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WRR

Research Article

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Posted Date: November 27th, 2025

DOI: <https://doi.org/10.21203/rs.3.rs-7823862/v1>

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Version of Record: A version of this preprint was published at Natural Hazards on May 5th, 2026. See the published version at <https://doi.org/10.1007/s11069-026-08079-9>.

Harnessing WRF Numerical Weather Prediction for Enhanced Flood and Damage Forecasting in Urban Environments

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Abstract

Accurate flood and damage forecasting is critical for mitigating the devastating impacts of floods, which globally affect millions and cause substantial economic losses. This study evaluates the efficacy of the Weather Research and Forecasting (WRF) model in simulating precipitation for flood forecasting and direct damage estimation in the Poldokhtar basin, Iran. By testing 87 WRF configurations, optimal schemes (e.g., WSM3, Kessler, Grell 3D, and YSU) were identified for accurate precipitation and flood simulation. Coupled with the HEC-HMS and HEC-RAS models, WRF outputs facilitated robust flood hydrograph and hydraulic simulations, achieving Nash-Sutcliffe efficiency above 0.85 and peak discharge errors below 15%. Bias correction using quantile mapping significantly enhanced peak flood accuracy, reducing errors to as low as 1.25% for the 2018 event. A depth-damage curve was developed, showed strong correlations ($CC > 0.92$) with observed flood damages, and the average damage estimates ranging from 41% to 70% across residential areas for the 2016–2019 events. The results demonstrate that integrating WRF with hydrological and hydraulic models provides a reliable and practical framework for flood forecasting and damage assessment in urban environments, offering valuable insights for flood risk management.

Keywords: Flood management, Urban hydrology, Damage Estimation, Flood risk.

Introduction:

Natural and anthropogenic disasters, such as floods and droughts, pose significant challenges to human societies (Pizzorni et al., 2024). Between 1998 and 2017, 91% of all recorded disasters were linked to weather-related events, with floods accounting for 43% of these occurrences (Fatdillah et al., 2022). The economic consequences of such disasters are increasingly severe in urban areas due to growing populations and higher infrastructure density (UN, 2018). In recent years, floods have become one of the greatest environmental hazards that can lead to significant social and economic losses, with floods accounting for almost a third of economic losses and more than half of human losses related to natural disasters (Abidin et al., 2015; Wu et al., 2017). The fact that 23.2 million square kilometers and 255 to 290 million people were directly affected by floods during the years 2000 to 2018 indicates the importance of this phenomenon and its effects (Dey et al., 2022). In addition, developing and less developed countries are more vulnerable to extreme climatic events such as floods (Mirza, 2003). Iran is also one of the countries that is not exempt from this natural phenomenon and is highly exposed to natural hazards such as floods and suffers a lot of financial and human losses due to floods every year. According to available statistics, nearly 40 small and large flood events occur annually in different regions of the country, which has imposed significant annual damage on the country (Energy, 2016). This has increased the importance of flood forecasting, as it is an effective means of providing timely information about the hazard to authorities and residents at risk, which also plays an important role in reducing flood risks and damages (Carsell et al., 2004). The accuracy of flood forecasting is significantly affected by the level of skill in determining the amount and spatial distribution of precipitation.

In recent years, advancements in satellite and remote sensing technologies have significantly enhanced the availability and application of numerical weather prediction (NWP) models. These models predict atmospheric conditions by solving complex mathematical equations and play a critical role in flood forecasting systems by providing reliable precipitation estimates for river flooding. NWP models are grounded in the principles of mass, momentum, and energy conservation, and their simulations are achieved through numerical methods that solve thermodynamic and dynamic equations. These models simulate atmospheric variables across various spatial and temporal scales (Trenberth, 1992). The use of numerous variables affecting precipitation processes, with different spatial resolutions, has made NWP models a focal point for

researchers over the past few decades. For instance, Kovalets et al., (2014) coupled the distributed hydrology soil vegetation model (DHSVM) with the weather research and forecasting (WRF) to reproduce severe flooding in a mountainous river basin in Ukraine. Their findings indicated that the precipitation time series simulated by the model very closely matched observed values, also river discharge simulations for return periods of 50 to 100 years aligned well with ground-based measurements. Alfieri et al. (2015) explored flood variability using climate projections from the European branch of the coordinated regional climate downscaling experiment (EURO-CORDEX) project in conjunction with a distributed hydrological model. Their research revealed a twofold increase in river discharge for return periods exceeding 100 years over a span of three decades. Amin et al. (2017) investigated the effects of climate change on hydrological processes in Malaysia's Moda and Dangon watersheds by employing the mesoscale modeling system (MM5) regional climate model and the physically based WEHY hydrological model. The results highlighted significant impacts of climate change on the average monthly flows between April to May and July to October post-2040. Additionally, an analysis of flood frequency indicated an upward trend in the second half of the 21st century. Silver et al. (2017) introduced a calibration method for the WRF-Hydro model, enabling the direct determination of specific input parameter values in arid and semi-arid regions. Their study demonstrated that coupling the WRF numerical prediction model with WRF-Hydro significantly improved runoff prediction accuracy, further emphasizing the value of integrating these advanced modeling systems. Yao et al. (2019) evaluated the flood forecasting performance of the Grid-Xin'anjiang model (GXM) using station-based observations and precipitation data from the WRF model. The results showed that using WRF data, it is possible to provide forecasts for longer periods prior to the time of flood occurrence. Additionally, the study highlighted that spatial and temporal precipitation patterns significantly influence the accuracy of predicting both the timing and intensity of future floods. Ming et al. (2020) introduced a flood forecasting system incorporating a two-dimensional hydrodynamic model coupled with numerical weather prediction data at a spatial resolution of 10 meters. Simulations revealed that the system effectively reproduced the hydraulic characteristics of the flood. Statistical metrics such as the Critical Success Index (CSI), False Alarm Rate (FAR), and Probability of Detection (POD) confirmed the system's high accuracy in forecasting flood extents. Tri et al. (2022) explored the impact of using IFS precipitation data with bias correction techniques on flood forecasting in central Vietnam. Results showed that bias correction substantially

minimized errors in precipitation forecasts. Moreover, the model provided practical flood predictions with an accuracy range of 76% to 85%. Dong et al. (2022) developed a flood forecasting framework utilizing remote sensing precipitation data alongside a hydrological model. Their study concluded that combining satellite-derived precipitation data with hydrological modeling yields reliable simulations of major flood events. This methodology was particularly effective in small catchments lacking observational data. Wang et al. (2022) investigated the application of WRF precipitation forecasts within the storm water management model (SWMM) to analyze flood conditions under varying precipitation scenarios in Zhengzhou City. Their research indicated that WRF data improves precipitation forecasting accuracy in urban areas, leading to more precise flood process simulations. This advancement offers valuable insights for enhancing flood warning and forecasting systems.

A review of recent research indicates a growing trend in the integration of meteorological modeling systems with hydrological models, particularly for flood forecasting and, in some cases, long-term predictions utilizing numerical weather predictions. The findings of most studies underscore the effectiveness of combining NWP systems with hydrological models, making their outputs valuable for flood predictions and assessing associated damages. NWP models offer notable advantages, including timely data availability, cost-effectiveness, and broad spatial coverage. These features are critical for developing efficient strategies for preparedness, damage mitigation, and flood management. Due to the short-term nature of the data provided by these models (daily and sometimes hourly time steps), they exhibit significant potential for integration into flood and damage prediction systems, especially for generating short- to medium-term predictions of flood intensity and damage extent. Moreover, employing NWP models to prediction the precipitation can extend warning times for severe and destructive flood events (Anderson et al., 2002; Cloke and Pappenberger, 2009). The establishment of a framework for predicting and assessing flood damage plays a vital role in supporting both individual and systemic decision-making processes to reduce flood-related damages, adapt effectively, increase preparedness, and strengthen resilience. Improving regional predictions of flood risks and damage levels, as a non-structural approach, significantly contributes to minimizing flood impacts. Despite the substantial research on the efficacy of NWP models in flood forecasting, limited attention has been given to their application in estimating the hydraulic variables of floods and quantifying direct flood damages. To address this gap, the present study aims to evaluate the performance evaluation of the

WRF precipitation forecasting system in simulating precipitation and floods. Furthermore, it investigates the utility of WRF model outputs for simulating hydraulic characteristics and estimating direct flood damages.

Materials and Methods

1. Study Area

The study area encompasses a basin located between latitudes $33^{\circ}7'$ to $33^{\circ}55'$ N and longitudes $47^{\circ}55'$ to $48^{\circ}43'$ E. Elevation within the basin ranges from 527 to 2,980 meters above sea level. This research utilized meteorological data recorded at several synoptic stations situated both within and beyond the basin boundaries to evaluate the outputs of WRF. Additionally, river discharge from hydrometric stations along the Kashkan river within the Poldokhtar basin (PB) served as the basis for the hydrological simulations conducted in this study. Figure 1 illustrates the geographical setting of the Poldokhtar basin, including elevation variations and the locations of the synoptic and hydrometric stations.

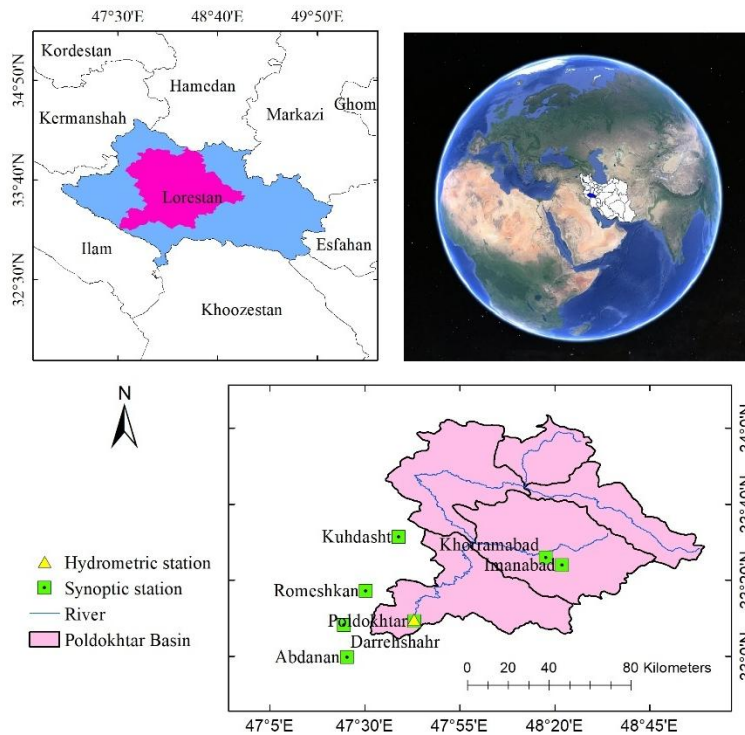


Figure 1. Geographical location of the Poldokhtar basin, synoptic and hydrometric stations

2. WRF Numerical Weather Forecasting Model

The WRF model is among the pioneering tools for both operational weather forecasting and atmospheric research, developed through collaboration among scientists from various universities and research institutions (Michalakes et al., 2001; Skamarock et al., 2005). Designed primarily for generating high-resolution weather forecasts (1 to 10 km), it is also adaptable for lower-resolution applications. To simulate real-time atmospheric conditions at high spatial resolution, the WRF model requires comprehensive parameterization of physical processes and boundary layers. Once configured for a specific region, the model effectively predicts precipitation patterns at high spatial scales. The WRF model incorporates two dynamical cores ARW (Advanced Research WRF) and NMM (Nonhydrostatic Mesoscale Model) both of which utilize Eulerian modeling techniques combined with geographic and meteorological data.

In this study, the WRF model was configured with two nested domains, employing a downscaling ratio of 3:1. The primary domain (parent domain) had a horizontal resolution of 15 km, while the nested domain (inner domain) achieved a resolution of 5 km (Figure 2). The model's initial and boundary conditions were provided by the final analysis (FNL) dataset, a critical meteorological dataset produced by the NCEP (National Center for Weather Prediction) in the United States.

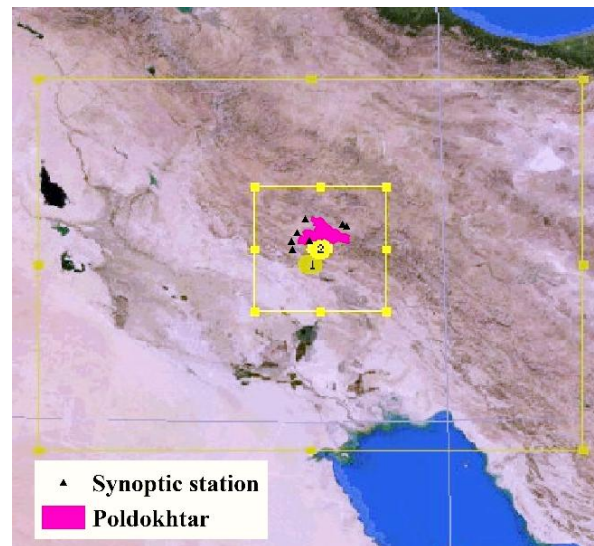


Figure 2. Domains considered for the WRF model in this study

The WRF model requires detailed parameterization of physical processes and boundary layers to perform high-resolution real-time simulations. Extensive research has been conducted

globally to evaluate the sensitivity of the WRF model to its various physical processes. These studies highlight that microphysics, boundary layers, and convection are the most influential components for simulating precipitation (Jankov et al., 2011; Madala et al., 2014; Pennelly et al., 2014). Each of these components includes multiple parameterization schemes, which affect the model's performance differently (Jankov et al., 2011; Madala et al., 2014; Pennelly et al., 2014). A review of precipitation simulation studies using the WRF model identified several schemes as particularly effective and widely applicable for this (Deng et al., 2023; Garcia et al., 2023; Kaewmesri et al., 2017; Moradian et al., 2020; Umer et al., 2021; Yazdanpanah Gharaei et al., 2023). These schemes served as the foundation for this research. So, the study considered a total of 11 microphysics schemes, 4 convection schemes, and 3 boundary layer schemes. This combination resulted in the evaluation of 132 different configurations of parameterization schemes. It is important to note that some schemes are incompatible with one another, which can result in the WRF model failing to produce outputs. Out of the 132 configurations analyzed, 87 successfully simulated precipitation (Table 1).

3. Bias Correction

Weather prediction model outputs often exhibit systematic biases compared to observed data, which can influence research outcomes and introduce errors (Maurer and Hidalgo, 2010). It is advisable to apply bias correction techniques before utilizing the data, aiming to minimize potential errors. Various approaches have been developed for bias correction, one of which is the nonparametric quantile mapping (QM) method (Kim et al., 2016). This technique aligns the cumulative distribution function (CDF) of the model's predictions with the CDF of observed data using an empirical transfer function. In the QM process, data values corresponding to specific quantiles in the climate model's output are replaced with those from the matching quantiles of observed data. One of the key advantages of this nonparametric approach is its flexibility, as it imposes no constraints on following a particular statistical distribution. Furthermore, it is particularly effective in correcting biases in extreme values, as well as in the mean and standard deviation of the dataset (Ali et al., 2019; Cannon et al., 2015; Amini et al., 2021).

Table 1. Final configurations used for the WRF model (each configuration from left to right in the order: microphysics-convection-boundary layer)

SBUY-G3D-YSU	M67	T-KF-BL	M45	WSM3-BMJ-ACM2	M23	K-KF-YSU	M1
SBUY-G3D-ACM2	M68	T-BMJ-YSU	M46	WSM3-BMJ-BL	M24	K-KF-ACM2	M2
SBUY-G3D-BL	M69	T-BMJ-ACM2	M47	WSM3-G3D-YSU	M25	K-KF-BL	M3
WDM5-KF-YSU	M70	T-BMJ-BL	M48	WSM3-G3D-ACM2	M26	K-BMJ-YSU	M4
WDM5-KF-ACM2	M71	T-G3D-YSU	M49	WSM3-G3D-BL	M27	K-BMJ-ACM2	M5
WDM5-KF-BL	M72	T-G3D-ACM2	M50	WSM5-G3D-YSU	M28	K-BMJ-BL	M6
WDM5-BMJ-YSU	M73	T-G3D-BL	M51	WSM5-G3D-ACM2	M29	K-G3D-YSU	M7
WDM5-BMJ-ACM2	M74	M2-KF-YSU	M52	WSM5-G3D-BL	M30	K-G3D-ACM2	M8
WDM5-BMJ-BL	M75	M2-KF-ACM2	M53	EF-G3D-YSU	M31	K-G3D-BL	M9
WDM5-G3D-YSU	M76	M2-KF-BL	M54	EF-G3D-ACM2	M32	L-KF-YSU	M10
WDM5-G3D-ACM2	M77	M2-BMJ-YSU	M55	EF-G3D-BL	M33	L-KF-ACM2	M11
WDM5-G3D-BL	M78	M2-BMJ-ACM2	M56	WSM6-KF-YSU	M34	L-KF-BL	M12
WDM6-KF-YSU	M79	M2-BMJ-BL	M57	WSM6-KF-ACM2	M35	L-BMJ-YSU	M13
WDM6-KF-ACM2	M80	M2-G3D-YSU	M58	WSM6-KF-BL	M36	L-BMJ-ACM2	M14
WDM6-KF-BL	M81	M2-G3D-ACM2	M59	WSM6-BMJ-YSU	M37	L-BMJ-BL	M15
WDM6-BMJ-YSU	M82	M2-G3D-BL	M60	WSM6-BMJ-ACM2	M38	L-G3D-YSU	M16
WDM6-BMJ-ACM2	M83	SBUY-KF-YSU	M61	WSM6-BMJ-BL	M39	L-G3D-ACM2	M17
WDM6-BMJ-BL	M84	SBUY-KF-ACM2	M62	WSM6-G3D-YSU	M40	L-G3D-BL	M18
WDM6-G3D-YSU	M85	SBUY-KF-BL	M63	WSM6-G3D-ACM2	M41	WSM3-KF-YSU	M19
WDM6-G3D-ACM2	M86	SBUY-BMJ-YSU	M64	WSM6-G3D-BL	M42	WSM3-KF-ACM2	M20
WDM6-G3D-BL	M87	SBUY-BMJ-ACM2	M65	T-KF-YSU	M43	WSM3-KF-BL	M21
		SBUY-BMJ-BL	M66	T-KF-ACM2	M44	WSM3-BMJ-YSU	M22

4. HEC-HMS Hydrological Model

In this study, the HEC-HMS hydrological model was employed to simulate hydrological processes in the Poldokhtar basin. Developed by the United States Army Corps of Engineers (USACE), HEC-HMS is a rainfall-runoff simulation model designed for basin-scale flood analysis. It falls under the category of link-lumped parameter models and is commonly used for

event-based flood simulations. Constructing a rainfall-runoff model in HEC-HMS involves three key steps: creating the basin model, incorporating meteorological data, and defining control parameters (such as the start time, end time, and simulation duration). The schematic representation of the Poldokhtar basin used in this research, consisting of five sub-basins and two channels, is shown in Figure 3. Meteorological data play a pivotal role in any rainfall-runoff model, particularly in HEC-HMS, as they provide critical inputs on weather conditions affecting the watershed during the simulation period. For this study, the Thiessen polygon method was utilized to determine the influence coefficients of meteorological stations in estimating precipitation for each sub-basin. Subsequently, the study employed the SCS Unit Hydrograph, SCS Curve Number, and monthly constant methods to simulate precipitation-runoff conversion, infiltration losses, and base flow in the sub-basins, respectively. The Muskingum method was adopted for flow routing within the channels. The model calibration process considered 14 decision variables, including five Curve Number (CN) values, five lag times (Tlag) for the sub-basins, and two parameters (X and K) related to the channels. Due to limitations and inefficiencies in the optimization algorithm integrated into HEC-HMS, the Simulated Annealing (SA) metaheuristic algorithm was applied to optimize these decision variables and locate the global optimum, particularly in scenarios involving extensive decision spaces. Simulated Annealing, introduced by (Metropolis et al., 1953), is a metaheuristic optimization technique suitable for problems with large search spaces. It employs a stepwise, randomized search mechanism. Initially, the algorithm explores the search space extensively with random moves, allowing it to escape local optima. As the process continues, the search becomes more focused, gradually narrowing down to identify the optimal solution.



Figure 3. Schematic of the Poldokhtar basin in the HEC-HMS hydrological model in this study

5. HEC-RAS 2D Hydraulic Model

The HEC-RAS hydraulic model, developed by the U.S. Army Corps of Engineers, is a widely used tool capable of performing one- and two-dimensional simulations of river flow hydraulics (Azizian, 2019). This study employed the two-dimensional (2D) HEC-RAS model for hydraulic simulations in the urban area of Poldokhtar, where complex features such as buildings, streets, and intricate topography necessitate the use of a 2D approach. The HEC-RAS 2D model applies physically based principles and is recognized as one of the most effective tools for hydraulic modeling. For 2D flow simulations, the model utilizes the Saint-Venant equations in both dynamic and diffusion wave forms. A crucial input for this modeling is the digital elevation model (DEM) of the region. Research by Azizian and Brocca (2020) demonstrated that remote sensing-derived elevation data with a resolution of 30 meters, such as those from ALOS and SRTM, are effective for constructing geometric river models and simulating floods using HEC-RAS. Additionally, the HEC-RAS model's performance is relatively unaffected by the grid cell dimensions of the topographic map (Azizian, 2019). Consequently, this study utilized elevation data from the ALOS dataset, with mesh dimensions of 100 x 100 meters for hydraulic simulations. Upstream boundary conditions for the hydraulic model were defined using the flood hydrograph derived from WRF model outputs and a normal depth condition at the river downstream. Calibration of the hydraulic model involved optimizing the Manning roughness coefficient. The objective function for calibration was based on the observed discharge-stage relationship at the Poldokhtar hydrometric station. Through this process, an optimal Manning coefficient value was determined, resulting in a discharge-stage curve that closely aligned with observed data.

6. Development of a Regional Depth-Damage Curve

Numerous studies have highlighted the significance of flow depth as a critical factor in estimating direct flood damage to buildings, despite the influence of other variables such as flow velocity and sediment concentration. Flow depth is often regarded as the most reliable predictor of flood damage (Paulik et al., 2022; Romali et al., 2019; Van Ginkel et al., 2021). In this research, an empirical depth-damage function will be developed using data on flood depth and associated damages collected in the Poldokhtar region. To establish the most suitable relationship between flood depth and damage, various mathematical functions have also been assessed. The selection of the optimal curve will be based on criteria such as the correlation index and the examination of

residuals for adherence to normality, variance stability, and independence. The resulting depth-damage curve will be specifically tailored to the study area.

8. Bootstrap confidence interval

In this study, the nonparametric bootstrap method was employed to construct a confidence interval and assess the uncertainty associated with the WRF numerical model. One of the key advantages of nonparametric approaches over parametric methods is that they do not require the original dataset to follow a normal distribution. The bootstrap technique, a subset of the Monte Carlo method, relies on generating random samples (Dehghani, 2009; Efron and Tibshirani, 1993). The process of constructing a confidence band using the bootstrap involves the following steps:

- 1- Choose a number of bootstrap samples to perform ($B=1000$)
- 2- For each bootstrap sample resampled of size n (same as the initial sample), as randomly and observing the permutation principle
- 3- Next, a statistical measure (θ) must be selected around which the confidence interval will be formed ($\theta=\text{Median}$)
- 4- For each of the B resampled datasets, the θ is computed, yielding a set of B median values ($\theta_1, \theta_2, \dots, \theta_B$).
- 5- θ values are then sorted in ascending order. To construct a confidence interval at a α confidence level, the $\alpha/2$ and $1 - \alpha/2$ percentiles of the ordered median values are identified as the lower and upper bounds of the confidence interval.

7. Evaluation Metrics

In this study, statistical indices including the correlation coefficient (CC), root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), and mean absolute error (MAE); and categorical indices such as the probability of detection (POD) and false alarm ratio (FAR) were utilized to assess the accuracy of the modeled precipitation and flood events in comparison to observed data. Table 2 provides details on the calculation methods and optimal values associated with each index.

289 **Table 2.** Statistical and Categorical Metrics used in this research

Type	Index	Formula	Optimal Value	Reference
Statistical indicators	CC	$CC = \frac{\sum_{i=1}^n (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (S_i - \bar{S})^2}}$	1	(Pearson, 1896)
	RMSE	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - S_i)^2}$	0	(Hyndman and Koehler, 2006)
	MAE	$MAE = \frac{\sum_{i=1}^n S_i - O_i }{n}$	0	(Stanski et al., 1989)
	NSE	$NSE = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$	1	(Nash and Sutcliffe, 1970)
Tabular indicators	FAR	$FAR = \frac{C}{A + C}$	0	(Panofsky and Brier, 1965)
	POD	$POD = \frac{A}{A + B}$	1	(Panofsky and Brier, 1965)

290 Where: O_i : observed values; S_i : simulated values; n : the number of data points; $\bar{X}_o$: the mean of observed
291 values; $\bar{X}_s$: the mean of simulated values; and σ_o : the standard deviation of observed values. Additionally,
292 A: corresponds to instances where both the synoptic station and the model recorded precipitation; B:
293 represents cases where the synoptic station recorded precipitation, but the model failed to predict it; and C:
294 indicates instances where no precipitation was observed, yet the model predicted precipitation.

295
296 To evaluate the performance of the WRF numerical model, a total of 87 different
297 configurations were tested. Since identifying the best-performing configuration based solely on
298 individual statistical indices is challenging, this study employed the concept of Euclidean distance
299 to provide a more comprehensive performance assessment. The Euclidean distance method
300 calculates the shortest distance between two points in a multidimensional space, as described by
301 (Van Cooten et al., 2009). For a quantitative evaluation of the model's efficiency, two statistical
302 indices (CC and NRMSE) and two categorical indices (POD and FAR) were used to compute the
303 Euclidean distance. The performance of each model configuration was measured by calculating
304 the Euclidean distance D (CC, NRMSE, POD, FAR) relative to an optimal reference vector Do

(1,0,1,0). Then, the similarity index value was calculated based on the Euclidean distance and using equation (2). The similarity index ranges from 0 to 1, where a smaller Euclidean distance (D) and a higher similarity index indicate greater consistency between the simulated and observed values.

$$D_{(S,S_0)} = \sqrt{(CC - CC_0)^2 + (NRMSE - NRMSE_0)^2 + (POD - POD_0)^2 + (FAR - FAR_0)^2} \quad (1)$$

$$Similarity = \frac{1}{1 + D_{(S,S_0)}} \quad (2)$$

Finally, the similarity index values were sorted from largest to smallest. The first quartile (22 highest-ranked simulations) was classified as the superior simulations. The confidence interval and the mean simulations were derived based on these 22 best configurations.

Results and discussion:

1. Identifying the Best Schemes for Precipitation Simulation

In this study, we examined the precision of c predictions within the Poldokhtar basin using 87 distinct configurations of the WRF model to identify the optimal configuration. Subsequently, we determined the top quartile of performances, comprising the 22 performances, based on their similarity index values, narrowing down to the best 22 performances. Figures 4 and 5 depict the mean time series and the confidence interval of the 22 simulations with the observed precipitation time series, along with the CC, RMSE, FAR, and POD indices for Khorramabad, Poldokhtar, and Kohdasht stations across all four events. By, analyzing the correlation between the modeled and observed values at the studied stations, we found that the average correlation indices for the of 2016, 2018, 2019_1, and 2019_2 events were 0.54, 0.72, 0.00, and 0.65, respectively. The highest correlation was observed during the 2018 and 2019 events. Evaluation of the results based on the FAR index indicates that across all studied stations during the events of 2016, 2018, 2019_1, and 2019_2, the false alarm rates are below 0.25%, 0.00%, 0.40%, and 0.25%, respectively. This signifies that the WRF numerical model accurately detected rainy conditions 75%, 100%, 60%, and 75% of the time. In general, analysis of the average time series and uncertainty band of the top simulations (22 top runs) reveals a tendency for the model to underestimate precipitation levels across most studied events and stations. The average RMSE values for the studied stations during the events of 2016, 2018, 2019_1, and 2019_2 are 14.48, 4.87, 9.26, and 15.42 mm, respectively. Dasari & Challa (2015) conducted a study on regional precipitation trends across Europe over a

60-year period using WRF regional model data with a spatial resolution of 25 km. Findings indicated that the model tended to underestimate precipitation amounts below 1500 mm. These results align with the findings of the present study. Also, Deng et al., (2023) assessed the effectiveness of the WRF numerical modeling system by examining 27 distinct combinations of physical parameterization schemes, focusing on convection, microphysics, and land surface processes. Their analysis revealed that the system tended to produce underestimations of precipitation within the study region. This finding highlights a systematic bias in the model's performance, which is consistent with broader challenges in accurately simulating precipitation patterns and flood using such numerical frameworks.

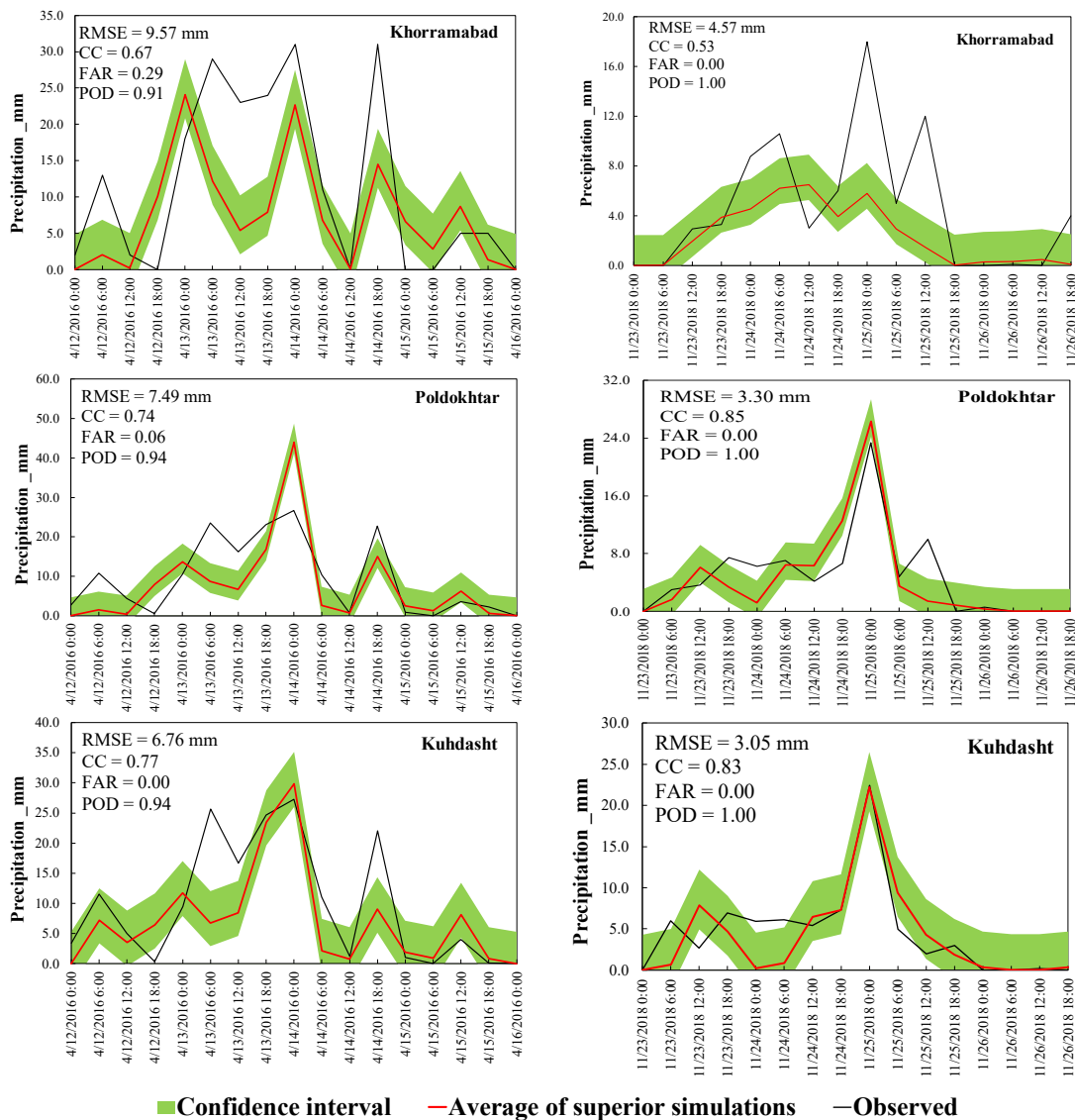


Figure 4. Time series and confidence interval obtained from the best combinations of schemas (Khorramabad, Poldokhtar, and Kuhdasht stations for events: 2016 and 2018) by non-parametric Bootstrap method.

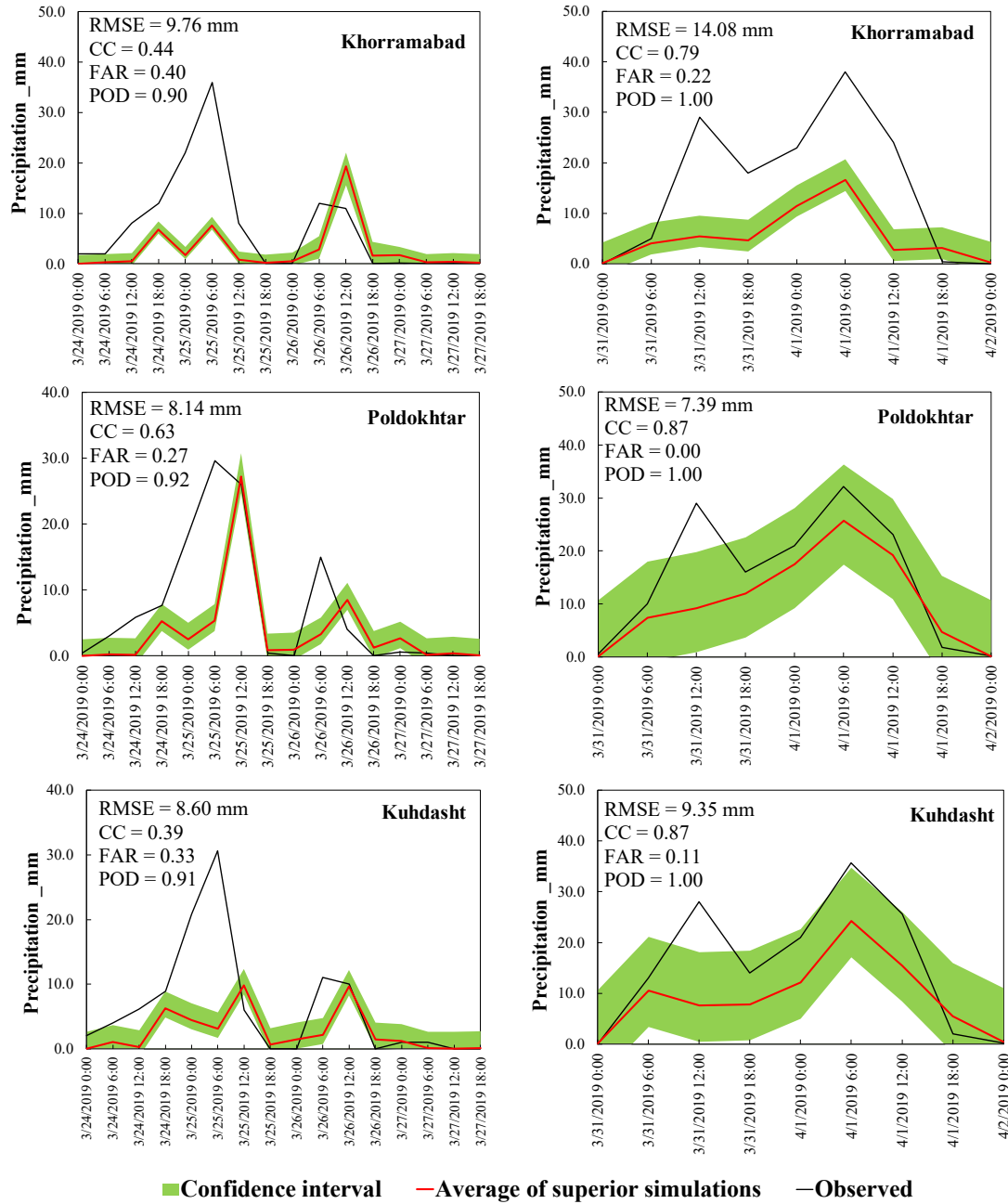


Figure 5. Time series and confidence interval obtained from the best combinations of schemas (Khorramabad, Poldokhtar, and Kuhdasht stations for events: 2019_1 and 2019_2) by non-parametric Bootstrap method.

Due to the extensive number of stations and events, as well as variations in the top configurations across different stations and events, the process of determining the optimal configuration involved initially identifying configurations with the highest occurrence frequency among different stations for each event. The configuration with the highest frequency across the study stations, which also demonstrated superior performance in a greater number of events, was

identified as the optimal configuration for the Poldokhtar basin. Analysis of the 2016 event revealed that selecting the Grell 3D scheme for the convection parameterization significantly enhanced the accuracy of simulated precipitation. This result was consistent across a wide range of configurations, regardless of the schemes chosen for the microphysics and boundary layer processes. Furthermore, the YSU scheme for the boundary layer parameterization was associated with improved precipitation accuracy in a larger number of stations. In the 2018 event, the findings indicated that independent of the microphysics scheme applied, the Grell 3D and YSU schemes for the convective and boundary layer processes performed effectively in simulating precipitation.

Table 3. The optimal configuration with the frequency of 4 and 5 stations in each events

2018		2016	
The optimal configuration in 4 stations	The optimal configuration in 5 stations	The optimal configuration in 4 stations	The optimal configuration in 5 stations
L-KF-YSU	K-G3D-YSU	EF-G3D-BL	EF-G3D-ACM2
WSM3-G3D-ACM2	L-G3D-YSU	SBUY-G3D-BL	
T-G3D-YSU		M2-G3D-YSU	
WDM5-G3D-ACM2		WSM3-G3D-YSU	
WSM3-G3D-BL		K-KF-ACM2	
WSM6-KF-YSU		T-BMJ-YSU	
K-KF-YSU		WDM5-G3D-ACM2	
K-G3D-BL		M2-G3D-ACM2	
		WDM5-BMJ-YSU	
2019_2		2019_1	
The optimal configuration in 4 stations	The optimal configuration in 5 stations	The optimal configuration in 4 stations	The optimal configuration in 5 stations
SBUY-BMJ-BL	K-G3D-YSU	T-G3D-BL	T-G3D-ACM2
WSM3-BMJ-ACM2	WSM3-BMJ-YSU	WDM5-G3D-ACM2	SBUY-G3D-YSU
		WSM3-G3D-ACM2	SBUY-G3D-ACM2
		WSM6-BMJ-BL	WDM6-G3D-ACM2
		M2-BMJ-BL	

The findings indicate that for the 2019_1 precipitation event, the Grell 3D scheme emerged as the optimal choice for the convection parameterization. Additionally, the Asymmetrical

Convective Model v2 scheme was identified as the most effective option for simulating the boundary layer in this event. According to Table 2 in the event of 2019_1, configurations numbered 7 (Kessler, Grell 3D, and YSU) and 22 (WSM3, Betts-Miller-Janjic, and YSU) ranked among the top-performing configurations. These configurations were within the first quartile of the similarity index in at least five stations. Similarly, configurations numbered 23 (WSM3, Betts-Miller-Janjic, and Asymmetrical Convective Model v2) and 66 (SBU_YLIN, Betts-Miller-Janjic, and Bougeault-Lacarrere) demonstrated superior performance, being in the first quartile of the similarity index in at least four stations. The analysis of the studied stations and precipitation events revealed that configuration number 77, comprising the WDM5, Grell 3D, and Asymmetrical Convective Model v2 schemes for the microphysics, convection, and boundary layer components, respectively, can be identified as the optimal configuration for this region. This configuration demonstrated superior performance compared to others across a greater number of stations and events. Specifically, configuration 77 ranked among the top-performing setups in the 2016 precipitation event at four stations, in the 2018 event at five stations, in the first precipitation event of 2019 at four stations, and in the second precipitation event of 2019 at one station within the study area. Overall, the analysis suggests that for the microphysics parameterization, the WSM3, Kessler, WSM6, Thompson, WDM5, and Lin schemes are among the most effective. For the convection parameterization, the Grell 3D scheme stands out as the preferred option, while for the boundary layer parameterization, the YSU scheme is recommended for accurate precipitation simulation in this region.

Figure 6 illustrates the variations in statistical indices (CC, RMSE) and categorical indices (FAR, POD) for the selected model configuration (Configuration 77) across different stations and precipitation events. An analysis of the correlation between WRF and observed precipitation indicates that for the 2018 event correlation values at most stations, except for Abdanan and Romeshkan, range between 0.52 and 0.87. In 2019_1, correlation values in stations (excluding Imanabad and Khorramabad) fall within the range of 0.28 to 0.77. Similarly, in 2019_2, correlation values (excluding Imanabad and Abdanan) vary between 0.48 and 0.78.

The changes in the RMSE error index shows that in 71% of the analyzed stations and events, the error remained below 15 mm. The highest simulation errors were recorded at Abdanan (31.92 mm in 2016, 24.47 mm in the 2019_2 event), Romeshkan (19.31 mm in 2016), and Imanabad (18.87 mm in the 2019_2 event). An evaluation of WDM5, Grell 3D, and Asymmetrical

Convective Model v2 configurations for precipitation prediction, based on FAR and POD indices, demonstrates that the average FAR values across all stations for the 2016, 2018, first 2019, and second 2019 events were 0.03, 0.00, 0.27, and 0.09, respectively, indicating a satisfactory performance. Additionally, the average POD values for these events were 0.89, 0.85, 0.91, and 0.92, respectively, highlighting the configuration's capability in accurately distinguishing between rainy and non-rainy periods.

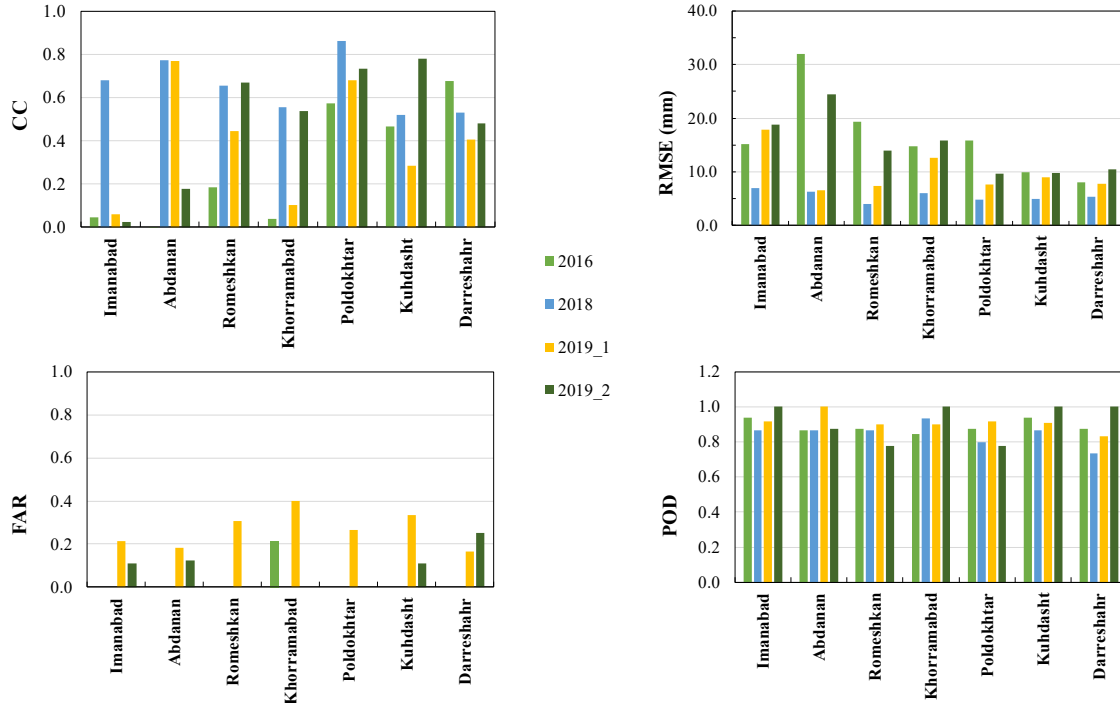


Figure 6. Changes in the value of CC, RMSE, FAR and POD of optimal configuration in the precipitation simulation

2. Identifying the Best Scheme Combination for Flood Simulation

In this section, the efficiency of the HEC-HMS hydrological model in simulating the studied events was evaluated by calibrating the model using observed precipitation data from the 2016 event and validating it against the 2018 event. The results of the model's performance during the calibration and validation periods are illustrated in Figure 7. During the calibration phase, the model's ability to simulate the flood hydrograph was deemed acceptable, with a Nash-Sutcliffe efficiency (NSE) index of 0.96. The error in estimating the peak discharge during this period was calculated as 3.15%. Similarly, the validation results demonstrated the model's satisfactory performance in simulating the flood event of 2018. The NSE index during the validation period was found to be 0.93, and the error in estimating the peak flood discharge was 8.98%, which is

considered reasonable. Overall, these findings suggest that the HEC-HMS hydrological model possesses reliable capabilities for flood simulation in the Poldokhtar basin and provides a robust framework for evaluating the performance of the WRF model in similar applications.

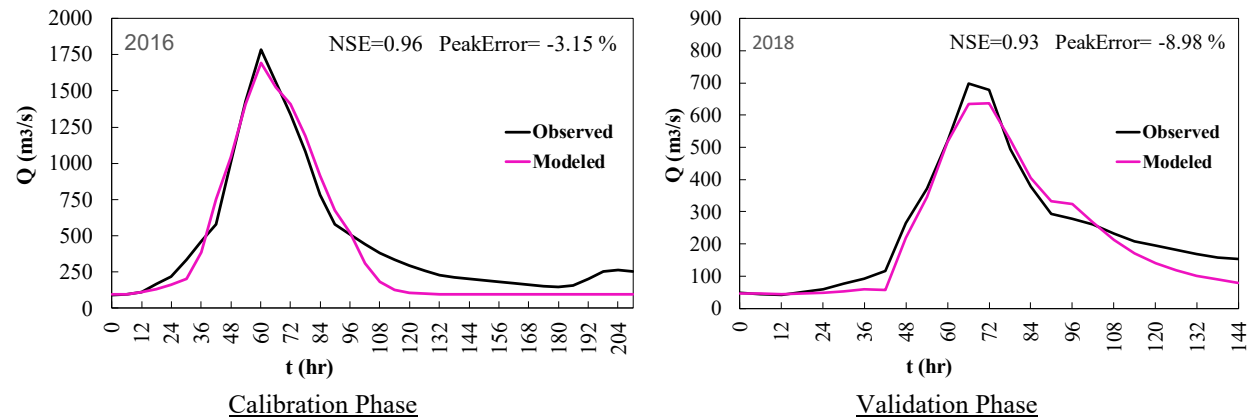


Figure 7. Calibration and validation of the HEC-HMS hydrological model with observed precipitation

One of the aims of this study was to identify the optimal configuration of the WRF numerical model for simulating flood events using the HEC-HMS hydrological model. To achieve this, the performance of various model configurations was assessed in precipitation simulation. Subsequently, the HEC-HMS model was employed to simulate floods using these configurations. The configurations were ranked based on the Nash-Sutcliffe efficiency index ($NSE > 0.75$) and the error in peak discharge estimation (less than 15%). Tables 4 summarize the results, including the best-performing configurations, the NSE values, and the percentage error in peak discharge estimation for each event analyzed. An evaluation of the results for the 2016 flood event revealed that only 3 out of the 87 configurations assessed were able to accurately replicate the hydrograph's shape and peak flood discharge. Configurations 83 (WDM6, Betts-Miller-Janjic, and ACM2), 16 (Lin, Grell 3D, and YSU), and 6 (WDM5, Grell 3D, and YSU) demonstrated superior performance, achieving NSE values greater than 0.85 and an error margin below 15% in estimating the peak discharge. These findings underscore the significant influence of using Grell 3D and Betts-Miller-Janjic schemes for the convection parameterization and ACM2 and YSU schemes for the boundary layer on the accuracy of flood simulations for this event. The analysis indicates more variability in the choice of superior schemes for simulating the microphysics scheme, although WDM6, Lin, and WDM5 consistently emerged as top-performing schemes for simulating the 2016 flood event. The analysis of the 2018 flood event reveals that six configurations of the WRF numerical model demonstrated strong performance in simulating the flood hydrograph and peak discharge. Among

these, the most effective configuration utilized the Kessler, KF, and YSU schemes for the microphysics, convection, and boundary layer parameterizations, respectively. This setup achieved a Nash-Sutcliffe efficiency index of 0.95 and a 2.10% error in estimating the peak discharge. Notably, for this event, the KF and Bougeult-Lacarrere schemes for convection and the boundary layer sections, respectively, consistently produced satisfactory results across multiple superior runs. Their performance exhibited a high degree of agreement with observed river discharge data recorded at the Poldokhtar hydrometric station, regardless of the choice of microphysics scheme. This highlights their effectiveness in accurately reproducing the flood hydrograph and peak discharge. The evaluation of the hydrological model's performance in simulating the first and second flood events of 2019 indicates that 7 and 4 configurations of the WRF numerical meteorological model, respectively, demonstrated satisfactory results. These configurations achieved a Nash-Sutcliffe efficiency index exceeding 0.75 and an error margin of less than 15% in estimating peak discharge. For these events, the Grell 3D scheme for the convection section and the Bougeult-Lacarrere scheme for the boundary layer were prominent among the configurations that exhibited superior performance. Additionally, the selection of the Kessler, Lin, and WDM6 schemes for the microphysics parameterizations was associated with improved flood simulation accuracy. It is noteworthy that, unlike the other three flood events, the KF scheme for the convection section performed acceptably during the 2018 event. This observation suggests that for flood events with peak discharges below 700 cubic meters per second, the KF scheme may offer better performance in simulating the convective processes. In contrast, for larger floods, the Grell 3D scheme is recommended for more accurate convection layer simulations.

The analysis revealed that the use of Lin, Kessler, WDM6, WDM5, WSM3, and M2 schemes for the microphysics section, Grell 3D and KF schemes for the convection section, and Bougeult-Lacarrere and YSU schemes for the boundary layer section are effective in achieving accurate flood simulations. A comparison of the optimal schemes for the microphysics, convection, and boundary layer sections in both precipitation and flood simulations suggests that the Kessler, Lin, WDM5, and WSM3 schemes for microphysics, along with Grell 3D and YSU schemes for convection and boundary layer sections, respectively, deliver reliable performance in the study area. The findings indicate that no single configuration can consistently provide the most accurate results for simulating floods caused by varying atmospheric systems. However, by evaluating a range of configurations (87 in total) across multiple events (four flood events), certain schemes

can be identified with relatively greater reliability as superior options for simulating specific sections of the flood simulation process. It is important to note the significant variability in peak discharge among the four studied events. At the Poldokhtar hydrometric station, the peak discharges for the floods in 2016, 2018, and the two events in 2019 were recorded as 1,784 m³/s, 698 m³/s, 2,597 m³/s, and 6,126 m³/s, respectively. This substantial range underscores the diversity of the events examined. Consequently, this study can be regarded as a relatively comprehensive investigation into the selection of optimal schemes for the WRF numerical meteorological model in flood simulation within the Poldokhtar basin, using the HEC-HMS hydrological model.

Table 4. Optimal WRF model configurations in flood simulation by HEC-HMS model

2016				2018			
WRF Configuration Code	Configuration of WRF	NSE	Error in peak flow estimation (%)	WRF Configuration Code	Configuration of WRF	NSE	Error in peak flow estimation (%)
M83	WDM6-BMJ-ACM2	0.87	-11.9	M1	K-KF-YSU	0.95	-2.1
M16	L-G3D-YSU	0.85	-10.8	M2	K-KF-ACM2	0.91	-10.6
M76	WDM5-G3D-YSU	0.87	-14.7	M21	WSM3-KF-BL	0.90	-11.9
				M12	L-KF-BL	0.87	-11.3
				M63	SBUY-KF-BL	0.90	-14.3
				M44	T-KF-ACM2	0.91	-14.9
2019_1				2019_2			
WRF Configuration Code	Configuration of WRF	NSE	Error in peak flow estimation (%)	WRF Configuration Code	Configuration of WRF	NSE	Error in peak flow estimation (%)
M69	SBUY-G3D-BL	0.94	-6.1	M16	L-G3D-YSU	0.74	-13.1
M9	K-G3D-BL	0.94	-8.8	M76	WDM5-G3D-YSU	0.72	-14.9
M53	M2-KF-ACM2	0.94	-9.9	M87	WDM6-G3D-BL	0.74	-14.2
M87	WDM6-G3D-BL	0.87	-1.1	M60	M2-G3D-BL	0.75	-14.4
M21	WSM3-KF-BL	0.93	-14.9				
M12	L-KF-BL	0.93	-11.4				
M60	M2-G3D-BL	0.85	-14.8				

This section presents the simulated flood hydrographs derived from precipitation data both before and after bias correction, alongside the calculated Nash-Sutcliffe efficiency indices and

relative errors in peak discharge estimation, as depicted in Figure 8. The results indicate that applying the quantile mapping method for bias correction of precipitation data significantly reduced the model's error in estimating peak discharge, thereby enhancing the accuracy of flood peak simulations. Prior to bias correction, the performance of the hydrological model using raw WRF precipitation data was satisfactory in simulating the flood hydrograph across the basin. The Nash-Sutcliffe efficiency indices for the 2016, 2018, 2019_1, and 2019_2 flood events were 0.87, 0.95, 0.95, and 0.81, respectively. However, the raw precipitation data exhibited a higher degree of error in estimating peak flood discharges. The application of bias correction to the WRF precipitation data substantially improved the model's accuracy in simulating peak flood discharges. Specifically, prior to bias correction, the errors in peak discharge estimation for the 2016, 2018, 2019_1, and 2019_2 events were 11.93%, 2.06%, 6.05%, and 8.91%, respectively. These errors decreased to 6.67%, 1.25%, 1.42%, and 3.12% after bias correction, indicating a significant improvement in the model's performance in simulating peak flood discharges. Saedi et al. (2020a) conducted a study on uncertainty analysis in flood forecasting, utilizing seven numerical ensemble precipitation prediction models in conjunction with the GR4J precipitation-runoff model to analyze the Golestan flood that occurred in spring 2019. Their findings highlighted that bias correction played a critical role in enhancing the accuracy of flood forecasts for this basin.

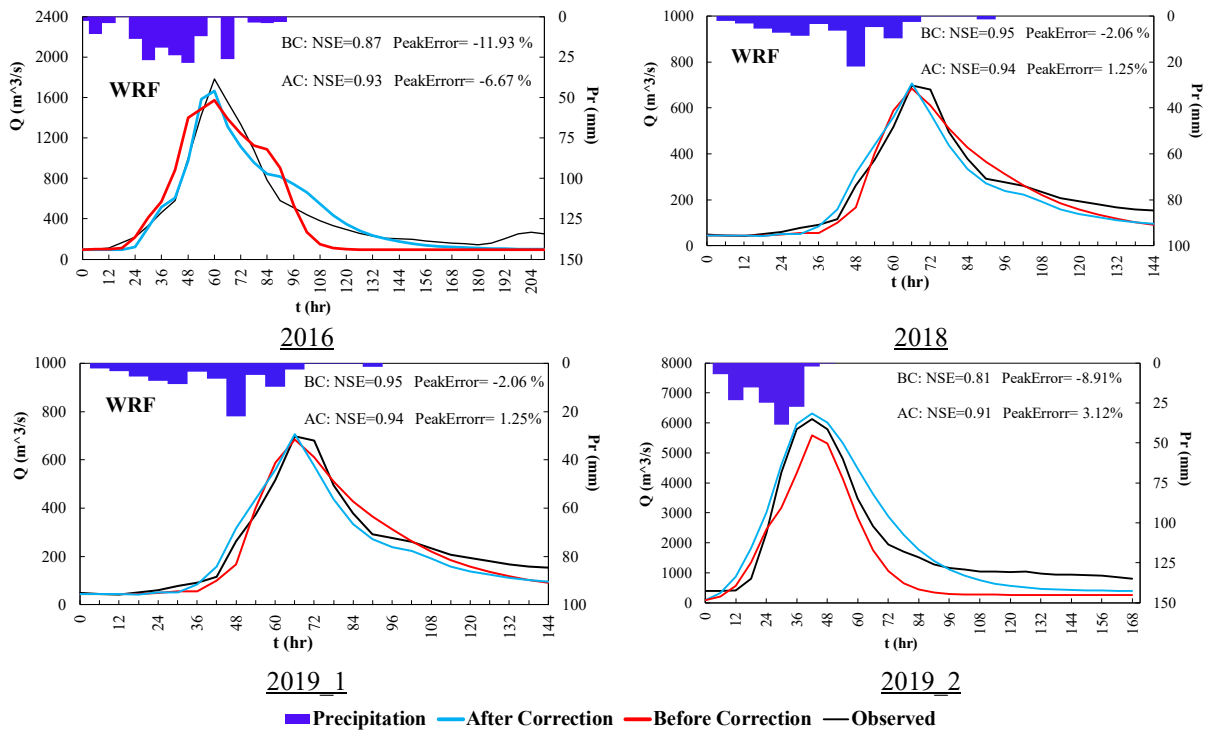


Figure 8. The flood hydrographs before and after bias correction of precipitation

3. Assessing the Performance of WRF Model in simulating flood hydraulic characteristics:

The calibration of the HEC-RAS hydraulic model was carried out by comparing the modeled discharge-stage curve with the observed curve at the Poldokhtar hydrometric station. Figure 9 illustrates both the recorded discharge-stage curve at the station for the events studied and the corresponding curve derived from the hydraulic model implementation. As shown in the figure, the discharge-stage curves produced by the hydraulic model closely match the observed discharge-stage curve at the station. The events of 2016 and 2018 exhibit the lowest and highest levels of agreement between the modeled and observed curves, the average Absolute Relative Error (ARE) index for these events have calculated at 7.03% and 1.29%, respectively. Overall, after calibrating the hydraulic model, the absolute value of the relative error in simulating the discharge-stage curve for the study events remains under 10%, which is considered an acceptable level of accuracy.

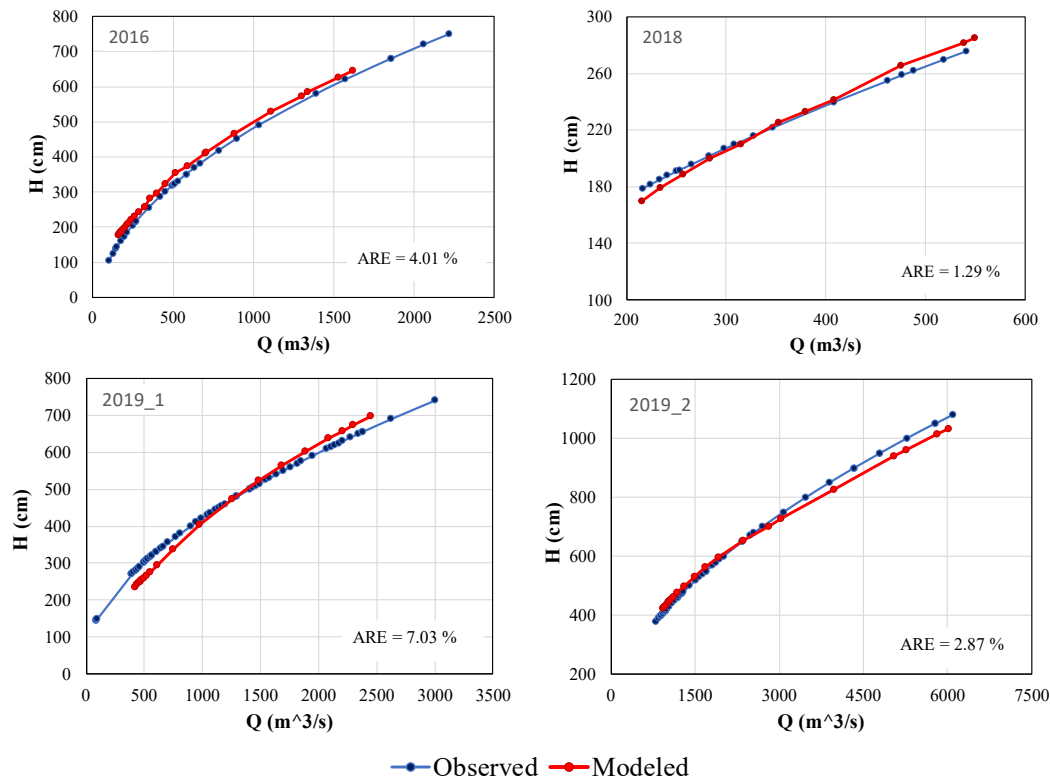


Figure 9. Comparison of the observed and modeled rating curve at the Poldokhtar hydrometric station

To assess the effectiveness of numerical meteorological models in hydraulic simulations, 15 cross-sections were selected during the study period, and flood depth were extracted for these sections. Figure 10 illustrate the variations in flood depth derived from the flood hydrograph associated with the 95% confidence interval and the mean of the WRF model, used as the upstream

boundary condition in the HEC-RAS hydraulic model. These results are compared with the values obtained from the observed flood hydrograph, which was applied as the upstream boundary condition in the hydraulic modeling. As shown in the figures, the use of the WRF numerical precipitation model to simulate the flood hydrograph and, subsequently, the hydraulic characteristics of the flow, demonstrated satisfactory performance in predicting flood depth in the study area. The results indicate that, despite a slight underestimation, the flood depths simulated by WRF precipitation are strongly correlated with the observed flood depth derived from the basin's observational flood hydrograph used in the two-dimensional HEC-RAS model.

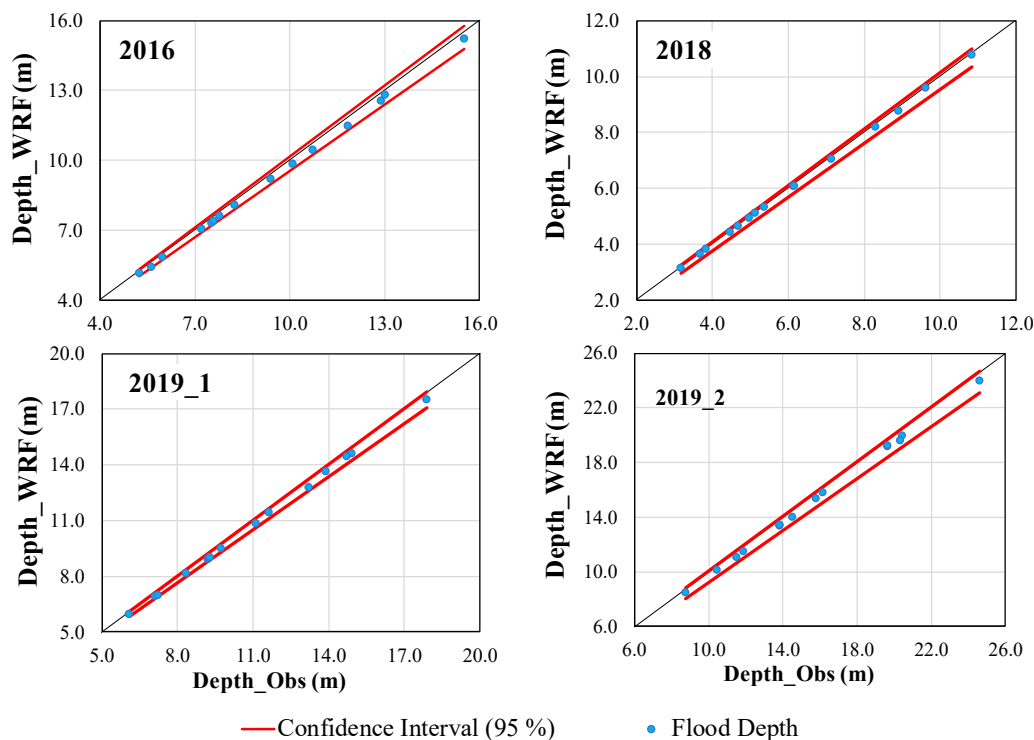


Figure 10. Comparison of flood depths obtained from the flood hydrograph related to observed and WRF output

Additionally, the floodplain derived from the WRF flood hydrograph model was compared with the floodplain generated using the observed flood hydrograph (Figure 8). The statistical F index, which measures the degree of similarity between the modeled floodplain from the observed and WRF flood hydrograph, was found to exceed 95% for all the events studied (Figure 8). This indicates a strong correlation between the floodplain generated using the WRF numerical model hydrograph as the boundary condition for the hydraulic model and the floodplain obtained from the observed flood hydrograph.

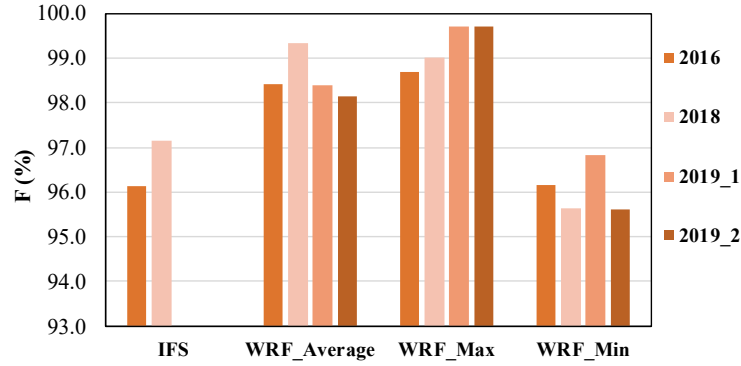


Figure 11. Similarity index F for comparing the flood area resulting from the use of flood hydrographs of WRF numerical model and observational hydrograph

4. Assessing the Performance of WRF Model in simulating flood damage:

To determine the best-fitting curve for the relationship between flood depth and damage data, several functions were analyzed, with the findings summarized in Table 3. The performance of each curve was evaluated using RMSE, MAE, and CC error indices. Based on the error metrics, the function exhibiting the lowest error was identified as the most accurate model for estimating flood-induced building damage. As indicated in Table 5, two distinct exponential functions were tested for fitting the observational data. Both functions displayed a horizontal asymptote at $Y=1$ as $X \rightarrow \infty$. Additionally, the observational data was segmented into two parts in one approach: for flood depths ranging from 0.1 to 2.4 meters, a linear function was employed, while a damage value of 100% was assigned for depths exceeding 2.4 meters. Lastly, a cubic curve with a defined depth range (0.1 to 4.5 meters) was used as the fourth function. This approach enabled a comprehensive evaluation of different models for accurately capturing the depth-damage relationship.

Table 5. Functions fitted to observational depth-damage data

Model	Equations	X (m)	RMSE (%)	MAE (%)	CC
M1	$Y = 1 - \exp(-X^{1.12})$	$0.1 \leq$	11.56	9.12	0.92
M2	$Y = 1 - \exp(-0.94 \times X)$	$0.1 \leq$	11.43	8.69	0.92
M3	$Y = 0.21 + 0.33 \times X$	$0.1 - 2.4$	13.23	10.07	0.89
	$Y = 1$	$2.4 <$	12.13	9.71	0.92
M4	$Y = 0.008 + (0.82 \times X) + (-0.24 \times X^2) + (0.024 \times X^3)$	$0.1 - 4.5$	11.56	9.12	0.92
	$Y=1$	$4.5 <$	11.43	8.69	0.92

Where, Y represents the percentage of damage, and X denotes the flood depth in meters.

Analysis of the error metrics for various models, as presented in Table 5, reveals that the second model, an exponential function, achieved the lowest error in estimating direct flood damages. Conversely, the highest error values were associated with the third and fourth models. These models utilized a combination of two distinct linear functions, resulting in an RMSE value of more than 12% for flood damage estimation. Additionally, the absolute error index for these models was the highest among the evaluated functions, at more than 9.50%. The findings indicate that the correlation between the calculated damages and the observed values shows minimal variation across the different models. Based on these results, the second exponential function was identified as the most accurate model for damage estimation. Subsequently, this selected model underwent further analysis to evaluate the normality, independence, and stability of the residuals' variance.

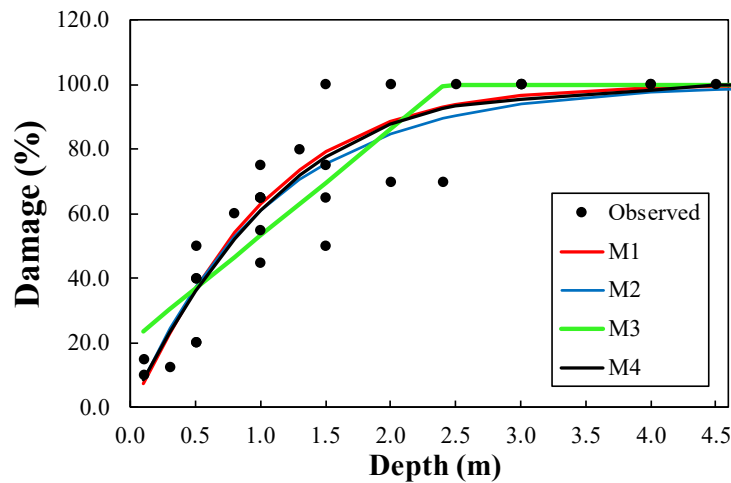


Figure 12. The depth-damage curves fitted to observational data

Figure 13 illustrates the analysis of statistical components. The probability graph for the normality of error values (the discrepancy between observed and calculated values) indicates that the P-Value for the damage function applied to residential areas is 0.04. Since this value is below the threshold of 0.05, it suggests that the error values do not follow a normal distribution at the $\alpha=5\%$. However, at the $\alpha=1\%$, they exhibit a normal distribution. The stability of errors was assessed using the residual time series and the MSE index. According to the findings, the error distribution is deemed acceptable in terms of stability, with the MSE index for residential areas calculated as 1.76%. This demonstrates that the function's performance remains consistent across

varying depth levels, showing no substantial discrepancies between low and high depths. Based on the statistical evaluation, it can be concluded that the proposed depth-damage function possesses sufficient accuracy and reliability for estimating flood-related damages in residential areas of Poldokhtar.

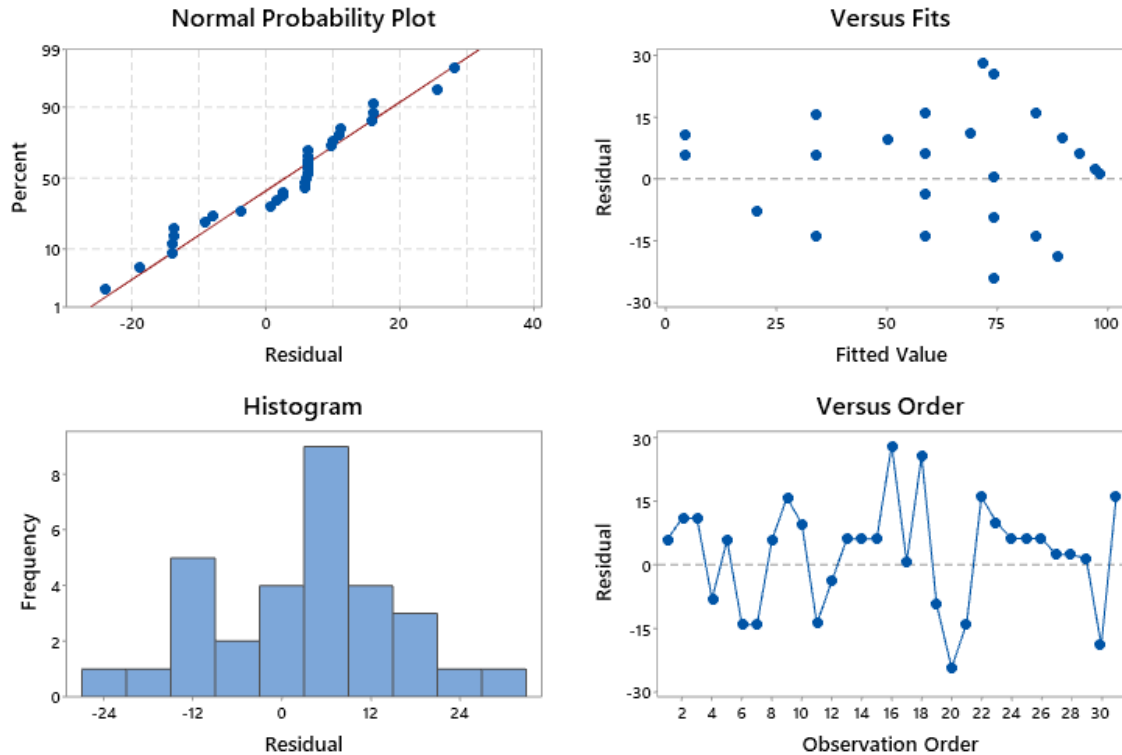


Figure 13. The examination of residuals in the depth-damage function for residential areas (M2)

Following the application of the damage function, a spatial distribution map illustrating the percentage of damage resulting from flood depths associated with the WRF model-generated flood hydrograph was developed, as shown in Figure 14. Table 6 summarizes the findings, indicating that during the 2016 flood, the areas experiencing 0-20% and 60-80% damage were estimated at approximately 0.29% and 14.3%, respectively, using the WRF numerical precipitation model. For the 2018 flood, results indicate that a significant portion of residential areas experienced damage within the 0-20% range when utilizing the WRF precipitation data. An analysis of the 2019 floods revealed that during the first event, a substantial portion of residential areas in Pol-e-Dokhtar (67.9%) sustained damage exceeding 40%, with an average damage level of 56%. During the second flood of 2019, the average damage to residential areas in this city was estimated at 70%, with 83.9% of the affected region incurring damage above 40%.

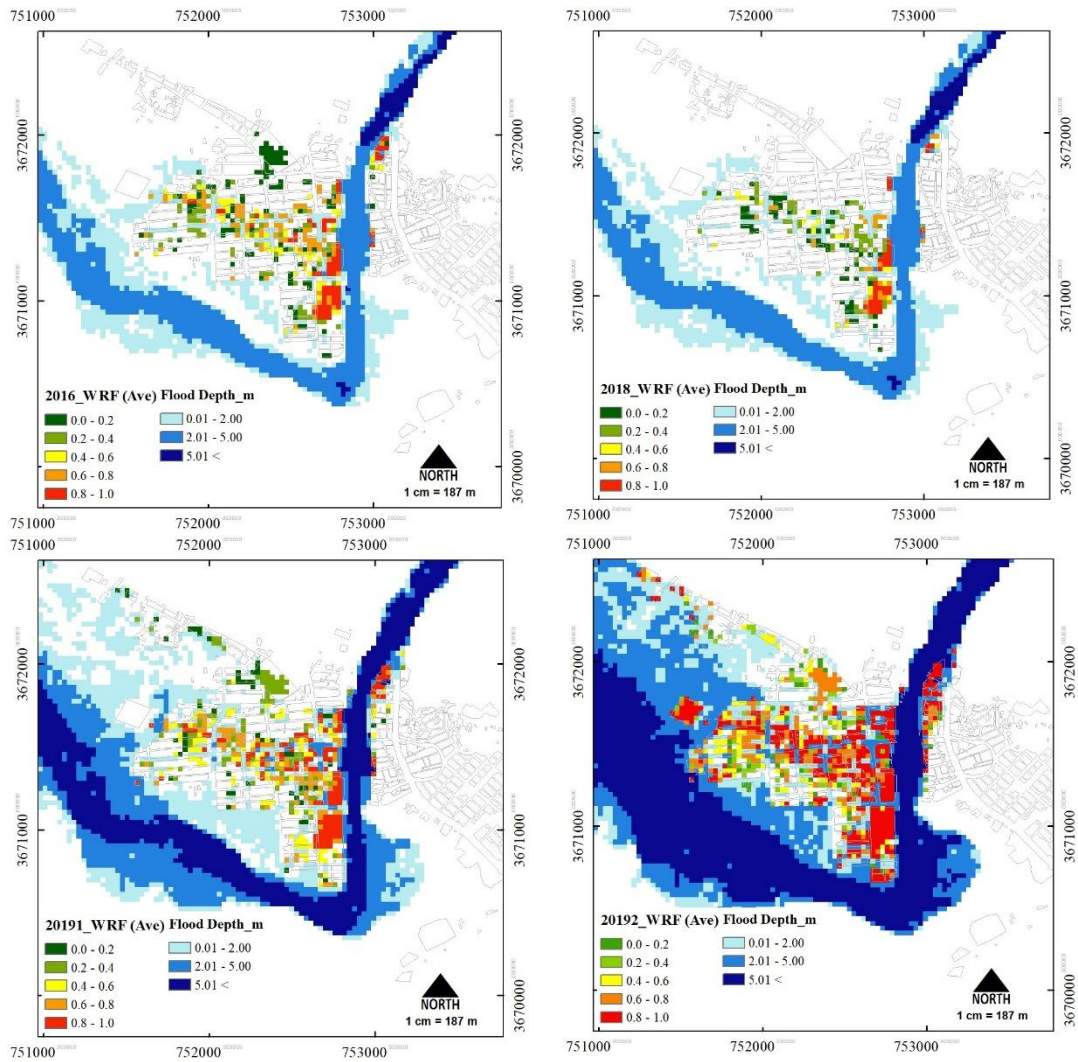


Figure 14. Spatial variations in the percentage of damage to residential buildings for the use of WRF precipitation data in Poldokhtar area.

Table 6. Percentage frequency of each damage range in the studied events

Damage (%)	0-20	20-40	40-60	60-80	80-100	Average damage (%)
2016_WRF	29.0	28.1	11.0	14.3	17.6	47
2018_WRF	29.0	28.1	11.0	14.3	17.6	41
2019_1_WRF	11.8	20.3	20.9	20.7	26.3	56
2019_2_WRF	7.5	8.5	12.8	24.3	46.8	70

Conclusion:

Floods, as one of the most devastating natural disasters, have historically inflicted significant loss of life and property on human societies. In recent years, the growing impact of climate change and the expansion of urban infrastructure into flood-prone areas have heightened the need for accurate flood forecasting. Reliable and precise flood predictions can mitigate the destructive consequences of such events by enabling officials and residents in at-risk regions to implement effective planning and rapid response measures. Given the importance of reliable precipitation forecasts as a key input for hydrological and hydraulic modeling, this study evaluates the performance of the WRF numerical meteorological model in simulating precipitation and its application in flood forecasting. Additionally, the study assesses the effectiveness of flood hydrographs derived from WRF precipitation data in simulating flood hydraulic characteristics and direct flood damage.

The findings indicate that the WRF model demonstrates satisfactory performance in distinguishing between rainy and non-rainy periods, as evidenced by the POD and FAR indices. The model correctly identified rainfall occurrences in over 75% of cases. However, an analysis of the superior simulations and their confidence intervals revealed a general tendency to underestimate precipitation amounts across most events and study locations. The RMSE values for the studied precipitation events in 2016, 2018, and two cases in 2019 were calculated as 14.48 mm, 4.87 mm, 9.26 mm, and 15.42 mm, respectively. An evaluation of 87 different model configurations for the Pol Dokhtar basin, based on statistical indices (NRMSE and CC) and categorical indices (POD and FAR), identified the most effective schemes for precipitation simulation. The optimal microphysics schemes were WSM3, Kessler, WSM6, Thompson, WDM5, and Lin, while the Grell 3D scheme performed best for convection, and the YSU scheme was most suitable for the planetary boundary layer.

Additionally, the findings indicated that selecting the Lin, Kessler, WDM6, WDM5, WSM3, and M2 schemes for microphysics, the Grell 3D and KF schemes for convection, and the Bougeault-Lacarrère and YSU schemes for the boundary layer significantly enhanced flood simulation accuracy. A comparative analysis of the best-performing schemes for precipitation and flood modeling further suggested that Kessler, Lin, WDM5, and WSM3 for microphysics, along with Grell 3D for convection and YSU for the boundary layer, yielded optimal results in the study area. Moreover, the study demonstrated that the WRF model's ability to reproduce hydrograph was

notably improved after bias correction of precipitation values, leading to a significant reduction in peak discharge errors. Performance assessment of hydrographs generated using WRF output as boundary conditions for hydraulic modeling with the two-dimensional HEC-RAS model revealed that WRF effectively simulated flood depth and extent. Furthermore, direct flood damage assessment for residential areas confirmed that the WRF model could provide a reliable representation of flood impact zones. Overall, the results highlight that integrating numerical weather prediction models such as WRF with hydrological, hydraulic and damage models can lead to the development of a robust and efficient flood forecasting system, particularly for high-impact flood events.

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