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Discussion

In flood susceptibility assessment, is it scientifically correct to represent flood events as a point vector format and create flood inventory map?

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ABSTRACT

In this discussion article, we try to highlight and discuss the wrong way for representing an areal phenomenon “flood” as a point vector format in GIS-based flood susceptibility studies and creating what is called “flood inventory map”. Two examples from the literature were taken to show that a flood event cannot be represented by point except with very small map scales (1: 10000000) and this flood event should be with other flood events to form the “flood inventory map”. With the help of the other two examples from the previous studies, this article showed the wrong used way for representing flood worldwide and suggested an appropriate method for mapping flood susceptibility.

In geosciences and environmental hazard analysis, the term “susceptibility” refers to the likelihood of an event (landslides, floods for example) occurring in an area based on the local terrain, environmental conditions, and triggering mechanism (Lee and Pradhan, 2007; Pourghasemi et al., 2012; Reichenbach et al., 2018). Susceptibility depicts areas likely to have that event in the future correlating some conditioning factors that contribute to that event with the past distribution of events (popularly known as inventory) (Brabb, 1985). It is an estimate of where an event such as landslide or flood is likely to occur (Saleh et al., 2020). The susceptibility modeling can be performed in geographic information systems (GIS) platform using three main approaches: (i) the simple overly technique by adding the thematic input layers (Basharat et al., 2016; Roslee et al., 2017); (ii) using knowledge driven-models such as multi-criteria decision-making (MCDM) or fuzzy logic inference system (Neaupane and Piantanakulchai, 2006; Pradhan, 2010; Roodposhti et al., 2014; Souissi et al., 2020), and (iii) using data-driven models such as statistical models (bivariate and multivariate), machine learning models, and hybrid statistical and machine learning models (Nandi and Shakoor, 2010; Bui et al., 2015; Hong et al., 2016; Pham et al., 2016). In the simple overly method, thematic maps of the factors influencing the event (landslide, flood, subsidence, …etc.) are combined linearly to produce the susceptibility map after giving a suitable weight for each factor (rating of each class). The second type of susceptibility modeling is similar to the first one, except that they depend on the advanced MCDM, for example, the analytical hierarchy process (AHP) for getting weights for each thematic layer in the susceptibility analysis and more advanced approaches such as fuzzy logic and the technique of order preference similarity to the ideal solution (TOPSIS), etc. for rating the classes of factors and getting the final susceptibility map. In the third category, the relationship between a group of factors affecting the events and the historical locations of these events (event inventory map) was used to model susceptiblity modeling. In this analysis, the factors are used as predictors and the geographical locations of events as the target variable. All three aforementioned categories of models provide maps that can help the decision-makers and local authorities for civil protective actions, assess damages, and make valid urban planning (Sadek and Li, 2019).

The term “inventory map” appeared in the eighties of the last century in the landslide susceptibility mapping to refer to the spatial distribution of landslides in a given area (Varnes, 1984). In the landslide susceptibility mapping, this term means the total number of registered landslides in an area (the area under consideration) with detailed descriptions such as type of landslides, year of occurrences, soil texture, etc. In the GIS environment, the most common format to represent a single landslide is point feature class (a vector format). The total

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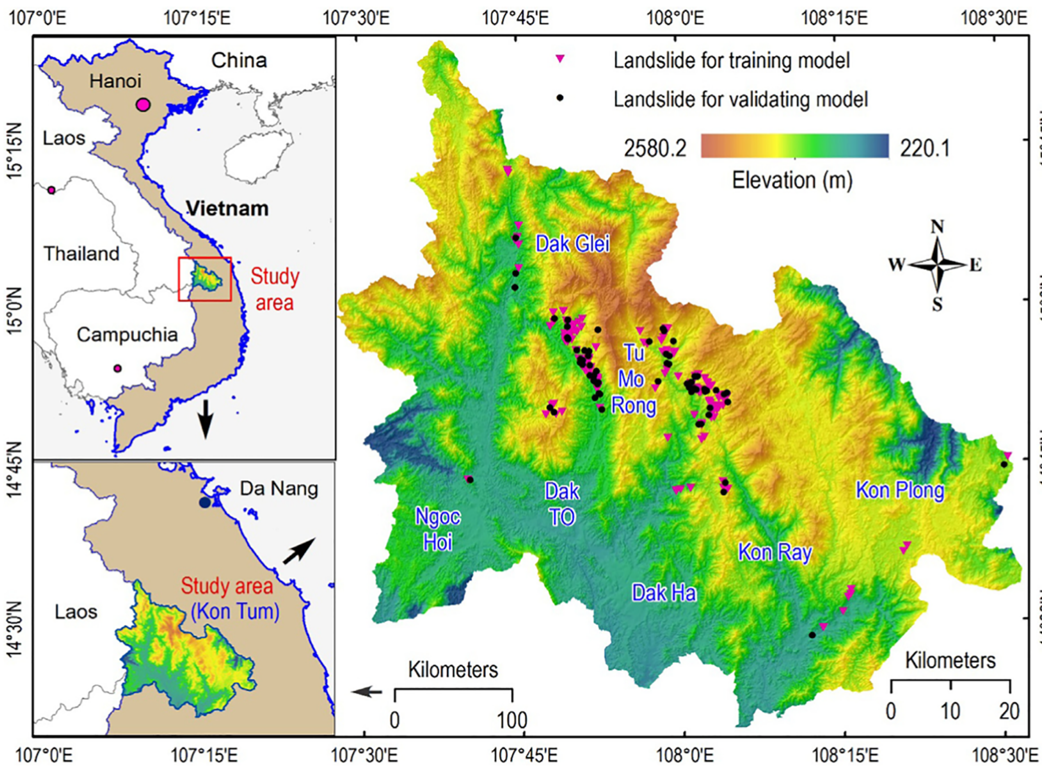

Fig. 1. Landslides are represented as points to make a "landslide inventory map" (after Bui et al., 2020). Adapted with permission from Elsevier, License No. 4847220866274, June 13, 2020.

number of landslides (points) is formed what is called the "landslide inventory map". Let's take an example from a published paper to understand how to represent landslide as a point vector format in GIS software to facilitate comparison when we move to the flood susceptibility analysis. Fig. 1 is taken from the work of Bui et al. (2020), in which every single point has been used as a single landslide and the total number of landslides is called the "landslides inventory map". Landslides are generally not an areal phenomenon, i.e. they do not distribute over a large area except for big landslides; therefore, represent them as point features is not a problem in the landslide susceptibility modeling. What if the landslide is big? Is it presentable as a point vector format? The answer: yes, it is but with taking into consideration that this landslide is just one single landslide and needs to be with other landslides to make a "landslide inventory map".

The "flood susceptibility mapping" in fact is an almost identical copy of the landslide susceptibility analysis. A careful observation of the literature review, it can be said that the researchers in spatial flood susceptibility mapping have been strongly motivated by the landslide researches - even in terms of the influencing landslide factors and the methods used. Flood susceptibility modeling has been done using three approaches mentioned in the previous section and mostly the flood modeling has been done for three major types of floods such as riverine, flash, and urban. What concerns us here is the third category of the models used in modeling landslide susceptibility, i.e. data-driven modeling approaches, which depend on the "inventory map" as a dependent variable (target). The big question here is the floods as a natural phenomenon like landslides to represent them as "points" in the GIS environment and formed what is named "flood inventory map". Let's take an example from the work of Al-Abadi (2018), in which the flash flood susceptibility of an arid region of southern Iraq was analyzed. In that work, the author used the big flash flood that hit the area on 7 May 2013 (flood event) along with 10 influential flood factors (elevation, slope, plain curvature, topographic wetness index, stream power index, distance to ephemeral rivers, drainage density, geology, soil, and land use/land cover) for modeling flood susceptibility using three machine learning models (rotation forest, random forest, and Adaboost). Fig. 2 shows the inundation area by that flood using different scales. It is clear from this figure that this flood cannot be represented using the point feature class (in GIS software) even on the small scale (map 2e). The reason for that, the flood usually distributes over large areas (an areal phenomenon). It is possible to represent flood events as points in a GIS environment but with regional studies and small map scales. Another example of how to represent flood is from the work of Tehrany et al. (2019). Authors of this article modeled the riverain flood susceptibility at the Brisbane catchment of Australia using two machine learning techniques, decision trees and support vector machine. The inundation areas caused by an extreme flood event in 2011 was used in that study along with elevation, slope, aspect, curvature, stream power index, topographic wetness index, topographic roughness index, sediment transport index, geology, soil, land use/land cover, distance from roads, and distance from the river for mapping the potential flood region. The representation of the inundation areas of that flood with different map scales is shown in Fig. 3 (redraw by authors of this essay). It is obvious that this flood cannot be represented by point feature in GIS environment except for very small-scale (1:10,000,000) (Fig. 3e).

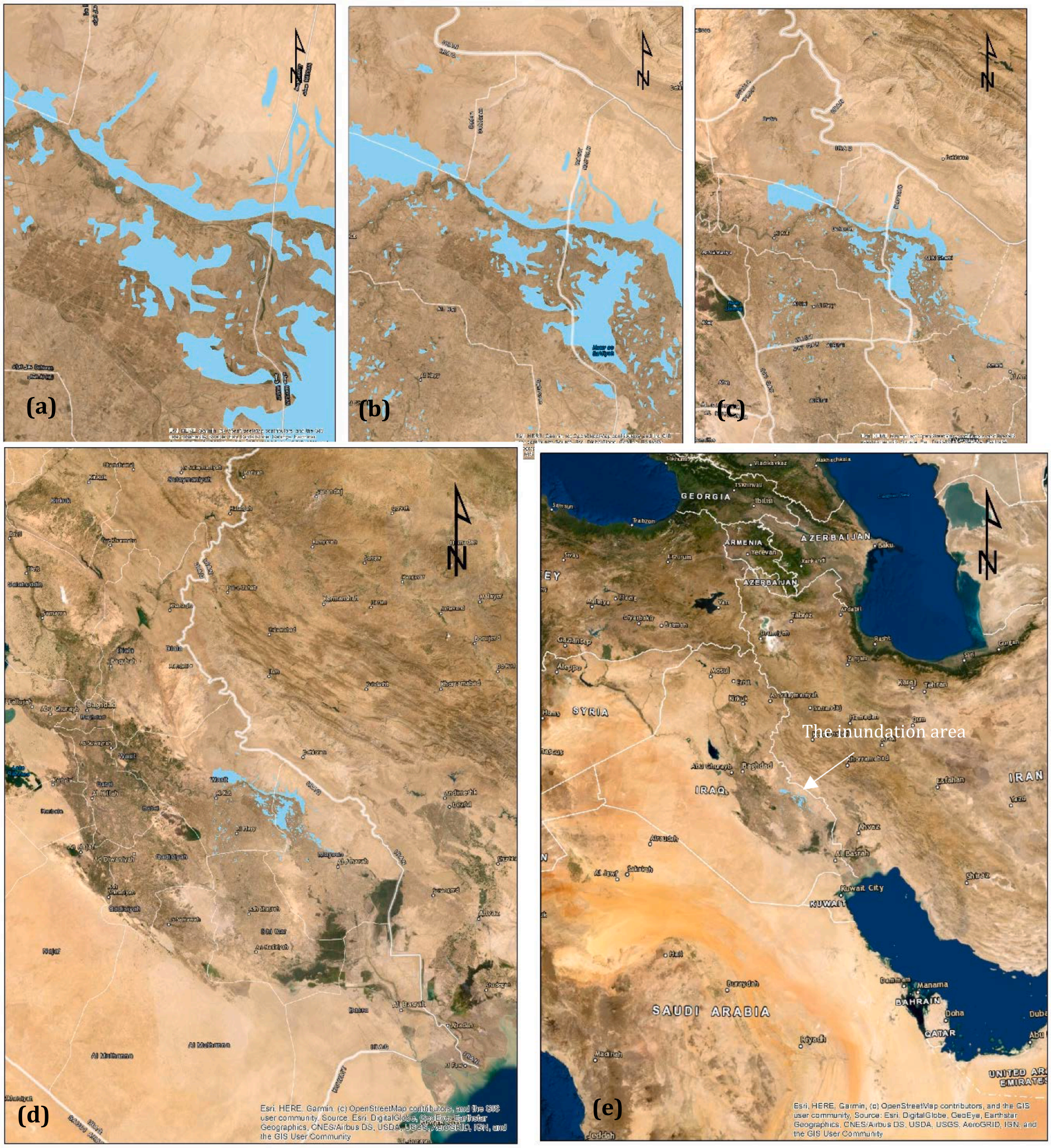

Fig. 2. The inundation area of flash flood by work of Al-Abadi (2018) with different scales (a) 1:250,000 (b) 1:500,000 (c) 1:750,000 (d) 1:1,000,000, and (e) 1:10,000,000.

Authors of the two previous papers used the inundation areas as a guide to create random flood points and non-flood points to create "flood inventory map" to use as a target in the classification problem solved in their studies. In fact, as the flood points selected based on one flood event; the result is not "Inventory map", they are only points affected by that single flood event.

In simple words, let's explain how to carry out flood susceptibility analysis using data-driven models. In the beginning, the flood locations (or flood events) are identified and then an equal number of non-flood locations are randomly determined from the non-flooded areas of the basin or watershed. These flood and non-flood locations are represented as points in the GIS environment and the total number of them formed a "flood inventory map". After that, as the flood susceptibility is a classification problem, each flood points assigned 1 (or yes) and non-flood points assigned 0 (or no). Depending on the data availability and the nature of the study area, many influential factors are prepared. In general, the most factors used in the analysis of flood susceptibility include the topographical related factors (such as elevation, slope, curvature, aspect, topographic wetness index, stream power index, etc.), soil, geology, land use/land cover, and distance to rivers

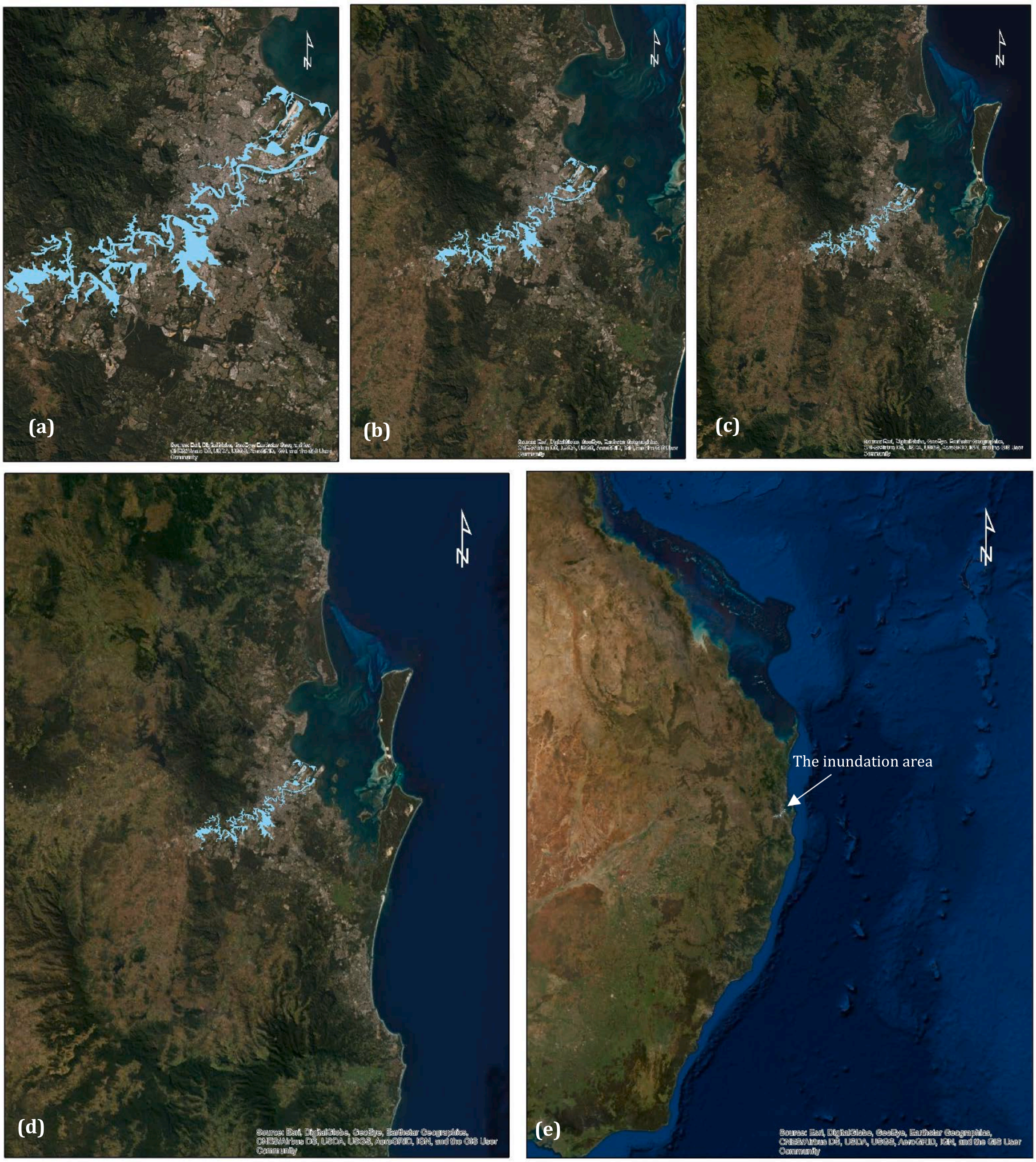

Fig. 3. The inundation area of riverain flood by work of Tehrany et al. (2019) with different scales (a) 1:250,000 (b) 1:500,000 (c) 1:750,000 (d) 1:1,000,000, and (e) 1:10,000,000.

(streams). All these factors are prepared as raster with a specified spatial resolution, for example, 30 × 30 m, 10 × 10 m, etc. For each point locations (flood and non-flood), the values of flood influential factors were extracted and arranged in a table (text file or excel file) and passed to the appropriate software (R software, python, or any other related software) to implement the classification problem and get the probability map of flood susceptibility. Notice, the values of the influential factors are extracted for each point from only one pixel of these factor raster's and depending on the cell size of that pixel.

After this introduction about how to represent flood in the real situation and how to use data-driven models for flood susceptibility mapping, let's take examples from published articles to explain how the researchers worldwide construct a "flood inventory map". Choubin et al. (2019) modeled the flood susceptibility in the Khiyav-Chai watershed in Iran using two algorithms namely multivariate discriminant analysis and classification and regression trees and compared the

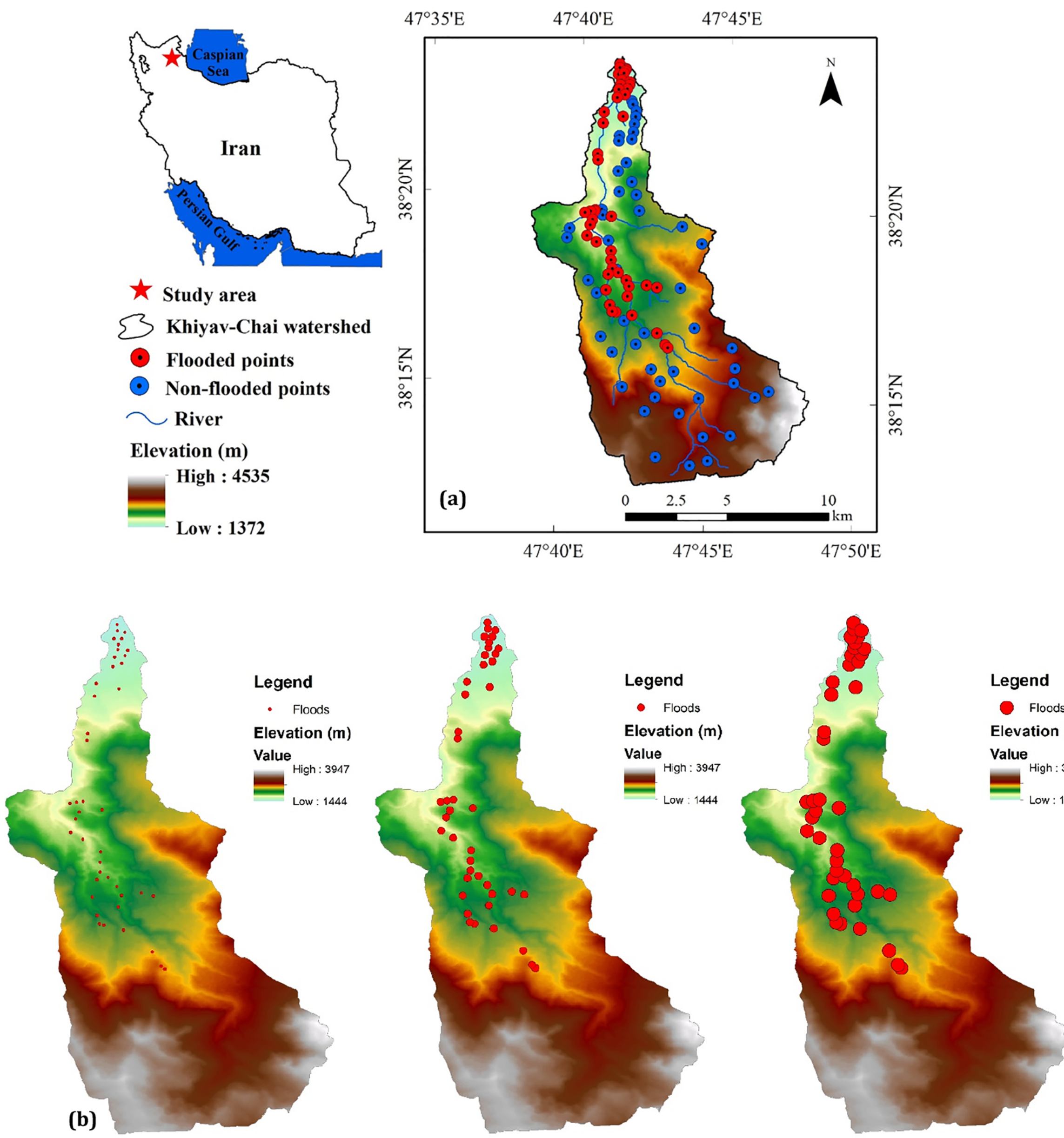

Fig. 4. (a) The study area of Choubin et al. (2019) with flood points (Adapted with permission from Elsevier, License No. 4847211404985, June 13, 2020 (b) the size of the points to represent flood in ArcGIS 10.5: 4, 10, and 18 point sizes (redraw by authors of this essay).

results with support vector machine algorithm. The watershed area is small with an areal coverage of 126 km^2. They used 51 flood location points that were identified between the years 2010 to 2017 to create a "flood inventory map" which was used as a target in the classification problem. They mentioned in their work that *flooding at these recorded flood locations points has caused serious damage to transportation infrastructure, residential areas, natural ecosystems, etc.* Fig. 4 showed the study area of their work along with "flood location map". Let's analyze Fig. 4. First, every redpoint in this figure is a flood caused severe damage; the size of this point, of course, can be controlled by the user in the GIS software; so, size of this point does not truly reflect the size of the flood that happen in that specific location (Fig. 4b), they only refer to the locations of the floods that happened. Let's assume several aspects of this problem and try to analyze each aspect separately. (i) we assume that each point in Fig. 4 is a flood event in the full meaning of this word; but what is the actual size of each point in the spatial modeling. When converting these points to the raster, every single point takes the size of the cell of that raster. For example, if the raster cell is, the size of this point will be 900 m^{2,} and if the raster cell is 10 × 10 m, the cell area becomes 100 m^2. As the size cell (pixel) used in this study is 30 × 30 m, then every flood location has an area of 900 m^2. This is a very small area to classify as a flooded area and how the flood event here destructive is questionable. Fig. 5 shows the areas covered by these flood events and the neighboring areas. Notice, that size of this flood is approximately the same size as a *car* and why the water stands at this location and does not cover the other parts of the area of the same

Fig. 5. Comparison between point size of flood and the neighbor areas of Choubin et al. (2019) study.

elevation is confusing. (ii) in the second aspect, we assume that all these flood locations (51 points) have come from a single flood event. In this case, the result is not an inventory map, they are just locations affected by that single flood.

The second example is taken from the work of Janizadeh et al. (2019). In this article, authors mapped the flash flood susceptibility in the Tafresh watershed, Iran using five machine learning classifiers (alternating decision trees, functional trees, kernel logistic regression, multivariate perceptron, and quadratic discriminant analyses) through using 320 historical flood events (target) and eight variables elevation, slope, aspect, distance from rivers, average annual rainfall, land use, soil type, and lithology as flood influencing factors (predictors). Fig. 6 shows the Tafresh watershed and the historical floods in the watershed; notice every red point in the figure is a historical flood event. The total number of these flood events (320) in this study is used as the "flood inventory map" along with 320 randomly non-flood points created by authors to refer to the locations that not affected by floods. The source of the data (flood locations) according to the authors is the Regional Water Organization of Markazi Province (Iran). Truly, it is confusing how these points represent floods here, especially, if we assume that the point size here reflects the size of the flood that occurred at a specific time, then merely comparing the point size with the scale used strikes the researcher with amazement, that the spatial distribution of this flood is very small Fig. 7. Suppose that these 320 points (floods) represent the places affected by one single flood, the question now is what is the scientific basis on which these 320 were chosen? and the points, in this case, do not form an inventory map, they are only flood locations extracted from one single flood.

Surprisingly, there are a lot of published scientific researches (Table 1) that uses the "point feature" to represent a flood event (not areas affected by the flood) without taking into consideration the actual spatial extent of flood and whether the flood a point phenomenon (in

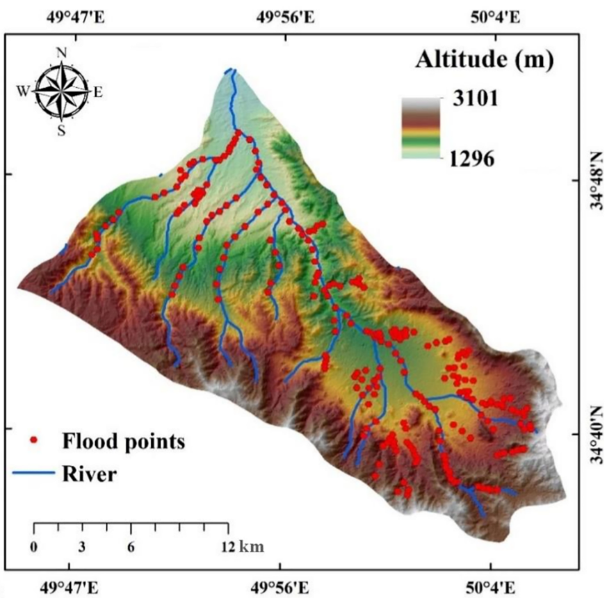

Fig. 6. The study area of Janizadeh et al. (2019) with "flood inventory map" (Adapted with permission from MDPI publishing house).

spatial analysis), such as landslides, a groundwater well, a spring, or subsidence to represent by a point and formed "inventory map". Therefore, from the authors' point of view, we think that creates an "inventory map" for an areal phenomenon like a flood is a great fallacy; simply it is impossible.

Now the question is what is the preferred way for mapping flood susceptibility? The answer lies in studying the historical floods in a considered watershed, basin, or area and obtaining a rough picture of its spatial extent and represent that extent by polygon shape in a GIS platform. From this polygon, a sufficient number of points can be generated that cover the entire polygon to represent areas affected by the flood and choose a similar number of points from the areas not affected by floods to refer to the areas not affected by floods. Each point affected by the flood is given a value of 1 (yes, flood, etc), and the non-affected is given 0 (no, non-flood, etc). Thus, the target variable necessary to conduct a classification problem is generated. For more information, see the works of Al-Abadi (2018) and Tehrany et al. (2019). In the case it is not possible to obtain an approximate map of the spread of floods in an area, indirect methods can be used to determine the spatial extent of the floods, as in the work of Hosseini et al. (2020) and Costache et al. (2019). The authors of the first work extracted the inundation area using the Modified Normalized Difference Water Index (MDNWI) of Sentinel-2 satellite through the Google Earth Engine environment. From the probable extension of the deduced inundation area, the author capable to sample less uncertain points to represent flood and non-flooded areas and generate the target variable in their study. In the second study, the authors used the torrential areas as a guide to estimate the potential for surface runoff and mapping the probable extension of a flash flood in their study area. They represented the torrential valleys as polygon (a realistic way) in GIS environment and then they used that polygon to sample flood points and non-flood points to generate a target variable in their study.

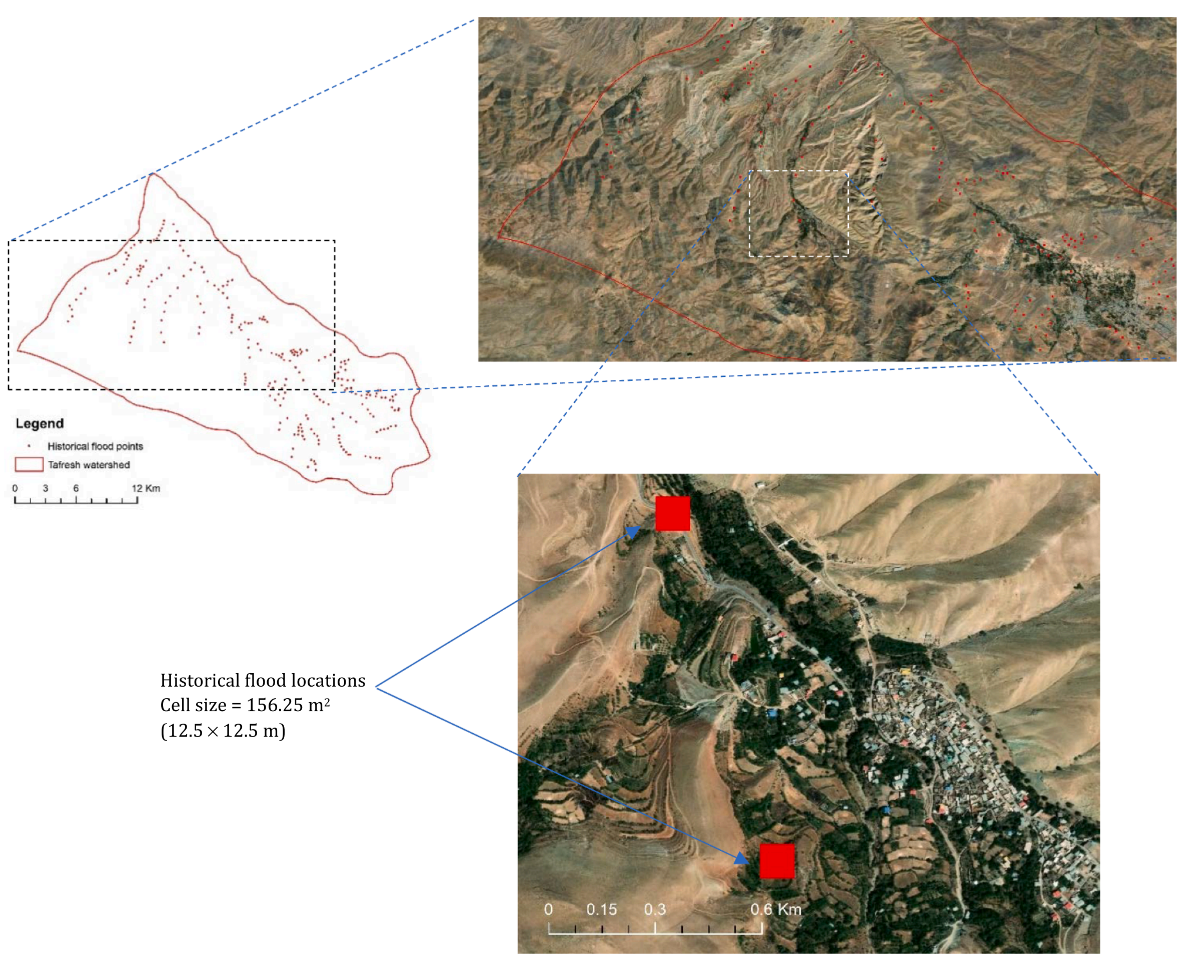

Fig. 7. Comparison between point size of flood and the neighbor areas of Janizadeh et al. (2019) study.

Table 1
Examples of published articles that used point format in GIS platorm to represent flood events or flood locations without giving a rough estimate of the spatial distribution of flood events.

Author/s	Factors affecting flood used	Technique used
(Pourghasemi et al., 2020)	Plan and profile curvatures, altitude, distance to rivers, slope degree, rainfall, land use, lithology, stream power index, topographic wetness index, soil type, aspect, and normalized difference vegetation index	Ensimble meta-heuristic approach, including the combinations of Adaptive Neuro-Fuzzy Inference System) with the genetic algorithm, simulated annealing, imperialist competitive algorithm, and differential evolution.
(Costache et al., 2020)	Elevation, slope, Slope-aspect, plan curvature, topographic position index, topographic wetness index, convergence index, hydrologic soil sroups, land use, distance from rivers, rainfall and lithology	Hybridizations of fuzzy Analytical Hierarchy Process, Index of Entropy, and Support Vector Machine
(Bui et al., 2019)	Elevation, slope, curvature, toposhade, aspect, topographic wetness index, stream power index, stream density, Normalized Difference Vegetation Index, soil type, lithology, and rainfall	Multivariate Adaptive Regression Splines and Particle Swarm Optimization
(Darabi et al., 2019)	Precipitation, slope, curve number, distance to river, distance to channel, depth to groundwater, land use, and elevation.	Genetic Algorithm Rule-Set Production and Quick Unbiased Efficient Statistical Tree
(Tehrany and Kumar, 2018)	elevation, aspect, plan curvature, slope, topographic wetness index, geology, stream power index, soil, land use/cover, rainfall, distance from roads and distance from rivers.	Dempster–Shafer-based evidential belief function, logistic regression and frequency ratio
(Tehrany et al., 2019)	altitude, slope, aspect, curvature, geology, soil, landuse/cover, topographic wetness index, stream power index, terrain roughness index, sediment transport index, and distance from rivers and roads	Statistical index, frequency ratio and logistic regression methods.

Author/s	Factors affecting flood used	Technique used
(Tehrany et al., 2014)	slope, stream power index, topographic wetness index, altitude, curvature, distance from the river, geology, rainfall, land use/ cover, and soil type.	Weights-of-evidence and support vector machine
(Chen et al., 2019)	Altitude, slope angle, slope aspect, curvature, stream power index, sediment transport index, topographic wetness index, distance to rivers, normalized difference vegetation index, soil, land use, lithology, and rainfall.	Machine learning-based Reduced-error pruning trees with Bagging and Random subspace ensemble frameworks
(Wang et al., 2020)	Altitude, aspect, curvature, slope, stream power index, sediment transport index and topographic wetness index, lithology, land use, normalized difference vegetation index, soil, distance to rivers and rainfall.	Convolutional neural network
(Khosravi et al., 2018)	Ground slope, altitude, curvature, stream power index, topographic wetness index, land use, rainfall, river density, distance from river, lithology, and normalized difference vegetation index.	Logistic Model Trees, Reduced Error Pruning Trees, Naïve Bayes Trees, and Alternating Decision Trees
(Khosravi et al., 2019)	Normalized difference vegetation index, lithology, land use, distance from river, curvature, altitude, stream transport index, topographic wetness index, stream power index, soil type, slope and rainfall.	Multiple-Criteria Decision Analysis, Naïve Bayes Tree and Naive Bayes classifiers
(Bui et al., 2016)	Slope, elevation, curvature, topographic wetness index, stream power index, distance to river, stream density, normalized difference vegetation index, lithology, rainfall.	Hybrid metaheuristic algorithms, Evolutionary Genetic and Particle Swarm with neural fuzzy inference system

Author/s	Factors affecting flood used	Technique used
(Al-Juaidi et al., 2018)	Altitude, slope, flow accumulation, rainfall, land use/ cover, and soil type	Logistic regression
(Hong et al., 2018a)	Slope, aspect, altitude, curvature, the sediment transport index, the stream power index, the topographic wetness index, rainfall, distance to rivers, lithology, soil type, land use and the normalized difference vegetation index	Adaptive neuro-fuzzy inference system coupled with a genetic algorithm and differential evolution
(Ahmadlou et al., 2019)	Altitude, aspect, slope, plan curvature, soil type, land use and rainfall	Biogeography-based optimization and BAT algorithm coupled with an adaptive neuro-fuzzy inference system
(Hong et al., 2018b)	Lithology, soil cover, elevation, slope angle, aspect, topographic wetness index, stream power index, sediment transport index, plan curvature, profile curvature and distance from river network.	Fuzzy weight of evidence, logistic regression, random forest and support vector machines
(Samanta et al., 2018)	Elevation, slope, topographical wetness index, geomorphology, soil type, drainage, rainfall, and land use/cover)	Frequency ratio
(Cao et al., 2016)	elevation, slope, curvature, land use, geology, soil texture, subsidence risk area, stream power index, topographic wetness index, and short-term heavy rain.	Frequency ratio and statistical index

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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