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Improving HEC-HMS Streamflow Prediction Through Localized Bias Correction of Stage IV Radar Rainfall: A Case Study of the Elm Fork Trinity River Basin During Tropical Storm Hermine

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ABSTRACT: Precipitation is the principal cause of runoff production and the source of much uncertainty in hydrologic modeling. While National Weather Service (NWS) Stage IV multisensor precipitation data have good spatial and temporal resolutions, localized biases could still be present in watershed-scale hydrologic modeling. Objectives: This study evaluates whether localization of Mean Field Bias (MFB) correction for NWS Stage IV precipitation can improve streamflow prediction in Elm Fork Trinity River Basin under the influence of Tropical Storm Hermine from September 5 to September 9, 2010. Methods: Rainfall hourly measurements from three Automated Surface Observing System (ASOS) stations were used for estimation of MFB correction factor. Three Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) simulations were performed for (1) spatially interpolated rainfall data from gauging network, (2) raw Stage IV precipitation data, and (3) MFB-corrected Stage IV precipitation data with the same basin settings. Results: The correction reduced precipitation PBIAS to about 0% at all three ASOS stations. At Gainesville Airport station, RMSE of precipitation was reduced from 6.77 mm to 5.88 mm. NSE of simulated streamflow was increased from 0.723 to 0.882, and the peak discharge was decreased from 11,210 ft³/s to 8,574 ft³/s (versus 6,560 ft³/s observed peak flow). Conclusion: Localized MFB correction for precipitation improved hydrologic modeling for this storm event using only three rain gauges without changing HEC-HMS basin settings.

1 INTRODUCTION

1.1 Statement of the Problem

The Stage IV rainfall estimates have already been corrected for regional gauge biases; nevertheless, regional corrections do not guarantee that rainfall estimates would be unbiased at the individual watershed scale. Such problem creates a technical difficulty for hydrologists, as the Stage IV is used as an input in rainfall-runoff modeling. Transmission of a bias in localized rainfall through the hydrological non-linear process can change peak discharge values and hydrograph shape, while keeping other model parameters unchanged. The main issue under investigation in this research is the possibility of further improvement of a corrected Stage IV rainfall dataset at the watershed scale in case of sparse gauge network.

1.2 Objectives of the Study

Goals of this research include (1) the measurement of bias associated with precipitation from Stage IV data against observations collected at three Automated Surface Observing System (ASOS) stations, (2) application of a local Mean Field Bias (MFB)

correction to the Stage IV precipitation data, and (3) the determination if there is improvement in HEC-HMS streamflow simulation due to this precipitation modification where all basin parameters are kept constant.

The scientific contribution of the project is the assessment of the effect of a secondary, watershed-specific bias correction of an already gauge-corrected Stage IV dataset using three gauges and a constant HEC-HMS model configuration. Previous studies have evaluated raw radar data, highly-dense gauge networks, or computationally complex merging techniques. This research evaluates the precipitation input effect in isolation by holding other model parameters constant and comparing hydrograph to USGS discharge observation. The engineering contribution of this project is an operationally simple procedure for watersheds with scarce gauge data.

2 LITERATURE REVIEW

2.1 Importance of Accurate Precipitation Estimation in Hydrologic Modeling

Precipitation is the main input data for rainfall-runoff modeling and affects infiltration, surface runoff, baseflow separation, and channel routing processes directly. The wrong precipitation estimation could affect runoff volume simulation, peak discharge, and flood occurrence time. Rain gauges provide direct point measurement but may not take into account the spatial variability of precipitation linked to convective storms. Radar precipitation data products are spatially extensive but provide indirect measurement of precipitation and may be affected by systematic and random errors (Berne and Krajewski, 2013). According to Ahmed et al. (2022), the streamflow simulations in an event-based HEC-HMS could differ based on rainfall inputs from rain gauges and NEXRAD. Thus, the assessment of precipitation inputs and model parameters calibration could be considered separately.

Rain gauges provide direct point measurement but may not take into account the spatial variability of intense convective storms. The hydrological model could be sensitive to the precipitation input data because of rainfall inaccuracies propagation through hydrological processes.

2.2 Radar-Based Rainfall Estimation

The weather radar system provides information on precipitation which cannot be provided by traditional rain gauges at both temporal and spatial resolutions. For example, in the USA, the Next Generation Weather Radar (NEXRAD) system obtains rainfall indirectly from the radar reflectivity data and then determines the rainfall rate using Z-R relationships.

The uncertainties in rainfall obtained through these methods include those caused by beam blockage, beam spreading, partial beam filling, attenuation, anomalous propagation, vertical reflectivity gradient, melting layer effects, and reflectivity-rainfall relationship among others. These sources of uncertainty can change with range and storms' characteristics (Krajewski and Smith, 2002; Berne and Krajewski, 2013). However, NEXRAD systems for determining rainfall through Z-R relationship works efficiently within varying meteorological conditions; the success of these methods depends upon

- melting layer contamination,
- beam blockage,
- beam broadening,
- partial beam filling,
- attenuation,
- anomalous propagation,
- vertical reflectivity gradients.

Rainfall estimation using radar becomes more and more uncertain as range increases because radar systems scan atmospheric volumes that become increasingly higher up and might not relate to surface rainfall.

This means that errors made by radar rainfall estimations are systematic, making it possible to correct for such errors through statistical bias correction (Krajewski and Smith, 2002; Habib et al., 2009).

2.3 Stage IV Multisensor Precipitation Product

The NCEP (National Centers for Environmental Prediction) Stage IV dataset is a regional multi sensor rainfall data set created by River Forecast Centers. Stage IV provides 4 km spatial resolution with hourly rainfall estimates through radar and gauge measurements (Lin and Mitchell, 2005). Due to the regional scale at which Stage IV is created, the gauge adjustment applied in Stage IV might not adequately correct for biases specific to the watershed. Li et al. (2023) showed that the success of the radar-gauge compositing process depends on gauge density and spatial resolution of radar.

Stage IV products provide (Lin and Mitchell 2005).

- hourly precipitation,
- national spatial coverage,
- quality controlled radar estimates,
- gauge adjusted rainfall fields,
- standardized formats for operational forecasting.

These products have become widely used within

- flood forecasting,
- watershed simulation,
- hydraulic design,
- climate analysis,
- reservoir management.

Stage IV incorporates gauge information during regional processing, but regional adjustment does not guarantee watershed scale unbiasedness.

2.4 Rain Gauge-Radar Bias Correction

Gauge corrections for radar bias include a range of methodologies from simple multiplication to more complex techniques of statistical fusion, among others. The selection of the method depends on gauge spacing, data quality, frequency of updates, and the use case.

2.4.1 Mean Field Bias (MFB)

Mean Field Bias assumes that the primary source of rainfall bias may be described as a multiplying factor throughout the analysis period. The event correction factor between the two data sets is:

$$\text{MFB} = \Sigma G_i / \Sigma R_i$$

where G_i is observed gauge precipitation and R_i is the corresponding Stage IV precipitation.

The corrected precipitation is calculated through the formula $P^c = \text{MFB} \times P^r$, where P^c stands for the corrected precipitation, and P^r stands for the Stage IV precipitation. The method of MFB correction is easy to implement from a computational point of view and suitable for sparse gauge network; however, one single factor cannot take into account spacial variation in bias or timing (Anagnostou et al., 1998; Seo et al., 1999).

The factor of correction is applied to all radar pixels. Pros of the method include:

- Computation simplicity,
- Reliability,
- Suitability for sparse gauge network,
- Operational simplicity.

Being a fairly simple and reliable method, MFB correction is one of the best techniques for engineering calculations since only a few gauge sites are needed.

2.4.2 Spatial Interpolation Methods

With increasing gauge densities, it is possible to make use of spatial techniques like ordinary kriging, co-kriging, inverse distance weighting, conditional merging, and Bayesian merging to represent spatial variations in the correction factors.

- Ordinary Kriging,
- Co-Kriging,
- Inverse Distance Weighting,
- Conditional Merging,
- Bayesian merging.

This usually requires more data than is found in the three-station gauge network used in this study. Goudenhoofdt & Delobbe (2009) have shown that geostatistical techniques can be better than MFB correction in situations with high gauge density.

2.4.3 Machine Learning Techniques

Recent studies have also evaluated machine learning and sequential data assimilation approaches for radar rainfall correction.

- Random Forest,
- Gradient Boosting,
- Artificial Neural Networks,
- Deep Learning,

Although these techniques frequently outperform traditional statistical corrections, they require

- large historical datasets,
- computational resources,
- extensive model training,

which limits operational implementation in many engineering organizations.

2.5 Influence of Rainfall Errors on Hydrologic Models

The uncertain rainfall may transfer into the hydrologic model and impact the simulated streamflow in terms of its magnitude and timing. Carpenter et al. (2001) found out that the rainfall uncertainty by NEXRAD may be significant in comparison with the hydrologic parameter uncertainty. Sexton et al. (2010) also found out that the replacement of the rainfall measured via rain gauge for the rainfall measured via radar significantly changed the output of the hydrologic model.

Carpenter et al. (2001) have investigated the usefulness of distributed hydrologic models based on the NEXRAD precipitation dataset and found out that the uncertainty of rainfall measurement is greater than the hydrologic parameter uncertainty related to the calibration of the watershed. Moreover, Sexton et al. (2010) have reported that the use of radar-based rainfall data instead of rain gauge-based data significantly impacts the model output.

2.6 Evaluation Metrics for Hydrologic Performance

Performance assessment involved the use of Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percent Bias (PBIAS). NSE is an indicator of agreement between observed and modeled hydrographs, RMSE is an indicator of error in prediction, and PBIAS shows either systematic over or under-prediction. The closer the value of NSE is to 1 and that of PBIAS to zero, the greater is the agreement (Moriassi et al., 2007; Gupta et al., 2009).

Peak discharge was considered as well for its importance in flooding assessment. NSE is used extensively to evaluate agreement between observed and modeled hydrographs since it indicates differences in magnitude and time. According to Moriasi et al. (2007), NSE values more than 0.75 are considered very good, 0.65-0.75 good, 0.50-0.65 satisfactory, and less than 0.50 unsatisfactory.

NSE	Model Performance
>0.75	Very Good
0.65–0.75	Good
0.50–0.65	Satisfactory
<0.50	Unsatisfactory

- Root Mean Square Error (RMSE),
- Percent Bias (PBIAS),
- Mean Absolute Error (MAE),
- Kling-Gupta Efficiency (KGE).

The present study uses NSE, RMSE, and PBIAS for the primary rainfall and streamflow comparisons.

2.7 Research Gap

The review shows that merging radar gauges may help improve rain gauge estimates; however, a number of limitations remain which have important practical implications for engineering applications. Existing literature often examines unadjusted radar data, relies on highly dense gauge networks, or uses complicated merging methods. It was rarely investigated whether an additional localized correction of already adjusted Stage IV may help improve watershed scale HEC-HMS models with a limited number of gauge measurements.

According to Mapiam et al. (2022), adding more gauge measurements may help better adjust radar hourly bias. Li et al. (2023) used a highly calibrated and validated network for evaluation of regression kriging and Bayesian regression kriging of Stage IV, Multi-Radar Multi-Sensor (MRMS), and RTMA products. Shazwani et al. (2024) compared gauge and radar quantitative precipitation estimates for an HEC-HMS application, showing higher correspondence of the former.

The novelty of the current research is in its context and methodology rather than algorithm: three gauges, one-time MFB correction factor, already adjusted by gauges Stage IV data, constant HEC-HMS parameters, and USGS streamflow data are used to separate the practical value of additional localized precipitation adjustment.

2.8 Research Questions and Hypothesis

Two questions have been addressed as follows:

Question 1: Does the correction of localized MFB minimize the precipitation error of the stage IV precipitation at the three ASOS locations?

Question 2: Does the modified precipitation increase HEC-HMS simulation of streamflow where the basin properties remain fixed? Hypothesis: By minimizing precipitation errors, there would be an improvement in the streamflow results.

3 STUDY AREA

3.1 Watershed Description

This research paper deals with the Elm Fork Trinity River Basin, one of the major tributaries of the Trinity River in North Texas. The area under study covers 131 square kilometers (50.7 square miles) of land. It drains into Lake Lewisville, which acts

as a flood control reservoir in the Dallas–Fort Worth metropolitan area. This basin has a mixture of land use activities, making it susceptible to heavy precipitation.

The climate in the study area is humid-subtropical with hot summers, cold winters, and high variations in precipitation from year to year and month to month. Storms that generate floods come from mesoscale convective storms, remains of tropical storms, and frontal systems. Due to its location in North-Central Texas, the basin receives heavy rains, causing floods.

The watershed was selected because it has:

- a well-defined drainage network,
- available U.S. Geological Survey (USGS) discharge observations,
- operational Stage IV precipitation data,
- multiple ASOS rain gauges,
- an established HEC-HMS model suitable for evaluating precipitation uncertainty.

Figure 1 illustrates the watershed boundary, drainage network, streamflow gauge location, and rainfall observation stations.

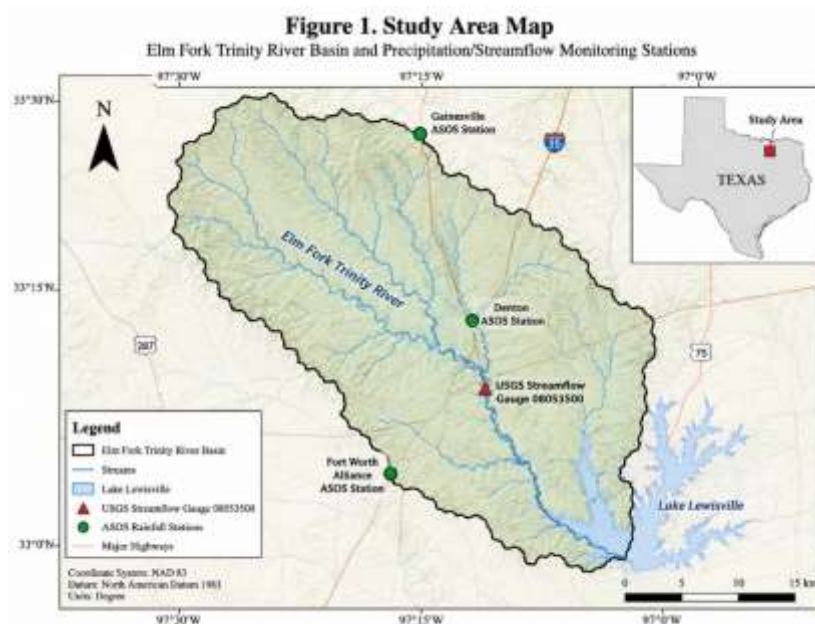


Table 1. Watershed Characteristics

Parameter	Value
Study Area	Elm Fork Trinity River Basin
Outlet Streamflow Gauge	USGS 08053500
Study Storm	Tropical Storm Hermine
Simulation Period	September 5–9, 2010
Rainfall Product	NWS Stage IV Multisensor Precipitation
Rain Gauge Network	Gainesville, Denton, Fort Worth Alliance ASOS
Hydrologic Model	HEC-HMS
Bias Correction Method	Mean Field Bias (MFB)

3.2 Selection of Tropical Storm Hermine

Tropical Storm Hermine was selected due to the presence of Stage IV precipitation data, hourly ASOS data, and full USGS discharge record. Moreover, the storm showed considerable rainfall variability within the basin, and the peak discharge reached 6,560 ft³/s.

The event was selected based on the following criteria:

- One of the biggest floods has occurred within the studied watershed;
- Stage IV precipitation data were available;
- Hourly ASOS data were available;
- Full USGS discharge record was available;
- Considerable spatial variability in rainfall was shown by the storm.

Peak discharge of about 6,560 ft³/s is the reference point for comparison of hydrological response to three different precipitations.

4 MATERIALS AND METHODS

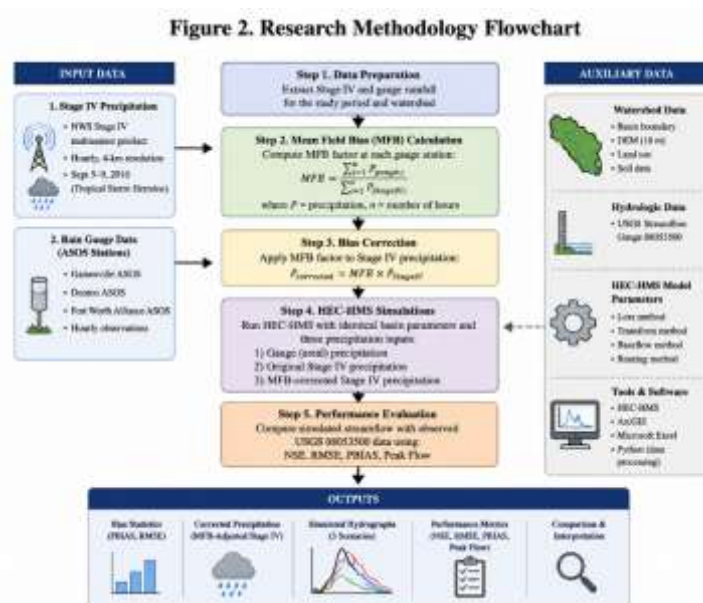
4.1 Overview

The analytical workflow consisted of five principal stages:

1. Acquisition of precipitation observations.
2. Computation of localized Mean Field Bias (MFB).
3. Development of corrected Stage IV precipitation.
4. HEC-HMS simulation.
5. Statistical evaluation of model performance.

All HEC-HMS basin parameters remained constant across the simulations. Only precipitation input was modified.

Figure 2 illustrates the complete methodological workflow.



4.2 Precipitation Data

4.2.1 Stage IV Radar Rainfall

The precipitation data of Stage IV came from the regional analysis of the National Weather Service using the Next Generation Weather Radar (NEXRAD) system from the KFWS site. This product provides an hourly precipitation estimate at a resolution of about 4 km. From the period of September 5 to September 9, 2010, there were 720 hourly data that are being analyzed for the pair of gauges with Stage IV. The Stage IV dataset has been filtered over the study watershed and then compared with the rainfall measurements from the ASOS gauges.

Even though Stage IV uses the gauge data during the regional processing, any bias can remain at the local level because of the regional nature of this product.

4.2.2 Rain Gauge Observations

Hourly rainfall data was obtained from three ASOS sites including; Gainesville Airport, Denton Airport, and Fort Worth Alliance Airport.

The three ASOS stations provide the ground base for comparing rain fall and also computing the Multiple Fallback Baseline (MFB).

- Gainesville Airport
- Denton Airport
- Fort Worth Alliance Airport

Table 2. Rainfall Observation Stations

Station	Agency	Dataset	Purpose
Gainesville ASOS	NOAA	Hourly Rainfall	Gauge Reference
Denton ASOS	NOAA	Hourly Rainfall	Gauge Reference
Fort Worth Alliance ASOS	NOAA	Hourly Rainfall	Gauge Reference
Stage IV Grid	NWS	Hourly Radar-Gauge Product	Radar Rainfall

These weather stations represent regular meteorological observations that have been done by the National Weather Service and the Federal Aviation Administration.

Although there are only three rain gauges, good spatial distribution of the data was made possible by arranging the rain gauges in a north-south direction.

4.3 Mean Field Bias Correction

Localized radar bias was estimated using the Mean Field Bias (MFB) approach.

The event correction factor is expressed as:

$$MFB = \Sigma G_i / \Sigma R_i$$

Where:

- G_i = GCM simulated precipitation at time i
- R_i = reference/observed precipitation at time i

MFB was selected because the available network contained only three gauges; spatially varying methods would require a denser observation network.

4.4 Hydrologic Model

Hydrologic modeling was conducted with the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS). The existing watershed model had been developed and calibrated using basin and routing parameters. Those parameters were held constant for every simulation so that precipitation input remained the principal experimental variable.

Three scenarios were simulated: spatially interpolated ASOS rainfall as the gauge-based benchmark; original Stage IV precipitation as the operational baseline; and MFB corrected Stage IV precipitation as the localized correction scenario.

4.4.1 Simulation 1

Spatially interpolated ASOS rainfall.

This simulation served as the gauge-based benchmark.

4.4.2 Simulation 2

Original Stage IV precipitation.

This represented the operational radar-based simulation without additional correction.

4.4.3 Simulation 3

Mean Field Bias Corrected Stage IV Precipitation. This simulation explored how correction of local radar affects streamflow forecasting. As a result, the modeling process separated precipitation variability from other uncertainties such as parameter calibration.

4.5 Performance Metrics

Hydrologic performance was evaluated using three widely accepted statistical indicators.

4.5.1 Nash Sutcliffe Efficiency (NSE)

$$NSE = 1 - [\Sigma(Q_{obs,i} - Q_{sim,i})^2 / \Sigma(Q_{obs,i} - Q_{obs})^2]$$

Where:

$Q_{obs,i}$ = observed value at time i

$Q_{sim,i}$ = simulated (predicted) value at time i

Q_{obs} = mean of the observed values

n = total number of observations

4.5.2 Root Mean Square Error (RMSE)

$$RMSE = \sqrt{[\Sigma(Q_o - Q_s)^2 / n]}$$

RMSE quantifies average prediction error. Lower values indicate improved simulation accuracy.

Q_o = actual observed value

Q_s = predicted observed value

n = total number of observations

4.5.3 Percent Bias (PBIAS)

$$PBIAS = 100 \times [\Sigma(Q_o - Q_s) / \Sigma Q_o]$$

Where:

Q_o = simulated value at time i

Q_s = observed value at time i

PBIAS measures systematic overprediction or underprediction.

Values approaching zero indicate unbiased simulations.

These metrics were computed for both precipitation comparisons and streamflow simulations following the guidelines proposed by Moriasi et al. (2007).

4.6 Validation Strategy

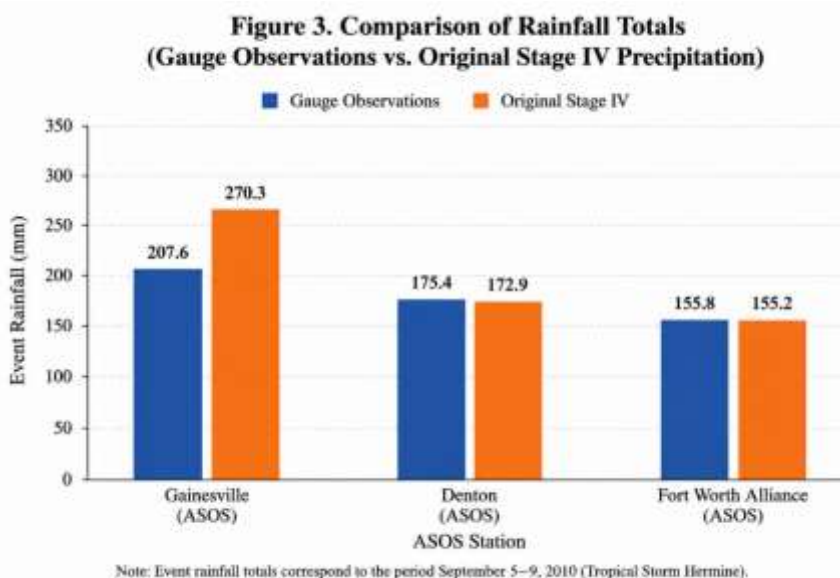
The three ASOS gauges have been used for the estimation of the MFB factor and hence cannot be considered independent precipitation validation gauges. The USGS 08053500 streamflow data is an independent hydrologic response evaluation because it has not been used in the estimation of the precipitation correction factor. This means that the analysis done in Figure 6 and Table 4 aims at determining if the corrected precipitation results in a better hydrological response. Using a withheld gauge or storm event would be an independent precipitation validation and is recommended for further research.

5 RESULTS

5.1 Radar Rainfall Bias

Figure 3 shows the comparison between rainfall amounts at the three ASOS stations and their respective Stage IV estimates. There was a greater overestimate at Gainesville Airport where Stage IV estimates were 270.3 mm while ASOS estimated 207.6 mm, thus having a PBIAS of +30.2%. The PBIAS for Denton Airport was -3.4%, and for Fort Worth Alliance, +1.5%. See Table 3 for station statistics pre- and post-corrected values.

Precipitation PBIAS was nearly 0% in all the three stations post-corrected. As shown in Figure 8, the mean rainfall in the event decreased from 266.2 mm at original Stage IV to 181.3 mm post-corrected compared with 178.0 mm at the average ASOS, representing a decrease of about 31.9% from the original Stage IV event mean.



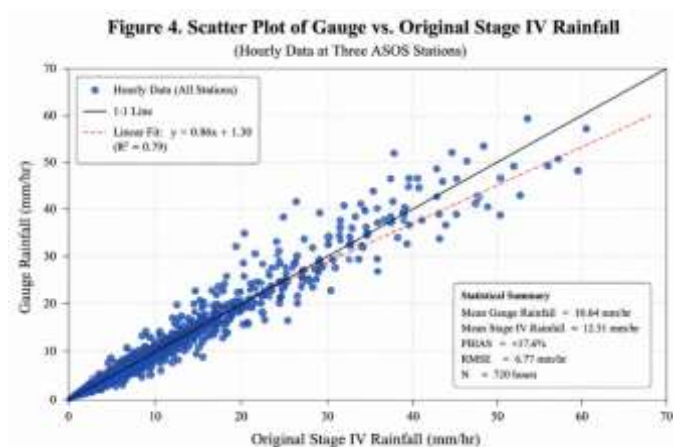


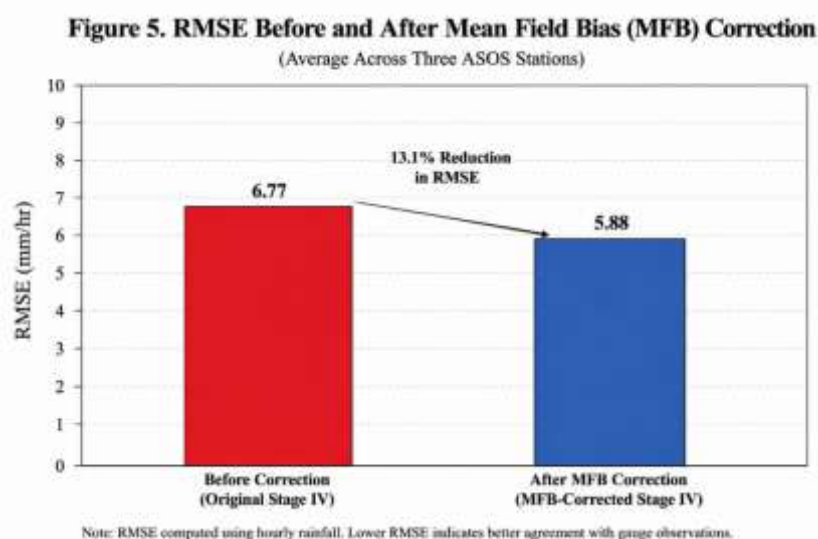
Table 3. Rainfall bias statistics before and after application of the localized Mean Field Bias correction

Station	Original PBIAS (%)	Corrected PBIAS (%)	RMSE Before (mm)	RMSE After (mm)
Fort Worth Alliance	+1.5	~0.0	6.18	6.14
Denton Airport	-3.4	~0.0	6.49	6.61
Gainesville Airport	+30.2	~0.0	6.77	5.88

5.2 RMSE Improvement

From Figure 5 and Table 3, it can be deduced that the largest improvement in accuracy happened at the Gainesville Airport station with an RMSE going down from 6.77 mm to 5.88 mm which is equivalent to about a 13.1% decrease. On the other hand, there was a slight improvement in RMSE in Denton increasing from 6.49 mm to 6.61 mm and in Fort Worth Alliance Station from 6.18 mm to 6.14 mm.

The largest improvement was seen at Gainesville Airport Station with an RMSE reducing from 6.77 mm to 5.88 mm which was equivalent to about 13% improvement. The RMSE changes at stations that had relatively small biases to begin with remained small as MFB can only correct volumetric error and not timing error at each individual station level since MFB correction is one single factor applied for the entire event.



5.3 Streamflow Simulation

The comparison between the observed hydrograph and simulations based on (a) gauge rainfall, (b) original Stage IV rainfall, and (c) MFB-corrected Stage IV rainfall are given in Figure 6. The highest peak flow was found with the original Stage IV rainfall, where the peak flow reached 11,210 ft³/s compared to the observed value of 6,560 ft³/s. The simulations using gauge rainfall resulted in 8,455 ft³/s, whereas the MFB-corrected Stage IV resulted in 8,574 ft³/s.

The Nash-Sutcliffe Efficiency (NSE) for (a) gauge rainfall was 0.935, (b) original Stage IV was 0.723, and (c) MFB-corrected Stage IV was 0.882. With the correction, the peak of the Stage IV was reduced by 23.5%, and the peak error compared to the observed discharge was decreased from 70.9% to 30.7%. This comparison is shown in Figure 7, while the simulation timing and shapes are illustrated in Figure 6.

Figure 6. Observed and Simulated Hydrographs Using Different Precipitation Inputs

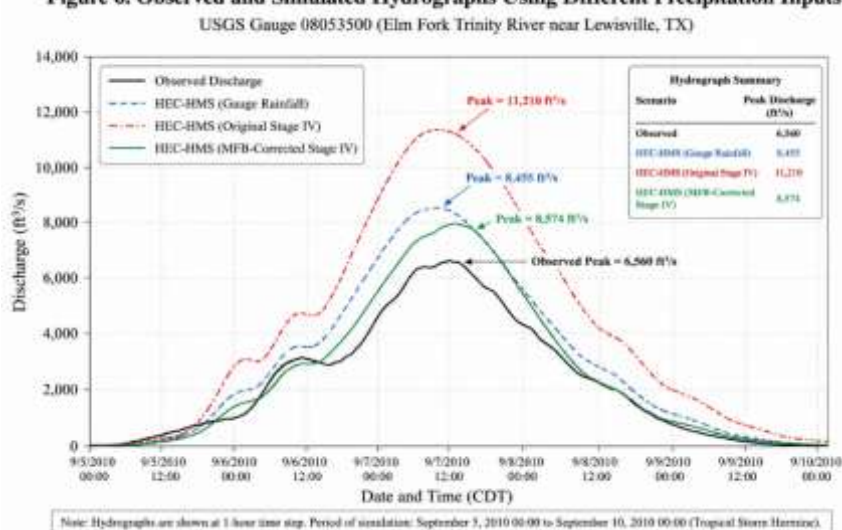


Figure 7. Comparison of Peak Discharge Across Different Scenarios

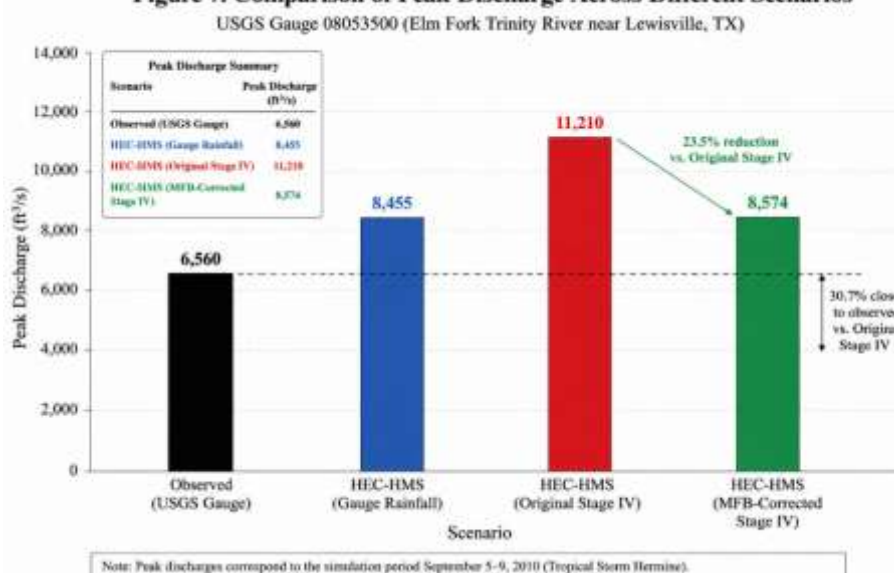


Table 4. Comparison of peak discharge and model performance for HEC-HMS simulations using different precipitation inputs.

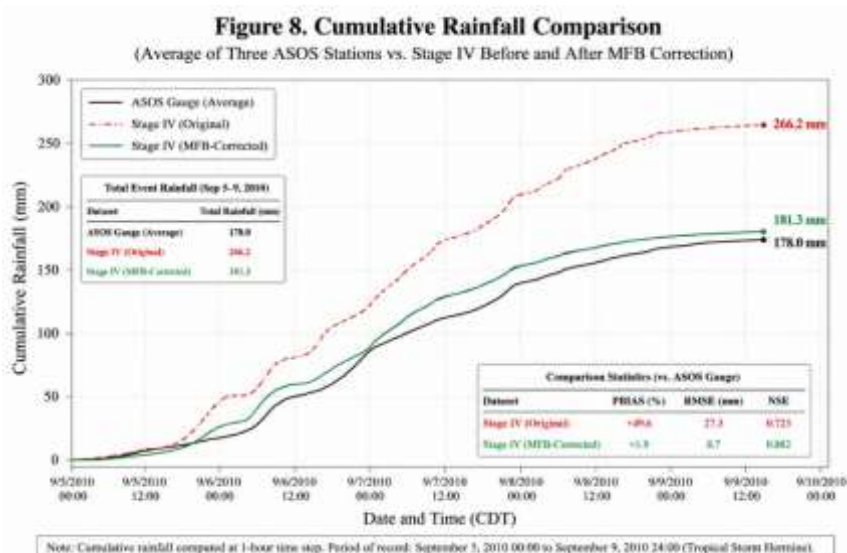
Simulation	Peak Discharge (ft ³ /s)	NSE	Peak Error vs. Observed (%)
Observed	6,560	—	0.0
Gauge Rainfall	8,455	0.935	28.9
Original Stage IV	11,210	0.723	70.9
MFB Corrected Stage IV	8,574	0.882	30.7

6 DISCUSSION

6.1 Influence of Localized Bias Correction on Hydrologic Simulation

Results reveal that an additional, localized correction of the Stage IV precipitation during stage IV could significantly impact the modeled streamflow, despite the fact that HEC-HMS basin parameters were kept the same. Specifically, the peak flow rate was 11,210 ft³/s with a Nash-Sutcliffe Efficiency (NSE) of 0.723 using the initial Stage IV precipitation. After applying MFB correction, the peak flow rate declined to 8,574 ft³/s with an NSE of 0.882. As the basin parameters remained the same, the increase in NSE was achieved due to modifications in the precipitation.

The results obtained are consistent with previous literature revealing the effect of precipitation source on the performance of hydrologic models. In particular, Ahmed et al. (2022) found differences in HEC-HMS streamflow simulations comparing rain gauge data to NEXRAD rainfall. Similar results were found by Shazwani et al. (2024) who observed better consistency between gauge rainfall and actual flood events compared to radar-estimated quantitative precipitation in HEC-HMS flood modeling. This study contributes to the existing body of literature by considering the effect of an additional correction applied to Stage IV gauge-corrected precipitation.



This is an indication that there is an important concept in hydrological modeling, which is that the quality of rainfall data has more impact on runoff prediction than changes made to the parameters of the model. Improvement in rainfall data is therefore expected to have better results for model simulations than the calibration of the hydrological model.

6.2 Spatial Variability of Radar Error

The station results show that Stage IV bias was not uniform across the watershed. Gainesville Airport had the largest overestimation, while Denton Airport and Fort Worth Alliance were much closer to the gauge observations. This spatial variation is consistent with the broader literature, which identifies range effects, storm structure, gauge density, and radar processing as contributors to rainfall error (Berne and Krajewski, 2013; Li et al., 2023).

The near zero PBIAS values after correction indicate that the dominant event scale error was sufficiently systematic to be reduced by a multiplicative factor. However, the mixed RMSE response demonstrates that MFB does not eliminate timing mismatch or all spatial errors. A spatially varying method would require additional gauge information and would represent a different methodological problem.

However, the minimal changes in the coefficient of determination in the initial study show that the timing mismatch still existed after the correction was made. Multiplicative correction cannot address the problem of different times of observation and storm cell movement. Thus, even though MFB significantly improves the total rainfall during an event, it does not eliminate all radar related errors.

6.3 Implications for Operational Flood Forecasting

One of the practical implications of this study is because it is possible to make substantial improvements to the accuracy of flood simulations using just three rain gauges. In many cases, engineering consultants, cities, and watershed agencies do not have access to an intensive network of precipitation sensors or a system capable of processing radar data. In such situations, relatively straightforward computational corrections become desirable.

The methodology evaluated here requires only:

- Stage IV precipitation data,
- hourly rain gauge observations,
- computation of a single correction factor,
- application of the corrected precipitation to an existing HEC-HMS model.

Given the availability of these datasets from operational agencies, the suggested process can be easily incorporated into the engineering work for post hazard assessment, floodplain mapping, and watershed management studies.

6.4 Comparison with Previous Research

Table 5 contextualizes the current study amidst a range of representative studies based on the use of precipitation datasets, gauge networks, corrections, metrics, and hydrologic applications. Goudenhoofdt and Delobbe (2009) found that geostatistical merging could perform better than multi-parameter bias correction (MFB) when gauge density is high. Mapiam et al. (2022) showed that adding more gauge information could improve the performance of hourly radar bias correction. Li et al. (2023) assessed Stage IV, MRMS, and RTMA products with regression kriging and Bayesian regression kriging with 150 calibration and 15 validation gauges. Ahmed et al. (2022) and Shazwani et al. (2024) provided direct examples of how the choice of rainfall input affected the HEC-HMS modeling.

The current study stands apart from others in the sparsity of gauge network and controlled experiment design. Three ASOS gauges, one-time MFB factor, gauge-corrected Stage IV dataset, fixed HEC-HMS parameters, and independent streamflow data from USGS are used. As a result, the evidence obtained is narrower compared to the evidence in large-scale validation studies: even though the methodology proved useful for the particular case study, further generalization requires withholding of precipitation gauges and storm events.

Table 5. Comparison of this study with representative investigations on radar rainfall correction and hydrologic modeling.

Study	Product / resolution	Gauge network	Correction / approach	Evaluation	Hydrologic relevance
Goudenhoofdt and Delobbe (2009)	Radar; daily	Dense network	MFB and geostatistical merging	Independent gauges; multiple error measures	MFB reduced error; geostatistical methods benefited from dense gauges
Mapiam et al. (2022)	Hourly radar	Conventional and citizen gauges	Two step Kalman filter	Rainfall bias performance	Additional gauge information improved hourly bias adjustment
Ahmed et al. (2022)	Rain gauge and NEXRAD; event based	Gauge network	HEC-HMS rainfall input comparison	Streamflow simulation	Rainfall source affected HEC-HMS results
Li et al. (2023)	Stage IV, MRMS, RTMA; hourly	150 calibration and 15 validation gauges	Regression kriging and Bayesian regression kriging	RMSE, correlation, NSE; separate validation	Gauge density and radar resolution affected merging performance
Shazwani et al. (2024)	Radar QPE and gauge rainfall	Gauge and radar inputs	HEC-HMS comparison	R ²	Gauge rainfall produced higher R ² than radar QPE
This study	Stage IV; approximately 4 km and hourly	3 ASOS gauges	Localized event MFB applied to gauge adjusted Stage IV	PBIAS, RMSE, NSE, peak discharge; USGS discharge	NSE increased 0.723 to 0.882; peak error decreased 70.9% to 30.7%

6.5 Engineering Significance

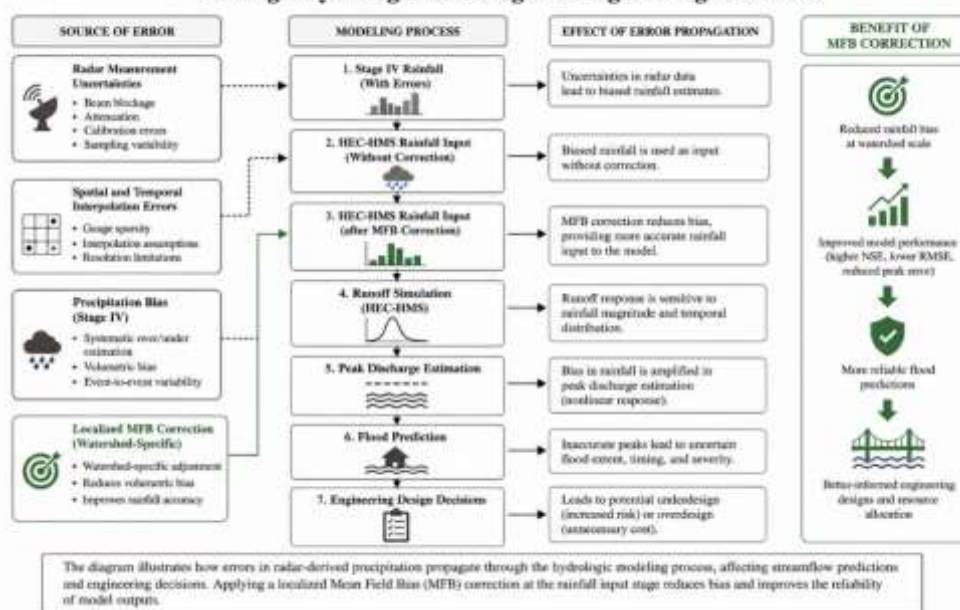
The engineering significance of this work extends beyond the specific case study. Accurate estimation of peak discharge directly influences:

- culvert design,
- bridge hydraulic analysis,
- detention basin sizing,
- floodplain delineation,
- stormwater infrastructure planning,
- dam safety evaluations.

The problem of too much runoff would result in overly conservative designs, making the cost of construction too high, while not enough runoff would make the design unsafe because of lack of sufficient capacity.

By showing that the use of local precipitation modification increases the accuracy of streamflow estimation without changing hydrologic modeling parameters, there is a way to minimize uncertainties in engineering calculations.

Figure 9. Conceptual Propagation of Rainfall Estimation Errors Through Hydrologic Modeling and Engineering Decisions



7 PRACTICAL IMPLICATIONS

The methodology that has been developed in this case is specifically designed to suit the needs of engineering projects. Unlike the complex methods of radar correction, which involve complicated observational procedures or complicated statistical procedures, the Mean Field Bias methodology is based on only a few rain gauges. Thus, this methodology can be applied effectively in the case of watersheds having limited data availability.

Potential applications include:

- Post flood forensic investigations,
- calibration of watershed models,
- FEMA flood studies,
- watershed master planning,
- reservoir inflow estimation,
- emergency flood forecasting,
- transportation drainage design.

The simple nature of the technique also makes it easy to incorporate into hydrologic modeling algorithms, wherein correction factors are calculated before running the models.

8 STUDY LIMITATIONS

The following are the four main weaknesses of this research. To start with, this study has analyzed one single extreme rainfall event of Tropical Storm Hermine. Though this analysis has passed a very strong test due to its significance in hydrology, it is

recommended that inferences made about the climatological conditions are done carefully. There is need to conduct further tests on other extreme rainfall events of different types.

Secondly, the correction of Mean Field Bias (MFB) is based on just three ASOS stations. Even though these stations are enough to establish a coefficient of the whole event, it would be better to have more number of stations in order to analyze how well other correction techniques such as Kriging or Conditional Merging work.

Third, the proposed technique of correction assumes spatial constancy of radar bias through the event. Though this assumption makes the analysis easier, it does not consider spatial variability that may be associated with developing convective system.

Fourth, there are some uncertainties associated with the hydrologic model which includes watershed parameterization, loss coefficient calculation techniques and routing techniques. Since it is assumed that all the parameters of the model will remain constant, this issue may be analyzed in further work. The USGS discharge data used to test the result of this research is an independent hydrologic response data, because it has not been used to calculate MFB.

9 CONCLUSIONS

The analysis evaluates the effect of the localized Mean Field Bias (MFB) correction of Stage IV precipitation on the simulated streamflows using the HEC-HMS model during Tropical Storm Hermine in the Elm Fork Trinity River Basin. The key results are summarized below:

1. Although regional gauge adjustment corrected the Stage IV precipitation bias, there was still localized event-level bias where Gainesville Airport had the highest overestimation (PBIAS = +30.2%).
2. Localized MFB correction of precipitation decreased the PBIAS to almost 0% at all three ASOS gauges. Precipitation RMSE at Gainesville Airport dropped from 6.77 mm to 5.88 mm.
3. The corrected precipitation provided better hydrological modeling, with NSE increasing from 0.723 to 0.882, and the peak flow rate falling from 11,210 ft³/s to 8,574 ft³/s, compared to the observed value of 6,560 ft³/s.
4. The localized precipitation adjustment constitutes an encouraging preprocessing technique for water-limited watersheds. However, the evidence is event-specific and needs to be further validated with withheld gauges and other storm events.

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