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Performance Evaluation of Rainfall Spatial Interpolation in Lower Vellar Watershed Using Inelastic Constitutive Artificial Neural Networks

Mr. Arun Shourie R[1*], Dr. Ezhisaivallabi K[2]

[1*]Research Scholar, Department of Civil Engineering, Faculty of Engineering and Technology, Annamalai University, Chidambaram, India.

[1*]Email: arunshourieravi86@gmail.com

[2]Associate Professor, Department of Civil Engineering, Faculty of Engineering and Technology, Annamalai University, Chidambaram, India.

Abstract

Rainfall patterns vary widely, making it challenging to get accurate measurements because rain gauges only provide limited and scattered data points. This challenge is particularly significant when estimating and simulating climate change models within diverse environmental settings, as accurate rainfall data is essential for various scientific applications like hydrological modeling and agricultural planning. In this manuscript, Performance Evaluation of Rainfall Spatial Interpolation in Lower Vellar Watershed Using Inelastic Constitutive Artificial Neural Networks (SIR-LVW-ICANN) is proposed. In this proposed approach data are collected from Weather data Indian cities (1990 to 2022). The input data is fed to pre-processing using High Accuracy Distributed Kalman Filtering (HADKF) to find Missing Data and Normalization. Then, pre-processed data are fed to Inelastic Constitutive Artificial Neural Networks (ICANN) to effectively predict the mean annual precipitation. Then the proposed SIR-LVW-ICANN is implemented in Python and the performance metrics like Accuracy, RMSE and MAE are analysed. Performance of the SIR-LVW-ICANN approach attains 19.36%, 26.42% and 23.27% higher accuracy and 22.36%, 15.42% and 18.27% lower RMSE when analysed through existing techniques like Deep Spatial Interpolation of Rain Field for U.K. Satellite Networks (DSI-RF-CNN) , Application of multiple spatial interpolation approaches to annual rainfall data in the Wadi Cliff basin (MSI-ARD-MLPNN), and Machine Learning Procedures for Daily Interpolation of Rainfall in Navarre (DIR-KNN) methods respectively.

Keywords: Geographic Information Systems, Geo-statistical Interpolation, Inelastic Constitutive Artificial Neural Networks, Monsoon Season, Rainfall, Spatial Interpolation, Water Resource Management.

1. INTRODUCTION

a) Background

Rainfall is a critical component of the hydrological cycle, influencing various environmental processes, including water resource management, agriculture, and climate modeling [1]. Traditionally, rainfall data has been collected through rain gauge networks, which record precipitation at specific locations [2]. While these networks provide essential information, they have significant limitations [3]. Rain gauges offer only point measurements, leading to sparse and discontinuous data, particularly in regions with complex topography or limited infrastructure [4]. This limitation makes it difficult to accurately capture the spatial variability of rainfall, which is crucial for applications such as watershed management, crop growth simulation, and climate modeling [5-6]. The primary challenge lies in the substantial variability of precipitation across different regions and times, compounded by the inadequacies of traditional rain gauge networks [7]. The sparse distribution of gauges and the resulting gaps in data make it difficult to create accurate, continuous rainfall maps [8]. This issue is particularly problematic for regions where precise rainfall data is essential for managing water resources, predicting floods, and understanding climate change impacts [9]. Moreover, the variability in the performance of spatial interpolation methods across different geographical areas adds to the complexity of obtaining reliable rainfall estimates [10].

b) Literature Review

Several investigations that evaluated different approaches and elements of spatial interpolation techniques for rainfall have already been published in the literature. Among those examined were the following:

Achite et al., [11] have recommended a Root Mean Square Error of 24.98, Random Forest had the best training performance among the 150 monitoring stations and nearly five decades of data analysed. When employed as an auxiliary variable, elevation shows up as a crucial component that improves prediction accuracy in complex and mountainous terrain. Cluster analysis enhances the understating of station distribution and precipitation aspects by identifying four different clusters, each with unique elevation zones and precipitation patterns. By promoting the integration of extra variables and the investigation of the effects of climate change, this study advances knowledge of precipitation prediction and aids in the development of well-informed environmental management and adaptation plans for a variety of climatic and terrain scenarios.

Yang et al., [12] have created the primary contribution was the effective integration, with a notable increase in accuracy, of the state-of-the-art deep learning technique into high-resolution (HR) rainfall rate prediction. This was critical to the successful application of fade mitigation strategies for satellite and terrestrial networks alike. The suggested models provide a satisfactory mean square error (MSE) and structural similarity (SSIM) in rainfall field reconstruction if the network depth is between 15 and 25 weight layers, according to a comparison of the models' performances with ground truth (radar observations). Using 20 layers, the final model forecasts the rate of HR point rain. This article particularly contrasts values derived from measured data with the rain rate exceedance distribution and Log-Normality property from the model estimations.

Militino et al., [13]have presented Because of this method's robustness, minor deviations from normalcy were permitted; nonetheless, Rigging cannot be applied because many environmental, contaminant, and meteorological variables have severely asymmetrical distributions. As an alternative, machine learning methods like k-nearest neighbour, random forest, and neural networks can be employed since they don't call for any particular distributional assumptions. The disadvantage was that they do not account for the spatial dependence; therefore, more sophisticated machine learning approaches might be taken into consideration for optimal performance in spatial random fields. Moreover, these methods were computationally demanding to use and call for a sizable amount of training data.

Borah and Deka [14] has suggested applying the multi-influencing factor approach to the investigation of possible groundwater zones in the Jamuna watershed of Assam. Groundwater is one of the most valuable natural resources on Earth for the conveyance of freshwater. Evaluating and regularly monitoring the prospective groundwater zones in various parts of the world was crucial for the sustainable and effective management of groundwater systems. The prior research attempts to discover multiple potential groundwater zones in the Jamuna watershed, Assam, by means of remote sensing, GIS, and multi-influencing factor methods. The suggested considers a wide range of factors that can either directly or indirectly affect groundwater revival, including rainfall geomorphology, sediment concentration, soil texture, slope, drainage density, geology and land use.

Fagandini, et al., [15] have presented the monthly semi-variorum models were fitted using the average daily rainfall from all available meteorological stations for each month in a reference period. With this approach, only 12 monthly semi-variorums can be used, as opposed to one semi-variorum for each day of the gap period. Using the semi-variorums for the relevant month, ordinary rigging and basic corking were employed to estimate the missing daily precipitation. While using the corking process, the elevation data was taken into account as the secondary variable. Three methodologies were applied to approximate the missing precipitation data from a year's worth of data from selected stations in order to assess the efficacy of the suggested methods.

Chutsagulprom, et al. [16] intends to assess and compare the effectiveness of well-known interpolation methods for estimating Thailand's monthly rainfall data. The inverse distance-based method was one of the chosen techniques. For certain of the previously described schemes, there was an additional requirement to use the nearest station search technique. The effectiveness of each approach was evaluated using the k-fold cross-validation technique, and comparisons were made using the metric scores, MAE and RMSE. Inverse distance weighting (IDW), especially inverse exponential weighting (IEW), and maximum likelihood regression (MLR) were highly comparable, even though the OK technique yields the most accurate prediction.

Pinthong et al., [17] the twelve rainfall stations were used as an investigation topic. They were situated in the surrounding basins and the Thale Sap Songkhla river basin. To determine which model would work best with the data sets under consideration, hyper-parameters for each machine learning technique were tuned. To compare the performance of the various approaches, 3 performance criteria matrices OI, NSE, and r were selected, and their sum was introduced. The experimental findings demonstrated that while using SI methods, choosing nearby stations was crucial; however, this was not the case for the method. Overall performance demonstrated that, by overcoming spatial limits was able to impute missing monthly rainfall more accurately than SI.

c) Research Gap and Motivation

The critical importance of accurate rainfall estimation for environmental management and the challenges posed by traditional measurement methods, there is a clear need for more reliable and robust spatial interpolation techniques. The variability in the performance of existing methods across different regions highlights the necessity of exploring and comparing various approaches to identify the most effective techniques for specific settings. This is especially important in the context of long-term climate analysis, where understanding rainfall patterns over several decades is essential for informed decision-making. Recently, there are several methods such as MLPNNs, CNNs, KNN used for the accurate rainfall estimation. MLPNNs may over fit the training set, resulting in insufficient generalization. It is also difficult to comprehend how variables like elevation affect forecasts because they may have difficulty with model interpretability and need a large amount of computational resources. When compared to other cutting-edge methods, CNNs might not adequately handle the intricacies and variability of rainfall data, which could have an impact on forecast accuracy. The k-nearest neighbours (KNN) technique can have difficulties with high-dimensional data and is not sensitive to small variations. It also ignores spatial dependence. For accurate performance, KNN needs a lot of training data and is computationally demanding. The multi-influencing factor approach to groundwater zone identification may encounter difficulties when attempting to integrate different data types and spatial variability. The above mentioned drawbacks are motivated to do this work.

There are various benefits to using Inelastic Constitutive Artificial Neural Networks (ICANN) for rainfall spatial interpolation in the Lower Vellar Watershed. When compared to conventional approaches, these networks improve the accuracy of precipitation estimations by modeling intricate, non-linear interactions in spatial rainfall data. Researchers can acquire more accurate spatial distributions of rainfall by utilizing the ICANN's ability to handle inelastic, changeable data conditions. This improves hydrological modeling, flood prediction, and water resource management in the watershed. This method offers reliable interpolation even in areas with erratic or scant rainfall data, which eventually helps with resource planning and improved decision-making.

d) Contribution

- In this research work, Performance Evaluation of Rainfall Spatial Interpolation in Lower Vellar Watershed Using Inelastic Constitutive Artificial Neural Networks (SIR-LVW-ICANN) is proposed.
- Initially, the rainfall data is acquired using Weather data Indian cities.
- The HADKF approach is utilized for pre-processing in order to address missing data in the dataset.
- Following the subsequent pre-processing stages, the result is given to the ICANN technique so that it can make predictions.
- The obtained results of the proposed SIR-LVW-ICANN algorithm is compared to the existing models such as MSI-ARD-MLPNN, DSI-RF-CNN and DIR-KNN methods respectively.

f) Novelty

The novelty of the SIR-LVW-ICANN model is new because it creatively combines deep learning, geo-statistical, and deterministic techniques to estimate mean annual precipitation in arid places. In comparison to conventional methods, the model greatly improves prediction accuracy and lowers error metrics by utilizing Inelastic Constitutive Artificial Neural Networks (ICANN) with historical meteorological data from Indian cities. This hybrid method represents a breakthrough in precipitation estimation methodologies, especially when combined with its successful application in semi-arid and dry environments.

g) Organization

The last part of the paper is structured as follows: Part 2 outlines the Proposed Methodology, Part 3 presents the results with discussions, and Part 4 concludes the manuscript.

3. Proposed Methodology

In this section, Performance Evaluation of Rainfall Spatial Interpolation in Lower Vellar Watershed Using Inelastic Constitutive Artificial Neural Networks (SIR-LVW-ICANN) is proposed. This process consists of four steps: Data Collection, Pre-processing and prediction. In the proposed data were collected and pre-processing to prepare them for further analysis. The final step involves employing Inelastic Constitutive Artificial Neural Networks (ICANN) for prediction. Southwest monsoon, Post-monsoon, Pre-monsoon, and Northeast monsoon seasons, as well as the mean annual rainfall for the entire Research region, The block diagram of proposed SIR-LVW-ICANN approach is represented in Fig 1. As a result, a thorough explanation of each step is provided below.

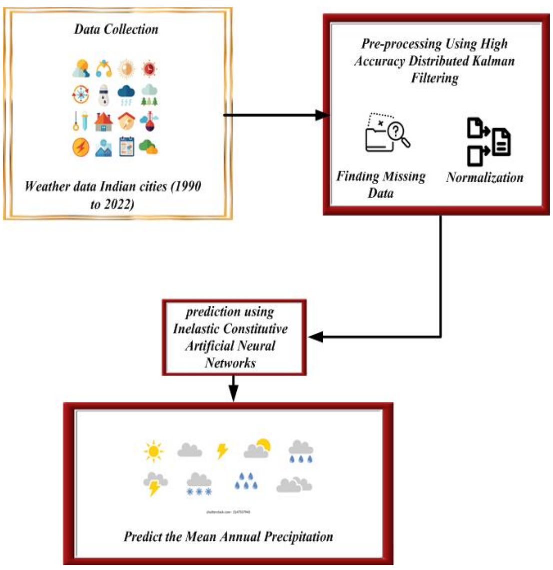

Figure 1: Block Diagram of SIR-LVW-ICANN methods

3.1. Data Collection

Initially, the input data is collected from Weather data Indian cities (1990 to 2022) [18]. The following data set includes precipitation data in millimetres and temperature data (minimum, average, and maximum) in degrees Celsius. Daily temperature and precipitation data from January 1, 1990, to July 20, 2022, are included in this data collection. The following cities' data is available: Delhi, Chennai, Bangalore, Luck now, Rajasthan, Mumbai, Bhubaneswar, Rourkela. The approximate location from where these measurements are taken can be found in the station Geo-location file.

3.2 Pre-processing Using High Accuracy Distributed Kalman Filtering (HADKF)

In this section, pre-processing using High Accuracy Distributed Kalman Filtering (HADKF) [19] is discussed. HADKF involves finding the missing data and normalizing it in the pre-processing stage. By combining many data sources and accounting for temporal and spatial fluctuations, High Accuracy Distributed Kalman Filtering enhances rainfall spatial interpolation. It improves forecast accuracy by offering accurate updates. Furthermore, HADKF efficiently reduces measurement noise and uncertainty, producing more precise rainfall estimates across a range of geographical areas. The measurement covariance can also be changed using (1) when the measurement function is non-linear. Equation (1)

$$Q_h^m = Q_{h-1}^m + m_h^n \tag{1}$$

Where, Q_h^m define the total number of training points, Q_{h-1}^m define the individual decision and m_h^n define the class probabilities, missing data in rainfall spatial interpolation by dynamically updating estimates based on available information are given in equation (2)

$$G_h^m = Q_h^m + S_h^m \tag{2}$$

Where, G_h^m define the count of data points, Q_h^m define the total count of samples and S_h^m define the input instance, This procedure ensures that the interpolation results are reliable and helps to minimize bias in spite of changes in data scales or unitsis given in equation (3)

$$\Delta\mu_h^m = \sum_{n\in N_m} \omega_{mn} M_h^n G_h^n \tag{3}$$

Where, Δ define the subset of instances, μ_h^m define the total number of instances, ω_{mn} define the density function, M_h^n define the evidence factor and G_h^n define the maximum posterior probability.Finally the HADKF has found the Missing Data and Normalization. Then the pre-processed data's are fed to Inelastic Constitutive Artificial Neural Networks.

3.3 Prediction using Inelastic Constitutive Artificial Neural Networks

In this section Prediction using Inelastic Constitutive Artificial Neural Networks (ICANN) [20] is discussed. ICANN is proposed to effectively predict the mean annual precipitation. Their ability to adjust to changing patterns and trends increases the precision of geographic forecasts. Additionally, ICANNs manage a variety of data sources well, providing stable performance even when there is inconsistent or scant data. Their adaptability allows for a more accurate depiction of the changes in rainfall in different regions. It is given in equation (4),

$$G : \frac{\partial\varphi(x_0,t)}{\partial x_0}, \quad G^{-1} = \frac{\partial\varphi^{-1}(x,t)}{\partial x} \quad with \;\; F_3^G > 0 \tag{4}$$

Where, x_0 is denoted as position vector, φ is indicated as objective function, t is indicated as time, ∂ is denoted as pseudo potential and G is denoted as a motion, given in millimetres or inches, which aids in determining the region's general moisture content and climate conditionsis given in the equation (5),

$$G^+ = Q^+G \quad \Leftarrow \frac{\partial\varphi^{-1}(x,t)}{\partial x} = \frac{\partial\varphi^{x^{-1}}(x^+,t)}{\partial x^+} \; \frac{\partial x^+}{\partial x} \tag{5}$$

Here , G^+ is denoted as objectivity, $\partial\varphi^{-1}(x,t)$ is second motion inversion, $\partial\varphi^{x^{-1}}(x^+,t)$ is denoted as the rigid rotation of the current position, The mean rainfall for a given time period can then be calculated by averaging the collected data over a predetermined period of time annually is given in the equation (6),

$$G^\# = G\,Q^\# \quad \Leftarrow \frac{\partial\varphi\;(x_0,t)}{\partial x} = \frac{\partial\varphi^\#(x^+,t)}{\partial x_0^\#} \; \frac{\partial x_0^{\;\#}}{\partial x_o} \tag{6}$$

Where, $G^\#$ is denoted as the rigid motion of the reference configuration, $\partial\varphi^\#(x^+,t)$ is denoted as second motion inversion and $Q^\#$ is denoted as the current configuration, In the end, the mean yearly precipitation was accurately predicted by using the ICANN.

4. RESULT AND DISCUSSION

Performance Evaluation of Rainfall Spatial Interpolation in Lower Vellar Watershed Using Inelastic Constitutive Artificial Neural Networks SIR-LVW-ICANN approach. In Implementation work was carried Python and evaluated by using several performance analysing metrics like, Accuracy, RMSE and MAEare analysed. The results of the proposed SIR-LVW-ICANN methodology are contrasted to the existing technique like MSI-ARD-MLPNN, DSI-RF-CNN and DIR-KNN respectively.

4.1 Performance Measures

Performance measures include Accuracy, RMSE and MAE. The confusion matrix has been used to scale the performance parameters and it is decided.

4.1.1 Accuracy

The ability to measure a precise value is known as accuracy. A metric called accuracy can be used to characterize the model's performance in all classes. It is quantified by the following equation (7)

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{7}$$

4.1.2 RMSE (Root Mean Square Error)

It is a common indicator used to evaluate the prediction method's accuracy, especially in the context of regression analysis. The average size of the errors between the projected and actual values is computed. It is given in equation (8)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{8}$$

4.1.3 MAE (Mean Absolute Error)

It is a metric that computes the mean magnitude of errors among expected and actual data. It is very useful to assess the performance of methods depending on regression as given in equation (9),

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{9}$$

4.2 Performance Analysis

Figure 2 to 10 displays the simulation results of the proposed SIR-LVW-ICANN approach. The proposed 3DSDNN-IBM-NIS techniques are linked to the MSI-ARD-MLPNN, DSI-RF-CNN and DIR-KNN techniques, in that order.

Figure 4 depicts the Lower Vellar Watershed rain gauge station location. Tamil Nadu, India's Lower Vellar Watershed is a sub-basin of the Vellar River Basin. At 225 kilometres (140 miles) in length, the Vellar River is the second-biggest river in the state of Tamil Nadu. It drains into the Bay of Bengal near Karaikal. Analysing the seasonal variation in rainfall at the four rain gauge sites in the studied area over the 30 years prior.

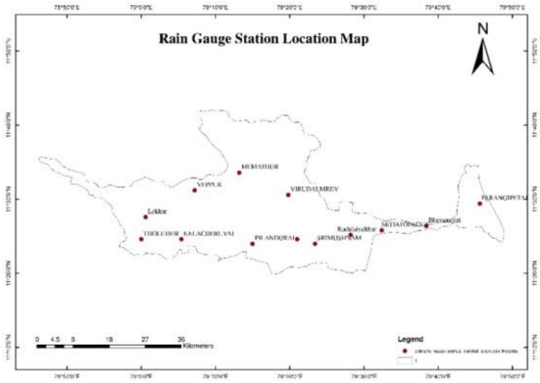

Figure 2: Rain Gauge Station of Lower Vellar Watershed

4.3. Mean Annual Rainfall

The total precipitation amount for a given month or year, recorded and averaged. Both mean and median rainfall are included in these figures, even though the median is usually the favoured measure of "average" or "typical" rainfall from a meteorological standpoint. A single extraordinary rainfall event has have less of an impact on the median than the arithmetic mean because of the large daily variability of rainfall. The annual average rainfall for 13 locations in the Lower Vellar watershed for a 30-year period, from 1991 to 2021, was investigated. Pre-monsoon, NE monsoon, post-monsoon, and SW monsoon were the four distinct research seasons. The Lower Vellar watershed's seasonally comprehensive rainfall analysis for each station is displayed in Figure 3.

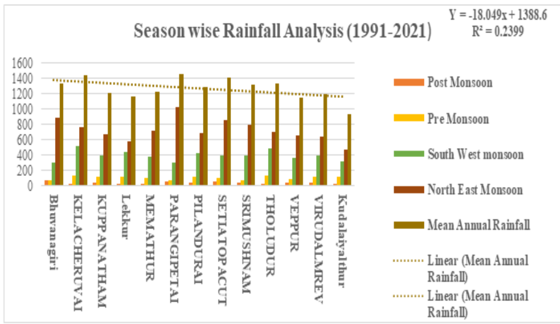

Figure 3: Season-wise Rainfall Analysis of Lower Vellar Watershed

4.4. Post Monsoon

Depending on where you reside, this time frame, which comes after the south-west monsoon peaks, might range from October to November. The vegetation begins to dry up as precipitation decreases. For most of India, this time of year marks the transition from the wet to the dry season. The study area experienced an increasing trend in post-monsoon average rainfall; the lowest recorded mean rainfall in 1995 was 2.00 mm, while the highest recorded mean rainfall in 2021 was 180 mm.

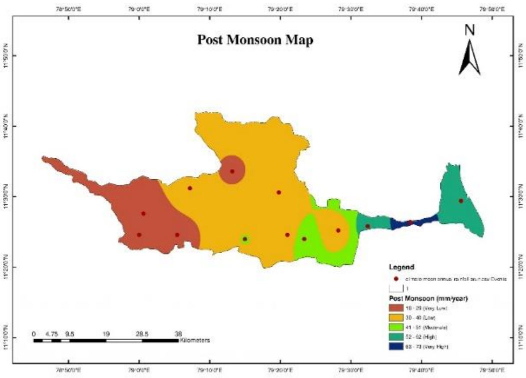

Figure 4: Post Monsoon Rainfall Map of Lower Vellar Watershed

4.5. Pre-Monsoon

Before the rainy season officially begins, there are pre-monsoon showers. It takes place from March to May. They can be anything from brief drizzles to violent thunderstorms. They aid in the early ripening of mangoes and are sometimes known as summer rains or mango showers. The study region witnessed a rising Pre-monsoon average rainfall trend, with the smallest mean rainfall observed in 1994 at 4.00 mm and the maximum average rainfall reported in 1995 at 210mm (Figures 10& 11). Fig 5 illustrates the spatial analysis of the Pre-Monsoon precipitation Distribution Map (mm/year) ranges from (75-87 (Very Low), (88-99 (Low), (100-111 (Moderate), (112-123 (High)), (124-135(Very High)).

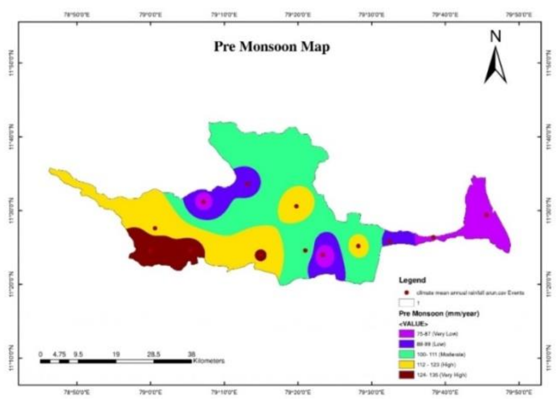

Figure 5: Pre -Monsoon Rainfall Map of Lower Vellar Watershed

4.6. South West Monsoon

Refer to the months of June through September as the South-west Monsoon season. The seasonal winds that carry rain and flow south westward from the Arabian Sea to the interior of India are known as the south-west monsoons. With the lowest mean rainfall recorded in 1992 at 138.00 mm and the highest recorded in 2000 at 772 mm, the study region had an increasing trend in the average rainfall from the South-west monsoon. That is why figure 6 displays the spatial analysis of the South West Monsoon Rainfall Distribution Map, with ranges of (mm/year) as low as 300-340, low as 350-390, moderate as 400-430, high as 440-480, and very high as 490-520.

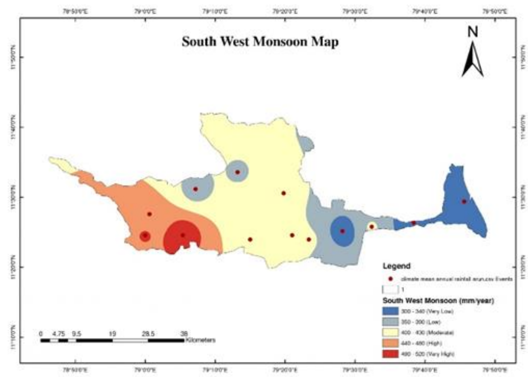

Figure 6: Southwest Monsoon Rainfall Map of Lower Vellar Watershed

4.7. North-East Monsoon

Call it the North-east Indian Monsoon season when there is a lot of rain in the south-east of the Indian peninsula between October and December (OND). The research area had an increasing trend in the average rainfall during the North East monsoon, with the highest recorded mean rainfall in 2015 at 1629 mm and the lowest recorded mean rainfall in 2009 at 318 mm. The spatial analysis of the North-east Monsoon Rainfall Distribution Map (mm/year) is therefore depicted in figure 7, which spans the following ranges: 460-570 (Very Low), 580-680 (Low), (690-800 (Moderate), (810-910 (High), and 920-1000 (Very High).

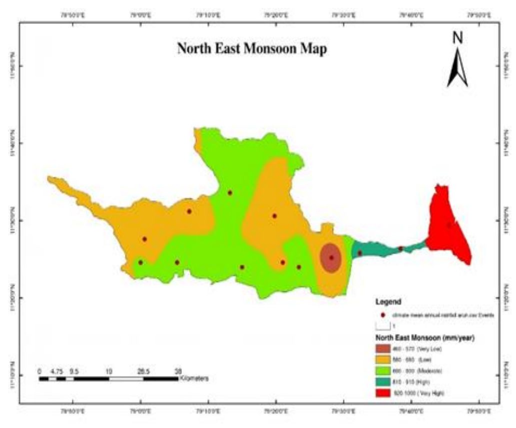

Figure 7: Northeast Monsoon Rainfall Map of Lower Vellar Watershed

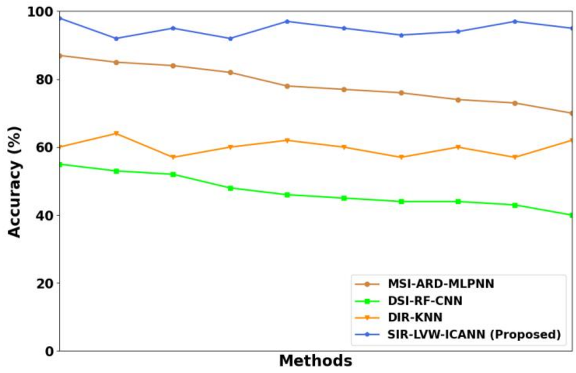

Figure 8: Performance analyses of Accuracy

Figure 8 depicts Performance analyses of accuracy. More accurate rainfall spatial interpolation results in more dependable data for agricultural planning, flood forecasts, and water resource management. Precise rainfall data is necessary for efficient planning and decision-making, especially in areas like the Lower Vellar Watershed where water supplies are critical to the local ecosystem and economy. The proposed SIR-LVW-ICANN technique reaches in the range of 19.36%, 26.42% and 23.27% higher accuracy Compared with existing techniques such as MSI-ARD-MLPNN, DSI-RF-CNN and DIR-KNN respectively.

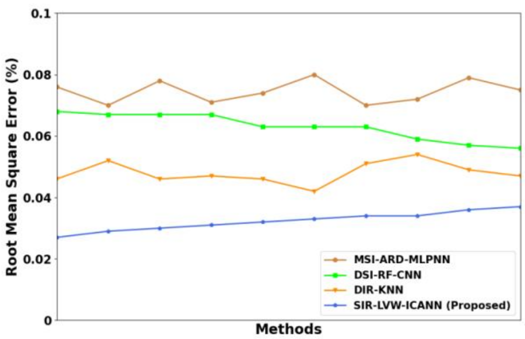

Figure 9: Performance analyses of RMSE

Figure 9 depicts Performance analyses of RMSE. This enhanced performance is essential for efficient management of watersheds since reduced RMSE values signify more accurate and consistent rainfall forecasts. For many uses, such as flood forecasting, agricultural planning, and water resource management, accurate rainfall interpolation is crucial. The proposed SIR-LVW-ICANN technique reaches in the range of 22.36%, 15.42% and 18.27% lower RMSE Compared with existing techniques such as MSI-ARD-MLPNN, DSI-RF-CNN and DIR-KNN respectively.

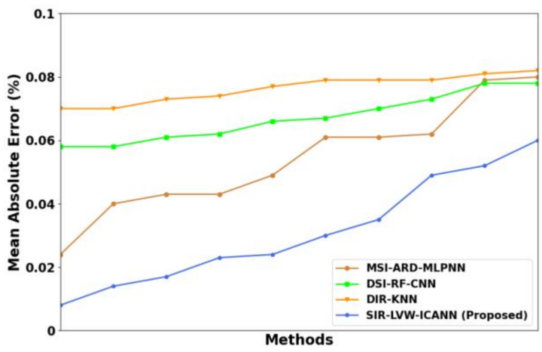

Figure 10: Performance analyses of MAE

Figure 10 displays Performance analyses of MAE This decrease in MAE suggests that the SIR-LVW-ICANN method can more accurately capture rainfall's geographical variability, resulting in more informed judgments about flood predictions, agricultural planning, and water resource management. The proposed SIR-LVW-ICANN technique reaches in the range of 22.36%, 35.42% and 28.27% lower MAE Compared with existing techniques like MSI-ARD-MLPNN, DSI-RF-CNN and DIR-KNN respectively.

4.8 Discussion

This study develops the SIR-LVW-ICANN model's initial step toward prediction of Rainfall Spatial Interpolation. ICANN was contrasted with earlier findings from different investigations. Also found that the models were far better at prediction of rain fall, ultimately SIR-LVW-ICANN prediction of rain fall. The Data is collected from Weather data Indian cities to examine the proposed Information from the Rainfall Spatial Interpolation. The dataset is first pre-processed to find Missing Data and Normalization. Significant regional variations in precipitation were found by spatial analysis, with greater values in the northern regions and changes driven by elevation. Differentiating across clusters according to elevation and precipitation patterns provides information on the behavior of the local climate. robust performance, it's critical to strike a balance between interpretability and model complexity.

5. Conclusion

In this section, SIR-LVW-ICANN is successfully executed. In this proposed model, the data are collected from Weather data Indian cities (1990 to 2022).Then, pre-processed data are fed to Inelastic Constitutive Artificial Neural Networks (ICANN) for effectively predict the mean annual precipitation. According to the experimental results, SIR-LVW-ICANN performed better when used with the Co-training technique than when used separately regards Accuracy, RMSE and MAE. The performance of SIR-LVW-ICANN approach attains 22.36%, 35.42% and 28.27% lower MAE when analysed with existing MSI-ARD-MLPNN, DSI-RF-CNN and DIR-KNN respectively. To improve precipitation forecasts, future studies should concentrate on combining data from remote sensing with outputs from climate models. Analysing how precipitation patterns are affected by climate change and expanding the investigation to longer time scales may yield insightful results. Accuracy may also be improved by investigating hybrid models that incorporate traditional interpolation methods with machine learning, as well as by increasing data coverage in underrepresented areas.

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