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Centralized and Decentralized Approach to Monsoon Precipitation Forecasting in Pakistan

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Abstract Rainfall, is one of the most important meteorological factors that affects many parts of our everyday lives including crop productivity, water quality, livestock availability, hydroelectric power generation to name a few. Rainfall prediction can significantly contribute to boosting the economy by enabling better planning, risk management, and resource allocation in various industrial sectors. In this study, forty years of monsoon precipitation data is gathered for 39 stations across five zones in Pakistan. We propose a multi-step Long Short-Term Memory (LSTM)-based prediction model capable of forecasting Monsoon yearly data. Three LSTM models stack, bidirectional and convolutional are applied on the dataset and the performance of these models are analysed using a centralized and a decentralized approach. It is observed that the RMSE score of the LSTM models across the centralized strategy was found better than the decentralized approach, whereby 100% of the models in the centralized had a lower RMSE as compared to the decentralized one. Moreover, in the centralized approach 78.7% of the models across the different zones exhibited R^2 > 0.9 values indicating a general fit to the model.

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1 Introduction

Rainfall drives a nation's economy. Rainfall directly affects a wide range of industries, including agriculture [1], livestock, energy [2, 3], and tourism. Water shortages and animal losses brought on by drought conditions can have an influence on farmers' and pastoral communities' quality of life [4]. Lack of rain diminishes crop productivity, causes food crisis, and raises food costs [5, 6]. Adequate rainfall refills groundwater sources and reservoirs, ensuring a steady supply of drinking water for both urban and rural populations. Moreover, regular rainfall patterns encourages other forms of tourism, like ecotourism [7, 8].

Monsoon crises can have significant social, economic, and environmental consequences, and they often require coordinated response efforts from governments, humanitarian organizations, and communities to mitigate their impact and provide relief to affected populations. In 2022, Pakistan suffered intense monsoon rainfall during mid June to late August causing floods on the Indus river. The southern province of Sindh, along with the neighboring province of Balochistan, formed the worst impacted region in the nation as a result of the Indus River overflowing [9]. Early forecast of heavy rainfall could minimize the effect of disaster.

Rainfall prediction can significantly contribute to boosting the economy by enabling better planning, risk management, and resource allocation in various sectors. Forecasting rainfall is challenging since weather conditions are always changing. In a place where agriculture is rainfed, rainfall is a key determinant in agricultural production. Therefore, its precise forecast is essential for controlling and planning farmers' plants. Many hydrological models include rainfall as one of its components since it is crucial to the symmetry of the water cycle [1, 10]. In water management, predictions can aid in the management of water resources, including planning the time of irrigation, lowering water waste, and assuring efficient use of scarce water supplies [11]. In the energy sector, reliable forecasts enable power firms to optimize energy output and avoid water shortage-related disturbances [12]. In supply chain management, to avoid supply chain delays and maintain economic activity, it is possible to better organise transportation and reroute vehicles when heavy rainfall and probable flooding are predicted [13, 14]. In the tourism industry, predictions of rainfall can help the tourism sector plan marketing initiatives and tactics. Tourism revenue can be increased by knowing whether to advertise indoor attractions during rainy seasons or outside events during good weather [15]. Extreme weather disasters like floods, hurricanes, and landslides can be better anticipated and handled by governments and local populations. This reduces damages and costs, preventing financial disasters [16, 17].

This study mainly focuses on predicting precipitation trends during the monsoon season and is the first to present a comparative analysis of the performance of rainfall forecasting models based on state-of-the-art deep learning algorithm i.e. Long-short-term-memory models (LSTM), in predicting yearly rainfall volume using averaged-monsoon weather time-series data from 39 stations spanned across five zones in Pakistan. Specifically, the main contribution of this study is mentioned below:

- Multi-source weighted total precipitation version 2.0, data collection and extraction of 42 years of Monsoon from the time-period 1979 – 2022, of 39 stations divided across 5 zones, covering main regions in Pakistan.
- To identify precipitation trend across various stations in the five zones by employing a multi-step LSTM forecasting models using a centralized and decentralized approach.
- To identify best performing LSTM models by reporting various metrics. Three LSTM models are investigated: stack, bi-directional and convolutional.

The research study is arranged as follows. Section 2 describes the existing work on rainfall predictions and description of the LSTM models investigated. Section 3 presents the data and its details. Section 4 represents the methodology and evaluation metrics. Section 5 presents the result analysis and discussion. Finally, Section 6 concludes with main outcome of our research along with possible future direction.

2 Literature Review

3 Pakistan's Monsoon Dataset

Weather forecasting has increasingly benefited from advancements in machine learning and deep learning algorithms, transforming traditional prediction methods that relied on numerical models [19]. Also the data features used has a significant impact on the accuracy of prediction. Some research [20, 21] focuses solely on precipitation data, using it as a key indicator for rainfall prediction. While precipitation is critical, other studies adopt a more multidimensional approach [22–24], incorporating various meteorological factors such as temperature, humidity, wind speed, pressure etc.

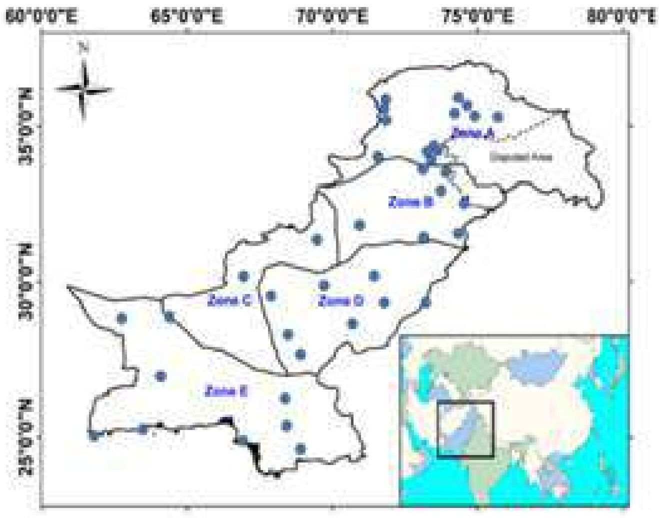

Figure 1. Station distribution across five zones in Pakistan. [18]

These multidimensional datasets allow for a more comprehensive analysis of atmospheric conditions, capturing the complex interactions between different variables that drive weather patterns.

In the research study [25] , a two-step ML model was generated for categorizing rainfall data and predicting features that are reused by the developed ML model for further forecasting. ML models developed were decision trees (DT), random forest (RF), k-nearest neighbour (k-NN), artificial neural networks (ANN) and support vector machine (SVM). ANN was found to perform best with a root means square error (RMSE) of 2.55.

Moreover in a study [26], rainfall dataset with 20 features were used to predict rainfall in Bangladesh. The features were reduced to 10 by using Principal Component Analysis. Various ML and DL algorithms were used in the generation of a prediction model, which includes KNN, LR, SVM, RF, Naïve Bayesian (NV), NN and LSTM and overall LSTM was reported to outperform other models with an accuracy of 97.14%. Similarly in the [27], an LSTM deep learning model has been applied on 32 years of precipitation dataset, acquired from NSMA of Ethopia. The dataset includes multiple features including maximum & minimum temperature, relative humidity, solar radiation, wind speed, and precipitation. The DL model is compared with other ML models (MLP, KNN, SVM, DT) whereby LSTM outperformed other ML models with an RMSE of 0.01. While in this study [28], long-term daily rainfall prediction in Tenerife, Spain was conducted on 36 years of captured data. 2 statistical model namely generalized linear with gaussian and gamma kernels and 6 ML model LR, RF, KNN, SVM, Kmeans, NN were trained on feature variables from atmospheric synoptic patterns. Hyperparameter grid search was performed for all the models to identify the optimal one. NN performed best for both occurrence and intensity prediction with an RMSE of 12.6. Similar studies on Australia [29] and Lahore, Pakistan [30] was conducted and best ML and DL models were reported.

In [31], models based on LSTM, stacked-LSTM, bidirectional-LSTM, XGBoost, and an ensemble of gradient boosting regressor, linear Support Vector Regression (SVR), and an Extra-trees Regressor were compared in the task of forecasting hourly rainfall volumes using 20 years of time-series data of five major cities in the United Kingdom. Stacked LSTM and Bidirectional LSTM were found to perform better than other ML models.

Apart from rainfall detection, drought prediction so as to improve and plan better water resource management practices has been focused of many studies including [32]. The drought was categorized as moderate, severe and extreme based on Standardized Precipitation and Evapotranspiration Index (SPEI). Three machine learning models, SVM, ANN and KNN were developed on the acquired dataset with features air temperature, geopotential height, relative humidity, U wind, V wind and sea level pressure. SVM model was found to perform well with a NRMSE of 0.42 and an R^2 of 0.97.

In the current research study we will use LSTM (Long Short-Term Memory) networks, a type of recurrent neural network (RNN) that are highly effective for time series prediction, making them well-suited for weather precipitation forecasting. LSTMs are designed to handle the vanishing gradient problem, which allows them to learn and retain information over long periods, making them ideal for capturing temporal

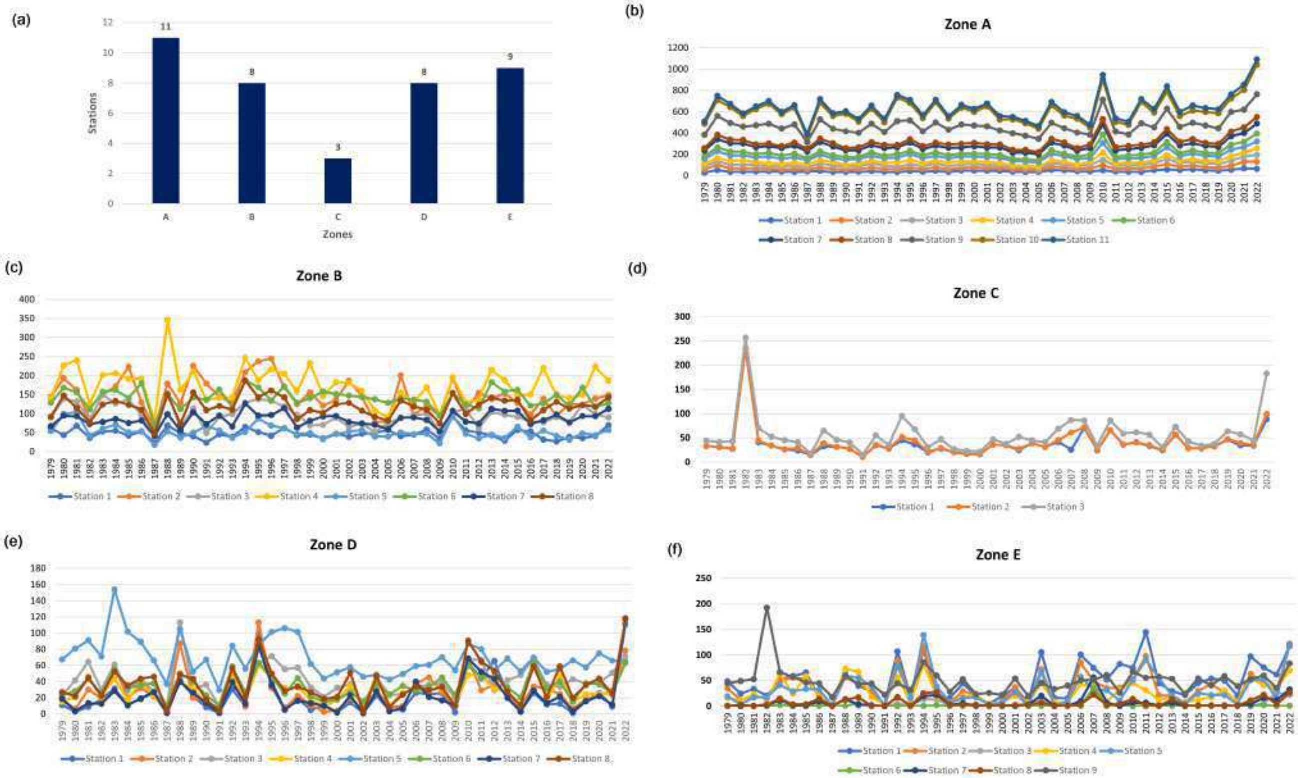

Figure 2. (a) Number of Pakistan Meteorological Department rain gauge stations across different zones (b-f) Precipitation trend in Zone A, B, C, D and E across Pakistan from 1979-2022.

dependencies in weather data. Their flexibility in handling noisy and irregular data, common in weather systems, makes LSTM a powerful tool for improving both short-term and long-term precipitation forecasting. In particular three different LSTM models shall be investigated. They are stack LSTM, bidirectional LSTM and convolutional LSTM. Detail performance analysis shall be the focus of our study.

This study uses the multi-source weighted total precipitation version 2.0 (MSWEP V2.0) data set developed by [33, 34] and is one of the most popular multi-source products [35]. MSWEP is a global precipitation product with a high spatial resolution (0.1°×0.1°) available at every 3-hours. The range of the datasets spans from 1979-2022 up to 3 hours from real-time [36]. The product is unique as it merges gauge observations, satellite derived, and reanalysis precipitation estimates to obtain the highest quality gridded data at every location [34].

Numerous studies have been performed on assessment of MSWEP products over at regional and global scales. [35] discussed that MSWEP V2.0 has the highest temporal correlation with ground based gauge observations on a long term average, compared and followed by reanalysis and satellite precipitation products, however MSWEP underestimates the precipitation over the monsoon regions in China and Australia, while there are overestimations in the Qinghai-Tibet Plateau, China. [37] checked the accuracy of MSWEP over India and found that the averaged accuracy was lower compared to the datasets such as that of the Climate Hazards Group Infrared Precipitation dataset.

[38] studied the gridded precipitation products in comparison with MSWEP (taken as in-situ observations) in order to determine their respective strengths and uncertainties on 51 stations, spanning 1998–2016, across Pakistan on daily, monthly, annual

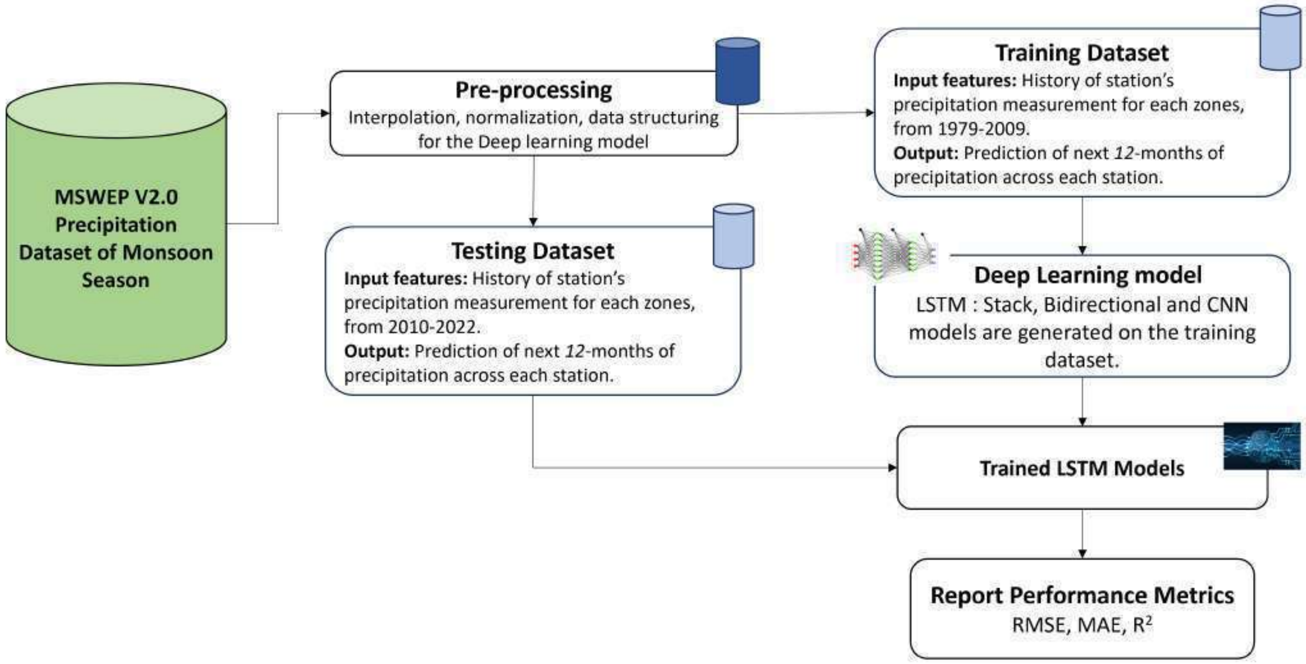

Figure 3. Overall methodology executed in the current research study.

and inter-annual time scales. They found that in daily precipitation data with values larger than 10 mm, a 95 percent significant agreement existed between MSWEP and other satellite precipitation datasets, on monthly basis. They found that MSWEP was able to capture extreme precipitation events quite consistently and the performance metrics improved with increased (>5 mm/day) thresholds with high correlation during peak precipitation events.

[39] studied the spatio-temporal characteristics of rainfall in Balochistan from 1980 to 2016 using multi-source data including MSWEP. Their results indicated that MSWEP dataset exhibited a higher correlation coefficient (0.92) compared to Climate Prediction Center (CPC) dataset with correlation coefficient (0.77). They also showed the monthly rainfall volume was predominantly contributed by rainfall events with an intensity exceeding 10 mm.

The present study makes use of this dataset over whole Pakistan from 1979 - 2022 in order to check its performance in the monsoon season (June, July, August, September). Time series estimates of 3-hourly precipitation data averaged to monthly data, were extracted from the gridded MSWEP V2.0 product over five different zones of Pakistan taken according to [18] and displayed in Figure 1. Each zone consists of a number of Pakistan Meteorological Department (PMD) rain gauge stations presented in Figure 2(a). MSWEP V2.0 time-series data was extracted on the PMD stations in order to present a comparative and comprehensive analysis of monsoon precipitation variations from point of view of a high resolution gridded datasets assessment which could be used over those those locations in Pakistan over which the PMD observatories are not available, station's distribution is presented in Figure 1. From Figure 2(b) it is observed that the rainfall amount vary significantly across the different stations. There are spikes and fluctuations in the rainfall data, indicating the dynamic and variable nature of the monsoon precipitation. The patterns between the stations do not appear to be perfectly aligned, suggesting potential localized differences in rainfall events or measurement variations between the stations.

The study aims to investigate the efficiency of MSWEP V2.0 product to assess the heavy precipitation events in the monsoon season in different climatic zones over whole Pakistan so as to be used at a policy level for devising effective monitoring strategies for meteorological and climate-related extremes especially in the monsoon region. The study also aims to assess the quality of MSWEP V2.0 product for PMD stations in order to fill the missing data gaps both on temporal and spatial scales across the country.

Many statistical and dynamical weather forecasting models [22–24] use various parameters such as humidity, wind speed, wind direction, temperature and precipitation etc to forecast climate and weather parameters of interest. The current study shall use deep learning algorithm LSTM models on the MSWEP V2.0 precipitation data.

4 Methodology

Figure 3 shows the overall methodology of the current research study. The MSWEP dataset is pre-processed and split into training and testing sets. The LSTM deep learning models are trained on the training set and the performance metrics are reported on the test set accordingly.

4.1 Data Augmentation

Deep learning models, require large amounts of data to train effectively and leading to better generalized AI Models. As the dataset acquired is limited to monsoon months in Pakistan, it is crucial to expand the dataset. Interpolation is a common data augmentation technique [40, 41] that enhances the quantity and quality of data. A linear interpolation technique is used to create new data points. Through this process the number of sample points increased 8 times, providing deep learning models enough data points to train on.

4.2 Training/Testing strategies

The 42-years monsoon precipitation data is divided into an 12-year testing set and a 30-year training set. The data set is set up to forecast a year at a monthly resolution based on the precipitation history of all zone's stations from the previous year. The LSTM models transfers the properties of the input data to the output forecast by learning the patterns and relationships of the data through the training set. Three different LSTM model namely stack, bidirectional and convolutional labelled as SLSTM, BLSTM and CLSTM, are assessed and their performances are compared using two different strategies; centralized and decentralized, discussed below. The input data represents 12 steps of previous history from all of the stations and the LSTM models forecasts 12 steps ahead. The number of nodes for each layer in an LSTM model was set to 100. The stack LSTM consists of two LSTM layers. 'return_sequence' was set to TRUE enabling the LSTM layer to provide an output at each iteration.

- Approach 1 [Decentralized Models]: The stations are spatially located across several kms in each zone. The precipitation trend is different for each station as shown in Figure 2. Independent LSTM models for each station is generated. Hence in this strategy, for each LSTM model type, x number of LSTM models per zone are generated, whereby *x* stands for the number of stations in each zone respectively.
- Approach 2 [Centralized Model]: To ensure consistency and uniformity among the different stations in each zone, one LSTM model for each zone is generated. Centralized models are found to benefit from more robust infrastructure, leading to faster training times and better performance [42]. Morevoer training and deploying the model in a single location can be more resource efficient. Centralized data allows for consistent preprocessing steps, reducing the risk of discrepancies that might arise in a decentralized setting. Hence, a single LSTM model is generated in this strategy that predicts precipitation across the all stations for each zone respectively.

4.3 Performance Analysis

For comparing the performance of different LSTM models, there exist a plethora of metrics summarized by different authors in the field [43–45]. The performance metrics used in the current research study

Table 1. Performance of LSTM models {SLSTM, BLSTM, CLSTM} across centralized and decentralized strategy for the different stations in Zone C averaged across a forecast horizon of 12 months. RMSE, MAE, R^2 are reported. Naive{NV} benchmark model has also been mentioned in the table for benchmark analysis.

		Centralized				Decentralized			
ZoneC	Metrics	NV	SLSTM	BLSTM	CLSTM	NV	SLSTM	BLSTM	CLSTM
S1	RMSE	20.18	10.29	3.18	5.51	22.07	11.4	11.78	13.89
	MAE	10.21	7.01	1.99	3.3	10.21	5.18	5.19	6.69
	R2	0.09	0.78	0.98	0.93	0.09	0.78	0.76	0.66
S2	RMSE	4.07	3.35	1.28	1.51	4.49	1.4	1.65	1.96
	MAE	1.73	1.96	0.87	1.12	1.73	0.68	0.76	0.67
	R2	0.28	0.6	0.93	0.91	0.28	0.93	0.9	0.86
S3	RMSE	5.31	5.34	2.13	2.54	5.87	3.09	3.22	3.25
	MAE	3.98	3.82	1.46	1.98	3.98	1.92	1.85	2.23
	R2	0.38	0.45	0.91	0.87	0.38	0.83	0.82	0.81

includes the most common ones reported in literature. Given the measured output as w and the predicted output as $\hat{w}$ with N observations, detail description of each metric along with Equations.1-3 are presented herewith.

- mean square error (MSE): is the mean square error which is the squared difference of measured and predicted values, expressed as in Eq. 1. MSE is sensitive to large forecast errors and hence suitable where small errors are tolerable.

$$\text{MSE} = \frac{1}{N}\sum_{i}^{N}(\hat{w}(i) - w(i))^2 \quad (1)$$

- Mean Absolute error (MAE): is appropriate for linear cost functions and represents an absolute difference between measured and predicted values expressed in Eq. 2.

$$\text{MAE} = \frac{1}{N}\sum_{i}^{N}|\hat{w}(i) - y(i)| \quad (2)$$

- Coefficient of determination (R^2): represents how well observed outcomes are replicated by the model, based on the total variation of outcomes by the model as in Eq. 3, where $\overline{y(i)}$ represents the mean of the observations.

$$R^2 = 1 - \frac{\sum_i^N(\hat{y}(i) - y(i))^2}{\sum_i^N(y(i) - \overline{y(i)})^2} \quad (3)$$

Whether the model predictions is a random walk or learnt, a benchmark comparison naive (NV) is essential.Naive models are simple time-series forecasting method whereby the previous value is used as a forecast for the next time step expressed in Equation. 4, where $\hat{NV}_t$ is the prediction at the time step t. In this model, at a given time-step, the prediction remains constant for all of the forecast horizons.

$$\hat{NV}_t = NV_{t-1} \quad (4)$$

The outcome of the LSTM models generated in both centralized and decentralized approach are compared with a naïve model for performance analysis.

5 Results and Discussion

Table 1 shows the performance of the LSTM models i.e. SLSTM, BLSTM and CLSTM using a centralized and decentralized approach across Zone C in terms of RMSE, MAE and R^2 across a forecast horizon of 12 months. The models are compared with a standard benchmark model labelled as NV. The performance results of the remaining zones, A, B, D, E are presented in Table 2- 5.

Which strategy overall had good performing models? From Table 1- 5, it is observed that the RMSE score of the LSTM models across the centralized strategy was found better than the decentralized approach, whereby 100% of the models in the centralized had a lower RMSE as compared to the decentralized one. Moreover, in the centralized approach 78.7%

Table 2. Performance of LSTM models {SLSTM, BLSTM, CLSTM} across centralized and decentralized strategy for the different stations in Zone A averaged across a forecast horizon of 12 months. RMSE, MAE, R^2 are reported. Naive{NV} benchmark model has also been mentioned in the table for comparative analysis.

		Centralized				Decentralized			
Zones	Metrics	NV	SLSTM	BLSTM	CLSTM	NV	SLSTM	BLSTM	CLSTM
S1	RMSE	4.17	2.59	2.72	2.03	4.59	3.18	2.84	3.06
	MAE	3.2	1.94	2.18	1.66	3.2	2.38	2.05	2.26
	R2	0.7	0.9	0.89	0.94	0.7	0.86	0.89	0.87
S2	RMSE	4.54	2.26	2.29	2.12	4.99	2.51	2.98	2.95
	MAE	3.48	1.75	1.81	1.68	3.48	1.69	1.94	1.96
	R2	0.52	0.89	0.89	0.91	0.52	0.88	0.83	0.84
S3	RMSE	4.1	2.14	2.24	1.76	4.52	2.35	2.35	2.65
	MAE	2.87	1.69	1.76	1.41	2.87	1.55	1.47	1.72
	R2	0.62	0.91	0.9	0.94	0.62	0.9	0.9	0.87
S4	RMSE	6.9	2.85	3.28	2.31	7.59	3.07	3.92	3.84
	MAE	4.46	2.05	2.29	1.78	4.46	1.74	2.05	2.14
	R2	0.25	0.89	0.85	0.93	0.25	0.88	0.8	0.81
S5	RMSE	8.43	2.51	3.59	2.63	9.24	4.36	4.75	5.28
	MAE	5.65	2	2.7	2.02	5.65	2.73	2.87	3.44
	R2	-0.2	0.9	0.81	0.9	-0.2	0.73	0.68	0.61
S6	RMSE	7.58	2.36	3.26	2.16	8.33	3.5	4.43	4.46
	MAE	4.18	1.78	2.13	1.67	4.18	2.07	2.19	2.46
	R2	0.24	0.93	0.87	0.94	0.24	0.87	0.79	0.78
S7	RMSE	6.6	2.83	3.01	2.5	7.26	9.78	5.11	5.1
	MAE	4.79	2.07	2.2	2.02	4.79	7.33	3.43	3.34
	R2	0.22	0.87	0.86	0.9	0.22	-0.45	0.61	0.62
S8	RMSE	3.86	2.02	1.96	1.87	4.25	2.44	2.39	2.78
	MAE	3.08	1.57	1.57	1.5	3.08	1.58	1.54	1.94
	R2	0.57	0.89	0.9	0.91	0.57	0.86	0.87	0.82
S9	RMSE	19.73	4	5.36	3.61	21.48	9.82	12.34	13.86
	MAE	14.89	3.16	4.15	2.87	14.89	6.97	9.29	10.08
	R2	-0.09	0.96	0.93	0.97	-0.09	0.77	0.64	0.55
S10	RMSE	26.37	4.67	6.22	4.24	28.72	14.02	18.22	16.32
	MAE	20.51	3.57	5.01	3.29	20.51	10.64	14.08	12.42
	R2	-0.05	0.97	0.95	0.98	-0.05	0.75	0.57	0.66
S11	RMSE	3.29	2.08	2.08	1.62	3.62	1.92	2.19	2.51
	MAE	2.52	1.64	1.68	1.28	2.52	1.32	1.34	1.71
	R2	0.75	0.91	0.91	0.95	0.75	0.93	0.91	0.88

Table 3. Performance of LSTM models {SLSTM, BLSTM, CLSTM} across centralized and decentralized strategy for the different stations in Zone B averaged across a forecast horizon of 12 months. RMSE, MAE, R^2 are reported. Naive{NV} benchmark model has also been mentioned in the table for comparative analysis.

		Centralized				Decentralized			
ZoneB	Metrics	NV	SLSTM	BLSTM	CLSTM	NV	SLSTM	BLSTM	CLSTM
S1	RMSE	9.56	4.52	4.29	6.08	10.5	5.09	5.19	5.65
	MAE	7.41	3.39	3.33	4.56	7.41	3.08	2.95	3.47
	R2	0.01	0.81	0.83	0.65	0.01	0.77	0.76	0.71
S2	RMSE	28.77	7.53	6.46	7.68	31.58	16.92	19.64	25.06
	MAE	23.3	5.71	4.89	6.04	23.3	11.84	14.44	17.59
	R2	0.25	0.96	0.97	0.95	0.25	0.79	0.71	0.53
S3	RMSE	15.56	6.24	5.56	6.6	16.91	8.37	9.55	9.28
	MAE	11.32	4.74	4.21	5.06	11.32	5.97	6.13	6.8
	R2	0.42	0.92	0.94	0.91	0.42	0.86	0.81	0.82
S4	RMSE	31.43	9.82	7.39	8.21	34.1	20.24	22.45	24.58
	MAE	22.38	6.84	5.54	6.51	22.38	15.17	15.9	16.86
	R2	0.25	0.93	0.96	0.96	0.25	0.73	0.67	0.61
S5	RMSE	11.24	4.18	5.28	6.51	12.43	4.44	5.34	6.04
	MAE	8.1	3.1	3.86	5.24	8.1	3.34	3.66	4.07
	R2	0.21	0.91	0.85	0.78	0.21	0.9	0.85	0.81
S6	RMSE	14.57	6.32	5.39	5.88	15.84	12.97	9.42	9.72
	MAE	11.05	4.54	4.26	4.52	11.05	10.06	7.26	6.9
	R2	0.05	0.84	0.89	0.87	0.05	0.36	0.67	0.64
S7	RMSE	11.4	5.16	4.36	4.62	12.41	6.55	6.69	7.17
	MAE	8.48	4.09	3.41	3.61	8.48	4.57	4.84	4.94
	R2	0.03	0.83	0.88	0.87	0.03	0.73	0.72	0.67
S8	RMSE	17.98	6.24	5.14	6.13	19.55	8.75	7.44	11.72
	MAE	13.67	4.59	4.14	4.69	13.67	6.31	5.09	7.74
	R2	0.06	0.91	0.94	0.91	0.06	0.81	0.86	0.66

Table 4. Performance of LSTM models {SLSTM, BLSTM, CLSTM} across centralized and decentralized strategy for the different stations in Zone D averaged across a forecast horizon of 12 months. RMSE, MAE, R^2 are reported. Naive{NV} benchmark model has also been mentioned in the table for comparative analysis.

		Centralized				Decentralized			
ZoneD	Metrics	NV	SLSTM	BLSTM	CLSTM	NV	SLSTM	BLSTM	CLSTM
S1	RMSE	11.49	2.13	2.03	1.98	12.54	5.34	4.91	6.74
	MAE	7.62	1.63	1.53	1.34	7.62	3.22	3.16	4.24
	R2	0.5	0.99	0.99	0.99	0.5	0.91	0.92	0.85
S2	RMSE	14.49	2.5	2.04	1.96	15.68	4.86	4.74	6.5
	MAE	9.79	1.8	1.52	1.42	9.79	2.94	3.02	4.25
	R2	0.25	0.98	0.99	0.99	0.25	0.93	0.93	0.87
S3	RMSE	12.31	2.2	2.24	1.8	13.3	5.38	5.63	7.07
	MAE	8.23	1.69	1.71	1.41	8.23	3.59	3.58	5.06
	R2	0.35	0.98	0.98	0.99	0.35	0.89	0.88	0.81
S4	RMSE	10.62	2.17	2.15	1.59	11.52	5.82	5.56	5.94
	MAE	8.04	1.72	1.53	1.18	8.04	3.66	3.92	4.02
	R2	0.04	0.96	0.97	0.98	0.04	0.75	0.78	0.74
S5	RMSE	10.76	2.58	2.39	1.96	11.62	6.79	5.65	8.8
	MAE	7.75	1.97	1.74	1.43	7.75	4.77	3.86	6.31
	R2	0.66	0.98	0.99	0.99	0.66	0.88	0.92	0.81

		Centralized				Decentralized			
ZoneD	Metrics	NV	SLSTM	BLSTM	CLSTM	NV	SLSTM	BLSTM	CLSTM
	RMSE	8.95	2	1.76	1.41	9.76	4.4	5.87	5.77
S6	MAE	6.95	1.57	1.34	1.11	6.95	3.06	3.89	3.62
	R2	0.17	0.97	0.97	0.98	0.17	0.83	0.7	0.71
	RMSE	11.06	2.12	1.85	1.8	12.12	4.49	7.1	6.67
S7	MAE	8.01	1.59	1.42	1.33	8.01	2.92	4.4	4.03
	R2	0.42	0.98	0.99	0.99	0.42	0.92	0.8	0.83
	RMSE	13.91	2.46	2.42	2.01	15.17	7.58	6.2	8.83
S8	MAE	10.4	1.82	1.76	1.52	10.4	5.01	3.89	5.8
	R2	0.18	0.98	0.98	0.99	0.18	0.79	0.86	0.72

Table 5. Performance of LSTM models {SLSTM, BLSTM, CLSTM} across centralized and decentralized strategy for the different stations in Zone E averaged across a forecast horizon of 12 months. RMSE, MAE, R^2 are reported. Naive{NV} benchmark model has also been mentioned in the table for comparative analysis.

		Centralized				Decentralized			
ZoneE	Metrics	NV	SLSTM	BLSTM	CLSTM	NV	SLSTM	BLSTM	CLSTM
	RMSE	21.65	3.09	3.88	5.14	23.79	9.19	7.41	11.41
S1	MAE	16.35	2.27	2.99	4.11	16.35	5.22	5.16	7.79
	R2	0.33	0.99	0.98	0.97	0.33	0.9	0.93	0.85
	RMSE	18.87	2.41	3.33	4.08	20.68	7.87	8.52	10.8
S2	MAE	14.41	1.81	2.54	3.24	14.41	4.91	5.81	7.16
	R2	0.16	0.99	0.98	0.96	0.16	0.88	0.86	0.77
	RMSE	4.02	1.13	1.78	1.52	4.4	2.2	2.23	2.34
S3	MAE	2.64	0.85	1.32	1.11	2.64	1.07	1.23	1.32
	R2	0.41	0.96	0.9	0.93	0.41	0.85	0.85	0.83
	RMSE	13.74	2.17	3.46	2.81	15.04	6.13	7.98	7.92
S4	MAE	10.37	1.65	2.69	2.05	10.37	4.1	5.06	5.42
	R2	0.15	0.98	0.95	0.97	0.15	0.86	0.76	0.76
	RMSE	17.04	2.74	3.22	4.01	18.62	7.82	7.65	8.57
S5	MAE	12.14	2	2.44	3.11	12.14	5.39	5.03	5.9
	R2	0.35	0.99	0.98	0.96	0.35	0.89	0.89	0.86
	RMSE	4.22	1.02	1.4	1.34	4.63	1.09	1.53	1.85
S6	MAE	1.41	0.73	0.95	0.98	1.41	0.45	0.61	0.61
	R2	0.21	0.97	0.93	0.94	0.21	0.95	0.91	0.87
	RMSE	6.7	1.4	2.14	1.73	7.38	2.27	2.37	2.41
S7	MAE	3.84	1.03	1.47	1.22	3.84	1.41	1.28	1.59
	R2	0.37	0.98	0.94	0.97	0.37	0.94	0.93	0.93
	RMSE	4.59	1.33	1.92	1.38	5.03	2.62	2.89	2.66
S8	MAE	3.22	1.01	1.46	1.04	3.22	1.35	1.72	1.64
	R2	0.41	0.96	0.91	0.96	0.41	0.84	0.81	0.83
	RMSE	15.25	2.96	4.67	4.82	16.63	9.05	8.37	9.85
S9	MAE	9.54	2.22	3.44	4.02	9.54	5.27	4.65	5.47
	R2	0.29	0.98	0.94	0.93	0.29	0.8	0.83	0.76

Figure 4. Precipitation Forecast for three stations in Zone B (a,d,g) Maximum precipitation (b,e,h) Minimum precipitation (c,f,i) Average precipitation, zone respectively. MSE, MAE and R^2 plots are shown herewith for the LSTM models along with benchmark prediction.

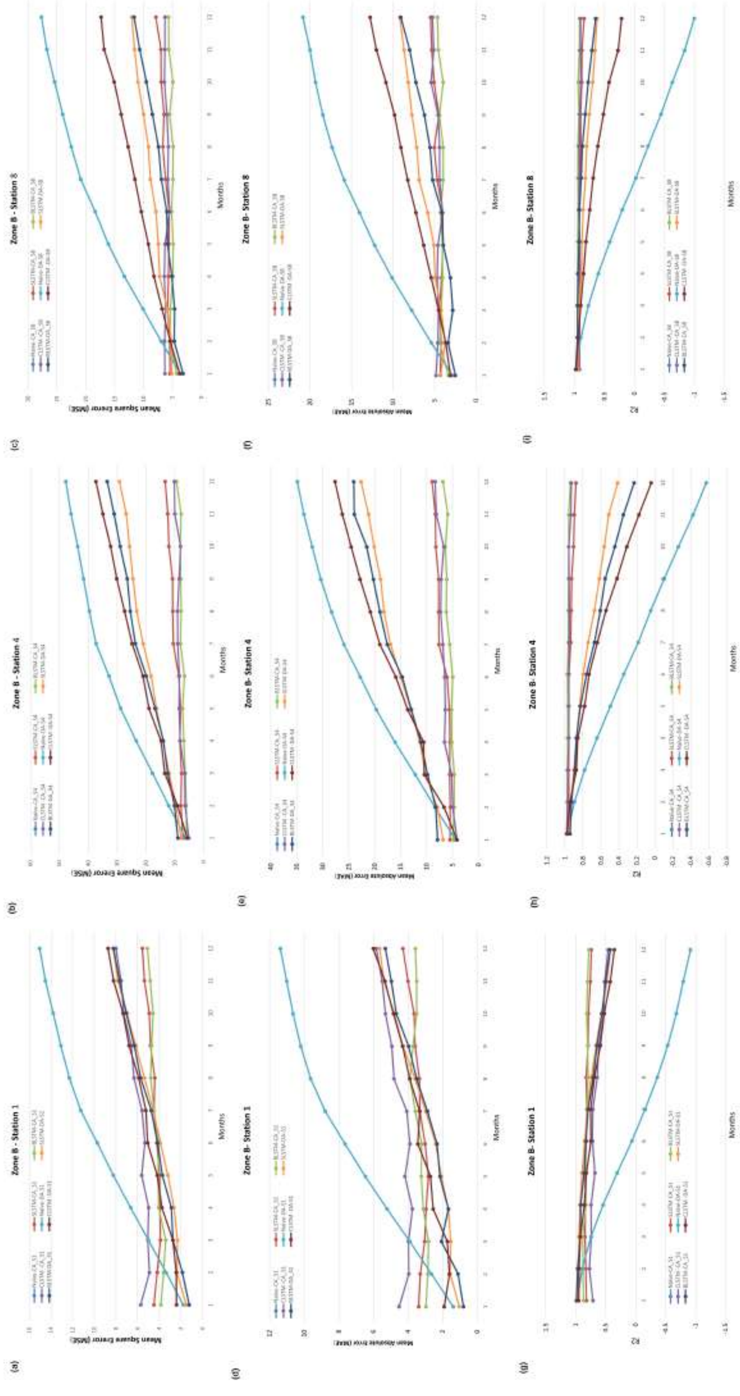

Table 6. Computational Time for the LSTM Models {SLSTM, BLSTM, CLSTM} using a centralized and decentralized approach, across all zones in Pakistan - Both Inference and Training Times are mentioned in seconds.

Centralized Approach							
		Training Time(s)			Inference Time(s)		
Zones	Stations	SLSTM	BLSTM	CLSTM	SLSTM	BLSTM	CLSTM
Zone A	11	48.72	54.13	21.06	0.36	0.32	0.25
Zone B	8	58.92	39.59	21.13	0.43	0.44	0.29
Zone C	3	50.73	34	24.59	0.48	0.28	0.28
Zone D	8	62.63	35.62	21.26	0.5	0.34	0.22
Zone E	9	51.22	37.83	19.88	0.35	0.31	0.22
Decentralized Approach							
		Training Time(s)			Inference Time(s)		
Zones	Stations	SLSTM	BLSTM	CLSTM	SLSTM	BLSTM	CLSTM
Zone A	11	71.7	46.35	28.55	0.39	0.44	0.34
Zone B	8	72.17	45.44	25.8	0.36	0.35	0.36
Zone C	3	58.13	44.21	21.34	0.37	0.31	0.34
Zone D	8	69.45	45.28	22.8	0.38	0.5	0.26
Zone E	9	68.99	45.08	24.2	0.53	0.36	0.27

of the models across the different zones exhibited $R^2 > 0.9$ values indicating a general fit to the model. *Which LSTM models performed best in centralized and decentralized strategy?* There is no model performing better across all zones. In the centralized strategy, CLSTM models performed better in Zone A & D, while BLSTM models in Zone B & C. In Zone E, SLSTM models had low score of RMSE and MAE. While in case of decentralized strategy, SLSTM and BLSTM models were found to perform better across the different stations in five zones. *Did the LSTM model performed better than the naive benchmark model across the different performance metrics?* Figure 4 shows the RMSE, MAE and R^2 for Zone B, which is a high precipitation zone overall. There are eight stations in Zone B and the minimum, maximum and average precipitation trend are only shown in the Figure 4 which corresponds to station 1, 4 and 8 respectively. It is observed that overall the LSTM models performed better than the standard benchmark model. Moreover in case of Zone B, the BLSTM model has been found to forecast more accurately than the other models.

Which LSTM models are computationally expensive? Table 6 shows the training and inference time of three LSTM models using a centralized and decentralized strategy across the 5 zones respectively. Both in centralized and decentralized strategy, SLSTM was found to be computationally expensive, taking more time, than BLSTM and CLSTM. Assuming parallel interpretation models across stations, the training and inference times in the decentralized approach represents the average times across the different stations. Same behaviour is observed in this strategy with SLSTM being more computationally expensive than BLSTM and CLSTM respectively. Inference time across both the strategies is approximately the same. Furthermore, from Table 6, as the centralized approach generates a single model that predicts for all of the stations within a zone simultaneously its training and inference time (in 96% cases) is lower than the decentralized approach. E.g. in the centralized approach, for an SLSTM model training took 48.72s while it took an average of 71.7s for training on 11 stations.

Is centralized or decentralized strategy better in terms of computational time? While considering the inference time 87% of the centralized models had lower inference times as compared to the decentralized models. Such insight is useful in scenarios where decision based on computational requirement is essential. Centralized models are found to benefit from more robust infrastructure, leading to faster training times and better performance [46]. Moreover training and deploying the model in a single location can be more resource efficient. Centralized data allows for consistent pre-processing steps, reducing the risk of discrepancies that might arise in a decentralized setting. The results obtained from the current research study further indicates the advantage of centralized models.

6 Conclusion

Precise predictions of precipitation help farmers arrange their planting and harvesting schedules more efficiently, which leads to better resource management and increased agricultural yields. Furthermore, reliable prediction models help reservoir managers schedule water releases in a way that lessens the chance of drought and flooding, which promotes effective management of water resources. In the current research study, three LSTM models (stack, bidirectional and convolution) were studied and applied on Pakistan's monsoon precipitation data. A centralized and decentralized strategy was deployed to explore the potential of a single and a multi-model based prediction. Centralized models were found to perform better in terms of RMSE, MAE and R^2 than decentralized across the different zones. There was no distinct LSTM model performing in all scenarios. While considering the inference time 87% of the centralized models had lower inference times as compared to the decentralized models. Future work will involve expanding the datasets by incorporating additional features, such as humidity, temperature, and others, for further analysis and modeling.

Author Contributions

Maryam Mahsal Khan: Conceptualization, Methodology, Software, Writing- Reviewing and Editing **Qudsia Zafar**: Data curation, Writing- Original draft preparation. **Sumayyea Salahuddin**: Visualization, Investigation, Validation.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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