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An Improved Flood Susceptibility Model for Assessing the Correlation of Flood Hazard and Property Prices using Geospatial Technology and Fuzzy-ANP

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ABSTRACT. This study proposes an integrated Geographic Information System (GIS) Fuzzy Multi-Criteria Decision Making (F-MCDM) model to assess the impacts of flood on residential property prices. Triangular Fuzzy numbers was implemented to address limitations such as uncertainty, bias and ambiguity inherent in the conventional Analytic Network Process (ANP) flood model criteria ranking thereby improving the accuracy and reliability of the susceptibility model. The developed Fuzzy-ANP's (F-ANP) pair-wise comparison technique was used to rank the relative importance of nine flood conditioning criteria based on experts' input. Utilizing GIS and re- mote sensing data and techniques on Kelantan, a perennially flooded state in Malaysia, FANP based criterion maps were generated and aggregated to produce flood susceptibility maps of the area, showing the flood vulnerability levels of different locations. A 10-year inventory of real estate prices from the National Property Information Centre (NAPIC), Malaysia was analyzed to investigate the trend in market prices of residential properties situated in the high flood probable zones highlighted by the spatial F-ANP model. Model validation results showed that 59.42% and 36.23% of past flood events fall within the very high and high susceptible locations of the susceptibility map respectively, confirming its high accuracy. A weak positive correlation also exists between the highly susceptible flood class and housing locations vs market prices. We conclude that the ensemble GIS-FANP flood susceptibility model can produce maps capable of conveying accurate risk information to a broad range of stakeholders thereby facilitating decision making. However, other factors such as supply and demand, construction cost, macro-economy and micro-economy tend to also exert some influence on real estate prices, together with location in hazard-prone areas.

Keywords: flood; fuzzy-ANP, real estate prices, GIS, RS, susceptibility

1. Introduction

Floods and other climate change-related disasters such as volcanic eruption, avalanches, earthquakes, heat waves, typhoons and hurricanes are natural catastrophes that cause economic, environmental and social discomfort, in addition to the loss of lives (Khan et al., 2014; Lawal et al., 2014a, b; Leal Filho et al., 2018, 2019; Balogun et al., 2020). Floods account for 34% of all casualties resulting from natural hazards (Below and Wallemacq, 2018). According to UN estimates, 43% of all the recorded natural hazards between 1995 and 2015 are related to flood, killing 157,000 people, and causing economic loss worth USD 662 billion (Wahlstrom and Guha-Sapir, 2015). Cumulatively, about 2.3 billion lives have been affected worldwide by floods.

Asia is one of the most vulnerable regions to the impacts of flooding (Busby et al., 2018), which is due to a variety of natural and anthropogenic factors. Several Asian countries including Malaysia, Bangladesh, Indonesia, India, Thailand, Pakistan, China, and Japan are vulnerable to flooding (Sanyal and Lu, 2004; Islam et al., 2016). According to Malaysia's Department of Irrigation and Drainage (DID), flood causes estimated damage worth about RM 915 million every year (Alias et al., 2016) with around 29,000 km^2 of the land area and over 22% of the people affected by flood annually. For instance, the flood event at Kota Bharu, Kelantan, in December 2014 led to the death of at least 21 individuals and over 200,000 people were evacuated, including children, women and aged residents (Baharuddin et al., 2015). Due to its devastating effects on infrastructure and risks posed to lives, the property market is vulnerable to the occurrence and magnitude of flood events (Properties Malaysia Investment, 2015; Aliyu et al., 2016a). Previous

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studies have examined the impacts of natural disasters on property prices. Hallstrom and Smith (2005) assessed the response of property markets to hurricane hazards while Donovan et al., (2007) looked at wildfire hazards. According to Graham et al., (1988), a significant drop in housing prices was observed immediately after the flooding event in California in 1986. More recently, Rajapaksa et al., (2017a, b) investigated the impact of flooding and flood plains on property markets. The former study concluded that proximity to environmental amenities such as river exerts more influence on property value than flood risks while the latter study found variations in the impact of flood risk on property prices, highlighting the limitations of adopting a generic approach without considering the uniqueness of each property and environmental traits. Similarly, Zhang (2016) noted that the location of residential houses within a floodplain reduces property value.

Other studies have also discovered that flooding and floodplain locations exert a negative influence on housing prices (Eves and Wilkinson, 2014; Atreya and Ferreira, 2015; Belanger and Bourdeau-Brien, 2018). However, the extent of influence varies across sub-markets and the peculiarity of the study area, particularly the environmental and climatic factors, should be taken into consideration while exploring appropriate mitigation initiatives (Rajapaksa et al., 2017b). Therefore, a reliable approach that accurately identifies locations that are highly susceptible to flood risk while accounting for differentials in environmental conditioning factors as a first step to estimating the potential impacts of flooding on housing prices is essential. Moreover, since flood risk is not constant over time, it is necessary to revise flood risk maps and plans periodically (Moel et al., 2009) in order to be well informed of current risk situations and plan adequately for possible interventions and future development.

The use of Multi-Criteria Decision Making (MCDM) models such as ANP for ranking flood conditioning factors required to produce valid flood susceptibility maps is well documented in the literature (Sun et al., 2016; Yang et al., 2018; Dano et al., 2019b; Wang et al., 2019). Similarly, ANP has been applied in many other research fields such as landslides (Gheshlaghi and Feizizadeh, 2017), earthquake (Alizadeh et al., 2018), soil erosion (SajediHosseini et al., 2018; Choubin et al., 2019), land suitability assessment (Malmir et al., 2016), housing (Hussey and Malczewski, 2018), urban transportation (Staš et al., 2015), landfill site selection (Afzali et al., 2014), solid waste management (Lami and Abastante, 2014), oil and gas (El-Abbasy et al., 2015), and sustainable tourism (Aminu et al., 2017). However, concerns have been raised regarding the accuracy of conventional MCDM techniques in quantifying decision makers' (DM) preferences regarding multiple conflicting flooding criteria. In many instances, the DM's preferences are uncertain or vague (Wang and Chen, 2010; Yang et al., 2013a; Urena et al., 2015; Alıyu et al., 2016b; Jøsang, 2016; Wang and Niu, 2019). Although classical MCDM models are generally able to handle exact and ordinary data, they face challenges managing fuzzy and vague data, which characterize flood modelling (Torfi et al., 2010; Chen et al., 2019). It has been argued that classical ANP's numerical or crisp values cannot precisely model comparison judgments in most real-world situations due to uncertainties in the human preference model (Koul and Verma, 2012). Non-consideration of some uncertainty likely to be associated with the decision makers' judgments affects the reliability of the final outcome (Balogun et al., 2015, 2017). Therefore, in this study, this limitation is addressed by implementing a Fuzzy -ANP model for handling the evaluations' uncertainty and imprecision wherein the expert's comparisons are represented as fuzzy numbers. This is due to the effectiveness of fuzzy algorithms in manipulating the vagueness in stakeholders' thinking and expressing preferences of decision makers (Chen et al., 2019).

Also, prices of houses in highly susceptible areas detected in the F-ANP flood susceptibility maps were analyzed over a 10-year period together with historical records of flood occurrences in those locations. This will provide insights on previous price responses to the occurrence of the flood as an indicator of likely responses to future flood occurrences in the most vulnerable locations. Considering that Government and Private sectors may be discouraged to invest in a cyclical flooding region, with the potential to cause stagnation in economic development, accurately identifying flood-vulnerable regions and the likely response of the property market to flooding in these regions is essential for proper city planning and development.

Based on the foregoing, this study's objectives are as follows:

I. To develop a spatial fuzzy-ANP model to accurately classify the flood susceptibility of the study area, addressing the limitations of uncertainty, imprecision and bias inherent in conventional ANP models.
II. To assess the impacts of flood susceptibility and occurrences on property prices in the study area.

2. GIS Based Fuzzy-ANP in Flood Mapping

Flood-related problems could be solved through planning studies. The use of Geospatial Information System (GIS) and Multi Criteria Decision Making (MCDM) methods can help decision makers to develop flood management measures. Broadly, flood management measures include structural and non-structural approaches. Physical structural measures are developed to mitigate the flood risk by controlling the flow of water while the flexible and comprehensive non-structural measures will protect people from flood through better township management. The combination of both measures is essential to minimize the impact of floods. Flood mapping is one of the nonstructural measures and it is important for sustianble city planning (Chan, 2015). The outcome of the geospatial analysis can be used for various applications such as disaster management and mitigation, land information system and planning, and environmental impact analysis. However, GIS alone is not sufficient to make complex decisions for challenges involving numerous criteria, goals and alternatives related to flooding (Lawal et al., 2011). Therefore, to enhance GIS spatial analysis, a range of Multi-Criteria Decision Making (MCDM) methods are being adopted as a decision-making support tool (Aminu et al., 2014; Ghorbanzadeh et al., 2018). The MCDM methods are complex decision-making tools capable of handling qualitative and quantitative factors that aid decision-making based on stake-holders' preferences. The purpose of integrating MCDA with GIS is to enhance the quality of decision making through transparency, explicit input, data standardization, criteria weighting and aggregation (de Brito and Evers, 2016; de Brito et al., 2018). The MCDM comprises different techniques such as analytical network process (ANP) and analytical hierarchy process (AHP). In this study, fuzzy-analytical network process (F-ANP) model, which is an improvement of the conventional ANP model, was integrated with the GIS to identify the flood susceptible areas in the study area.

The ANP is a sophisticated MCDM model designed as a generalization of the original AHP model (Aminu et al., 2014; Ghorbanzadeh et al., 2018). Different from the AHP, the ANP method would model the decision-making problems into nonlinear networks and consider the interdependency between elements and alternatives (Dano et al., 2019a) thereby minimizing some shortcomings of the conventional AHP (Kadoić et al., 2017). Defining a proper network relationship between factors is crucial as complicated spatial problems like flooding require consideration of quantitative and qualitative criteria. This will help produce a precise criterion weightage computation which is essential for developing an accurate susceptibility map. Despite its merits, ANP is unable to manage the uncertainties related to the expert-based criteria ranking and the evaluation of the decision maker's perception (Yang et al., 2013b; Abedi and Feizizadeh, 2017). Thus, fuzzy logic algorithms are being integrated with the ANP to minimize uncertainty and bias in stakeholders' criteria preference rankings. F-ANP has been used to assist DM's in proper site selection (Wu et al., 2018), accurate criteria weighting of aviation fuel evaluation (Chen and Ren, 2018), assessment of watershed health (Alilou et al., 2019) and wind power evaluation (Wang and Niu, 2019). However, there are limited attempts to utilize the enhanced criteria weighting strengths of F-ANP for flood susceptibility mapping in the literature (Azareh et al., 2019; Darabi et al., 2019).

3. Study Area Characteristics

Figure 1 shows the study area, Kelantan, in Peninsular Ma-
Figure 1 shows the study area, Kelantan, in Peninsular Malaysia. Kelantan is a state located at the northeast coast of Peninsular Malaysia. Its geographical coordinates are 6.12 °North & 102.25 °East. The total population of the study area is approximately 1,860,000 with a total area of 15,101 km^2 based on records from the Department of Statistics Malaysia. The capital city of Kelantan is Kota Bharu (Khan et al., 2014). Kelantan is surrounded by Thailand, Pahang and Perak. The rainy season of the study area falls in the months of June to December. November is the wettest month of the state due to the northeast monsoon and the rainfall precipitation for November and December is significantly higher compared to the other months (World Weather Online, 2018). The Kelantan River is a river extending 248 km long and drains an area of 13,100 km^2. The Kelantan River Basin in the study area occupies approximately 85% of the state (Ibrahim et al., 2017; Pour and Hashim, 2017). The river basin is composed of a flat slope to moderately sloping area in the northern part, and steep scraps and high slopes in the southern part of the river basin. Historically, Kelantan has been a flood-prone state due to its geographical characteristic, unplanned urbanization and proximity to the South China Sea (Khan et al., 2014).

The topography of the state is divided into mountainous areas, hilly areas, plain areas and coastal areas. The rain distribution of Kelantan is influenced by the northeast monsoon between November to March, exposing it to high rainfalls. As a result of high rainfall accompanied by high runoff due to urbanization and reduced river capacity, the flood frequency and magnitude has increased drastically over the years.

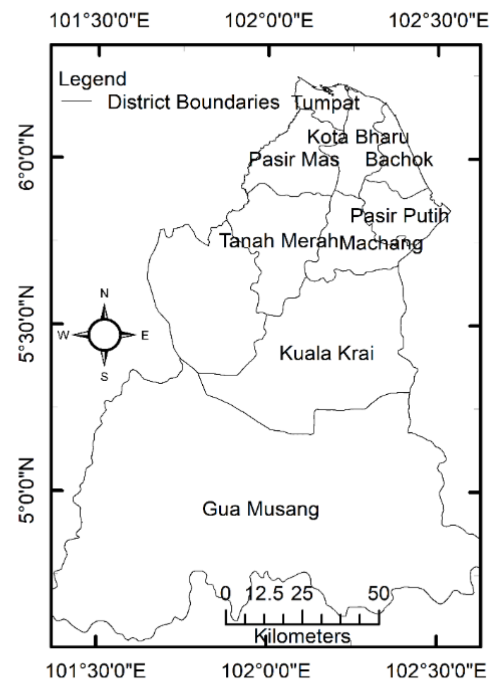

Figure 1. Map of Kelantan Showing Different Districts.

The surface geology in Kelantan is classified into 4 types, which are granitic rocks, sedimentary/metasedimentary rocks, volcanic rocks and unconsolidated deposits. Granitic rocks are found at the West (the Main Range Granite) and East Borders (the Boundary Range Granite). The Main Range Granite is located at the southwest of the state, which stretches along Kelantan to the boundary of the neighbouring states, Perak and Pahang, and Thailand. The Boundary Range Granite located at the East part of the location stretches along the Kelantan East boundary to Terengganu State. The Quaternary deposits found in coastal areas at the northern Part of Kelantan consists of alluvium deposits or unconsolidated sediments. Other sedimentary rocks such as siliciclastics, volcaniclastics, sandstones and limestones are found in the middle part of the Kelantan State. The highest point in Kelantan is found to be the Mount Chama (2,171 m), which is in the Gua Musang District, the Western part of Kelantan (Pour and Hashim, 2017).

Table 1. Data Sources for This Study

Data	Source
Boundary map	DIVA-GIS (An open source data platform that provides free spatial data)
Precipitation	Department of Irrigation and Drainage (DID), Malaysia
Rainfall stations	Department of Irrigation and Drainage (DID), Malaysia
Runoff	Derived from Precipitation map using empirical equations (Quenzer and Maidment, 1998)
Slope angle	Derived from DEM using spatial tools
Flow accumulation	Derived from DEM using spatial tools
SPI	Derived using raster calculator (Abdou et al., 2017)
TWI	Derived using raster calculator (Pourali et al., 2016)
Elevation	Digital Elevation Model (DEM) from United States Geological Survey (USGS)
Land use	RS Image classification referring to Pour and Hashim (2017)
Rivers in Kelantan	DIVA-GIS (An open source data platform that provides free spatial data)
Soil types	Modified from Department of Minerals and Geoscience, Malaysia

4. Data and Methodology

4.1. Data

Considering the peculiarity of the study area and pertinent information from literature, eight main flood conditioning factors were selected for this study (Pradhan, 2010; Lawal et al., 2012; Matori et al., 2014; Tehrany et al., 2019): elevation, slope angle, Stream Power Index (SPI), Topographic Wetness Index (TWI), distance from streams, runoff, land use, and soil types.

Spatial data were sourced from relevant agencies and used to develop the database for the study. LANDSAT 8 satellite images were used for extraction of land use layer. The images were imported into the GIS environment and geo-referenced. Attribute data such as the monthly rainfall of the study area was also input into GIS as part of the database development procedure. Table 1 shows the study's data inventory.

The flood conditioning factors (See Supporting Information Figures S1(a) ~ S1(i)) were modelled using the ArcGIS 10.4 software. Details of the modelling procedure are presented below.

The runoff layer was produced from precipitation map using empirical Equations (1) ~ (4) (Tehrany et al., 2014):

$$Q_{agriculture} = 0.008312e^{0.011415P} \tag{1}$$

$$Q_{forest} = 0.0053e^{0.010993P} \tag{2}$$

$$Q_{urban} = 0.24P \tag{3}$$

$$Q_{water} = 0 \tag{4}$$

where Q = runoff (mm/year), and P = rainfall (mm/year).

The maximum rainfall for every rainfall station is used to produce the precipitation map. The precipitation of areas between rainfall stations was interpolated using the ArcGIS software Kriging tool. Figure S1a (See Supporting Information) shows the precipitation layer from Kriging interpolation, while Figure S1b (See Supporting Information) shows the generated runoff data layer.

The slope angle map was produced using ArcGIS' slope tool. The elevation values for the cells are extracted from the DEM raster layer. Kelantan's slope angle map is shown in Figure S1c (See Supporting information).

SPI represents the power of water flow in terms of erosion and it is used to assess the flood risks by estimating the sediment transfer rate in basin hydrology (Abdou et al., 2017). Similarly, TWI identifies wet areas that are highly susceptible to overland flood. Higher TWI indicates higher likelihood of water puddles and it is often found at locations with mild slope. In contrast, locations with steep slopes will have lower TWI, indicating lesser likelihood of water puddles (Pourali et al., 2016; Riadi et al., 2018). The TWI and SPI layers (Figure S1d and Figure S1e in the supporting information) were produced using Equations (5) and (6) (Pourali et al., 2016; Abdou et al., 2017):

$$TWI = \ln\left(\frac{a}{\tan\beta + 0.01}\right) \tag{5}$$

$$SPI = \ln\left(\left(\alpha + 0.001\right) \times \left(\frac{\beta}{100} + 0.01\right)\right) \tag{6}$$

where α = flow accumulation, and β = slope angle in degrees.

DEM obtained from the United States Geological Survey (USGS) was used to extract the elevation of the study area (Figure S1f). As water flows from higher to lower elevations, the areas located at the lower elevation have higher susceptibility to flood occurrence than the areas located at higher elevation (Chapi et al., 2017).

The change of land use and land cover affects the earth's hydrological processes. Impermeable land surfaces enlarge rapidly with urban land development, decreasing the rainfall retention capability and increasing the runoff coefficient (Shi et al., 2007). The Land Use layer was generated using ArcGIS' Maximum Likelihood Classification. Landsat 8 satellite images obtained from USGS were analysed using seven spectral bands for the classification of the study area. Figure S1g shows the classified land use layer.

The flood susceptibility of an area increases with proximity

Table 2. Scale of Relative Importance (Adapted from Dano et al., 2019)

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favour one activity over another
5	Strong importance	Experience and judgment strongly favour one activity over another
7	Very strong importance	Experience and judgment favoured very strongly over another; its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between adjacent scale values	When compromise is needed
Reciprocals of the above	If activity I has one of the above nonzero numbers assigned to it when compared with activity *j*, the j has the reciprocal value when compared with *i*	

to streams (floodplains) and decreases when the area is located further from the streams (floodplains). The distance of each cell (area) in the raster layer to the closest drainage was computed using ArcGIS' Euclidean Distance tool. Figure S1h (Supporting information) shows the distance from streams map. The study area is classified into four distinct soil types (Figure S1i of the Supporting information): alluvial, granite, limestone, and shale/sandstone.

4.2. ANP Model Using Expert Opinion Survey

An ANP questionnaire was designed to prioritize the influence of the nine diverse factors, which will be evaluated to produce an accurate flood susceptibility map. The questionnaire was designed systematically to identify the interaction, relationship, relative comparison and feedback among the criteria. This is implemented using pair wise comparison technique that compares two criteria at a time, similar to previous studies on GIS-based ANP for suitability analysis (Aminu et al., 2014; Dano et al., 2019b). The questionnaires were initially distributed to 4 experts and follow up interviews were conducted to ensure that all the respondents properly comprehend the contents of the questionnaire, without ambiguity. In such expert-based surveys, the judgment of a single expert suffices (Saaty and Sagir, 2009), however considering more than one expert minimizes bias in the computation of the conditioning factors' priorities (Ishizaka and Labib, 2011).

The respondents, with competencies in diverse backgrounds including hydrology, geomatics and disaster management were selected based on their expertise on the subject matter, experience and knowledge of the study area. Their opinions were quantified using Saaty's fundamental scale of judgment (Table 2) with ratings from 1 (Equal Importance) to 9 (Extreme Importance).

The ANP model for the study was developed, with the factors grouped into clusters and criteria. The clusters (main criteria) include topography, hydrology, land use and soil type. Each cluster was subsequently decomposed into subfactors (criteria). The topography cluster consists of 4 criteria i.e., elevation, slope angle, SPI and TWI; while the hydrology cluster comprises distance from streams and runoff (precipitation); the land use cluster consists of seven land use criteria: water body, forest, urban areas, paddy, mixed agriculture, rubber and oil palm; lastly, the soil type cluster comprises alluvial soil type, granite, limestone, sand and gravel, and shale and siltstone.

Using the super matrix (Saaty and Vargas, 2006; Portillo et al., 2019), the completed questionnaires were analyzed to compute the factors' priorities. The ANP computations were done with the Super Decisions software version 2.10.0 and the priorities of the four experts were aggregated using the geometric mean method (Dano et al., 2019b).

4.3. Fuzzy-ANP Model

Elevation, slope angle, SPI, TWI, distance from streams, runoff, land use, and soil types (Figures S1a-i) were used to determine areas susceptible to flood inundation events. The relative weights of these factors were determined using FANP, which is an ensemble of the Analytical Network Process (ANP) with Fuzzy set theory. The FANP was implemented using the procedures in (Torfi et al., 2010; Balogun et. al, 2015, 2017) by transforming the normalized ANP matrix into fuzzy numbers. Transformation can be done using the triangular fuzzy numbers (TFN) or trapezoidal fuzzy numbers. The triangular fuzzy numbers (TFN) is used in this study due to its computational simplicity and information processing in the blurred environment. The TFN is denoted with (a, b, c), where a is the lower bound, b is the median and c is the upper bound. The notations are important because they determine the range of the membership function. The TFNs are denoted by the linear representations on its right and left sides such that its membership function μ can be defined as shown in Equation (7) (Khan et al., 2019; Wang et al., 2020):

$$\mu\left(\frac{x}{\tilde{M}}\right) = \begin{cases} 0, & x < a \text{ or } x > c \\ \dfrac{x-a}{b-a}, & a \le x \le c \\ \dfrac{c-x}{c-b}, & b \le x \le c \end{cases} \tag{7}$$

The triangular fuzzy numbers and the corresponding linguistic variables are presented in the fuzzy transformation table (Table 3). Experts adopt the linguistic variable to assess the relative importance of the various criteria (Balogun et al., 2015).

From Table 3, the fuzzy linguistic variable, VL, is associated with the triangular fuzzy number (0.00, 0.10, 0.25), representing the minimum, modal and maximum values respectively. A similar approach of associating each linguistic variable to a corresponding TFN in the ranking of the relative importance of the flood conditioning factors is adopted to transform the other fuzzy variables to obtain the fuzzy matrix in Table S1(See Supporting information). The fuzzy weights were derived using Equation (8) and subsequently defuzzified into crisp values compatible with the GIS platform using Equation (9) (Singh and Benyoucef, 2011). The FANP was implemented in the Super Decisions software, and the output layers were overlaid in the GIS environment to produce flood susceptibility maps:

$$\frac{a}{b} = \left(\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1} \right) \tag{8}$$

$$x = \frac{a + 2b + c}{4} \tag{9}$$

Table 3. Fuzzy Triangular Membership Function

Linguistic variable	Triangular Fuzzy Number
Very Low (VL)	(0.00, 0.10, 0.25)
Low (L)	(0.15, 0.30, 0.45)
Medium (M)	(0.35, 0.50, 0.65)
High (H)	(0.55, 0.70, 0.85)
Very High (H)	(0.75, 0.90, 1.00)

4.4. Correlating Flood Risk Locations with Trend in Housing Prices

To determine the correlation between the flood susceptibility of the property locations and market prices, the following steps were implemented:

I. Identification of locations with high flood susceptibility from the FANP susceptibility map.
II. Deriving the geometric mean of real estate price per square meter from a sample size of 10 real estates with similar residential building categorization from the year 2008 to 2018 in the vulnerable areas spotted in (I). Geometric mean is adopted because it is more appropriate to calculate growth rates in addition to not being affected by extreme numbers among the sample size.
III. Changes in real estate price per square meter during flood events period were evaluated.

5. Results and Discussions

5.1. Fuzzy ANP Weights

The outcome of the pair-wise comparison fuzzy matrix of the 4 main criteria (clusters) and 18 sub-criteria (nodes) based on the first expert's (R1) input is presented in the supporting information file (Table S1) while the fuzzy weights and defuzzified weights are presented in Tables 4 and 5.

Table 6 shows the aggregated weights of all the expert respondents based on the geometric mean computation. Analysis of the results reveals that runoff (RO) is the most significant criteria among the other flood triggering factors with a weight of 14%, followed by the distance from streams (DS), elevation (EL), and slope angle (SA) and with weights of 13, 12, and 9%, respectively.

5.2. Flood Susceptibility Map

Figure 2 shows the flood susceptibility map developed from the fuzzy Analytical Network Process (F-ANP) model. The flood susceptibility indices from the model were classified into five categories using the reclassification tool in GIS: very-low, low, moderate, high and very-high. The classification signifies an increasing level of susceptibility to flooding with "very-low" being the least susceptible and safest, while "very-high" is the most susceptible and hazardous. The classification threshold is based on earlier studies (Pradhan, 2010; Dano et al., 2019) which used similar characterization of flood susceptibility levels.

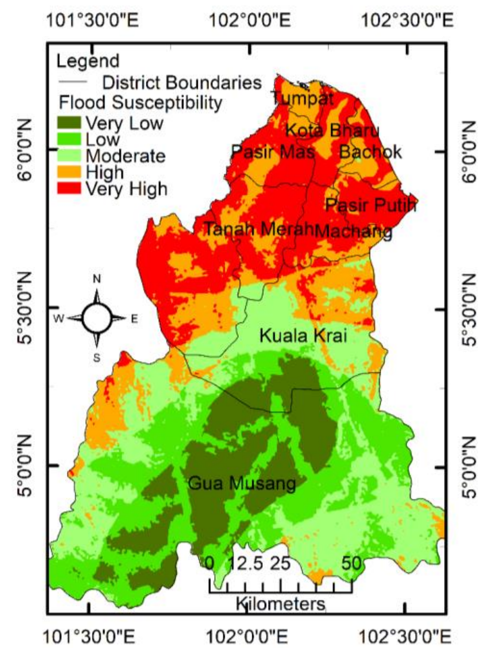

Figure 2. Flood susceptibility map generated by F-ANP model.

5.3. Flood Risk Analysis

Based on the aggregated FANP weights in Table 6, runoff has the highest weight (18%) followed by elevation and slope angle, with weights of 9% and 8% respectively. Generally, the FANP model prioritizes hydrological factors in the study area (e.g., runoff and distance from stream) and topographic factors (e.g., elevation and slope angle) over land use and soil types. In related studies, Zhu et al., (2018) and Lee et al., (2019) highlighted the significance of river runoff in increasing flood risks in separate Chines cities, agreeing with the expert rankings in this present study. Contrary to some studies such as Pradhan (2010), wherein land use/land cover is prioritized in identifying flood susceptible areas, landcover has the lowest weight in the FANP model as seen in Table 6. According to Zhu et al., (2018), a rapidly accelerating urbanization process is causing urban

Table 4. Fuzzy Weights of Flooding Criteria (R1)

Cluster	Criterion (Nodes)	Fuzzy weight		
Hydrology	Distance from stream (DS)	0.2727	0.0918	0.0718
	Runoff (RO)	0.3000	0.0969	0.0740
Land Use	Forest (FO)	0.0000	0.0459	0.0513
	Mixed agriculture (MA)	0.0000	0.0459	0.0513
	Paddy (PA)	0.0000	0.0459	0.0513
	Palm oil (PO)	0.0000	0.0459	0.0513
	Rubber (RU)	0.0000	0.0459	0.0513
	Urban Area (UA)	0.0000	0.0459	0.0513
	Waterbody (WB)	0.0000	0.0459	0.0513
Soil Type	Alluvium (AL)	0.0000	0.0459	0.0513
	Granite (GR)	0.0000	0.0459	0.0513
	Limestone (LS)	0.0000	0.0459	0.0513
	Sand & gravel (SG)	0.0000	0.0459	0.0513
	Shale & siltstone (SS)	0.0000	0.0459	0.0513
Topography	Elevation (EL)	0.2182	0.0867	0.0695
	Slope Angle (SA)	0.1545	0.0714	0.0626
	SPI	0.0000	0.0459	0.0513
	TWI	0.0545	0.5610	0.5580

Table 5. Defuzzified Weights and Ranking of Criteria (R1)

Cluster	Criterion (Nodes)	DFW	%	Ranking
Hydrology	Distance from stream (DS)	0.1320	13	2
	Runoff (RO)	0.1420	14	1
Land Use	Forest (FO)	0.0358	4	6
	Mixed agriculture (MA)	0.0358	4	6
	Paddy (PA)	0.0358	4	6
	Palm oil (PO)	0.0358	4	6
	Rubber (RU)	0.0358	4	6
	Urban Area (UA)	0.0358	4	6
	Waterbody (WB)	0.0358	4	6
Soil Type	Alluvium (AL)	0.0358	4	6
	Granite (GR)	0.0358	4	6
	Limestone (LS)	0.0358	4	6
	Sand & gravel (SG)	0.0358	4	6
	Shale & siltstone (SS)	0.0358	4	6
Topography	Elevation (EL)	0.1153	12	3
	Slope Angle (SA)	0.0900	9	4
	SPI	0.0358	4	6
	TWI	0.0556	6	5

area's landcover to undergo considerable changes in recent times, triggering significant changes in the underlying surface condition. Impervious surfaces such as concrete structures and hardened roads have increased considerably, which increases the risk of flooding. However, Kelantan is an agrarian state dominated by paddy fields, fishing communities and coastal beaches. Its relative isolation and largely rural lifestyle minimize the impact of urbanization and its influence in triggering flooding there. Hence, it is relatively low weight.

Figure 2 reveals the various susceptibility levels of different locations in the study area, from very high susceptibility to very-low susceptibility. Locations in the northernmost part of the state, such as Pasir Mas and Tanah Merah are highly susceptible to flooding while those in the southernmost part have moderate to low susceptibility. The elevation map (Figure S1f) shows that the northernmost locations have the highest elevation (5) and slope angle (Figure S1c), accounting for their high vulnerability considering the high weight of elevation and slope angle in the FANP model. Overlay of the runoff map (Figure S1b) with the flood susceptibility map (Figure 2) shows that the regions with low run-off values have the least susceptibility to flooding. Also, the highly susceptible northern region is characterized by high rainfall as shown in Figure S1a while the low susceptible southern region generally experiences low rainfall. In a flood risk assessment of multiple cities, Lye et al., (2019a) showed that the regions with the higher rainfall occurrence similar to this study's flood risk classification.

Table 6. Geometric Mean Computation of Experts' Opinion

		DFW						
Cluster	Criterion (Nodes)	R1	R2	R3	R4	Aggregate	%	Ranking
Hydrology	Distance from stream (DS)	0.1320	0.0704	0.0370	0.0834	0.0732	7	4
	Runoff (RO)	0.1420	0.1713	0.2219	0.1880	0.1785	18	11
Land use	Forest (FO)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Mixed agriculture (MA)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Paddy (PA)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Palm oil (PO)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Rubber (RU)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Urban Area (UA)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Waterbody (WB)	0.0358	0.1241	0.0609	0.0574	0.0628	6	5
Soil Type	Alluvium (AL)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Granite (GR)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Limestone (LS)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Sand & gravel (SG)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	Shale & siltstone (SS)	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
Topography	Elevation (EL)	0.1153	0.0523	0.0968	0.1045	0.0884	9	2
	Slope Angle (SA)	0.9000	0.0884	0.0787	0.0729	0.0822	8	3
	SPI	0.0358	0.0380	0.0370	0.0364	0.0368	4	7
	TWI	0.0556	0.0380	0.0609	0.0574	0.0521	5	6

Table 7. Level of Similarity (F-ANP)

Historically Flooded Points	Flood Susceptibility				
	Very high	High	Moderate	Low	Very low
70	42 (59.42%)	25 (36.23%)	1 (1.45%)	1 (1.45%)	1 (1.45%)

Similarly, from the land use map (Figure S1g), it is seen that the very low and low susceptibility areas are dominated by forest, paddy fields and mixed agriculture land use. Vegetation influence landscapes' hydrology and the water balance of river basins, and the water retention capacity of forests has been used as an effective flood risk management strategy in many countries (Reinhardt-Imjela et al., 2018). According to (Wahren et al., 2009), water storage in forest soils is generally higher than in soils of other land cover types so locations with high concentration of forests will probably have a high water retention capacity and lower risk of flooding. Lyu et al., (2018) confirmed that forests and unused land are less vulnerable to flooding since rainstorms rarely cause flooding in these forest types of land use.

Thus, the prevalence of vegetation land cover in the southern region of the state is a major factor responsible for its low vulnerability in the susceptibility map. Furthermore, the largest concentration of urban areas is found in the northern region (Figure S1g) and the role of urbanization in exacerbating flooding is well documented in literature. For instance, the urbanizetion process in Flanders, Belgium caused a 20% rise in surface runoff over a 24-year period, increasing the vulnerability of the surrounding suburbs to flooding (Poelmans et al., 2010). It is noteworthy that while the occurrence of unfavorable hydrological and topographic factors and existence of urban area land use will probably increase the susceptibility of a location to flooding (Lyu et al., 2019), and the prevalence of vegetation land use will likely decrease susceptibility, this is not always the case. A careful study of Figure S1g and Figure 2 shows that some locations in the study area have high susceptibility despite the presence of vegetation land use and some locations have low susceptibility to flooding despite the presence of urban areas. Thus, it is necessary to take into consideration various flood conditioning factors and assign accurate weights to them to be able to determine the susceptibility of locations in relation to the occurrence and significance of the diverse factors.

5.4. Validation

The performance of the flood susceptibility model was validated using the historical flooded areas in Kelantan, from 2013 to 2017. (Lyu et al., 2018, 2019) used historical locations of previous fatalities and historical flood records for several locations in China to assess the reliability of flood risk models.

The historical flood data was obtained from the Department of Irrigation and Drainage (DID), Malaysia. According to Baharuddin et al., (2015), the flood occurrence during 2014 to 2015 is the worst flood recorded in recent times, displacing more than 200,000 victims (MalaysiaKini, 2014). Thus, the data for this period is suitable for the validation purpose. Figure 3 shows the locations of previously flooded areas (worst hit areas from 2013 to 2017) used for the validation of the flood susceptibility model.

The historically flooded areas (70), represented as point features in ArcGIS, were overlaid on the flood susceptibility maps (Figure 4). The outcome of the procedure is summarized in Table 7.

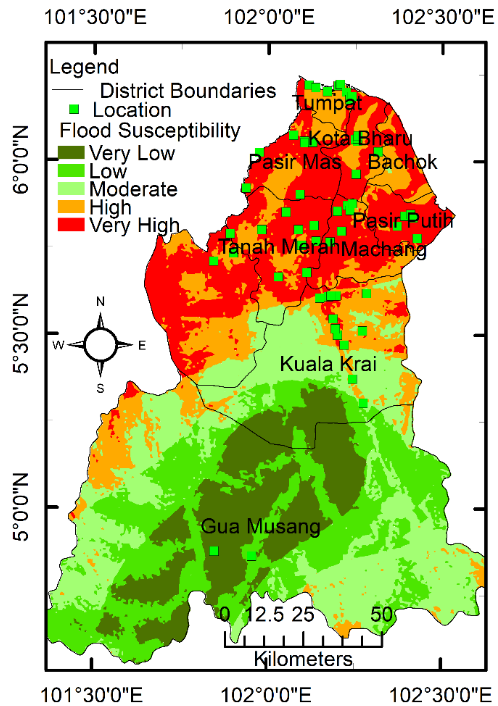

Figure 3. Locations of previous flood events 2013 ~ 2017.

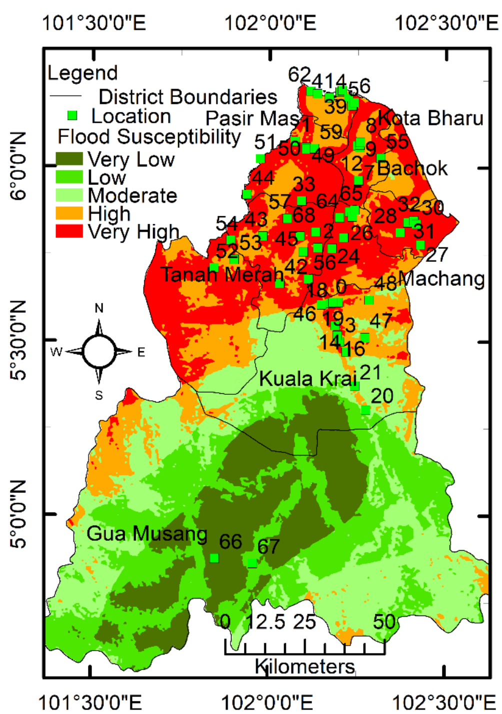

Figure 4. Historical flooded areas overlaid with flood susceptibility map generated by F-ANP.

Figure 4 and Table 7 show that 59.42% of the previously flooded locations fall within the very high susceptible level of the map while 36.23% fall in the high susceptible level, both of which are within the northern region of the study area. From the flood events data, it was found that Tanah Merah, Kota Bharu and Kuala Krai were some of the most flooded locations during 2013 to 2017 and these areas are all located in the very high to high susceptible regions of the F-ANP susceptibility map thereby validating the map's accuracy. The high congruence between this study's map's classification and the actual flood occurrence/non-occurrence in selected locations validate the robustness and accuracy of the spatial Fuzzy MCDM model.

Interestingly, flood occurrences were documented in some regions classified as very low to low susceptible areas. Kampung Panggung Lalat (66) and Kampung Kundur (67) in Gua Musang were identified by DID as some of the worst hit areas during the 2015/2016 flood events despite being situated in the very low risk southern region as represented by points 66 and 67 in Figure 4. This is likely due to a number of inter-related reasons. For instance, an unusually large amount of rainfall with a return period of 1:1000 years was experienced during this period (Ismail and Haghroosta, 2018), causing river levels to exceed those of recent floods (Davies, 2015). The area's low elevation (Figure S1f) and predominant rubber land use (Figure S1g) are other possible factors. Studying the effects of flooding and topography on rubber plantations, Hardanto et al., (2017) reported that plantation locations in areas of low elevation are more likely to be flooded than those at higher topographic locations, particularly during periods of high rainfall. Therefore, under such unusual climatic condition, even the low susceptible regions could experience flooding as seen in this scenario.

Although some researchers (Saaty, 2006; Saaty and Tran, 2007) argued against the fuzzification of AHP and ANP, this study's outcome aligns with other more recent researches that have shown a strong justification for the fuzzification of these MCDM methods. In a practical comparison of AHP and fuzzy AHP GIS-modelling for locating a dam in Costa Rica, Kordi (2008) observed that fuzzy AHP gives a different result than crisp AHP, contrary to Saaty's claim that the fuzzification of the process does not give much different results. Using the Chi-Square test, the study concluded that AHP/FAHP outcomes are not the same and the difference between the results increase significantly by increasing the uncertainty level. Using catastrophe fuzzy membership function, Kaur et al., (2020) concluded that the fuzzy approach is technically superior and more reliable than the AHP for the identification of groundwater potential zones due to the elimination of subjectivity which increased the model's precision. Similarly, Kanani-Sadat et al., (2019) demonstrated that the Fuzzy-DEMATEL ANP model has a higher performance accuracy in comparison to the AHP model for flood susceptibility assessment.

5.5. Correlation of Flood Hazard Risk and Property Prices

The correlation between the flood susceptibility of real estate locations and the property market prices was investigated based on a 10-year inventory of market prices obtained

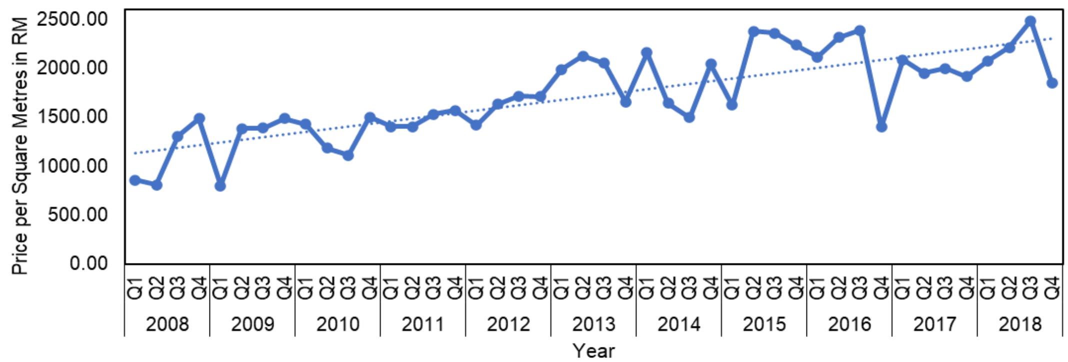

Figure 5. Graph of real estate price per square metres against year (Kota Bharu).

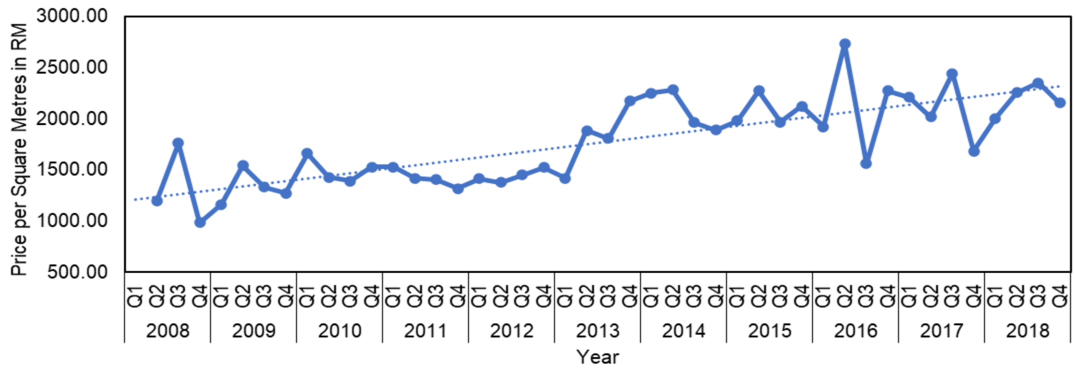

Figure 6. Graph of real estate price per square metres against year (Kuala Krai).

from the National Property Information Centre (NAPIC), Malaysia. The average price per square metre for the real estates located in Kota Bharu and Kuala Krai are presented in Figure 5 and 6. The choice of these two locations is due to their high flood vulnerability based on the susceptibility map from the spatial FAHP model (Figure 4).

A comparison of the property prices with flood occurrences in the selected districts from the year 2008 to the year 2018 was subsequently undertaken.

From Figure 5, it is observed that there was a significant price drop in Q1 2009. The average price per square metres dropped from RM 1485.70/m^2 to RM 797.10/m^2. Based on the flood report obtained from DID Malaysia, one of the worst-hit districts from the 2008 ~ 2009 flood is Kota Bharu. The second significant price drop occurred in Q2 2010. The record shows that the price dropped from RM 1429.80/m^2 to RM 1186.15/m^2. However, reports showed that there is no flood occurrence in Kota Bharu during this period. There was a slight price drop recorded between Q4 2010 and Q1 2011, from RM 1499.40/m^2 to RM 1403.60/m^2. During the period, there was a flood occurrence in Kota Bharu. The third notable price drop was observed in Q1 2012. The price differential between Q4 2011 and Q1 2012 is a reduction of RM 146.40/m^2. Again, there was a flood reported during the period. However, in year 2012/2013, it is observed that there is a price hike in the real estate price despite the occurrence of flood. The flood is reported to be a flash flood due to an ineffective drainage system. The flood in Year 2014 /2015 was considered one of the worst flood events in history. It is also observed that there is a significant price drop in Q1 of the year 2015, from RM 2043.20/m^2 in Q4 2014 to RM 1621.65 /m^2 in Q1 2015. Similarly, another significant price drop was observed in Q4 2016. Coincidently, DID reported flood occurrence in Kota Bharu during the period.

Kuala Krai was the second worst-hit area after Pasir Mas in the 2008 flood event in Kelantan. DID reported that the damages caused by the flood in 2008 cost approximately RM 2.3 million. It is observed that there was a drastic price drop in the period (Q4 2008) and a slight price hike in Q1 2009. A hike in price was documented during the monsoon season, despite the occurrence of flood in Kuala Krai. The real estate prices dropped from RM 1527/m^2 in Q4 2012 to RM 1420.55/m^2 in Q1 2013. DID reported that the flood in December 2012 had caused the relocation of 867 people and infrastructure damages worth approximately RM 230000. In February 2013, DID reported that another flood with the depth of 0.25 ~ 0.5m occurred in Kuala Krai. Despite flood occurrences reported in 2013/2014 and 2014 /2015 respectively, the real estate prices per square meters increased during the monsoon season. In contrast, price reduction occurred in Q3 of the year 2014 and the year 2015. Then, the real estate prices dropped from RM 2122/m^2 to RM 1923.60/m^2 in Year 2015/2016, coinciding with a flood event reported by DID. No casualty or damage was reported. Another significant drop of real estate price was reported in Q3 of Year 2016. However, there was no flood reported during the period. A price drop was also reported at the end of the year 2017. However, due to flood data unavailability, the analysis of the correlation between the flood occurrence and real estate price could not be done.

The foregoing flood susceptibility, flood occurrence and market prices trend analyses reveal that drop in property prices is generally synonymous with the occurrence of flood events. This aligns with previous researches that established a negative impact on residential properties due to flooding (Rajapaksa et al., 2017a). Hirsch and Hahn (2018) revealed that the occurrence of flooding reduces the prices of real estate by 299 Euros per square meter in the time period 2012 to 2015. However, there are instances of price drop despite non-occurrence of floods, which could be due to other factors. According to (Kamal et al., 2016), the most important factor that influences the housing price is the location of the properties followed by macroeconomic and demographic factors such as population growth, living standard and lifestyle. Haron and Ibrahim (2019) identified interest rate, gross domestic product (GDP) and population change as factors that also influence real estate prices in the study area. Interest rates is a major determinant of the affordability of real estate properties since high interest rates cannot be afforded by the largely agrarian community with the potential to cause an oversupply of properties due to low demand, resulting in a drop in the prices. Kelantan is one of the poorest states in Malaysia, having a GDP per capita of 5,685 USD in 2013 (Brian, 2015). This is linked to a decline in the agricultural sector, exemplified by low productivity of palm oil and rubber. Growth in the manufacturing sector has also slowed down (Statistics, 2018). Population and demographic dynamics equally influence the value of real estate in Kelantan (Haron and Ibrahim, 2019). For instance, due to static or limited population growth, the demand for real estate decreases, causing a drop in prices. In March 2019, the state recorded an oversupply of 670 housing units worth 280.5 million Malaysian Ringgit (Reserve, 2019).

A novel perspective provided in this present study is the exploration of the probable nexus between flood susceptibility of locations and price trends in the study area. Analysis of the study locations indicates significant drop in prices in the very highly susceptible area (Kota Bahru) after major flood events. Over 45% drop in price was documented in Kota Bahru between Q4 2008 and Q1 2009, following the 2008/2009 major flood disaster. In contrast, the moderately susceptible region (Kuala Krai) experienced a price hike of about 20% during the same period. Similarly, after the major flood event in 2014/2015, Kota Bahru experienced a significant drop in price in Q1 2015 while a moderate rebound was seen in Kuala Krai. Kota Bahru witnessed further decline in prices in Q3 and Q4 2019, extending until Q2 2016 in contrast to Kuala Krai, which experienced a mix of rise and fall during the same period, with the price peaking in Q2 2016. During non-major flood events, both regions had stable prices although a drop in price occurred in Kota Bahru during Q4 2013 while Kuala Krai observed a spike in price at the same period. This trend suggests that highly susceptible locations are likely to experience fall in property prices, particularly after major flood disasters while moderate to low susceptible regions might be less impacted. Therefore, Pasir Mas, Tumpat and the other localities classified as very high to highly susceptible areas (Figures 3 and 4) are prone to experience similar price responses to flood hazards in future while the response of moderate to low risk areas like Gua Musang can be deduced from the trend in Kuala Krai.

In addition to exploring the previous impacts of flood occurrences on housing prices in Kelantan, this study offers insights on likely future hotspots of flooding and possible price responses in the various regions, taking into consideration their respective flood susceptibility levels. Such early warning spatial information that accurately delineates flood risks of locations will be valuable to decision makers, real estate developers and other stakeholders in planning for flood disasters on one hand and proposing feasible economic interventions to mitigate the impacts of property price fluctuations on the other hand.

However, it is important to note that price hikes were sometimes observed despite the occurrence of flood events in the floodprone areas. This might not be unconnected with the positive effects of amenities. As documented in Zhai et al., (2003) study, local members of the community have a preference for residing in close proximity to areas with amenities such as river view or waterfront, the river or water stream in spite of the possible flood risk. The positive effects of amenities were expected to dominate the negative effect of floods, exerting an upward price trend in spite of nearness to a river. According to Hirsch and Hahn (2018), properties located close to water body or within a floodplain subject to wave action provide good amenities value and thus have higher property values. Although theories of natural hazards predict that the market will capitalize the risk of flooding into the value of the residential property and the risk may be ignored in areas where the probability is low (Tobin and Montz, 1988), the same does not necessarily hold true for high-risk areas wherein the risks need to be taken into consideration. In order to meet the Malaysia real estate challenges, the government has set forth certain initiatives to control the real estate market including individual tax relief on loan interest and construction of low and medium low-cost housing units (Hashim, 2010) to help the low-income earners.

6. Conclusions

The severity and frequency of floods in Malaysia is projected to increase in future due to the increasing urbanization and climate change impacts, and the flood insurance for properties located in high-risk areas will likely double in the next 10 years. Unfortunately, there is a low-level awareness of flood-prone areas and limited public information on the risks of living there.

Consequently, this study develops an enhanced flood susceptibility model for accurately identifying highly susceptible flood locations. Limitations of bias, vagueness and uncertainty in existing MCDM weighting techniques were addressed by developing a fuzzy ANP weighting model which was integrated with GIS to produce different classes of flood susceptibility in the study area. The model's outcome was validated with locations of previous fatalities and historical flood records for several locations in the study area. Results from the validation procedure were promising, confirming the reliability of the study's outcome.

Using the flood susceptibility map, a strong correlation was seen between drop in property prices and occurrence of flood events in the high-risk locations. However, some exceptions were recorded with drop in prices of real estates despite non-occurrence of floods and price hike in spite of the occurrence of flood events. This study thus provides a systematic approach to investigating the impact of flood susceptibility and occurrences on real estate prices. In future, it will be necessary to incorporate other factors that could influence real estate prices such as construction costs as well as macro and microeconomics of the community.

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References

Abdou, B., Mohammed, G., El Battay, A., Mohamed, N., and Rouai, M. (2017). Detection of Areas Associated with Flash Floods and Erosion Caused by Rainfall Storm Using Topographic Attributes, Hydrologic Indices, and GIS. *In Global Changes and Natural Disaster Management: Geo-information Technologies*. Springer, Cham.

Abedi, G.H. and Feizizadeh, B. (2017). An integrated approach of analytical network process and fuzzy based spatial decision making systems applied to landslide risk mapping. *J. Afr. Earth. Sci.*, 133, 15-24. https://doi.org/10.1016/j.jafrearsci.2017.05.007

Afzali, A., Sabri, S., Rashid, M., Samani, J.M.V., and Ludin, A.N.M. (2014). Inter-municipal landfill site selection using analytic network process. *Water Resour. Manag.*, 28, 2179-2194. https://doi.org/10.1007/s11269-014-0605-3

Alias, N.E., Mohamad, H., Chin, W.Y., and Yusop, Z. (2016). Rainfall analysis of the Kelantan big yellow flood 2014. *J. Teknol*., 78. https://doi.org/10.11113/jt.v78.9701

Alilou, H., Rahmati, O., Singh, V.P., Choubin, B., Pradhan, B., Keesstra, S., Ghiasi, S.S., and Sadeghi, S.H. (2019). Evaluation of watershed health using Fuzzy-ANP approach considering geo-environmental and topo-hydrological criteria. *J. Environ. Manage.*, 232, 22-36. https://doi.org/10.1016/j.jenvman.2018.11.019

Aliyu, A.A., Garkuwa, A.I., Singhry, I.M., Muhammad, M.S., and Baba, H.M. (2016). Impact of Flooding on Residential Properties Values: A review and analysis of previous studies. *Proceedings of the Academic Conference of Nightingale Publications and Research International on Sustainable Development*, 2016.

Alizadeh, M., Ngah, I., Hashim, M., Pradhan, B., and Pour, A.B. (2018). A hybrid analytic network process and artificial neural network (ANP-ANN) model for urban earthquake vulnerability assessment. *Remote Sens*., 10, 975. https://doi.org/10.3390/rs10060975

Aminu, M., Matori, A.N., Yusof, K.W., Malakahmad, A., and Zainol, R.B. (2017). Analytic network process (ANP)-based spatial decision support system (SDSS) for sustainable tourism planning in Cameron Highlands, Malaysia. *Arab. J. Geosci*., 10, 286. https://doi.org/10.1007/s12517-017-3067-0

Aminu, M., Matori, A.N., Yusof, K.W., and Zainol, R.B. (2014). Application of geographic information system (GIS) and analytic network process (ANP) for sustainable tourism planning in Cameron Highlands, Malaysia. *Appl. Mech. Mater*., 769-774. https://doi.org/10.4028/www.scientific.net/AMM.567.769

Atreya, A. and Ferreira, S. (2015). Seeing is believing? Evidence from property prices in inundated areas. *Risk Anal*., 35, 828-848. https://doi.org/10.1111/risa.12307

Azareh, A., Rafiei Sardooi, E., Choubin, B., Barkhori, S., Shahdadi, A., Adamowski, J., and Shamshirband, S. (2019). Incorporating multi-criteria decision-making and fuzzy-value functions for flood susceptibility assessment. *Geocarto Int.,* 1-21. https://doi.org/10.1080/10106049.2019.1695958

Baharuddin, K.A., Wahab, S.F.A., Ab Rahman, N.H.N., Mohamad, N.A.N., Kamauzaman, T.H.T., Noh, A.Y.M., and Majod, M.R.A. (2015). The record-setting flood of 2014 in Kelantan: challenges and recommendations from an emergency medicine perspective and why the medical campus stood dry. Malays. *J. Med. Sci*., 22,1.

Balogun, A.L., Marks, D., Sharma, R., Shekhar, H., Balmes, C., Maheng, D., Arshad, A., and Salehi, P. (2020). Assessing the Potentials of Digitalization as a Tool for Climate Change Adaptation and Sustainable Development in Urban Centres. *Sustain. Cities Soc*., 53, 101888. https://doi.org/10.1016/j.scs. 2019.101888

Balogun, A.L., Matori, A.N., and Hamid-Mosaku, A.I. (2015). A fuzzy multi-criteria decision support system for evaluating subsea oil pipeline routing criteria in East Malaysia. *Environ. Earth Sci*., 74, 4875-4884. https://doi.org/10.1007/s12665-015-4499-z

Balogun, A.L., Matori, A.N., Hamid-Mosaku, A.I., Umar Lawal, D., and Ahmed Chandio, I. (2017). Fuzzy MCDM-based GIS model for subsea oil pipeline route optimization: An integrated approach. *Mar. Georesources Geotechnol*., 35, 961-969. https://doi.org/10.1080/1064119X.2016.1269247

Belanger, P. and Bourdeau-Brien, M. (2018). The impact of flood risk on the price of residential properties: the case of England. *Hous. Stud*., 33, 876-901. https://doi.org/10.1080/02673037.2017.1408781

Below, R. and Wallemacq, P. (2018). Centre For Research On The Epidemiology of Disasters. *Annu. Disaster Stat. Rev*. 2017.

Brian, K. 2015. *OECD insights income inequality the gap between rich and poor: The gap between rich and poor*, oecd Publishing.

Busby, J., Smith, T.G., Krishnan, N., Wight, C., and Vallejo-Gutierrez, S. (2018). In harm's way: Climate security vulnerability in Asia. *World Dev*., 112, 88-118. https://doi.org/10.1016/j.worlddev.2018.07.007

Chan, N.W. (2015). Impacts of disasters and disaster risk management in Malaysia: The case of floods. *Resil. Rec. Asian Disasters*. https://doi.org/10.1007/978-4-431-55022-8_12

Chapi, K., Singh, V., Shirzadi, A., Shahabi, H., Tien Bui, D., Pham, B., and Khosravi, K. (2017). A novel hybrid artificial intelligence approach for flood susceptibility assessment. *Environ. Modell. Softw.* https://doi.org/10.1016/j.envsoft.2017.06.012

Chen, L. and Ren, J. (2018). Multi-attribute sustainability evaluation of alternative aviation fuels based on fuzzy ANP and fuzzy grey relational analysis. *J. Air Transp. Manag*., 68, 176-186. https://doi.org/10.1016/j.jairtraman.2017.10.005

Chen, Z., Ming, X., Zhang, X., Yin, D., and Sun, Z. (2019). A rough-fuzzy DEMATEL-ANP method for evaluating sustainable value requirement of product service system. *J. Clean. Prod*., 228, 485- 508. https://doi.org/10.1016/j.jclepro.2019.04.145

Choubin, B., Rahmati, O., Tahmasebipour, N., Feizizadeh, B., and Pourghasemi, H.R. (2019). Application of fuzzy analytical network process model for analyzing the gully erosion susceptibility. *Natural hazards gis-based spatial modeling using data mining techniques.* https://doi.org/10.1007/978-3-319-73383-8_ 5

Dano, D.U.L., Balogun, A.L., Matori, A.N., Wan Yusouf, K., Rimi Abubakar, I., Ahmed Said Mohamed, M., Aina, Y., and Pradhan, B. (2019). Flood Susceptibility Mapping Using GIS-Based Analytic Network Process: A Case Study of Perlis, Malaysia. *Water*. https://doi.org/10.3390/w11030615

Darabi, H., Choubin, B., Rahmati, O., Haghighi, A.T., Pradhan, B., and Kl øve, B. (2019). Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques. *J. Hydrol*., 569, 142-154. https://doi.org/10.1016/j.jhydrol.

2018.12.002
Davies, R. (2015). Malaysia Floods-Kelantan Flooding Worst Recorded as Costs Rise to RM1 Billion. http://floodlist.com/asia/malaysia-floods-kelantan-worst-recorded-costs
De Brito, M.M. and Evers, M. (2016). Multi-criteria decision-making for flood risk management: a survey of the current state of the art. *Nat. Hazards Earth Syst. Sci*., 16, 1019-1033. https://doi.org/10.5194/nhess-16-1019-2016
De Brito, M.M., Evers, M., Almoradie, S., and Delos, A. (2018). Par ticipatory flood vulnerability assessment: a multi-criteria approach. *Hydrol. Earth Syst. Sci*., 22. https://doi.org/10.5194/hess-22-3732018
Donovan, G.H., Champ, P.A., and Butry, D.T. (2007). Wildfire risk and housing prices: a case study from Colorado Springs. *Land Econ*., 83, 217-233. https://doi.org/10.3368/le.83.2.217
El-Abbasy, M.S., Senouci, A., Zayed, T., and Mosleh, F. (2015). A condition assessment model for oil and gas pipelines using integrated simulation and analytic network process. *Struct. Infrastruct. E*.,11, 263-281. https://doi.org/10.1080/15732479.2013. 873471
Eves, C. and Wilkinson, S. 2014. Assessing the immediate and short-term impact of flooding on residential property participant behaveiour. *Nat. Hazards*, 71, 1519-1536. https://doi.org/10.1007/s11069-013-0961-y
Gheshlaghi, H.A. and Feizizadeh, B. (2017). An integrated approach of analytical network process and fuzzy based spatial decision making systems applied to landslide risk mapping. *J. Afr. Earth. Sci*., 133, 15-24. https://doi.org/10.1016/j.jafrearsci.2017.05.007
Ghorbanzadeh, O., Feizizadeh, B. and Blaschke, T. 2018. Multi-criteria risk evaluation by integrating an analytical network process approach into GIS-based sensitivity and uncertainty analyses. *Geomat. Nat. Haz. Risk*, 9, 127-151. https://doi.org/10.1080/1947-5705.2017.1413012
Hallstrom, D.G. and Smith, V.K. 2005. Market responses to hurricanes. *J. Environ. Econ. Manag*., 50, 541-561. https://doi.org/10. 1016/j.jeem.2005.05.002
Hardanto, A., Röll, A., Niu, F., Meijide, A., Hendrayanto, and Hölscher, D. (2017). Oil Palm and Rubber Tree Water Use Patterns: Effects of Topography and Flooding. *Front. Plant Sci*., 8, 452-452. https://doi.org/10.3389/fpls.2017.00452
Haron, R. and Ibrahim, K. (2019). Residential Property Price Hike and Speculation. *Plan. Malaysia*., 17. https://doi.org/10.21837/pmjournal. v17.i9.609
Hashim, Z.A. (2010). House price and affordability in housing in Malaysia. *Akademika*. 78.
Hirsch, J. and Hahn, J. (2018). How flood risk impacts residential rents and property prices: Empirical analysis of a German property mar- ket. *J. Prop. Invest. Finance*, 36, 50-67. https://doi.org/10.1108/JPIF- 11-2016-0088
Hussey, L.K. and Malczewski, J. (2018). Housing quality evaluation using Analytic Network Process: a case study in the Ashanti Region, Ghana. *Afr. Geogr. Rev*.,37, 209-226.
Ibrahim, N.F., Zardari, N.H., Shirazi, S.M., Mohd Haniffah, M., Mat Talib, S., Yusop, Z., and Mohd Yusoff, S. (2017). Identification of Vulnerable Areas to Floods in Kelantan River Sub-basins by using Flood Vulnerability Index. *Int. J. GEOMATE*, 12, 107-114. https://doi.org/10.21660/2017.29.11110
Ishizaka, A. and Labib, A. (2011). Review of the main developments in the analytic hierarchy process. *Expert Syst. Appl*., 38, 14336-14345. https://doi.org/10.1016/j.eswa.2011.04.143
Islam, R., Kamaruddin, R., Ahmad, S.A., Jan, S., and Anuar, A.R. (2016). A review on mechanism of flood disaster management in Asia. *Int. Rev. Manag. Mark.*, 6, 29-52.
Ismail, W.R. and Haghroosta, T. 2018. Extreme weather and floods in Kelantan state, Malaysia in December (2014). *Mar. Biol. Res*. 3, 231-244.
Jøsang, A. (2016). Decision making under vagueness and uncertainty. *Subj. Logic*. Springer. https://doi.org/10.1007/978-3-319-42337-1
Kadoić, N., Ređep, N.B., and Divjak, B. (2017). Decision making with the analytic network process. *The 14th International Symposium on Operational Research in Slovenia*, 2017.
Kamal, E.M., Hassan, H., and Osmadi, A. (2016). Factors influencing the housing price: developers' perspective. *Int. J. Humanit Soc. Sci*., 10, 1603-1609.
Kanani-Sadat, Y., Arabsheibani, R., Karimipour, F., and Nasseri, M. (2019). A new approach to flood susceptibility assessment in data-scarce and ungauged regions based on GIS-based hybrid multi criteria decision-making method. *J. Hydrol*., 572, 17-31. https://doi.org/10.1016/j.jhydrol.2019.02.034
Kaur, L., Rishi, M.S., Singh, G., and Thakur, S.N. (2020). Groundwater potential assessment of an alluvial aquifer in Yamuna sub-basin (Panipat region) using remote sensing and GIS techniques in conjunction with analytical hierarchy process (AHP) and catastrophe theory (CT). *Ecol. Indic*., 110, 105850. https://doi.org/10.1016/j.ecolind.2019.105850
Khan, M.M.A., Shaari, N.A.B., Bahar, A.M.A., Baten, M.A., and Nazaruddin, D.A.B. (2014). Flood impact assessment in Kota Bharu, Malaysia: a statistical analysis. *World Appl. Sci. J*., 32, 626-634.
Khan, A. A., Shameem, M., Kumar, R. R., Hussain, S., and Yan, X. (2019). Fuzzy AHP based prioritization and taxonomy of software process improvement success factors in global software development. Applied Soft Computing, 83, 105648.
Kordi, M. (2008). Comparison of fuzzy and crisp analytic hierarchy process (AHP) methods for spatial multicriteria decision analysis in GIS.
Koul, S. and Verma, R. (2012). Dynamic vendor selection: A fuzzy AHP approach. *Int. J. Anal. Hier. Proc*., 4, 1936-674. https://doi.org/10. 13033/ijahp.v4i2.25
Lami, I.M. and Abastante, F. (2014). Decision making for urban solid waste treatment in the context of territorial conflict: Can the Analytic Network Process help? *Land Use Policy*. 41, 11-20. https://doi.org/10.1016/j.landusepol.2014.04.010
Lawal, D.U., Matori, A.N., and Balogun, A.L. (2011). A geographic information system and multi-criteria decision analysis in proposing new recreational park sites in universiti teknologi malaysia. *Mod. Appl. Sci*., 5, 39. https://doi.org/10.5539/mas. v5n3p39
Lawal, D.U., Matori, A.N., Yusof, K.W., Hashim, A.M., Aminu, M., Sabri, S., Balogun, A.L., Chandio, I.A., and Mokhtar, M.R.M. (2014a). Flood Susceptibility Modeling: A Geo-spatial Technology Multi-cri- teria Decision Analysis Approach. *Res. J. Appl. Sci. Eng. Technol*., 7, 4638-4644. https://doi.org/10.19026/rjaset.7.845
Lawal, D.U., Matori, A.N., Yusuf, K., Hashim, A.M., and Balogun, A.L. (2014b). Analysis of the flood extent extraction model and the natural flood influencing factors: A GIS-based and remote sensing analysis. *IOP Conference Series: Earth and Environmental Science,* IOP Publishing, 012059. https://doi.org/10.1088/17551315/18/1/012059
Lawal, D.U., Matori, A.N., Hashim, A.M., Wan Yusof, K., and Chandio, I.A. (2012). Detecting flood susceptible areas using GIS-based analytic hierarchy process.
Leal Filho, W., Balogun, A.L., Ayal, D.Y., Bethurem, E.M., Murambadoro, M., Mambo, J., Taddese, H., Tefera, G.W., Nagy, G.J., and Fudjumdjum, H. (2018). Strengthening climate change adaptation capacity in Africa-case studies from six major African cities and policy implications. *Environ. Sci. Policy*, 86, 29-37. https://doi.org/10.1016/j.envsci.2018.05.004
Leal Filho, W., Balogun, A.L., Olayide, O.E., Azeiteiro, U.M., Ayal, D.Y., Muñoz, P.D.C., Nagy, G.J., Bynoe, P., Oguge, O., and Toamukum, N.Y. (2019). Assessing the impacts of climate change in cities and their adaptive capacity: Towards transformative approaches to climate change adaptation and poverty reduction in urban areas in a set of developing countries. *Sci. Total Environ*., 692, 1175- 1190. https://doi.org/10.1016/j.scitotenv.2019.07.227
Lee, C., Hwang, S., Do, K., and Son, S. (2019). Increasing flood risk due to river runoff in the estuarine area during a storm landfall.

Estuar. Coast. Shelf Sci., 221, 104-118. https://doi.org/10.1016/j.ecss.2019.03.021

Lyu, H.M., Shen, S.L., Zhou, A.N., and Zhou, W.H. (2019). Flood risk assessment of metro systems in a subsiding environment using the interval FAHP-FCA approach. *Sustain. Cities Soc*., 50, 101682. https://doi.org/10.1016/j.scs.2019.101682

Lyu, H.M., Sun, W.J., Shen, S.L., and Arulrajah, A. (2018). Flood risk assessment in metro systems of mega-cities using a GIS-based modeling approach. *Sci. Total Environ*., 626, 1012-1025. https://doi.org/10.1016/j.scitotenv.2018.01.138

Malaysiakini. (2014). 237,000 displaced, 21 dead from floods. 30 December ed.

Malmir, M., Zarkesh, M.M.K., Monavari, S.M., Jozi, S.A., and Sharifi, E. (2016). Analysis of land suitability for urban development in Ahwaz County in southwestern Iran using fuzzy logic and analytic network process (ANP). *Environ. Monit. Assess*., 188, 447. https://doi.org/10.1007/s10661-016-5401-5

Matori, A.N., Lawal, D.U., Yusof, K.W., Hashim, M.A., and Balogun, A.L. (2014) Spatial analytic hierarchy process model for flood forecasting: An integrated approach. *IOP Conference Series: Earth and Environmental Science.* IOP Publishing, 012029. https://doi.org/10.1088/1755-1315/20/1/012029

Moel, H.D., Alphen, J.V., and Aerts, J. (2009). Flood maps in Europe-methods, availability and use. *Nat. Hazard. Earth Sys.*

Poelmans, L., Van Rompaey, A., Ntegeka, V., and Willems, P. (2010). Assessing the relative impact of urban expansion and climate change on high flows in a small catchment in Flanders (Belgium). *Land Use Policy*, 2010.

Portillo, L.A.F., Nekhay, O., and Mohedano, L.E. (2019). Use of the ANP methodology to prioritize rural development strategies under the LEADER approach in protected areas. The case of Lagodekhi, Georgia. *Land Use Policy*, 88, 104121. https://doi.org/10.1016/j.landusepol.2019.104121

Pour, A. and Hashim, M. (2017). Application of Landsat-8 and ALOS-2 data for structural and landslide hazard mapping in Kelantan, Malaysia. *Nat. Hazard. Earth Sys*., https://doi.org/ 10.5194/nhess-17-1285-2017

Pourali, S.H., Arrowsmith, C., Chrisman, N., Matkan, A.A., and Mitchell, D. (2016). Topography Wetness Index Application in Flood-Risk-Based Land Use Planning. *Appl. Spat. Anal. Policy*, 9, 39-54. https://doi.org/10.1007/s12061-014-9130-2

Pradhan, B. (2010). Flood susceptible mapping and risk area delineation using logistic regression, GIS and remote sensing. *J. Spat. Hydrol*.9(2).

Properties Malaysia Investment. (2015). Impact Of Flooding On Property Market. http://www.propertymalaysiainvestment.com/impact-flooding-property/#header-toggle-sidebar.

Quenzer, A.M. and Maidment, D.R. (1998). A GIS assessment of the total loads and water quality in the Corpus Christi bay system. *Center for Research in Water Resources*, University of Texas at Austin.

Rajapaksa, D., Wilson, C., Hoang, V.N., Lee, B., and Managi, S. (2017a). Who responds more to environmental amenities and dis-amenities? *Land Use Policy*, 62, 151-158. https://doi.org/10.1016/j.landusepol.2016.12.029

Rajapaksa, D., Zhu, M., Lee, B., Hoang, V.N., Wilson, C., and Managi, S. (2017b). The impact of flood dynamics on property values. *Land Use Policy*, 69, 317-325. https://doi.org/10.1016/j.landusepol.2017.08.038

Reinhardt-Imjela, C., Imjela, R., Bölscher, J., and Schulte, A. (2018). The impact of late medieval deforestation and 20th century forest decline on extreme flood magnitudes in the Ore Mountains (Southeastern Germany). *Quat. Int*., 475, 42-53. https://doi.org/10.1016/j.quaint.2017.12.010

Reserve, T.M. (2019). Housing supply versus population in Malaysia. https://themalaysianreserve.com/2019/08/09/housing-supply-versus-population-in-malaysia/

Riadi, B., Barus, B., Yanuar, M., and Pramudya, B. (2018). Identification and delineation of areas flood hazard using high accuracy of DEM data. *IOP Conference Series: Earth and Environmental Science, 2018.* IOP Publishing, 012035. https://doi.org/10.1088/17551315/149/1/012035

Saaty, T.L. (2006). There is no mathematical validity for using fuzzy number crunching in the analytic hierarchy process. *J. Syst. Sci. Syst. Eng*. 15, 457-464. https://doi.org/10.1007/s11518-006-5021-7

Saaty, T.L. and Sagir, M. (2009). Extending the measurement of tangibles to intangibles. *Int. J. Inf. Technol. Decis. Mak*., 8, 7-27. https://doi.org/10.1142/S0219622009003247

Saaty, T.L. and Tran, L.T. (2007). On the invalidity of fuzzifying numerical judgments in the Analytic Hierarchy Process. *Math. Com- put. Model*., 46, 962-975. https://doi.org/10.1016/j.mcm.2007.03.022

Saaty, T.L. and Vargas, L.G. (2006). Decision making with the analytic network process, Springer.

Sajedi-Hosseini, F., Choubin, B., Solaimani, K., Cerdà, A., and Kavian, A. (2018). Spatial prediction of soil erosion susceptibility using a fuzzy analytical network process: application of the fuzzy decision making trial and evaluation laboratory approach. *Land Degrad. Dev.,* 29, 3092-3103. https://doi.org/10.1002/ldr.3058

Sanyal, J. and Lu, X. (2004). Application of remote sensing in flood management with special reference to monsoon Asia: a review. *Nat. Hazards*, 33, 283-301. https://doi.org/10.1023/B:NHAZ.0000037035.65105.95

Shi, P.J., Yuan, Y., Zheng, J., Wang, J.A., Ge, Y., and Qiu, G.Y. (2007). The effect of land use/cover change on surface runoff in Shenzhen region, China. *Catena*, 69, 31-35. https://doi.org/10.1016/j.catena.2006.04.015

Singh, R.K. and Benyoucef, L. (2011). A fuzzy TOPSIS based approach for e-sourcing. *Eng. Appl. Artif. Intell*., 24, 437-448. https://doi.org/10.1016/j.engappai.2010.09.006

Staš, D., Lenort, R., Wicher, P., and Holman, D.J.S. (2015). Green Transport balanced scorecard model with analytic network process support. *Sustain.*, 7, 15243-15261. https://doi.org/10.3390/su71115243

Pourali, S. H., Arrowsmith, C., Chrisman, N., Matkan, A. A., and Mitchell, D. (2016). Topography Wetness Index Application in Flood-Risk-Based Land Use Planning. Applied Spatial Analysis and Policy, 9, 39-54.

Quenzer, A. M. and Maidment, D. R. (1998). A GIS assessment of the total loads and water quality in the Corpus Christi bay system. Center for Research in Water Resources, University of Texas at Austin.

Statistics, M.D.O. (2018). Demographic Statistics. http://dosm.gov.my/v1/index.php?r=column/ctwoByCatandparent_id=115andmenu_id=L0pheU43NWJwRWVSZklWdzQ4TlhUUT09.

Sun, H., Cheng, X., and Dai, M. (2016). Regional flood disaster resilience evaluation based on analytic network process: a case study of the Chaohu Lake Basin, Anhui Province, China. *Nat. Hazards*, 82, 39-58. https://doi.org/10.1007/s11069-016-2178-3

Tehrany, M. S., Jones, S., and Shabani, F. (2019). Identifying the essential flood conditioning factors for flood prone area mapping using machine learning techniques. *Catena*, 175, 174-192. https://doi.org/10.1016/j.catena.2018.12.011

Tehrany, M.S., Pradhan, B., and Jebur, M.N. (2014). Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. *J. hydrol*., 512, 332-343. https://doi.org/10.1016/j.jhydrol.2014.03.008

Tobin, G.A. and Montz, B.E. (1988). Catastrophic flooding and the response of the real estate market. *J. Soc. Sci*., 25, 167-177. https://doi.org/10.1016/0362-3319(88)90004-3

Torfi, F., Farahani, R.Z., and Rezapour, S. (2010). Fuzzy AHP to determine the relative weights of evaluation criteria and Fuzzy TOPSIS to rank the alternatives. *Appl. Soft Comput*., 10, 520-528. https://doi.org/10.1016/j.asoc.2009.08.021

Urena, R., Chiclana, F., and Herrera-Viedma, E. (2015). Consistency based completion approaches of incomplete preference relations in uncertain decision contexts. 2015 *IEEE International Conference on Fuzzy*

Systems (FUZZ-IEEE), 2015. IEEE, 1-6. https://doi.org/10.1109/FUZZ-IEEE.2015.7338034

Wahlstrom, M. and Guha-Sapir, D. (2015). The human cost of weather-related disasters 1995-2015. *Geneva*, Switzerland: Unisdr 2015.

Wahren, A., Feger, K.H., Schwärzel, K., and Münch, A. (2009). Land-use effects on flood generation-considering soil hydraulic measurements in modelling. *Adv. Geosci*., 21, 99-107. https://doi.org/10.5194/adgeo-21-99-2009

Wang, M. and Niu, D. (2019). Research on project post-evaluation of wind power based on improved ANP and fuzzy comprehensive evaluation model of trapezoid subordinate function improved by interval number. *Renew. Energ*., 132, 255-265. https://doi.org/10.1016/j.renene.2018.08.009

Wang, T.C. and Chen, Y.H. (2010). Incomplete fuzzy linguistic preference relations under uncertain environments. *Inf. Fusion*, 11, 201-207. https://doi.org/10.1016/j.inffus.2009.05.004

Wang, Y., Hong, H., Chen, W., Li, S., Pamučar, D., Gigović, L., Drobnjak, S., Bui, D.T., and Duan, H. (2019). A hybrid GIS multi-criteria decision-making method for flood susceptibility mapping at Shangyou, China. *Remote Sens*., 11, 62. https://doi.org/10.3390/rs11010062

Wang, Y., Xu, L., and Solangi, Y. A. (2020). Strategic renewable energy resources selection for Pakistan: Based on SWOT-Fuzzy AHP approach. Sustainable Cities and Society, 52, 101861.

World Weather Online. 2018. Kota Bahru Monthly Climate Changes http://worldweatheronline.com/kota-bharu-weather-text/kelantan/my.aspx

Wu, Y., Zhang, B., Xu, C., and Li, L. (2018). Site selection decision framework using fuzzy ANP-VIKOR for large commercial rooftop PV system based on sustainability perspective. *Sustain. Cities Soc*., 40, 454-470. https://doi.org/10.1016/j.scs.2018.04.024

Yang, C.L., Shieh, M.C., Huang, C.Y., and Tung, C.P. (2018). A derivation of factors influencing the successful integration of corporate volunteers into public flood disaster inquiry and notification systems. *Sustain*., 10, 1973. https://doi.org/10.3390/ su10061973

Yang, X.L., Ding, J.H., and Hou, H. (2013). Application of a triangular fuzzy AHP approach for flood risk evaluation and res- ponse measures analysis. *Nat. Hazards*, 68, 657-674. https://doi.org/10.1007/s11069-013-0642-x

Zhai, G., Fukuzono, T., and Ikeda, S. (2003). Effect of flooding on megalopolitan land prices: a case study of the 2000 Tokai flood in Japan. *J. Nat. Disaster Sci*., 25, 23-36.

Zhang, L. (2016). Flood hazards impact on neighborhood house prices: A spatial quantile regression analysis. *Reg. Sci. Urban Econ*., 60, 12-19. https://doi.org/10.1016/j.regsciurbeco.2016.06.005

Zhu, H., Yu, M., Zhu, J., Lu, H., and Cao, R. (2018). Simulation study on effect of permeable pavement on reducing flood risk of urban runoff. *Int. J. Trans. Sci. Tech*., https://doi.org/10.1016/j.ijtst. 2018.12.001