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ANALYSIS OF THE EFFECT OF CLIMATE CHANGE ON RAINFALL INTENSITY AND EXPECTED FLOODING BY USING ANN AND SWMM PROGRAMS

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ABSTRACT

The flooding of the storm water network is caused by climate change, land use change and an increase in urbanization and the wider population. This study deals with the development of models to extrapolate future change in rainfall events in order to protect the infrastructure of the storm water network from flooding. The Al-Abbas quarter in Karbala city, Iraq was selected as a case study. For the first analysis, the effect of climate change on the predicted rainfall intensity for the future period (2017-2070) depends on historical data for the period of 1980-2016. This was conducted using the artificial neural network (ANN) model. Following this, a Storm Water Management Model (SWMM) model is constructed in order to assess the flood conditions of the study area for expected rainfall intensities. The results indicate that the maximum rainfall intensity will reach 46.48 mm/h. in 2067. This figure represents 400% of the design intensity.

Keywords: climate change, model prediction, urban flooding, ANN, SWMM.

1. INTRODUCTION

Climate change includes changes in the parameter of the climate such as rainfall, temperature, wind speed, humidity and sunshine etc. The rainfall and temperature have significant impact parameters on flooding. For example, the Intergovernmental Panel on Climate Change (IPCC) states that an increase in temperature of between 1˚C and 3.5˚C due to an increase in greenhouse gases would occur by the end of this century.

Houghton (1996) and Bijlsma *et al.* (1996) state that there is a rise in the sea level between 13-94 cm. This leads to an in increase flooding. Flooding is exacerbated by the incapability of the storm water network to accommodate the influx of water. A number of reasons may causing flooding such as climate change, land use change, increase of urbanization, population and CO_2 concentration. Schreider *et al*. (2000) Reported how a significant amount of CO_2concentration in the atmosphere could contribute to the extent of flooding. The study features two main sections. Firstly, the modelling of frequency and magnitude of the flood in the context of global warming is assessed.

This phenomenon is associated with rainfall intensities. The second section involves the estimation of changes in the susceptibility of flooding that appears in urban areas with the use of greenhouse effect-related flood data. The results of modeling for all cases indicated that when CO_2 conditions were dual this led to a rise in the magnitude and frequency of the flooding events and these vary from one place to another. Reynard *et al*. (2001) discussed the effect of climate and land use changes on the flood regimes of large U.K. catchments by using continuous flow simulation model (CLASSIC). They concluded that in the2050s, climate change would increase the frequency and magnitude of flooding events in these catchments. However, land use changes show a marginal impact on the flooding.

Artificial neural network (ANN) was a technique used to build a model for prediction. There are many applications for this including rainfall intensity, coefficient of discharge, inflow of reservoir and water quality index. Dawson and Wilby (1998) studied predictions of flow using actual hydrometric data in two flood-prone UK areas by using artificial neural network (ANN). The results found the prediction to be similar to that obtained from operational systems of the River Amber.

Tokar and Johnson (1999) evaluated the prediction of daily rainfall as a function of daily precipitation, temperature and snowmelt for the Little Patuxent River watershed in Maryland by using artificial neural network (ANN).The study concluded that prediction data from ANN had more accuracy and flexibility and the study concluded that using ANN shortens calibration data and reduces the length of time spent in calibration of the models. Al-Ansari *et al.* (2014) used artificial neural network (ANN) to evaluate rainfall for a long term and the study discovered that the average rainfall decreased.

The EPA Storm Water Management Model (SWMM) is a simulation model used to simulate runoff quantity and quality from primarily urban locations. It was first develop in 1971 (Rossman, 2010). Denault *et al*. (2006) studied the effects of increased rainfall intensity and evaluated infrastructure future drainage capacity in Mission/Wagg Creek watershed in British Columbia, Canada by utilizing the SWMM technique. The result concluded that, in future, rainfall intensity with short duration may be slightly increased. However, this does not happened as sharply in the Mission/Wagg Creek system. Jung *et al*. (2015) studied climate change effects on urban flooding in the drainage basin of Gunja, utilizing the SWMM model to make a single event simulation of runoff quantity. They has been concluded that when there were increases in the short duration rainfall intensity, this led to the rising of the simulated peak discharge from SWMM. *Jiang et al*. (2015) utilized planning and management models for urban flooding, in the Dongguan City in southern China, an area which rapidly became urbanized.(SWMM) is a tool used for this application. The results indicate that the area studied will not experience flooding when the return period precipitation is one year. However, the area studied will be submerged when the return period precipitation is 2, 5, 10 and 20years.

Recently, Hassan *et al.* (2017) evaluated the behavior of storm networks of the Middle East region (Karbala city, Iraq) to predict future flooding hazards caused by climate change, specifically in case of inadequate sewer connections. The study utilized the SWMM model for Karbala's storm drainage network simulation by using continuous hourly rainfall intensity data from 2008 to 2016.It was concluded that, without consideration of additional sewage due to an illegal sewer connection, the system was sufficient as designed. The results indicated that the SWMM was efficient for modelling urban flood forecasting, and without surface runoff routing, the urban flooding might not perfectly forecast.

After a comprehensive review of the previous studies, this paper regarding the future prediction of climate change presented by estimating rainfall intensity, utilizing the artificial neural network (ANN) model, in addition to employing the SWMM model to assess the effect of variation of rainfall intensity on flooding events for specific years (2017 to 2070).

2. STUDY AREA

Geographically, the Al-Abbas section has been selected. This area is located to the north-east of the center of Karbala city, Iraq, which lays between latitudes 32°37'56.7"N-32°38'15.9"N, and longitudes 44°02'39.8"E-44°03'08.9"E, as shown in Figure-1. Additionally, the selected area was flat with slight slopes and sandy clay soil. Regional elevations range between 34-41m above sea level. The distance is 2 km from the center of the study area to the center of Karbala city. The total area is approximately 0.373 km². The total impervious area is approximately 0.257 km², (70% of total area) including (roofs and paved area). The previous area is approximately 0.116 km², (30% of total area) including (green area and unpaved area). The network of the case study is a storm water network divided into 63 sub-catchments. The land use reference of the study area is a residential quarter which features 8%paved roads 12%gardens and service building and 80% houses. Some new developments are expected to take place in relation to the case study according to the Kerbela master plan. The climate of the case study is shown in Table-1.

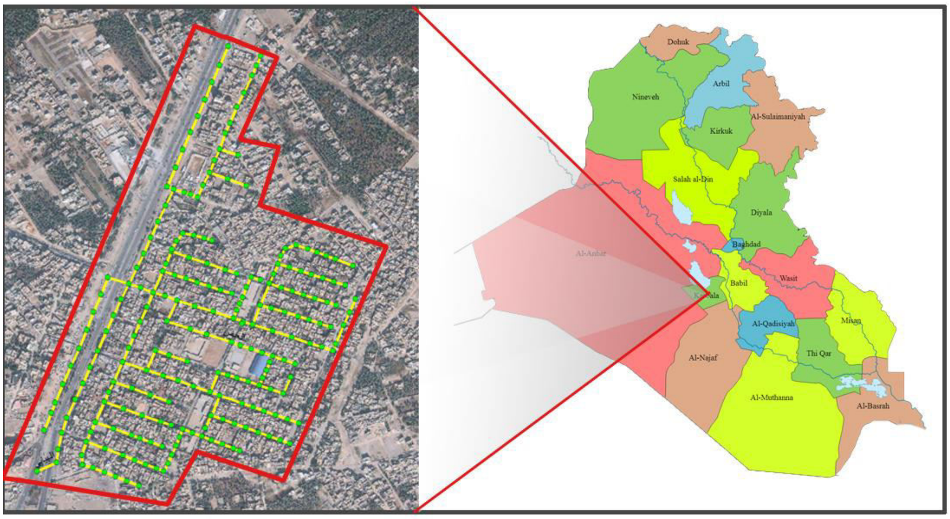

Figure-1. Geographical location of the study area according to Iraqi map.

Table-1. Clarify min. and max. value of climate of the case study for period (1980-2016).

Climate	Min value	Max value
Temperature (C°)	1.6	46
Monthly rainfall (mm)	0	48
Humidity (%)	23	83
Wind speed (m/s)	1.9	5.2
Sun shine (hrs./day)	5.2	12.6

3. METHODOLOGY

The aim of this paper is to study the impact of climate change on expected rain intensities in the study area and to determine the expected flood ratios in rainwater drainage networks. To achieve the target, the data collected should involve the prediction of rainfall intensity depending on climate change by using the artificial neural network (ANN) model and determining the flood ratio by using a storm water management model (SWMM).

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3.1 Collection data

3.1.1 Metrological data

Collection of metrological data from the General Authority for Aeronautical and Seismic Observations (G.A.A.S.O) for the period of 1980 to 2016including (monthly rainfall (mm), mean maximum temperature(C̊), mean minimum temperature(C̊), mean relative humidity (%), mean wind speed (m/s), mean sun shine (hr./day), and the data collected for the period of 1981 to 1990 including rainfall intensity for Karbala station in (mm) for 1 hr. The location of the station is near the study area with coordinate of latitudes32°35'14.33"N and longitudes 44°1'8.6"E. It is the only one available for this period of data in the region.

3.1.2 Field data

Field data collection for the Al-Abbas quarter from the Directorate of the Streams of Karbala (D.S.K) including pipes and manholes and its properties for storm water networks, the properties of network include 222PVC pipes and concert manholes. The diameter of the pipe of the network ranged from 315 to 600 mm. The total length of the network is 8360 m, and the maximum depth of the manhole is 3.632 m near the outlet.

3.2 Artificial neural network (ANN) model

The ANN system consists of as minimum three main parts, the first part define as input layer, the second part define as hidden layer at least one layer and this layer processing of input layer and the third define as the output layer. Sigmoid function was used and weights were determination during this study, the number of hidden layer depending on training (Murata *et al.*, 1994). The structure of neural network can showed in Figure-2.

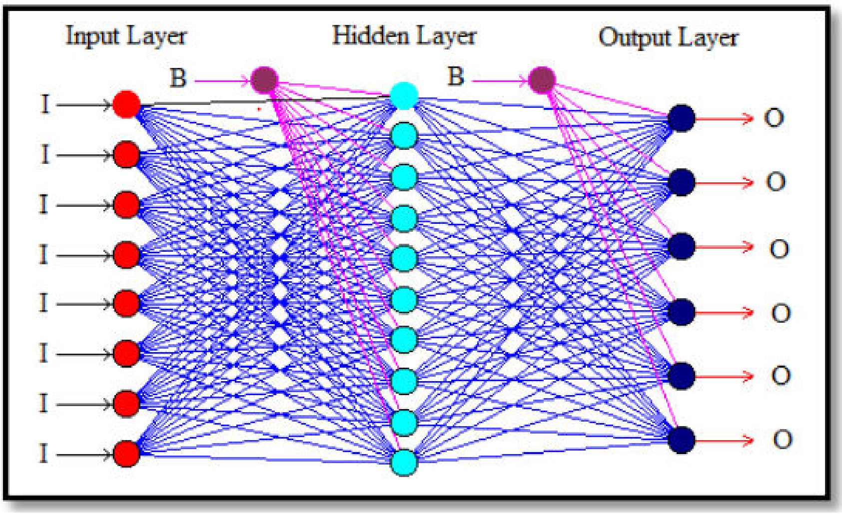

Figure-2. Structure of neural network system.

The development of the Artificial neural network model (ANN) is dependent on input layers and output layers, input layers include climate change parameters (monthly rainfall, max. and min. temperature, humidity, wind speed, sunshine), the output layer includes rainfall intensity (mm) for 1 hr. The sequence of prediction of rainfall intensity was done by ANN over the following steps:

- Built ANN model for 10 yrs. (first model) due to rainfall intensity available (output layer) from (G.A.A.S.O) only for 10 yrs. for the period (1981-1990).
- ANN model for 10 yrs. (first model) used to predict rainfall intensity for the period (1991 – 2008).
- From (A.C.D.)the rainfall intensity was found from 2008 to 2016.
- Built ANN model (second model) for the period (1981-2016).This model is used to predict future rainfall intensity.
- SPSS program made a simulation to find the input layer (climate change).
- Input data found from step 5 into the second model to find rainfall intensity for period (2017-2070).
- The models will be calibrated with the data obtained to verify the accuracy of the model.

There are five models built which depend on the number of hidden layers. The number of nodes in each layer following this is chosen as the best depending on several statistical indexes including root mean square error RMSE and correlation coefficient Square R^2.Therefore, the best model chosen has the least RMSE(nearest to zero) and

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greatest R^2(nearest to 1). The equations of RMSE and $R^2$are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - M_i)^2} \qquad \ldots\ldots\ldots\ldots 1$$

Where N is the number of verification data, O is observed data and M is modeled data

$$R^2 = \frac{\left(\sum_i^n (O-\bar{S})(S-\bar{S})\right)^2}{\sum_i^n \left(S-\bar{S}\right)^2 \sum_i^n \left(S-\bar{S}\right)^2} \qquad \ldots\ldots\ldots\ldots 2$$

Where n is a number of verification data, S is a predicted value by ANN, O is an observation data

3.3 Application of SWMM

The Storm Water Management Model (SWMM) was first developed by US EPA, in 1971. SWMM is a model used to simulation runoff quantity and quality from urban areas. It is used for the assessment of single or long-term (continuous) events(Rossman, 2010). The process of estimating the time and magnitude in any point of the drainage systems depending on hydrographs (known or estimated) at one or more upstream location is referred to as flow routing. There are three levels of sophistication used in SWWM for flow routing to solve the conservation of mass and momentum equations for conduits in open channels. This equation is the comprehensive one-dimensional (Rossman, 2010).

The SWMM allows the modeler to select the level of sophistication to solve the equations. The three levels of flow routing in SWMM are steady flow routing, kinematic flow routing and the dynamic flow routing. In this study the dynamic flow routing has been used because it has the ability to account for pressurized flow, channel storage, flow reversal, backwater and entrance/exit losses so the dynamic flow routing is considered to have the most theoretically precise results. In dynamic routing, the full flow closed pipe is represented as pressurized flow and flooding occurs when the water depth exceeds the maximum available depth at the node.

For the Saint-Venant, the flow can be represented by the two partial differential equations. Firstly, the momentum equation as described in Eq 3. and the second is the continuity equation as presented in Eq 4.

$$\frac{1}{A}\frac{\partial q}{\partial t} + \frac{1}{A}\frac{\partial}{\partial x}\left[\frac{q^2}{A}\right] + g\,\frac{\partial y}{\partial x} - g\,[S_0\text{-}S_f] = 0 \qquad \ldots\ldots\ldots 3$$

$$\frac{\partial A}{\partial t} + \frac{\partial q}{\partial x} = 0 \qquad \ldots\ldots\ldots\ldots 4$$

Where:

q = system flow rate (m^3/sec); **y** = flow depth (m);

g = gravity acceleration (m/s^2); $\mathbf{S}_\circ$ = slope of bed (m/m);

S_f = friction slope (m/m);

x = distance along the channel (m); A = area of channel cross-sectional (m^2);

and t = time in sec (Pitt *et al.*, 1999)

The terms in the momentum equation can be clarified as follows:

$\frac{1}{A}\frac{\partial q}{\partial t}$ = the momentum changes due to velocity change over time

$\frac{1}{A}\frac{\partial}{\partial x}[\frac{q^2}{A}]$ =the momentum changes due to velocity change alongside the channel

$g\,\frac{\partial y}{\partial x}$ = the water depth changes along the channel

g [S_0-S_f] = gravity force term, proportional to the bed slope and friction force term, proportional to the friction slope.

While the terms in the continuity equations can be clarified as follows:

$\frac{\partial A}{\partial t}$ = area rate of change over time;$\frac{\partial q}{\partial x}$ = the rate of change of channel flow width distance.

The two partial differential equations are solved numerically as for runoff surface routing. The dynamic flow routing used manning equation determines flow rate [Q]. The Hazen-Williams or Darcy-Weisbach equation is used for circular force main shapes under pressurised flow(Rossman, 2010).

The result of climate change scenario represented as rainfall intensity from (ANN) model for predicting the period (2017-2070) was used as an input for SWMM in order to estimate the flooding values in the study area.

4. RESULTS AND DISCUSSION

4.1. Rainfall intensity model

The difficulty of predicting rain intensity due to the fact that it is subject to non-continuous daily functions such as temperature and is dependent on the seasons and rainy periods. The data used in ANN model was selected by the SPSS program randomly 95% for training and 5% for verification. Table-2 shows the number of models, number of hidden layers, R^2, RMSE for ANN models which were used to prediction the rainfall intensity in the study area.

Model 1 was the first model chosen and model 3 was the second model chosen. This is due to the fact that the models had the least RMSE (1.67, 3.46) and greater R^2 (0.722, 0.64) respectively. Figure-3 shows the results of verification for the dependable model (model 3). This figure shows that the mathematical model is able to predict values well and can be used for prediction in the coming years with some ratios of errors. Figure-4 shows the intensity value for three periods from 1981- 1990 which are gated from (G.A.A.S.O.). The second period of (1991-2008) which was predicted from model 1 and the third period (2008-2016) which gated from (I.A.C.D), the trend line of the intensity increases with the progress of time in general. Using model 3 to predicted rainfall intensity from 2017-2070, in general the trend line of the prediction increases with the progress of time. This is illustrated in Figure-5. The maximum value of each year is illustrated in Figure-5. When utilizing SWMM, model 3 can be used to predict rainfall intensity at any period due to it being developed depending on climate change over 36 years.

Table-2. Show model description, number of hidden layers, and their parameters.

Number of model	Description	Number of hidden layers	R^2	RMSE
Model 1	First model for 10 years for period (1981-1990)	2	0.722	1.67
Model 2	First model for 10 years for period (1981-1990)	3	0.684	2.68
Model 3	Second model for 36 years for period (1981-2016)	2	0.64	3.46
Model 4	Second model for 36 years for period (1981-2016)	1	0.62	3.68
Model 5	Second model for 36 years for period (1981-2016)	3	0.41	5.25

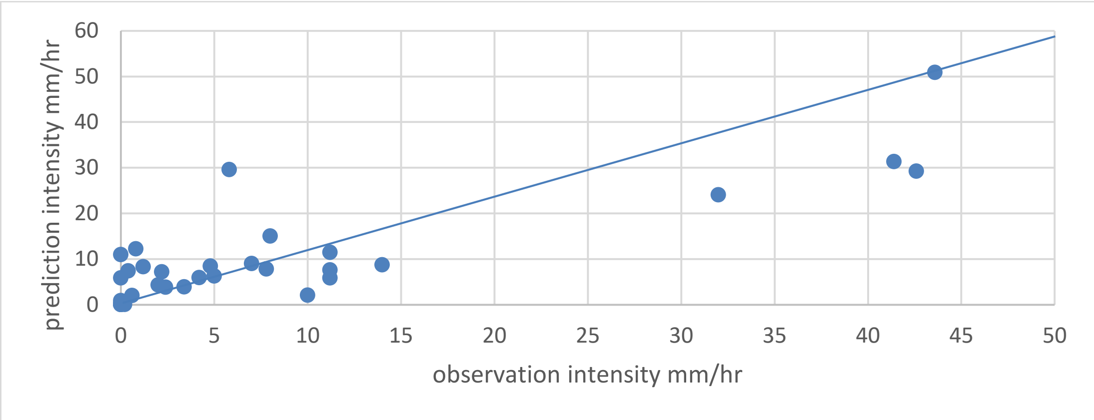

Figure-3. Prediction versus observation intensity for model 3.

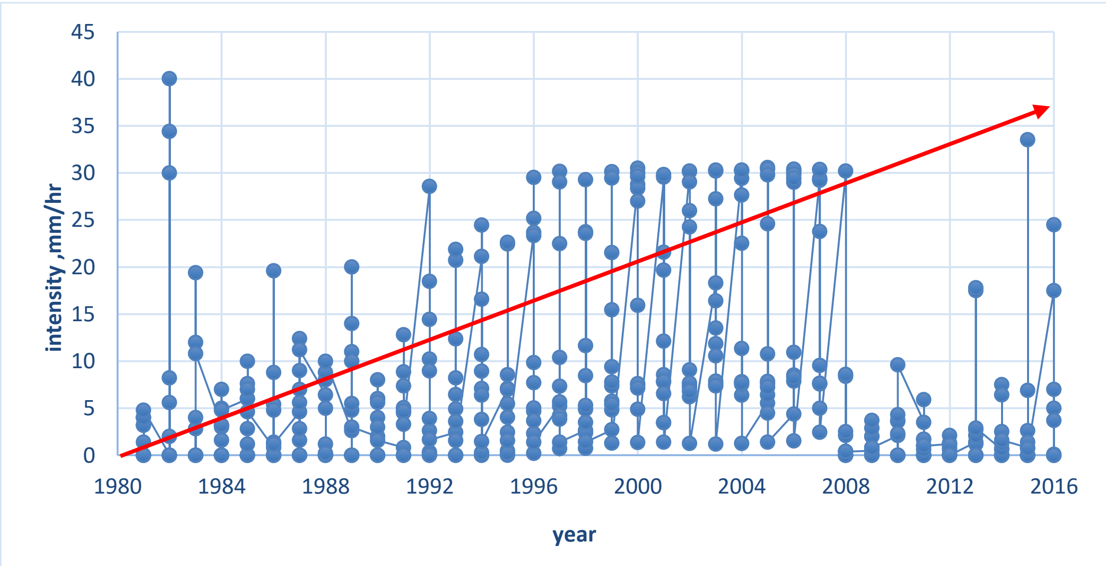

Figure-4. Observation data of rainfall intensity.

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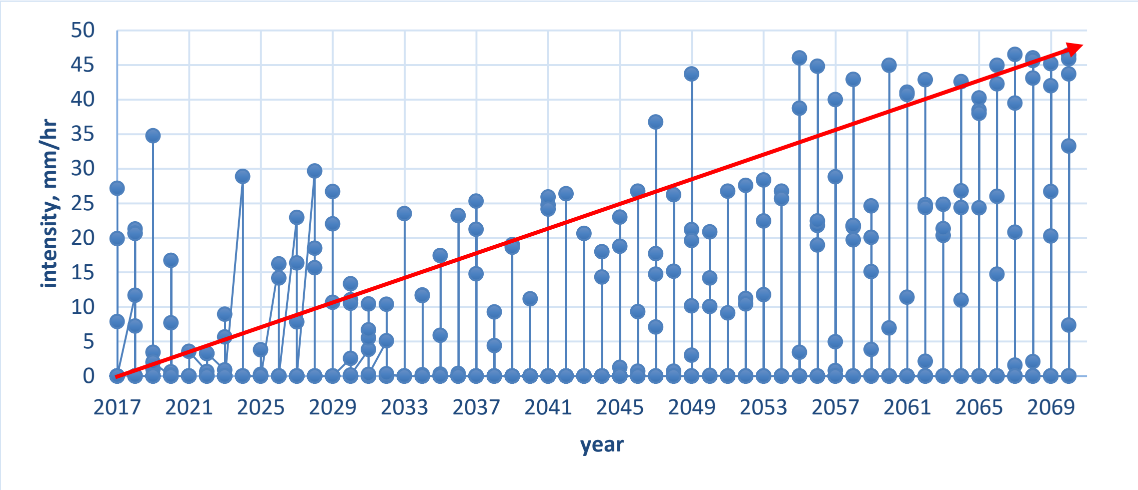

Figure-5. Prediction of rainfall intensity by the ANN model (model 3).

4.2 Flooding model

The Al-Abbas storm drainage network section had been designed to withstand a rainfall intensity of 9.6 mm/h over a 2-year return period (D.S.K). Nevertheless, it has been exposed to climate change effects represented by increasing rainfall intensity to reach maximum capacity in 2067. This is four times higher than the designed intensity. The study area was more exposed to flooding due to an increase in rainfall intensity. The flooding discharge of the manholes is divided into five cases. Case 1 is presented as no flooding occurrence(from 0-0.001 m3/s); case 2, slight flooding occurrence (> 0.001- 0.01 m^3/s); case 3, medium flooding rate(>0.01-0.05 m^3/s); case 4, high flooding appearance (>0.05 to 0.12 m^3/s)and finally case 5, very high rates of flooding (>0.12 m^3/s).

In order to study this effect on rain intensity changes, a set of expected rainfall intensities will be applied over the next years on the network. It will be focused on the high intensities expected to determine the extent of the network's ability to deal with these intensities.

Figure-6 shows the behavior of the storm network in winter 2019, 81% of manholes had no flooding (stage 1) and 19% of the manholes had very light flooding (stage 2) so the behavior of the network is considered to be good. The duration of flooding is 45 minutes. Figure-7. illustrates the behavior of the storm network in winter 2028. 86% of the manholes were not affected by flooding (stage 1), 13% of the manholes had very light flooding (stage 2) and 1% of the manhole flooding had high flood rates (stage 4). The duration of the flooding is 50 min.

Figure-8 shows the behavior of the storm network over winter 2055. 56% of the manhole had no flooding (stage 1), 14% of the manhole had had very light flooding (stage 2) ,21% of the manhole had medium flooding (stage 3), 3% of the manhole flooding had high flooding (stage 4) and 6% of the manhole had very high flooding (stage 5). The duration of flooding is 20 min.

Figure-9 shows the behavior of the storm network in winter 2067 under maximum rainfall intensity, 59% of the manholes had no flooding (stage 1), 16% of the manholes had very light flooding (stage 2), 19% of the manholes had medium flooding (stage 3).6% of the manholes had very high rates of flooding (stage 5). The duration of flooding is 45 min. From the cases selected above it may be concluded that the percentage of flooding increases with the progress of time and the increase of rainfall intensity. At the first design period the flooding of manholes reaches stage4 (the manhole flooding had high flooding) while at the end of design period, the flooding manhole reached to stage5 (the manhole had very high flooding).

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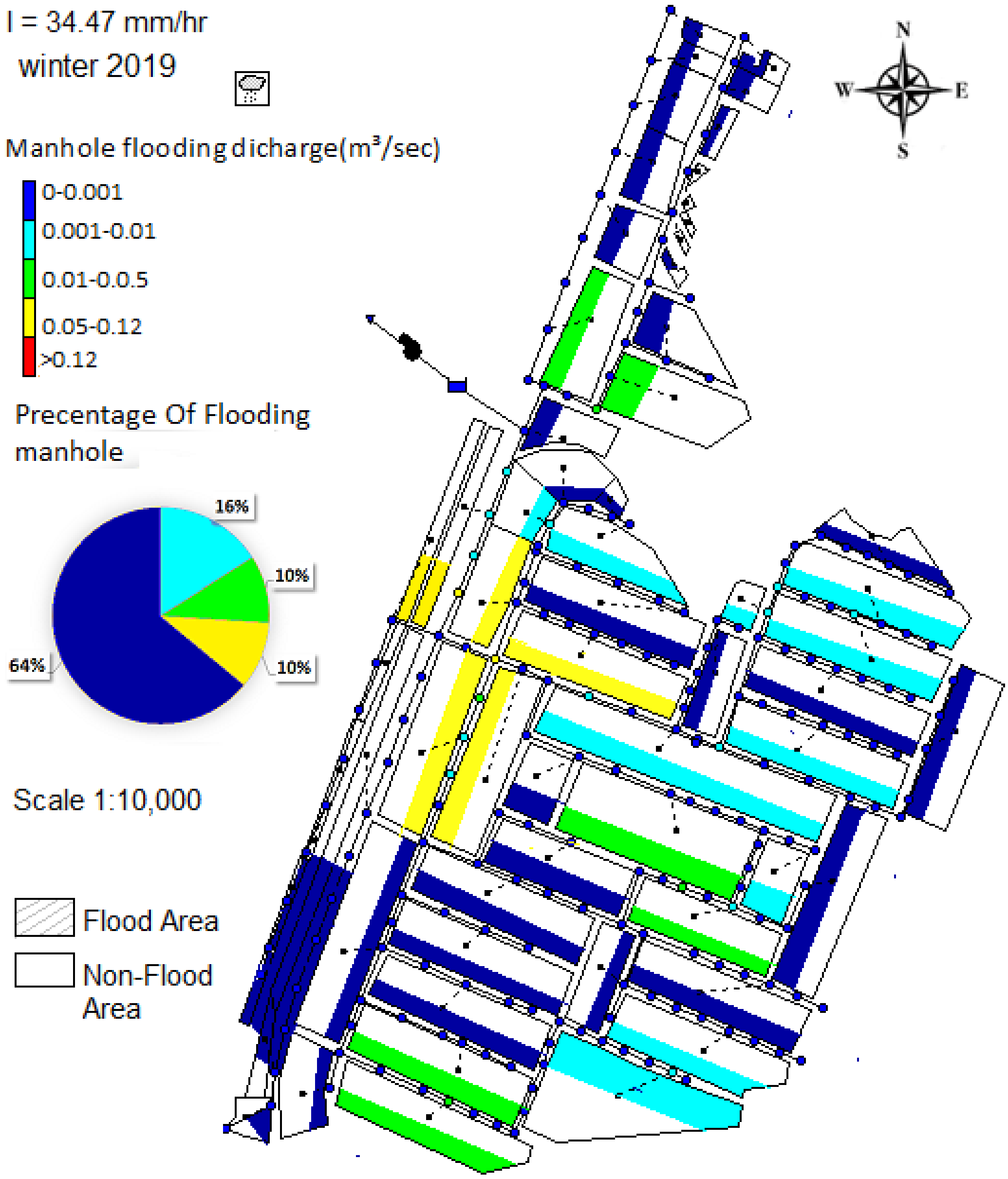

Figure-6. Storm network behavior of under rainfall intensity of 34.74 mm/hat peak time.

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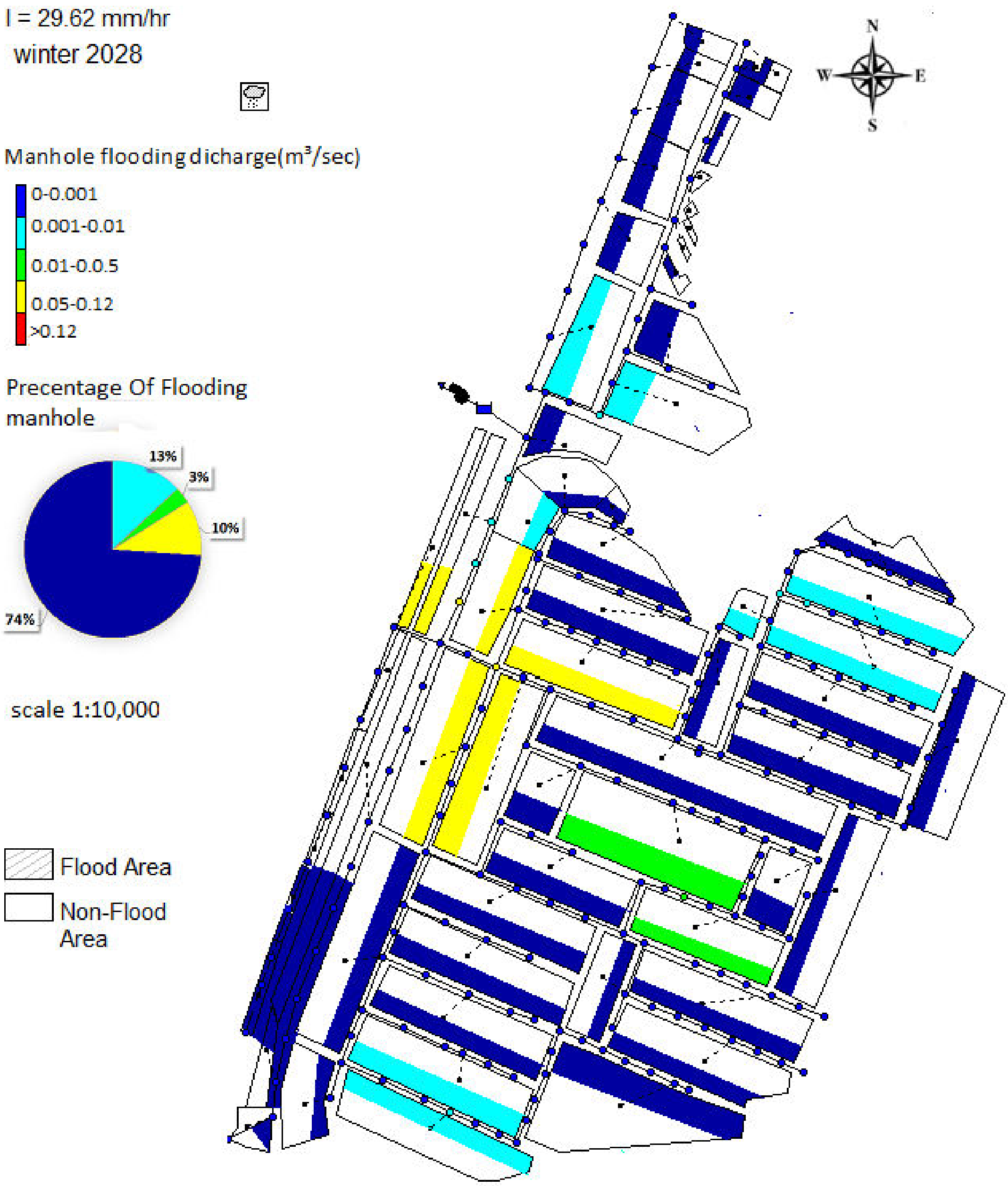

Figure-7. Storm network behavior of under rainfall intensity of 29.62 mm/h at peak time.

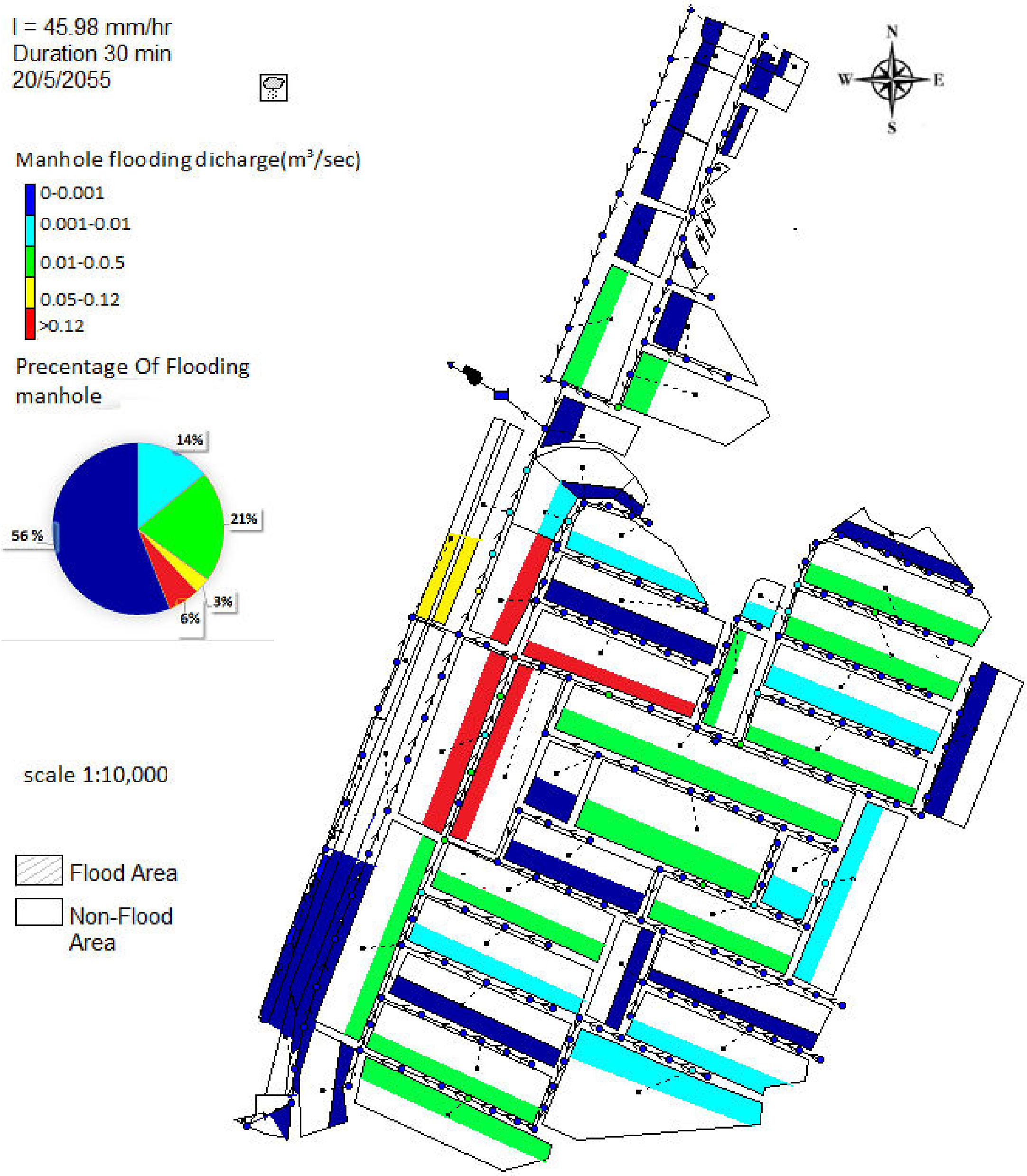

Figure-8. Storm network behavior of under rainfall intensity of 45398 mm/h at peak time.

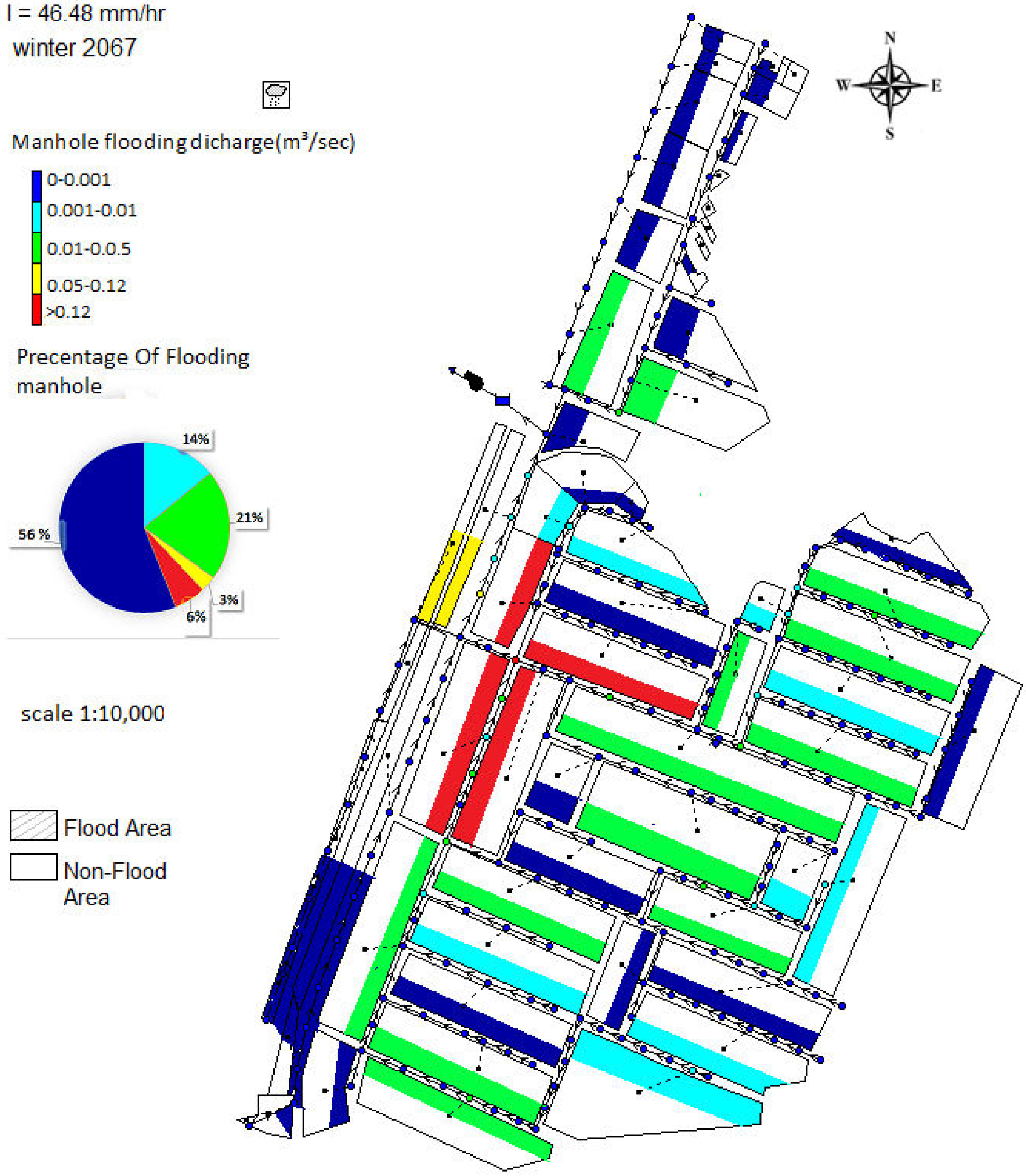

Figure-9. Behavior of storm network under maximum rainfall intensity of 46.48 mm/h at peak time.

5. CONCLUSIONS

This paper aims to study climate change effects on expected rain intensities on the selected study area and to determine the expected flood ratios in rainwater drainage networks. Prediction of rainfall intensity by the artificial neural network (ANN) model was found to depend on climate change. The selection of ANN model depends on maximum R^2 and minimum RMSE, the model was chosen which had (R^2 = 0.64, RMSE = 3.46). Prediction scenarios show that with the progress of time there is an increase in rainfall intensity with climate change reaching to 46.48 (mm/h) in winter 2067. The SWMM technique was employed for storm drainage system evaluation in the Al-Abbas sector, Karbala, Iraq as a case study. This study assesses the behavior of the drainage system of the study area under various rainfall intensities and the predictable flooding discharge for the flooding area. SWMM analysis rainfall intensity is greater than design intensity 9.6 mm/h reach to 46.48 mm/h that maximum intensity in the future design period (2017-2070).The percentage of flooding manholes in 2019 reached stage 4 (0.05-0.12) m^3/s while the percentage of flooding manholes in 2067 reached stage 5 (greater than 0.12) m^3/s. The duration of the flooding ranged from (20-50) min for the selected cases. The proposed mechanism for dealing with the flood situation is to increase the diameter of the pipes or to add a second outlet to rid the network of this phenomenon.

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