Anticipation of Flood Susceptibility in Urbanized Regions Using Machine Learning Technique: Case Study of New Cairo City, Egypt

Mohamed Wahba (✉ mohamed.wahba@ejust.edu.eg)

Egypt-Japan University of Science and Technology

Mahmoud Sharaan

Egypt-Japan University of Science and Technology

Wael Elsadek

South Valley University

Shinjiro Kanae

Tokyo Institute of Technology

H. Shokry

Egypt-Japan University of Science and Technology

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Abstract

Climate change is driving growth in extreme weather events through vast world regions. Therefore, one of the most destructive calamities of climate change is flash flooding. This research aims to predict the most prone areas to flash floods in urban regions using machine learning techniques. Moreover, the runoff depth has been calculated via HEC-RAS software to use it as a conditioning parameter. Subsequently, seven environmental factors (elevation, slope, flow length, distance to streams, maximum runoff depth, land use, and curve number) were adopted in New Cairo city, Egypt, where the flash flood occurs persistently. A combination of spatial flooded points and environmental parameters has been utilized using a genetic algorithm for Rule-set Prediction (GARP) to generate a flood susceptibility map (FSM). Furthermore, the FSM accounted nearly fifth of the total area for very high prone to floods whilst 40.03% and 13.14% of the city have very low and low hazards, respectively. Additionally, the receiver operating characteristic curve (ROC) method was used to validate the FSM which gave 71.5% for the area under curve (AUC). Eventually, Decision-makers can use the produced flood danger map to better understand the consequences of flash floods and to prepare alternative plans to mitigate this hazard.

1. Introduction

Recently, the deleterious effect of climate change has sprung up, leading to unprecedented environmental catastrophes. Climate change and intensive human activity have resulted in broad changes to streamflow regimes necessary to meet world socio-economic requirements and ecological health (Poff, 2018). Therefore, cities may become more susceptible to floods if climate change alters the precipitation patterns (Kim et al., 2017). Moreover, various detrimental effects of flash floods can be witnessed, such as disruption in people's live, damage in urban traffic, failure of houses, and spread of pollution (Norallahi and Kaboli, 2021). Therefore, to avoid the detrimental repercussions of flooding, it is essential to identify the flooded regions (Wahba et al. 2022). Consequentially, watershed hydrology can be altered by expanding imperviousness and tubing or channeling natural drainage ways in urban areas (Li et al., 2013; Hester and Bauman, 2013; Liu et al., 2015).

Additionally, the study area has no stations to record the rainfall rate; therefore, overcoming this scarcity in recorded rainfall is essential. Meanwhile, the geomorphological index can be beneficial to figure out how the watershed responds to an abundance of rainfall. This will be advantageous since we investigate the hazards of floods in unrecorded areas (Martini and Loat 2007; Muzik 1996; Lastra et al. 2008).

Numerous models were utilized to generate flood prone mapping either physical or statistical models, regarding the flash floods modeling. Physical models like HEC-RAS (Wiles and Levine 2002; Rangari et al. 2019), Storm Water Management Model SWMM (Laouacheria et al. 2019), and Hydrological Simulation Program-FORTRAN (HSPF) (Fonseca et al. 2018; Bicknell et al. 1993), while statistical models are like logistic regression, generalized linear models, entropy, frequency ratio, weighting factors, weights of

evidence, flexible discriminant analysis, statistical index, and multivariate statistical methods (Youssef et al. 2016; Giovannettone et al. 2018).

In machine learning techniques, there are several approaches of machine learning employed to investigate the flash flood hazard, such as classification and regression trees, the approach of support vector machines, least-squares SVM, random forest, Naïve Bayes, method of adaptive neuro-fuzzy inference system, decision trees, genetic algorithm rule-set production (GARP), and quick unbiased efficient statistical tree (Darabi et al. 2019, 2020; Hong et al. 2018; Chen et al. 2017; Yan et al. 2018; Lee et al. 2017; Rahmati et al. 2019; Hosseini et al. 2020; Eini et al. 2020).

Meanwhile, as far as hazard mapping is concerned, machine learning algorithms have shown auspicious results in locations where adequate hydraulic and hydrological data is unavailable (Mahmood et al., 2019; Mahmood and Rahman 2019).

As a result of the negative consequences of flash floods in Egypt, in October 2016, a rainstorm ravaged Egypt's northern area, killing and injuring 73 and 30 citizens, respectively (Elnazer, Salman, and Asmoay, 2017; FloodList, 2016; IFRC, 2017).

Furthermore, during years of 2018 and 2019, multiple devastating floods damaged the city of New Cairo, causing displacement of a considerable number of residents, possessions devastation, loss of significant monetary, and the lives of 7 individuals. (FloodList, 2018; FloodList, 2019; FloodList, 2020). In Alexandria and Beheria, respectively, at least six and twenty-five people were killed in 2015. Moreover, New Cairo city witnesses acceleration in rainfall rate as according to the Egyptian Meteorological Authority, the recent torrential rains in Egypt were caused by climate change, which is impacting the whole planet (Egypt Today, 2018). In addition, the studied area has been founded recently on major streamlines, which leads to a dramatic increase in runoff.

The current study aims to predict vulnerable urban areas to flash floods using machine learning techniques. The novelty of this research is to estimate the maximum runoff depth and to utilize it as a conditioning factor to produce the flood susceptibility map.

2. Study Area

New Cairo City resembles one of the most prestigious cities in Egypt. Meanwhile, it was founded recently in 2000 to alleviate the overcrowding in Cairo city with an area of 267 Km². The position of the studied region is illustrated in Fig. (1). Moreover, New Cairo city is one of Egypt's most attractive and populous cities since it contains 6 international universities and a plethora of economic and luxurious residential buildings. Furthermore, the region of New Cairo city has been witnessing periodic devastating flash floods every year. Figure (2) depicts the impact of different rainfall storms that struck New Cairo city. Figure (2) sources: Egyptian Streets (2018) (<https://egyptianstreets.com/2018/04/26/heavy-rains-cause-chaos-in-Cairo/>), and Youm7 (2020) (<http://www.youm7.com/4668611>).

3. Materials And Methods

Digital Elevation Model (DEM) plays a vital role in hydrologic and hydraulic modeling, and its precision is critical for flood inundation mapping (Xu et al., 2021). The utilized DEM for the current study has a 12.5 m resolution. The DEM was extracted using ALOS-PALSAR (Advanced Land Observing Satellite-Phased Arrayed L-band Synthetic Aperture Radar) from the Earthdata website (<https://search.asf.alaska.edu/#/>). Moreover, 7 bands of land use were composited and classified using ArcMap to get the land use/ land cover map. The land use bands were obtained from the Earthexplorer website (<https://earthexplorer.usgs.gov/>). with a cell size of 30m. Additionally, the Hydrologic Soil Groups (HSG) was acquired from the ORNL DAAC website (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1566) to estimate the values of curve number (CN). In addition, HEC-RAS 6.0 and GARP Desktop software were utilized to determine and predict the runoff depth and flood hazard map, respectively.

3.1. Data gathering

The terrain elevation is declined from south to north to be 433m to 156m, respectively. Figure (3) shows the New Cairo elevation. Moreover, Fig. (4) presents about 20 delineated subbasins in the studied area.

The rainfall data were obtained from the NASA power website (<https://power.larc.nasa.gov/data-access-viewer/>). The two studied storms were extracted per hour from 7:00 AM to 12:00 PM on 30 November 2016 and 8:00 AM to 4:00 PM on 25 April 2018. These two rainfall storms are presented in Fig. (5) and Fig. (6) respectively.

3.2. Methodology framework

A watershed delineation was conducted using DEM with a resolution of 12.5m. Consequently, basins, subbasins, and streamlines were allocated to the studied area. After that, subbasins and DEM were exported to HEC-RAS 6.0 to generate a hydrodynamic model. Meanwhile, the boundary conditions for both inputs (precipitation on-grid) and outputs (downstream) were determined. The precipitation data was extracted from the two adopted storms. The downstream boundary conditions were assigned at the end of streamlines, where the downstream flow was calculated from the friction slope. Also, the losses during infiltration were evaluated by adopting the Soil Conservation Service (SCS) Curve Number approach. Subsequently the values of runoff have been spatially figured. In addition, the estimated flow depth (runoff depth) during the selected 2018 rainfall storm was used as an environmental parameter.

Furthermore, the environmental parameters (elevation, slope, distance to streams, land use, curve number, flow length, and the estimated runoff depth) were proceeded via ArcMap and then converted to ASCII files to be exported to GARP Desktop software. This software is based on the Genetic Algorithm Rule-Set Production method, which has been accounted for the determination of FSM. Moreover, flooded points were specified during actual rainfall storms on the New Cairo city, and then they were adopted to create the flood inventory map.

Ultimately, both the flood inventory map and environmental conditions have been used to generate the FSM. The generated map was validated using ROC method. Figure (7) presents the applied methodology framework.

4. Data Analysis

4.1 Soil classification

Soil has been categorized according to USDA-based soil texture classes (National Engineering Handbook (NEH)); this classification consists of four soil groups described in Table (1). Consequently, New Cairo city's soil involves two hydrologic soil groups (B and C), as shown in Fig. (8). According to this classification, HSG (B) represents the potentiality of low runoff, whereas HSG (C) denotes the likelihood of high runoff.

Table (1) Hydrologic soil groups classification

Soil Group	Description
Group (A)	Low likelihood of runoff when totally wet, contains clay < 10% and sand > 90%.
Group (B)	The potentiality of little runoff contains clay between 10–20% and sand between 50–90%.
Group (C)	The possibility of significant runoff contains clay between 20–40% and sand under 50%.
Group (D)	The significant likelihood of runoff containing clay outnumbers 40% and sand lesser 50%.

4.2 Curve number

Curve number is a factor created by Soil Conservation Service (SCS) in the US. It is commonly used for predicting immediate runoff from precipitation on tiny to intermediate basins that are not gauged (L. Silveira et al., 2000). This parameter is illustrated in “National Engineering Handbook, Section 4-Hydrology (1964)”.

SCS-CN approach is premised on the water-equilibrium equation described in Equ. (1) and two basic propositions in Equ. (2) and Equ. (3).

$$P = I_a + F + Q \text{ Equ. (1)}$$

$$\frac{Q}{P - I_a} = \frac{F}{S} \text{ Equ. (2)}$$

$$I_a = \delta \cdot S \text{ Equ. (3)}$$

Where “P” denotes precipitation, “ I_a ” is the initial abstraction, “F” designates to infiltration, “Q” describes the immediate runoff, “S” is the maximum potential retention, “ δ ” is the ratio of initial abstraction. All these mentioned parameters have length (L) dimension except the initial abstraction ratio, which is dimensionless.

Equ. (1) and Equ. (2) are combined to produce the well-known Equ. (4) (Sahu et al., 2010).

$$\left\{ \begin{array}{l} Q = \frac{(P - I_a)^2}{P - I_a + S} \text{ at } P > I_a \\ Q = 0.00 \text{ at } P < I_a \end{array} \right. \text{ Equ. (4)}$$

Furthermore, the initial abstraction value “ δ ” can be assumed 0.2 according to (Thomas and Jaiswal 2002; White, 1988; McCuen, 2002; Silveira et al., 2000). However, “ δ ” is assumed less than 0.2 in compliance with (Mishra et al., 2003) and (Hawkins et al., 2001). Subsequently, the potential maximum retention (S) can be estimated from Equ. (5).

$$S = \left(\frac{1000}{CN} - 10 \right) 25.4 \text{ Equ. (5)}$$

Where “S” is calculated in (mm), meanwhile, the determination of storage depends on curve number (CN) estimated for different soil types, and land uses (Chow et al., 1988; NEH-4, 1964; Pilgrim & Cordery, 1993).

The Curve number map has been generated according to hydrologic soil group and land use (USDA, 1986). Figure (9) demonstrates the estimated spatial curve number in New Cairo city.

4.3 Roughness (Manning’s) coefficient

The roughness of the bottom is an efficacious quantity in modeling flash floods (Lane 2005) since it resembles agglomerated impacts of various absent factors like the flow dispersion, turbulence, the existence of buildings and barriers (Brown et al. 2005).

Meanwhile, in accordance with laboratory research employing building scale, the head losses account for buildings can be governed by the roughness-induced head losses (Testa G, et al., 2007).

Therefore, the roughness coefficient has been estimated through the entire studied area considering the roughness of streets, vegetation, buildings, and the blank regions. Figure (10) shows the values of manning’s coefficient.

4.4 Environmental parameters

Seven environmental factors were utilized to generate the flood hazard map (elevation, slope, flow length, distance to streams, maximum runoff depth, land use, curve number). The utilized factors have been

described as follows:

- a) Elevation; is a paramount factor affecting flood susceptibility (Bui et al., 2016), considering there is an opposite linkage between elevation and floods. i.e., the more increase of the elevation, the lesser effect of flash floods (Khosravi et al., 2016a).
- b) Slope; directly accelerates the flow velocity (Rahmati et al., 2016). Flooding is a physiographic phenomenon closely connected to the slope. (Khosravi et al., 2016b; Meraj et al., 2015; Bui et al., 2016).
- c) Flow Length; represents the length of flow in each cell to the flow outlet. The degree of flood risk reduces with the higher values of flow length (El-Fakharany, et al., 2021).
- d) Distance to streamlines; Streamlines resemble the major pathway for flood discharge, and the close areas to streams are more prone to floods (Opperman et al., 2009).
- e) Land use; can significantly influence the celerity of runoff, infiltration, interception, and evapotranspiration (Yalcin et al., 2011). Therefore, the land cover map is an indispensable factor affecting flood susceptibility (Komolafe et al., 2018; Karlsson et al., 2017).
- f) Runoff depth; is the only parameter representing the flash flood source. Since with the increase of runoff depth, the flash flood hazard is potentially high (El Alfy, 2016).
- j) Curve number; is an experiential quantity included in the hydrological formula to anticipate immediate runoff and infiltration from excessive precipitation (Cronshey et al., 1985). Furthermore, curve number values are directly proportional to flash floods' hazard degree.

4.5. Flood conditioning map

The flood conditioning map is a fundamental map used to determine flood vulnerability. (Rahmati et al., 2016; Tehrany et al., 2014). In addition, the precision of the flood hazard map can be improved as we increase the number of flooded points (Tien Bui and Hoang, 2017). Consequently, flooded points were observed during various flood events. Most of these data were gathered from previous literature conducted to determine the accumulating points in New Cairo city (Elwatannews, 2020). Forty-eight flooded points were identified in New Cairo city; 34 flooded points (represents 70%) were employed for training while the kept 14 points (represents 30%) were withheld for examining the model. The proportions of training and testing were adopted according to (Bordbar et al. 2022, Lee et al. 2020, Fernandes et al. 2021, Gadalla et al. 2019). Figure (12) describes the flood inventory map.

4.6. Machine learning technique

The genetic Algorithm for Rule-set Prediction (GARP) was employed as a machine learning technique to predict the flood susceptibility areas. Furthermore, GARP is based on genetic assessment models developed by Holland in 1975. The genetic algorithm model promises efficacious results in the ecological modeling field (Stockwell 1999; Sobek-Swant et al. 2012; Peterson et al. 2002; Padalia et al. 2014). Contemporarily, it has been employed in flash floods in urbanized regions (Darabi et al., 2019).

5. Results And Discussion

5.1 Runoff estimations

A simulation of two-dimensional hydrodynamic model was implemented via HEC-RAS software to estimate the runoff depth in the studied area by running rain-on-grid. The rain-on-grid simulation on HEC-RAS has been investigated recently by (Zeiger and Hubbart, 2021). The simulated hydrodynamic model was conducted using the two selected rainfall storms in Fig. (5) and Fig. (6). Moreover, the runoff depth has been estimated on the entire investigated region. Figure (13) and Fig. (14) demonstrate the runoff depth for the 2016 and 2018 studied storms respectively.

Furthermore, two landmarks were considered as flooded points during an observation of the 2018 studied storm. For instance, collapsing of the Petrified Forest fence during the extreme water velocity and water inundation in front of the American University in Cairo (AUC). These two featured flooded points, predicted and detected in the model. Figure (15-a-b) shows the two observed flooded points (Egypt Today, 2018 (In pics: Heavy rains impact buildings throughout Cairo - EgyptToday); M.C. News, 2018 (<https://mediacreativity.org/article/1090>)).

Moreover, in this study, the storm in Fig. (6) has been adopted to be utilized as environmental parameter since the results of this event have been verified in both Fig. (15-a) and Fig. (15-b).

5.2 GARP model generation

ArcMap has been utilized to develop and convert the applied environmental parameters to ASCII files. The pixel resolution of ASCII files was resembled to be 10m for all parameters. Consequently, the flooded training points and the environmental factors were exported to GARP Desktop to generate the model.

According to (Boeckmann and Joyner 2014), the training data was partitioned internally to 50% for training and 50% for testing. Moreover, four rules were employed (Logistic Regression, Negated Range, Bioclimatic, and Range) and then adapted to the training points. Therefore, the best 10 subsets out of 200 runs were selected and summed via ArcMap. The best ten subsets were adopted according to models closer to the median of commission error in a range less than 10% of omission error (McNyset and Blackburn, 2006). Ultimately, the summed best models have been classified into five levels (very low, low, moderate, high, very high) to generate the flood susceptibility map (FSM) as illustrated in Fig. (16). Furthermore, the area and proportion of the New Cairo city have been categorized according to the hazard class in Table (2) and Fig. (17), respectively.

Table (2) Hazard classification according to area and percentage.

Hazard	Very low	Low	Moderate	High	Very high
Area (Km ²)	107.01	35.06	41.3	29.36	54.22

The FSM indicates that most areas that are overwhelmingly prone to flood risks are located in high dense buildings, while baren areas are less susceptible to the hazard of floods. Therefore, this result can prove that the urbanized areas with low infiltration values are more vulnerable to flood hazards. The results

show that about 20% of the study area is categorized under very high risk to flash flood hazards, see Fig. (13). In contrast, more than 50% of the investigated area is less vulnerable to flood risks (40.09% are categorized as very low, and 13.14% are low hazard levels, respectively).

5.3 Examination of the model

To evaluate the efficacy of the GARP model, the Receiver Operator Characteristic curve (ROC) was utilized to verify the precision of predictions (Jiménez-Valverde et al., 2012; Gorsevski et al., 2006; Tehrany et al., 2015). The vertical axis represents the True Positive Rate (TPR) or the sensitivity, whereas the horizontal axis resembles the False Positive Rate (FPS) or (100- specificity) (Negnevitsky, 2002). The estimated models have been ranked as poor, medium, good, very good, or excellent in AUC-ROC limits of 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9, and 0.9–1, respectively (Yesilnacar, 2005). The calculated area under the curve (AUC) has been found 71.5%, as shown in Fig. (18), which indicated good efficacious model that could provide trusted results.

6. Conclusion

Two-dimensional hydrodynamic model has been developed to estimate the maximum runoff depth in the New Cairo city. Consequently, seven conditioning factors (elevation, slope, flow length, distance to streams, maximum runoff depth, land use, and curve number) have been established and employed as an input with the training data in the GARP technique. Furthermore, GARP desktop software was utilized to produce the flood vulnerable map by using four rules (Logistic Regression, Negated Range, Bioclimatic, and Range). Accordingly, the best 10 subsets out of 200 runs have been adopted to develop the flood susceptibility map (FSM). The hazard map has been categorized to very low, low, moderate, high, and very high, representing 40.09%, 13.14%, 15.48%, 10.97%, and 20.32% of the entire extent of the city, respectively. The generated risk map could be utilized as a guide to decision-makers to intensify protective measures in highly prone areas to flash flood risks. Ultimately, the FSM was examined using the AUC-ROC method, resulting in 71.5% for the area under curve.

Declarations

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Author contributions

All authors have contributed in this research during all the scientific steps, starting from laying the research framework, data gathering, modelling, mapping the results, and ending with analysis and discussions.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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Figures

Figure 1

The location of the studied area “New Cairo City”

Figure 2

Some different impacts of rainfall storms that struck New Cairo city (Egyptian street, 2018; youm7.com, 2018)

Figure 3

The New Cairo elevation

Figure 4

The New Cairo subbasins as well as the flow streamlines

Figure 5

Rainfall rate on 30 November 2016

Figure 6

Rainfall rate on 24 April 2018

Figure 7

The applied methodological framework

Figure 8

Hydrologic soil groups in New Cairo city

Figure 9

the estimated values of curve number in New Cairo city

Figure 10

Spatial values of roughness coefficient over New Cairo city

Figure 11

The conditioning parameters (a) elevation(m), (b) slope(degree), (c) flow length(m), (d) distance to streams(m), (e) maximum runoff depth(mm), (f) land use, (j) curve number

Figure 12

Flood inventory map

Figure 13

Simulated runoff depth during the 2016 storm

Figure 14

Simulated runoff depth during the 2018 storm

Figure 15

a) Failure of the Petrified Forest fence

b) Runoff inundation in front of the American University in Cairo (AUC)

Figure 16

The flood susceptibility map (FSM)

Figure 17

Categorization of the study area according to hazard level

Figure 18

Rate of AUC-ROC for the generated GARP model