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Verification of Rainfall Forecasts for the South Central Climate Region of Vietnam

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Abstract

This study aims to investigate the performance of the Weather Research and Forecasting (WRF) model for rainfall forecasts in the South Central climate region of Vietnam. The investigation was carried out by analyzing the accuracy of the model outputs at station sites and the spatial structure of rain events for different rainfall thresholds over the whole year and in the flood and dry seasons. The traditional (standard) method was utilized to analyze the accuracy of the WRF model in predicting precipitation point-by-point, whereas the Contiguous Rain Area (CRA) method was applied to analyze the spatial structure of rain events. The results showed that rainfall forecasts by the WRF model for the South Central region had certain limitations because the model scores and measured error criteria were not close to their perfect values. The proportion of hit forecasts decreased from 30 % with the traditional verification method to 10% with the spatial structure verification method. The pattern error was a main contributor to the total error at 53%, followed by the intensity error at 34%. The location error accounted for the lowest percentage contribution to the total error, at only 13%. The performance of this model could lead to substantial errors in weather and streamflow predictions for the south-central region and may lead to a lack of forecast effectiveness for mitigating the damage from natural disasters. Thus, improvements in the performance of the Numerical Weather Prediction (NWP) model for the studied area are necessary.

Keywords: QPF; WRF model; traditional and spatial structure verification; South Central; Vietnam.

1. Introduction

The South Central climate region of Vietnam consists of five provinces bordered by the highland, north-central and south areas, and the region extends along the East Sea coast (Figure 1). The region has an area of 27,195 km^2 and a population of approximately 8.22 million and is damaged every year by several natural disasters, such as storms, flooding, and drought, causing human and property losses. To mitigate the damage, improving the capability of weather forecasts is very important. In addition to improvements in the structure of the numerical weather prediction (NWP) model, verification of the model outputs plays a very important role as well and is required (Diomede et al., 2008). This work is crucial for evaluating model accuracy for data assimilation (enhance the accuracy of initial conditions) and bias corrections (Ebert et al., 2013). The results of the model accuracy analysis should help model developers and forecasters understand how a NWP model performs in weather forecasts for the South Central climate region and find ways to address deficiencies. This study focuses on verifying the prediction of precipitation, which is one of the most important variables in weather forecasting.

Quantitative precipitation forecasts (QPFs) can be verified by traditional (or standard) or spatial techniques (Casati et al., 2008). The former only focuses on calculating one or more verification scores or error measure criteria over an observation-forecast dataset at observation station sites or onto grids. Standard techniques are useful in demonstrating forecast model performance at station or grid sites, but they do not often explain spatial correlations and cannot easily account for meaningful physical terms (Casati et al., 2008). In addition, spatial techniques have been increasingly developed over approximately the last 20 years and designed to account for the spatial structures of rain events. These approaches explain the spatial nature of the QPF field and take into account the physical nature of the predicted error, adding new and supplementary information to the standard methods. In addition, it may be helpful to initially evaluate the accuracy of streamflow predictions before running hydrological models. The Contiguous Rain Area (CRA) approach is representative of this kind of method.

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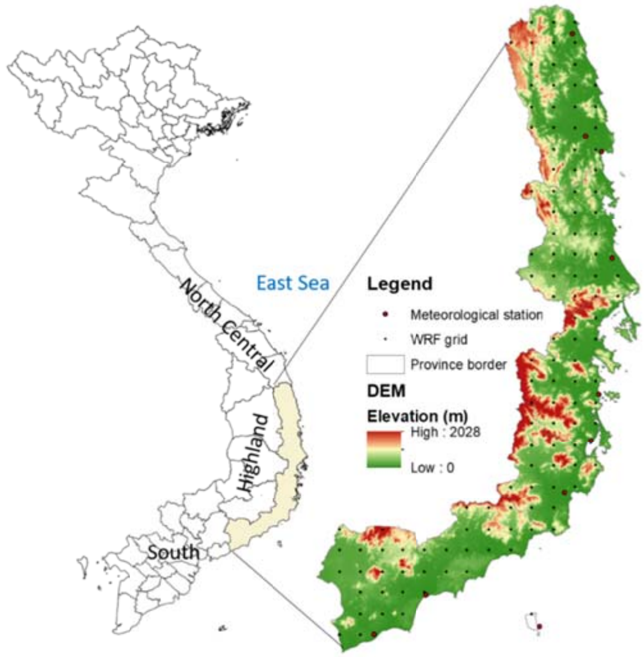


Figure 1. Map of study area and location of meteorological stations.

Over the past decades, several studies have been conducted to verify the accuracy of rain forecasts by applying traditional verification techniques (e.g., Ran et al., 2018; Song et al., 2019; Nguyen and Bae, 2019; Wilks, 2006) and spatial verification methods (e.g., Bytheway and Kummero, 2015; Chen et al., 2018; Hu et al., 2019; Ebert and McBride, 2000; Gofa et al., 2018; Weusthoff et al., 2010). These studies only focused on analyzing the performance of the NWP model by either a traditional or spatial verification method, without applying both of them. Verification using both approaches would provide an overview and a detailed picture of how a NWP model performs in predicting precipitation in a domain.

This study aims to investigate the performance of an NWP model for rain forecasts in south-central Vietnam by analyzing the point-by-point and spatial structure accuracy of rain events. The traditional method was applied to analyze the accuracy of the model station sites. For spatial rain structure investigation, the CRA method proposed by Ebert and McBride (2000) was used. Detailed descriptions of the data and methods, the results and analysis, discussions, and conclusions are provided in the sections below.

2. Data and methods

2-1. Data

The rainfall forecasts from the Weather Research and Forecasting (WRF) model derived from the Vietnam Meteorological and Hydrological Administration (VNMHA) were prepared for verification in this study. The model produced deterministic precipitation forecasts four times a day with a spatial resolution of 15 km, temporal resolution of 6 h, and prediction for 72 h in advance. The WRF model covers 0°N ~ 26°N and 100°E ~ 130°E as its domain (Figure 2) and uses Global Forecast System (GFS) model outputs, which are products of the National Centers for Environment Prediction (NCEP) and have a spatial resolution of 0.5°x0.5°, as boundary conditions. Notably, because of the limited hard disk space in the VNMHA, model products have been only saved since 2014, with up to a 60-hour advance forecast at 12 UTC and 00 UTC. These data were used in association with the 6-hour accumulated observation rainfall data from 10 meteorological stations, which were obtained from the VNMHA, to perform the verification.

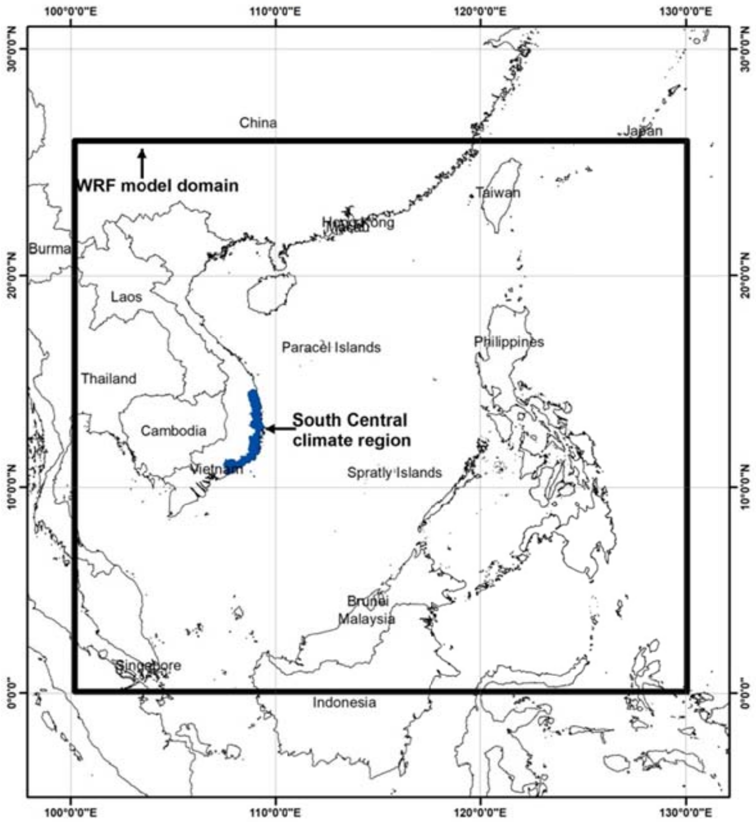


Figure 2. WRF model domain and location of the South Central climate region in the domain.

2-2. Traditional verification method

The accuracy of rainfall forecasting is evaluated in terms of qualitative and quantitative skills. The former indicates the success of forecasts in terms of rainfall occurrence, whereas the latter shows the accuracy of forecasts in terms of rainfall magnitude. Model scores containing proportion correct (PC), critical success index (CSI), bias ratio (BR), and false alarm ratio (FAR) are used to evaluate the qualitative performance of a model. At the same time, measured error criteria consisting of Root Mean Square Error (RMSE), Mean Error (ME), Mean Absolute Error (MAE), and Correlation Coefficient (CC) are calculated to illustrate the quantitative performance of a model. The purpose and calculation of each score and measured error criteria are as follows:

$$PC_{t,s,k} = \frac{a_{t,s,k}+d_{t,s,k}}{a_{t,s,k}+b_{t,s,k}+c_{t,s,k}+d_{t,s,k}} \quad (1)$$

where a, b, c, and d are the total number of hit, false alarm, miss event, and correct rejection, respectively. These parameters are determined by using a 2×2 contingency table (Table 1). The subscripts t, s, and k denote the evaluated time, station, and lead time, respectively. The PC score demonstrates the success of the NWP model in forecasting rainfall occurrence. Values of PC range from 0 to 1; if the PC value is equal to 1, then, the model performance is very accurate.

Table 1. 2×2 contingency table.

		Forecast	
		Yes	No
Observation	Yes	a (hit)	b (miss)
	No	c (false alarm)	d (correct rejection)

$$\mathrm{CSI}_{t,s,k} = \frac{a_{t,s,k}}{a_{t,s,k}+b_{t,s,k}+c_{t,s,k}} \quad (2)$$

The CSI score evaluates the fraction of observed and/or predicted events that were accurately forecasted. The values of CSI are in the range of 0 to 1. If the CSI is equal to 0, then, the model does not perform; otherwise, if CSI tends to 1, then, the model performs perfectly.

$$BR_{t,s,k} = \frac{a_{t,s,k}+b_{t,s,k}}{a_{t,s,k}+c_{t,s,k}} \quad (3)$$

The BR score evaluates the proportion of the frequency of predicted events to the frequency of observed events. Its values range between 0 and infinity, and a value of 1 indicates that the model performs very well. It shows whether the forecast system tends to underforecast (Bias less than 1) or overforecast (bias greater than 1) events.

$$FAR_{t,s,k} = \frac{b_{t,s,k}}{a_{t,s,k}+b_{t,s,k}} \quad (4)$$

The FAR score evaluates the fraction of forecasted events that are false alarms. The forecast should be accurate if FAR tends to 0. The RMSE criteria indicate how concentrated the data are around the best fit line.

$$RMSE_{t,s,k} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(RF_{t,s,k,i} - RO_{t,s,i}\right)^2} \quad (5)$$

where RF and RO are forecasted and observed rainfall, respectively; i is the time step; and n is the total number of time steps. Values of RMSE range from 0 - +∞; if RMSE is close to 0, then, the forecast is very good.

$$ME_{t,s,k} = \frac{1}{n}\sum_{i=1}^{n}(RF_{t,s,k,i} - RO_{t,s,k,i}) \quad (6)$$

The ME shows the difference between the forecast and actual rainfall and indicates whether the forecast is overestimated or underestimated.

$$MAE_{t,s,k} = \frac{1}{n}\sum_{i=1}^{n}\left|RF_{t,s,k,i} - RO_{t,s,k,i}\right| \quad (7)$$

The MAE is utilized to estimate the difference between the forecasted rainfall and the observed rainfall amounts and shows how large an error can be expected from the forecast on average.

$$CC_{t,s,k} = \frac{\sum_{i=1}^{n}(RF_{t,s,k,i}-\overline{RF}_{t,s,k})(\mathrm{R}O_{t,s,k,i}-\overline{RO}_{t,s,k})}{\sqrt{\sum_{i=1}^{n}(RF_{t,s,k,i}-\overline{RF}_{t,s,k})^2}\sqrt{\sum_{i=1}^{n}(\mathrm{R}O_{t,s,k,i}-\overline{RO}_{t,s,k})^2}} \quad (8)$$

where the overbar denotes the mean value.

2-3. CRA verification method

The CRA method, which was first proposed by Ebert and McBride (2000), defines a rain system as an area of contiguous forecasted and observed rainfall enclosed within a particular isohyet. Thus, the accuracy of a rain event would be defined in terms of rainfall intensity, location, and extent.

To evaluate the qualitative performance of rain forecasts, a 2×3 contingency table was proposed (Table 2). The table shows the accuracy of precipitation prediction according to the maximum rain rate and its location. In the table, the performance of the NWP model is classified into six categories: 1) underestimate, if the distance between the forecast and observed maximum rain rates is small but the forecast is too small compared to the observation; 2) hit, if the distance is small and the rain rates are approximately equal to each other; 3) overestimate, if the distance is small but the forecast is too much; 4) missed event, if the distance is far and the rain rate is too little; 5) missed location, if the distance is far but the rain rates are approximately similar; and 6) false alarm, if the distance is far and the maximum rain rate is too much. Ebert and McBride (2000) defined a close location as lower than 2° longitude/latitude or effective radius of the observed rainfall system, whereas a good forecast of maximum rain rate should be within a category of the observed value (1-2, 2-5, 5-10, 25-50, 50-100, 100-150, 150-200, and >200 mm).

Table 2. 2×3 contingency table.

		Forecast maximum rain rate		
		Too little	Approx. correct	Too much
Displacement of forecast rain pattern	Close	Underestimate	Hit	Overestimate
	Far	Missed Event	Missed Location	False Alarm

Source: Ebert and McBride (2000)

For quantitative verification, Mean Square Error (MSE) is used to define the best fit of the forecast to the observation (Ebert and McBride, 2000). The QPFs error sources are decomposed into displacement, volume, and pattern errors. The displacement indicates the errors due to mislocation, the volume represents the errors caused by the differences between the forecasted and observed rain rates, and the pattern shows the differences in the shape and structure. The total MSE is calculated as:

$$MSE_{total} = MSE_{displacement} + MSE_{volume} + MSE_{pattern} \quad (9)$$

where MSE_{total} is calculated as:

$$MSE_{total} = \frac{1}{NGR}\sum_{g=1}^{ngr}\left(RF_g - RO_g\right) \quad (10)$$

where *ngr* is the number of grids in the verification domain.

After displacement, the rain entity is shifted to a zero displacement position. The MSE is recalculated as:

$$MSE_{shift} = \frac{1}{NGR}\sum_{g=1}^{ngr}\left(RF'_g - RO_g\right) \quad (11)$$

where RF' is the shifted rainfall forecast. The difference between the MSE before and after the shift is the displacement error.

$$MSE_{displacement} = MSE_{total} - MSE_{shift} \quad (12)$$

The remaining error components are calculated as:

$$MSE_{volume} = (\overline{RF'} - \overline{RO})^2 \quad (13)$$

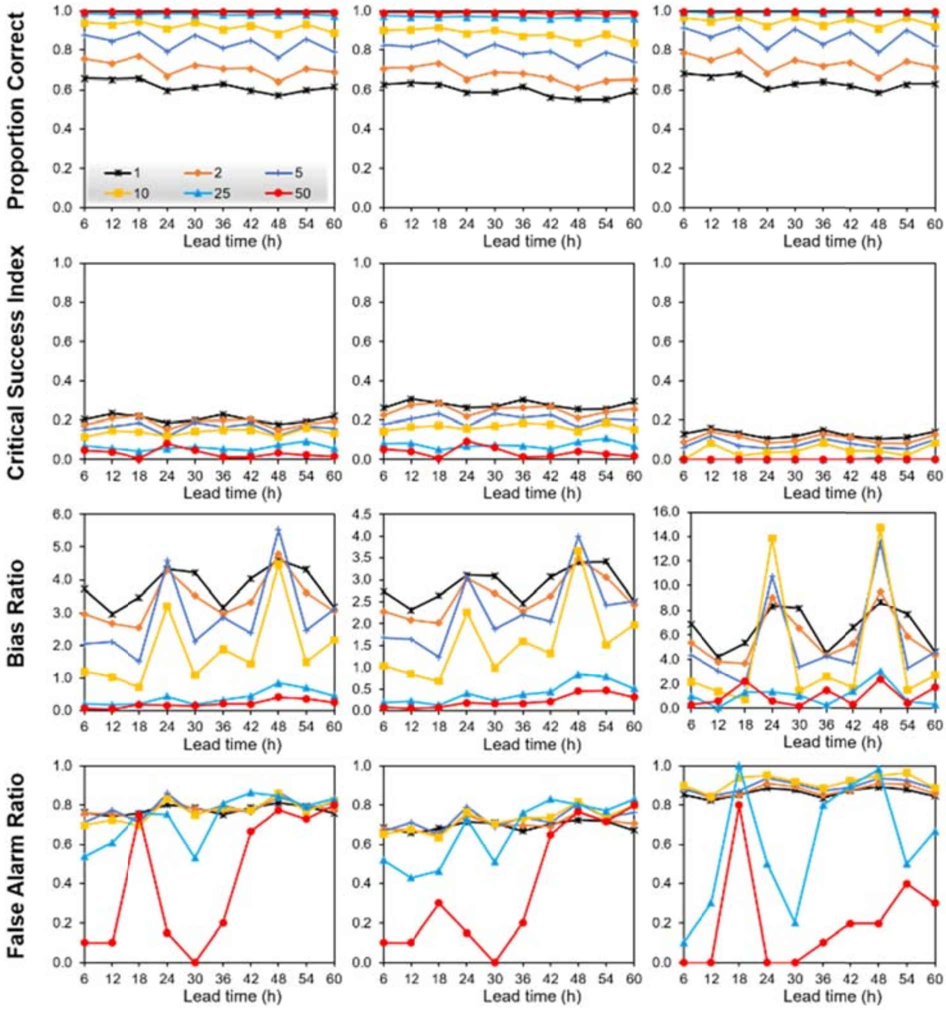
$$MSE_{pattern} = MSE_{shift} - MSE_{volume} \quad (14)$$

3. Results and discussion

3-1. Traditional verification

The WRF rainfall forecasts were verified point-by-point for the whole year and in the flood and dry seasons at each lead time (from 6 h to 60 h) with different rainfall thresholds (<1, 1-5, 5-10, 10-25, 25-50, 50-100, and >100 mm). The measured error criteria were also calculated when there was no consideration of the rainfall threshold. This approach was implemented to investigate the variation in the model performance following the various weather situations. Because the spatial distributions of the forecasted and observed rainfall did not match, an Inverse Distance Weighting (IDW) method was applied to transform the predicted rainfall from grid to station sites. The model scores and measured error criteria were calculated for each station and then averaged over the domain to show the model performance for the study region. The performance of the WRF model for south-central of Vietnam are shown in Figure 3 and Figure 4. The analysis of each performance is as follows:

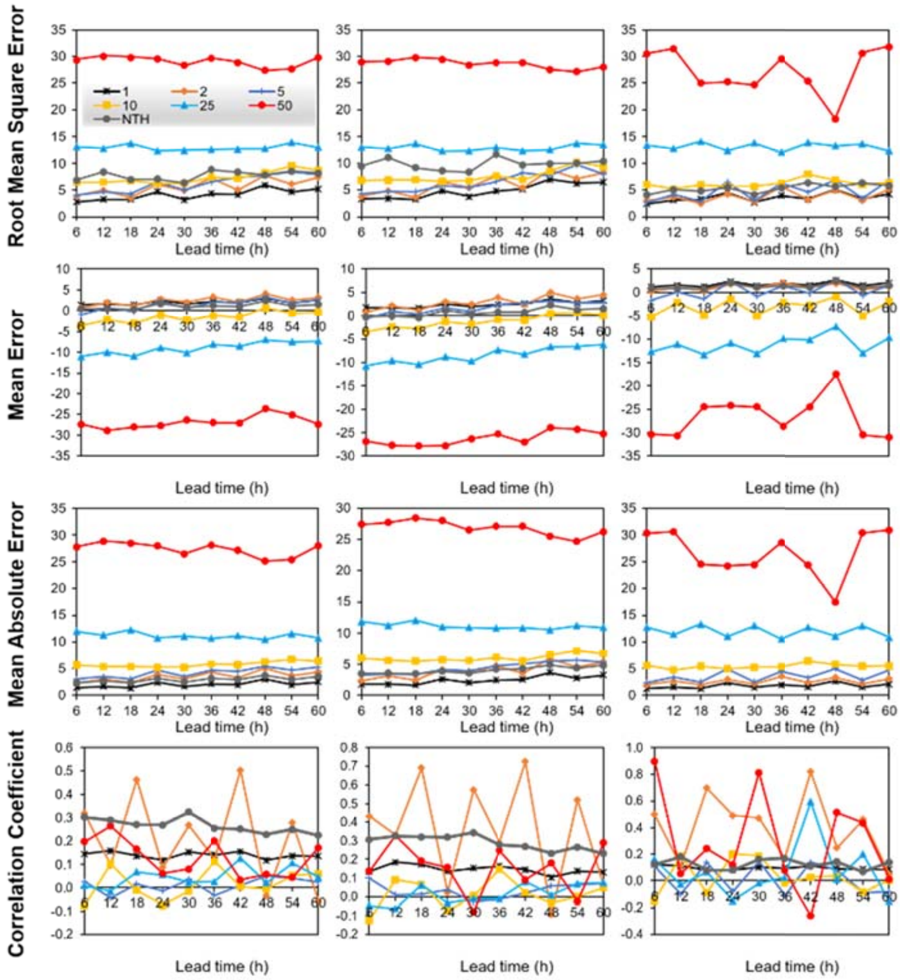
For the qualitative performance, the WRF model performed well in predicting rain occurrence/nonoccurrence, with PC values greater than 0.6 over all thresholds for the three cases considered (whole year and flood and dry seasons). A relatively higher performance was indicated by the increase in rainfall threshold value. This was explained by the increase in the correct rejection (*d*) when the threshold value increased. In contrast, the model prediction did not perform well during rain events with CSI values lower than 0.3, a BS far from 1.0, and a FAR close to 1. The WRF performance during rain events decreased when the rainfall threshold value increased. According to lead time, the accuracy of the QPFs decreased when the lead time was longer. Specifically, the PC and CSI values for a threshold of 1 mm for 6 h ahead were 0.66 and 0.20, respectively, and these values slightly decreased to 0.59 and 0.19, respectively, for 24 h ahead and reached their lowest values of 0.57 and 0.18, respectively, for 48 h ahead. The values of BS and FAR displayed the contrasting trends in the PC and CSI, which indicated a decrease in the accuracy according to the increase in lead times. Similar trends were also demonstrated for the other thresholds. With respect to the seasonal analysis, the WRF model performance for the dry season was better than that for the rainy season in terms of forecasting the occurrence of rain with higher PC values. However, during the rain event periods, the model prediction for the wet season performed relatively better with better values of CSI, BS and FAR.



(a) (b) (c)

Figure 3. Variations in the WRF model scores according to the increase in lead times and different rainfall thresholds for: a) year, b) flood season, and c) dry season. The black line with the star maker, the orange line with the circle maker, the blue line with the plus maker, the yellow line with the square maker, the light blue line with the triangle maker, and the red line with the circle maker denote the model scores for thresholds of 1 mm, 2 mm, 5 mm, 10 mm, 25 mm, and 50 mm, respectively.

For the quantitative performance, the WRF model performance was very different between the low (<10 mm) and high (>25 mm) thresholds. The RMSE values for thresholds under 10 mm were lower than 8 mm/6 h, generally at approximately 12 - 13 mm/6 h for the 25 mm threshold, and greater than 29 mm/6 h for thresholds over 50 mm. The WRF QPFs were overestimated for thresholds under 5 mm but indicated an underestimation with higher thresholds, especially for thresholds higher than 50 mm. The difference in the CC values among the thresholds was obvious, but the variations in addition to the lead times were irregular. The reasons are unknown and will be determined in further studies. All measured error criteria also showed a decreasing trend in the WRF model performance according to the increase in lead times. The difference in the accuracy was not substantial among the whole year and flood and dry seasons.



(a) (b) (c)

Figure 4. Similar to Figure 2 but for the measured error criteria and the inclusion of not considered rainfall threshold (NTH).

3-2. CRA verification

A total of 5881 CRAs were considered for verification in this study. The number of CRAs was defined based on the number of rain events occurring from 2014 to 2018 and considered for the 10 different lead time groups (from 6 to 60 h). To date, there have been no criteria to define the distance between the forecasted and observed maximum precipitation intensities as near or far. In this study, the distances in the range of 0 - 100 km were defined as close. This accepted distance was obtained after discussions with forecasters in VNMHA. The model performance for all rain thresholds according to the spatial verification is shown in Table 3 and Figure 5. In general, the qualitative performance was relatively poor, with only 10% (614 CRAs) of the hit forecasts and 44% (2575 CRAs) of the missed events and locations. However, the difference in the location was acceptable, with 43% (2524 CRAs) of the locations of the forecast maximum rain intensity being close to those of the observations. For the quantitative performance, the location error was acceptable. The distance between the two maximum points averaged over all CRAs was approximately 91.2 km, which is lower than the acceptance distance in this study. This explains why the displacement error only contributed 13% (7.18 mm/h) to the total error. The main contribution to the QPFs error was the pattern component at 53%, followed by the error in volume at 34%.

Table 3. Averaged MSE, percentage of error due to components and location error.

	Total	Displacement	Volume	Pattern
MSE due to (mm^2/6 h)	55.23	7.18	18.72	29.33
MSE due to (%)	100%	13%	34%	53%
Location error (km)	91.2			

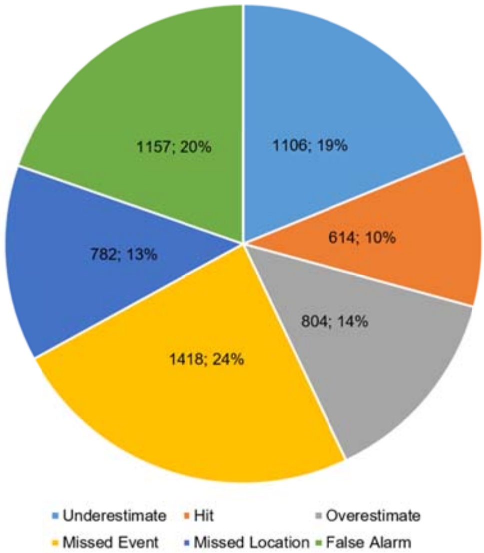


Figure 5. Qualitative verification of the WRF model following the CRA method.

The variations in the categories according to the increase in lead times are shown in Figure 6. The hit, overestimation, missed location and false alarm categories had increasing trends with positive slope parameters, whereas the underestimated and missed event categories tended to decrease with negative slope parameters. These results imply that the WRF model tended to predict a relatively higher amount of precipitation at longer lead times for the South Central climate region of Vietnam. This finding provides useful information for model developers to improve the performance of the NWP model in weather forecasts for the region.

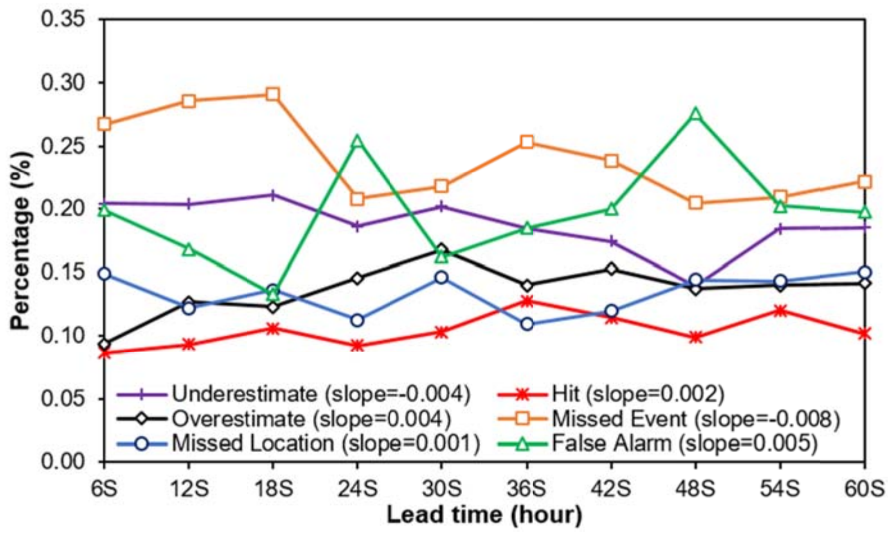


Figure 6. Variations in the percentage of categories following the lead times.

To clarify the effects of selecting the acceptance distance on the verification results, a comparative analysis was performed for the three different distances, specifically 25 km, 50 km, and 100 km. Figures 7 to 9 illustrate the WRF model verification results over the South Central region for 6-h, 24-h, and 48-h lead times, respectively, according to the three acceptance distances over the rainfall thresholds of 5 mm, 10 mm, 25 mm, and 50 mm. The results showed that the number of underestimated, hit, and overestimated events increased at all lead times and all rainfall thresholds when we increased the acceptance distance. In contrast, decreasing trends in missed events, missed locations, and false alarm events occurred. With respect to the variation in the rainfall threshold, the missed event and underestimate events increased at all lead times and acceptance distances when the rainfall thresholds were higher, whereas the hit, overestimate, false alarm, and missed location events decreased. These results indicated that precipitation predictions by the WRF model for the South Central region during heavy rain events were not as good as those during light rain events. This suggests that model developers should pay more attention to enhance the performance of the NWP model during convective events.

5 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 5	H 6	O 1
Far	ME 34	ML 33	FA 59

10 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 6	H 6	O 2
Far	ME 42	ML 20	FA 30

25 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 15	H 1	O 0
Far	ME 62	ML 42	FA 12

50 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 8	H 0	O 0
Far	ME 43	ML 14	FA 2

5 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 8	H 8	O 2
Far	ME 31	ML 31	FA 58

10 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 7	H 6	O 4
Far	ME 41	ML 20	FA 28

25 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 19	H 5	O 0
Far	ME 58	ML 38	FA 12

50 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 10	H 0	O 0
Far	ME 41	ML 14	FA 2

5 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 16	H 14	O 17
Far	ME 23	ML 25	FA 43

10 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 22	H 11	O 11
Far	ME 26	ML 15	FA 21

25 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 35	H 15	O 0
Far	ME 42	ML 28	FA 12

50 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 19	H 4	O 0
Far	ME 32	ML 10	FA 2

Figure 7. CRA verification of the WRF model for the 6-h lead time according to the variations in the rainfall threshold and acceptance distance over the south-central region of Vietnam. The abbreviations U, H, O, ME, ML, and FA denote underestimate, hit, overestimate, missed event, missed location, and false alarm, respectively.

5 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 8	H 3	O 6
Far	ME 21	ML 23	FA 76

10 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 7	H 2	O 3
Far	ME 23	ML 14	FA 48

25 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 7	H 8	O 1
Far	ME 49	ML 37	FA 18

50 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 17	H 1	O 1
Far	ME 43	ML 11	FA 2

5 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 9	H 3	O 7
Far	ME 20	ML 23	FA 75

10 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 7	H 2	O 6
Far	ME 23	ML 14	FA 45

25 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 9	H 10	O 2
Far	ME 47	ML 35	FA 17

50 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 19	H 3	O 1
Far	ME 46	ML 9	FA 2

5 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 13	H 9	O 27
Far	ME 16	ML 17	FA 55

10 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 15	H 4	O 25
Far	ME 15	ML 12	FA 26

25 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 20	H 24	O 6
Far	ME 36	ML 21	FA 13

50 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 37	H 7	O 1
Far	ME 28	ML 5	FA 2

Figure 8. Similar to Figure 6 but for the 24-h lead time.

5 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 5	H 4	O 6
Far	ME 16	ML 24	FA 78

10 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 11	H 3	O 1
Far	ME 23	ML 17	FA 54

25 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 3	H 6	O 2
Far	ME 37	ML 53	FA 22

50 mm, 25 km

	Too litte	Approx. correct	Too much
Close	U 9	H 3	O 1
Far	ME 43	ML 15	FA 2

5 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 5	H 5	O 10
Far	ME 16	ML 23	FA 74

10 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 12	H 4	O 3
Far	ME 22	ML 16	FA 52

25 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 5	H 7	O 2
Far	ME 35	ML 52	FA 22

50 mm, 50 km

	Too litte	Approx. correct	Too much
Close	U 13	H 5	O 1
Far	ME 39	ML 13	FA 2

5 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 8	H 7	O 26
Far	ME 13	ML 21	FA 58

10 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 15	H 11	O 22
Far	ME 19	ML 9	FA 33

25 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 13	H 24	O 5
Far	ME 27	ML 35	FA 19

50 mm, 100 km

	Too litte	Approx. correct	Too much
Close	U 22	H 10	O 3
Far	ME 30	ML 8	FA 0

Figure 9. Similar to Figure 6 but for the 48-h lead time.

3-3. Discussion

In general, the WRF model performance for south-central of Vietnam was relatively poor during rain events with low CSI values and high BS and FAR values despite the high percentage of rejected corrections and relatively low RMSE and ME values. The proportion of hit forecasts decreased from 30% with the traditional verification method to 10% with the spatial structure verification method. This should cause large errors and high uncertainty in hydrological predictions and may lead to a lack of forecast effectiveness for mitigating the damage from natural disasters. The reasons for this low accuracy were mainly as follows: 1) the spatial resolution of the WRF model was relatively coarse (15 km), 2) the model was conducted without data assimilation, and 3) the South Central climate region was only a small area in the WRF domain, which results in a lower accuracy than when verification is performed for the whole domain, as it is a very large region (Robert, 2008). Thus, since March 2019, the VNMHA has started operating various models for different purposes. The WRF model used for verification in this study was launched operationally with a higher resolution at 9 km and a higher ensemble prediction (10 km). In addition, a WRF model with a 3-km spatial resolution and the Integrated Forecast System (IFS) used as boundary conditions was launched. Further study needs to be conducted to verify these models after the historical forecast data are long enough.

4. Summary and Conclusions

This study was conducted to analyze the accuracy of WRF model rainfall forecasts for the south-central climate region of Vietnam. The analysis was performed with respect to grid sites and the spatial structure of rain events in terms of both qualitative and quantitative performances with different rainfall thresholds for a whole year and in the flood and dry seasons. The results of this study led to the following conclusions:

- The WRF model detects the occurrence/nonoccurrence of rain well, but the model performance during rain events is relatively limited.
- The model error magnitude was not high, with values of RMSE and MAE for not considering rainfall thresholds lower than 10 mm/6 hour.
- The performance of the WRF model decreased substantially according to the increases in rainfall threshold value and lead time.
- Rainfall forecasts by the WRF model were overestimated for rainfall thresholds under 5 mm and underestimated for the higher thresholds.
- Only 10% of the rain events forecasted matched the observations for both the rain threshold categories and locations. However, the prediction of the locations of maximum precipitation intensity was acceptable, with 43% correct.
- The pattern error accounted for 53% of the total error, followed by the intensity error account for 34% of the total error. The location error contributed the lowest percentage to the total error. This was because the distance between the two maximum points averaged over all CRAs was approximately 91.2 km, which was much lower than the radius of the domain (239.5 km).
- The performance of the WRF model in predicting precipitation for the south-central region of Vietnam was relatively better at the lower rainfall thresholds.
- The spatial verification results were highly dependent on the selection of the acceptance distance that was used to define the location of the maximum rain intensity of the accurate forecast.
- The proportion of hit forecasts decreased from 30% with the traditional verification method to 10% with the CRA verification method. This should cause large errors and high uncertainty in hydrological predictions and may lead to a lack of forecast effectiveness for mitigating the damage from natural disasters.

The results in this study provide very useful information for model developers to improve the performance of the WRF model in terms of weather predictions for the south-central climate region of Vietnam. The results also indicate the need to improve the NWP forecast systems in Vietnam. Therefore, since March 2019, the VNMHA has been launching various operational models for different purposes to address the issues mentioned above. Further study will be employed to verify the operational models after the historical forecast data are sufficiently long.

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