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A rainfall threshold-based approach to early warnings in urban data-scarce regions: A case study of pluvial flooding in Alexandria, Egypt

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Abstract

Rapidly expanding cities in the Middle Eastern and North African (MENA) region are at risk of flooding due to heavy rainfall, insufficient drainage capacity, a lack of preparedness and insufficient data to conduct required studies. A low regret Early Warning Systems (EWS) using rainfall thresholds is proposed as a cost-effective short-term solution. This study aims to utilise a probabilistic approach to characterise and predict urban floods by assessing critical rainfall thresholds likely to cause flooding combined with ensemble precipitation forecast in Alexandria, Egypt. Rainfall thresholds were inferred by associating observed rainfall and historical flood information sourced from social media and newspapers. Floods were classified in a colour-coded hazard matrix as no flood (green), minor flood (yellow), significant flood (orange), and severe flood (red). Probability of occurrence of hazard classes was derived by incorporating ensemble rainfall into the hazard matrix to jointly evaluate likelihood and hazard severity. Results from this study showed that three of four severe events analysed could have been predicted with a high likelihood up to 24 hr before. The presented approach supports decision making to issue warnings and flood control actions with limited data and is a model for other data scarce regions.

KEYWORDS

early warning systems, Egypt, pluvial flood forecasting, rainfall thresholds

1 | INTRODUCTION

Damages and the number of persons affected by floods have increased over the last century (EM-DAT, 2016). Although global hazards are on the rise, flood risk emerges from the combination of extreme weather events, exposure, and vulnerability attributed to human interaction with the environment. In cities, rapid urbanisation and exposed assets increase impacts from flooding

(Abbas, Bloch, & Lamond, 2012). The Middle East and North Africa (MENA), have experienced significant increases in damage due to floods (Banerjee et al., 2014). Once considered rare, these areas are now subjected to more extremes and frequent floods as observed in 2018 (Floodlist, 2018).

In the wake of increased flood risk, there is an emphasis on the implementation of resilient adaptation strategies focusing on extreme events, long-term changes,

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and trends in slow-changing drivers (Ashley, Pathirana, Gersonius, & Zevenbergen, 2012; Balica, Wright, & van der Meulen, 2012; Carter et al., 2015; De Bruijn, 2005; Gersonius, 2012; Mens, Klijn, Bruijn, & van Beek, 2011; Zevenbergen et al., 2016). In Flood Risk Management (FRM), Early Warning Systems (EWS), and flood forecasting allow the timely generation and dissemination of warnings and are among the most widely used tools to increase preparedness and reduce impacts (Alfieri, Salamon, Pappenberger, Wetterhall, & Thielen, 2012; Carsell, Pingel, Asce, & Ford, 2004; Cools et al., 2012; UNISDR, 2009). In addition to its potential to reduce impacts, EWSs are considered a “low regret” measure against future uncertainties with a high benefit-to-cost ratio (Hallegatte, 2012).

Forecasting for early warnings and subsequent actions requires reliable knowledge of hazard forecast at appropriate spatial and temporal scales and sufficient lead-times; the time between threat notification and a flood event and is considered the minimum time required to implement effective actions. Recently, technological advancements in rainfall forecasting techniques such as radar now-casting, Numerical Weather Predictions (NWP), and the availability of high-resolution satellite data combined with improved communication methods, have cemented the way for more efficient and effective EWS. Numerical Weather Prediction models, allow forecasters to extend lead-times and the use of probabilistic ensembles rather than a single deterministic forecast can better quantify reliability and confidence in decision making (Alfieri et al., 2012; Cloke & Pappenberger, 2009; Dale et al., 2012; Kok, Schreur, & Vogelesang, 2011; Ramos, Van Andel, & Pappenberger, 2013). Despite these advancements, many countries in the MENA region and global South are still challenged with poor data quality and availability (data-scarce) for model development and calibration leading to the emergence of nontraditional data sources. This is compounded by the challenges of forecasting on a smaller urban pluvial scale, a need for high temporal and spatial resolution data, and short response times associated with high-intensity events.

In data-scarce catchments, the EWS must strike a balance between technical feasibility and the need to reduce flood impacts. Real-time simulation forecast with real-time hydrodynamic and inundation models attempt to forecast the flood extent, locations, and impact. These models demand high-resolution spatial data and copious input parameters into complex models associated with uncertainty and long computational times (Ochoa-Rodríguez et al., 2015). Presimulated scenario-based systems, utilise a catalogue of hydrodynamic simulations and the accuracy depends on both model complexity and input data (Henonin, Russo, Mark, & Gourbesville, 2013). In

catchments of short response times and insufficient data, empirical methods offer a simplified approach to issue warnings and predict rainfall depths likely to cause flooding by directly comparing precipitation forecast with critical rainfall thresholds derived from examining rainfall accumulations from previous flood events (Falconer et al., 2009; Georgakakos, 2006; Martina, Todini, & Libralon, 2006; Parker, Priest, & McCarthy, 2011; Wu, Hsu, Lien, & Chang, 2015). Comparing critical rainfall thresholds with ensemble rainfall forecast sourced from NWP has the additional benefit of providing timely forecast while allowing decision-makers to incorporate uncertainty in the forecast. This simplified EWS approach provides an immediate short-term solution for data-scarce regions, which lack the technical capacity and resources to implement complex methods.

Few studies have demonstrated how rainfall thresholds have been used to predict pluvial floods in urban areas (Bouwens, Ten Veldhuis, Schleiss, Tian, & Schepers, 2018; Candela & Aronica, 2016; Jang, 2015), and fewer show how critical thresholds can be compared with probabilistic rainfall forecast (Hurford, Parker, Priest, & Lumbroso, 2012; Yang, Do Hwang, Tsai, & Ho, 2016). This article presents a practical approach of incorporating critical rainfall thresholds, historical flood data (crowdsourced) and ensemble precipitation forecast for forecasting extreme rainfall and flooding. This has the potential to improve decision-making especially in data-scarce regions or cities in the genesis of developing EWS.

Alexandria city in Egypt was selected as the case study for this research. Like many other cities in the MENA region, they suffer from occasional flooding from runoff accumulation and sewer surcharge but lack an enabled EWS and are least prepared to the rising threats of floods. With emerging risk, Anticipatory Flood Management (AFMA) has been proposed as a viable solution to increase preparedness and reduce damage (Bhattacharya, Zevenbergen, Young, & Radhakrishnan, 2018; Zevenbergen et al., 2016). The research objectives will be achieved by addressing the following research questions:

- Can rainfall thresholds characterise and predict urban floods in Alexandria, using limited data such as crowdsourced flood images?
- Can derived rainfall thresholds and currently available ensemble prediction systems be used to improve decision-making?

Ibrahim and Afandi (2014) previously evaluated the use of a Weather Research Forecast (WRF) model to predict extreme rainfall in Egypt but did not evaluate the use of ensemble forecast. The success of such an approach will

allow an immediate short-term solution to emerging flood risk in cities in the MENA region. In the interim, cities can acquire more comprehensive data that will contribute towards the development of more sophisticated flood forecasting systems which are otherwise very demanding and time-consuming in data-scarce regions.

2 | THRESHOLD-BASED EARLY WARNING SYSTEMS

The complexity of the detection and forecast methods depends on factors related to data availability, severity, frequency, and vulnerability to flooding and the lead-times required to issue warnings (WMO, 2011). A simple forecasting system can be developed from rainfall forecast and a historical account of past flood events with no hydrological/hydraulic modelling (Henonin et al., 2013) and can be implemented at regional, national, catchment, and city scales.

The Flash Flood Guidance System (FFGS), an empirical approach, initially developed by the US National Weather Service (NWS), uses forecast rainfall depths that are likely to result in discharges associated with floods. Georgakakos (2006), studied FFG based systems and found they produce a high probability of detection to flash floods. Such alerts are issued based on different rainfall thresholds considering the prevalent soil moisture condition. This system has been implemented in many regions including the new Black Sea and Middle East FFGS and the Central American FFGS (WMO, 2019).

The “FLOODsite” project assessed the advantage of using rainfall threshold as an alternative to traditional EWS (Borga, Anagnostou, Blöschl, & Creutin, 2011) and proved successful in identifying several flash floods across Europe (Alfieri et al., 2012). Meteo-alarm is another rainfall threshold-based EWS, implemented in approximately 30 European countries and alerts are issued based on a comparison between precipitation and local thresholds. Also at a regional scale Alfieri and Thielen (2015) successfully proposed a European Precipitation Index based on simulated Climatology (EPIC), which is calculated using COSMO-LEPS ensemble weather forecasts.

On a national scale, England and Wales initially adopted Extreme Rainfall Alerts (ERA) and Flood Guidance Statement (FGS) providing warnings of extreme rainfall based on intensities (depth/duration) likely to cause severe surface water flooding (SWF) in urban areas based on a 1 in 30 return period (Hurford, Parker, et al., 2012). The Second-Generation Surface Water Flood Risk Assessment (SWFRA) programme has replaced this system. It empirically estimates surface water flooding risk based on a weighted score of rainfall probability,

spatial extent, soil moisture deficit, and proxies for urbanisation (Ochoa-Rodríguez et al., 2015).

Although the application of thresholds is similar, the methodology of how rainfall threshold methods are applied in urban and fluvial areas varies when considering precision and parameters required (Jang, 2015). For example, FFGS thresholds are adjusted based on antecedent moisture conditions (AMC). However, urban areas tend to adopt static thresholds (Figure 1) without considering AMC; soil moisture becomes less significant as urbanisation increases (Bouwens et al., 2018; Falconer et al., 2009; Hurford, Priest, Parker, & Lumbroso, 2012). The maintenance state of sewers and canals also then become more important.

It is acknowledged there are limitations to using this approach such as: rainfall events of the same return period can produce floods of different extent and water depths and non-linearity between rainfall and floods (Stephens, Day, Pappenberger, & Cloke, 2015) due to spatial and temporal variability of rainfall, the characteristics of the sewer system, topography, storage, and runoff characteristics of the catchment (Simões et al., 2015). Current research is aimed at methods for improving critical thresholds, accuracy, and reliability of forecast and incorporating catchment characteristics. In gauged basins, calibrated rainfall-runoff models and rainfall hyetographs are iteratively used to search for critical rainfall or discharge values (Candela & Aronica, 2016; Jang, 2015; Wu et al., 2015). Montesarchio et al. (2015) compared methodologies for flood rainfall threshold estimations including (Martina et al., 2006) which adopted a probabilistic approach by analysing the joint probability of a given duration of rainfall depths and corresponding peak discharge values combined with a Bayesian utility function. In smaller, semi-gauged basins, empirical methods use of historical data to determine rainfall thresholds and assume rainfall is distributed uniformly in time and space. Bouwens et al., (2018) correlated

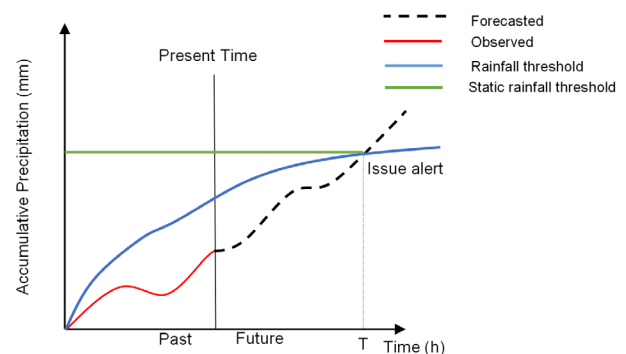


FIGURE 1 Example of rainfall threshold-based approach for the issuance of flood alerts. Modified from Martina et al. (2006) to include static rainfall thresholds

sub-daily rainfall with citizen incident flood reports and overflow pumping values to determine critical rainfall thresholds. Yang et al. (2016), successfully used a rainfall threshold approach and quantitative precipitation forecasts (QPFs) to evaluate urban inundation risk in Taiwan. This article capitalises on the simplicity of this methodology in data scarce regions and on a local scale.

3 | EARLY WARNING SYSTEMS FOR DECISION SUPPORT/ DECISION-BASED APPROACH TO EARLY WARNING

Lead time considers the minimum period of warning necessary for preparatory action to be effective (Carsell et al., 2004; Verkade & Werner, 2011). An important part of an EWS is allowing sufficient lead-times to issue warnings, or take actions. However, uncertainty exists with predictions at longer lead-times. Probabilistic forecasts are key to quantifying uncertainty in forecasting floods and can be useful in assessing the likelihood of extreme events while providing more consistent successive forecasts (Alfieri et al., 2012; Boelee, Lumbroso, Samuels, & Cloke, 2018; Buizza, 2008; Cloke & Pappenberger, 2009; Dale et al., 2012; Ramos, Mathevet, Thielen, & Pappenberger, 2010; Todini, 2017). However, all authors agree there are several challenges including but not limited to (a) improving forecast with high-resolution data and assimilation; (b) coupling models at differing scales and real-time operational forecasting; and (c) how end users can best use this information to improve decision making for warnings and response. Still, compared with deterministic forecasts, probability forecasts allow an optimal balance between uncertainty and lead-time time (Verkade & Werner, 2011). When issuing warning messages or taking actions, decision-makers require clear informed guidance and decision rules to make confident decisions (Economou, Stephenson, Rougier, Neal, & Mylne, 2016; Van Andel, 2009).

Traditional yes or no extreme weather warnings are issued once the forecasted rainfall exceeds a critical rainfall threshold. However, such binary forecasts do not indicate the likelihood or severity of an expected hazard. The use of a colour-coded hazard or risk allows a visual expression of a priority matrix (WMO, 2015). When combined with ensemble forecasts, the likelihood of an expected hazard and its potential severity can be considered to aid decision making. The United Kingdom Met Office and several other countries contributing to the Meteo alarm system (WMO, 2015) are examples using such systems. The UK Met Office's Flood Guidance Statement (FGS) provides daily flood risk forecast for the UK to assist in strategic and tactical operational planning and decision making (Flood Forecasting Centre, 2017). Assessments are made and presented in a coloured 4×4 risk matrix based on forecast risk (hazard, vulnerability, and exposure: and likelihood (Figure 2). When model-based detailed hazard information cannot be produced due to data constraints, a hazard matrix based on hazard severity versus rainfall thresholds derived from historical data is an alternative. This provides benefits through the selection of suitable thresholds severities to provide approximate (often nominal) flood forecasts, which serve as the basis for decision making regarding flood warning and preparedness. Dale et al. (2012) also proposed using probabilistic flood forecasting and a benefit-cost inspired decision-support framework for flood management actions. However, such an elaborate system is only transferrable and compatible with similar flood forecasting systems which have flood impact and monetary data which is rarely the case in data-scarce regions.

4 | METHODOLOGY

A threshold-based framework to support early warning decisions based on ensemble forecasts is being proposed.

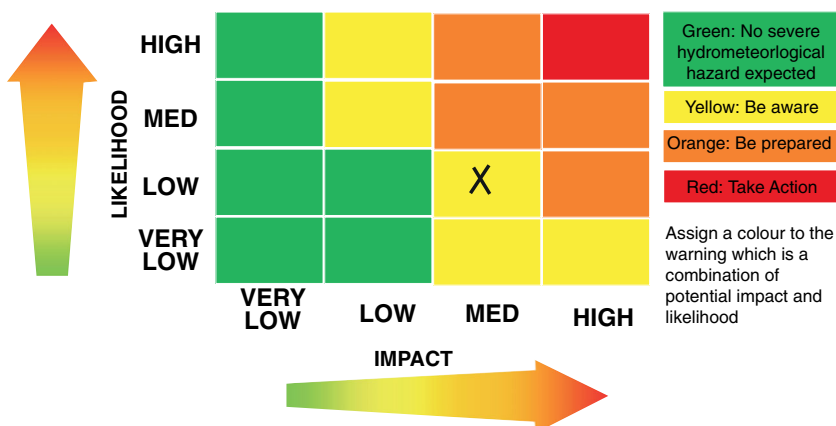


FIGURE 2 F2Operational application of warning concept, combining impact with the likelihood to create a risk matrix, expressing risk through a simple colour-coded scheme (WMO, 2015, UK Met Office)

Critical rainfall thresholds are defined and used to classify hazards. These are derived by examining rainfall depths associated with historical flood events and the associated hazard severity. The framework used to derive the respective warning classes follows the operational approach of The UK Met office (Figure 2). However, exposure and vulnerability data were only sparsely available and not assessed (neither quantitatively nor qualitatively). In lieu, a hazard matrix was developed which allows the likelihood and severity of hazards to be considered in tandem.

4.1 | Identification of rainfall thresholds

This research adopted an approach using observed rainfall accumulation and rainfall intensity for a training period (using previous floods over a specific duration). Historical flood data were derived from social media mining, archived newspapers, blogs, and eyewitness accounts, which have proven useful in assessing evidence of flood (Chow, Cheong, & Ho, 2016; Herman Assumpção, Popescu, Jonoski, & Solomatine, 2017; Paul et al., 2017). Sewer design rainfall and knowledge of local drainage conditions were also considered relevant as it is assumed that floods occur once this rainfall depth is exceeded.

Hazards are classified as “No to minimal flooding,” “Minor Flooding,” “Significant flooding,” and “Severe flooding.” Thresholds were determined using data from a suitably identified training period and tested with data from a validation period. The methodology used to identify thresholds is presented in Figure 3.

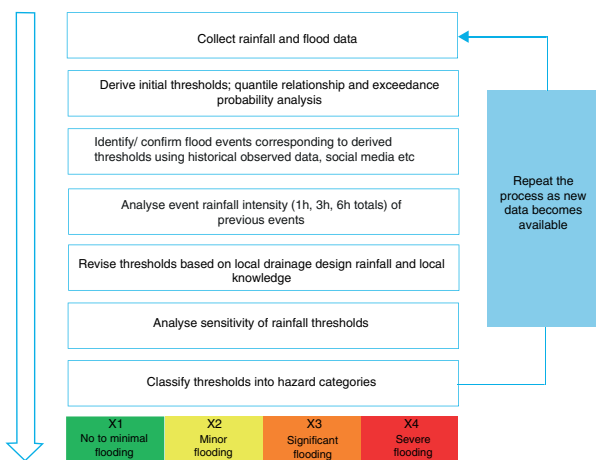


FIGURE 3 Methodology for identifying critical rainfall thresholds using historical data and hazard categories and social media. Modified from Wu and Wang (2009) and Yang et al. (2016)

4.2 | Hazard matrix

Once the critical thresholds have been determined, an operational system is proposed. This integrates ensemble precipitation forecasts and rainfall thresholds into the hazard matrix to assess the possibility of issuing inundation alerts. The system generates a hazard forecast for various forecast horizons using rainfall forecast from a NWP model such as from the European Centre for Medium-Range Weather Forecasts (ECMWF) or Global Forecast System (GFS). Rainfall forecast values are then cross-checked against derived rainfall thresholds. To determine the warning classification (hazard class), the likelihood of ensembles is categorised based on probability thresholds ranges. The concept of probability thresholds has been used by the UK Met Office and the Rijnland Water Board (Van Andel, 2009). Higher probability threshold result in more hits but also result in more false alarms. The method adapted from Yang et al. (2016) calculates the likelihood of exceeding a particular threshold, Equation (1). The higher the number of ensemble members exceeding the rainfall threshold, the higher the forecasted probability that the rainfall threshold will be exceeded.

$$Pr = \frac{1}{N} \sum_{i=1}^N f_i \times 100, i = 1, 2, \dots, N \text{ and } N = 50 \quad (1)$$

$$f_i = \begin{cases} 1, & \text{if } X_j \leq F_i < X_{j+1}, j = 1, 2, 3, 4 \\ 0, & \text{if } F_i \text{ otherwise} \end{cases} \quad (2)$$

where, Pr is the likelihood of threshold exceedance, F_i is the forecasted rainfall of the i th ensemble member of N ensembles and X_j is the rainfall threshold for hazard class j . If a threshold is exceeded then f_i is assigned a value of 1; 0 otherwise (Equation (2)). The Pr for each lead-time is evaluated to derive the hazard matrix for the floods occurring. A decision-based rule based on probability thresholds is used to assign the category as high, medium, low, and very low. A high likelihood meaning a high probability of occurrence and very low meaning low to no probability of occurrence. The probabilistic thresholds (PT)s have been adopted from the UK Met Office. However, probability thresholds should be specific to a particular site and updated regularly based on experience. The operational system approach, including the PTs used is presented in Figure 4.

4.3 | Performance indices

Categorical scoring was used to evaluate if the warning class was consistent with the observed event category.

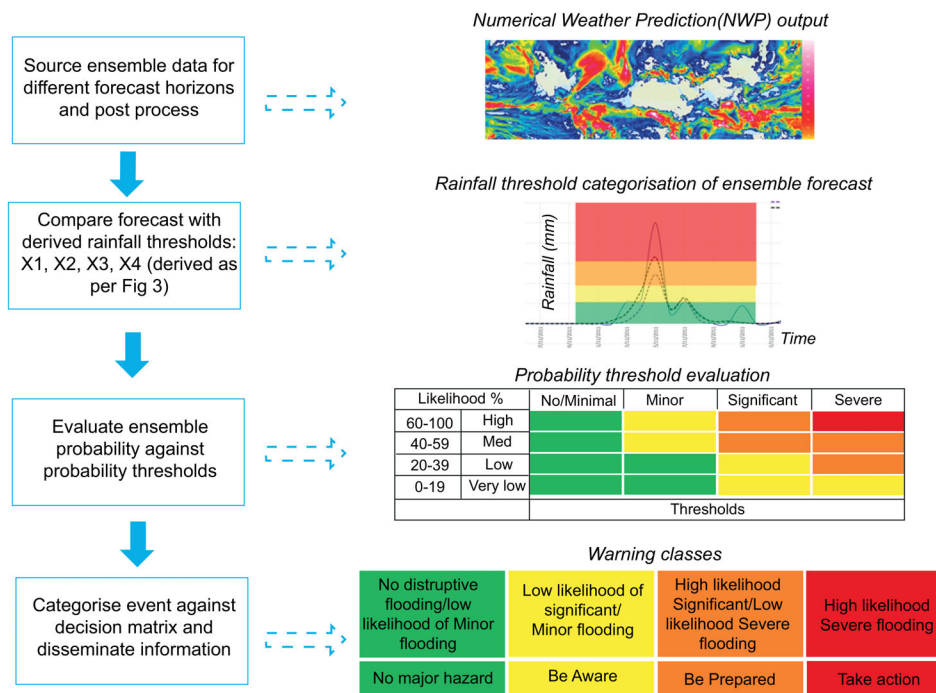


FIGURE 4 Operational flow chart for the proposed urban inundation early warning system

TABLE 1 Categorical descriptions of a hit, miss, and false alarm

| Category | Description |
|-------------|---|
| Hit | Forecast warning class (green/yellow/orange/red) matches the observed class (no flooding/minor flooding/significant flooding/severe flooding) |
| Miss | Forecast warning class is anything lower than the observed hazard class (e.g., “yellow” for significant flooding will be treated as a missed alarm) |
| False alarm | Forecast warning class is Observed hazard class is anything higher than the observed hazard class (e.g., “red” for minor flooding will be treated as a false alarm) |

Categorical descriptions of a hit, miss and or false alarm are presented in Table 1. The Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI) were used as the performance indices and are defined as follows:

$$\text{Hit rate (probability of detection)} = \frac{\text{Hit}}{\text{Hit} + \text{Miss}} \quad (3)$$

$$\text{False alarm ratio (FAR)} = \frac{\text{False alarm}}{\text{Hit} + \text{false alarm}} \quad (4)$$

$$\text{Threat score/critical success index (CSI)} = \frac{\text{Hit}}{\text{Hit} + \text{false alarm} + \text{miss}} \quad (5)$$

5 | STUDY AREA

Alexandria, the famed Egyptian coastal city, is located in the Alexandria Governorate, Nile Delta on the southern boundary of the Mediterranean Sea (Figure 5a). A renowned tourist destination, the city is known for its cultural heritage and landmarks. It is the second largest city in Egypt spanning over 2,300 km² with a population of approximately 4 million (2011). Like many North African cities, it has experienced urban expansion over the years with informal settlements accounting for a third of Alexandria's total population (AASTMT and Egis BCEOM International, 2011). Zevenbergen et al. (2016) reported urban areas have grown almost 40% (from semi-bare) during the past 15 years suggesting a significant reduction in open permeable areas.

Alexandria is characterised by the irregular hills in the southern parts with an elevation from 0 to 40 m above mean sea level (UNISDR, 2010). As the city progresses away from the coast, the topography is characterised by low-lying areas below mean sea level with a significant portion below 5 m sea level (Figure 5b).

5.1 | Climate

Characterised by an arid Mediterranean climate, the city experiences brief, mild, rainy winters and storms from Oct and long warm summer months (May to Sept) with no rain. There is high variability of annual rainfall between 368 mm (maximum, observed in 2004) and

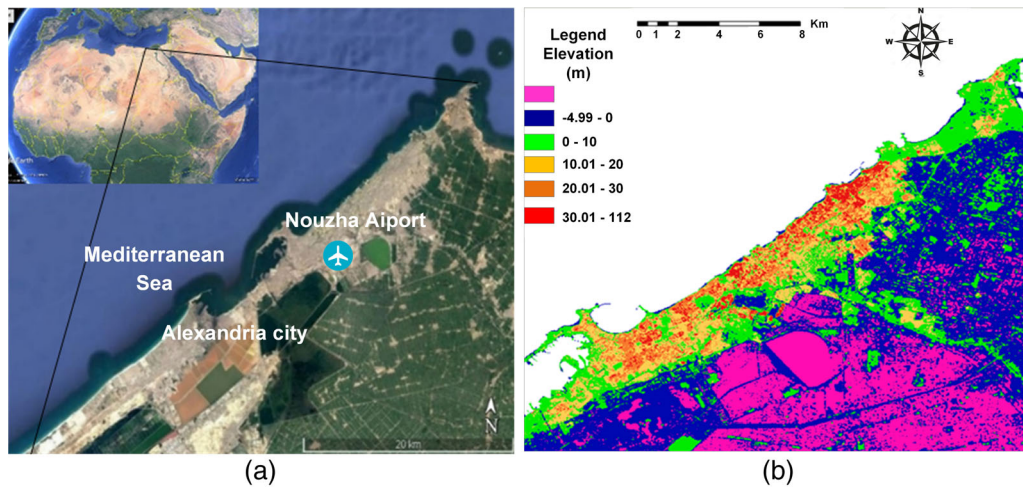


FIGURE 5 (a) Location of Alexandria City. Source: Google Earth (2018), (b) Alexandria City DEM. Resolution 30 m. Source: Japan Aerospace Exploration Agency (JAXA)

70 mm (minimum, observed in 2014) with an average 195 mm/year. In the winter months, it is associated with a high temporal rainfall variability which is a distinguishing characteristic of the Mediterranean climate (Hasanean, 2004). Winter storms are locally referred to as “Nawas or Nawats”; a storm accompanied with strong winds and rains. These migratory cyclones and fronts approach from the west over water and extreme conditions usually last less than a day.

5.2 | Drainage and sewer infrastructure

The system receives domestic and industrial wastewater and stormwater. Recent data from the Alexandria Sanitary Drainage Company (ASDCO) indicate approximately 93.4% of the urban area is connected to the sewer system and the system has a capacity of approximately 1.6 million m³/day (Zevenbergen et al., 2016). During the summer, the load on the system can double due to tourists. Due to the city's rapid urbanisation over the years much of the aged drainage and sanitation infrastructure has become increasingly overwhelmed. The drainage capacity of the system is estimated at a 2-year return period and flooding is experienced during winter storms.

6 | DATA PREPARATION

6.1 | Historically observed rainfall and flood data

Daily rainfall data was sourced freely from an online weather service provider Tutiempo.net for the Nouzha

Airport gauge (Tutiempo, 2018). This data was previously used in several studies including an extensive World Bank study (AASMTT and Egis BCEOM International, 2011). It was further verified by comparing with WMO monthly averages, which are considered a reliable and verifiable source. The selected dataset was then tested for outliers and homogeneity. Only one observed gauge was available, therefore does not represent rainfall spatial variability. A search was done to identify floods on days where the observed rainfall exceeded the 90th percentile of the daily rainfall data from 2010 to 2012. These rainfall events were used as historical reference events (calibration period). Evidence of flooding was sourced from online newspaper archives, blogs, YouTube videos, social media, and other literature, which provided valuable flood data. No social media data or evidence of floods was available before 2010. The rainfall thresholds derived from this period were then tested on the events for the 2013–2015 period. To verify intensity, 3 hourly data from TRMM (Tropical Rainfall Measuring Mission) Multi-satellite Precipitation Analysis 3B42 (version 7) was disaggregated using observed rainfall (Equation (6)). This 3 hourly post-real time 3B42 7 dataset (mm/hr) is estimated monthly and makes indirect use of rain gauges by performing bias monthly accumulations. A proportional adjustment procedure was applied to disaggregate daily gauge data to three hourly data using TRMM data (Koutsoyiannis, 2003; Pontien & Bhattacharya, 2011). A summary of data sources used is presented in Table 2.

$$X_s = \tilde{X}_j \left(Z / \sum_{j=1}^8 \tilde{X}_j \right) \quad (6)$$

TABLE 2 Summary of rainfall data used

| Historical rainfall | | | | |
|--------------------------------|------------------------------|-----------|----------------------------------|---------------------------------|
| Data source | Station | Period | No. of years | Resolution |
| Tutiempo.net | Nouzha International Airport | 1957–2015 | 53. years missing 1967–1973 | Daily |
| WMO | Nouzha International Airport | 1961–1990 | Climate normals | Monthly |
| TRMM 3B42 7 (GES DISC 2016) | 31.5N, 30E, 31.5N, 30E | 2010–2012 | Three years (rainfall intensity) | Three hourly 0.25° × 0.25° grid |
| Ensemble forecast data | | | | |
| Data source | Location | Period | No. of ensembles | Resolution |
| ECMWF (2018) | 31.5N, 29.5E, 31N, 30E | 2010–2015 | 50 | 0.5° × 0.5° grid |

where, X_s is adjusted 3 hourly TRMM gauge rainfall, \tilde{X}_j is the uncorrected 3 hourly TRMM rainfall at time j , Z is the daily gauge rainfall, and j is the subperiod.

6.2 | Ensemble rainfall forecast

The Egyptian Meteorological Agency (EMA) forecast rainfall uses a deterministic limited area, Weather Research Forecast (WRF) model propagated from GFS and ECMWF Global models (EMA, 2017). Ensemble rainfall forecast TIGGE (THORPEX International Grand Global Ensemble) from the ECMWF is part of the THORPEX (Observing System Research and Predictability Experiment) and provides medium-range forecasting up to 15 days ahead (ECMWF, 2015). TIGGE precipitation dataset is available as 50 perturbed forecasts and one control forecast. For the period 2010–2015, 50 ensembles were retrieved from the ECMWF data portal using the Meteorological Archival Retrieval System (MARS) for the corresponding 0.5° × 0.5° (55 km × 55 km) grid for the Alexandria study area. Each member represents an equally likely prediction of total precipitation, forecasted at 6, 12, 24, 48, 72, and 96 hr forecast lead-times with a starting time of 0:00 UTC. Ensembles for the test period (2013–2015) were bias-corrected (Equation (8)) using ratios derived from the linear scaling methods (Equation (7)) used by (Crochemore, Ramos, & Pappenberger, 2016; Teutschbein & Seibert, 2013) and then disaggregated to a daily resolution (Arias-Hidalgo, Bhattacharya, Mynett, & Van Griensven, 2013) (Equations (9) and (10)). The monthly mean values of the 2010–2012 data were used as the training set and applied to the daily 2013–2015 data. Data length used for forecast post-processing was limited but should be extended for future studies.

$$K_{i,m} = TP_m / ENS_{tr,i,m} \quad (7)$$

$$ENS_{cor,i,m} = K_{i,m} \cdot ENS_{t,i,m} \quad (8)$$

$$f_{d,m} = P_{d,m} / TP_{d,m} \quad (9)$$

$$ENS_{cor,i,d} = f_{d,m} \cdot ENS_{cor,i,m} \quad (10)$$

where, TP_m is the average observed rainfall at month, m ; $K_{i,m}$ is the ensemble i correction factor for month, m ; $ENS_{tr,i,m}$ is the uncorrected ensemble i rainfall for the month m for training period; $ENS_{cor,i,m}$ is the bias-corrected ensemble i for month, m ; $ENS_{t,i,m}$ is the uncorrected ensemble i rainfall for the month m for test period; $f_{d,m}$ is the disaggregation factor for day d of month m ; $P_{d,m}$ is the gauge rainfall at day d of month m ; and $ENS_{cor,i,d}$ is the bias-corrected ensemble i for day, d .

7 | RESULTS AND DISCUSSION

7.1 | Rainfall thresholds

The rainfall threshold methodology used a quantile relationship for rainfall data from 1957 to 2012. Combined with historical flood evidence, 24 hr accumulated rainfall depths were associated with flood incidents (Table 3). Rainfall data were fit using a gamma distribution and the percentiles for wet days, that is, when precipitation was more than 0 mm was evaluated. The following thresholds were found – 75th percentile: 6.1 mm, 90th: 11.94 mm, 95th: 19.04 mm, and 99th: 32.1 mm. For the 2010–2012 training period, all the events above the 75th percentile are identified as shown in Table 3. Of the 19 rainfall events identified, evidence of flooding was found for three events (highlighted blue) in Table 3. In the absence of subdaily data, corrected TRMM 3 hourly (Figure 6) data was used to corroborate high intensities on the days identified in Table 3. Maximum intensities of 9.8 and

TABLE 3 Summary of rainfall events during 2010–2012 which exceeded the rainfall amount corresponding to the 75th percentile of the daily rainfall data for the period 1957–2012 (Some of these days were shown to be clustered events [Events 2, 5, 9, 17, and 18] which took place over 1–3 days)

| No | Date | mm | No | Date | mm | No | Date | mm | No | Date | mm |
|----|----------|------|----|----------|------|----|----------|------|----|----------|------|
| 1 | 20/01/10 | 9.9 | 5 | 13/11/11 | 10.9 | 9 | 12/01/12 | 7.8 | 17 | 05/12/12 | 6.1 |
| 2 | 11/12/10 | 5.1 | | 14/11/11 | 11.9 | | 13/01/12 | 7.8 | | 06/12/12 | 21.0 |
| | 12/12/10 | 6.1 | | 15/11/11 | 5.08 | | 14/01/12 | 6.1 | 18 | 11/12/12 | 7.11 |
| | 13/12/10 | 20.1 | | 16/11/11 | 50.0 | 10 | 17/01/12 | 7.8 | | 13/12/12 | 28.1 |
| 3 | 15/01/11 | 16 | | 17/11/11 | 10.9 | 11 | 25/01/12 | 7.1 | | 14/12/12 | 6.1 |
| | 16/01/11 | 7.1 | 6 | 21/11/11 | 8.89 | 12 | 18/02/12 | 9.9 | 19 | 21/12/12 | 7.1 |
| 4 | 19/01/11 | 7.1 | 7 | 24/12/11 | 6.1 | 13 | 29/02/12 | 9.9 | | | |
| | 07/02/11 | 7.8 | 8 | 02/01/12 | 10.9 | 14 | 01/03/12 | 20.0 | | | |
| | | | | | | 15 | 04/03/12 | 7.1 | | | |
| | | | | | | 16 | 25/11/12 | 7.8 | | | |

FIGURE 6 (a) Hyetograph for November 15 and 16, 2011 and (b) Hyetograph December 12, 2011 showing rainfall intensity. Source: GES DISC (2016)

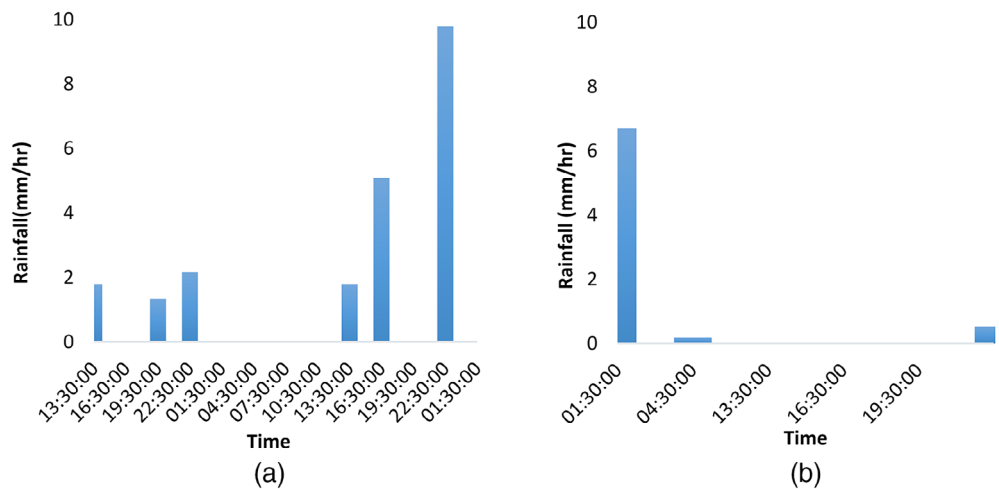


FIGURE 7 Flooding on December, 2010 showing submersion of cars. Source: Nader (2010)



6.78 mm/hr were found for the 2011 and 2010 events, respectively (Figure 6). Evidence of the inundation observed for the December 2010 event is presented in Figure 7.

There was significant coverage of the flooding event in 2010 by news agencies and it was also indicated as a major event in the study of the World Bank (2011) with damage to buildings and disruption of traffic. Casualties

were also reported with this event. The observed rain gauge event was associated with a daily rainfall of 20 mm on December 12. The 2011 event was also highlighted as a major flood by the ADSCO. Local drainage capacity (2 year return period) for Alexandria is reported as 26 mm/day and considering events last no longer than 2 hr. Flooding assumed to occur once exceeded.

On November 16, 2011, the maximum observed rainfall was 50 mm, which also caused significant flooding. Rainfall frequency analysis shows that 26 mm has a 2-year return period and 50 mm/day has a 10-year return period (Awadallah, Magdy, Helmy, & Rashed, 2017). Therefore, we assume a 50 mm event would have a higher severity. From this criterion, we infer a 20 mm rainfall leads to significant flooding and severe flooding occurs when the rainfall exceeds the 99th percentile; exceeding 32 mm. Based on the evidence of flooding observed in the floods for 2010, 2011, and 2012, the hazard classification was assumed for the following events (Table 4). Thresholds were classified as either “No to minimal,” “minor,” “significant,” or “severe.”

7.2 | Application to 2013–2015 storms

The assessment was performed for a total of five storm events identified during 2013–2015 (Table 5). A visual representation of the threshold categorisation for event #1 and #2 in 2015 is shown in Figure 8.

7.3 | Performance indices

A contingency table was developed to evaluate the ability of this approach in discerning the severity of floods inferred with respect to lead-time. Results of this analysis are presented in Table 6 for the validation period 2013–2015. A POD of more than 33% is considered useful

(WMO, 2011). The POD and CSI scores for minor events suggest all minor events were correctly forecasted at 12 hr and half at 6 hr. At 24 hr lead-time, severe events received a CSI of 0.75 which suggest at these lead-times three-fourth of all severe forecasted events were observed. This is demonstrated for both the November 4 and October 25 events. The forecast did indicate some level of persistence as three-fourth of all severe events were forecasted as significant events at 48 hr before being upgraded to a severe event at 24 hr. Incidentally, significant events were not well detected at short lead-times but scored a POD of 0.5 at 48 and 72 hr and a FAR of 1 at 24 hr implying that at 24 hr these events were always forecasted at a higher value. All hazard event categories showed poor discrimination at the 72 and 98 hr lead-time. Only 3 years of data were used to calibrate the rainfall thresholds, which is seen as a considerable limitation. The results indicate, even with a relatively coarse spatial resolution, the ECMWF data was still capable of predicting events and performed better for more severe events. These results could be improved using higher spatial resolutions from limited area forecast models and more robust bias correction methods and longer calibration test datasets.

7.4 | Hazard matrix

The hazard categorisation, ensemble probability exceedance, and the corresponding decision/warnings to be taken are summarised in Figure 9. UK Met Office

TABLE 4 Revised rainfall thresholds considering location drainage conditions, non-exceedance probability and return periods

| (mm) | 0–11.99 | 12–19.99 | 20–31.99 | >32 |
|-------------------|------------------------|----------------|----------------------|-----------------|
| Hazard class 2011 | No to minimal flooding | Minor flooding | Significant flooding | Severe flooding |

TABLE 5 Summary of major events in 2013–2015 (validation period) to be evaluated including the bias-corrected forecast depths at different lead times

| Event | Date | Obs (mm) | Lead-time | | | | | |
|-------|------------|-------------|-----------|-----------|-----------|-----------|-----------|-----------|
| | | | 6hr (mm) | 12hr (mm) | 24hr (mm) | 48hr (mm) | 72hr (mm) | 96hr (mm) |
| 1 | 04/11/2015 | 20.1 | 8.6 | 17.9 | 41.6 | 35.9 | 26.6 | 20.4 |
| | 05/11/2015 | 43.9 | 43.8 | 31.4 | 41.3 | 24.8 | 16.7 | 12.8 |
| | 06/11/2015 | 44.9 | 5.2 | 5.8 | 8.3 | 5.1 | 3.5 | 2.8 |
| 2 | 25/10/2015 | 32.0 | 46.9 | 28.6 | 36.0 | 20.0 | 13.8 | 11.1 |
| 3 | 07/01/2015 | 20.1 | 16.7 | 15.4 | 12.6 | 7.1 | 5.2 | 6.2 |
| 4 | 06/01/2013 | 18.0 | 19.3 | 16.8 | 21.4 | 22.9 | 20.3 | 16.4 |
| | 08/01/2013 | 36.1 | 24.5 | 22.3 | 35.7 | 12.6 | 9.7 | 7.7 |
| 5 | 13/12/2013 | 25.9 | 8.5 | 7.1 | 7.9 | 4.2 | 2.9 | 2.5 |

FIGURE 8 Threshold categorisation for 25 October and 4 and 5 November event (mean ensemble and mean ± 2 SDs at different LTs)

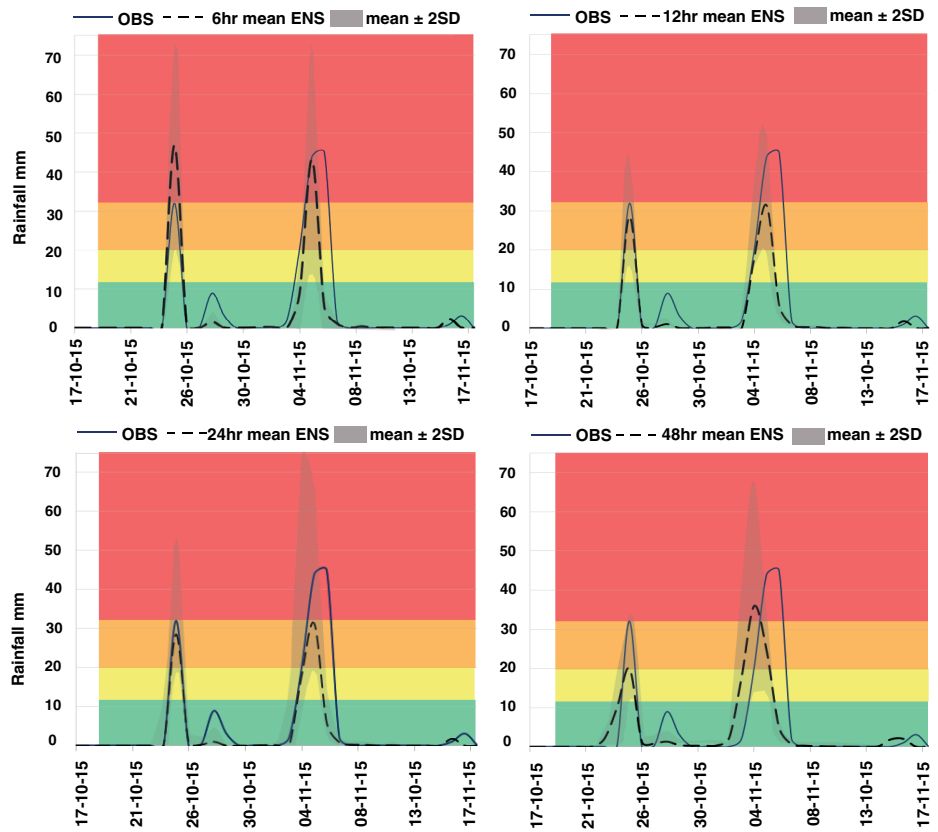


TABLE 6 Summary of categorical scores for observed events (2013–2015): Probability of Detection (POD), False Alarm Ratio (FAR), and Critical success ratio (CSI) or Threat score

| Lead-time (hr) | Minor | | | Significant | | | Severe | | |
|----------------|-------|-----|-----|-------------|-----|-----|--------|-----|------|
| | POD | FAR | CSI | POD | FAR | CSI | POD | FAR | CSI |
| 6 | 0.5 | 0 | 0.5 | 0 | 0 | 0 | 0.5 | 0 | 0.5 |
| 12 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 0 | 1 | 0 | 0 | 1 | 0 | 0.75 | 0 | 0.75 |
| 48 | 0 | 1 | 0 | 0.5 | 0 | 0.5 | 0 | 0 | 0 |
| 72 | 0 | 1 | 0 | 0.5 | 0 | 0.5 | 0 | 0 | 0 |
| 98 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

probability thresholds were used in the absence of established probability thresholds (Figure 4). For both events, severe events were predicted at both 6 and 24 hr lead-times with over 60% likelihood warranting a “take action” decision. At 48 hr the events were predicted with a “high likelihood of significant event” or “low likelihood of a severe event”; “Be prepared” and no major hazard at 96 hr. The agreement on the decision category while definite at some longer lead-times also shows uncertainty at longer lead-times and ambiguity in making a confident decision.

It is acknowledged that these results are highly dependent on the threshold as discussed in the next

paragraph. Thresholds derived should not be final but need to be updated regularly as more data becomes available. Sourcing evidence of floods was one of the biggest challenges in the research as there are no official existing historical records of floods in Alexandria. In addition to having a limited number of years, there are many circumstantial factors, which contribute to urban flooding such as rainfall intensity, localised flooding in surface depressions, sewer blockages, pump reliability, functionality, and changes in permeability over time, of which could not be accessed.

There is uncertainty associated with the derivation of the thresholds. Table 7 evaluates how the warning class

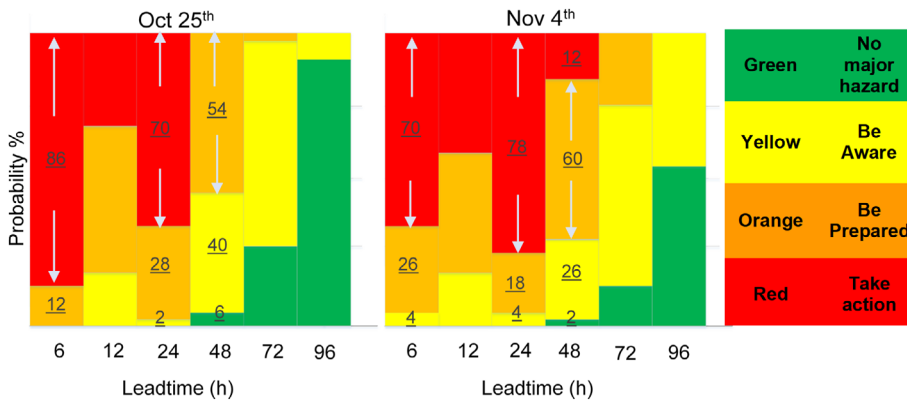


FIGURE 9 Hazard matrix and decision categorisation for 25 October and 4 November events. Probability of ensemble exceeding a threshold is shown

TABLE 7 Sensitivity of hazard classification at the 6 hr lead time with changing thresholds

| No. | Threshold range (mm) | Hazard classification | | |
|-----|----------------------|-----------------------|--------|--------|
| 1 | 0–16–25–36 | Yellow | Green | Yellow |
| 2 | 0–15–24–35 | Yellow | Yellow | Yellow |
| 3 | 0–14–23–34 | Yellow | Yellow | Yellow |
| 4 | 0–13–22–33 | Yellow | Yellow | Yellow |
| 5 | 0–12–20–32 | Yellow | Yellow | Yellow |
| 6 | 0–11–19–31 | Yellow | Yellow | Yellow |
| 7 | 0–10–18–30 | Yellow | Yellow | Yellow |
| 8 | 0–9–17–29 | Yellow | Yellow | Yellow |

| Date | Day | 6 hr | 12 hr | 24 hr | 48 hr |
|----------|-----|--------|--------|--------|--------|
| Jan 2013 | 5 | Yellow | Yellow | Yellow | Yellow |
| | 6 | Yellow | Yellow | Yellow | Yellow |
| | 7 | Yellow | Yellow | Yellow | Yellow |
| | 8 | Yellow | Yellow | Yellow | Yellow |
| Oct 2015 | 24 | Green | Red | Green | Green |
| | 25 | Green | Red | Green | Green |
| | 26 | Green | Red | Green | Green |
| Nov 2015 | 4 | Green | Red | Green | Green |
| | 5 | Green | Red | Green | Green |
| | 6 | Green | Red | Green | Green |

for these specific events would vary had slight changes to the thresholds been made. In general, there was less variability with the shorter lead-times and at higher severity events. For the Oct and Nov events, the hazard characterisation remained unchanged from a range of 26–38 mm. For the January 6 and 8 event, the classification remained “significant” for most ranges as well. For the purposes of this analysis, the October 25 and November 4 events were perceived as two independent events but in reality, there is an interdependency as the previous event would have saturated the system resulting in lower thresholds for the subsequent flood. Thresholds were derived based on daily-accumulated totals; however, it is also necessary to examine multiday accumulation thresholds to address clustered events.

7.5 | Experimentation of the system on a real case: The 2018 storm

The above derived rainfall thresholds and hazard classifications are currently being utilised by the Alexandria Sanitation and Drainage Company (ASDCO) to issue

warnings and initiate anticipatory actions. In December 2018, officials were put on alert for an extreme rainfall event on December 5. The 24 hr rainfall accumulation was forecast to be 33 and 27 mm at the 48 and 24 hr forecast time horizons, respectively. Applying the rainfall threshold categorisations, these events were forecast as “Severe” 48 hr before and “Significant” 24 hr before. The probabilistic forecast at both leadtimes indicated a “high likelihood of significant flooding/be prepared” would have been issued. ASDCO used the deterministic forecast, combined with their knowledge of the past flood and critical hot spot areas. The city initiated pre-emptive actions including pumping and checking of pumps at specific locations and cleaning of drains. In actuality, the observed rainfall for the event on December 5 was observed to be 23 mm; a “Significant” flood but minimal reports of flooding were received. Probabilistic forecasts are not yet being used, but it is anticipated this will be the next phase as city officials realise the benefits and how to use probabilistic forecast. The pre-emptive measures implemented by the city were able to prevent flooding and disruption. Before these threshold categorisations, there was no formal process for pluvial flood warnings or

plans for anticipatory actions in the city. Additionally, new pumps have been installed to facilitate anticipatory flood actions. With this approach, the city mitigated the 2018 flood and are now more prepared for future floods. This is a useful, practical, and simple method when proactive actions are not highly objectionable under false alarms. This is one step toward improved adaptation to the increasing severity and intensity of rainfall events observed in recent years and likely to increase in the coming years. If probabilistic forecast had been used, “high likelihood significant flooding/be prepared” would have been issued. In the interim, the city continues to use the thresholds classifications.

8 | CONCLUSION

In Alexandria and other MENA cities there is high rainfall variability, insufficient drainage capacity, flood preparedness is low and often the risk of pluvial flooding is unknown. In data-scarce regions the threat is imminent; there needs to be an interim trade-off between complexity and technical feasibility to effectively reduce impacts until the necessary detailed studies can be done. This research demonstrated and applied a practical approach of predicting extreme rainfall events associated with floods using limited data and no flood models by incorporating available data such as historical flood data from social media and satellite precipitation products (SPPs). In addition to assessing uncertainty, ensembles combined with a rainfall threshold approach allowed characterisation of exceedance likelihood associated with flooding. From an operational forecasting perspective, this probabilistic information was used to support decision making.

In urban areas, subdaily rainfall intensity is essential to predicting floods. TIGGE ensemble forecast has a forecast grid of approximately 50×50 km and may present difficulties in forecasting in small areas as values are averaged over $2,500 \text{ km}^2$. The nonlinearity of rainfall and flood events in addition to the low number of events and historical data limited extensive validation of this method which is one of the main challenges of using ensembles. However, results were very favourable and the methodology is developed so that it can be used with higher resolution NWP models or radar estimates as available.

The simplified phased warning and response approach is consistent with operational forecasting agencies. Combined with the ensemble forecasting and rainfall threshold approach, this method adds some complexity over the widely used deterministic rainfall forecasts. However, it can strike a balance between a simplified approach and forecast uncertainty estimation. It does not assess exposure and vulnerability or indicate

possible impacts but when combined with previous knowledge of “hot-spot” areas, can prove valuable in supporting decision-making as was demonstrated in the 2018 event. This method is not proposed as an absolute substitute for EWS using stormwater models but rather it allows “buy-in time” to increase preparedness until more data becomes available. Additionally, the benefit of site-specific thresholds applied on a local scale rather than on the national scale means local authorities can make specific independent decisions and increase preparedness of their cities and communities.

Notwithstanding, communication of warnings still needs to be incorporated to ensure effective warnings. Consideration should be made for different durations and significant changes in catchment characteristics over time. This emphasises the importance of flexible anticipatory mitigation measures that can be adapted to uncertainties in the forecast and other urban drivers.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in ECMWF public data TIGGE Data Retrieval at <http://apps.ecmwf.int/datasets/data/tigge/>, reference number 26. The data that support the findings of this study are openly available in Tutiempo at <https://en.tutiempo.net/climate/ws-623180.html>, reference number 58. The data support the findings of this study are openly available at GES DISC at https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_7/summary, reference number (to be assigned).

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