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Article

Spatial Drought Prediction Using a Drought-Weighted CONVLSTM Framework with Tail-Focused Evaluation

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Abstract: Accurate prediction of drought is essential to mitigate the climate risk and water resource management. The conventional methods to assess the drought predictions, emphasis on the global metrics such as the Root Mean Square, Mean Absolute Error and Correlation co-efficient and the others. This may dilute the accuracy of the prediction of the extreme events. This study introduces a Drought Weighted Convolutional Long Short-Term Memory (DW-CONVLSTM) framework for pixelwise image prediction and short-term forecasting of Standardised Precipitation Index (SPI) maps. From the monthly rainfall images, SPI3 maps are derived. Twelve-month sequences are constructed and augmented with seasonal encoding and spatial validity mask. To address the underestimation of drought severity in the deep learning methods, drought weighted masked Huber loss function is proposed to prioritise the moderate to extreme drought conditions. The proposed framework is evaluated across four regions- Bid, Jaisalmer, Lalitpur and Tumkur. The model performance is evaluated using the global metrics such as RMSE, Correlation and R2 and tail focused conditional metrics based on the threshold values of SPI. The proposed model DW-CONVLSTM achieves a strong predictive skill, reducing the error, while maintaining comparable global accuracy. The tail focused conditional metrics, extreme drought skill curves and spatial analysis improve spatial representation of drought severity. The results highlight the importance of drought aware learning objectives, tail focused evaluation and multi-month forecasting for reliable drought image prediction.
Keywords: Image Prediction, DW- CONVLSTM, Droughts, Huber loss, SPI

1. Introduction.

Droughts are the result of the dryness, accumulated over a period of time, challenging water resilience, agricultural activities and other anthropogenic necessities. Unlike other calamities which has a rapid onset and termination, droughts intensifies gradually and across large space impacting soil moisture, ground water and the terrestrial water resource. They are characterised by slow onset and undefined period of termination, making it challenging for accurate prediction [1]. Hence a reliable drought forecasting is essential for the mitigating the climate and to manage the robust water management system [2].

Standardised Precipitation Index (SPI) is a tool which is widely used to quantify and monitor droughts [3]. It is a robust index that is applied across diverse climate regions, for different time scales and simplicity in its use and calculation. Satellite based data have enhanced the predictive capabilities of SPI for pixel wise assessment of drought severity [4]. Indian Meteorological Department uses the SPI values for the historical data; however, it does not provide the SPI predictions for the future time periods. Recent developments in artificial intelligence have enabled the modelling the hydroclimatic systems. The use of machine learning models, deep learning models such as Artificial neural Networks, Kolmogorov Neural Networks and other models such as the probabilistic models, Gaussian models and Gaussian and Gamma mixture models have effectively predicted the extreme events such as flood and droughts [5-14]

The neural network is well suited for the image predictions based on historical images. The models like convolution neural network, Recurrent Neural Network and Convolutional neural networks are used in the image prediction [15]. These models learn spatial and temporal patterns using the historical images to predict the future images [16]. Though these models show promising results, the evaluation of the models is based on the global metrices such as RMSE, Mean Absolute Error, R2 and others. These metrices concentrate on the near normal conditions, resulting in insufficiently examination of the severe and extreme drought which constitute only a small percentage of the historical data. There by limiting the prediction accuracy of the drought severity.

Many existing models have used point-based SPI prediction, considering the average of the region at any point of time which can ignore the heterogeneity of a region. There is an emerging necessity for pixelwise image to image prediction framework to increase the reliable drought prediction.

To alleviate these limitations, this study develops a Drought-Weighted Convolution Long Short-Term Memory frame work for pixel-wise image to image prediction of SPI maps. A sequence of historical maps is used to obtain the SPI maps. To increase the robustness of the model, drought aware learning method is used to emphasis on the severe and extreme drought conditions during training. Additionally, this paper introduces the tail focused conditional metrics computed for the evaluation of severe and extreme droughts. This evaluation framework provides a comprehensive view on the model reliability which are very appropriate for drought risk management. The proposed framework is demonstrated across 4 varied regions of India – Jaisalmer, Bid, Lalitpur and Tumkur region in India.

The main contribution of the study is (i) Pixel wise image to image predicted of SPI maps (ii) Development of Drought weighted Convolutional Long Short-Term Memory framework using drought weighted Huber loss for improved drought severity prediction. (iii)Implementation of the tail focused conditional metrics for the evaluation of the severe and extreme droughts. (iv)

2. Study Area and Data

2.1 Study regions.

The study is conducted across four climatologically different regions of India – Bid (Maharashtra), Jaisalmer (Rajasthan), Lalitpur (Uttar Pradesh) and Tumkur (Karnataka). These regions differ in their climatic conditions, drought vulnerability and rainfall variability, thus providing a representative dataset, to generalise the proposed drought framework.

Bid has semi-arid climate, experiencing hot summer and general dryness throughout the year. The district faces moderate and severe drought conditions [17]. Jaisalmer a district in the western Rajasthan, is an arid region with hot summers and very less precipitation [18], Lalitpur, a district in Uttar Pradesh, is sub humid with hot summer and cold winter [19]. Tumkur experiences semi-arid climate. It is categorised as Central dry agro-climatic zone and drought prone region of Karnataka [20]

2.2 Data Sources

Monthly Precipitation images for 40 years from 1985 to 2024 is obtained from Climate Hazard Group InfraRed Precipitation with Station data (CHIRPS) dataset from Google Earth Engine (GEE) is collected. CHIRPS data sets have been widely used recently in various hydrological studies as it is reliable and spatially consistent rainfall data [21-25]. The resolution is 0.050, enabling pixelwise analysis of rainfall variability. The data was spatially clipped to the boundaries of each district in GEE. The monthly totals of the precipitation values for each pixel of the considered regions are the primary input data to obtain the pixelwise SPI.

2.3 Standardised Precipitation Index (SPI)

The SPI index is the most widely used index recommended by the World Meteorological Organisation (WMO) for assessing drought conditions. The pixelwise SPI is computed using accumulated monthly precipitation, based on the methodology proposed by Mackee (1993). SPI-3 is obtained by considering the three-month rolling window for the precipitation totals given by equation (1).

$$P_k(t) = \sum_{i=0}^{k-1} P(t-i)\#(1)$$

Where P(t) is the observed precipitation at time t, $P_k(t)$ is the accumulated precipitation over ‘k’ months.

The accumulated precipitation is assumed to follow gamma distribution as in equation (2).

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}}\#(2)$$

where x>0, α, β are parameters. The cumulative probability function of the gamma distribution is represented by $G(x) = \int_0^x g(u)du,\ \#(3)$

The cumulative probability distribution is transformed to a standard normal variable using the inversefunction $SPI = \Phi^{-1}(G(x))\#(4)$

Where $\Phi^{-1}(.)$ is the inverse cumulative function of the Standard normal distribution.

The droughts are categories based on the SPI values, if -1≤SPI≤0, it is mild drought, if, -1.5≤SPI≤-1.0, then it is moderate drought, if -2.0≤SPI≤ -1.5, then it is severe drought and if SPI≤-2.0, then it is extreme drought [26].

3. Methodology

3.1 Overview of the proposed Framework

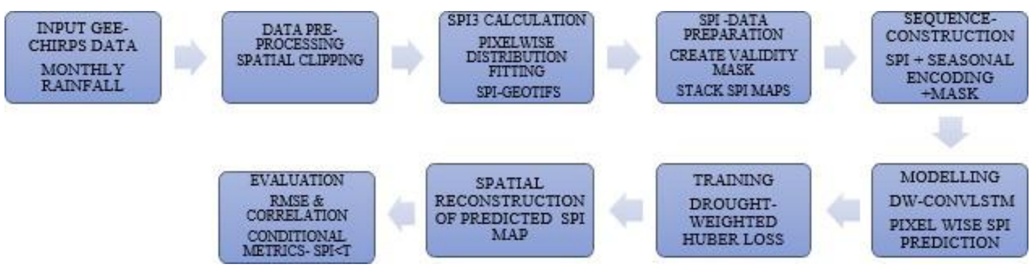


Figure1: The workflow of the proposed DW-CONVLSTM framework for the drought image prediction.

The monthly rainfall data are retrieved from GEE and converted into SPI maps through pixel-wise standardization. The SPI maps are organised into 12-month Spatio-temporal sequences with seasonal encoding and validity masks. A drought weighted CONSVLSTM model predicts the next-month SPI image. The performance of the model is evaluated using tail focused conditional metric and global metrices.

3.2 SPI Data Preparation.

The SPI data preparation is based on the standard methodology followed by Mackee (1993). In this study SPI for the time scale of 3-month, is considered, which is ideal for the assessment of short-term droughts. The monthly precipitation maps are obtained from GEE, where each pixel contains the monthly rainfall total. The precipitation values are accumulated over a 3- month moving window, for each pixel. The gamma distribution is fitted for the accumulated values for each pixel. SPI values are obtained by standardising the accumulated precipitation for each pixel [27].

The SPI maps are generated using each pixel SPI values and stored as GEOTIF files and the SPI values are stored as a NumPy arrays. The pixels with no data are stored as NAN values. A spatial validity mask created, where in the valid pixel are assigned ‘1’ and the invalid pixel is assigned the value ‘0’. This enables to avoid the invalid pixel to participate in the model training evaluation. The valid maps of SPI are stored as a three-dimensional array (T, H, W), where T represents the timescale and H and W represents the grid.

3.3 Spatio-Temporal Sequence Construction.

Sequence to image learning method is widely used in deep leaning for climatic predictions [15]. In order to capture the seasonal variation in the data, a twelve-monthly SPI sequence is constructed. For each SPI map prediction, the twelve-month preceding maps of the SPI are extracted as model input. To achieve this, a cyclical monthly encoding using the sine and cosine function is incorporated. It is defined as $sin\ sin\ \left(\frac{2\pi m}{12}\right)$, $Cos(\frac{2\pi m}{12})$, where 'm' denotes the month index. Now, each input for the image has the shape (12, H, W, 4), where 4 correspond to SPI values, Sine and Cosine values and the spatial validity mask.

3.4 DW-CONVLSTM architecture

The proposed model for the image prediction is based on Drought Weighted Convolution Long-Short Term Memory (DW-CONVLSTM) architecture. Here in the regular LSTM the matrix multiplication is replaced by convolution operators [28]. The network has two layers, the first layer captures the spatio-temporal features from the input data, and the second layer integrates the temporal features for prediction. Batch normalisation and dropout features are applied after each layer to reduce overfitting. The output layer based on the features learnt, produces a predicted SPI image, a pixel wise prediction for the target.

3.5 Drought Weighted Huber loss.

Since the extreme and severe drought occurrences are the rare, there is tendency to underestimate the events. A drought weighted Huber loss function is implemented during the training [29]. Huber loss is the combination of Mean Absolute Error and Mean Squared Error, making it suitable for outliers. The loss is multiplied by a drought severity weight, based on the SPI values. Higher weights are assigned to severe and extreme drought pixels. Additionally, the spatial validity mask is applied so that only valid pixels contribute to the loss. The final loss function is the weighted average of the over-all valid pixels.

3.6 Model Training and implementation.

The chronologically ordered SPI time series data is divided into training and testing data in the ratio 80:20. The temporal split avoids data leakage and ensures realistic drought forecasting. Adam optimiser is used for model training with a fixed rate. Early stopping, Batch normalisation and dropout regularization is implemented to avoid overfitting and for model stability. TensorFlow- Keras framework is employed for the implementation. The model is trained using the preceding 12-month SPI maps to predict the map of the next month. Invalid pixels are excluded from model training and loss computation.

3.7 Evaluation

The performance of the model is evaluated using the global metrices and the conditional tail metrices concentrating on the severe extreme droughts. Global metrices such as RMSE, R2, Correlation Co-efficient and bias are employed. To evaluate the model for the severe and extreme droughts, tail focused conditional metrices are employed based on the threshold values. The conditional error is defined as in equation (5)

$$E(SPI \leq T)\#(5)$$

The conditional metrices are calculated for the threshold values T, of -1, -1.5 and -2. The SPI<= T, corresponds to the mild, severe and extreme drought events [30].

Bias is a metric, that is computed as the difference between the predicted and the observed SPI values of the selected pixel is given by equation (6)

$$Bias = E[\hat{y} - y]\#(6)$$

Where $\hat{y}$, is the predicted SPI and y is the observed SPI respectively. Positive bias indicates underestimation; negative bias indicates overestimation and bias around zero indicates no systematic error [31]

4. RESULTS AND DISCUSSION

4.1 Global Predictive Performance of DW-CONVLSTM

The proposed Drought-weighted ConvLSTM framework is evaluated across four diverse study regions: Bid, Jaisalmer, Tumkur and Lalitpur to assess pixel-wise image prediction of SPI3 maps. The global metrics: RMSE, R2 and Pearson's correlation are calculated for all the valid pixels for the training and validation dataset as given in Table 1.

Table 1: Table describing the total number of pixels used for the study for the different districts and drought categorised as the pixels.

District	Total Valid Pixels	SPI ≤ −1.0	SPI ≤ −1.5	SPI ≤ −2.0
Bid	430,584	63,175 (14.67%)	20,872 (4.85%)	4,707 (1.09%)
Jaisalmer	1,453,920	171,415 (11.79%)	34,873 (2.40%)	00
Lalitpur	212,496	21,807 (10.26%)	3,372 (1.59%)	1,553 (0.73%)
Tumkur	465,534	61,410 (13.19%)	35,888 (7.71%)	13,016 (2.80%)

The proposed DW-CONLSTM model exhibits strong predictive skills across the study regions as represented by Table 2. For Bid district, the model achieved a RMSE of 0.2647 during training and 0.3005 during validation, the Co-efficient of determination (R2) values are 0.9058 and 0.8900 and the correlation are 0.9655 and 0.9475 respectively for the training and the validation period, respectively. The result indicates the agreement between predicted and observed SPI.

In Jaisalmer, an arid region with high climate variability, the RMSE were 0.3175 and 0.3977, R2 was 0.8366 and 0.0.8011, while correlation is 0.919 and 0.905 for the training and the validation period respectively. Although the RMSE values are slightly higher as compare to the other regions, the high correlation values indicate that the model was able to predict the drought events with the challenging arid climate.

In Lalitpur, the model exhibits strong performance with the training values of 0.297, 0.8788 and 0.948 and the validation values of 0.3027, 0.8812 and 0.951 as RMSE, R2 and the correlation co-efficient, respectively. Likewise, for Tumkur district, the RMSE values are 0.2854 and 0.3260, R2 values are 0.8825, 0.8491 and the correlation co-efficient values are 0.9434 and 0.9233, for the training and the validation data respectively.

The strong alignment during the testing and validation period across all regions, strong learning and no overfitting.

Table 2: Global Performance of the DW-CONLSTM model across four different districts during the training and the testing period.

Region	Dataset	RMSE	R^2	Correlation
Bid	Training	0.2647	0.9058	0.955
	Validation	0.3005	0.8900	0.9475
Jaisalmer	Training	0.3175	0.8366	0.9190
	Validation	0.3977	0.8011	0.9050
Lalitpur	Training	0.2970	0.8788	0.9480
	Validation	0.3027	0.8812	0.9510
Tumkur	Training	0.2854	0.8825	0.9434
	Validation	0.3260	0.8491	0.9330

The global metrices asserts the overall reliability of the model, but the performance of the model during the drought events are of primary interest in drought monitoring. Hence it is required to study performance of the model during the extreme drought event [32].

4.2 Extreme Drought Skill and Tail behaviour

The drought conditional tail-based evaluation is conducted for the severe and extreme droughts with threshold values less than -1.0,-1.5 and -2.0. This tail focus analysis is pivotal to examine the model behaviour under drought conditions [33]. Table 3, exhibits the systematic and consistent behaviour of the model as drought increases. There is an increase in the error as drought severity increases, highlighting the difficulties faced in predicting the rare events. The magnitude of the error growth remains controlled, signifying the model's predictive skill for the tail values. In the semi-arid regions of Bid and Tumkur, where there is frequent occurrence of droughts, the DW-COVNLSTM model accurately predicts the extreme values. In Lalitpur, the performance of the model is stable for the rare occurrence of drought, providing a limited sample for the analysis. For the arid region of Jaisalmer, the model performs extremely well for the moderate and severe drought, which is consistent with the region's climate. Extreme drought skill curve of the DW-CONLSTM presents lower RMSE values which is gradually evolving without an abrupt deviation with the increase in the drought severity.

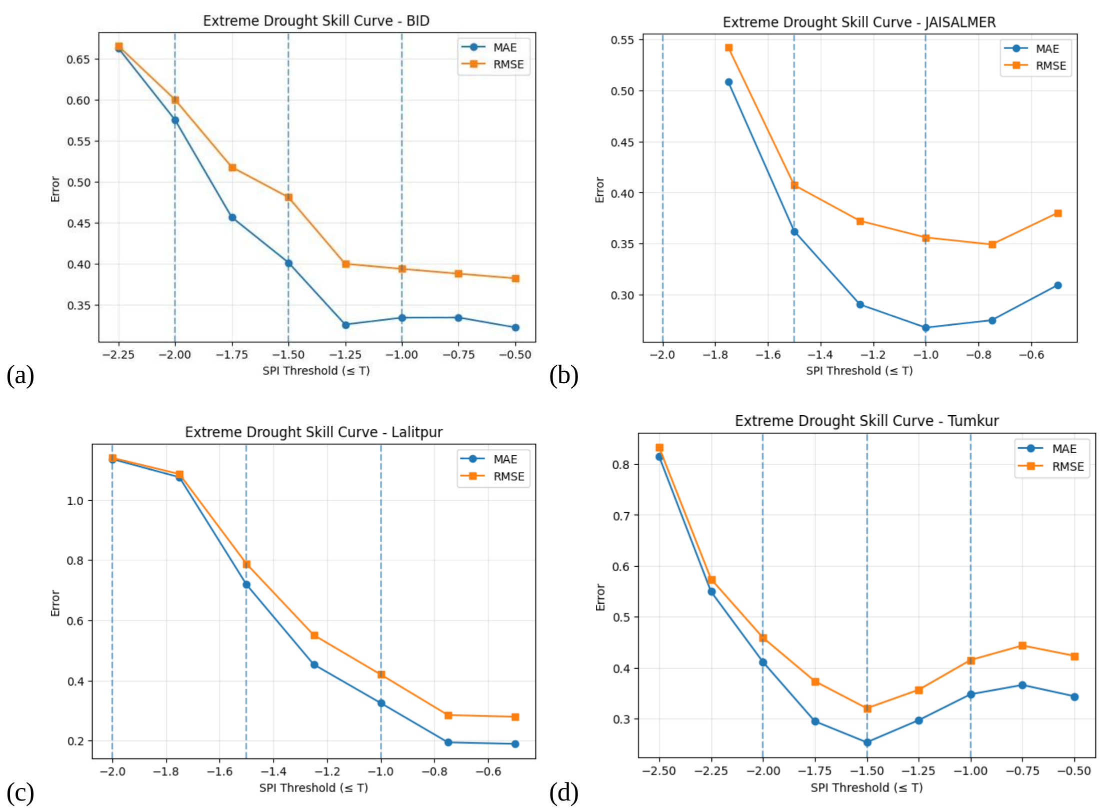


Figure 2. (a), (b), (c) and (d), represents the extreme drought skill curve for the various thresholds for the districts- Bid, Jaisalmer, Lalitpur and Tumkur respectively.

3.3 Comparison of the DW-CONVLSTM with Baseline Model

The proposed drought weighted DW-CONVLSTM model is compared to the baseline model trained with the uniform loss function. Both the models show similar accuracy of the global metrics, while the DW-CONVLSTM model reduces the bias and error across moderate, severe and extreme drought thresholds, across all regions. The Baseline model exhibits higher bias and underestimation of drought severity across moderate, severe and extreme drought. These findings are key to understand that it is necessary to demonstrate the tail-based evaluation of metrics for a reliable model.

Table 4. Global performance of the Baseline ConvLSTM model across four districts

Region	Dataset	RMSE	R^2	Correlation
Bid	Training	0.237	0.924	0.963
	Validation	0.263	0.915	0.958
Jaisalmer	Training	0.285	0.869	0.933
	Validation	0.336	0.858	0.935
Lalitpur	Training	0.246	0.916	0.959
	Validation	0.231	0.930	0.965
Tumkur	Training	0.307	0.863	0.930
	Validation	0.326	0.849	0.933

By categorically focusing on the pixel-wise image prediction, including drought weighted model and concentrating on the tail threshold values, the model is trained represent the extreme conditions, thereby improving the drought prediction.

4.3 Conditional tail focused performance Evaluation

Table 5 is a comparative study of the DWCOVLSTM and the baseline model using the tail focused Conditional metrics for the different threshold (SPI <= -1.0,-1.5, -2.0), corresponding to moderate, severe and extreme drought conditions. This highlights that the model's ability to capture the extreme droughts. Across all regions, DW-CONVLSTM demonstrates systematics reduction in bias and RMSE.

In Bid district, DW-CONVLSTM reduces bias from 0.256 to −0.002, for SPI<-1 and for extreme drought bias further reduces from 0.677 to 0.394 at SPI < -1.5, and finally 0.872 to 0.575 at SPI< -2, decreasing the underestimation. Also, the RMSE values also decreases from 0.717 to 0.481 at SPI< -1.5 and from 0.882 to 0.6 at SPI< 2.0 when baseline model is compared to the proposed model highlighting the improved accuracy. In Tumkur, DW-CONVLSTM, shows consistent improvements across all thresholds. At SPI< -1, the baseline model has a bias of −0.003 and DW-CONVLSTM model shows a negative bias of −0.082, representing improved drought estimation. The RMSE values are decreasing from 0.361 to 0.320 at SPI <-1.5 and 0.509 to 0.459 at SPI< -2.0, showing improved accuracy.

In Lalitpur, DW-CONVLSTM model outperforms baseline model across all the threshold values. consistently reduces RMSE and bias across all thresholds, indicating a robust tail behaviour. For the arid regions of Jaisalmer, the reduction is evident for the moderate and severe droughts with RMSE decreasing from 0.438 to 0.345 at SPI<-1.0 and 0.498 to 0.403 at SPI< -1.5. The non-availability of the data for SPI <-2.0 is consistent with the climate of the region.

Overall, the conditional tail focused metrics evaluation demonstrates the advantages of the DW-CONVLSTM model in reducing the underestimation of droughts, enhancing the model.

Table 5: Conditional Tail Focused Metrices for The Different Districts for Various Threshold Values.

Region	SPI ≤ T	RMSE (Base)	RMSE (DW)	Bias (Base)	Bias (DW)
Bid	−1.0	0.447	0.394	0.256	-0.002
	−1.5	0.717	0.481	0.677	0.394
	−2.0	0.882	0.600	0.872	0.575
Tumkur	−1.0	0.476	0.415	-0.003	-0.082
	−1.5	0.361	0.320	0.106	0.076
	−2.0	0.509	0.459	0.434	0.411
Lalitpur	−1.0	0.427	0.335	0.275	0.161
	−1.5	0.822	0.682	0.775	0.635
	−2.0	1.144	0.960	1.141	0.956
Jaisalmer	−1.0	0.438	0.345	0.301	0.210
	−1.5	0.498	0.403	0.423	0.365

4.4 Comparison of Evaluation Maps, Multi-month forecasts and regional RMSE.

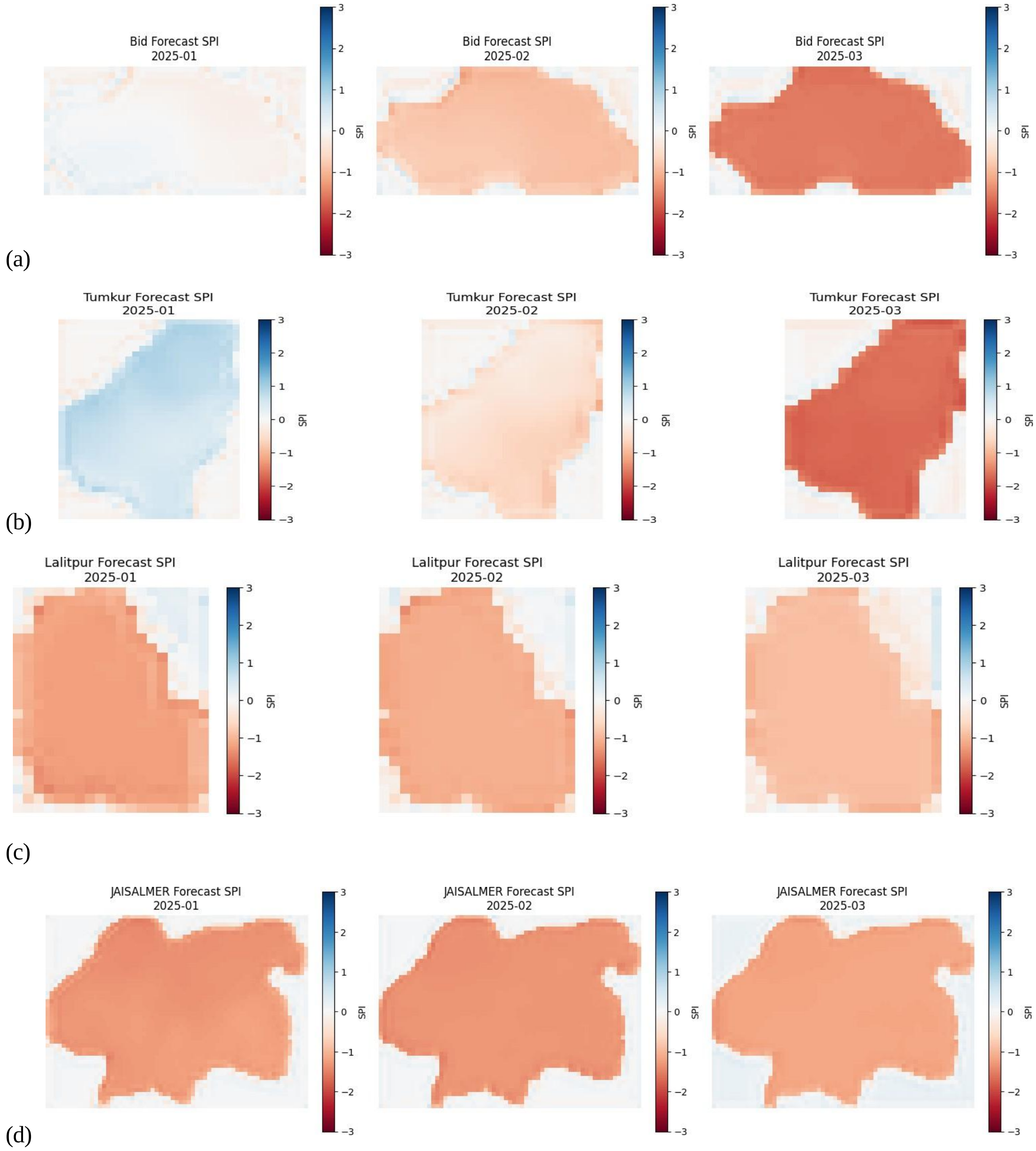


Figure 3. (a) – (d). Spatial distribution of Multi-Month SPI drought forecasts for four study regions: Bid, Tumkur, Lalitpur and Jaisalmer.

Among the four regions, Lalitpur shows close agreement between the observed and predicted maos, with low RMSE of 0.19 indicating high predictive accuracy. Bid region has comparable accuracy with moderate variablility. The maps of Jaisalmer and Tumkur exibit has higher RMSE values of 0.4-0.45. The difference are consistent with the climate of a region. The multi-month forecast maps for the month of January to march 2025 exhibit consistent evolution of drought pattern that are realistic, suggesting stable generalistion of the model. Overall, the combined evalution of maps, forecast maps and the RMSE values confirms the robustness of the DW-CONVLSTM model

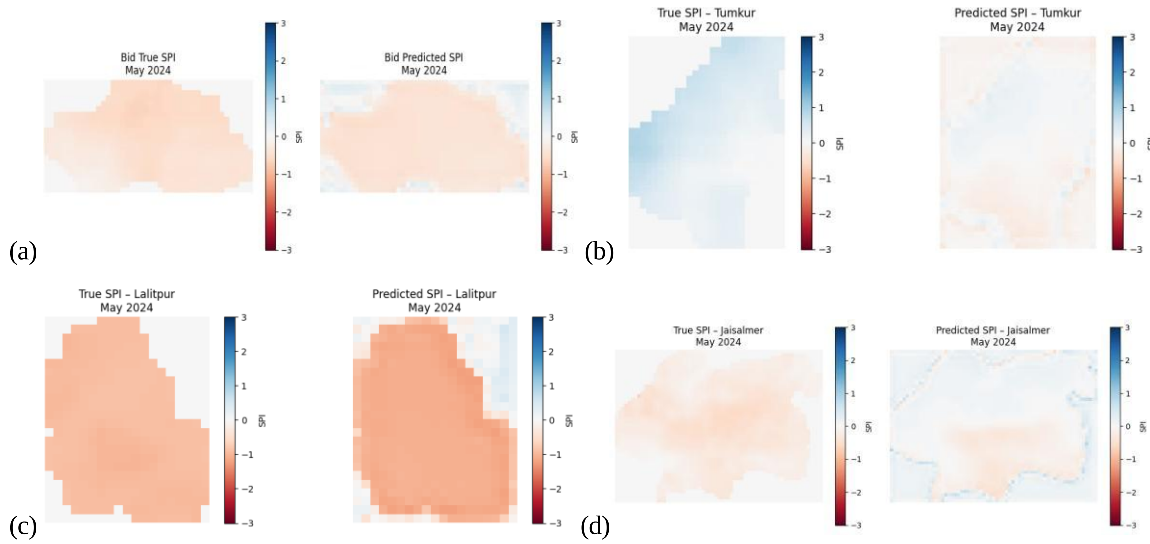
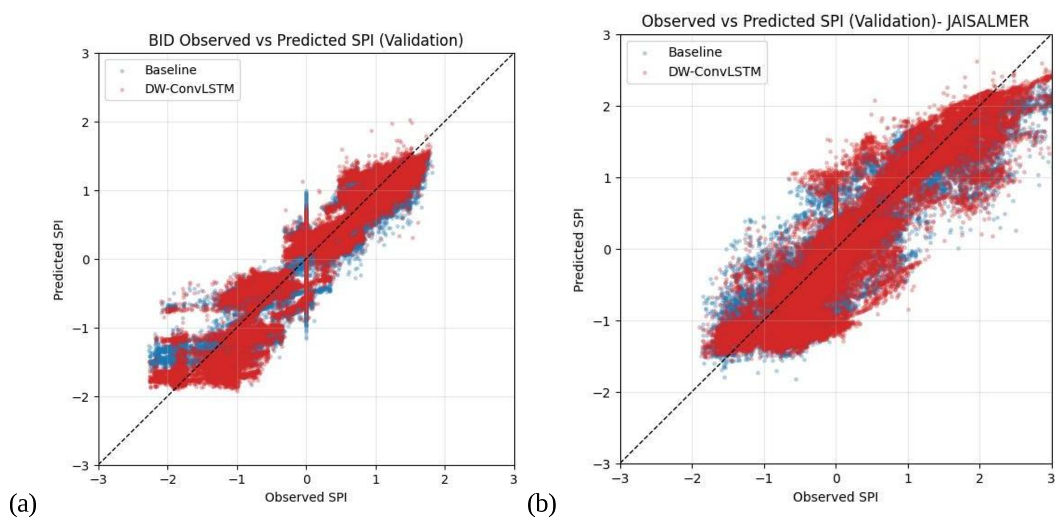


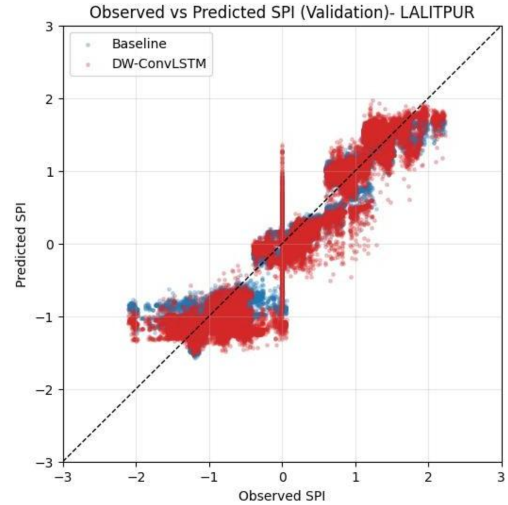
Figure 4. Comparison of the observed and predicted SPI maps for the month of May 2024: (a) Bid, (b) Tumkur, (c) Lalitpur and (d) Jaisalmer

Figure 3(a), 3(b), 3(c) and 3(d) presents the comparison between true and predicted SPI maps for the month of May 2024 across the four study regions, while the figures 4(a)-4(d) represnts the muli-month forecasts from January to March 2025. The evaluation mpas for May 2024 demostrate the strong spatial agreement between observed and predicted drought patterns across all regions, indicating the DW-CONVLSTM model effetiely captures the spatial distributuion and drought intensity. .

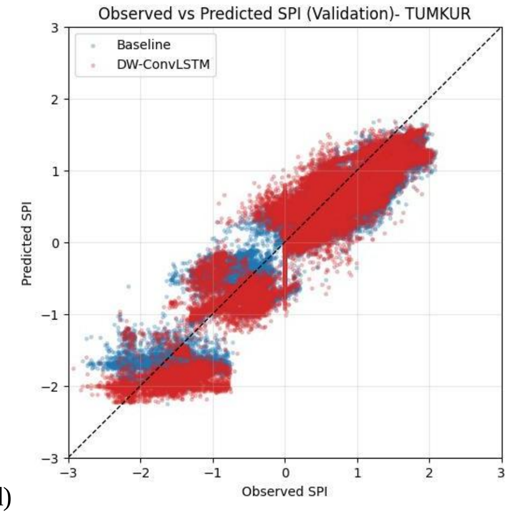
4.5 Scatter Plots.

The scatter plots of the four regions for the validation sets are presented in the figures 4a,4b, 4c and dd for the study regions, comparing DW-COVNLSTM model and the baseline models. The DW-COVNLSTM model predictions cluster around the 1:1 reference line indicating reduced bias and the model predictivity, as compared to the baseline model. The baseline model represents underestimation for negative values of SPI





(c)



(d)

Figure 5. Scatter plots comparing observed and predicted SPI values during the validation period across four regions – Bid Jaisalmer, Lalitpur and Tumkur respectively

5. Conclusion.

This study presents a drought aware deep leaning framework, DW-CONVLSTM for pixel-wise image to image prediction of SPI-3 drought maps. The proposed framework, emphasis on the tail focused learning and evaluation addressing the key limitation of the other conventional deep learning models that depend on the general optimizations. The DW-CONVLSTM demonstrated a strong predictive performance across all the study regions achieving low RMSE, high R2 values and a high Correlation co-efficient with observed values. Moreover, the proposed model consistently reduces the error as compared to the baseline model. There by confirming that drought weighted model, mitigates the underestimation of the severity of droughts.

Spatial analysis reveals that the model preserves coherent pattern generating the meaningful SPI maps. The tail focused model evaluation and the extreme drought skill curve, provides detailed understanding of the model's behaviour under various threshold conditions. In addition, the multi month forecast demonstrates stable temporal evaluation and spatial consistency, indicating model's stability.

Over all, the finding of the study emphasis the drought aware learning and tail focused evaluation methods enhances the drought image prediction, that are essential for the drought mitigation activities and early warning systems. Future work may extend this using additional hydroclimatic variables, different drought indices and apply other deep learning techniques to enhance drought assessment and prediction capabilities.

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