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Stormwater management modeling and machine learning for flash flood susceptibility prediction in Wadi Qows, Saudi Arabia

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Abstract:

Predicting flash flood-prone areas is essential for proactive disaster management. However, such predictions are challenging to obtain accurately with physical hydrological models owing to the scarcity of flood observation stations and the lack of monitoring systems. This study aims to compare machine learning (ML) models (Random Forest, Light, and CatBoost) and the Personal Computer Storm Water Management Model (PCSWMM) hydrological model to predict flash flood susceptibility maps (FFSMs) in an arid region (Wadi Qows in Saudi Arabia). Nine independent factors that influence FFSMs in the study area were assessed. Approximately 300 flash flood sites were identified through a post-flood survey after the extreme flash floods of 2009 in Jeddah city. The dataset was randomly split into 70 percent for training and 30 percent for testing. The results show that the area under the receiver operating curve (ROC) values were above 95% for all tested models, indicating evident accuracy. The FFSMs developed by the ML methods show acceptable agreement with the flood inundation map created using the PCSWMM in terms of flood extension. Planners and officials can use the outcomes of this study to improve the mitigation measures for flood-prone regions in Saudi Arabia.

KEYWORDS pcswmm model; machine learning; flash flood; wadi qows; Saudi Arabia

INTRODUCTION

In the last two decades, there has been an extensive evaluation of machine learning strategies worldwide for forecasting flood risk. As a result, flood modeling has advanced greatly due to recent innovations in machine learning techniques. Information may be captured without establishing assumptions, and complicated datasets can be processed quickly and accurately using these approaches (Arabameri *et al.*, 2020). Machine learning techniques are widely applicable in water-related applications (e.g. Random forest, LightGBM and CatBoost), and can accurately predict flash flood susceptibility in arid regions with high performance (Saber *et al.*, 2021). Due to extremely short lag durations, flash floods are more disastrous than any other form of floods (Vinet, 2008), particularly in dry regions (Abdel-Fattah *et al.*, 2018; Abdrabo *et al.*, 2020; Saber *et al.*, 2020). Flash floods have been recorded and verified to have severe impacts in developing and developed nations (Bisht *et al.*, 2018; Esmaiel *et al.*, 2022); nevertheless, flood occurrences are more severe in developing nations, such as those in the Middle East and North Africa (MENA). Flash floods are becoming more common as a result of changes in violent storm patterns and global climate change (Hirabayashi *et al.*, 2013; IPCC, 2014). Flash flood susceptibility mapping is one of the most critical metrics according to researchers and governments throughout the globe (Ali *et al.*, 2020). In Saudi Arabia, climate change has a substantial impact on flash flood variability, and flash floods have increased over the last two decades. For instance, flash floods occurred in Jeddah city in 2009 and 2011. The number of "Jeddah drowning" victims reached 113 in 2009 (Youssef *et al.*, 2016). The flood susceptibility map can provide a better understanding of which areas are most at risk for future flooding (Band *et al.*, 2020; Chowdhuri *et al.*, 2020; Saha *et al.*, 2021; Malik *et al.*, 2021), and such flood susceptibility mapping can be a good guide for the decision maker for future effective flash flood management strategies.

In Saudi Arabia, there are limited previous studies focused on ML approaches for flood susceptibility (Al-Areeq *et al.*, 2022; Youssef *et al.*, 2022a; 2022b), and to our knowledge, there is no study comparing physically based approaches and ML algorithms. Therefore, the aim of this study is to develop flash flood susceptibility maps (FFSMs) by adopting machine learning (ML) models (random forest, LightGBM, and CatBoost) and hydrological modeling analyses (Personal Computer Storm Water Management Model; PCSWMM). Wadi Qows in Saudi Arabia was selected as a case study (Figure 1a). The main

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framework of this paper consists of an introduction, study area, methodology (datasets and features, ML algorithms, and model accuracy), results, and finally a conclusion.

Study area

Saudi Arabia (Figure 1a) is located in southwestern Asia between 32° and 55° east longitude and between 15.5° and 32.5° north latitude; the country is divided into 13 administrative regions. Saudi Arabia has a desert climate with very low average annual rainfall, except in the southwestern region, which receives an average of approximately 300 mm of precipitation annually. This region receives the highest precipitation amount in the country, while precipitation decreases significantly in the rest of the regions. Wadi Qows is situated in eastern Jeddah city between 39.1° E and 39.6° E and between 21.2° N and 21.8° N.

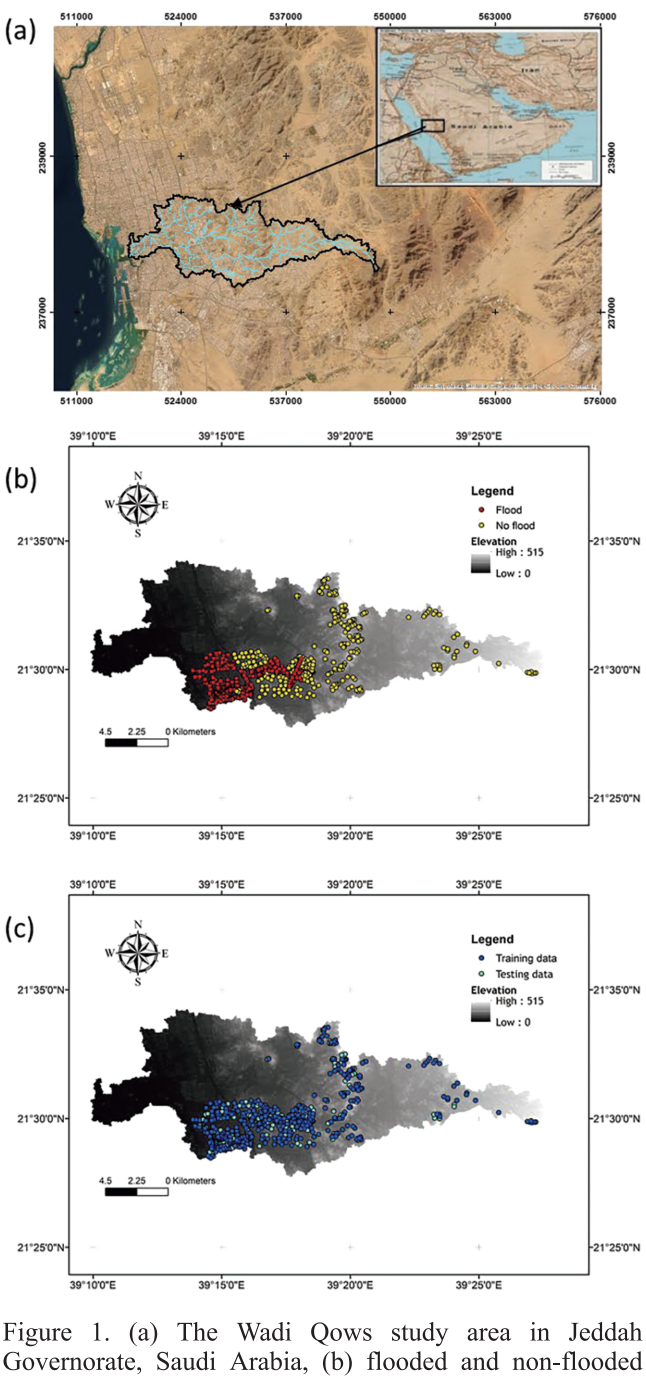

Figure 1. (a) The Wadi Qows study area in Jeddah Governorate, Saudi Arabia, (b) flooded and non-flooded locations, and (c) the flood inventory map used to construct the training and testing datasets

DATA AND METHODS

The FFSMs in both approaches of ML and the physical model have been estimated. First, in preparing the flood and non-flood inventory map, about 300 points were selected based on the post-flood survey of the most extreme event of 2009 that hit the region with very destructive impacts. Secondly, the effective influencing factors were prepared and developed. To select the effective contributors for flood susceptibility, the selection features methods were applied. To develop the flood susceptibility mapping, ML algorithms, namely, the random forest (RF), LightGBM, and CatBoost algorithms (Saber *et al.*, 2021), were employed. Also, the accuracy of their performance was assessed based on several statistical measures, in addition to comparing with the physical-based model in terms of flood extent.

Datasets and influencing factors

First, a flood inventory map (Figures 1b and 1c) is generated based on 300 inundated sites. These places were determined based mostly on post-flood studies undertaken after the flash floods on November 25, 2009 that hit Jeddah, Saudi Arabia. Non-flooded locations (300) across the watershed were randomly picked using GIS tools from the topographic information such as DEM based on our experience. In this research, in order to use machine learning for flood susceptibility mapping, observational flooded and non-flooded points were collected from the post flood survey of the flood event of 2009, with datasets divided into 70% for training and 30% for testing. Then, after model training and validation, we applied the model over the whole basin to predict the flooded and non-flood regions and finally we could create a spatial map for the whole region for the flood susceptibility. Eleven flood-controlling factors such as elevation, aspect, slope, hillshade, flow accumulation, horizontal flow distance, vertical flow distance, stream power index (SPI), rainfall, land use/land cover, and topographic wetness index (TWI) were developed by using ArcGIS spatial tools with the same resolutions of 10 m (Figure 2). These factors were selected based on the previous studies as the most dominant and effective influencing factors for flooding occurrences. Additionally, we performed feature selection to identify the factors that contribute most significantly to flood susceptibility in the study area.

Machine learning

ML algorithms, namely, the RF, LightGBM, and CatBoost algorithms, were employed. The accuracy of the final results of the ML models was assessed by considering different statistical measures, including the most dominant factor, the area under the curve (AUC). The final flood susceptibility maps developed by the ML models were compared with the flood inundation maps obtained from the

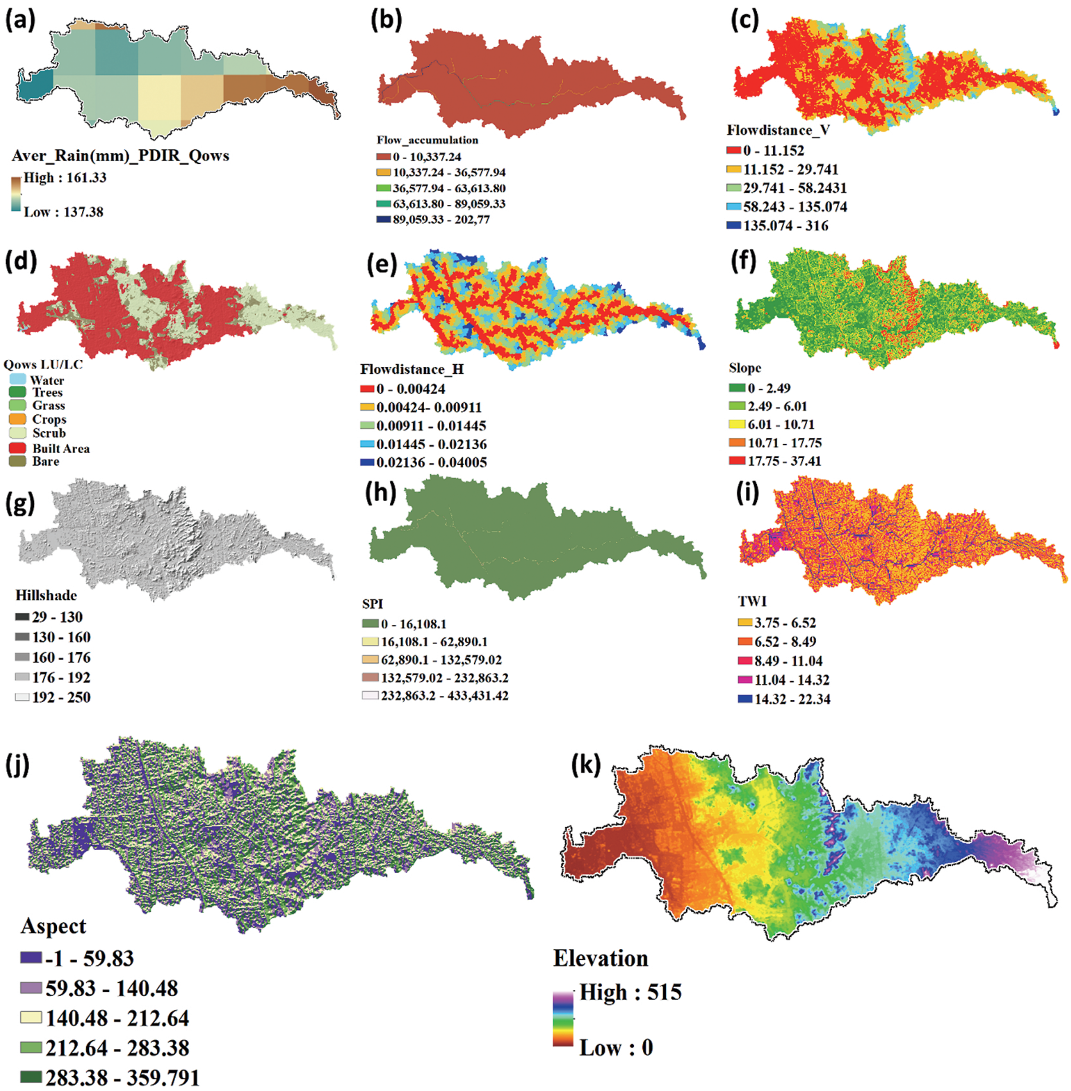

Figure 2. Flood-influencing factors: (a) rainfall, (b) flow accumulation, (c) flow distance, (d) land use/land cover, e) flow distance, (f) slope, (g) hillshading, (h) stream power index (SPI), (i) topographic wetness index (TWI), (j) aspect, and (k) elevation

physical hydrological model. In this study, we used three ML Algorithms: 1) CatBoost: An algorithm proposed by Dorogush *et al.* (2018), which uses gradient boosting for regression trees and builds a model in a gradient manner through increasingly precise approximations. 2) LightGBM: A variant of the gradient boosting decision tree (GBDT) algorithm developed by Microsoft (Ke *et al.*, 2017). The structure of this algorithm is based on weak learners being combined to form a strong learner. 3) RF: A ML algorithm that belongs to the category of ensemble learning methods. The algorithm of RF was introduced by Breiman (2001) based on binary decision trees as a combination of the random subspace method and bagging ensemble learning. More details can be found in Saber *et al.* (2021).

Multicollinearity assessment and feature selection

Spearman's coefficient correlations between two features were calculated, and multicollinearity was tested among all influencing factors studied here. This research used the variance inflation factor (VIF) methods to conduct a multicollinearity analysis, which measures the behavior of variance against the correlation with other independent variables and provides a measure of how much a variable is contributing to the standard error in the regression. The purpose of which was to identify pre-existing relationships between variables. Research of a community's susceptibility to flooding frequently includes this factor (Bui *et al.*, 2019), and a threshold >5 denotes multicollinearity. However, in other research, the relevant predictors are deemed collinear if the VIF value is more than ten and are therefore advised to be left out of the models (Dou *et al.*, 2019). This value was adopted in this study to detect the existence of correlations between the flood-influencing factors identified as being mutually correlated (Table SI). The influencing features show information gain ratio (IGR) scores greater than zero, which indicates their relative importance in flood prediction. The IGR was computed and is illus-

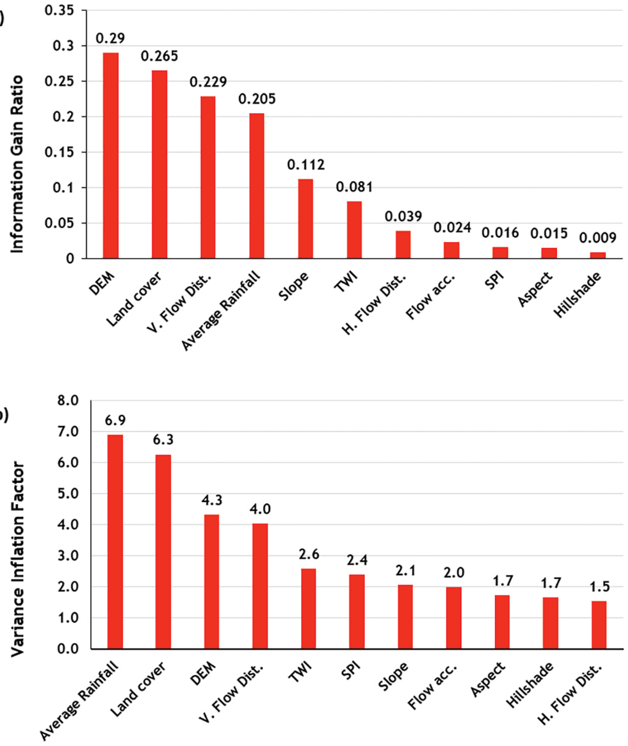

Figure 3. Analyses of influencing factors: (a) information gain ratio (IGR) and (b) variance inflation factor (VIF) flood susceptibility results: Digital elevation model (DEM), land cover, vertical distance to rivers (V. Flow Dist.), average rainfall, slope, topographic wetness index (TWI), horizontal distance to rivers (H. Flow Dist.), flow accumulation (Flow acc.), stream power index (SPI), aspect, hillshade

trated in (Figure 3a). The influencing features show IGR scores greater than zero, which indicates their relative importance in flood prediction. Also, the VIF values for the average rainfall (= 6.90) and LCLU (= 6.26) factors were greater than the threshold value (> 5), indicating a multicollinearity problem (Figure 3b). Based on these feature selections, from among 11 factors, only nine features were selected as shown in Table SI.

Evaluation of the models

The receiver operating characteristic (ROC) curve measure is a commonly used and validated strategy for assessing the reliability of a model in geospatial research. Therefore, the AUC-ROC parameter and other quantitative metrics (accuracy, recall, precision, and the F1-score) were employed to check the model performance and compare its classification ability with the abilities of other models. Table SII shows the details of statistical measures of model performance. All category techniques resulted in roughly the same outcomes in terms of statistical indicators. According to the AUC-ROC results, the random forest algorithm outperformed the other models (Figure 4). Still, the other two models (CatBoost and LightGBM) showed higher accuracy and precision values than the RF (Table SII).

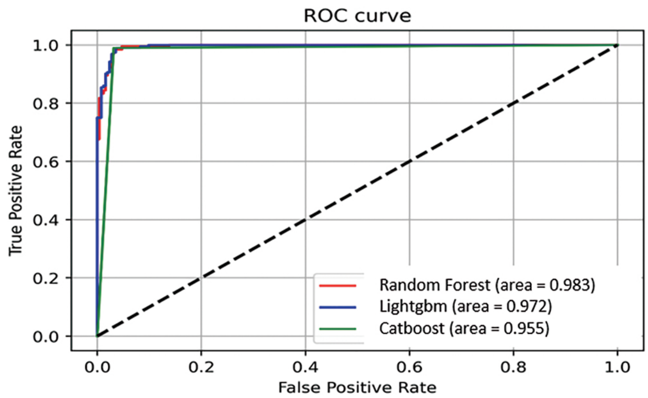

Figure 4. Performance of the Random Forest, CatBoost, and LightGBM models based on the areas under the receiver operating characteristic (ROC) curves

Personal Computer Storm Water Management Model (PCSWMM)

PCSWMM is a software tool for the simulation and analysis of urban stormwater systems, and it was developed by Computational Hydraulics International (CHI) (Computational Hydraulics International (CHI) 2023). The model requires input datasets as follows: 1) The DEM was acquired from the Shuttle Radar Topography Mission (SRTM) satellite data at a resolution of 30 m. 2) Rainfall data was generated from the PERSIANN rainfall satellite data (Center for Hydrometeorology and Remote Sensing 2017). 3) The land use was divided into two types namely Urban and Desert based on Google Earth data. The catchment model was run to estimate the event that occurred on November 25, 2009 in Jeddah city, a devastating flood event with a total daily rainfall rate exceeding 85 mm within four hours. The 2D cells were generated based on the attributes of the bounding polygon. The model was calibrated based on the flood depth data collected from the post-flood survey of the storm event of 2009.

RESULTS

Machine learning

The assessment system of measurement of the newly assessed algorithms (CatBoost, LightGBM, and RF) validated their high overall performances when predicting flooding in an arid environment. Accordingly, those techniques were employed to estimate flood susceptibility maps for Wadi Qows. Several statistical indices (Accuracy, Precision, Recall, F1_score, and AUC) were used to evaluate the ML algorithms. From the results, the highest AUC was obtained by the RF model (98.3%). AUC was 97.2% and 95.5% for LightGBM and CatBoost, respectively. However, CatBoost displayed the best accuracy and precise classification performance, with an accuracy = 95.5% and precision = 93.3%, followed by the LightGBM model, with an accuracy = 93.8% and precision = 90.3%, and finally the RF model with an accuracy = 93.2% and precision = 89.4%. In comparison with previous studies (Saber *et al.*, 2021), the AUC for RF indicated higher accuracy, however, LightGBM and Catboost had lower accuracy.

PCSWMM

The model has been calibrated based on the observed data obtained from the field survey in the 2009 event. The model accuracy based on the comparison with the flood depth was about 80%. The most influential parameters were Manning's roughness coefficients with a range from 0.015–0.04, and soil porosity with a range from 0.05–0.6. The PCSWMM model analysis revealed that the areas with high impervious surface coverage were more prone to flooding and runoff issues, highlighting the importance of implementing effective stormwater management strategies in urbanized areas to mitigate the negative impacts of urbanization on the hydrological cycle.

Flood susceptibility mapping

The three FFSMs developed using the ML models were compared with the flood inundation map obtained with the PCSWMM, as shown in Figure 5. The FFSMs developed by the ML methods show reasonable spatial distributions. They agree somehow in the flood extent with the actual situation in the case of the flood of 2009 in Jeddah city, revealing that the adopted ML approaches are efficiently applicable for FFSMs in arid regions. The FFSMs were classified from low to very high levels of susceptibility. Most downstream areas dominated by high populations are affected mainly by high and very high flood levels, as shown in Figure 5. Figures 5 and 6 indicate that the FFSMs developed by these three models are comparable with the PCSWMM results in terms of flood extension. Nevertheless, other flood levels, such as the estimated areas of high and extremely high flood risk zones, comprise 40% (RF), 43% (CatBoost), and 41% (LightGBM) of the study area. Generally, the results show acceptable agreement between the two approaches in the spatial extent of the flooding area.

The hydrological model used in this study (PCSWMM) can simulate a flood inundation map (depth and extent). This depth and extent are based on the input storm which varies from one event to another. Also, ML can give the probability of flood occurrence as an extent (flood susceptibility). Due to the limited observational data, we attempt to develop a ML model to predict flood susceptibility in the region. Additionally, we implement a physical model to explain somehow the efficiency of the ML model by comparing the flood inundation extent with the flood susceptibility. Therefore, we compare the extent of the flood event of 2009 with the existing flood susceptibility map that shows that somehow ML is reliable in this application. However, the flood inundation map developed by physical model can be variable if we change the input storm. Therefore, currently, we are working on two issues; the first one, using ML to develop flood depth prediction which allows us to directly compare with the flood inundation map developed by the physical model, and the second one, to develop a hybrid model of both ML and physical models to accurately predict the flood depth and susceptibility in such data-scarce regions.

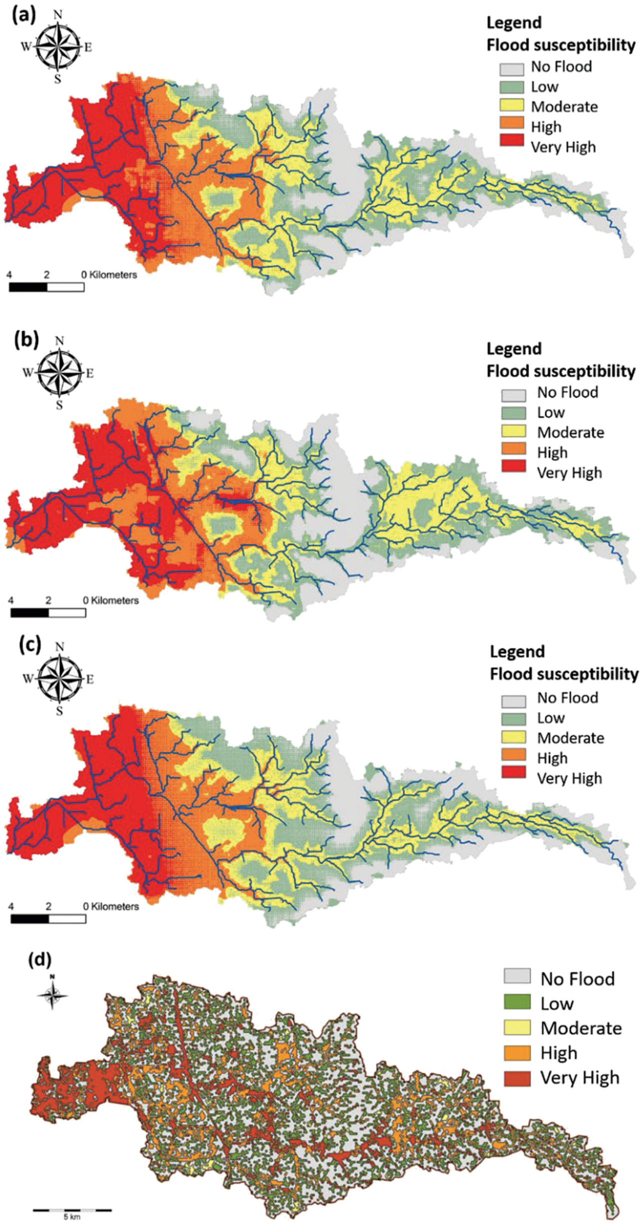

Figure 5. Flood susceptibility maps produced by the LightGBM (a), Random Forest (b), CatBoost (c), and PCSWMM (d) analyses

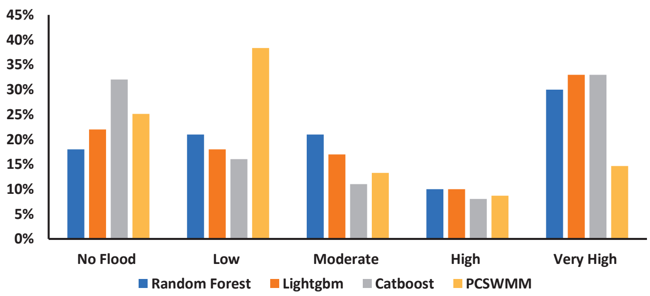

Figure 6. Affected flood susceptibility areas obtained with three ML methods and the flood inundation map of the PCSWMM model

CONCLUSION

This research demonstrates the feasibility of using ML algorithms (RF, LightGBM, and CatBoost) for evaluating FFSMs in dry environments. The FFSMs developed by the machine learning model show an acceptable consistency with the FFSM by PCSWMM from the aspect of their spatial distributions. The area under the ROC is greater than 97%, revealing that the applied approaches can reliably forecast flood zones. According to the FFSM, the densely populated coastal region is among the most vulnerable to floods, placing it in the highest risk category. However, one of the crucial limitations of this study is the lack of data which leads to uncertainty in both hydrological and machine learning models. The availability of high-quality data is often a challenge, especially in regions with limited monitoring stations or in areas with a lack of historical flood records such as Saudi Arabia. Therefore, addressing the data limitation issue is crucial to improve the accuracy and reliability of these models and to support effective decision-making in flood risk management. Such a limitation can be improved by developing a hybrid approach combining both physical-based models and machine learning algorithms to accurately predict flood risk maps. A logical extension of this work is to develop such a hybrid model for flood depth prediction.

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SUPPLEMENTS

Table SI. Spearman's correlation coefficients for FFS mapping

Table SII. Statistical measures used for the model performance evaluation

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