JOURNAL OF
HYDRO-METEOROLOGY

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Research Article

Improving skill precipitation forecast of the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecasting System (IFS) model by using the quantile mapping method for Central Vietnam

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Received: 28 December 2024; Accepted: 05 February 2025; Published: 25 March 2025

Abstract: The research employs the Quantile Mapping (QM) post-processing method to improve the skill forecasts of the deterministic forecast of the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecasting System (IFS). The selected research areais Central Vietnam, and the analysis utilizes observation data from 41 stations and 10-year ECMWF-IFS data from 2013 to 2022, with a lead time of up to 10 days for the QM applications. The findings indicate that the QM facilitates enhanced forecasting skills in the IFS model for all lead times up to 10 days, exhibiting varying magnitudes based on the specific lead time and rainfall thresholds. Notably, the impact of QM is found to be negligible for heavy rainfall events, with the skill limit being determined as insignificant for lead times up to 72 hours in summer and 144 hours in winter.

Keywords: Quantile Mapping; the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecasting System (IFS); Skill precipitation forecast.

1. Introduction

Statistical evidence from the last two decades indicates that the substantial floods that occurred in November and December 1999 in Central Vietnam engulfed hundreds of villages, resulting in significant fatalities and substantial material losses. In 1999, within a period of just over one month (from 1 November to 6 December), two extremely heavy rainfall events occurred in most provinces of Central Vietnam, causing two rare floods in a substantial area. The consequences of these events were devastating, with over 700 fatalities, almost 500 injuries, and tens of thousands of households losing their homes and assets. The economic impact was estimated at almost 5,000 billion VND, far exceeding the level of damage that occurred in 1996. It is evident that the primary cause of these natural disasters in Central Vietnam is flooding, primarily triggered by heavy rain events. Consequently, the accurate prediction of precipitation in Central Vietnam is imperative for effective disaster prevention and mitigation strategies. In recent decades, the utilisation of rain forecast products derived from numerical weather forecast systems, encompassing both deterministic and ensemble prediction methodologies, has become a prevalent component of daily operations on both global and regional scales. A substantial volume of applied research and development on rain forecast technologies for Central Vietnam has been undertaken over the past decade [1–5]. Findings of these studies have indicated that the rain forecast problem in Central Vietnam, particularly the heavy rain forecast, remains challenging and necessitates technological advancements to enhance the quality of forecasts and satisfy societal needs.

To enhance the weather forecasting capabilities in Vietnam from a short to seasonal scale, the products and dataset of the globally integrated forecast system (IFS) of the European Centre for Medium-Range Weather Forecast (ECMWF) have been procured and utilised in daily operations at Vietnamese weather forecast offices from national to provincial levels. A number of studies have been conducted on the assessment of model skills, including the IFS model [3, 6, 7]. These studies primarily focused on evaluating the skill in forecasting rainfall, and the findings revealed that both the validation of station-based and spatial-based models indicated a deficiency in their ability to predict high thresholds, such as heavy and very heavy rainfall, when it comes to 24-hour accumulated rainfall forecasts [7]. The IFS model has demonstrated superior forecasting capabilities in comparison to other models. However, it has been observed that all models underestimate the occurrence of extreme heavy rainfall events [3]. With regard to the forecast of rainfall quantity, the IFS model demonstrates proficiency for 24- to 48-hour lead times, though its efficacy is reduced at 72-hour lead times. Nonetheless, the IFS model exhibits competence in several instances of heavy rainfall [6].

Numerical weather prediction (NWP) models employ estimates and assumptions to predict future weather phenomena. Notwithstanding, these models are prone to certain drawbacks stemming from their structural design and parametrization. Such limitations can lead to less precise weather forecasts, which, in turn, can propagate errors into the forecasting system and, consequently, compromise the accuracy of rainfall forecasts [12]. A considerable number of studies have documented the effectiveness of statistical post-processing in improving the precision of weather forecasts. The implementation of weather post-processing methodologies entails the adjustment of the mean and variance of forecasts, thereby ensuring a more precise alignment with the distribution of observed data [13]. Statistical post-processing has emerged as a significant tool for reducing errors in deterministic and ensemble forecasts, given its computational efficiency and capacity to handle a large number of forecasts, encompassing all ensemble members and lead times [14]. The objective of statistical post-processing is to minimise simulation errors by adjusting model output based on observations. This methodology has been extensively utilised in climate research [14] and in the field of weather forecasting [15].

In the field of atmospheric science, two distinct post-processing methodologies are employed. These post-processing methodologies frequently involve a process of downscaling. The first category comprises Perfect Prog methods, which entail the establishment of statistical correlations between observed predictors and observed predictands, subsequently applied to model output. The second category encompasses Model Output Statistics (MOS) methods, wherein links between simulated predictors and observed predictands are established. The former method is frequently employed to establish links between large-scale atmospheric states and local or regional meteorological variables, while the latter is predominantly utilised to link the same physical variables on analogous spatial scales. However, a moderate downscaling step is often incorporated into the approach. The context of weather forecasting, MOS is the preferred approach.

Quantile mapping (QM) is the most commonly used MOS method for postprocessing weather forecasts [13, 16–18]. It involves adjusting the raw weather forecast so that it matches the distribution of the observations. QM improves the accuracy of the forecast by ensuring greater consistency with historical observations. It is considered to be one of the more flexible bias correction methods, which attempt to adjust the variance of the model distribution in order to better match the observed variance [14]. In the context of post-processing of rainfall forecasts, the QM method involves the implementation of a quantile-specific correction factor to the forecast rainfall distribution. This ensures that the forecast aligns with the observed actual distribution. As demonstrated by [19], the QM technique effectively eliminates the systematic bias in the CFSv2 reforecasts. In a distinct study [20] conducted a comparative analysis of various downscaling and error correction methods. Their analysis concluded that the QM method exhibited the optimal performance for the purpose of daily precipitation estimation. In their seminal work [21] pioneered the evaluation of a post-processing technique for bias correction in four meteorological variables, namely, temperature, precipitation, relative humidity, and wind speed. Their findings signalled the efficacy of QM in mitigating biases, both annual and monthly, to almost undetectable levels for all variables, with precipitation exhibiting the most substantial enhancement. Precipitation is widely recognised as the input data with the greatest source of uncertainty [22–24].

The objective of this study is to enhance the precision of daily rainfall forecasts at all stations in Central Vietnam. To this end, the Quantile Mapping post-processing method is employed to refine the deterministic forecast of the IFS model provided by the ECMWF. The subsequent section delineates the study area and the methodologies employed to investigate this matter. Section 3 presents the obtained results, and finally, Section 4 provides concluding remarks.

2. Data and methods

2.1. Observational precipitation data and the ECMWF-IFS data

The study area was selected is Central Vietnam, the area is 151.234 km² consisting of 14 provinces. In the research, the authors utilise observation data from 41 stations in order to verify the model data. The spatial distribution of all local observations is illustrated in Figure 1a, and the information of each station is presented in Table 1. Of these 41 stations, it is reported that only approximately 21 stations are reported to WMO every six hours.

Regarding to the ECMWF-IFS data, wwith the license, ECMWF will send the raw limited domain data (covering Southeast Asia) to the National Center for Hydro-Meteorological Forecasting’s (NCHMF) ftp-servers. The gridded data will be interpolated to station locations (Table1) for further processing. The efficacy of this technique is evaluated through the utilisation of 10-year multi-year from 2013-2022 with a lead time of up to 10 days. An additional validation for heavy rainfall events will be carried out and listed in Table 2.

Table 1. Information about synoptic stations at Central Vietnam.

Station Name	Code	Station Name	Code
Hoi Xuan	48842	Nam Dong	48/92
Yen Dinh	48/67	Da Nang	48855
Sam Son	48/68	Tam Ky	48/93
Bai Thuong	48/69	Tra My	48/94
Quynh Luu	48/77	Ly Son	48/85
Do Luong	48/80	Quang Ngai	48863
Hon Ngu	48/81	Ba To	48/95
Vinh	48845	Hoai Nhon	48/96
Huong Son	48/82	An Nhon	48864
Ha Tinh	48846	Quy Nhon	48870
Huong Khe	48/84	Son Hoa	48/97
Hoanh Son	48/73	Tuy Hoa	48873
Ky Anh	48/86	Nha Trang	48877
Tuyen Hoa	48/87	Cam Ranh	48879
Dong Hoi	48848	Song Tu Tay	48892

Station Name	Code	Station Name	Code
Ba Don	48847	Phan Rang	48890
Con Co	48/89	Phan Thiet	48887
Dong Ha	48849	La Gi	48888
Khe Sanh	48/90	Phu Quy	48889
Hue	48852	Phan Ri	48891
A Luoi	48/91		

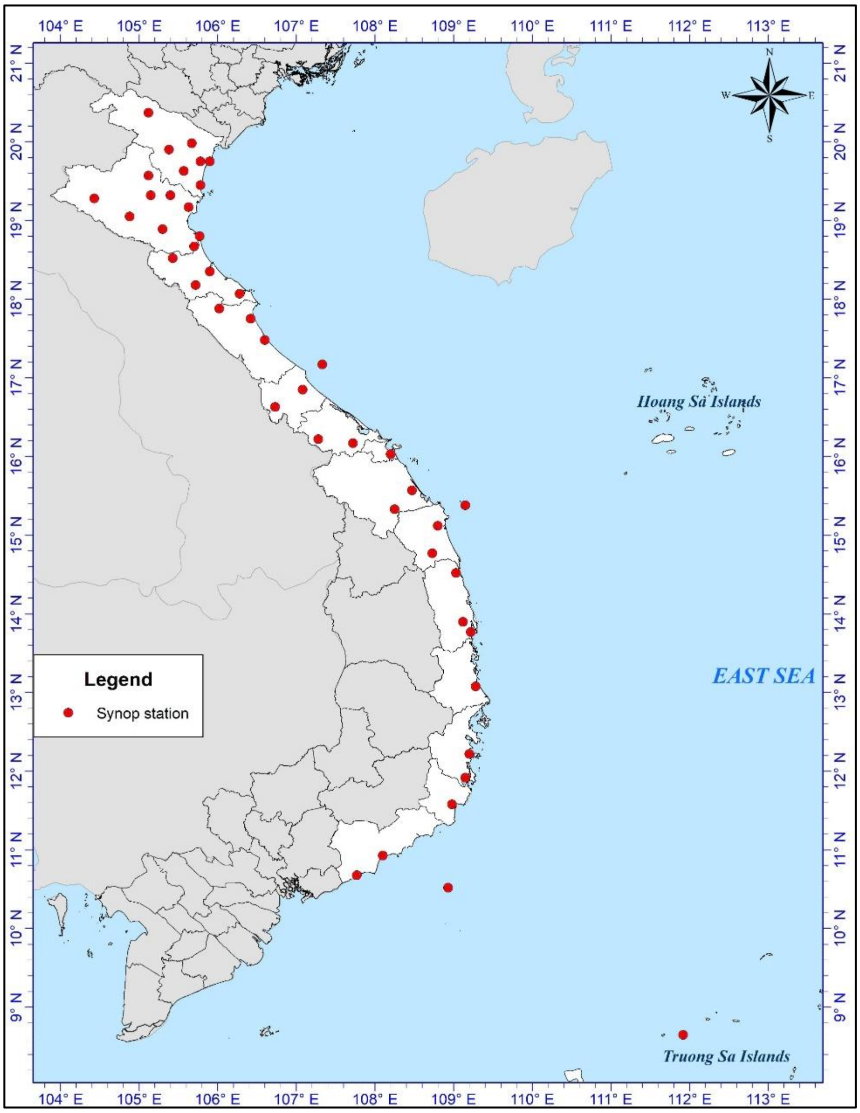

Figure 1. The spatial distribution of all synoptic stations in Central Vietnam.

Table 2. Information of heavy rainfall events in Central Vienam in 2023.

Index	Period	Reason caused heay rainfall	Rainfall intensity
1	14-16/02/2023	The combination of cold surges and the tropical easterly disturbances at the level of 850mb	The accumulated rainfall is typically 60-120 mm, although in some locations it has been recorded to exceed 140 mm.
2	10-12/05/2023	The interaction between the monsoon trough and the cold surges	The accumulated rainfall is typically 60-120 mm, although in some locations it has been recorded to exceed 150 mm.
3	22-27/06/2023	The combination of the trough and convergence at the level of 500mb	The accumulated rainfall is typically 80-180 mm, although in some locations it has been recorded to exceed 200 mm.

Index	Period	Reason caused heay rainfall	Rainfall intensity
4	31/07-05/08/2023	The combination of the trough and convergence at the level of 500mb	The accumulated rainfall is typically 60-120 mm, although in some locations it has been recorded to exceed 130 mm.
5	15-17/09/2023	The interaction between the monsoon trough and the cold surges	The accumulated rainfall is typically 70-130 mm, although in some locations it has been recorded to exceed 150 mm.
6	24-29/09/2023	The interaction between the ITCZ and the cold surges	The accumulated rainfall in the North Centre is typically 300-500 mm. The accumulated rainfall in the other area is typically 100-300 mm.
7	11-18/10/2023	The combination of cold surges and the tropical easterly disturbances at the upper level	The accumulated rainfall is typically 300-500 mm. Although in some locations it has been recorded to exceed 1000 mm.
8	23-24/10/2023	The combination of cold surges and the tropical easterly disturbances at the upper level	The accumulated rainfall is typically 100-200 mm. Although in some locations it has been recorded to exceed 300 mm.
9	29-31/10/2023	The combination of cold surges and the tropical easterly disturbances at the upper level	The accumulated rainfall in the North Centre is typically 250-450 mm. The accumulated rainfall in the other area is typically 70-150 mm.
10	13-17/11/2023	The combination of cold surges and the tropical easterly disturbances at the upper level	The accumulated rainfall is typically 200-400 mm. Although in some locations it has been recorded to exceed 500 mm.
11	25-26/11/2023	The combination of cold surges and the tropical easterly disturbances at the upper level	The accumulated rainfall is typically 60-120 mm. Although in some locations it has been recorded to exceed 130 mm.
12	20-22/12/2023	The combination of cold surges and the tropical depression	The accumulated rainfall is typically 150-3000 mm. Although in some locations it has been recorded to exceed 500 mm.

2.3. Quantile mapping post-processing method

The present study employed the QM method (see equation 1) to post-process weather forecasts and precipitation forecasts. This method involves the application of a quantile-based transformation of distributions. Specifically, it entails replacing the quantile of the present-day simulated distribution with the corresponding quantile of the present-day observed distribution [14].

$$x^{f}_{i,corr} = qD^{p}_{y}\left(pD^{p}_{x}\left(x^{f}_{i,raw}\right)\right) \quad (1)$$

In the context of the given time series, denoted "x" _"I", future simulations and derived measures are indicated with a superscript f. The quantile for a probability α of a distribution D is represented as qD(α), and is defined as the value which is exceeded with a probability 1 - α when sampling from the distribution. The probabilities corresponding to a given quantile qD(α) (i.e. the cumulative distribution function, CDF) are denoted as pD(q) = α.

For illustration, consider a station with 3,652 days of calibration data (10 years) and 365 days of validation data. In this scenario, each day includes a 10-day precipitation forecast by the IFS model with a 24-hour time step. Consequently, each day's data can be represented as a vector of length 10, and the vector of length 3,6520 for the entire calibration period. The calculation of 100 quantiles, both for observed and forecasted precipitation, results in two matrices: one for observed quantiles (qDobs) and one for simulated quantiles (qDcal), for each of the 10 lead-times. The correction factor (quantilecorr) for each quantile is subsequently determined using the following equation:

$$\text{quantile}_{\text{corr}} = \frac{\text{qD}_{\text{obs}}}{\text{qD}_{\text{cal}}} \tag{2}$$

The aforementioned procedure is then repeated for all ten-time steps, thereby resulting in a [100 × 10] matrix of correction factors. The total number of correction factors is thus equal to 1,000. The member-quantile assignment is executed in the following manner: In the event that the precipitation forecast from the IFS model exceeds the last quantile, it is allocated to the 100th quantile. Conversely, if the precipitation forecast from the IFS model corresponds to an existing quantile, it is assigned accordingly. Finally, in the event that the precipitation forecast from the IFS model does not precisely align with a quantile, it is assigned to the subsequent quantile. The quantile mapping correction is achieved by multiplying the direct forecast precipitation value from the IFS by the appropriate correction factor.

$$x_{\text{valcorr}} = x_{\text{val}} \times \text{quantile}_{\text{corr}} \tag{3}$$

where $x_{valcorr}$ is the corrected forecast value from IFS model, x_{val} is the forecast value from IFS model in the validation period, and quantilecorr is the quantile function probability of the observed distribution and simulated calibration period.

The correction factor is calculated independently for each quantile forecast, ensuring accurate adjustment of the entire forecast distribution [18, 25, 26]. Extensive research has demonstrated the efficacy of quantile-based post-processing methodologies (e.g., QM method) in enhancing the accuracy of rainfall forecasts, particularly concerning extreme rainfall events [18, 25, 26]. Despite the abundance of methods available for correcting bias in meteorological and hydrological forecasts [27, 28]. this study selected the QM correction method. This approach was selected due to the predominance of the QM correction method within the scientific community as the prevailing technique for precipitation forecast bias correction [29–33]. The QM method was applied in two distinct temporal configurations, which are outlined below.

1. Seasonal QM: The first configuration, designated as "seasonal QM", entails the implementation of the QM method in precipitation forecasts, meticulously grouped by season. The seasonal distribution of raw precipitation forecasts for each lead time is meticulously calibrated to mirror the seasonal distribution of observed precipitation (summer season: April-September; winter season: October-March).

2. Annual QM: The second configuration, termed "annual QM", involves the concurrent application of the QM method to all precipitation forecasts. The annual distribution of raw precipitation forecasts for each lead time is adjusted to match the yearly distribution of the observed precipitation.

In order to validate the effectiveness of the QM method, the approach will be implemented in two distinct periods and the results will be compared with the forecasts derived from the IFS model. The calibration period encompasses the years from 2013 to 2022, while the validation period is scheduled for 2023. Additionally, the performance of the QM method in the 2023 heavy event will be examined. The application of the QM to different temporal configurations (i.e., seasonal and annual) enables the evaluation of the performance of the post-processing method at different temporal scales and the determination of the most appropriate configuration for precipitation forecasting.In the context of this study, the distinct seasonality of rainfall in Central Vietnam is a salient feature, and the QM method with seasonal configuration predominance the annual configuration in providing the precipitation forecast. Consequently, the subsequent section will focus exclusively on the results derived from the QM method with a seasonal configuration.

3. Results

3.1. Evaluation in the year of 2023

In this section, we will evaluate the skill score of the IFS model and the IFS model applied the QM method for post-processing on forecasting rainfall in 2023, will the lead-time up to 10 days. We will use skill score TS (range from 0-1, best score at 1) and metric score RMSE (range from 0 to infinite, best score at 0) to validate the results [6, 7].

Tables 3 and 4 present the findings of the TS index skill IFS model and the IFS model applied the QM method in the summer and winter season of 2023 inCentral Vietnam for all ranges with a lead time of up to 10 days. It is evident that as the TS value increases, the QM method demonstrates its capacity to enhance the PQF, surpassing the direct forecasts from the IFS model across all precipitation ranges. During the summer season, when the threshold for heavy rainfall is set at 50-100 mm, the TS skill score undergoes a substantial decline after 72 hours, from 0.08 to 0.03 (using the IFS-applied QM method) and 0.07 to 0.02 (using the IFS model). In the winter season, when the threshold for heavy rainfall is set at 50-100 mm, the TS skill score experiences a sudden decline after 144 hours, from 0.13 to 0.08 (when the IFS QM method is applied) and from 0.10 to 0.06 (when the IFS model is employed. These findings highlight the IFS model's inadequacies in accurately capturing heavy rainfall with a lead time of up to six days in winter and three days in summer, despite the application of advanced postprocessing methods such as QM.

Table 5 provides more evidence about the performance of the IFS model and the IFS model applied QM method for post-processing through the RMSE index of all models in the summer and winter season of 2023 inCentral Vietnam. It is evident that the QM method enhances the precipitation forecast skill of the IFS model over Central Vietnam, as evidenced by the reduced value of the RMSE index in comparison to the direct forecast from the IFS model for all lead-times in both summer and winter seasons. Conversely, with TS skill score, The RMSE in winter is substantially greater than the RMSE in summer. Furthermore, the findings in Table 4 reveal a substantial increase in the RMSE index after 120 hours of lead time in winter and 144 hours of lead time in summer.

The QM method has been shown to enhance the forecasting skill of the FS model for all lead times up to 10 days. However, in the case of heavy rainfall categories, the impact of QM is negligible for lead times up to 72 hours in summer and 144 hours in winter.

Table 3. The TS index skill of the IFS model and IFS model applied the QM method in the summer of 2023 in Central Vietnam.

Lead time	**0.1- 5mm**		**5-10mm**		**10-15mm**		**15-25mm**		**25-50mm**		**50-100mm**	
Model	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**
24	0.18	0.17	0.07	0.07	0.07	0.06	0.08	0.07	0.10	0.08	0.09	0.08
48	0.19	0.17	0.07	0.06	0.05	0.04	0.08	0.06	0.10	0.08	0.08	0.07
72	0.17	0.17	0.07	0.06	0.05	0.03	0.08	0.07	0.10	0.09	0.03	0.02
96	0.18	0.17	0.08	0.06	0.04	0.03	0.06	0.06	0.09	0.07	0.03	0.02
120	0.18	0.17	0.08	0.06	0.04	0.04	0.06	0.04	0.10	0.09	0.03	0.02
144	0.17	0.17	0.06	0.04	0.05	0.04	0.06	0.05	0.08	0.04	0.03	0.02
168	0.18	0.17	0.06	0.06	0.05	0.04	0.05	0.03	0.09	0.06	0.02	0.01
192	0.18	0.16	0.06	0.05	0.03	0.03	0.05	0.04	0.08	0.06	0.04	0.03
216	0.18	0.16	0.06	0.05	0.03	0.03	0.05	0.04	0.08	0.05	0.04	0.03
240	0.18	0.16	0.06	0.04	0.03	0.02	0.05	0.04	0.06	0.05	0.0	0.0

Table 4. The TS index skill of the IFS model and IFS model applied the QM method in the winter of 2023 in CentralVietnam.

Lead time	**0.1- 5mm**		**5-10mm**		**10-15mm**		**15-25mm**		**25-50mm**		**50-100mm**	
Model	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**
24	0.31	0.27	0.10	0.09	0.08	0.06	0.12	0.10	0.18	0.14	0.14	0.12
48	0.30	0.26	0.12	0.09	0.08	0.06	0.12	0.10	0.12	0.09	0.16	0.14

Lead time	0.1- 5mm		5-10mm		10-15mm		15-25mm		25-50mm		50-100mm	
Model	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**	**QM**	**IFS**
72	0.28	0.25	0.11	0.09	0.06	0.04	0.11	0.09	0.12	0.11	0.14	0.11
96	0.27	0.26	0.10	0.09	0.06	0.04	0.10	0.08	0.10	0.08	0.14	0.10
120	0.27	0.25	0.10	0.08	0.06	0.04	0.10	0.07	0.10	0.08	0.13	0.10
144	0.27	0.24	0.10	0.08	0.06	0.05	0.10	0.09	0.10	0.08	0.08	0.06
168	0.27	0.25	0.10	0.08	0.06	0.04	0.11	0.06	0.11	0.09	0.09	0.07
192	0.26	0.25	0.09	0.07	0.06	0.04	0.10	0.07	0.09	0.07	0.06	0.04
216	0.26	0.25	0.08	0.07	0.04	0.02	0.07	0.05	0.09	0.08	0.10	0.08
240	0.25	0.23	0.07	0.05	0.05	0.03	0.07	0.06	0.09	0.08	0.04	0.04

Table 5. The RMSE index of the IFS model and IFS model applied the QM method in the summer and winter of 2023 in CentralVietnam.

Leadtime	Summer 2023		Winter 2023	
Model	**QM**	**IFS**	**QM**	**IFS**
24	14.50	14.69	20.18	20.08
48	15.00	15.30	21.00	21.22
72	15.30	15.49	19.90	22.05
96	16.10	16.40	19.85	22.17
120	17.10	17.35	22.55	22.78
144	17.70	17.97	23.70	23.93
168	20.40	20.56	23.50	23.72
192	20.50	20.82	24.40	24.58
216	19.60	19.83	24.75	24.98
240	20.50	20.84	24.85	25.03

3.2. Evaluation in the heavy rainfall events in 2023

In this section, we will evaluate the skill score of the IFS model and the IFS model applied the QM method for post-processing on forecasting rainfall in all heavy rainfall events in 2023.

According to the result in Table 6, The IFS model applied the QM method demonstrated superior performance in terms of the RMSE index when compared to the direct forecast from the IFS model, with a smaller value, for all lead times up to 10 days. The RMSE index in heavy rainfall events from both the IFS model and the IFS model applied QM method is substantially greater than the RMSE index in both summer and winter seasons 2023. The RMSE index increases with increasing lead time. These findings substantiate the limitations of global models, such as the IFS, in accurately capturing QPF at stations during heavy rainfall events, even when employing advanced postprocessing methods like QM.

Table 6. RMSE index of the IFS model and IFS model applied the QM method in the heavy rainfall events of 2023 in Central Vietnam.

Leadtime	Summer 2023		Leadtime	Winter 2023	
Model	**QM**	**IFS**	**Model**	**QM**	**IFS**
24	35.03	35.39	144	43.43	43.95
48	38.35	38.67	168	44.24	44.75
72	39.59	39.90	192	46.80	46.90
96	41.75	42.18	216	46.69	46.87
120	42.20	42.60	240	45.16	45.40

In regard to the TS skill index in Table 7, analogous to the RMSE, the findings from the IFS model employing the QM method displayed superior performance in comparison to the direct IFS model outcomes for both medium rainfall (25-50 mm) and heavy rainfall (50-100 mm) categories, across all lead times up to 10 days, as indicated by elevated TS values. However, for heavy rainfall category, the findings from Table 6 indicate a sudden decrease in the TS skill index after 72 hours of lead time. These results underscore the IFS model's limitations in accurately capturing rainfall with a lead time of up to 72 hours, in spite of the implementation of advanced postprocessing methods such as QM.

Table 7. The TS skill index of the IFS model and IFS model applied the QM method in the heavy rainfall events of 2023 in Central Vietnam.

Lead time	25-50mm		50-100mm	
Model	QM	IFS	QM	IFS
24	0.14	0.13	0.15	0.14
48	0.12	0.10	0.13	0.13
72	0.13	0.12	0.07	0.06
96	0.10	0.09	0.05	0.05
120	0.12	0.11	0.05	0.04
144	0.09	0.08	0.04	0.04
168	0.10	0.09	0.05	0.05
192	0.10	0.10	0.02	0.02
216	0.10	0.09	0.06	0.05
240	0.08	0.08	0.02	0.01

4. Conclusion

The objective of this study is to examine the efficacy of the QM method in enhancing the PQF forecast from IFS model across all synoptic stations in Central Vietnam. The research design is predicated on the utilization of observational data from 41 stations and 10-year ECMWF-IFS forecast data from 2013 to 2022, with a lead time of up to 10 days. The validation process, encompassing both skill and metric verifications, was conducted for the year 2023.

The findings indicated that the incorporation of QM method has a positive impact on the forecasting skill of the IFS model for all lead times up to 10 days. However, the magnitude of this impact varies based on the lead time and rainfall categories. Additionally, it must be acknowledged that QM is not a flawless method; it has been evidenced that the impact of QM is negligible for lead times up to 72 hours in summer and 144 hours in winter, as demonstrated in the context of heavy rainfall categories forecasting.

In the subsequent phase of the investigation, the integration of QM with Machine Learning (ML) and Deep Learning (DL) techniques is proposed to enhance the BIAS removal capacity of QM.

Author contribution statement: Writing and original draft preparation: T.D.D., H.M.K., Q.D.D.; Review and editing, L.R.H., D.T.A., T.D.D.; Calculation and visualization: D.T.A., N.H.G., T.D.T.; Project administration: T.D.D., D.T.A. All authors have read and agreed to the published version of the manuscript.

Acknowledgements: This research was supported by the Ministry of Natural Resources and Environment of Vietnam "Research on establishing a 10-day quantitative precipitation forecasting system to serve hydrological forecasting problems", intervention code TNMT.2023.06.01. Hole received funding from the Norwegian Agency for Development Cooperation (NORAD).

Competing interest statement: The authors declare no conflict of interest.

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