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Mean Field Bias Correction to Radar QPE as Input to Flood Modeling for Malaysian River Basins

Wardah Tahir[1], Muhammad Azizi Mohd Ariffin[2*], Jazuri Abdullah[1], Zaidah Ibrahim[2], Suzana Ramli[1], Sayang Mohd Deni[2], Hafiz Hassan[3], Lariyah Mohd Sidek[4], Yip Weng Sang[5], Diong Jeong Yik[5], Nursalleh K Chang[5]

[1]School of Civil Engineering, College of Engineering
Universiti Teknologi MARA, 40450 Shah Alam, Selangor, MALAYSIA

[2]Faculty of Computer Science and Mathematics,
Universiti Teknologi MARA, 40450 Shah Alam, Selangor, MALAYSIA

[3]Department of Irrigation and Drainage, 50626 Kuala Lumpur, MALAYSIA

[4]ZHL Engineers Sdn Bhd, 43300 Seri Kembangan, Selangor, MALAYSIA

[5]Malaysian Meteorological Department, 46667 Petaling Jaya, Selangor, MALAYSIA

*Corresponding Author

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Abstract: The occurrence of unprecedented flood events has increased in Malaysia recently. To mitigate the impact of the disaster, the National Flood Forecasting and Warning Centre has endeavored to improve the warning system to produce more accurate and reliable early warning to the public. The paper describes the use of radar composites from the radar network in Peninsular Malaysia to produce quantitative precipitation estimates (QPE) as input to the flood model. The processing of the raw radar data and the conversion of rain rate are described. The comparison between radar QPE and gauge rainfall shows that radar QPE underestimates the gauge rainfall, and the results are better at the western parts of Peninsular Malaysia compared to the eastern parts of Peninsular Malaysia. The comparison between Marshall Palmer (MP) and Rosenfeld (RF) conversion equations shows that there is not much difference in performance between the two equations. Both underestimate the rainfall, although RF estimates higher radar QPE for high rainfall intensity. The underestimated radar QPE is improved by calibration process via the Mean Field Bias (MFB) correction technique. The study introduced zoning into smaller regions for the MFB factors derivation. Results indicated that the radar QPE is much improved after the calibration process. Simulation of flood event in December 2021 for the case study of Langat River basin indicates the improvement of correlation coefficient from 0.67 to 0.99 after the calibration process via MFB for smaller zones.

Keywords: Radar QPE, Mean Field Bias (MFB), National Flood Forecasting and Warning System (NaFFWS), calibration

1. Introduction

Extraordinary floods in Malaysia have been on the rise recently. The flood that hit the country in December 2021 had caused 56 deaths as well as overall RM6 billion losses and damage to public assets, infrastructure, living quarters,

*Corresponding author: mazizi@fskm.uitm.edu.my

business premises, manufacturing, living quarters and agriculture sector [1]. As a country that is located on the equator and experiences heavy annual rainfall, Peninsular Malaysia is very vulnerable to floods. Many efforts have been made to mitigate the flood problem in Malaysia, including the construction of a SMART tunnel worth RM1.88 billion in the heart of Malaysia’s capital, Kuala Lumpur and the development of the National Flood Forecasting and Warning System (NaFFWS). Numerous studies have also been conducted regarding floods in Malaysia, among others, flood modeling and simulation [2], [3], flood hazard mapping [4], rainfall forecast [5], [6] and flood forecasting [7], [8].

One of the efforts to reduce the impact of floods is to provide accurate and reliable forecasts. Through the implementation of NaFFWS project, the Malaysian government is enhancing the country's flood forecasting capabilities by employing numerical weather prediction model product and meteorological radar to estimate and forecast rainfall.

Rainfall measured by rain gauges is often considered to be the true value of rainfall; however, rain gauges are often installed sparsely that they cannot capture well the spatial variability of rainfall, which has a considerable impact on hydrological systems and flood modeling. In contrast, radar can better capture the spatial variability of rainfall fields. Although radar has many advantages, its accuracy is not as good as rain gauge because it is influenced by several errors caused by radar hardware, scanning strategy, distance from the radar, atmospheric conditions, and rainfall estimation algorithms [9].

To improve the accuracy of radar rainfall, we can combine the strength of the rain gauge and the advantages of the radar by using various merging techniques. Numerous radar-rain gauge merging techniques have been developed, which have proven to be effective in improving the accuracy of radar QPEs. Various classification schemes for existing merging methods have been proposed such as bias reduction methods and error variance minimization methods [10]; geostatistical and non-geostatistical methods [11] and a more application-oriented adjustment methods and integration methods.

Radar bias adjustment methods attempt to correct radar QPE accumulations bias by using rain gauge accumulations as the true rainfall value. The entire radar field is used as the background, which is adjusted with a multiplicative correction factor [9]. The correction factor is estimated using gauge-radar comparison at gauge locations over a given time period, which can be long (i.e., nearly static adjustment) or short (i.e., dynamic adjustment; [13]-[15]). One of the operationally convenient and effective methods in this category is the mean field bias (MFB) correction, which assumes that the radar QPEs are influenced by a spatially uniform multiplicative error. The most common and straightforward method for estimating the MFB adjustment factor is to use a spatially averaged ratio of rain gauge and collocated radar accumulations over a given time period [9]. Mean Field Bias (MFB) merging technique will be employed in this study using static and dynamic calibration steps to improve the radar QPEs. An innovation in this study compared to the previous studies for NaFFWS project is the use of composite radars for the generation of QPEs instead of a single radar as the data source for QPE derivation [16], [17].

1.1 Radar Composites from Malaysian Radar Network

Radar composite products are generated by mathematically combining data from different radars and radar sites. For Peninsular Malaysia, the products are generated through the integration of data from 10 radar stations throughout Peninsular Malaysia and are combined to one grid using Inverse Distance Weighted (IDW) Interpolation. IDW uses the calculated values around a data point to approximate a value for every unmeasured position. IDW provides more weights to the positions that are the nearest to the point of interest and reduces the weights according to the distance. The final outcome of the product is the maximum of reflectivity data from 10 stations re-gridded [18]. The location of each radar station is shown in Fig. 1, while the description is provided in Table 1.

Table 1 - Description of 10 radar stations in Peninsular Malaysia

Band and Description	Stations
S (10 cm wavelength) It is useful for weather observation for any condition and can operate on a wavelength of 8-15 cm with a frequency of 2-4GHz with coverage up to 300 km radius.	Subang, Kluang, Alor Setar, Kota Bharu, Kuantan, Butterworth
C (5 cm wavelength) It has the same function with radar band S but it can only do short range weather observation and does not require much power. This radar band can operate on a wavelength of 4-8 cm with a frequency of 4-8 GHz.	KLIA
X (3 cm wavelength) It works well on smaller particles such as tiny waters and light precipitation such as snow. It can operate on a wavelength of 2.5-4 cm with a frequency of 8-12GHz with shorter range coverage of 100 km radius.	WSDS Langkawi, WSDS Bayan Lepas, WSDS Senai

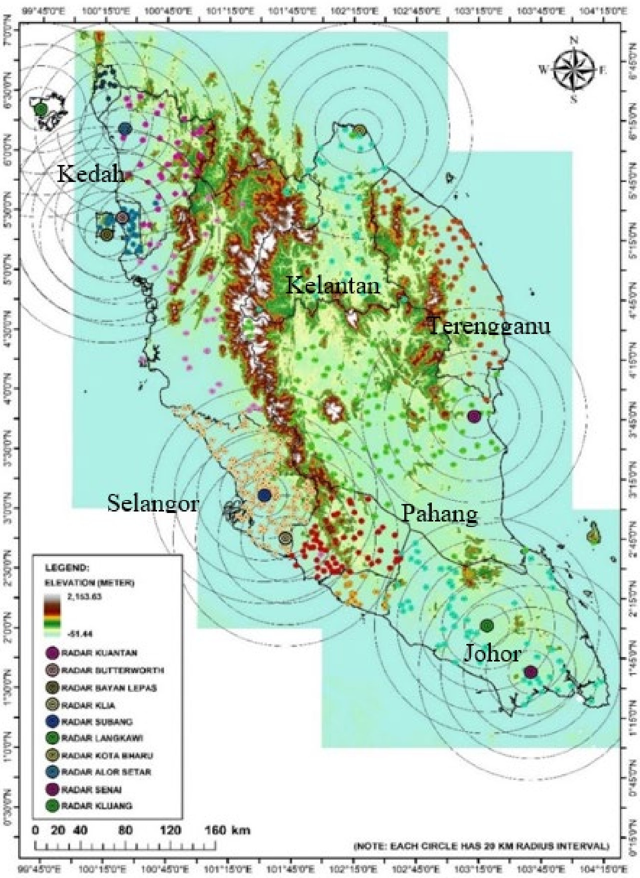


Fig. 1 - Map showing radar location and rainfall stations in each state in Peninsular Malaysia

1.2 Radar Data Type

The radar data file type is in Network Common Data (netCDF) and is formatted into HDF5 format. The data contains four variables with different dimension, namely Latitudes, Longitudes, Time and Zradar. NetCDF is a set of software libraries and machine-independent data formats that support the creation, access and sharing of array-oriented scientific data [19]. HDF5 or Hierarchical Data Format is a set of file format and data model which is designed to store and organize large amounts of data. It supports an unlimited variety of data types. It is designed not only for flexible and efficient I/O, but also for high volume and complex data.

2. Methods

The research methods involve the processing of radar data, conversion of rain rate, calibration and performance analysis as illustrated in Fig. 2.

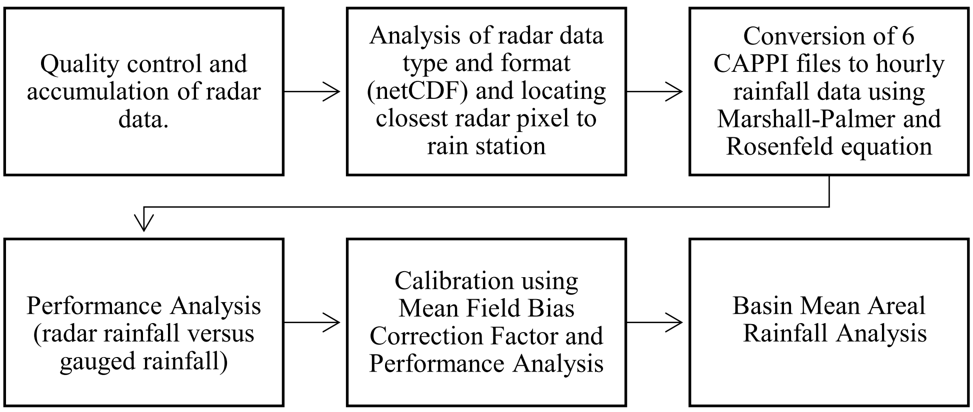


Fig. 2 - Research flowchart

2.1 Conversion of netCDF Reflectivity File to Human Readable Value

Python script is programmed to read, manipulate and extract the radar data to human-readable value which is stored in comma-separated value file (CSV). For this activity, Python version 3 is used via Anaconda distribution. To read and manipulate data in netCDF file via Python, netcdf4-python library can be used to provide interface to the netCDF C library. The first step is to obtain radar reflectivity value array, latitude size and longitude size from the group in the netCDF file. After that, variables are needed to be initialized to store index value of latitude and longitude. Since the radar data contains the reflectivity value of the whole Malaysia, the amount of data stored in the array is huge. Processing data in the normal array/list will take a longer time; thus, the data must be stored in the N-dimensional array (ndarray) to reduce the processing time. An instance of class ndarray consists of a contiguous one-dimensional segment of computer memory. By utilizing the concept of memory locality, processing time can be reduced significantly [20]. Numpy library ndArray which is available in python can be used to implement N-dimensional array. The next step is to convert radar reflectivity array to numpy ndarray in order to increase performance.

2.2 Locating Closest Radar Pixel to Rainfall Station

Python script is developed to automate the process of locating the nearest pixels of the radar data with the corresponding rain station. It is quite impossible to do the process manually as it involves huge dataset of radar data and hundreds of rain stations that are located all over Malaysia. By using a netCDF library, the python codes are able to extract the radar dataset from the netCDF file and combine the 10-min radar to hourly data. The script calculates the square distance for all the latitude and longitude values available in the radar data. After the script completes calculating the square distance for all the latitude and longitude values, it will find the closest pixels to the rain station by finding the index of latitude and longitude which has the minimum value of the square distance. By using the index of the latitude and longitude value, the script is able to obtain the reflectivity value (dBZ) of the pixels based on the latitude and longitude value that corresponds to the index. To significantly speed up the mathematical calculation which occurs during the rainfall conversion process, Numba Just-in-Time compilation technique is used. The technique will translate the function in python codes into optimized machine codes so that it can be executed more efficiently by the CPU. As a result, execution time for the codes can be reduced significantly. Fig. 3 shows the process of the Just-in-time compilation for python code [21]

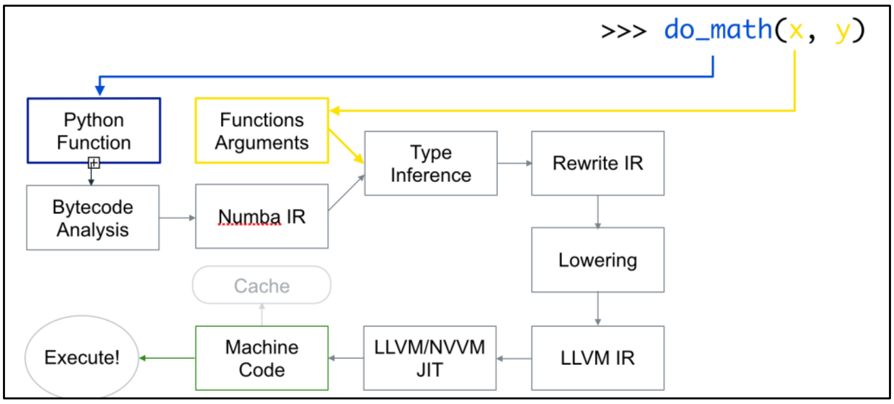


Fig. 3 - Just-in-Time Compilation for Python code using Numba [21]

2.3 Static and Dynamic Calibration using MFB Technique

This technique removes the bias introduced through the uncertainty in the radar calibration or an erroneous coefficient in the Z-R relationship. MFB assumes that the radar QPEs are affected by a uniform multiplicative error. Therefore, a single adjustment factor (C_{mfb}) is estimated with formula as follow:

$$MFB\_Correction\_Factor = \frac{\sum_{i=1}^{n} G_i}{\sum_{i=1}^{n} R_i} \tag{1}$$

where, G = gauged rainfall (hourly depth), R = radar rainfall (hourly depth), and n = number of gauge station involved in calibration.

2.4 Performance Analysis

The performance of the calibrated QPEs will be evaluated based on three evaluation criteria for deterministic continuous values, namely root mean square error (RMSE), mean absolute error (MAE) and correlation coefficient, *r*. Eq. (2) to Eq. (4) show the calculation involved where G represents the gauge rainfall, R represents the radar rainfall and i is the number of rainfall stations.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(G_i - R_i)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}| G_i - R_i | \quad (3)$$

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (4)$$

where, $Gi = x$, $Ri = y$.

3. Results and Discussion

This section will discuss examples of findings from QPE radar accuracy analysis, calibration and validation processes for selected areas in the northern (N), southern (S), western (W) and eastern (E) parts of Peninsular Malaysia. Examples of analysis presented are from Johor (S), Kedah (N), Perak (W), Selangor (W), Pahang (E) and Kelantan (E).

3.1 Performance Comparison Between Radar QPE Derivation Using MP and RF

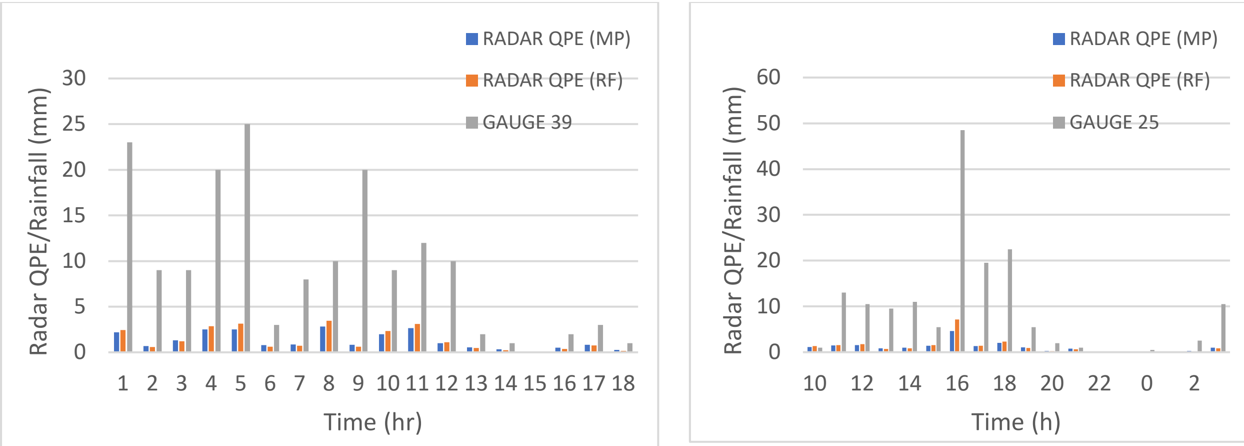
There is no single relation that can satisfy all meteorological phenomena in radar rainfall estimation. [22] listed more than 69 separate Z − R relationships proposed by various studies. Radar Operations Center in the US has recommended to use Rosenfeld equation ($Z=250R^{1.2}$) as optimum relationship for tropical convective systems [23]. In this project, the reflectivity (dBZ) was converted to radar QPE (mm/h) using Rosenfeld (RF) equation and the results were compared with radar QPE that was calculated with Marshall Palmer (MP) equation. The findings indicated insignificant difference between radar QPE via MP. Table 2 shows the performance analysis of both equations at selected stations. The RMSE and MAE indicate that errors can be less or more for RF while most correlation coefficient, r indicate MP is better equation to be used for the selected events. QPEs using RF are slightly better for heavy rainfall as compared to MP as shown by Fig. 4. Nevertheless, the accuracy may be less as compared to the MP, and both MP and RF underestimate the radar QPE for most cases.

Table 2 - Performance comparison between Marshall Palmer (MP) and Rosenfeld (RF) equation

Station	Duration	RMSE		MAE		Correlation, r	
		MP	RF	MP	RF	MP	RF
Ladang Nam Heng Kota Tinggi, Johor	10-18/1/21	3.43	3.38	0.88	0.87	0.88	0.86
Lepau, Kota Tinggi, Johor	10-18/1/21	6.76	6.67	1.67	1.65	0.92	0.86
Kg Chenulang Kuala Krai, Kedah	1-9/1/21	6.13	6.17	2.69	2.71	0.79	0.73

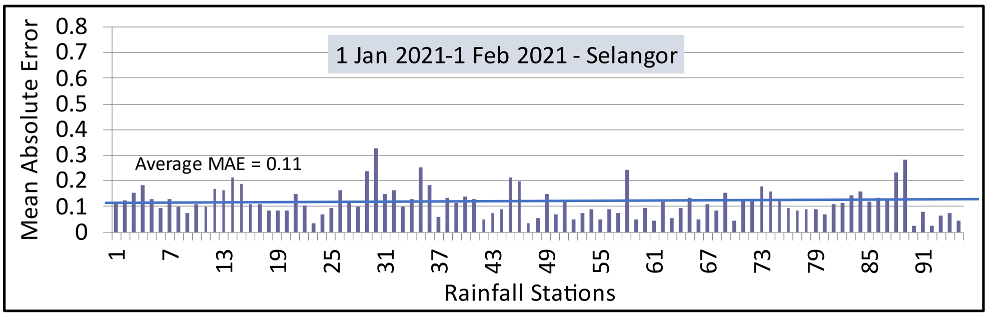
3.2 Performance Variation Between Radar QPE at the Eastern and Western Regions of Peninsular Malaysia

Hourly radar QPE derived using MP equation was compared with gauged value at collocated time and location. Examples are provided in Fig. 5(a)-(d) for observation period from 1 January until 1 February 2021 in Selangor (95 stations), Pahang (58 stations), Kelantan (25 stations) and Perak (25 stations). The graphs show that MAE is higher in Kelantan (0.32 average), Pahang (0.3 average), Perak (0.2 average) and Selangor (0.11 average). It can be concluded that the radar composites perform better at the western parts of Peninsular Malaysia compared to the eastern parts of Peninsular Malaysia.

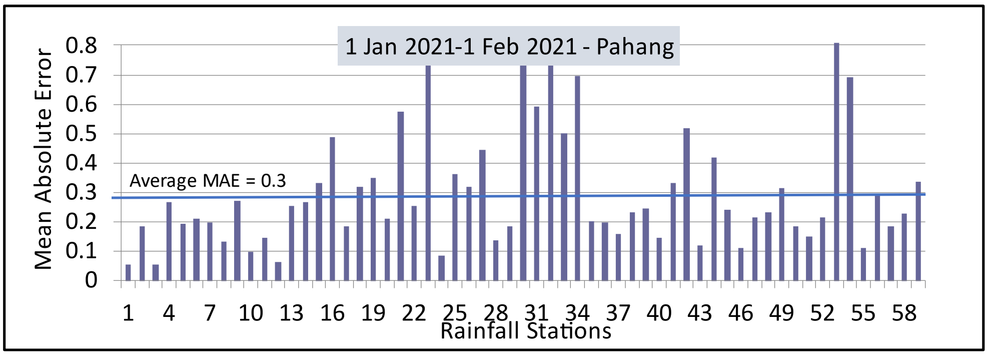


(a) (b)

Fig. 4 - QPEs using MP and RF Comparison, (a) Station Ladang Nam Heng Kota Tinggi Johor 10th January 2021, and (b) Station JPS Machang Kelantan 5-6th January 2021



(a)



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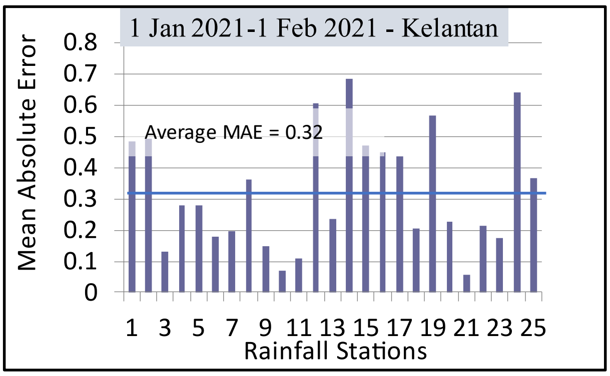
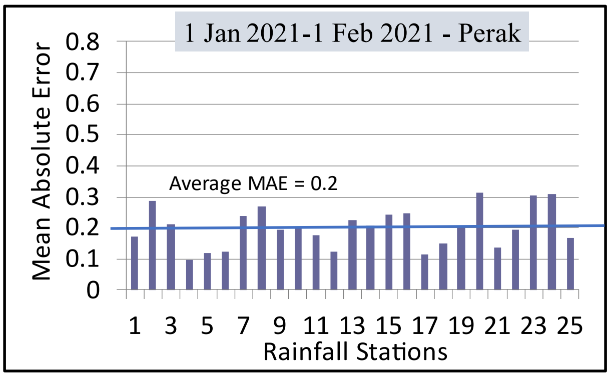


(c)



(d)

Fig. 5 - Mean absolute error of hourly radar QPE with respect to gauge rainfall for observation period of 1 January 2021 - 1 February 2021; (a) Selangor; (b) Pahang; (c) Kelantan; and (d) Perak

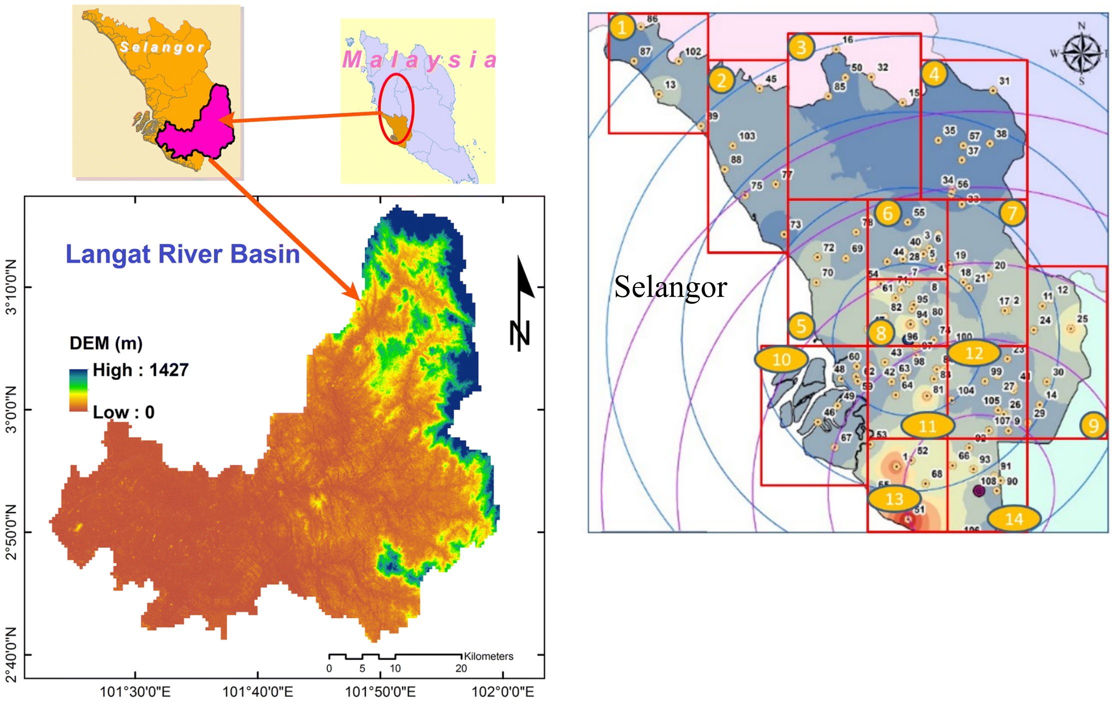
3.3 Calibration Using MFB Correction

The radar QPE accuracy can be improved by bias correction via the gauge rainfall value. Based on the MFB equation, the calibration factor is derived by dividing the sum of all gauge rainfall values with the sum of all radar rainfall at the collocated time and closest pixel location. Since a single factor for a large area leads to large error due to spatially non-uniform rainfall events, we applied creating smaller regions with clusters of rain gauges in determining the MFB correction factor. The smaller regions were delineated based on the analysis of median of radar/gauge ratio. Using the available data, the median was determined, isopleths of similar median were drawn, and clusters of rainfall stations were determined. Fig. 6(b) shows an example of zoning Selangor state into smaller regions of MFB correction factor. During the calibration process, each region will have its unique adjustment factor. A mid-point will be identified in each region and radar pixels will be multiplied with the mean of five (5) closest factors for bias adjustment. The haversine formula was used to determine the closest factors based on midpoint coordinates. The formula is shown as follow:

$$\begin{gathered} a = \sin^2(\frac{\Delta\varphi}{2}) + \cos\varphi 1 . \cos\varphi 2 . \sin^2(\frac{\Delta\lambda}{2}) \\ c = 2.(a\tan 2)(\sqrt{a}, \sqrt{(1-a)}) \\ c = R * c \end{gathered} \tag{5}$$

where, φ is latitude, λ is longitude, R is earth's radius (radius = 6,371km), and the angles need to be in radians to pass to trig functions.

To avoid noise and invalid data from radar value or gauge, the calibration process has set certain threshold. For gauge value, only gauge with value which is more than or equal to 3 mm and less than or equal to 100 mm is considered in the calculation process. As for radar rainfall value, only value which is more than 0 mm is considered. Moreover, the threshold value is also set for the calibration factor. If the derived calibration factor is more than 10, the calibration factor will be set as 10. This is to avoid the presence of extreme values for the calibration factor. The calibration results throughout Peninsular Malaysia are very encouraging. Fig. 7 shows one of the results that displays more than 50% improvement in correlation coefficient between radar-gauge for a number of rainfall stations in Selangor.



(a) (b)

Fig. 6 - (a) Map showing the location of Selangor and Langat River Basin, Selangor, Malaysia [24]; and (b) radar coverage from KLIA and Subang radar and zoning of smaller region for MFB based on rainfall gauge cluster over isopleth of median ratio

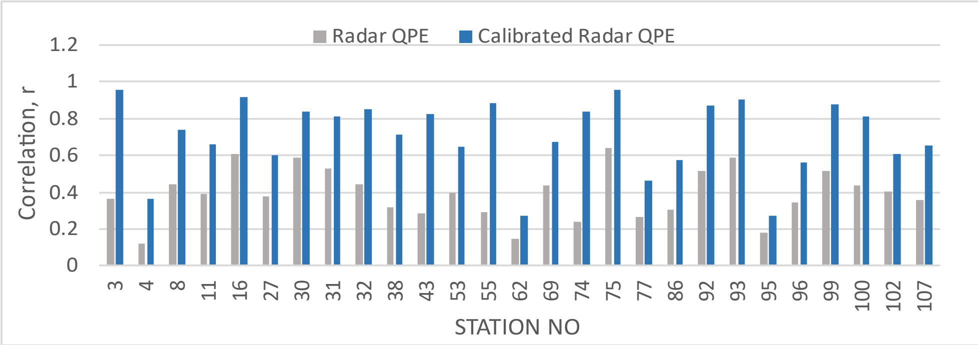


Fig. 7 - Rainfall stations in Selangor which experienced more than 50% improvement in correlation coefficient after calibration

3.4 Case Study of Langat River Basin, Selangor During Flood Events December 2021

Fig. 8 shows the radar display for Langat River Basin dated 17th December 2021 during an extreme flood event. The image indicates an increase in overall radar pixel intensity after the calibration. As indicated by the earlier results on point gauge-radar comparison, radar QPE underestimates the gauged rainfall. Calibration involves the multiplication of radar pixels with the MFB correction factor for each zone which is based on radar-gauge merging concept. Table 3 shows that the basin mean areal calibrated radar QPE values are much closer to the gauge rainfall value. The distribution of radar QPE pixels over the river basin can easily be observed from the radar images as displayed in Fig. 7. The radar displays illustrate how the rainfall is spatially distributed over the catchment which is a clear advantage of radar QPE over point gauge rainfall. It can be observed from the radar displays that the storm during the flood event on 17th December 2021 had concentrated at the lower basin in Kuala Langat and Sepang which was badly affected by flood [25].

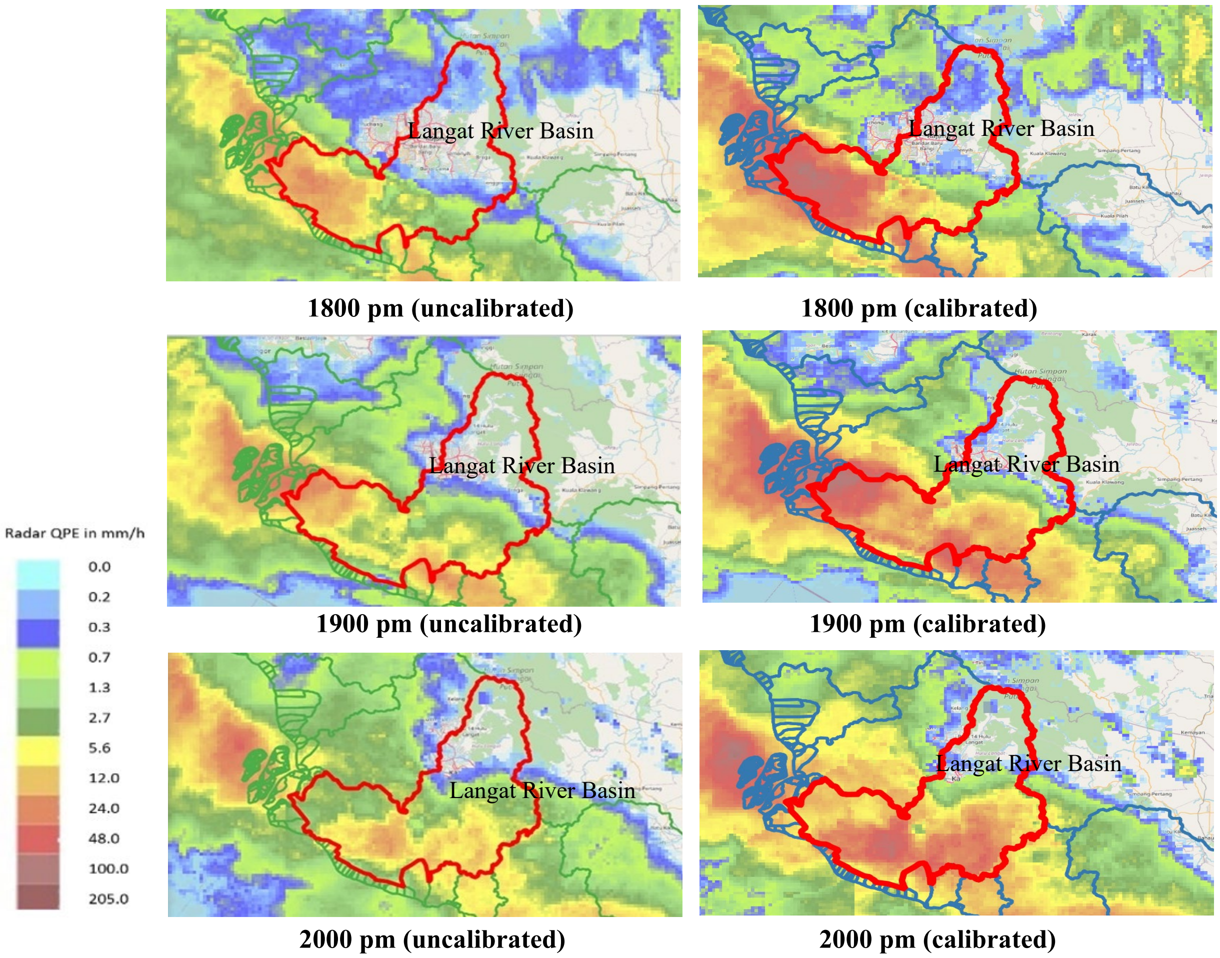


Fig. 8 - Comparison between uncalibrated radar QPE and calibrated radar for Langat River Basin during flood event on 17th December 2021

Table 3 - Comparison between calibrated and uncalibrated mean areal basin rainfall

Time	Gauge Rainfall (mm)	(Mean pixels) (mm/hr/grid)	Relative Error	(Mean pixel uncalibrated) (mm/hr/grid)	Relative Error
18:00	14.65	15.50	0.06	4.20	0.71
19:00	9.37	13.95	0.49	3.79	0.60
20:00	12.70	14.30	0.13	3.40	0.73
21:00	6.26	7.86	0.26	2.23	0.64

The effectiveness of calibration via MFB technique with zoning to smaller regions is illustrated by the significant improvement in correlation coefficient, r value from 0.67 before calibration to 0.99 after calibration, which is shown in Fig. 9. The analysis was conducted for hourly rainfall value from 16th. Until 19th December 2021. The MAE and RMSE are also significantly reduced after calibration as given in Table 4.

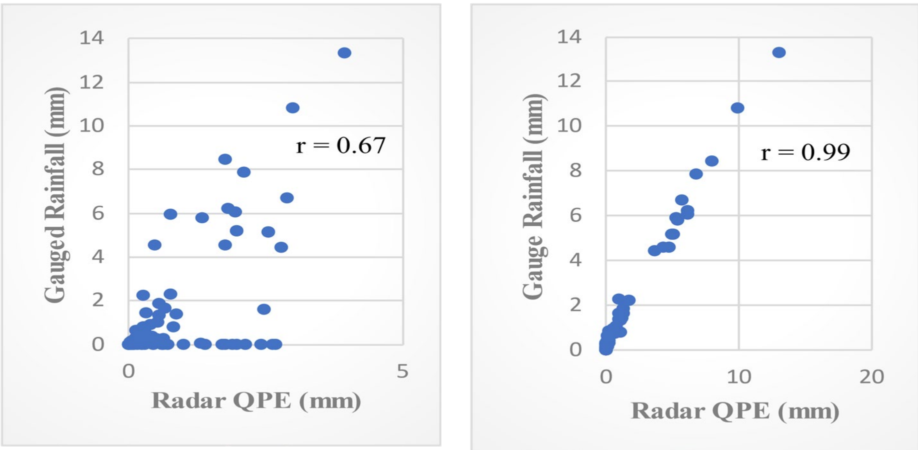


Fig. 9 - Scatter plot showing correlation between calibrated and uncalibrated radar QPE with the gauged measured mean areal basin rainfall (16-19 December 2021) for Langat River Basin

Table 4 - Performance measurement of Langat River Basin means areal rainfall (16-19 December 2021)

	Uncalibrated Radar QPE	Calibrated Radar QPE
MAE	2.11	0.32
RMSE	2.24	0.18
Correlation coefficient, r	0.67	0.99

4. Conclusion

The paper discusses a technical advancement in the National Flood Forecasting and Warning System of Malaysia in terms of utilizing the radar data as a complementary rainfall input to the hydrological model to generate a more reliable and accurate flood forecasting and warning. Instead of using a single radar, this project used the composites from the radar network throughout Peninsular Malaysia for radar QPE derivation. The description of the source of radar data and its processing for QPE conversion have been discussed in the paper. Analysis was conducted to investigate the radar QPE performance, and it was found that radar QPE underestimates the gauge rainfall. The underestimated radar QPE values were significantly improved by calibration via the MFB technique. Results obtained also depicted meaningful radar display illustrating intensity and distribution of pixel-based radar QPE values over Langat River Basin during a flood event.

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