid wastes from anthropogenic activities that clog culverts, water drainage systems within the area. Moreover, in the southern part, heavy rains coupled with severe environmental damages ensuing from deforestation and poor land use practices have resulted in soil erosion and floods [68]. Additionally, the reason of this part being highly susceptible as previously discussed by MIDIMAR [50] can be justified by the geomorphologic characteristics of these areas whereby they cover around 90% of the major water catchments (Nyabarongo, Mukungwa, Sebeya, Akanyaru, Rusizi, etc.). The latter catchments are always saturated in areas where water is stagnant for a long period of rainy seasons which eventually result into severe flood events. Generally, the problem of flood in urban zones (Kigali city) of the study area has been exacerbated by rapid urbanization in combination with extreme weather, poor drainage system, less infiltration that contributes to high runoff, rapid structural development and the presence of unplanned and poor urban settlement. This last have increased anthropogenic activities resulting into sedimentation of culverts and dumping of wastes which block drainage systems.

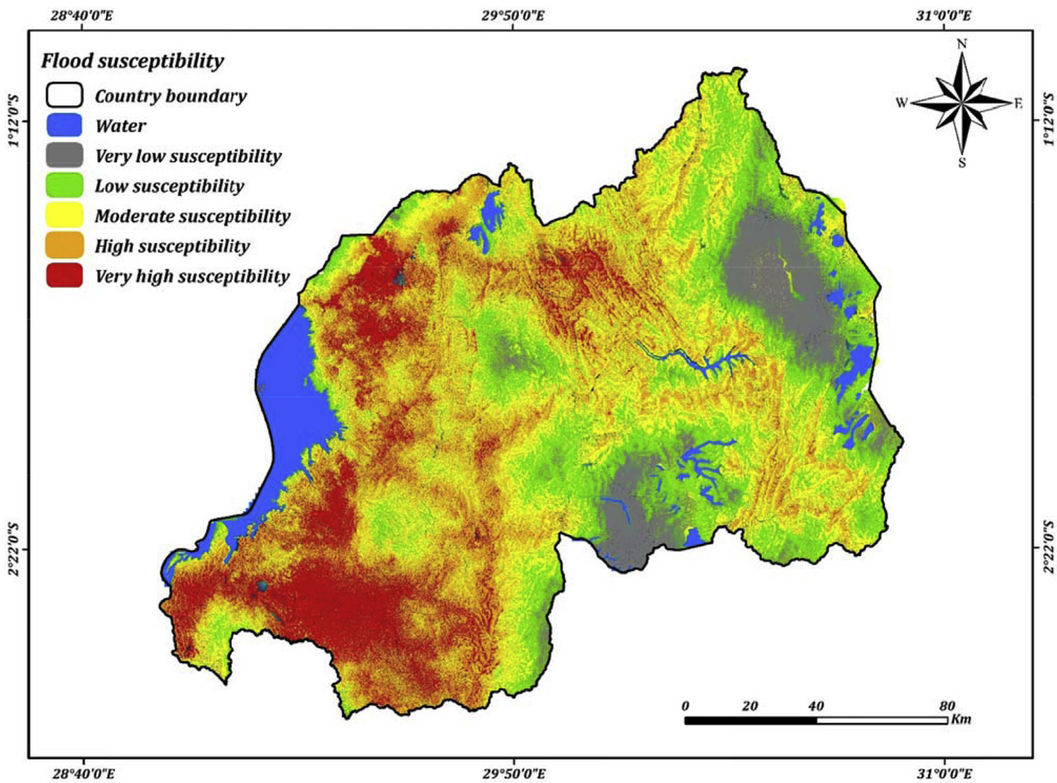


Fig. 4. Flood susceptibility map generated using LR model.

The results (Table 4) disclosed that NDVI, rainfall and profile curvature among others are the factors that highly induce flood susceptibility in different regions of the study area. Accordingly, as indicated in Fig. 4, steep slope areas (northern, western and southern parts of the study area) fell into highly susceptible classes, and after modeling, the slope portrayed a negative spatial correlation with flood occurrences. This can be scientifically justified by the amount of heavy downpours that these areas receive in terms of frequency, intensity and magnitude of rainfall. From the analysis, rainfall was confirmed among the influential factors that presented very high positive correlation with flood occurrences. Moreover, NDVI influenced flood occurrence due to accelerated deforestation caused by agricultural activities and infrastructure developmental facilities (roads, recreational, grouped settlement) taking place in these areas that were modeled as highly susceptible. Additionally, the curvature was considered for flood susceptibility modeling due to the fact that its values denote several erosive settings of water, runoff conditions and topographical structures [69]. Therefore, the profile curvature was used and found positively correlated to flood susceptibility, which can be attributed to its ability in controlling the flow of water influencing the occurrence of flood within the area.

From the above detailed discussion, it can be confirmed that Rwanda is a country susceptible to flood hazard. Previous studies [35,70] stressed that during the rainy seasons, the regions with high precipitation are exposed to flood disaster, which corroborates with the results of the present study where regions with high amount of precipitation fell into high to very high susceptibility to flood occurrence.

Rwanda, as a developing country, has to take serious measures to control floods. Because once they happen, many different effects occur, and they destroy some development activities. According to Ref. [71], flooding usually causes different effects which can be categorized as follows: (1) Primary effects: Physical damage which can damage any type of structure including bridges, cars, buildings, sewerage systems, roadways and canals; (2) Secondary effects: Water supplies, diseases, crops and flood supplies, trees, vegetation and transport; (3) Tertiary and long-term effects: Economic. In the same line, a large part of the study area is covered by cropland (Fig. 1), so floods impact a huge number of crops and many hectares are washed away (Table 1). Thus, hampering the agricultural productivities and the country's economy as well. Besides, a significant number of houses and infrastructure have been demolished as a result of previous flood events [50]. Hence, all these effects should be mostly expected in areas susceptible to flood and mitigation efforts should be mostly deployed in areas modeled as high and very highly susceptible. This should be based on factors that have proved to be positively correlated to flood occurrence (Fig. 4). Among these efforts, the monitoring and forecasting of meteorological and hydrological data has to feed flood early warning systems to predict and anticipate extremes related events [72]. This would be so significant to minimize the level of the aforementioned categories of effects and impacts in order to quickly and timely respond once disasters occur. Being proactive to flood management entails a continuous monitoring of indicators to support predicting the onset and level of flood, as well as to help determine when and how-to bring things to normal towards building back better and flood resilience attainment.

3.2. Validation through the area under the curve (AUC)

The prediction rate of flooding is decided from the prediction curve. Thus, it has to be assessed as an essential result of a model to examine flood susceptibility mapping efficiency [25]. In the present study, AUC parameter (Fig. 5), which plots sensitivity on the y-axis against 1 specificity on the x-axis, was used to validate the model and was estimated using equation (7):

$$AUC = \frac{\Sigma TP + \Sigma TN}{P + N} \tag{7}$$

where P is the total number of floods and N is the total number of non-floods; TP (true positive) and TN (true negative) are the number of pixels that are correctly classified [73]. Among the total number of flood points, 25% were utilized in the validation step. After testing, the

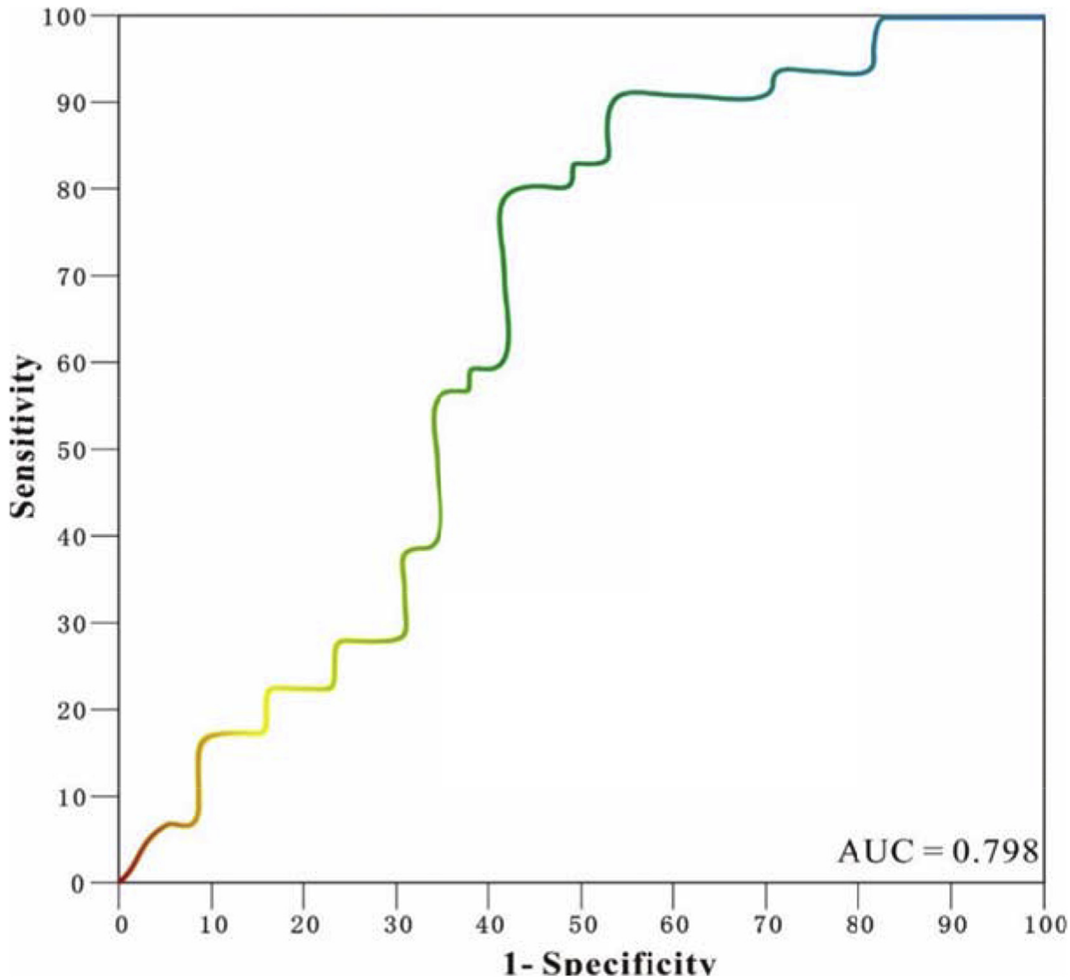


Fig. 5. AUC for model performance and validation.

AUC showed the model's performance of 0.798 (Fig. 5), corresponding to 79.8% of performance rate. This percentage is considered satisfactory despite the input data limitation and accuracy. It also explains how well LR model and factors performed or predicted flood in the study area.

3.3. *Perception of flood and mitigation*

3.3.1. *Flood experience and concern*

Previous studies have stressed the importance of past hazard experiences in local community's judgments [43,74]. As illustrated in Table 5, the majority of respondents (76%) have experienced flood. This percentage was expected since the areas were selected based on flood frequency and occurrence (Table 1). Results of Q2 revealed that a high percentage (74%) of respondents believe that their residences are at risk of flooding. This was in line with studies stipulating that the local community respond sincerely based on earlier experiences, and their judgment depends on qualitative aspects such as severity of the consequences, sense of control, perceived frequency of the hazard and feelings [75,76]. As argued by Anilan [77] in his study, disaster experience is a good predictor of many risk perceptions. Also, studies conducted by Refs. [46,78] analyzed flood experiences of communities by requesting their assessment of the incidence of flood events in their regions and found that community' experiences with flooding are connected to levels of risk perception. Individual experiences like suffering damage or loss of assets are known to result in increased risk perception and past experience shape people's attitude as well as response to future flood events. This makes sense in the current study since the results obtained from Q2 were totally related and not far from those in Q1.

Table 5
Flood experience and concern (answers to the close-ended questions).

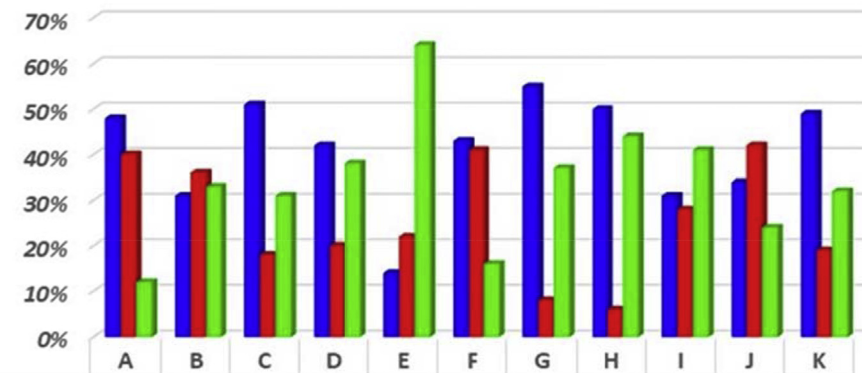
Question	Yes (%)	No (%)
Have you ever experienced flood?	76	24
Do you think that your region is under risk of flooding?	74	26
Do you believe that any action may be taken to mitigate the effects of flood?	81	19

Finally, the majority of the respondents (81%) on Q3 believed that actions could be taken to mitigate flood and be helpful to reduce flood effects in their regions, which implies a positive perspective on future flood risk reduction if well adopted and implemented.

3.3.2. *Capacity and mitigation measures*

The capacity of people to cope with hazards, to a large extent, minimizes their vulnerability and susceptibility to an exposure [79]. Multiple choice questions were intended to ascertain the capacity of participants to deal with flood and get to know about their awareness and skill levels to carry out mitigation measures and finally have an insight on what is expected.

With the aim of knowing local community's perception on who is responsible for taking and implementing flood mitigation measures, the results revealed that high percentage of participants among the selected districts think that the government is responsible for adopting and implementing measures. This result was highly observed in rural areas



	A	B	C	D	E	F	G	H	I	J	K
Government	48%	31%	51%	42%	14%	43%	55%	50%	31%	34%	49%
Citizens	40%	36%	18%	20%	22%	41%	8%	6%	28%	42%	19%
Everyone	12%	33%	31%	38%	64%	16%	37%	44%	41%	24%	32%

ANyabihu, BRwamagana, CBurera, DRubavu, EGasabo, FKarongi, GRutsiro, HMusanze, INyaruguru, JRulindo, KRusizi.

Fig. 6. Community perception on flood mitigation responsibility.

than in urban area (Gasabo) where 64% of the respondents argued that flood mitigation measures are under everyone's responsibility. The UNISDR [80] argued that disaster risk reduction is a collective responsibility between the government, partners and community members; and a previous study [79] echoed that the risk profile of citizens and disaster fatalities somewhat depend on the organizations that serve them and control social life. Thus, the findings imply that probably, the relevant institutions in charge of community awareness, education and social protection guarantee do not go great length in disseminating information related to the responsibility of developing and implementing flood mitigation measures as well as the role of community members in the process of reducing the impacts and effects caused by the hazard.

The opinion of the majority (Fig. 6) on this question has significant implications on people's development of mitigation measures, preparedness as well as coping measures such that this strand of thinking can serve the community members as a way to escape responsibility and leave nothing done regarding measures to cope with the hazard, which may consequently lead to the community's lack of resilience as well as increases in vulnerability and susceptibility of their areas.

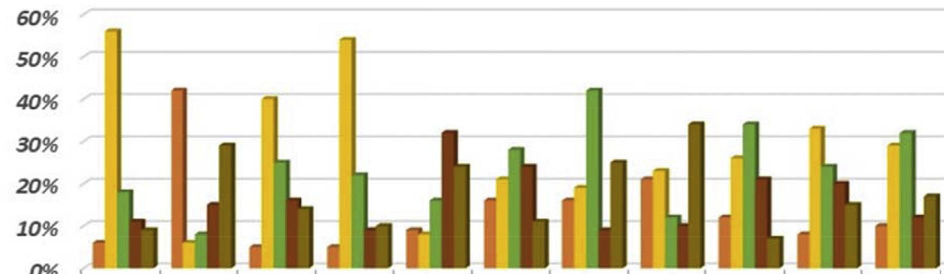
The results in Fig. 7 reveal that relocation and resettlement from flood prone to safe zones is one of the best measures to be adopted to reduce flood impacts; a prevalent phenomenon in Nyabihu and Rubavu districts (western province) and Burera district (northern province). This result is in agreement with the inventory map (Fig. 1) because the three districts contain several floods points and different losses have been encountered during past flood events as observed in Table 1. The results also matched the generated susceptibility map because the spatial distribution of the susceptibility showed that the three districts are highly flood susceptible zones. For the current study, results generated from LR model revealed NDVI as a significant factor contributing to flood occurrence in different regions, which means that some districts are flood prone due to vegetation loss resulting from different anthropogenic activities such as agriculture, mining, deforestation, housing among others. Generally, in the rural areas of Rwanda, the majority of the residents depend on agriculture as means of livelihood. Due to the shortage of land for agriculture and the increasing demand for agricultural commodities, these people incentively change forest and grass lands to cultivated lands. Thus, meaning that afforestation is not of interest to the inhabitant and comes at their economical loss. Consequently, when flood occur, the agricultural sector is seriously affected (Table 1). Due to their economic interest, these community members are seriously contributing to factors leading to the increase in flood susceptibility. This justifies the small percentage of participants on afforestation as a measure to be taken into consideration as far as flood mitigation is concerned for the study area.

In contrast, the respondents in Rwamagana district have mentioned afforestation as a good measure (Fig. 7). This district appears to be in the eastern province with rainfall deficit and which is mostly impacted by drought. The region lacks forest cover and can easily face the problem of flood events when it rains heavily. In the urban area (Gasabo district), the 32% of the participants argued that community participation is a good measure to deal with flood as well as the construction of waterways (24%), a result implying a different mindset from that of rural community members. Finally, the result has also revealed that the community in rural areas does not participate in the process of reducing flood impacts. This corroborates with the results in Fig. 6 where citizens leave flood mitigation issues under government responsibility. Eiser, Bostrom [81] stressed that the risk related to disasters depends not only on physical conditions and procedures but also on human perceptions, conditions (vulnerability factors, etc.), decisions, and culture toward risk reduction. The gravity of the impacts of any disaster will rest on how many people choose, or sense that they have no choice but to live and work in areas at higher risk by adopting strong mitigation measures.

In a nutshell, many community members especially in rural areas are unaware and lack enough information and knowledge on their roles and responsibilities in flood risk reduction. This makes their immediate environment more susceptible to flood since they do not take measures to lessen flood occurrence but instead, expect the government and local leaders to take actions on their behalf.

4. Conclusion

Flood susceptibility mapping is essential to delineate flood-prone areas and assess mitigation measures. This research applied logistic regression model using flood inventory and ten predicting factors to study and map flood susceptibility in Rwanda. The relationships between the occurrence of flooding and the variables were evaluated, and the outcomes showed NDVI and rainfall to have a significant relationship with floods. This was in conformity with other previous studies confirming rainfall as a major trigger of flood events in any study area. Thus, it implied that less vegetated with higher rainfall areas are supposed to have greater susceptibility to floods. The study also assessed



	A	B	C	D	E	F	G	H	I	J	K
AF	6%	42%	5%	5%	9%	16%	16%	21%	12%	8%	10%
RE	56%	6%	40%	54%	8%	21%	19%	23%	26%	33%	29%
PA	18%	8%	25%	22%	16%	28%	42%	12%	34%	24%	32%
CP	11%	15%	16%	9%	32%	24%	9%	10%	21%	20%	12%
CW	9%	29%	14%	10%	24%	11%	25%	34%	7%	15%	17%

[A]Nyabihu, [B]Rwamagana, [C]Burera, [D]Rubavu, [E]Gasabo, [F]Karongi, [G]Rutsiro, [H]Musanze, [I]Nyaruguru, [J]Rulindo, [K]Rusizi. **AF**. Afforestation, **RE**. Resettlement and relocation, **PA**. Public awareness, **CP**. Community participation, **CW**. Construction of waterways.

Fig. 7. Community perception on mitigation measures (answers to the question 4).

community's perception on flood mitigation about the produced susceptibility map and was, therefore, noted that majority of community members perceive the government as the key actor and implementor of flood mitigation ignoring that flood risk reduction has to be everyone's responsibility [80]. Thus, this perception may contribute to the risk and susceptibility increase of the area, a finding that implicates the need of establishing programs to inculcate a sense of mitigation and prevention in communities, especially in rural areas.

Basically, flood risk maps contain information of flood hazard in terms of available data on population, properties and resources prone to hazard [2]. This information can be used as a baseline for planners, future researchers, disaster risk managers and be used as a supplementary decision-making tool in the country as far as flood risk mainstreaming is concerned. Hence, the results of this study could be of help to citizens and engineers to reduce losses using appropriate measures. As a recommendation to future works, it will be significant to conduct further studies on flood susceptibility using other current modeling approaches such RF, Logistic Model Tree (LMT), SVM among others considering more predicting factors and seek for high resolution satellite images interpretation to use in mapping flood susceptibility. As well, further studies should use appropriate methods such as ReliefF and information gain (IG) in selecting conditioning factors, so as to address uncertainties inherent to inventory datasets and conditioning factors. Thus, this will assist and help in finding sustainable solutions to flood in the study area.

Conflicts of interest

The authors declare no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2019.101211.

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