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Forecasting and Simulation of Urban Floods Based on the Integration of RegCM and Stormwater Management Models

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Abstract

Meteorological forecasting is an effective method for helping to reduce the human and financial risks during the occurrence of floods. Hydrological forecasting is often considered a component of flood warning systems, which can improve the accuracy of alerts and the lead time of existing forecasts, providing more time for property protection and evacuation of at-risk areas. In this study, the Regional Climate Model (RegCM) for dynamic/meteorological forecasting, combined with the Storm Water Management Model (SWMM) for hydrological analysis, was employed to forecast and simulate monthly floods in the urban basin of Sabzevar. To apply the RegCM meteorological model, six convection schemes, two boundary layer schemes and six schemes were implemented, and their best configuration was set. The hydrological model was analyzed for sensitivity using 11 basin parameters. Its calibration and validation were performed. Subsequently, precipitation from the output of meteorological model was used as input to the hydrological model. Evaluating the results of the integrated models showed that the coefficient of determination (R^2) of the predicted monthly runoff is effective between 0.53 and 0.92. This shows the accuracy of RegCM and SWMM models in forecasting and simulating rainfall-runoff in the urban basin. The results also showed that this approach could be used by planners, programmers, and engineers in flood risk assessment and the design of flood control projects, both in Sabzevar and through the application of these models in other locations with similar climate condition Worldwide. This is because the runoff associated with different storms can be estimated one month prior to their occurrence, and forecast data is used to identify flood-prone areas. Additionally, by integrating such models, forecasted data from meteorological models can be used for the desired period instead of observational data, enabling the establishment of an accurate flood warning system for the entire urban basin.

Keywords Urban flood · Flood forecasting · Integration of modeling · SWMM · RegCM

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1 Introduction

Urban floods are responsible for a significant portion of runoff and landslides, causing substantial economic and social damages every year. One of the most important causes of flooding in cities is heavy rains. Heavy rains are often torrential, as 3/4 of the average monthly rainfall can occur within 30 min (Sobieraj et al. 2022). Impervious land cover leads to increased surface runoff, faster runoff rates, and higher peak discharge (Li et al. 2016; Qin et al. 2013). Managing the quantity and quality of urban runoff becomes a serious concern in the management of the urban environment (Ouyang et al. 2012; Tsihrintzis and Hamid 1997). Because the most direct significant increase in surface runoff, flood peak frequency, and volume intensify the risk and frequency of urban flood events (Pauleit et al. 2005). These events threaten the security and livelihood of urban residents (Baxter et al. 2001; Dougherty et al. 2007; Kong et al. 2017). Identifying flood hazard events requires reliable and accurate precipitation data in hydrological studies, as it is the primary driving force behind runoff generation (Liu et al. 2013; Tian et al. 2017). This information greatly contributes to climate-hydrological modelling that leads to accurate flood forecasting (Wu et al. 2014; Yesubabu et al. 2016). Numerical modelling of climate and modern computing technologies provide the possibility of providing accurate simulations and predictions with increasingly higher resolutions in different places and time (Liu et al. 2012). One of these climate models is the Regional Climate Model (RegCM). This model can provide accurate and seasonal rainfall forecasts for urban areas. Currently, the RegCM model is widely used in small- and large-scale quantitative precipitation forecasting. The SWMM model is also used in many basins. Precipitation data in urban areas are limited, for the purpose of hydrological modelling with high certainty that requires high accuracy spatial and temporal resolution data. Also, to employ the SWMM model as an urban flood model, high temporal resolution rainfall data is needed for the prediction period. In other words, the RegCM model is essential for forecasting rainfall in urban areas and using its numerical output for the hydrological model. Consequently, it is essential to assess the accuracy and efficiency of the integrated RegCM and SWMM models for rainfall forecasting to anticipate and simulate floods before they occur in urban areas. Several research has been carried out to forecast and simulate floods in urban areas. For example, some of the most important research are given in Table 1. These researches have employed either meteorological or hydrological models to forecast and simulate floods. Studies have been conducted to simulate precipitation in the basin and suburban areas by integrating meteorological and hydrological or remote sensing hydrological models.

The most significant contribution of this study is the integration of the regional meteorological model with the hydrological model, which is used to predict and simulate short-term (less than one month) and long-term (more than one month) floods, whereas in most previous studies the neural networks have been used to forecast floods for less than a month.

In this study, one of the main aspects of innovation is the use of advanced dynamic meteorological models such as RegCM to forecast extreme rainfall in urban areas. This high-resolution model can forecast precise rainfall patterns that often lead to urban flooding. This model is particularly suitable for areas needing more accurate seasonal forecasts. On the other hand, combining these forecasts with hydrological models such as SWMM allows for accurate simulation of urban runoff and identification of areas prone to flooding. This integration of meteorological and hydrological models at the urban scale is an important

Table 1 Example of the research conducted worldwide

Authors	Model	Case study	Description
Murthy et al. (2018)	SARIMA[a]	India	The results showed that the SARIMA (0, 1, 1) (1,0, 1) model is suitable for analyzing future rainfall patterns.
Zeyaeyan et al. (2017)	WRF[b]	Iran	The results showed that cumulus schemas are more sensitive and microphysical schemas are less sensitive.
Berkhahn et al. (2019)	ANN[c]	Germany	The present study presents an artificial neural network-based model for the prediction of maximum water levels during a flash flood event
Chen et al. (2021)	RegCM	China	The challenge of flooding and precipitation was predicted by urban areas
Ma et al. (2022)	SWMM[d]	China	By analyzing the distribution characteristics of urban waterlogging points, a real-time model calibration method is proposed to adjust the model parameters from time to time during the flooding process.
Zeng et al. (2022)	SWMM and WCA2D[e]		In general, the coupled model shows acceptable applicability and can be recommended for rapid simulation of urban flood episodes.

[a] Seasonal autoregressive integrated moving average

[b] Weather Research and Forecasting Model

[c] Artificial neural network

[d] Storm Water Management Model

[e] Weighted cellular automata 2D inundation model

step in improving forecast accuracy and developing flood management tools. This unique approach also allows for the accurate identification of high-risk areas and the provision of practical solutions to reduce flood effects.

2 Materials and Methods

2.1 The Study Area

Sabzevar city is located in Razavi Khorasan province, Iran and the center of Sabzevar city as the third city of Razavi Khorasan province, has an area of 3175.46 hectares and is located in the west of the province. This city is located at 57° 40′ east longitude and 36° 12′ north latitude with a height of 978 m above sea level (Zanganeh and Khodashahi 2021), Fig. 1. The average amount of annual precipitation is 163 mm. The average annual temperature is 15 to 17 degrees Celsius. The rainy season is the same as the cold season (autumn and winter to early spring). The duration of rainfall in Sabzevar starts in October and continues

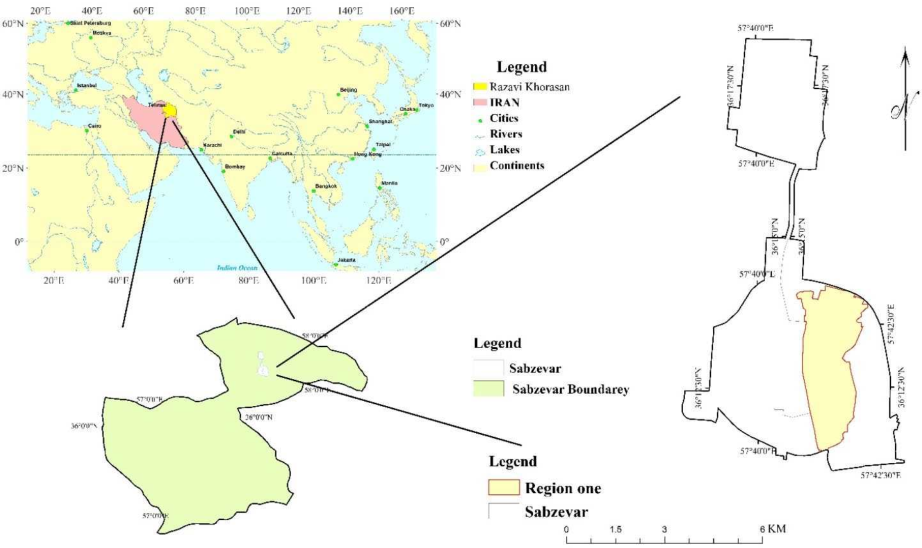

Fig. 1 Geographical location of the study area

until June. The rainiest months of the year are March and April with 32 and 27.3 millimeters respectively, followed by December with 26.6 millimeters. The rainfall at Sabzevar like other dry lands is seasonal with 48% of rain falling during the winter season and 28% in spring. The autumn season with 37.6 mm has accounted for 16% of the annual rainfall, and the summer season has no significant rainfall and has only 8% of the total annual rainfall in the form of scattered showers. The maximum rainfall in one day was reported in May at 35 mm (Zanganeh and Khodashahi 2021).

2.2 Method

In this study, for combining the meteorological and hydrological models to forecast and simulate the flood in urban areas, the meteorological model is first forecasted with different schemes, and the best suitable scheme is determined. Thereafter, to prepare the hydrological model platform at the level of the study basin, sensitivity analysis, calibration, and validation are done first. Finally, the hydrological model platform will be established which can be applied on the regional scale with the least simulation errors for runoff. To forecast and simulate rainfall in the study area, the rainfall output of the RegCM4.7 meteorological model is used in the SWMM 5.1. With this integration, RegCM-SWMM models are used to forecast and simulate the amount of precipitation and runoff in the urban basin before they occur. Figure 2 shows the steps of the research method.

2.3 Required Data

In this research, to perform a forecast the meteorological model from the boundary condition of the coupled forecast system model version 2 (CFSv2). Forecast model of the American Oceanographic Organization from the Global Forecast System (GFS) data is used. The spa-

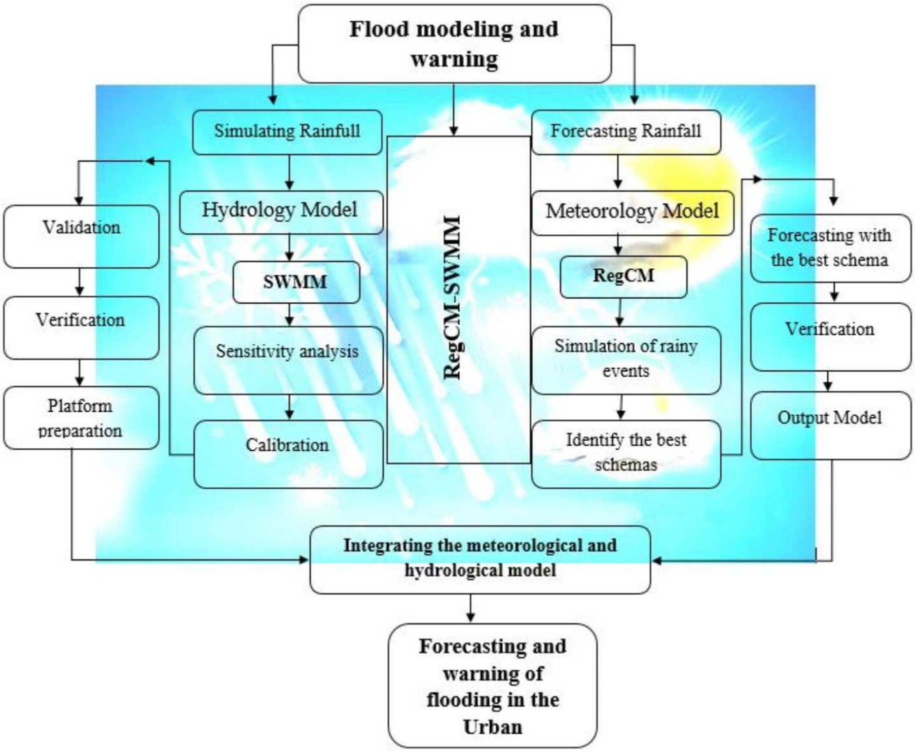

Fig. 2 Flowchart of the research method

tial resolution of the data is the initial and boundary conditions of 1 × 1 geographic degree. The data including pressure, relative humidity, and wind were obtained from the aforementioned center[1](Falamarzi et al. 2023). The RegCM model uses Global 30 Arc-Second Elevation (GTOPO) and Global Land Cover Characterization (GLCC) data for topography and vegetation information. GLCC data using the Advanced Very High-Resolution Radiometer (AVHRR) gauges are available from April 1992 to 1993 and are determined by the Biosphere Atmosphere Transfer Scheme (BATS) scheme based on land surface and vegetation. There are two options for selecting the Sea Surface Temperature (SST). The Optimum Interpolation Sea Surface Temperature (OISST) data are available weekly[2]Sabzevar synoptic station data has been used for the accuracy and verification of forecasts.

2.4 RegCM Model

The first version of the RegCM model was presented by Dickinson et al. and Giorgi in 1989. The second edition was published in 1993 by Giorgi et al. and the third edition was published in 2000 by Pal et al. (Giorgi et al. 1993). The dynamic core of the model is based on hydrostatic equations with the Sigma coordinate system. This model uses equations of hori-

[1]. https://www.ncei.noaa.gov/.

[2]. https://www.ecmwf.int/en/forecasts/datasets.

zontal motion, continuity and pressure, thermodynamics, omega, and hydrostatics (Giorgi et al. 1993). Community Climate Model version 3 (CCM3) is used to calculate the radiation. Cloud radiation is estimated by the percentage of cloud cover and the amount of water in it (Kiehl 1996).

The cloud radiation equation is generally defined as the radiant energy exchange between clouds and other atmospheric components (such as the Earth's surface, atmospheric gases, and the clouds themselves). Longwave and shortwave radiation equations are usually used to calculate cloud radiation.

Shortwave Radiation (SW):

The equation for shortwave radiation affected by clouds is as follows:

$$atm^{T}.S.\ (cloud^{\alpha}\ -1) =\ SW^{R} \tag{1}$$

Where:

SW^R	Shortwave radiation passing through or absorbed by clouds.
$cloud^{\alpha}$	Albedo (reflectivity) of clouds.
S	Incoming solar radiation.
atm^T	Atmospheric transmissivity above the clouds.

Longwave Radiation (LW):

The equation for longwave radiation emitted by clouds is as follows:

$${}_{cloud}{}^{T}.\sigma\ .\ \ cloud^{\epsilon}\ =\ LW^{R} \tag{2}$$

Where:

LW^R	Longwave radiation emitted by clouds.
$cloud^{\epsilon}$	Emissivity of clouds (usually close to 1 for thick clouds).
σ	Stefan-Boltzmann constant (5.67×10^−8 W/m²·K⁴).
$cloud^T$	Cloud temperature in Kelvin (Kiehl 1996).

2.5 SWMM Model

The amount of surface runoff resulting from atmospheric precipitation in a watershed depends on factors such as the amount of rainfall, the physical characteristics of the basin such as slope, type of bedrock, percentage of impermeability, and the width plus length of the basin. SWMM simulates a storm event based on the hydrograph, basin system and drainage network to generate the output hydrograph and the water transport in drainage pipes and open channels (Yarahmadi et al. 2019).

SWMM hydrograph resulting from precipitation and the pressure exerted on sub-basin surfaces are determined and routed as a nonlinear reservoir within small sub-basins and channels. In this approach, the nonlinear reservoir is derived using the continuity equation and Manning's equation (Farokhzadeh et al. 2020; Sin et al. 2014).

2.6 Verification

Finally, to evaluate of the verification methods, the four verification indices was used as shown in Table 2. Figure 2 represents the proposed rainfall simulation flowchart, the optimal rain gauges location, and the rainfall forecast process based on the WRF 4.1.5 model simulation. where n is the total number of observational events; a is the number of events that the rainfall occurs and its occurrence is forecasted; b is the number of events that the rainfall does not occur but its occurrence is forecasted; c is the number of events that rainfall occurs but its occurrence is not forecasted; and d is the number of events that the rainfall does not occur and its occurrence is not forecasted. To make a good forecast, the b values need to be large, while the c and d values should be small.

Where n is the number of the observational data and the total output values of the WRF meteorological model, $\varrho_{\mathbf{obs}}$ is the observational value of rainfall and, $\varrho_{\mathbf{sim}}$ is the simulated value of rainfall determined.

3 Results and Discussion

3.1 Forecast with RegCM Model

The main goal of this part of the research is to achieve the optimal configuration of the RegCM4.7 model. Four monthly rainfall events (representing the heavy rainfall of the region) from June to April 2021 were selected to set up and configure the dynamic meteorological model. The analysis of precipitation data from Sabzevar station for the years 2021 and 2022 reveals notable variations in monthly rainfall. In 2022, the highest precipitation was recorded in March, reaching 49.7 mm, indicative of heavy rainfall during this month. Similarly, May received 48 mm of rainfall, highlighting the significance of spring precipitation in the region. Conversely, April and February experienced significantly lower rainfall, with 13 mm and 10.02 mm, respectively. This rainfall pattern underscores seasonal fluctuations and suggests potential influences of climate change or specific weather events during the period under study. As a result, these four months were selected for evaluating the performance of the models.

In climate forecasting, the optimal configuration of the regional model is the most important part of modelling modeling. The main strategy in choosing the optimal configuration is to eliminate schemes with less efficiency; so that after adjusting and selecting the range, center, and horizontal resolution of the model, among the six different combinations of con-

Table 2 The verification indices for evaluating the accuracy of interpolation methods

Verification criterion	Verification equation	Acceptable value
False Alarm Ratio (FAR)	$FAR = \frac{b}{a+b}$	0
Threat Score (TS)	$TS = \frac{a}{a+b+c}$	1
R-squared (R^2)	$\boldsymbol{R}^2 = 1 - \frac{First\ Sum\ of\ Errors}{Second\ Sum\ of\ Errors}$	1
Nash–Sutcliffe (NS)	$\mathbf{NS} = 1 - \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}(\varrho_{\mathbf{sim}} - \varrho_{\mathbf{obs}})^2}{\sum_{\mathrm{i=1}}^{\mathrm{n}}(\varrho_{\mathbf{obs}} - \varrho_{\mathbf{av}})^2}$	
BIAS	$\mathbf{BIAS\%} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}(\varrho_{\mathbf{sim}} - \varrho_{\mathbf{obs}})^2}{\sum_{\mathrm{i}}^{\mathrm{n}}\varrho_{\mathbf{obs}}}$	
Root Mean Square Error (RMSE)	$\mathbf{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}(\varrho_{\mathbf{sim}} - \varrho_{\mathbf{obs}})^2}$	0

vection schemes, the more efficient schemes were kept and other schemes were removed from the configuration process; then, in the next step, the capabilities of the boundary layer schemes were verified. This strategy was applied to all three rainfall systems in June 2021 and April 2022.

After choosing the optimal configuration, the RegCM4.7 climate model was run with different initial conditions to cover the maximum forecast uncertainty. All the above steps were performed for each forecast performance.

3.2 Convection Scheme

In the stage of choosing the best cumulus convection schemes, six schemes of Grell, Emanuel, Tiedtke (Sinha et al. 2019), MM5 shallow water, Kou, and Kain were examined.

The performance of each of the convection schemes using the performance criteria for the first month of the rainy season with heavy precipitation along with forecasts 1 to 6 is shown in Fig. 3. As can be seen, the highest value of the TS index for preview 1 is related to Tiedtke, Emanuel, and Grell schemes with values of 0.72, 0.66, and 0.61, respectively.

Due to the more or less identical results of TS and FAR values in other forecasts, these three schemes were kept for the next stages of configuration selection and the rest of the convection schemes were removed from the configuration process.

According to the verification criteria, the efficiency is given in Table 3 to achieve the best precipitation forecasting result. Among the six convection schemes examined, Tiedtke, Grell and Emanuel schemes were kept for the next stage of selecting the optimal configuration (boundary layer scheme), and three shallow convection schemes, as well as Kain and Kou, were removed from the optimal configuration selection cycle.

3.3 Boundary Layer

At this stage of configuration, considering that the RegCM4.7 model has two default boundary layer schemes, Therefore, considering the remaining convection schemes (Tide, Emanuel and Grell) in the previous step, the effectiveness of the regional model was investigated by changing the boundary layer schemes (Holtslag and University of Washington) to obtain an optimal combination of convection-boundary layer schemes. The experiments designed for this step are listed in Table 4.

As in the previous step, the capability of each of the boundary layer schemes was evaluated using the verification criteria of false alarm ratio (FAR) and threat score (TS) for four target months, the results of which are given in Table 5; Fig. 4. According to the quantity of the threat score and the ratio of false alarms of each pair of selected convection schemes (Tide, Emanuel and Grell) - boundary layer scheme. Is. Based on the investigations carried out on the quantity of threat score ratio, the highest capability of the model in forecasting cumulative monthly rainfall is related to the first month, and from the second month, TS quantity values decrease to lower values; On the contrary, TS values in other months are acceptable and the closer the forecast range is to the target month of the forecast, the higher the rainfall difference values.

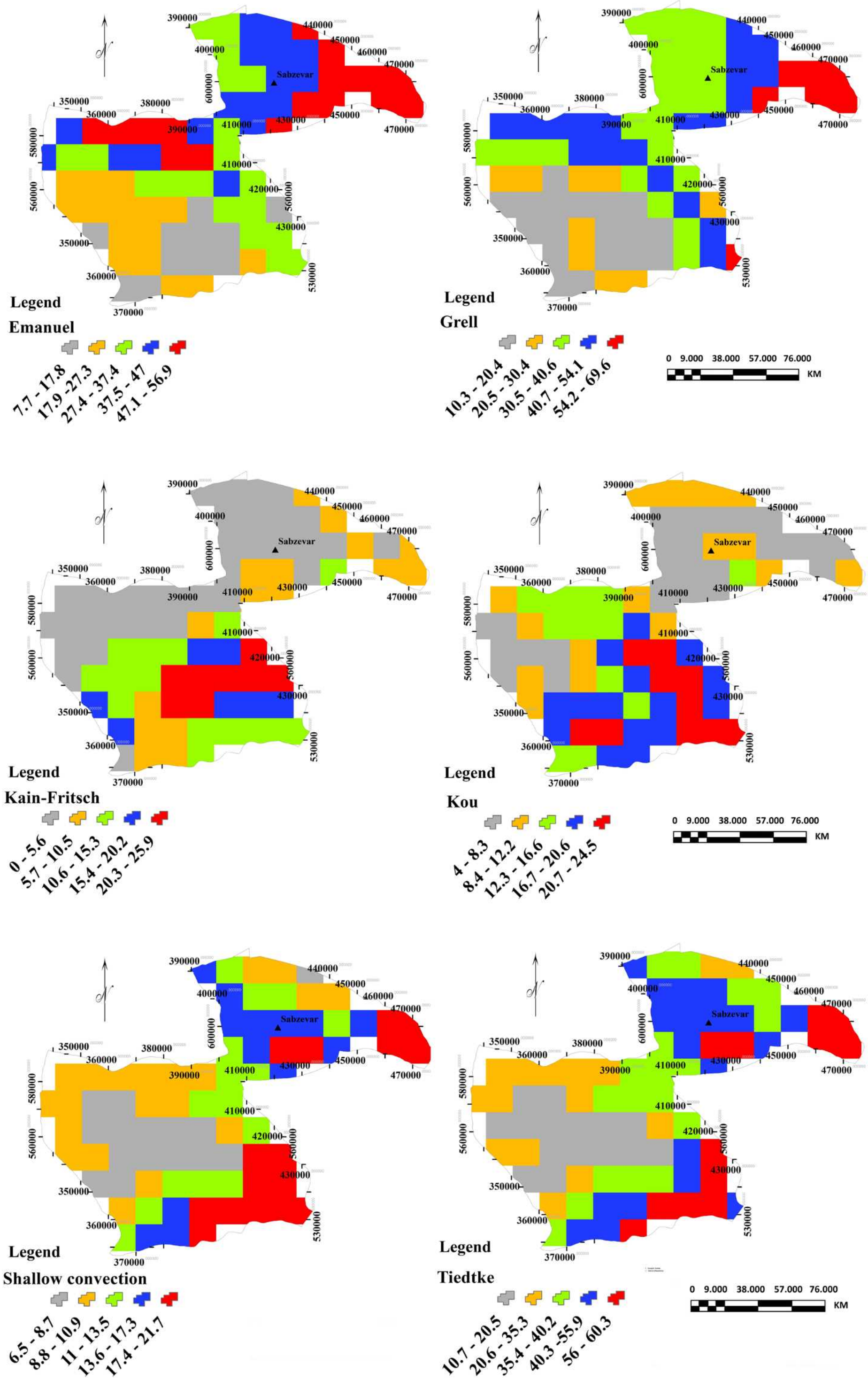

Fig. 3 The amount of precipitation forecasted for each of the RegCM4.7 convection schemes in March

Table 3 Threat score (TS) measure and false alarm ratio (FAR) for the period February to May: effect of convection

Verifications	Runs	Events			
		Feb	Mar	Apr	May
TS (%)	Kain	55	44	35	21
	Kou	27	20	18	10
	TID	72	68	45	32
	GRL	61	51	28	19
	SHL	31	31	21	15
	EMA	66	51	41	28
FAR (%)	Kain	45	56	65	79
	KOU	73	80	82	90
	TID	28	32	55	68
	GRL	39	49	72	81
	SHL	69	69	79	85
	EMA	34	49	59	72

Table 4 Different run of boundary layer scheme to choose the optimal configuration, during February to May (Li et al. 2023; Wang 2022)

Boundary layer	Convection scheme	Runs
UW PBL	Grell	Hol-TID
UW PBL	Emanuel	Hol-GRL
UW PBL	Tiedtke	Hol-EMA
Holtslag PBL	Grell	UW-TID
Holtslag PBL	Emanuel	UW-GRL
Holtslag PBL	Tiedtke	UW-EMA

Table 5 Threat score (TS) measure and false alarm ratio (FAR) for February to May period: boundary layer effect

Verifications	Schemes	Events			
		Feb	Mar	Apr	May
TS (%)	Hol-TID	58	47	41	30
	Hol-GRL	60	51	33	21
	Hol-EMA	62	54	45	17
	UW-TID	57	42	31	13
	UW-GRL	54	47	29	15
	UW-EMA	61	49	25	12
FAR (%)	Hol-TID	32	43	59	70
	Hol-GRL	40	49	67	79
	Hol-EMA	38	46	55	83
	UW-TID	43	58	69	87
	UW-GRL	46	53	71	85
	UW-EMA	39	51	75	88

3.4 Rainfall Simulation with SWMM Model

To simulate the runoff from rainfall in this urban basin, it is necessary to have a digital twin of the existing drainage infrastructure consisting of catchments and channels. For this purpose, after taking field measurements of the canal such as diameters, length, width, height and type of channel, the SWMM model platform was prepared for the study basin. After preparing the mode to investigate the direction canals simulation and determine the effective

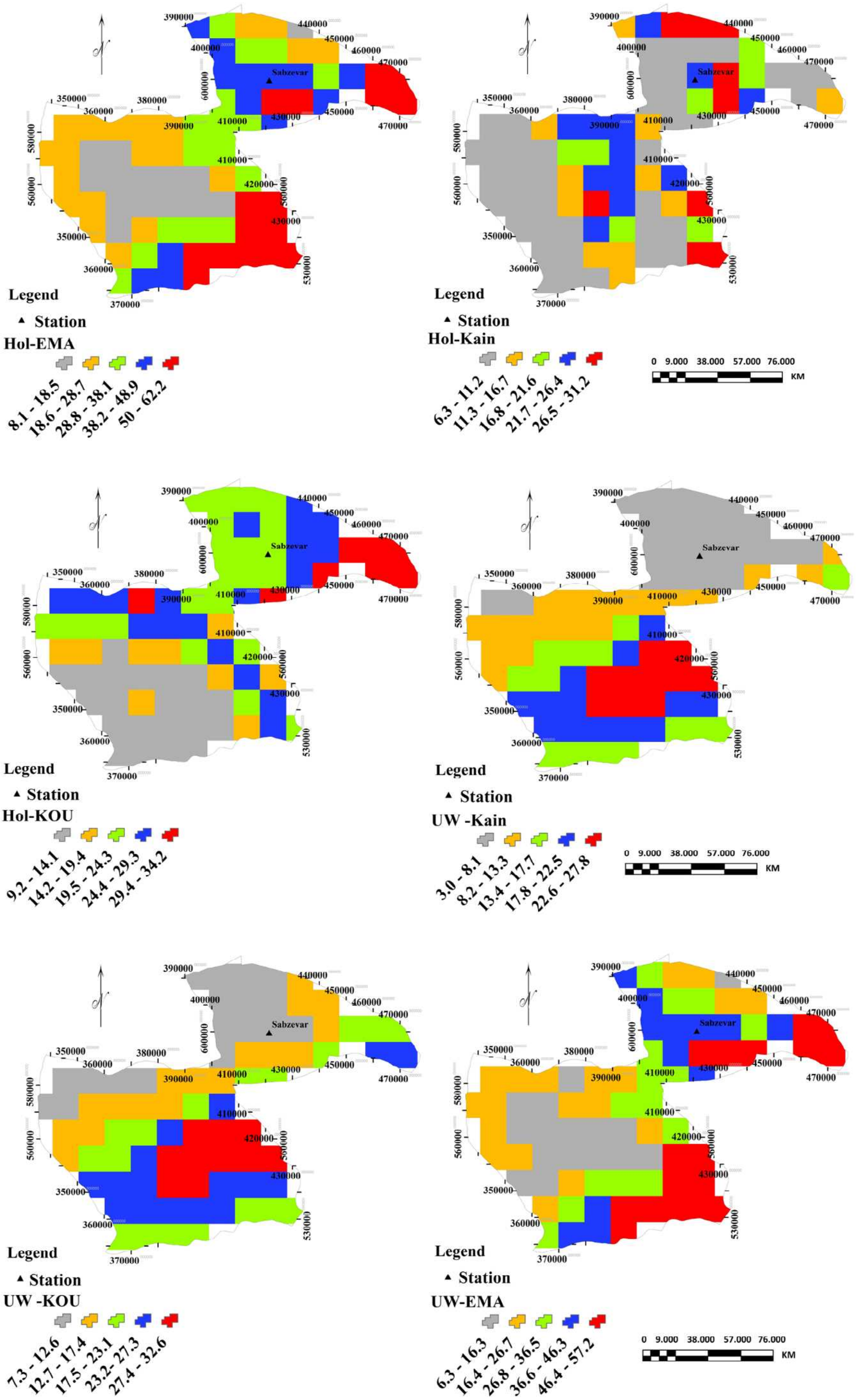

Fig. 4 The amount of rainfall forecasted in each of the boundary layer schemes of the RegCM4.7 model in March

parameters of the runoff for the model, four events were calibrated and two events were used to evaluate the model.

3.5 Sensitivity Analysis

To perform the sensitivity analysis, a one-hour design of one-hour was used according to the calculation of basin concentration time which is one hour (with a return period of 25 years). Each of these parameters was changed from −30 and +30% respectively, and the percentage of changes resulting from them on the discharge is shown in Fig. 5. According to the obtained results, it is clear that among the 11 parameters used, the percent imperviousness of sub-catchment (Imperv) has the greatest effect on the peak flow rate of the study basin, which is 2.53%. The lowest impact is related to the depression storage for the previous sub-area (Sperv) parameter with −0.014%.

After this parameter, parameters rate on Horton curve (MaxRate), minimum infiltration rate on Horton curve (MinRate), characteristic width of subcatchment (Width), Manning's n for overland flow over the impervious sub-are (Nimp), Manning's n for overland flow over the previous sub-area (Nperv), percent subcatchment slope (Slope), depression storage for impervious sub-area (Simp), total curb length (Clength), and percent of the impervious area with no depression storage (%Zero) they are in order from the most to the least impact. The values of the highest percentage of their influence are −2.25, 1.41, 1.19 1.1,−0.96, −0.80, −0.73, 0.31 and 0.05 respectively are percentage which are in accordance with the findings of Bahremand (2019); Rafiee et al. (2022), Sun et al. (2022).

3.6 Calibration and Validation

The results of the model calibration are given in Fig. 6. The observed data and simulated discharge values of the model for four events are compared. The analysis of the calibration results indicates that the amount of volume between the observed and simulated discharge in the event of 26.02.2020 has the largest difference and the event of 12.04.2020 has the smallest difference. The difference is 2.23 m^3/s and 1.49 m^3/s, respectively. The analysis of the peak discharge of the validation stage also shows that the simulation event of 23.03–24.2020 has the biggest difference from the observed value, which is 0.34 cubic meters per second. The peak flow differences from the highest to the lowest are related to the events of 26.02.2020 with 0.20, 12.08.2020 with 0.17, and 04.12.2020 an amount to 0.15 cubic meters per second.

In order to validate the flood management model, two events in Fig. 7 have been used. Examining the results shows that the simulated event 13.03.2020, has a greater difference from the observed value. This difference is 0.39 m^3/s and the difference between the simulated flow volume and the observed value is 2.23 m^3/s.

The results of model calibration and validation showed that the discharge simulation in the investigated events has high compliance with the observed data that the NS value for the events is more than 0.5. These results are listed in Table 6.

The values for simulation events resulting from SWMM model calibration are 0.75, 0.72, 0.79, and 0.64, and for validation are 0.67 and 0.55 respectively.

Also, the values of the R^2 coefficient for the simulation events resulting from the calibration and validation of the SWMM model were 0.81, 0.84, 0.86, 0.73, 0.79, and 0.70, respec-

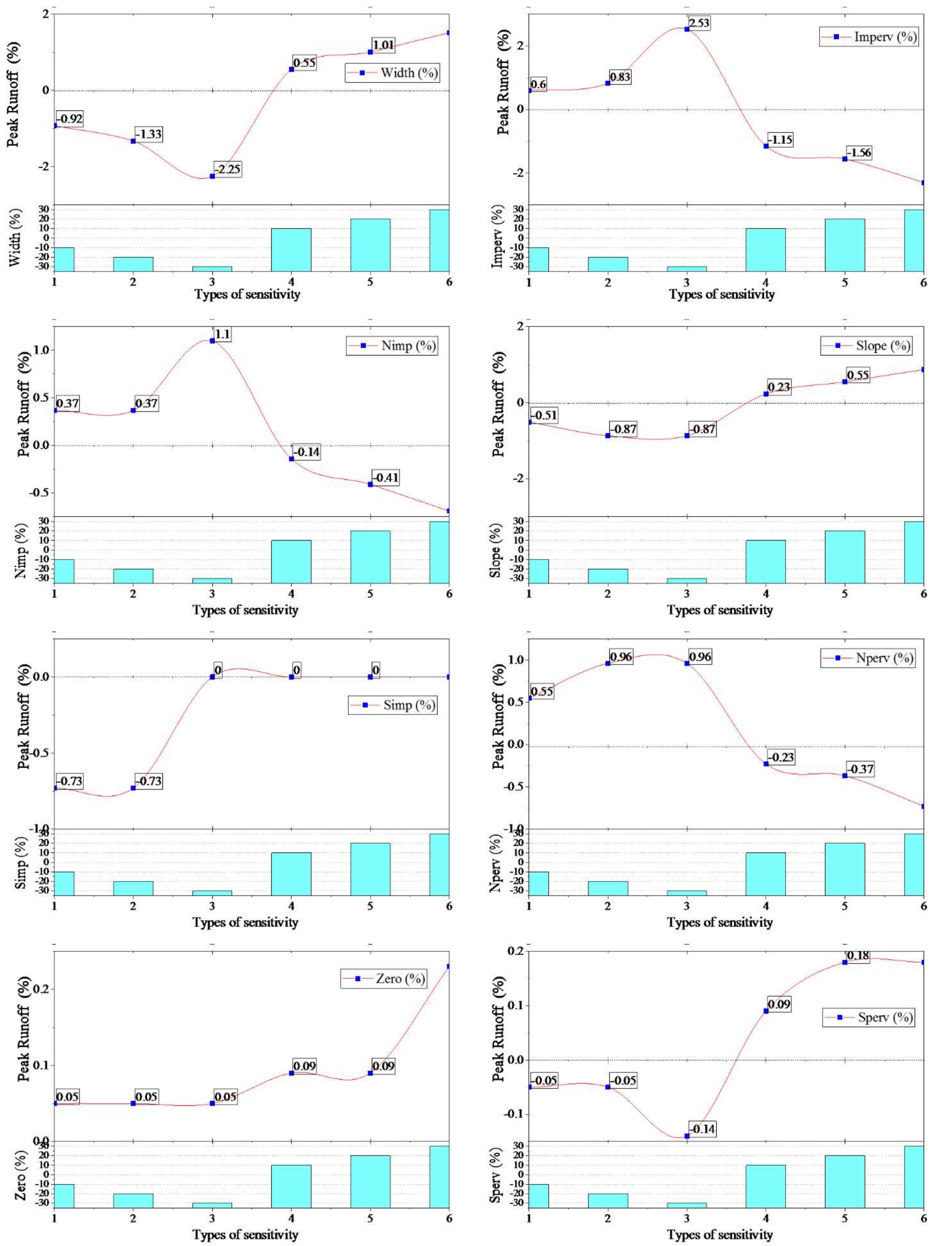

Fig. 5 The percentage of changes in sensitivity analysis parameters of Sabzevar urban basin

tively, which indicates the acceptable results of the model. The results also show that model is capable of simulating surface runoff, which is in line with the findings of Badiezadeh et al. (2016) who used the mentioned model in the simulation of Gorgan city runoff and came to the conclusion that the SWMM model has the required accuracy for the simulation of surface runoff is consistent.

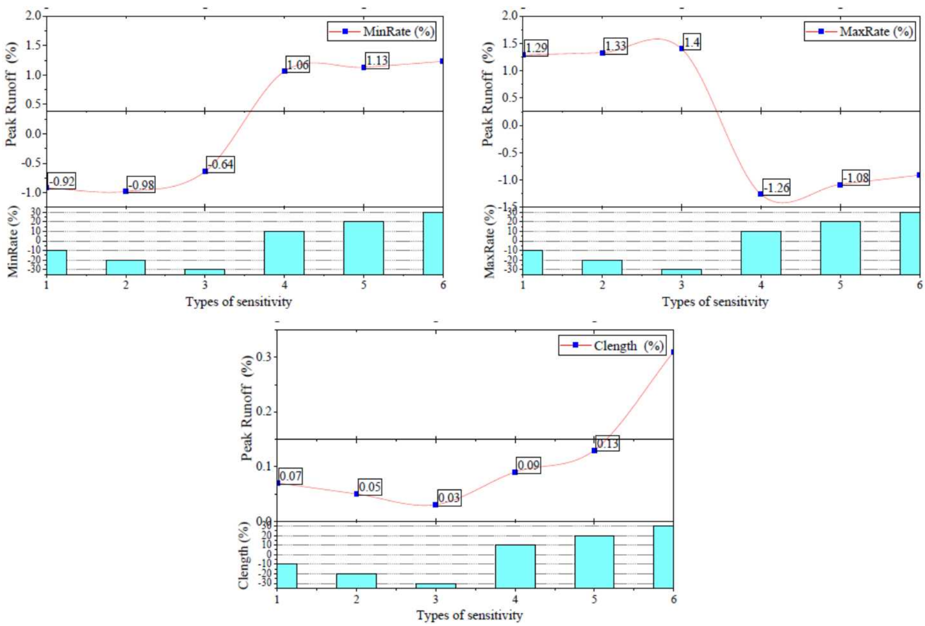

Figure 5 (continued)

3.7 Integration of RegCM and SWMM Model

In this part of the research, after configuring the meteorological model and then preparing the hydrological model platform, the rainfall data output of the meteorological model used as input to the hydrological model.

The results of this integration of models are given in Fig. 8; Table 7. The results of four study months period indicates that the biggest difference between the observed peak flow and the simulated value is for April with 1.5 m^3/s. The peak flow of the simulated months from the highest to the lowest flow rate difference corresponds to the months of March 2021, March 2020, and February 2020, which were obtained as 1.40, 1.14, and 0.52 m^3/s, respectively.

For a better analysis of the output of the integrated models, Table 7 shows the observed and forecasted cumulative monthly rainfall by the RegCM model, as well as the observed and simulated monthly runoff volume of the SWMM model. According to these results, the largest difference in runoff with the observed amount occurred in April 2020. Whose R^2 value is 0.53. Studying the effectiveness of integrated models in forecasting and simulating runoff in the Sabzevar study basin shows when the R^2 value is 0.5, it can be concluded that the models in question have good accuracy in forecasting and simulating runoff from rainfall in a one-month period (Fig. 9).

These results are consistent with the studies of Badiezadeh et al. (2016), Pachaly et al. (2021), and Rabori and Ghazavi (2018). The aforementioned studies demonstrated that simulating rainfall-induced flooding in urban catchments using the SWMM model closely matches the observations of flooding in these areas, highlighting the high accuracy of the

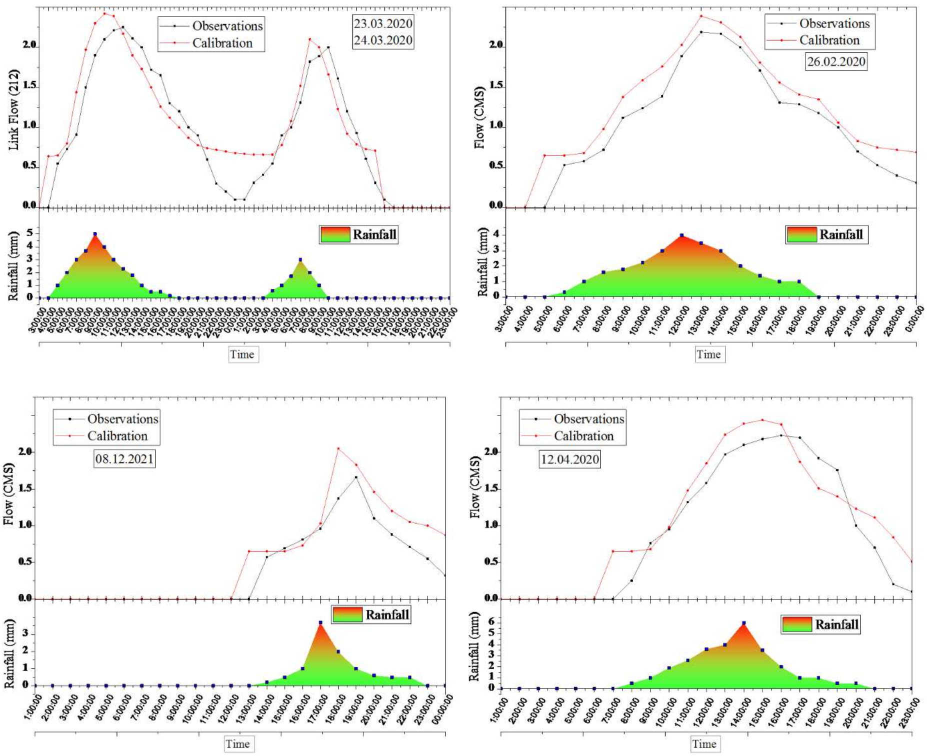

Fig. 6 Calibration results of the SWMM model in the basin of one urban area of Sabzevar

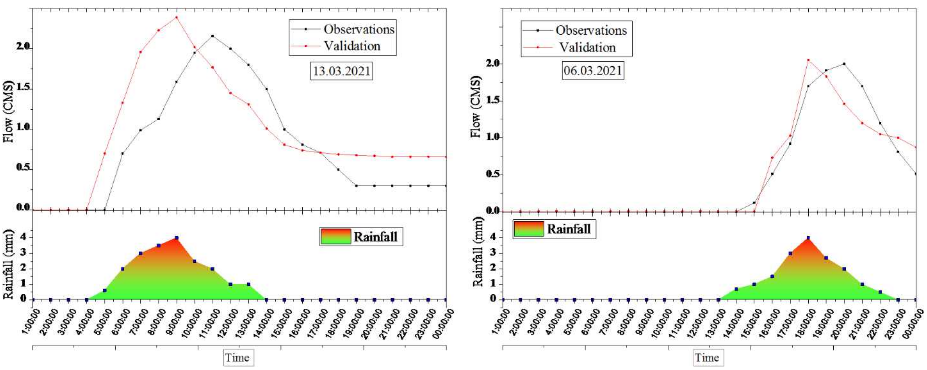

Fig. 7 Validation results of the SWMM model in the basin of one urban area of sabzevar

model's simulations. In general, the results of the calibration and evaluation of their model showed that the simulation of the investigated events has good compliance.

This research provides an in-depth understanding of the integration of flood forecasting and warning models in urban areas. The models used for different applications in different parts of the world are examined based on the data from three aspects of remote sensing/

Table 6 Validation and calibration results of the SWMM model for the basin of one urban area of Sabzevar

Events	Stage	Parameter	BIAS (%)	RMSE	NS	R^2
26.02.2020	Calibration	Flow	15.01	0.0081	0.75	0.81
23.03–24.2020	Calibration	Flow	7.917	0.0089	0.72	0.84
12.04.2020	Calibration	Flow	4.12	0.0093	0.79	0.86
12.08.2021	Calibration	Flow	9.10	0.0097	0.64	0.73
06.03.2021	Validation	Flow	8.17	0.0093	0.67	0.79
13.03.2021	Validation	Flow	12.32	0.0230	0.55	0.70

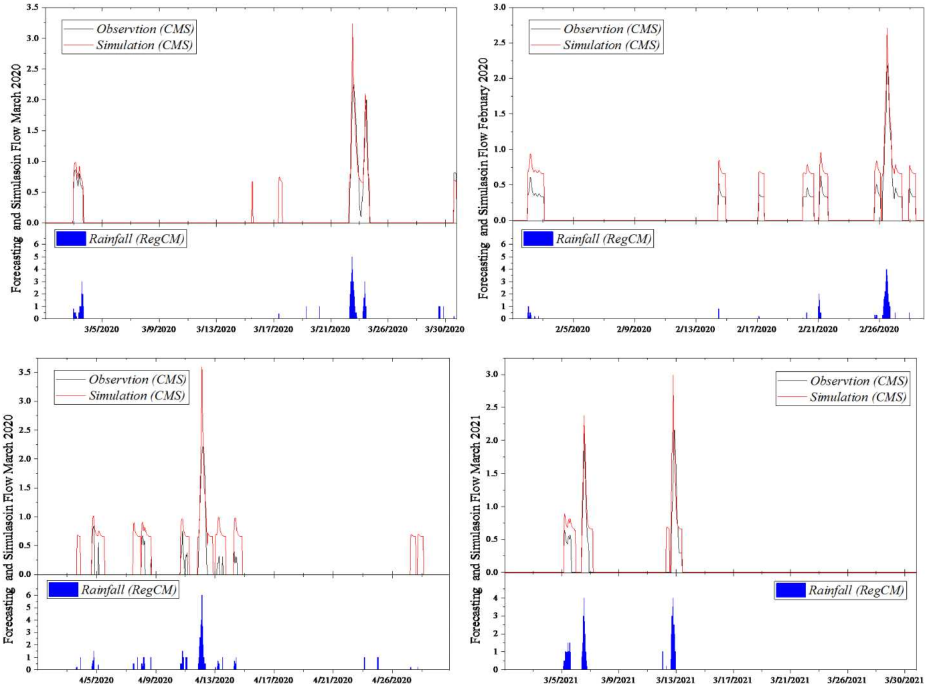

Fig. 8 Rainfall amount (mm) obtain from RegCM model in blue, the amount of observed runoff and simulated runoff of the SWMM model (with the output of the RegCM meteorological model) in black and red, respectively (CMS)

Table 7 Cumulative rainfall amount and volume of runoff simulation of the integration of meteorological and hydrological model for the monthly period

Event		RegCM model		SWMM model	
		Rainfall (mm)		Flow (CMS)	
Month	Year	Observation	Forecasting	Observation	Simulation
February	2020	31.2	38/32	29/15	41/24
March		41/3	48/6	54/6	63/79
April		47.1	58/38	52/2	75/13
March	2021	45/2	50/61	41/89	60/18

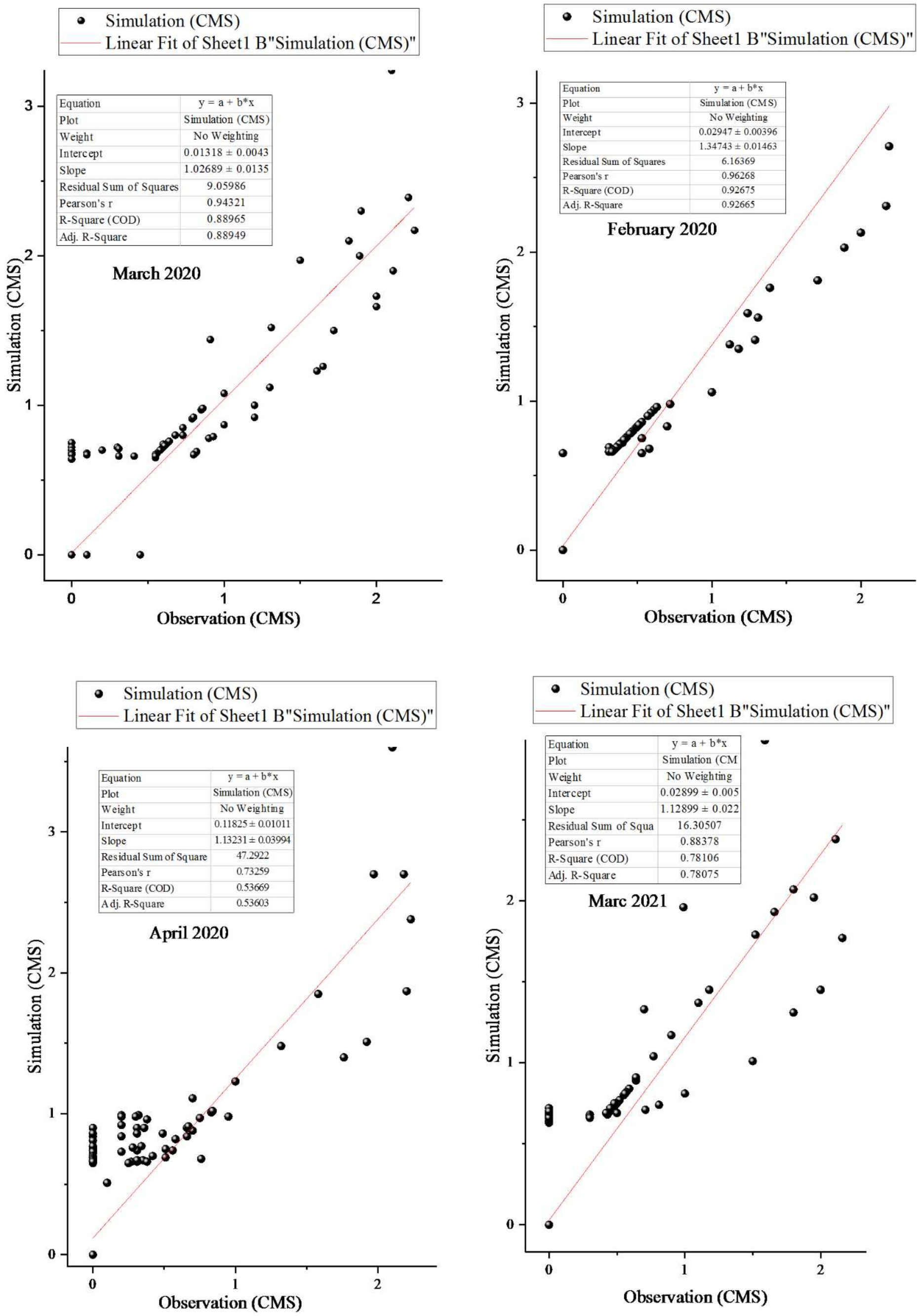

Fig. 9 The performance of integrated models in forecasting and simulating the monthly runoff of the study basin

satellite, meteorological and hydrological. Based on previous works, it can be noted that remote sensing and satellite models are considered as a representation of important processes related to flooding (for example, the amount of rainfall at the urban level, the amount of runoff in channels, etc.) in urban areas has low accuracy due to spatial resolution Lammers et al. (2021). With the current lack of data, most studies incorporate satellite modelling and re-analyze the data. These products have coarse spatial resolution and high uncertainty in their estimates at sub- and sub-basin scales, which in turn affect model performance (Mohtaram et al. 2025).

However, using output in hydrological and numerical models provides inaccurate results and cannot provide reliable and accurate flood forecasts. In addition, these models are site-specific, which means that they depend on the physical properties and climate of the specific study area, Therefore, they cannot be applied to a new area without modification, which is consistent with the results of (Munawar et al. 2022). Furthermore, to satellite products, models based on artificial neural network data, machine learning in analysis, and input to hydrological models are used to forecast urban floods. These methods have good accuracy and precision for short-term forecasting (6 h to 24 h) Kim and Han (2020). These tools are less important in estimating rainfall above this interval. Therefore, there is less time for flood planning and control in urban areas. Therefore, to solve this problem and prepare sufficient time for floods, a period of one month has been used (Liu et al. 2024; Wang et al. 2022). By examining the results of the integration of the meteorological model with the flood management model for the Sabzevar urban basin, it can be said that there is a good match between the simulated and observed runoff. This can indicate that the RegCM and SWMM models have the required accuracy for predicting and simulating runoff in urban areas. The combination of these models can be used for urban/suburban runoff management plans in different parts of the world, which is consistent with Gu et al. (2022), Tanhapour et al. (2025).

Using this proposed method, due to the existence of a regional model compatible with the climate of each region, it is possible to adapt to each region by changing the configuration of the meteorological model (as the most important source of rainfall input to hydrological models).

4 Conclusion

Forecasting that is obtained by numerical simulation is an important method to solve urban flood disasters in the future. In recent years, urban flood forecasting using numerical weather models combined with flood models in urban areas effectively improves urban flood forecasting and simulation. Therefore, in this study, an integrated RegCM_SWMM model is build The RegCM model was used to generate rainfall forecast, which was compared with the observational rainfall of the urban basin site, and then the SWMM model was used to evaluate the capability of simulation of the urban flood process. For the urban area of Sabzevar, spatial and temporal resolution data can better predict the precipitation process and meet the requirements of urban flood simulation. In addition, RegCM precipitation forecast data for numerical simulations can effectively improve the forecast of numerical simulation of flood disasters. Most importantly, accurately describing the quantitative accuracy of rainfall forecasts plays an important role in urban flood simulation. The results showed that the

RegCM-SWMM model has effective flood forecast and simulation results that can provide more accurate flood warning information, so they provide an important reference to flood disaster warning and forecasting systems in cities.

The flood forecasting and simulation process and warning applied in the target area can be adequately applied to hydrological drainage systems in other complex urban watersheds in the world. By creating accurate forecasts and warnings through RegCM-SWMM models and carrying out preventive flood warnings through the integration and application of these models in a systematic way, it is possible to take appropriate measures for flood damage reduction by considering early warnings.

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