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A GIS-Based Fuzzy Hierarchical Modeling for Flood Suscepti-bil-Ity Mapping: A Case Study in Ontario, Eastern Canada †

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Abstract: Natural disasters such as floods have severely destroyed the natural environment and infrastructure because of their destructive effects and caused socio-economic losses. In the present study, the authors attempt to present a flood hazard susceptibility map of an eastern region in Ontario, Canada to facilitate flood prevention and mitigation. To this purpose, a combination of Multi-criteria decision-making (MCDM) model and the Geographic Information System (GIS) has been considered. Herein, an Analytical hierarchy process (AHP) model is applied based on Triangular Fuzzy Numbers (TFNs) in GIS environment. A total of eight quantitative criteria including elevation, land use/land cover, geology, rainfall, drainage density, slope, soil type, and distance from river have been used for the flood modeling. Fuzzified pairwise comparison matrices of values have determined the Importance Weights (IWs) of these criteria in Saaty's scale. By calculating IWs, the impact of each effective criterion on flood risk was investigated using the fuzzy AHP method. The consistency Index of each pairwise comparison of criteria has been checked. Based on the calculated IWs results of each criterion, the precipitation, slope, and soil criteria play significant roles as the most eminent flood occurrence criteria. In addition, the obtained results demonstrate percentages of flooded areas and the flood hazard index of the study area.

Keywords: flood susceptibility; GIS; Multi-Criteria Decision-Making (MCDM); Analytical Hierarchy Process (AHP); Fuzzification; TFNs

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1. Introduction

In recent years, natural disasters have been considered the principal problems affecting both developed and developing countries [1]. The frequency of natural disasters has risen considerably over the past decades due to a variety of human and natural parameters such as degradation of the environment, climate change, rapid population growth, and intensified and inappropriate land use [2–4]. Flood is a complicated phenomenon among natural disasters; it causes significant and irreversible damage, leading to considerable human and economic losses [5]. This naturally complex phenomenon happens essentially due to global warming that is responsible for changing the rate and precipitation intensities [6]. It occurs rapidly and negatively impacts cities' population and infrastructure [7]. As a result, assessing and regionalizing flood risks are becoming essential and urgent [4]. A crucial step is to map flood susceptibility to predict the probability of a flood. Flood susceptibility mapping makes it possible to determine and predict future flood risks using statistical or deterministic techniques. Mapping areas vulnerable to historic disasters is essential for flood mitigation and management [8].

This paper presents to identify flood susceptibility map in the region of Ottawa city in Ontario, Canada, to find solutions for the assessment and management of floods by combining Multi-Criteria Decision-Making (MCDM) and Geographical Information Systems (GIS). The Analytic Hierarchy Process (AHP) is known as one of the most popular technique [9,10] which has been integrated by GIS to assign a specific weight for each criterion, estimate the Flood Hazard index, and create a special decision-making solution for flood susceptibility mapping [11]. Eight spatial criteria used in this study include Land use/Land cover, Drainage Density, Precipitation, Geology, Elevation, Slope, Soil, and Distance from River. Moreover, a fuzzy mathematical set based on Triangular Fuzzy Numbers (TFNs) is utilized in the proposed method in order to reduce the uncertainties and improve the evaluation of flood-susceptible areas [12–14]. Integrating the MCDM method and GIS is considered an appropriate tool and is widely used in various engineering fields. For example, Hammami et al. 2019 applied a GIS-based AHP to evaluate Tunisia's flood susceptibility mapping. They used eight criteria in order to calculate Flood Hazard Index (FHI) and determine a flood susceptibility map [17]. In a recent study, Msabi and Makonyo 2020 used GIS and multi-criteria decision analysis considering seven influencing criteria: elevation, slope, geology, drainage density, flow accumulation, land-use/cover, and soil for mapping the flood susceptibility area in central Tanzania [18]. Souissi et al. 2019 for flood susceptibility mapping in southeastern regions of Tunisia, developed a GIS-based AHP model. They also considered eight criteria in flood modeling: elevation, land use/land cover, lithology, rainfall intensity, drainage density, distance from the river, slope, and groundwater depth. The obtained results showed that the most important flood occurrence criterion was the elevation [19]. Furthermore, Rincón et al. 2018 in another research utilized GIS and AHP method to define the optimal weight of each criterion related to flood risk and develop the accuracy of the flood risk maps of Don River basin in Toronto, Canada [20]. In the other study related to Flood Susceptibility Mapping, Swain et al. 2020 used an integration of GIS-AHP Technique to investigate flood susceptible areas in India [5]. Some of the limitations of previous studies that use the GIS-based multi-criteria flood susceptibility mapping approach include criteria weighting methods that are not appropriate, or in some cases are not used at all which can lead to unreliable results. Therefore, this study bridges this gap by applying a hierarchical GIS-based model to assign weights to the criteria and then, determine flood susceptibility map. The rest of this paper is arranged in the following manner: In Section 2, a study area is discussed and describes the framework of the proposed methodology in detail and third Section of this study presents the results and Discussion of this study, and the conclusions is provided in Section 4.

2. Materials and Methods

2.1. Study Area

Ottawa is located at latitude 45°25′29″ N and longitude 75°41′42″ W in the east of southern Ontario, with an elevation of 70 m above sea level (see Figure 1). The climate is semi-continental, with a warm, humid summer and a very cold winter. The area and population of Ottawa district are about 2790 km² and 780,000 people, respectively. The temperature typically varies from −14°C to 27°C, while the mean precipitation is 920 mm. Rainfalls throughout the year in Ottawa. The higher mean monthly rainfall in Ottawa is in July, with an average rainfall of 76 mm, while the least rainfall month is February, with an average rainfall of 12.7 mm. Ottawa experiences extreme seasonal variation in monthly snowfall. The snowy period of the year lasts from October to April with at least 25.4 mm. Snowfall does not occur in July, with an average total accumulation of 0.0 mm. The cold season lasts from December to March, with an average daily high temperature below 1 °C, and the wetter season lasts from April to December. The southern Ontario region has suffered several severe flood events during the last 100 years, resulting in high economic and social impacts.

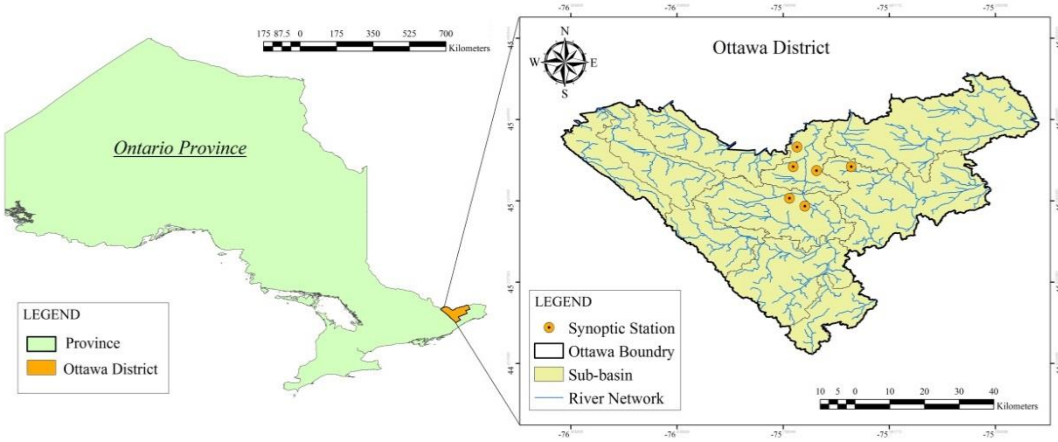

Figure 1. Location of the study area.

2.2. Methodology

The main objective of this paper is to determine flood-susceptible areas based on the combination of MCDM and GIS [15]. Afterward, the Importance Weights (IWs) value of the qualitative criteria and FHI are calculated using AHP method, respectively [21]. The AHP approach is one of the MCDM models that address the complexity involved in decision-making process using Pairwise comparisons and considering the effects of quantitative criteria [9,22]. The Saaty's scale is proposed in this technique for scoring the importance value of criteria [23] (see Table 1).

Table 1. The Saaty's scale for scoring the importance value of criteria [9].

Numerical value	Definition
1	Equal important
3	Weakly more important
5	Strongly more important
7	Very Strongly more important
9	Absolutely more important
2, 4, 6, and 8	Intervals of adjacent expressions

Combining AHP method and GIS tool into a decision support system holds significant promise for enhancing decision-making in the planning process [15]. The GIS-based hierarchical mode, incorporating qualitative spatial layers and expert opinions, allows prioritizing criteria utilizing Pairwise Comparison Matrix (PCM) [15]. Moreover, there are different criteria in this study, and there is a lack of agreement among experts within this field due to the presence of uncertainty. In these situations, applying fuzzy memberships to reduce uncertainties is highly recommended. Therefore, in this study, a hierarchical model is applied based on a combination of AHP method and GIS in the form of fuzzy sets. First of all, various spatial layers and maps were used and introduced in ArcGIS. However, the present study selected eight criteria, including drainage density, land use/land cover, precipitation, slope, soil type, elevation, geology, and distance from the river, according to their essential role in flood region selection.

In the next stage, the weight assigned to each criterion has been established through the application of GIS-based hierarchical integration model [15], respectively. The weighting procedure is fully implemented in ArcGIS software based on raster layer analysis by 30m cell size. Having selected the criteria, it is imperative to carry out the subsequent steps sequentially. The arrangement of the hierarchical model based on GIS is depicted in Figure 2.

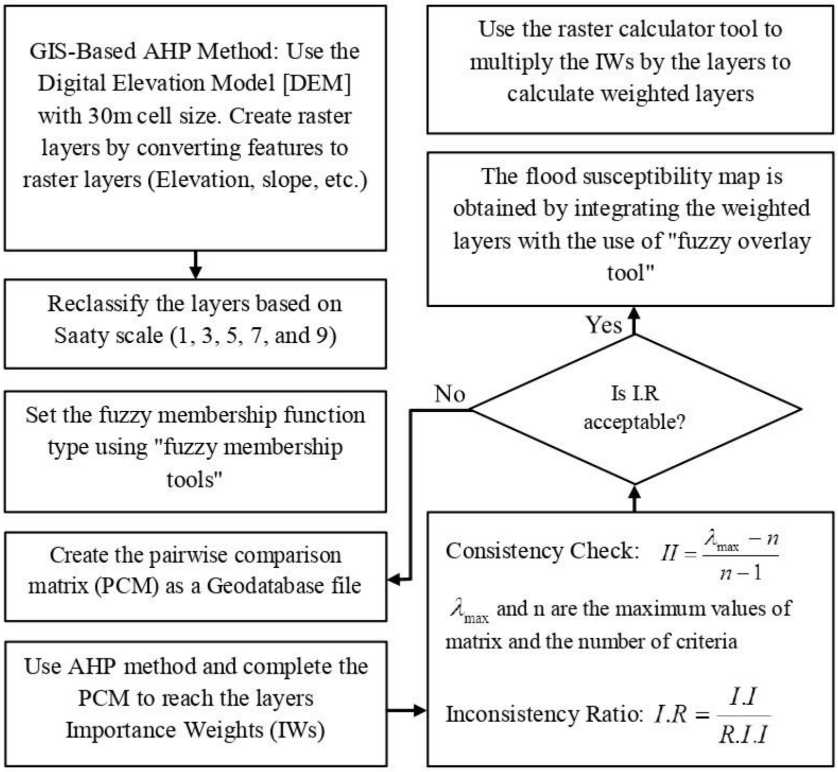

Figure 2. The arrangement of the GIS-based hierarchical model.

In the following, the classification of the layers has been redefined in accordance with common interval scales, which are depicted in Table 1 [24]. The subsequent phase entails computing the criteria weights by applying the AHP based on the PCM [9]. Employing the fuzzy membership tool to establish the nature of the fuzzy membership function is advisable. And lastly, the "fuzzy overlay tool" is utilize to combine the specific weights of each raster layer. Then, the validity of the PCM must be examined. The AHP employs the Inconsistency ratio to assess the compatibility of the experts' opinions with the questionnaire. Prior to commencing data processing within a GIS framework, it is crucial to calculate the Inconsistency Index (I.I), the Random Inconsistency Index (R.I), and $\lambda_{\max}$. The calculation of I.I can be performed as follows:

$$II = \frac{\lambda_{\max} - n}{n-1} \tag{1}$$

The maximum eigenvalue of the matrix, denoted as $\lambda_{\max}$ and the number of criteria by the variable n, are represented in the Equation (1).

The ratio of inconsistency (I.R) is obtained by dividing the value of I.I by the value of R.I.I as stated in Equation (2). The values of R.I.I for the matrix are presented in Table 2.

$$I.R = \frac{I.I}{R.I.I} \tag{2}$$

Table 2. The Random Inconsistency Index values of matrices.

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RII	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The Inconsistency ratio must be 0.1 or less for the comparisons to be consistent and the respondents to be valid.

The GIS tool was utilized for specifying the weight of criteria in the subsequent step due to its remarkable ability to store and integrate spatial layers. The spatial layers for each criterion were created using ArcGIS software to achieve this. Each layer was considered the main quantitative criterion for the flood susceptibility mapping process. The primary classification of the critical criteria for flood sustainability mapping in the Ottawa district and their attributed requirements for converting to raster layers are briefly introduced in Table 3. It should be noted that preparing the precipitation data layer involved gathering statistical and synoptic gauge data from the study area, covering the period from 1985 to 2022, focusing on obtaining the long-term annual average. And the process of interpolating precipitation data was carried out using the Kriging method, which resulted in the transformation of the data into a raster layer. Furthermore, the drainage density criterion was determined by dividing the total length of the river network by the area of the watershed. The drainage density is calculated using Equation (3) [15].

$$U = \frac{\sum L_i}{A} \quad (3)$$

where *Li* stands for the length of the river system measured in kilometers, while *A* represents the watershed area in square kilometers.

Table 3. Categorization of spatial layers of each criterion with their requirements.

Criteria	References	Attribute class
Slope	Digital Elevation Model (DEM) of Canada, cell size 30m	It is of greater significance to have a lower value Slopes 0% -2%: the most critical, Slopes exceeding 45%: the least significant [15]
Elevation	DEM of Canada, cell size 30m	A lower value has higher significance, Altitudes higher than 2,500 m have the least importance [15]
Geological class	Canada Geological map with a scale of 1: 250,000	The higher value represents more importance of sensitivity level
Precipitation	Annual long-term average precipitation of 6-gauge stations from 1985 to 2022.	More amount of precipitation is more important
Land-use	Canada Land-use/land cover map with a scale of 1: 500,000	Denser landcover has lower importance
Soil Type	Soil type classification map with a scale of 1: 1,000,000	Soil near the ground level is more significant than the deeper soil below. Additionally, soils that can either shrink or expand are of lesser significance [15]
Distance from River	Shape file rivers of Ontario	Having a shorter distance to the river is considered more important
Drainage Density	shape file rivers and sub-basin boundaries of Ontario	Higher river density of the basin is more important

In the next stage, the reclassification tool is employed to categorize the raster layers according to the available classification system. A fuzzy membership tool based on linear fuzzy sets is utilized to transform the raster layers into fuzzy numbers to accomplish this task. Subsequently, the resulting fuzzified raster layers are subjected to reclassification utilizing the Saaty scale, as presented in Table 1. Then, the reclassified fuzzy raster layers are evaluated using an AHP-based GIS approach to calculate the weight of the fuzzy raster layers. Additionally, the Inconsistency Ratio of PCM is determined using Equations (1) and (2). Furthermore, a demonstration of how to calculate the weighted elevation criterion and form a weighted layer can be seen in Figure 3.

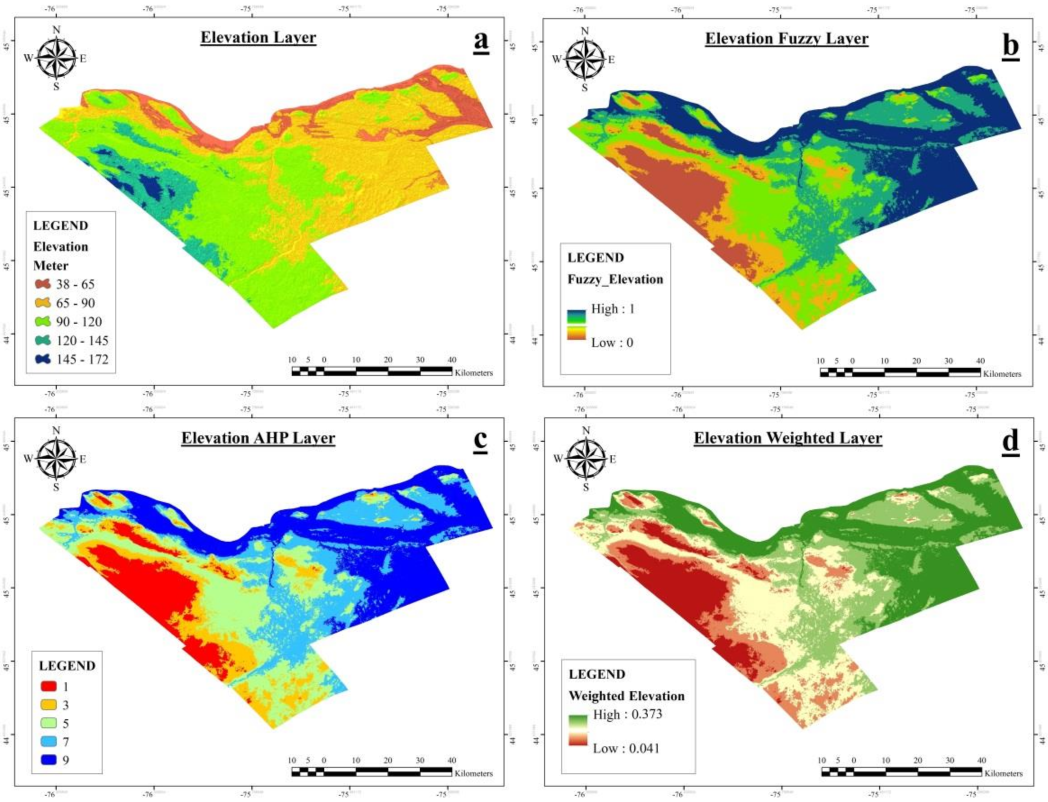

Figure 3. The process of fuzzy weighted Elevation layer within a hierarchical GIS model: (**a**) Elevation raster layer, (**b**) Fuzzy Elevation layer, (**c**) Reclassified AHP layer, (**d**) Weighted Elevation layer.

In the next step, the FHI is calculated by the following Equation (4) to evaluate the flooding probability rate:

$$FHI\sum_{i=1}^{n} WiRi \tag{4}$$

where *Ri* is each criterion's raster layer, *Wi* is each criterion's weight, and *n* corresponds to the number of the criteria. Therefore, Equation (5) is written in the following form:

$$\begin{aligned} FH = {} & W_{EL}R_{EL} + W_{LULC}R_{LULC} + W_{DD}R_{DD} + W_{GEO}R_{GEO} \\ & + W_{SL}R_{SL} + W_{SP}R_{SP} + W_{PR}R_{PR} + W_{DR}R_{DR} \end{aligned} \tag{5}$$

In this research, to attain FHI within a GIS environment, the weights of each criterion are calculated by multiplying them in their respective raster layer through the utilization of the Raster Calculator tool.

Finally, to determine the final flood susceptibility map of the study area, all the fuzzy weighted layers are integrated using the Fuzzy Overlay tool. In the following, the categorization of weighted fuzzy overlay layers of criteria is shown in Figure 4.

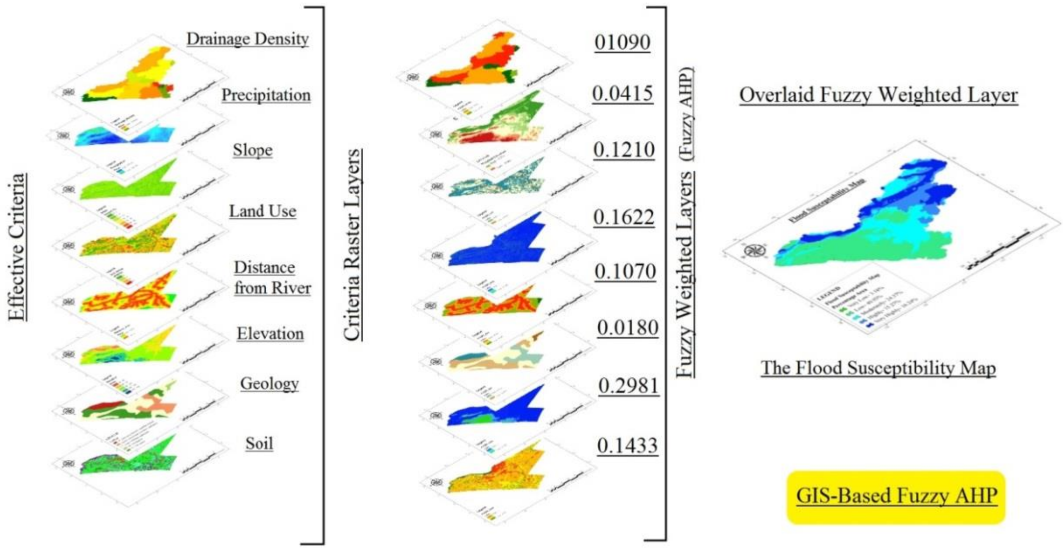

Figure 4. Classification of overlaying weighted fuzzy layers' process based on the criteria specified.

3. Results and Discussion

Table 4 presents the results of the PCM and the average weight per layer. Furthermore, Table 4 showcases the calculated inconsistency ratios of each PCM, which were determined using Equations (1) and (2). In this study, the criteria are eight and the result R.I.I = 1.41. Finally, the consistency ratio has been calculated I.R = 0.041, since I.R value is inferior to 0.1 and the consistency of the weight are accepted. Based on the obtained IWs of criteria in Table 4, the precipitation, slope, and soil criteria with the values of 0.298, 0.162, and 0.143 have the highest IW for the flood assessment, respectively. Also the geology and elevation criteria with values of 0.018 and 0.041 are the least important in assessing food susceptible areas of the case study.

Table 4. The results of the PCM for the spatial layers and their respective weights.

Layer name	Soil	Slope	Precipitation	Land Use	Geology	Elevation	Drainage Density	Distance from River	Weight
Soil	1	0.33	0.2	3	6	7	5	3	0.143
Slope	3	1	0.2	5	7	1	0.25	7	0.162
Precipitation	5	5	1	4	8	3	4	7	0.298
Land Use	0.33	0.2	0.25	1	7	7	7	0.2	0.121
Geology	0.167	0.143	0.125	0.143	1	0.5	0.2	0.143	0.018
Elevation	0.143	1	0.33	0.143	2	1	0.167	0.143	0.041
Drainage Density	0.2	4	0.25	0.143	5	6	1	1	0.109
Distance from River	0.33	0.143	0.143	5	7	7	1	1	0.107
I.R	0.041	The matrix is satisfactory in term of consistency							

In addition, the FHI is found to evaluate the rate of flooding probability [25], which was calculated as follow:

$$\begin{aligned} FH = {} & 0.041R_{EL} + 0.121R_{LULC} + 0.109R_{DD} + 0.018R_{GEO} \\ & + 0.143R_{SL} + 0.162R_{SP} + 0.298R_{PR} + 0.107R_{DR} = 5.23 \end{aligned} \tag{6}$$

The proposed method, which considers a multitude of quantitative criteria, is utilized to achieve the mapping of flood susceptibility. The final map of the flood susceptibility mapping of the study area was constructed and classified into five major classes with flood potentiality from very low to very high (see Figure 5). Respectively, based on Figure 5, 3.18% of the study area represents the very low class, 40.93% of the area represents the low class, 24.37% of the area represents the moderate class, 15.27% of the area represents the high class, and 16.24% of the area represents the very high class.

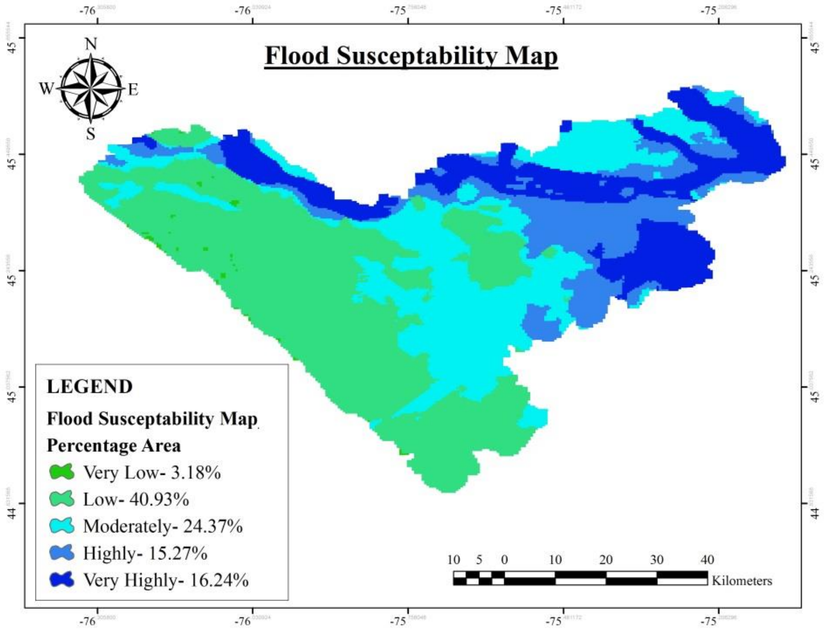

Figure 5. The flood susceptibility map of the Ottawa district.

4. Conclusions

Flood susceptibility mapping is an effective technique that allows for reducing flood hazard dangers in order to assist decision-makers to have proper management over the prone areas, and thereafter ensure appropriate and sustainable socio-economic development. In this paper, to produce the flood susceptibility map of the Ottawa district in southern Ontario, Canada, a MCDM hierarchical approach is proposed based on AHP method and GIS with the capability to check the consistency of the obtained model. Eight flood influencing criteria were considered for mapping the flood-susceptible areas, i.e., precipitation, soil, distance from the river, drainage density, elevation, land use/land cover, geology, and slope data. The Importance Weights (IWs) of criteria were evaluated using a hierarchical model based on Geographic Information System (GIS). This approach was employed to establish the IW of each criterion. The evaluation results of the IWs of the precipitation, slope, and soil criteria play a prominent role in investigating flood-prone areas. And also, the geology and elevation criteria are far less important than other criteria and have less impact on Flood susceptibility mapping. Further, the flood-susceptibility map is classified into five major classes with flood potentiality from very low to very high. Respectively, we find 3.18% (very low), 40.93% (low), 24.37% (moderate), 15.27% (high), and 16.24% (very high). After that, FHI was calculated to evaluate the impact of each criterion on the method, which leads to a better understanding of each criterion on the flood susceptibility map. Finally, the flood susceptibility map presented in this paper will serve as a valuable tool and will play a vital role in assessing flood management not only in the Ottawa region but also in other regions prone to flood events within the country.

Author Contributions: Conceptualization: A.N. and H.B.; methodology: A.N. and H.B.; software: A.N.; validation, A.N.; formal analysis, H.B. and A.N.; data curation, A.N.; writing—original draft preparation, A.N. and H.B.; writing—review and editing, H.B.; visualization, A.N. and H.B.; supervision: H.B. All authors have read and agreed to the published version of the manuscript.

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