

## [Geology] Review

# Data used for GIS-based Flood Susceptibility Mapping

Saro Lee<sup>1,2,\*</sup> and Fatemeh Rezaie<sup>1,2</sup>

Geological Research Division, Korea Institute of Geoscience and Mineral Resources (KIGAM), Daejeon 34132, Republic of Korea<sup>1</sup>

Department of Geophysical Exploration, Korea University of Science and Technology Daejeon 34113, Republic of Korea<sup>2</sup>

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**Abstract** The dramatic increase in flood incidents as a significant threat to human life and property, environment, and infrastructure indicates the necessity of mapping spatial distribution of flood susceptible areas to reduce destructive effects of flooding. During the last decade, the integration of the geographic information system (GIS) with the remote sensing data provide efficient means to generate a more reliable and precise flood susceptibility map. The present study contains a review of 200 articles on the application of GIS-based methods in indicating flood vulnerable areas. The papers were reviewed in terms of influential variables, study area, and the number of articles published in the last 10 years. The review shows that the number of studies has increased since 2012. The total study areas covered 39 countries that were mostly located in Asia where the major developments and infrastructures have been constructed in the floodplains. The most common study areas was Iran (44 articles, 22%), followed by India (26 articles, 13%), China (26 articles, 11%), and Vietnam (15 articles, 7.5%). More than 90 variables were considered to map flood susceptible areas that the top 5 widely used flood conditioning factor are slope (98% of total articles), followed by elevation (92% of total articles), land use/land cover (79.5% of total articles), distance to the river (76.5% of total articles), and rainfall (73% of total articles). The review implies that many natural and anthropogenic factors affect flooding and the combination of both groups of factors is necessary to accurately detect and map flood-prone parts of the study area.

**Keywords:** Data, Systematic literature review, GIS, Flood, Susceptibility map

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\*Corresponding author: [leesaro@kigam.re.kr](mailto:leesaro@kigam.re.kr)

## 1. Introduction

Flood as a result of climate changes is the most widespread and serious geological hazard around the world which one-third of the global surface, including more than 90 countries, is more exposed to flood incidence (Costache et al., 2020). Moreover, the frequency of flood occurrence is more than the other type of natural disasters such as landslide, earthquake, tsunami, and volcanic eruptions (Msabi and Makonyo, 2021). Flood is often responsible for numerous environmental damages, loss of human life, and many destructions of urban infrastructure and incur large direct and indirect costs. Flood occurrences have increased globally due to the incapability of a natural or modified system for drainage to contain the water after heavy rainfalls or long duration of precipitation (Gudiyangada Nachappa et al., 2020). The methods through which counties, cities, and towns plan for land use and engineer new construction and infrastructure can reduce the human and financial costs of floods. Although some causes of many floods cannot be removed, good engineering practices, geological investigations, and effective management regulations of land use can reduce flood hazard. Therefore, it is essential to understand the science of floods, including their causes and associated geological features as well as the locations where they are likely to occur.

Studies show that flooding has affected almost all countries of the world especially many Asian countries and most parts of Iran, India, China, and Vietnam have experienced devastating floods in recent years (Kourgialas and Karatzas, 2017). Flood events are the main cause of more than 90% of fatalities and damages in Asia and it could rise by about 200% over the next three decades (Arabameri et al., 2020; Shahabi et al., 2021). The rapid change in land use/ land cover and developing cities with dense settlements in flood plain regions as well as poor drainage systems, riverside civilization, and intervention into the natural system influence water infiltration rate and increase the probability of flooding (Paul et al., 2019; Tella and Balogun, 2020). In addition to human activities such as deforestation, soil degradation, and urbanization, various natural factors can play a critical role in flood occurrence. Heavy prolonged rainfall causes the rapid release of a high amount of runoff waters from upstream to downstream areas and leads to a decrease in the holding capacity of the river (Saha et al., 2021; Suppawimut, 2021). River overflowing into areas closest to the river bank is important for the initiation of flooding (Karymbalis et al., 2021). Hydro-geological morphometric characteristics of the catchment have effect on the permeability and infiltration capacity of the river (Sarkar et al., 2020). Soil physical properties including soil texture, soil types, soil porosity, and soil structure can cause variations in the degree of water infiltration (Morea and Samanta, 2020). Slope, elevation, topographic wetness index (TWI), aspect, and stream power index (SPI) are frequently used to show the effect of topographic factors on hydrological processes and flood creation. In fact, DEM-derived factors influence the surface run-off velocity, soil moisture, and plant distribution in the most flood-affected regions.

Generating flood susceptibility map is an effective and efficient approach to reduce the negative effect of floods which the map illustrates the possibility of flood occurrence in an area based on the local environmental characteristics and terrain condition. To map the possibility of flood occurrence, rainfall-runoff models need different types of data which are usually unavailable at a regional scale (Ahmadlou et al., 2021). Therefore, previous studies have mapped flood-prone areas using several multiple criteria decision analysis-based methods in combination with geographic information system (GIS), such as analytical network process (ANP) (Dano et al., 2019), analytical hierarchy process (AHP) (Vojtek and Vojteková, 2019), simple additive weighting (SAW) (Setyani and Saputra, 2016),

VlseKriterijumska optimizacija I Kompromisno Resenje (VIKOR) (Analytics and Akay, 2021), and technique for order preference by similarity to ideal solution (TOPSIS) (Rafiei-Sardooi et al., 2021) which the flood conditioning factors are weighted and prioritized based on an expert opinion and expertise. Nowadays, using machine learning methods such as artificial neural network (Ahmed et al., 2021), random forest (Pal and Singha, 2021; Saber et al., 2021), support vector machine (Gudiyangada Nachappa et al., 2020; Siam et al., 2021), and convolutional neural network (Zhao et al., 2020) reduce operating costs and improve the speed of analysis, which has become increasingly important for spatial analysis as large datasets become available. In all mentioned methods, selecting flood conditioning factors play a crucial role in increasing model accuracy and improving the ability of methods to handle multiple variables. Therefore, selecting the optimized number of parameters is obviously important to achieve the best results for a given set of environmental characteristics due to the complexity of the flood conditioning factors and their variation across the study area. Generally, the steps of flood analysis can be classified into three parts including susceptibility, hazard, and risk assessment which the interest in flood susceptibility mapping has been increased in recent years.

The main objective of the current study is to provide an updated overview of the status and trends of GIS-based flood susceptibility mapping in terms of determinant factors, location of the case study, and the number of articles. This review will provide valuable information that will benefit flood mitigation studies when trying to consider more effective factors for determining areas with high susceptibility to flooding.

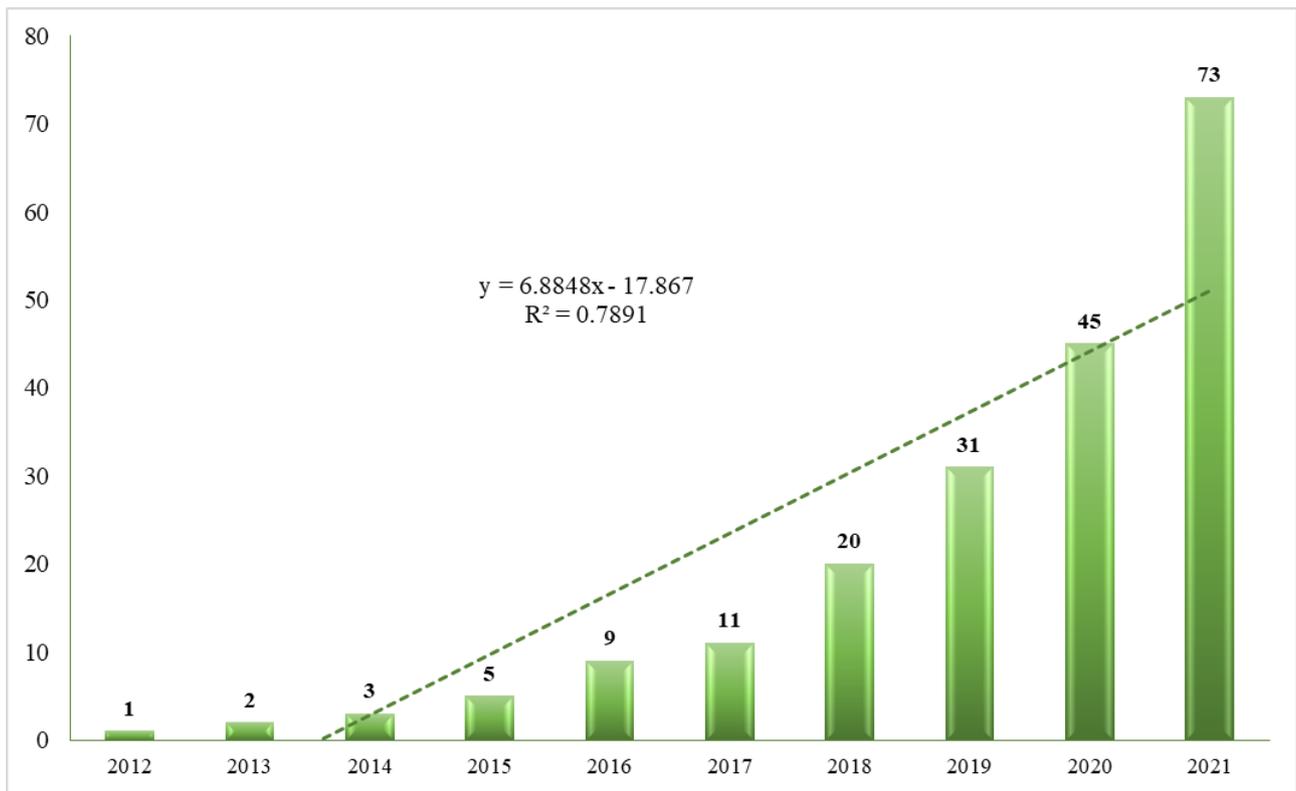
## 2. Methodology

With the aim of clarifying the status of GIS-based flood susceptibility mapping during 2012-2021, Scopus ([www.scopus.com](http://www.scopus.com)) databases were used to search for reviews and research studies published in English using the search terms: "GIS", "flood susceptibility mapping", "flood hazard mapping", "flood susceptibility prediction", "flood susceptibility assessment", "flood hazard susceptibility mapping", "flood susceptibility analysis", "flood susceptibility modelling" and "flood spatial prediction". Following this search, an initial selection of articles was made according to their titles and abstracts. Subsequently, a second selection was made based on reading of the articles. Afterwards, the articles were classified by year to determine the number of articles published per year. This information was used to identify yearly trends in GIS-based flood susceptibility mapping studies. Then, papers were categorized based on the study area, and conditioning factors. Furthermore, VOSviewer software (<https://www.vosviewer.com/>, Version: 1.6.18) as a well-known visualization tool was used to analyze the keyword co-occurrence according to the purpose of the research.

## 3. Results

### 3.1 Temporal trends in published articles

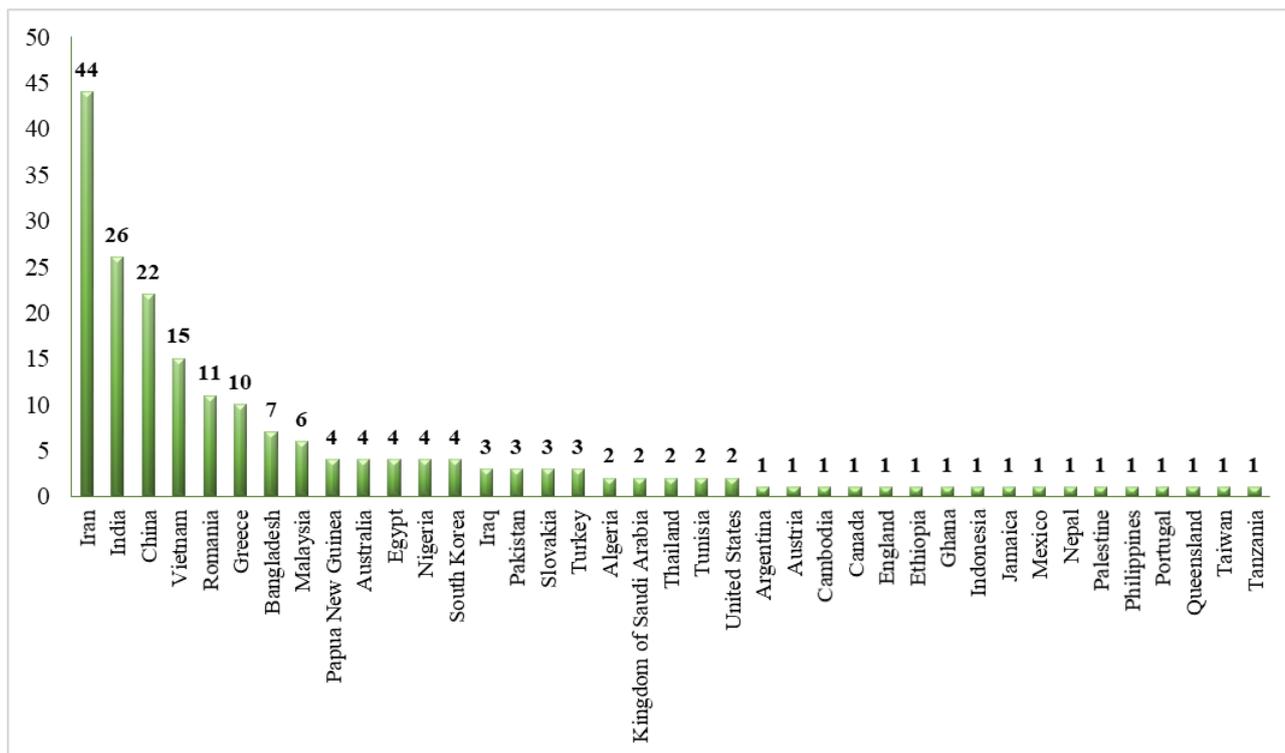
During 2012–2021, 200 articles on GIS-based flood susceptibility mapping were published by a continuous increasing trend over time (Fig. 1). Whereas only one article was published in 2012, 73 articles were published during 2021. During the last decade, the gradient of the trend line of the number of published papers per year was 6.88 and the coefficient of determination ( $R^2$ ) was 0.79, which reflects a significant increase with a reliable fit.



**Figure 1.** Number of published articles in the flood susceptibility mapping field from 2012 to 2021

### 3.2 Study area

The study areas of the investigated articles spanned regions from 39 countries (Fig. 2); however, 64% of articles originated from 6 countries. The most common study area was Iran (44 articles, 22.00%), followed by India (26 articles, 13.00%), China (22 articles, 11.00%), Vietnam (15 articles, 7.50%), Romania (11 articles, 5.50%), and Greece (10 articles, 5.00%). Some examples of these studies included GIS-based flood susceptibility mapping in the mentioned study areas are Arabameri et al. (2020); Arya and Singh, (2021); Costache et al. (2019); Skilodimou et al. (2021); Tien Bui et al. (2020); and Zeng et al. (2021). These regions have large area and multiple climates, variable temporal and spatial rainfall as well as land use and climate changes in the most parts cause flooding every year; therefore, many studies have been conducted for flood mitigation and prevention to decrease its damage to human life, economy, environmental ecosystems, and infrastructure.

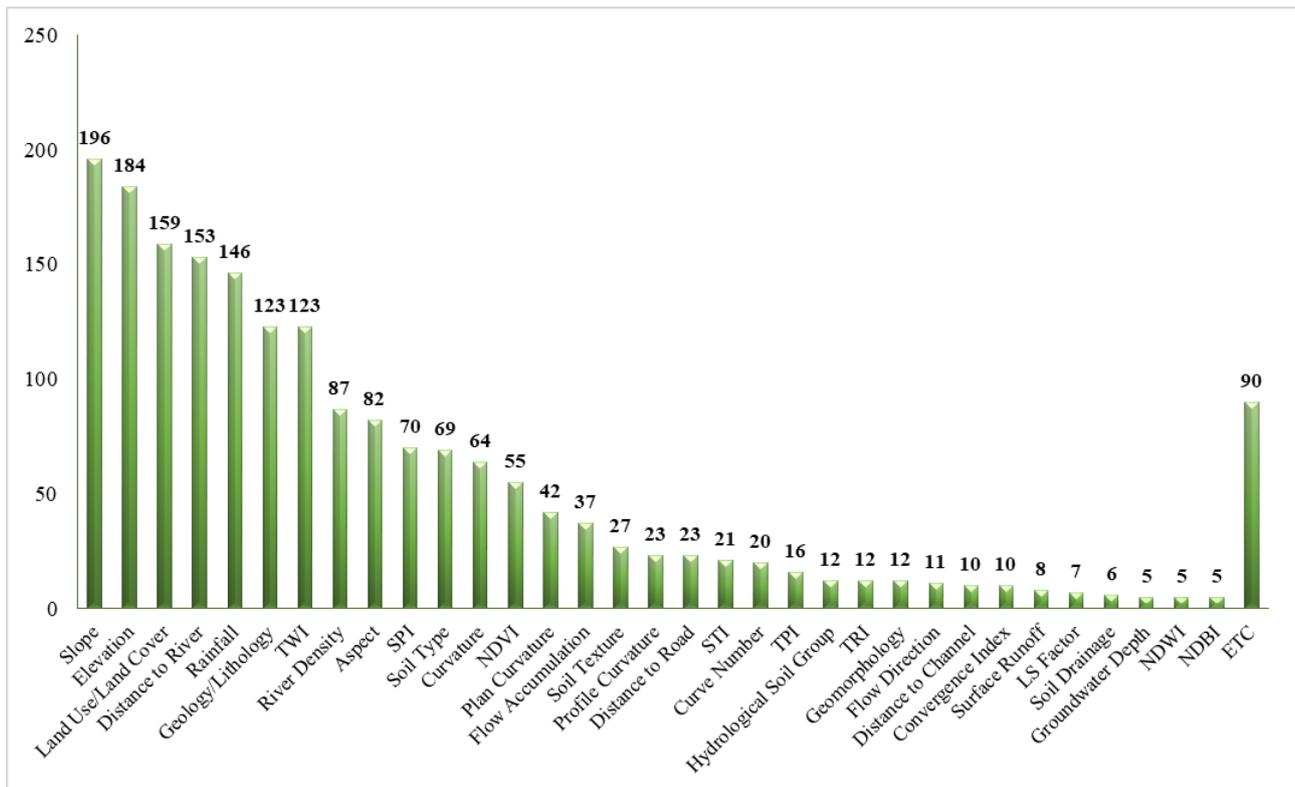


**Figure 2.** Number of published articles with respect to study area from 2012 to 2022

### 3.3. Conditioning factors

As shown in Fig. 3, based on literature review, the top 10 widely used conditioning factors to identify areas susceptible to floods were slope (98.00% of total articles), elevation (92.00%), land use/ land cover (79.50%), distance to the river (76.50%), rainfall (73.00%), geology (61.50%), TWI (61.50%), river density (43.50%), aspect (41.00%), and SPI (35.00% of total articles). The factors were considered very frequently in some studies such as Chakraborty et al. (2021); Malik et al. (2020); Pham et al. (2021); Sahana and Patel, (2019); Yousefi et al. (2020); and Zzaman et al. (2021) (Fig. 4).

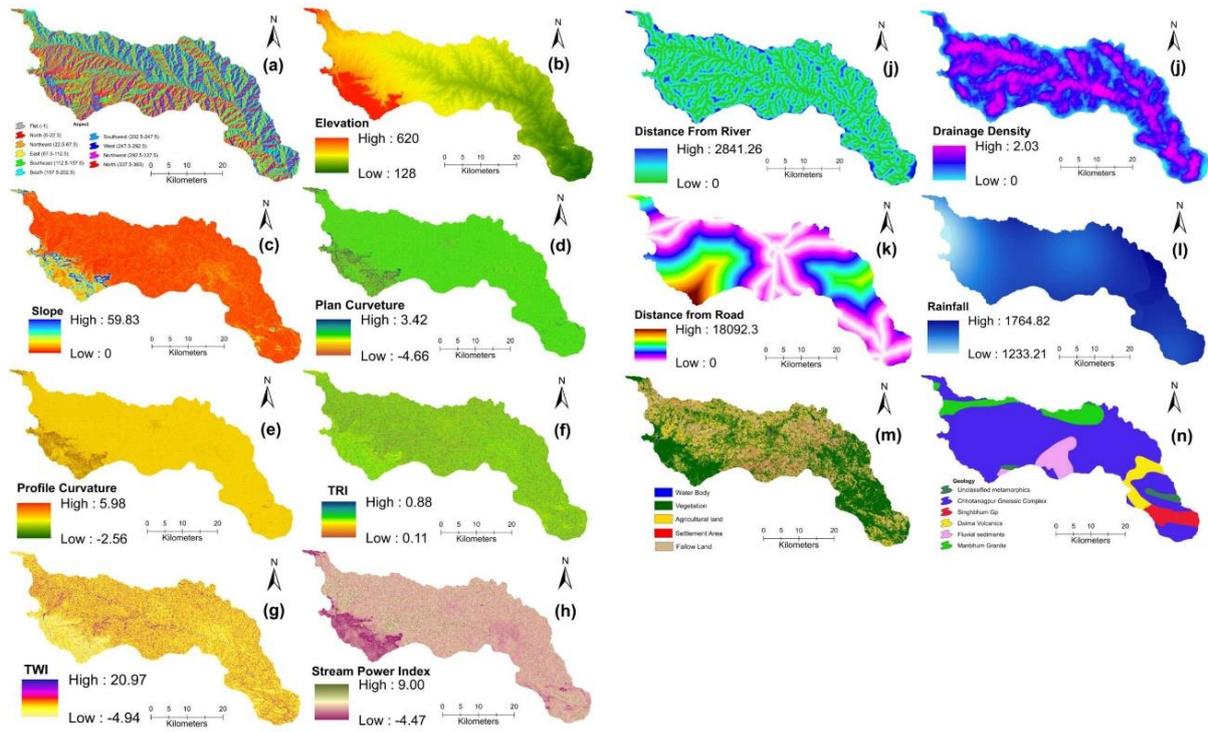
It should be emphasized that selecting reliable explanatory factors can affect the method prediction accuracy. It can lead to more efficiently handling over-fitting problems, prevent redundancy, and decrease the dimensionality of input space (Shirzadi et al., 2020).



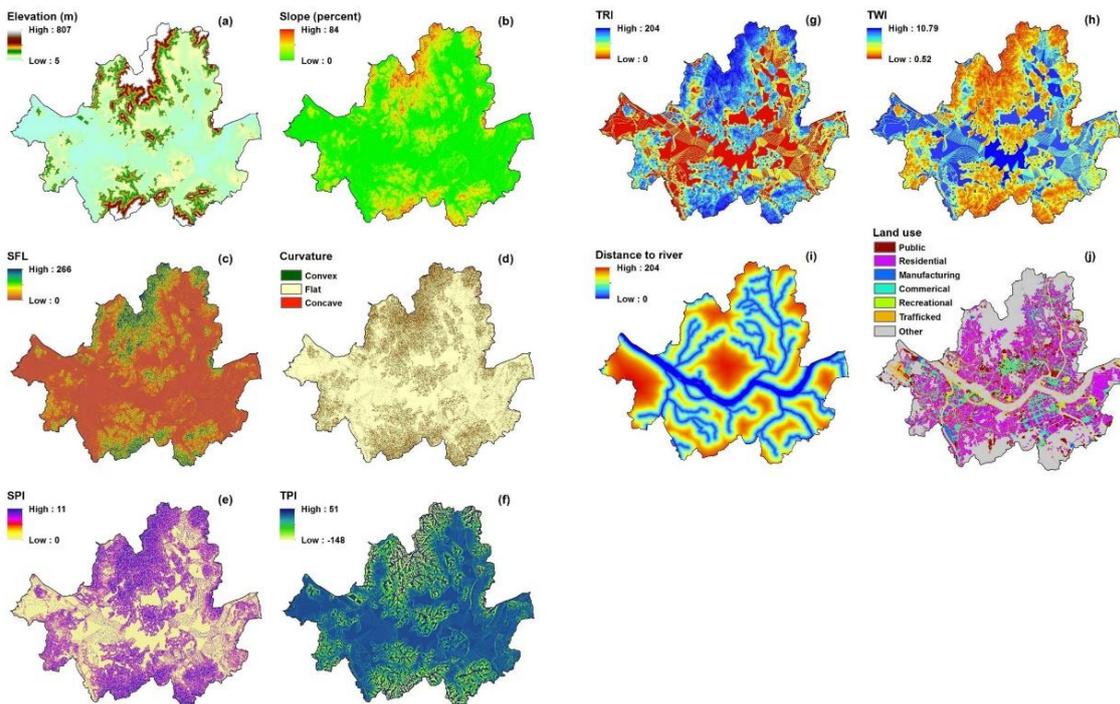
**Figure 3.** Number of published articles with respect to the conditioning factors used to map areas susceptible to flooding from 2012 to 2022 (NDVI: Normalized Difference Vegetation Index, STI: Sediment Transport Index, TPI: Topographic Position Index, TRI: Terrain Ruggedness Index, NDWI: Normalized Difference Water Index, and NDBI: Normalized Difference Built-up Index)

### 3.4 Mapping of keywords

Keywords are the main elements showing the aim of the research. Literature reviews on flood susceptibility mapping revealed that the top 5 occurring keywords with the minimum occurrence of 3 times are spatial prediction, frequency ratio, GIS, statistical models, and flood susceptibility (Fig. 5). The results show that GIS- based data-driven methods are commonly used in flood susceptibility analysis.



(A)



(B)

**Figure 4.** Example of using the top 10 conditioning factors in flood susceptibility mapping, A: India and B: South Korea (SLF: Slope Length Factor) (Chakraborty et al., 2021; Lei et al., 2021)



**Table 1.** The purpose for use of the most important conditioning factors

Conditioning Factor	Purpose of use
<b>Slope</b>	It controls the velocity of surface runoff and opportunities for permeation (Tien Bui et al., 2019). In areas with steep slopes time for infiltration decreases which leads to an increase in water flow (El-Haddad et al., 2021). Slope can control the amount of water infiltration into the soil and it has impact on the depth and capacity of water retention (Dodangeh et al., 2020).
<b>Elevation</b>	Elevation plays an important role in the the direction and amount of surface runoff in an area (Tiryaki and Karaca, 2018). Moreover, different elevations have altered climate characteristics and can cause the differences in vegetation and soil conditions (Natarajan et al., 2021; Rahmati et al., 2016).
<b>Land use/Land cover</b>	It can indirectly or directly affect surface runoff, evapotranspiration, permeability and penetration rate (Yariyan et al., 2020). In urban areas runoff increases due extensive impervious soil. In fallow farmland lack of vegetation cover to control and prevent the rapid flow of water to the soil surface increases runoff (Ullah and Zhang, 2020).
<b>Distance from river</b>	River-overflows are critical for the initiation of a flood event. The probability of inundation is lower in areas far away from riverbeds (Das, 2020; Kazakis et al., 2015; Tehrany and Kumar, 2018).
<b>Rainfall</b>	Rainfall is the most dependable factor of flood which cannot imagine flood occurrence except it (Chowdhuri et al., 2020). flood has been occurred due to huge volume of run-off flows and overbanking as a result of excessively heavy rainfalls or prolonged rainfall (Ahmadlou et al., 2019; Shahiri Tabarestani and Afzalimehr, 2021).
<b>Geology/Lithology</b>	Variations of lithological units can impact on the stream profile on temporal floods and has effect on the development of floods due its influence on permeability power and surface runoff (Haghizadeh et al., 2017; Hong et al., 2018a). In fact, subsoil materials with high permeability and high resistant rocks have lower drainage densities (Hong et al., 2018b).

<b>Topographic wetness index (TWI)</b>	TWI is used to quantify the topographical effect on hydrological processes. It shows the tendency of water to accumulate at a specific location or move downward due to the gravitational force (Tehrany et al., 2019). Moreover, TWI shows spatial patterns of soil moisture and flow intensity (Bui et al., 2019; Lei et al., 2021).
<b>River density</b>	Drainage systems often influences river overflow and continuous flooding in an area (Choubin et al., 2019). Higher drainage density results in lower infiltration and higher runoff (Arabameri et al., 2020; Pandey et al., 2021).
<b>Aspect</b>	Aspect has indirect effect on flooding by controlling some environmental factors such an amount of rainfall, vegetation development, evapotranspiration, and moisture content of the soil by defining where lightning strikes (Dodangeh et al., 2020; Liu et al., 2021; Siahkamari et al., 2018).
<b>Stream power index (SPI)</b>	SPI is a factor to express the erosive power of flowing water (Gudiyangada Nachappa and Meena, 2020; Lee et al., 2017; Shahabi et al., 2020).

The conditioning factors are not fixed and a universal guideline is not available for selection of them. In each area, the selection of flood-controlling factors is performed according to the literature review, expert opinion, data availability, as well as physical and natural characteristics of the study area (Ullah and Zhang, 2020). The accuracy of identification areas actually affected by floods can vary considerably based on selecting the causative criteria.

## 5. Conclusion

In this study, a systematic review was conducted to determine the trend of using GIS-based approaches in spatial modelling and delineating flood susceptible areas. As a result of increasing the frequency of weather-driven disasters, the number of studies to assess flood susceptibility has annually increased in Iran, India, China, Vietnam, and Romania that much attention was paid during 2017-2021 (112 articles).

Flooding is a function of six main groups of factors including topography (i.e. slope, elevation, TWI, aspect, SPI, curvature, plan curvature, and flow accumulation), land use/land cover, meteorological (spatial variability of rainfall intensity), geology, soil property (i.e. type, texture, drainage, moisture, and depth), and forest-related factors (i.e. NDVI, age, type, and density). The top 8 conditioning factors (i.e. slope, elevation, land use/land cover, distance to the river, rainfall, geology, TWI, and river density) were considered 18 times among 200 papers which shows the importance and effect of them in the modelling. The study pointed out that the flood susceptibility assessment was adequately carried out in vulnerable countries, and more research should be undertaken on the flood hazard and risk to minimize human deaths and damages to the economy, farmlands, and urban infrastructure.

## 6. Acknowledgement

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