A GIS based flood vulnerability modelling of Anambra State using an integrated IVFRN-DEMATEL-ANP model

E.C. Chukwuma\textsuperscript{a,b,}\textsuperscript{*}, C.C. Okonkwo\textsuperscript{b}, J.O. Ojediran\textsuperscript{a}, D.C. Anizoba\textsuperscript{b}, J.I. Ubah\textsuperscript{b}, C.P. Nwachukwu\textsuperscript{b}

\textsuperscript{a} Department of Agricultural and Biosystems Engineering, College of Engineering, Landmark University, Omu Aran, Kwara State, Nigeria
\textsuperscript{b} Department of Agricultural and Bioresources Engineering, Faculty of Engineering, Nnamdi Azikiwe University, Awka, Nigeria

\textbf{ARTICLE INFO}

\textbf{Keywords:}
GIS
Flooding
Vulnerability assessment
Climate change
Nigeria

\textbf{ABSTRACT}

Flooding is a major environmental problem facing Anambra State of Nigeria, which also threatens food security in the state. To address this issue, continual flood vulnerability mapping exploring more efficient methods is needed to facilitate flood risk management in the state. The advantages of employing spatial information technologies such as Remote Sensing (RS) and Geographic Information System (GIS) in flood vulnerability mapping has been widely documented; the limitations of employing GIS alone in effective vulnerability analysis have also been documented by researchers. To overcome these limitations, this study adopted the use of GIS and the integration of Interval Value Fuzzy Rough Number (IVFRN), Decision Making Trial and Evaluation Laboratory (DEMATEL), and Analytical Network Process (ANP) method in vulnerability assessment of flood hazard. The result of the study shows that the state is very vulnerable to flood with 73% of the total area of the state lying between Very High and Medium vulnerable zones. The most vulnerable Local Government Area (LGA) in the State is Anambra West with 95% of the total area of the LGA lying between Very High and Medium vulnerable zones. Furthermore, the obtained values of $\tilde{R}/C_0^0$ show that Rainfall Intensity factor is the major cause of flood in the study area with the highest positive value of 1.55 and Soil factor is the major effect with the highest negative value of -0.93. The IVFRN-DEMATEL-ANP assessment model was validated using AUC-ROC method; an AUC value of 0.946 was obtained, this indicates that the model has excellent prediction accuracy. This study was able to establish the feasibility of integrating the IVFRN, DEMATEL and ANP methods in flood vulnerability assessment. It is recommended that the provision of adequate drainage systems should be prioritized to areas of high flood vulnerability index; to help mitigate flood hazards in the State. Also, strategic planning of infrastructures and emergency routes for moving people and key assets from vulnerable areas especially during the rainy season should be geospatial-based and systematic.

1. Introduction

Climate change and its related repercussions is a global issue with Africa as one of the most vulnerable parts of the world (Seredczyzny et al., 2017). Climate change has made a significant impact on the land (Miller and Hutchins, 2017), as global warming triggers moisture concentration in the warmer atmosphere which in turn increases the intensity of rainfall events (Zhou et al., 2017). This increase in the frequency and intensity of rainfall causes rainfall extremes and has resulted in the rapid onset of flooding especially in areas with inadequate or badly maintained drainage systems (Garsen et al., 2015; Pradhan-salike & Pokharel, 2017; Pregnolato et al., 2017). These extreme events have been recently recorded in areas that have no previous history of such events as heavy rainfall events is increasing in more land areas when compared to areas where they decreased (Hettiarachchi et al., 2018). Depending on the vulnerabilities that exist, these extreme events can cause natural disasters as they favor hazardous conditions such as floods and landslides (Debortoli et al., 2017). Future projections also indicate that a combination of changes in rainfall and land use will make more urban areas increasingly vulnerable to extreme rainfall and flooding (Miller and Hutchins, 2017). Changes in land use due to urbanization increases flood susceptibility (Kaspersen et al., 2015) as urbanization is largely associated with the removal of soil and vegetation and these are important factors for limiting surface runoff (Pradhan-salike & Pokharel, 2017). Furthermore the introduction of

\textsuperscript{*} Corresponding author.
\textit{E-mail address:} ecchukwuma@yahoo.com (E.C. Chukwuma).

https://doi.org/10.1016/j.heliyon.2021.e08048
Received 14 April 2021; Received in revised form 11 June 2021; Accepted 17 September 2021
2405-8440/© 2021 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
impervious surfaces within urban areas as a means of infrastructural development largely influences the amount and velocity of surface run-off during high-intensity rainfall and as such exposes these areas to flood hazards (Kaspersen et al., 2015). Another important aspect of climate change impact on flood hazards is sea-level rise as change in climate is likely to cause an overflow of the sea into coastal areas and this seems to be the case in most parts of Nigeria (Orji, 2015).

Flooding is one of the most destructive widespread natural hazards of the world with a high frequency of occurrence and a huge impact on large population (Akukwe et al., 2020; Zhao and Gao, 2016). It is a major threat to the survival of the human race with associated risks that include the destruction of lives and properties, the displacement of livelihoods, and the impoverishment of flood victims (Okafor, 2020). Extreme precipitation and related flooding events have both economic and human consequences which have rapidly increased over the years (Kaspersen et al., 2017). Akukwe et al. (2020) asserted that flooding has the capability to make communities food insecurity hotspots and thus hamper the achievement of Goal 2 of the Sustainable Development Goals. In Nigeria, floods are the most frequent and severe natural hazards which have significantly affected lives and properties negatively (Olorunfemi et al., 2020). Flood hazard has displaced more people in the country than any other natural hazard with the population at risk estimated to be 20% (Cirelila and Iyalomhe, 2018). The country has experienced several flood episodes with the 2012 flood episode being tagged the most severe and devastating flood episode ever witnessed in the country over the years (Ajaero et al., 2016; Akukwe et al., 2020; Eboh et al., 2017; Ezeokoli et al., 2019; Nemine, 2015; Okafor, 2020; Tami and Moses, 2015). The 2012 flood episode affected over 30 states in the country with an estimated total of seven million people affected and an economic loss estimate of 2.6 trillion naira (Okafor, 2020). Anambra state was among the states affected by 2012 flood disaster with the four local government areas of Anambra West, Anamabum, Anambra East and Ogbaru being the worst hit in the state (Okoli and Chiaghana, 2020). Flooding and excessive rainfall have constituted one of the most important environmental problems in the country (Ebuode, 2015). Studies have been carried out to determine the causes of flooding in various parts of the state. Onyeizugbe & Onyejiaka (2019) attributed the major causes of flood hazard in Ogbaru Local Government Area of Anambra State to the water body present in the area, the topography of the area and human encroachment. In the same area, Okoye et al. (2015) indicated the siting of buildings on waterways amongst other factors as the cause of flooding in the area. Onwuka et al., (2015a, b, c, d) investigated the causes of flooding in six Communities of Awka, Anambra State and observed that the causes include inadequate drainage channels, dumping of refuse in drainage channels, bad roads and poor planning in the area. In Anambra East local government area of the state, Onwuka et al., (2015a, b, c, d) summarized the cause of flooding as anthropogenic activities and thus recommended flood hazard mapping to determine the areas vulnerable. Studies have also been carried out to determine how flood hazard has affected the state. Enete et al. (2016) carried out a socio-economic assessment of flood hazards among farm households in the state and observed that over 70% of farm lands were destroyed by flood, resulting in the loss of over 80% of staple crops and livestock. Ebuoemo (2015) and Onwuka et al., (2015a, b, c, d) observed similar effects of flooding in Awka and Umuleri areas of the state respectively and these effects can be summarized into road congestion and accident, damage of infrastructures, loss of farmlands, health problems, a decrease in the environment’s aesthetic beauty, an increase in poverty level and death. In Ogbaru, Osoh (2020) observed that flood hazards affected agriculture, health, education, water, property and assets in the area.

Flood hazards and its associated negative effects cannot be completely eliminated, as such a lot of attention has been given to the effective establishment of adequate risk mitigation and adaptation strategies (Onwuka et al., 2015a, b, c, d). In recent years, the non-structural flood mitigation strategies which include land use planning, forecast and the application of Geographic Information System (GIS) and Remote Sensing have gained more attention (Ugoibo et al., 2017). In order to deal with the associated risk of flood hazard, it has become essential to develop tools to aid the decision on local hazard vulnerability for risk prevention (Ndiiaye et al., 2016). One of such tools is the flood vulnerability mapping, an essential tool in flood risk management as it helps to identify areas prone to flood hazards (Ejekeme et al., 2015). In Nigeria and other parts of the world, GIS and remote sensing techniques have been employed in creating flood vulnerability maps (Emmanuel et al., 2015; Ismail & Saanyol, 2013; Seethath et al., 2016; Tas, 2016). These techniques are quite effective in identifying the spatial aspect of flood for management practices as they can be used to determine and checkmate the extent of flooded areas, hence providing reliable information on the size of affected land area and infrastructure (Ismail & Saanyol, 2013). But these GIS techniques also have certain drawbacks as they cannot model accurately the relative significance of the different conditioning factors (Tella and Balogun, 2020). To address this drawback, several models have been combined with GIS techniques and one of such is the Multi-Criteria Decision Making Models such as the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP). Costache et al. (2020) assessed the susceptibility of flood hazards in the South-central part of Romania using the AHP model. Hoque et al. (2019) also employed the AHP model to examine spatial flood vulnerability at Kalapara Upazila in Bangladesh. Gudiyangada Nachappa et al., (2020) carried out a comparative assessment of flood susceptibility in Salzburg, Austria using the AHP and ANP models, and observed an accuracy of 86.6% and 85.9% for ANP and AHP models respectively.

The MCDM models are used to construct and clarify judgments and forecasting problems using multiple criteria analysis, and these are done with the aid of mathematical tools and a set of alternatives and decision criteria (Ali et al., 2020). MCDM models have been modified over the years to improve their efficiency in flood vulnerability mapping, thus giving birth to hybrid models such as the combination of ANP and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique. The DEMATEL technique is a useful method for determining the relationship between effect and cause group by examining the importance of the factors and sub-factors (Rahman et al., 2017). It was developed in the Geneva Research Centre of the Battelle Memorial Institute (Pamucar et al., 2017), between 1972 and 1979 to aid the study and analysis of complex intertwined groups (Kadoic et al., 2019). The major advantage of the hybrid DEMATEL-ANP is that it uses matrices to transform the interdependency of conditioning factors into causal relationships thus determining the most important criteria from a complex multi-criteria decision structure (Ali et al., 2020). Despite the advantage of this hybrid model, the drawback which exists in other MCDM models still exist as inconsistency or bias may occur in the pairwise comparison which in turn gives rise to uncertainties and imprecision (Tella and Balogun, 2020). To address this drawback, several algorithms have been integrated with several MCDM models for various purposes and these include Fuzzy sets (Hategekimana et al., 2018; Kanani-Sadat et al., 2019), Interval Rough Numbers (Hatefi and Tamoaisatien, 2019; Pamucar et al., 2017; Wang et al., 2019), Neutrosophic sets (Abdel-Basset et al., 2019; Liu et al., 2018; Nabeeh, 2020) and Interval Valued Fuzzy Rough Numbers (IVFRN) (Pamucar et al., 2018, 2019; Roy et al., 2019).

But to the best of our knowledge, the IVFRN algorithm is yet to be integrated with the DEMATEL-ANP model. The IVFRN algorithm eliminates the subjectivity which exists in the definition of borders for fuzzy sets (Pamucar et al., 2018). This algorithm integrates the fuzzy and interval rough numbers approach, by considering the benefits of both concepts to eliminate the drawbacks of both algorithms (Roy et al., 2019). In applying this algorithm, an initial fuzzy set is defined and the uncertainties which exist in the evaluations of the decision-makers are calculated using rough sets (Deveci et al., 2020). In view of the various advantages of the IVFRN algorithm over other algorithms, this study aims to investigate the feasibility of the IVFRN-DEMATEL-ANP hybrid model in flood vulnerability assessment using Anambra State as a case study. The state was specifically selected due to its history of flood episodes.
Due to the danger flood hazards and climate change impact in the study area, there is a need for continuous vulnerability assessment of flood hazards in the study area. Previous flood vulnerability assessments in the study area also failed to determine the relative significance of the conditioning factors. Furthermore, a major drawback with conventional vulnerability assessment is the imprecision encountered in determining the relative significance of various conditioning factors. Consequently, vulnerability assessment of flood hazard in the study area should consider the integration of algorithms which deal with imprecision and vagueness in decision making for efficient vulnerability assessment. The vulnerability assessment should also be able to determine the degree of influence of the various conditioning factors in order to proffer an effective solution to flooding.

2. Study area

The study area is Anambra state (Figure 1), situated in the Eastern part of Nigeria. The State is bounded by Delta State, Imo State, Enugu State and Kogi State to the West, South, East and North respectively (Agbo et al., 2015). The state lies between latitudes 5° 40’ and 6° 48’ North and longitudes 6° 35’ and 7° 50’ East with a landmass of about 4,415.54 km² (Agbo et al., 2015; Emmanuel et al., 2015) and an estimated population of over 6 million people (Obioji and Eze, 2019). The state lies within the humid tropical rainforest belt of southeastern Nigeria with two main climatic periods that comprise of the rainy season which last from April to September and the dry season lasts from October to March (Enelwechi, 2017). The effect of climate change has varied the beginning and cessation of these two seasons in the state (Okoyeh et al., 2014). Heavy and abundant rainfall usually accompany the rainy season with annual rainfall ranging from 1400 mm in the northern part to about 2500 mm in the Southern part (Fagbohun et al., 2017). The state has major surface waters which include springs, lakes, streams, and major rivers such as the southward-flowing Niger River that drains into the Atlantic Ocean, and the Anambra River that drains into the Niger River (Egboka and Okoyeh, 2019; Okoyeh et al., 2014). The State has an annual average temperature that ranges from 20.78 °C to 30.24 °C, with a relative humidity that ranges from 34% annual minimum during the dry season to 89% maximum during the rainy season (Chukwuma et al., 2021 ). Topographically, the state has two major landforms consisting of the high-lying regions which are located in the southern part, and the low-lying regions which are located in the western, northern, and northeastern parts of the state (Okoyeh et al., 2014). The State is predominantly a low-lying region with elevation ranging from 13 – 388 m above sea level.

3. Materials and method

This section describes the process and method employed to determine the vulnerability of the study area to flood hazards. The methodological flowchart in Figure 2 shows the various steps that were used to achieve the aim of this study. Seven conditioning factors were considered for the purpose of this study and they include Rainfall Intensity (C1), Soil (C2), Land Use (C3), Drainage Distance (C4), Drainage Density (C5), Slope (C6) and Elevation (C7). GIS was employed to delineate the thematic

Figure 1. Map of the Study Area. (a) Map showing the Study Area within the African Continent; (b) Map showing Nigeria; (c) Map of the Study Area and the Local Government Areas (LGAs) within.
map layers of the conditioning factors. The IVFRN-DEMATEL-ANP model was used to evaluate their degree of influence in causing floods and their final weight. Based on their final weight, the conditioning factors were integrated into the GIS environment using the Weighted Linear Combination (WLC) method to obtain the flood vulnerability map.

3.1. Data management software

MATLAB software was used in carrying out all the matrix operations used in determining the total relationship between the conditioning factors and their final weights. Microsoft Excel was used for tabular computations to calculate the rainfall intensity of the study area based on the Modified Fourier’s Index (MFI). ArcGIS 10 software was used to perform all the GIS operations such as the delineation of thematic map layers for the various conditioning factors and their integration to obtain final vulnerability map.

3.2. Data acquisition and processing

Shuttle Radar Topography Mission (SRTM) satellite imagery of the study area was obtained from the United States Geological Survey (USGS) website. The data was used to delineate the slope, elevation and stream network of the study area using surface, 3D analyst tool and hydrology analysis tool respectively in ArcGIS software. The delineated stream network was processed further to obtain the drainage density and drainage distance using the line density tool and spatial analysis tool respectively. Soil data were extracted from the Harmonized World Soil Database (HWSD) by Food Agriculture Organization (FAO). The data was geo-referenced, digitized and then converted to a raster format. The average monthly data of seven locations within the study area were acquired from World Bank’s climate database for the period of 115 years (1901–2016). The obtained data was transferred to the Microsoft Excel spreadsheet and the rainfall intensity was calculated using MFI as shown in Eq. (1).

\[
MFI = \frac{\sum_{i=1}^{12} P_i^2}{P}
\]

where \(P_i\) is the average for i-th month and \(P\) is the annual average rainfall (Kanani-Sadat et al., 2019). The calculated rainfall intensity was then imported in the ArcGIS environment and interpolated using the Inverse Distance Weighting method to generate the spatial distribution of rainfall intensity over the study area. Three Landsat 8 Operational Land Imager (OLI) imageries covering the study area was acquired from the United State Geological Survey (USGS) website (See Table 1 below). The three imageries were mosaic, clipped and classified using supervised classification to generate the landuse and landcover map of the study area.

| Table 1. Landsat Images obtained for the study. |
|-----------------------------------------------|
| Landsat satellite | Date | Path/row |
| Landsat 8 OLI/TIRS | 27 December 2018 | 188/56 |
| Landsat 8 OLI/TIRS | 1 February 2018 | 189/55 |
| Landsat 8 OLI/TIRS | 1 February 2018 | 189/56 |
The soil and land use thematic layers (factors) were reclassified and all factors were put into a fuzzy membership class based on their influence on flood occurrence (See Table 2). This was done to create conformity among the factors and provide a basis for their integration. The fuzzy membership tool in ArcGIS was used to create a fuzzy membership class for the criteria using the Fuzzy Large and Fuzzy MS Small for the analysis. The Fuzzy Large function is used when high input values of a particular factor is the most likely to induce flooding, while the Fuzzy MS Small function is used when small input values of a particular factor is most likely to induce flooding (Okonufua et al., 2019). They are defined based on specified mean and standard deviation with values of criteria that enhance flooding set as 1 and those that do not support flooding set as 0 (Okonufua et al., 2019).

3.3. Flood model

The proposed model in this work is based on the GIS MCDM structure, taking advantage of the use of GIS to manage geospatial data and the flexibility of MCDM to integrate spatial information such as land cover, slope, and elevation, with value-based information such as standards, surveys, etc (Hategekimana et al., 2018; Wang et al., 2019). The model employs the integration of the IVFRN, DEMATEL, and ANP methods to calculate the weight of the conditioning factors. In the first step, the IVFRN-DEMATEL method is used to create a relationship network between the flood conditioning factors and determine their degree of influence in the system. The second step involves the use of the DEMATEL output to calculate the final weight of the criteria based on the ANP method. In the final step, a combination of the factors with GIS is used to prepare and present a spatial model of the flood risk in the area. This section goes further to describe the three methods integrated and their order of integration.

3.4. IVFRN

The IVFRN is a new method for dealing with uncertainties and imprecision in decision making and it depends on the internal knowledge from the data, using objective indeterminacy without depending on models of any assumption to make decision making possible (Pamucar et al., 2019). This approach combines both the benefit of the fuzzy set and the rough number set and this combination helps to eliminate the drawbacks of both the traditional fuzzy sets and interval-valued fuzzy sets (Roy et al., 2019). The IVFRN method generally involves the definition on an initial reference fuzzy set through which the uncertainty in MCDM is described and the use of rough sets after the definition to measure the uncertainties that exist in the evaluations of the decision-makers (Pamucar et al., 2018). In other words, this method uses border approximation areas to define borders (Deveci et al., 2020). The basic logic of the IVFRN method is a representation of the actual data.

3.5. Preliminary

We will define a fuzzy set as a set of ordered pairs $A = \{(x, (\mu(x))) \mid x \in X, 0 \leq \mu(x) \leq 1\}$ which is described by means of a triangular membership function. Then we can represent fuzzy number $A$ as $A = (a_1, a_2, a_3)$, where $a_1$ and $a_2$ respectively represent the left and right limits of the interval of fuzzy number $A$, and $a_2$ represents the modal value (see Figure 3 above).

We assume that $U$ universe contains all of the objects and let $Y$ be an arbitrary object from $U$. We assume there is a set of $k$ classes which represent the preferences of the Decision Maker, $G^* = (A_1, A_2, ..., A_k)$, with the condition that they belong to a series which satisfies the condition $A_1 < A_2 < ... < A_k$. All objects are defined in the universe and connected with the preferences of the Decision Maker. Each element $A_i = (1 \leq i \leq k)$ represents a fuzzy number that is defined as $A_i = (a_{i1}, a_{i2}, a_{i3})$. Since element $A_i$ from the class of objects $G^*$ is represented as fuzzy number $A_i = (a_{i1}, a_{i2}, a_{i3})$, for each value $a_{i1}$, $a_{i2}$ and $a_{i3}$ we obtain one object that is represented in the interval $I(a_{i1}) = (l_{i1}, l_{i2}, l_{i3}) = (a_{i1} - 1, a_{i1}, a_{i1} + 1)$ where the condition is fulfilled that $I(a_{i1}) \frac{1}{2} I(a_{i3}) = (q_{i1}, q_{i2}, q_{i3}) = (a_{i1} - 1, a_{i1}, a_{i1} - 0.5)$, as well as the condition $l_{i3} < a_{i1} < l_{i2}$.

If both limits of the classes of objects (upper and lower limits) respectively are compared so that $l_{i1} < l_{i2} < ... < l_{i3}$, then for any of the classes of objects $I(a_{i1})_q = (a_{i1} - 1, a_{i1}, a_{i1} + 1)$ and $I(a_{i3})_q$ we can define the lower approximation $I(a_{i1})_q$ using the following equations:

![Figure 3. Type 1 fuzzy number.](image-url)
cause and effect factors, thus providing a better understanding of the relationship between the level of the structure and strength of influence of a factor (Pamucar et al., 2017).

### 3.7. ANP

The ANP method was proposed in 1996 by Saaty (Mirhosseini et al., 2020). It is basically a generalization of the AHP method, where decision-making problems are modelled as networks and not as hierarchies as with the AHP (Kadoic et al., 2019). The ANP uses a feedback-based system to model the problem and does not depend entirely on a hierarchical structure to address the problem (Hatefi and Tamosaitiene, 2019). The ANP involves the use of matrices called supermatrices to describe the dependencies of the factors and these supermatrices must follow the column stochastic principle which states that the sum of elements in each column must be equal to 1 (Pamucar et al., 2017).

### 3.8. IVFRN-DEMATEL integration

In order to handle the imprecision, vagueness and uncertainty of judgments for the group decision-making process, this study integrates the IVFRN with the traditional DEMATEL method. This integration can provide a network of relationships between the factors and the steps taken to achieve this are shown as follows:

#### Step 1: Acquiring the IVFRN-based Direct Relation Matrix

First of all, experts provide a bundle of pairwise comparison between each two distinct criteria. \( \hat{A}_k \) is a triangular fuzzy number where \( k \) denotes the number of corresponding experts in which \( k = 1, \ldots, N \). The judgment of \( k \)-th expert about the influence of \( i \)-th criterion on \( j \)-th one is \( \hat{A}_k^{ij} \). Questionnaires were distributed to 4 experts with considerable years of experience in flood modeling and their opinion about the influence of each criterion on the other was gathered based on a predefined fuzzy scale as shown in Table 3.

We use Eqs. (2), (3), (4), (5), (6), (7), and (8) to transform each triangular fuzzy number \( \hat{A}_k^{ij} \); \( \hat{A}_k^{ij} \) into rough sequences \( RN(\hat{A}_k^{ij}) \), \( RN(\hat{A}_k^{ij}) \).

#### Step 2: Acquiring the IVFRN-based Indirect Relation Matrix

Firstly, the ANP is used to calculate the indirect influence of each criterion and for this purpose, a supermatrix of the ANP is calculated where each element of the supermatrix represents the indirect influence of one criterion on another.

#### Step 3: Data Aggregation

After calculating the ANP data, these data are aggregated with the direct influence data, the bivariate influence is calculated which consists of both direct and indirect influence. For this purpose, the supermatrix of the ANP is multiplied by the supermatrix of the DEMATEL method and the final supermatrix is the aggregation of both methods.

#### Step 4: Correction of the Aggregated Matrix

The final aggregated supermatrix is corrected to ensure the sum of each row is equal to 1. This correction is done by normalizing each row of the supermatrix.

#### Step 5: Identifying the Influential Factors

Finally, the influential factors are identified by the column-wise sum of the supermatrix. The factors with a high column-wise sum are considered to be the influential factors.
\[
RN(t_k) = RN\left(\frac{z_1, z_2, \ldots, z_K}{1} \right) = \frac{1}{m} \sum_{k=1}^{m} z_k
\]

where \( k \) represents the \( k \)-th expert (\( k = 1, 2, \ldots, n \)), \( RN(t_0), \ RN(t_k) \) and \( RN(t_j) \) represent the rough sequences that together make up IVFRN \( d_0 = (t_0, t_j, \tilde{t}_j, \tilde{t}_j), \tilde{t}_j, \tilde{t}_j, \tilde{t}_j) \). Hence we obtain the initial decision matrix \( D \) as

\[
D = \begin{bmatrix}
d_{11} & d_{12} & \cdots & d_{1n} \\
d_{21} & d_{22} & \cdots & d_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
d_{n1} & d_{n2} & \cdots & d_{nn}
\end{bmatrix}_{n \times n}
\]  

Step 2: Defuzzify the Initial Decision Matrix

As recommended by Kanani-Sadat et al. (2019), it is necessary to defuzzify values in order to understand the relationship between the criteria. Hence we defuzzify \( D \) using the score function for IVFRN as shown below to obtain the matrix \( D' \).

\[
[D'_0] = \left(1 + \frac{\tilde{t}_j + \tilde{t}_j}{2}\right) \times \frac{\tilde{t}_j + \tilde{t}_j + 2\tilde{t}_j + \tilde{t}_j + \tilde{t}_j}{8}
\]  

\[
D' = \begin{bmatrix}
D'_{11} & D'_{12} & \cdots & D'_{1n} \\
D'_{21} & D'_{22} & \cdots & D'_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
D'_{n1} & D'_{n2} & \cdots & D'_{nn}
\end{bmatrix}_{n \times n}
\]

Step 3: Calculate the Normalized Direct Relation Matrix

By normalizing the elements of the defuzzified initial matrix \( D' \), we obtain normalized matrix \( \tilde{Z} \) given as

\[
\tilde{Z} = \begin{bmatrix}
\tilde{z}_{11} & \tilde{z}_{12} & \cdots & \tilde{z}_{1n} \\
\tilde{z}_{21} & \tilde{z}_{22} & \cdots & \tilde{z}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{z}_{n1} & \tilde{z}_{n2} & \cdots & \tilde{z}_{nn}
\end{bmatrix}_{n \times n}
\]

Elements \( \tilde{z}_{ij} \) of the normalized matrix \( \tilde{Z} \) are obtained using Eqs. (15) and (16).

\[
\tilde{z}_{ij} = \frac{D'_{ij}}{\lambda}
\]

where \( \lambda \) is defined as

\[
\lambda = \max_{1 \leq i \leq n} \left( \min_{1 \leq j \leq n} D'_{ij} \right)
\]

Step 4: Obtain the Total Relation Matrix

The total-relation matrix \( \tilde{T} \) which illustrates the direct/indirect relationships of the criteria can be calculated using Eqs. (17) and (18). In this equation, \( I \) is Identity matrix.

\[
\tilde{T} = \begin{bmatrix}
\tilde{t}_{11} & \tilde{t}_{12} & \cdots & \tilde{t}_{1n} \\
\tilde{t}_{21} & \tilde{t}_{22} & \cdots & \tilde{t}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{t}_{n1} & \tilde{t}_{n2} & \cdots & \tilde{t}_{nn}
\end{bmatrix}_{n \times n}
\]

The values \( \tilde{R} + \tilde{D} \) and \( \tilde{R} - \tilde{D} \) are used to illustrate the importance of the criteria and understand the causal relationship between criteria. \( \tilde{R} + \tilde{D} \) indicates the degree of influence \( i \)-th criterion on the remaining criteria and as such indicates its importance in the problem. \( \tilde{R} - \tilde{D} \) indicates the influence of the criteria in the system, with a positive value indicating that the \( i \)-th criterion is an effective criterion and falls into the category of “causes”. Also, a negative value of \( \tilde{R} - \tilde{D} \) shows that \( i \)-th criterion will be under the influence of others and fall into the category of “effects”. Criteria with a high value of \( \tilde{R} - \tilde{D} \) have higher priority, while those with low values have a lower priority.

3.9. IVFRN-DEMATEL-ANP integration

We apply the ANP method to obtain the final weight of the criteria using the total relationship matrix \( \tilde{T} \) which was obtained from the IVFRN-DEMATEL integration, as our input value. The use of ANP to calculate the relative weights of criteria ensures that the interdependence levels of factors are treated as reciprocal values (Wang et al., 2019). The integration of the three methods (IVFRN, DEMATEL and ANP) is a novel approach and the steps taken to achieve this objective are shown below.

Step 1: Creating an Unweighted Super-Matrix

Here we obtain the unweighted super-matrix from the matrix \( \tilde{T} \). Before creating the unweighted super-matrix, it is also necessary to define a network model for the ANP method based on the total relation matrix and CER diagram. First of all, we define the \( \alpha \)-cut threshold to filter out the minor influences from \( \tilde{T} \). The \( \alpha \)-cut threshold is defined by experts and a general schema of \( \alpha \)-cut total-relation matrix \( T_{\alpha} \) is shown in Eq. (21).

\[
\tilde{t}_{ij} = \tilde{z}_{ij} \times \left( I - \tilde{z}_{ij} \right)^{-1}
\]

Step 5: Obtain the Values of \( \tilde{R} + \tilde{D} \) and \( \tilde{R} - \tilde{D} \)

The matrix \( T^\alpha \) gives us our unweighted super-matrix. Step 2: Obtaining a Weighted Super-Matrix

A weighted super-matrix is created when the total relation matrix \( T^\alpha \) is normalized. To normalize the matrix, it is necessary to determine the sum of elements of the matrix by columns. Once \( T^\alpha \) has been created, its normalization yields the weighted super-matrix \( W \) and the equation is shown below:
weights, such as limit function was used to fuzzify the rainfall intensity numeric values before fuzzification. The weighted super-matrix has converged and become a long-term stable super-matrix obtained from the normalized matrix \( W^n \), where \( W \) denotes the limit super-matrix and \( k \) denotes any number. Then finally, after calculating their weight coefficients, we aggregated the criteria (Wang et al., 2019).

3.10. Final vulnerability map

To obtain the flood vulnerability map, the weighted linear combination method was used to aggregate the various conditioning factors based on their individual weights. The weighted linear combination equation is shown below

\[
VI = \sum_{i=1}^{n} W_i C_i
\]

where \( VI \) is the vulnerability index, \( W_i \) is the weight of each criterion and \( C_i \) is the relevant score of each criterion (in this study, the fuzzified map layer). The final vulnerability index map produced was then classified into five distinct categories of “very high”, “high”, “medium”, “low” and “very low”.

4. Results

4.1. Conditioning factors

The selection of the conditioning factors (criteria) for this study was based on literature review, expert opinion and available data for the study area. As earlier mentioned, seven conditioning factors were considered for the purpose of this study. The various data required for this study were collected and processed in the GIS environment to obtain thematic layers of the conditioning factors. The rainfall data of the study area was used to calculate and delineate the rainfall intensity factor map. The soil data of the study area was used to delineate the soil factor map. The Landsat Imagery of the study area was classed to obtain the Drainage Distance, Drainage Density, Slope and Elevation factor maps. The obtained thematic layers of the various factors were further normalized to create a basis for their comparison and to facilitate the interpretation of data.

The defuzzified values of the initial decision matrix was normalized using Eqs. (16), (17), and (18) to obtain the matrix \( \tilde{D} \). Using Eqs. (19) and (20), the total relation matrix \( \tilde{D} \) (see Table 5 below), which illustrates all direct/indirect relationships between the conditioning factors was obtained from the normalized matrix \( \tilde{D} \).

The rows \( \tilde{R} \) and the columns \( \tilde{D} \) of the matrix \( \tilde{D} \) were calculated as shown in Table 6 to examine the impact of each conditioning factor and their role in flood occurrence.

The values of total direct and indirect effects that each conditioning factor received from other conditioning factors and transferred to others was obtained (see Table 6) using Eqs. (21) and (22). These values were used to visualize the complicated causal relationship of the conditioning factors by creating the CER diagram (see Figure 5 below), where \( \tilde{R} + \tilde{D} \) represents the x axis and \( \tilde{R} – \tilde{D} \) represents the y axis.

The obtained values of \( \tilde{R} – \tilde{D} \) show that Rainfall Intensity, Land Use and Drainage Distance fall in the cause group while Soil, Drainage Density, Slope and Elevation are influenced by other conditioning factors and fall into the effect group. Rainfall Intensity is the major cause with the highest positive value of 1.55 and Soil is the major effect with the highest negative value of -0.93. This indicates that the intensity of rainfall has the most influence on other factors while soil is the most influenced by other factors. This is corroborated by the fact that the study area experiences heavy rainfall which range from 1400mm to 2500mm annually.
Figure 4. Fuzzified maps of conditioning factors. (a) Rainfall intensity; (b) soil; (c) landuse; (d) drainage distance; (e) drainage density; (f) slope; (g) elevation.
4.4. Determination of final weights of conditioning factors

The ANP method was used to determine the final weights of the conditioning factors. The total relation matrix obtained from the DEMATEL method was used as the input data. Minor dependencies from the matrix $T$ was filtered out to obtain our unweighted super-matrix and to achieve this, experts opinion about the optimum threshold was obtained and averaged to arrive at an a threshold value of 0.02. The threshold value was used to filter out only the minor influences from $T$, hence we obtained the matrix $T'$. The matrix $T'$ was then normalized to produce the weighted super-matrix $W$ (see Table 7).

| Table 7. Weighted super-matrix. |
|----------------------------------|
| $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|------|------|------|------|------|------|------|
| 0.2817 | 0.2113 | 0.2079 | 0.1832 | 0.2113 | 0.1947 | 0.2317 |
| 0.0000 | 0.0868 | 0.1337 | 0.1139 | 0.1321 | 0.1150 | 0.1220 |
| 0.3803 | 0.1660 | 0.1089 | 0.1584 | 0.1434 | 0.1372 | 0.1524 |
| 0.3380 | 0.1509 | 0.1535 | 0.1238 | 0.1623 | 0.2035 | 0.2073 |
| 0.0000 | 0.1283 | 0.1337 | 0.1436 | 0.0868 | 0.1150 | 0.1341 |
| 0.0000 | 0.1396 | 0.1485 | 0.1485 | 0.1660 | 0.1018 | 0.1524 |
| 0.0000 | 0.1170 | 0.1139 | 0.1287 | 0.0981 | 0.1327 | 0.0000 |

Then finally, the weighted super-matrix $W$ was limited by raising it to power 25 to produce convergent values and these values represent the final weights of the conditioning factors as shown in Table 8.

The results above show that Rainfall Intensity has the highest priority with a final weight of 0.2204, followed by Drainage Distance, Land Use, Slope, Drainage Density, Soil and Elevation with final weights of 0.1989, 0.1941, 0.1118, 0.0990, 0.0927, 0.0831 respectively. This indicates that rainfall intensity, drainage distance, land use and slope are the most important conditioning factors for modeling flood vulnerability in the study area and the mapping of areas vulnerable to flood is highly dependent on these four factors. The result also shows that the effect of drainage density, soil and elevation is less in flood hazard occurrence.

4.5. Production of flood vulnerability map

Anambra State experiences yearly episodes of flood hazard which has destroyed several lives and properties over the years. As such there is need for adequate flood risk management practices in the state to mitigate the adverse effects of this hazard. A proper flood vulnerability map is a very essential tool in flood risk management for effective planning and implementation of resilient measures. Flood hazard is a complex phenomenon that is dependent on several conditioning factors (Das and Gupta, 2021). To overcome the complexities which exist between the various factors that influence the occurrence of flood hazard, the IVFRN-DEMATEL-ANP model was employed in determining their individual weight.

The weighted linear combination method was used to integrate the various conditioning factors to obtain the flood vulnerability map. The fuzzified layers of the various conditioning factors were integrated in the GIS environment using the raster calculator function. The final vulnerability index map produced was then be classified into five distinct categories of “very high”, “high”, “medium”, “low” and “very low” using the classification methods of “Natural Breaks”. The flood vulnerability map is shown in Figure 6. The study area covers an area of about 4559 sq km. 351.80 sq km, which represent 8% of the study area lie in the very low vulnerable zone, 874.60 sq km (19%) lie in the low vulnerable zone, 1354.49 sq km (30%) lie in the medium vulnerable zones, 1195.96 sq km (26%) lie in the high vulnerable zones and 781.85 sq km (17%) lie in the very high vulnerable zone. The high vulnerability to flood hazard observed in the study area can be mainly attributed to heavy rainfall recorded in the area and the location of various waterbodies within and the environment such as textile waste has also increased the soil erosion and flooding tendency. By implication this can also be attributed to the increased urbanization of the area. The percentage flooded area can be classified as very low vulnerability, low vulnerability, medium vulnerability, high vulnerability and very high vulnerability. Out of the total area, 8% (351.80 sq km) lie in the very low vulnerability zone, 19% (874.60 sq km) lie in the low vulnerability zone, 30% (1354.49 sq km) lie in the medium vulnerability zones, 26% (1195.96 sq km) lie in the high vulnerability zones and 17% (781.85 sq km) lie in the very high vulnerability zone. This can be expressed in the following equation:

$$V = \sum_{i=1}^{n} w_i \times x_i$$

where $V$ represents the flood vulnerability index, $w_i$ is the weight of the ith conditioning factor, and $x_i$ is the score of the ith conditioning factor.
around the study area. The flood vulnerability map also shows that based on land mass, the most vulnerable LGA is Anambra West with 700.53 sq km which represents 95% of the total Anambra West area lying in Very High, High and Medium Vulnerable zones. Anambra West experiences high annual rainfall and is in very close proximity to major rivers such as the Anambra River and the River Niger. These two factors amongst other factors trigger flood hazard as intense rainfall events potentially lead to extreme river overflows (Eccles et al., 2019). Other notable LGAs which are vulnerable to flood hazard include Ogbaru, Ayamelum, Anambra East, and Ihiala.

4.6. Validation of flood vulnerability map

Validation of a hazard vulnerability assessment model is a very essential tool in examining the probability accuracy of the resultant map. Various statistical methods have been employed over the years for the validation of hazard maps. Amongst these statistical methods, the Area Under the Curve of Receiver Operator Characteristic (AUC-ROC) is widely used for the validation of assessment models and evaluation of vulnerability map accuracy (Kanani-Sadat et al., 2019). Hence, this study employed the AUC-ROC method to validate the IVFRN-DEMATEL-ANP model and examine the accuracy of our resultant vulnerability map. The AUC is a calculated synthetic index for ROC curves which determines the probability that an event classified as positive by the test is actually positive considering all the possible values of the test (Wang et al., 2019). The quantitative-qualitative relationship which exists between AUC and prediction rate is given as follows: unsatisfactory (0.5–0.6), satisfactory (0.6–0.7), good (0.7–0.8), very good (0.8–0.9), and excellent (0.9–1) (Falah et al., 2019; Kanani-Sadat et al., 2019).

To validate the IVFRN-DEMATEL-ANP model using the AUC-ROC method, historical flood locations in the study area were obtained and used as the validation set. These locations were imported in the GIS environment and the ROC tool was used for validation. Figure 7 below shows the results of the validation. According to the results obtained from the validation, the IVFRN-DEMATEL-ANP method achieved excellent validation accuracy with an AUC value of 0.946. This shows that the IVFRN-DEMATEL-ANP model is an efficient model for assessing flood vulnerability as it eliminates uncertainty in decision making, examines the relationship between conditioning factors of flood and determines their individual weights through a network model.

5. Conclusion

This study aimed at determining the vulnerability of Anambra State to flooding by integrating GIS and the IVFRN-DEMATEL-ANP model to delineate vulnerable zones based on seven conditioning factors. The IVFRN-DEMATEL integration was able to determine the degree of influence of the conditioning factors with rainfall intensity being the major cause of flood hazard in the study area. The IVFRN-DEMATEL-ANP
model was used to determine the weights of the factors. GIS operations were used to obtain fuzzified maps of the conditioning factors which include Rainfall Intensity, Soil, Land Use, Drainage Distance, Drainage Density, Slope, and Elevation. Based on their weights, these factors were integrated in GIS environment using the weighted linear combination method to produce the vulnerability map of the study area. The result of the study shows that Anambra State is vulnerable to flooding with 73% of the state lying in the Very High, High and Medium vulnerable zones. The validation of the assessment model using the AUC-ROC method produced an AUC value of 0.946 to indicate that the model has excellent assessment accuracy. The feasibility of integrating the IVFRN, DEMATEL and ANP methods as a model for assessing flood hazard vulnerability has been proven in this study. However, it is recommended that this model’s efficiency should be evaluated in comparison to other traditional MCDM models and hybrid MCDM models. The study also revealed that Anambra state is vulnerable to flood. Consequently, stakeholders in the state need to intensify efforts towards flood mitigation and adaptation. With rainfall intensity being the major cause of flood in the study area, it is recommended that adequate drainage systems should be provided to help mitigate flood hazard in the state. In addition, people and key assets should be moved away from vulnerable areas during the rainy season.

The limitations of this study are related to the accuracy of some of these data used such as the land use map resolution, a higher resolution map's accuracy. The field based validation during a flood episode might offer an improved validation of the flood vulnerability map.

Declarations

Author contribution statement
C. C. Okonkwo: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
E. C. Chukwuma: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.
O. J. Ojediran, D. C. Anizoba, J. I. Ubah, C. P. Nwachukwu: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement
Emmanuel Chibundo Chukwuma was supported by Nigeria Academy of Engineering in partnership with Arco Petrochemical Company Limited (travel grant).

Data availability statement
Data will be made available on request.

Declaration of interests statement
The authors declare no conflict of interest.

Additional information
No additional information is available for this paper.

References
Abdel-Basset, M., Aref, A., Smaanadache, F., 2019. A hybrid neurosporphic multiple criteria group decision making approach for project selection. Cognit. Syst. Res. 57, 216–227.
Agbo, F.U., Arua, R.N., Okonkwo, E.A., 2015. Effects of climate variability on the choices of livelihood among farm households in Anambra State, Nigeria. Afr. J. Agric. Res. 10 (44), 4134–4141.
Ajargo, J.D., Okoro, N.M., Ajargo, C.K., 2016. Perception of and attitude toward mass media reportage of the 2012 flood in rural Nigeria. SAGE Open 1–8.
Akutve, T.T., Okoko-edongo, A.A., Khoda, A., 2019. Do floods affect food security? A before-and-after comparative study of flood-affected households’ food security status in South-Eastern. Bull. Geogr. Soc. Econ. Series 47, 115–131.
Ali, S.A., Parvin, F., Pham, Q.B., Vojtek, M., Vojtková, J., Costache, R., Linh, N.T.T., Stroeven, H.Q., Ahmad, S., Ghorbani, M.A., 2020. GIS-based comparative assessment of flood susceptibility mapping using hybrid multi-criteria decision-making approach, naïve Bayes tree, bivariate statistics and logistic regression: a case of Topola basin, Slovakia. Ecol. Indicat. 117, 106420.
Chukwuma, E.C., Okey-onyeola, P.C., Ani, R.A., Nwana, E.C., 2021. GIS bio-waste assessment and suitability analysis for biogas power plant: a case study of Anambra state of Nigeria. Renew. Energy 163, 1182–1194.
Girella, G.T., Iyakollame, F.O., 2018. Flooding conceptual Review: sustainability-focalized best practices in Nigeria. Appl. Sci. 8 (1558), 1–14.
Costache, R., Pham, Q.B., Sharif, E., Linh, N.T.T., Abba, S.I., Vojtek, M., Vojtková, J., Nghi, P.T.T., Khoi, D.N., 2020. Flash-flood susceptibility assessment using multi-criteria decision making and machine learning supported by remote sensing and GIS techniques. Rem. Sens. 126 (10), 1–26.
Das, S., Gupta, A., 2021. Multi-criteria decision based geospatial mapping of flood susceptibility and temporal hydro-geomorphic changes in the Subarnarekha basin, India. Geosci. Front. 12 (5), 101206.
Debortoli, N.S., Samarina, M.P., Marengo, J.A., Rodrigues, R.R., 2017. An index of Brazil’s vulnerability to expected increases in natural flash flooding and landslide disasters in the context of climate change. Nat. Hazards 86 (2), 557–582.
Deveci, M., Orcan, E., John, R., Covig, C.F., Panswar, D., 2020. A study on offshore wind farm siting criteria using a novel interval-valued fuzzy-rough based Delphi method. J. Environ. Manag. 270, 110916.
Eboh, H.C., Ezereue, A.M., Ajator, U.O., Nwosu, N.U., Odoanyanwu, N., 2017. Flooding in the Anambra East local government area and adaptation strategies in building designs. Trop. Built Environ. J. 1 (6), 70–80.
Etsozemo, O.D.F., 2015. Evaluating the effects of flooding in six communities in Awka anambra state of Nigeria. J. Environ. Earth Sci. 5 (4), 26–39.
Eyenche, R., Zhang, H., Hamilton, D., 2019. A review of the effects of climate change on riverine flooding in subtropical and tropical regions. J. Water Clim. Change 10 (4), 687–707.
Egboka, B.C.E., Okoye, E.L., 2019. Review and assessment of environmental impacts of ecological disasters on biodiversity in Anambra state, Nigeria. Biodivers. Int. 3 (2), 53–58.
Eijkeme, J.O., Igbokev, J.L., Ezremode, I.C., Aweh, D.S., Akinnoye, R., 2015. Analysis of risks and impacts of flooding with satellite remote sensing. J. Environ. Earth Sci. 5 (4), 1–9.
Emmanuel, U.A., Baywood, C.N., Gih, U.A., Ojinnaka, O.C., 2015. Flood hazard analysis and damage assessment of 2012 flood in anambra state using GIS and remote sensing approach. Am. J. Geogr. Inf. Syst. 4 (1), 38–51.
Enelwech, E.E., 2017. Effects of pollution and contamination of water bodies: a case of anambra state. Afr. J. Educ. Sci. Technol. 3 (4), 41–47.
Enete, A.A., Obi, J.N., Ozo, N., Mba, L.C., 2016. International journal of climate change strategies and management article information. Int. J. Climat Change Strateg. Manag. 8 (1), 96–111.
Ezeokoli, F.O., Okolie, K.C., Anyigbuna, A.I., 2019. The physiognomy of flooding and flood disasters in Nigeria: stakeholders’ perception of flooding events of ogbaru in anambra state. Jurr. J. Appl. Sci. Technol. 33 (6), 1–12.
Faghbouh, B.J., Olahode, O.F., Olufemi, A., Akinloyi, F.O., 2017. GIS-based sub-basin scale identification of dominant runoff processes for soil and water management in anambra state of Nigeria. Contemp. Trends Geosci. 6 (2), 80–93.
Falali, F., Rahmati, O., Kostami, M., Ahmadsharaf, E., Dalalakopos, L.N., Pourghasemi, H.R., 2019. Artificial neural networks for flood susceptibility mapping in data-scarce urban areas. In: Spatial Modeling in GIS and R for Earth and Environmental Sciences. Elsevier Inc.
Garsen, A.G., Baattrup-pedersen, A., Vosjek, L.A.C.J., Verhoeven, J.T.A., Soons, M.B., 2015. Riparian plant community responses to increased flooding: a meta-analysis. Global Change Biol. 21, 2881–2890.
Gudiyangada Nachappa, T., Tavakkoli Piraillos, S., Gholamnia, K., Ghorbanzadeh, O., Rahmati, O., Blaschke, T., 2020. Flood susceptibility mapping with machine learning, multi-criteria decision analysis and ensemble using Dempster Shafer Theory. J. Hydrod. 590, 125275.
Hathei, S.M., Tamsaitiene, J., 2019. AN integrated fuzzy dematal-fuzzy ANP model for evaluating construction projects BY considering interrelationships among risk factors. J. Civ. Eng. Manag. 25 (2), 114–131.
Hategekimana, Y., Yu, L., Nie, Y., Zhu, J., Liu, F., Guo, F., 2018. Integration of multi-parametric fuzzy analytic hierarchy process and GIS along the UNESCO World Heritage: a flood hazard index, Mombasa County, Kenya. Nat. Hazards 92 (2), 1137–1153.
Hettiarachchi, S., Wasko, C., Sharma, A., 2018. Increase in flood risk resulting from climate change in a developed urban watershed – the role of storm temporal patterns. Hydro. Earth Syst. Sci. 22, 2041–2056.
Hoque, M.A.A., Tasfia, S., Ahmed, N., Pradhan, B., 2019. Assessing spatial flood vulnerability at kalapara upazila in Bangladesh using an analytic hierarchy process. Sensors (Switzerland) 19 (6), 1–19.
Iler, M., Sanzoyl, I.O., 2013. Application of remote sensing (RS) and geographic information systems (GIS) in flood vulnerability mapping: case study of river Kudna. Int. J. Geomatics Geosci. 3 (3), 618–627.
Kadar, N., Divjak, B., Reddy, N.B., 2019. Integrating the DEMATEL with the analytic network process network for flood risk assessment. Geoen. Eur. J. Oper. Res. 7 (3), 653–678.
