



## RESEARCH ARTICLE

# Deep Learning Approaches for Regional Rainfall Time Series Prediction Using ERA5 Dataset

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## Abstract

Precise monthly rainfall forecasting is crucial for Gujarat, India, where agriculture depends heavily on monsoon patterns. This study compares three deep learning architectures—Convolutional Neural Network (CNN), Convolutional Long Short-Term Memory (Conv-LSTM), and hybrid Discrete Wavelet Transform-ConvLSTM (DWT-ConvLSTM)—using 10 years (2010-2020) of high-resolution ERA5 meteorological data processed via Google Earth Engine across approximately 14,600 grid points. The CNN baseline achieved a Mean Absolute Error (MAE) of 0.0471 and Root Mean Square Error (RMSE) of 0.0747. Conv-LSTM improved performance with MAE 0.0421 and RMSE 0.0723. The proposed DWT-ConvLSTM hybrid model excelled, attaining the lowest errors of MAE 0.0370 and RMSE 0.0570—a 12% improvement over Conv-LSTM. This superior performance stems from wavelet decomposition, which isolates complex climate signals into frequency components for enhanced pattern recognition. These findings demonstrate that integrating frequency-domain analysis with deep learning effectively uncovers hidden spatiotemporal climate patterns. Though computationally intensive, the hybrid model offers significant potential for agricultural planning, water resource management, and climate adaptation in monsoon-dependent regions.

**Keywords:** Google Earth Engine, ERA5 dataset, Conv-LSTM, CNN, DWT-ConvLSTM, rainfall prediction

## Introduction

In Gujarat's agriculture-dependent economy, accurate rainfall prediction is essential for water resource management, crop planning, and disaster preparedness [FAO-2021]. Agriculture

employs 60% of India's population and contributes 18% to GDP, making monsoon-dependent farming particularly vulnerable to rainfall variability [FAO-2021]. With climate change increasing the frequency of floods and droughts, traditional linear models like ARIMA struggle to capture the nonlinear, chaotic nature of meteorological data [Gupta, S.-2021].

Recent advances in deep learning have revolutionized climate modeling. Long Short-Term Memory (LSTM) networks excel at capturing long-term temporal dependencies without vanishing gradient problems [Lim, B., & Zohren, S.-2021]. Studies demonstrate LSTM's effectiveness for regional rainfall prediction in India [Kumar, A. et al. 2021], [Shukla, P. et al. 2019]. However, computational costs and region-specific calibration remain challenges [Hershach, H. et al. 2020].

This study introduces a hybrid DWT-ConvLSTM model tailored for Gujarat using high-resolution ERA5 reanalysis data (2010-2020). We compare three architectures: CNN for spatial patterns, Conv-LSTM for spatiotemporal features, and DWT-ConvLSTM combining frequency-domain preprocessing with deep learning. Our objectives are: 1) Compare model performance for Gujarat rainfall prediction; 2) Incorporate key meteorological variables (rainfall, temperature, wind speed); 3) Develop an extensible forecasting framework for agricultural applications.

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The paper has been broken down as follows: Section 2 provides literature survey of various neural network architectures and deep learning strategies employed by scientists in the rainfall prediction. Moreover, the proposed methodology is given in Section 3 of the paper, and the methodology will involve description of the study area and data collection (Section 3.1), data preprocessing and feature engineering, and data partitioning and experimental design. Section 4 provides the details of the results of the experiments and the discussion of the rainfall prediction with the use of CNN and ConvLSTM models. Finally, 5, a summary of the findings of the study is provided and some suggestions concerning future research are presented.

### **Literature Survey**

The forecasting of precipitations is of the utmost importance in climate studies, farming and planning of water resources. There are several studies that have been conducted on the development of effective forecasting techniques through the application of the statistical and machine learning techniques.

Gupta et al. (2020) also made a comparative analysis between conventional statistical models of prediction of rainfall based on ARIMA and neural networks in India. In their search, they proposed that neural networks outperformed ARIMA models by a small margin because they could be used to model nonlinear trends. The research, however, was based on a limited sample that encompassed a few years, and therefore, generalization could not be done easily. The authors observed that though neural networks had the ability to learn seasonal variations with more accuracy, insufficiency of data and computational capacity, and lack of hyperparameter optimization hampered their performance.

Kumar et al. (2021) studied the forecasting of monsoon rain in the northern part of India with the LSTM networks. Their findings revealed that LSTMs had a much higher ability to capture the temporal dependencies than the conventional machine learning models, as they had better accuracy metrics. Nevertheless, they found that computational issues were encountered when developing the models especially in terms of hyperparameter optimization. They emphasized that their strategy was efficient in northern India, and it is necessary to create the region-specific models and features to ensure the regional flexibility, as well as localized preprocessing specific to regions like Anand.

The ERA5 dataset was presented by Hersbach, H. et al. (2020), which is a worldwide meteorological re-analysis dataset in terms of both time and space. The application of ERA5 to regional rainfall prediction in Gujarat is not well studied, although ERA5 is commonly applied to global climate models. This paper uses the high-resolution of ERA5 of temperature, precipitation, and wind speed to fill this gap.

In their study, Shukla et al. (2019) utilized LSTM models to predict rainfall in the southern part of India on the daily

basis. The model was very effective in capturing seasonal and temporal characteristics particularly during monsoon seasons. It was however not very effective in capturing extreme weather events like heavy downpours or droughts that entail interactions of multiple climatic variables. To address them, the study suggested applying hybrid models, i.e. LSTM + external feature engineering.

Chen, J. et al. (2020) examined the effectiveness of LSTM models on temperature time series with respect to conventional statistical methods. Although they noted that LSTMs were capable of capturing the long-term nonlinearity dependencies, their research did not explicitly consider precipitation and so no definitive use of the findings as applied to rainfall prediction was provided.

A hybrid CNN-LSTM-based drought prediction model was proposed by Jain et al. (2022) and showed better performance in the spatiotemporal dependence of pure models. Nonetheless, the architectural complexity raised the demand of computational requirements which made it difficult to implement the system on resource-constrained hardware. These findings point to the required trade-off between the accuracy and the computational efficiency in hybrid deep learning models.

Ahmad, A. et al. (2021) have introduced a LSTM model forecasting rainfalls using the wavelet-transform. The wavelet transformations enabled the model to capture the high-frequency and low-frequency components of data and therefore provided high accuracy. Nonetheless, domain expertise in the wavelet transformation limits the non-expert user accessibility, and hence automated feature engineering may be used in the future work.

Singh, V. et al. (2021) researched the ensemble techniques with LSTM and Random Forest models. The structure improved the performance of both deep learning and traditional, but required complicated data preprocessing and hyperparameter maximization. The study by Das et al. (2023) introduced methods of transfer learning in forecasting regional climates and saved much time on training, as the researchers resorted to pre-trained global datasets. Nevertheless, they observed that they are not able to represent regions that are vastly different to the pre-training data, and thus they require domain adaptation techniques.

S, J. T. (2025) suggested the machine learning model of predicting the indoor thermal comfort based on environmental sensor measurements. The level of comfort was categorized by using decision tree and ensemble. The findings indicated that there was better prediction of intelligent environmental monitoring systems.

Menaha, M., & Lavanya, J. (2024) come up with an ensemble learning model that predicts the crop yield when the conditions are different. The prediction model incorporated climatic and soil factors. The research had

better performance compared to traditional machine learning models.

Zoraida, B. S. E., & Magdalene, J. J. C. (2024) made a comparison between deep learning architectures like CNN, RNN, and LSTM in making energy consumption predictions. Patterns of the temporal data were examined to enhance the accuracy of prediction. The results indicated that deep learning is effective in time-series forecasting activities.

In short, the paper is based on these premises and refers to ERA5 monthly satellite data, which enhances the accuracy of forecasting rainfall. To overcome the shortcomings of the literature, we introduce a hybrid model which uses CNNs to extract spatial patterns and ConvLSTM to extract spatiotemporal patterns.

## Methodology

### Study Area and Data Collection

The chosen study area is Gujarat, India, which means that the agricultural sector and water resources of the state entirely depend on the monsoon rains. The region is found in the western part of India and it receives enormous rains because of the South-West monsoon. Proper prediction can play a significant role in controlling climatic risks, irrigation optimization and water resource planning [Das,P et al.-2023]. Figure 1 shows the distribution of rainfalls in Gujarat with dry spell in northwestern areas (Banaskantha, Patan, Mehsana) and increased rainfall in the coastal south (Valsad, Dangs). It is interesting to note that there is a considerable decline in rainfall at Kutch and Rajkot that can be of concern to the water sustainability in the long term.

In order to have a sound prediction, we used ten years of climatic information (2010-2020) represented as the ERA5 reanalysis database using the Google Earth Engine (GEE) platform. ERA5 was chosen due to its climatic data which is rich and monthly resolved. Some of the important variables were total rainfall, the speed of the wind, and the ground temperature because these are vital in determining the nature of rainfalls. Satellite images were also taken to determine the spatial distribution and intensity of rainfall which enabled a careful examination of changes in different seasons and also year to year variation.

### Data Preprocessing and Feature Engineering

A high level of predictive accuracy has been maximized by an extensive data processing pipeline. The pipeline processes data from the ERA5 reanalysis dataset, with multi-band satellite images that depict the values of rainfall and weather.

Satellite Imagery is captured and transmitted to the ground by satellites. Preprocessing of Satellite Imagery: Cloud Masking and Noise Reduction: A complete data cleaning pipeline was created to guarantee quality and the missing data, outliers and spatial alignment.

Spatial and Temporal Resampling: All the satellite images were regridded at a standard bilinear interpolation of 0.25deg x 0.25deg. Resampling in time was performed to daily and monthly levels to provide a short-term variation and long-term trends.

Management of Missing Data: Missing data were filled in with the use of spatiotemporal interpolation. Inverse Distance Weighting (IDW) was used to overcome spatial

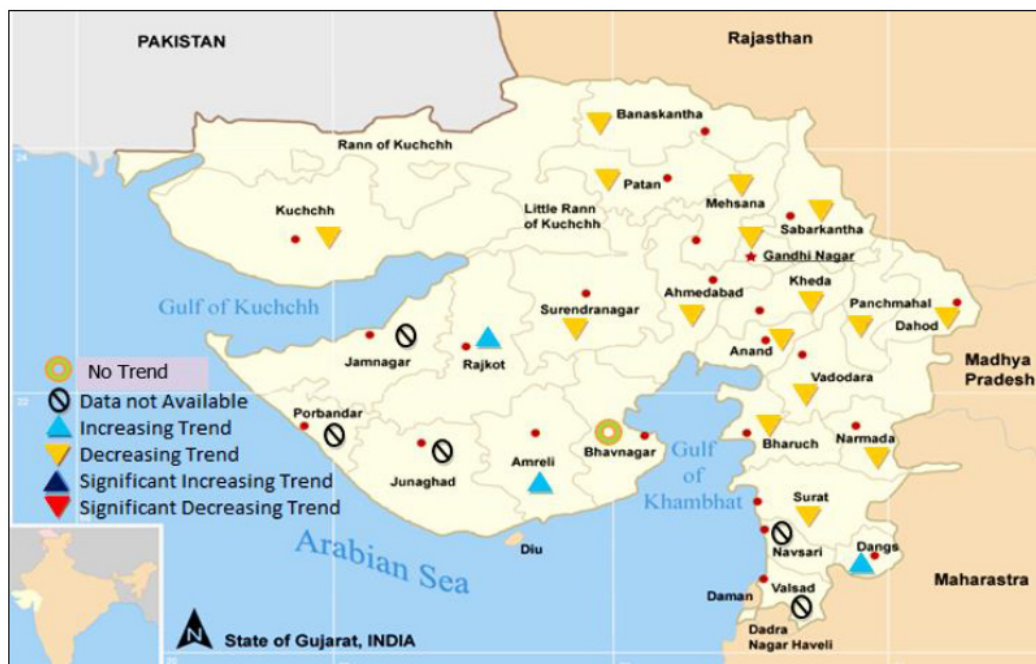


Figure 1: Rainfall Pattern in Gujarat State, INDIA

gaps whereas linear interpolation was used to overcome the time gaps to recreate the rainfall variations without the artificial artifacts.

Outlier Detection and Removal: Statistical thresholding on the basis of Z-score method was used to detect extreme outliers:

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

Values that are more than three standard deviations above the mean value were eliminated to guarantee data integrity.

Feature Scaling: To bring the variables to the numerical scale and speed up the convergence, the input variables were normalized with Min-Max scaling:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

This transformation values features in [0, 1].

### Feature Engineering

#### Spatial Features

This is based on ERA5 multi-band data as follows; rainfall intensity data, gridded temperature data (min,max and mean data), and wind velocity data (U and V data).

#### Temporal Features

These are designed to describe seasonality and sequential relationships, time-lagged sequences (1-day, 7day), patterns of monsoon onset with moving average filters and seasonal changes determined using Fourier-based decomposition.

#### Data Partitioning and Experimental Design

We used a spatial-temporal partitioning method instead of random splitting to form an 80:20 traintest split. This methodology made sure that the training and testing datasets represented different times and regions and thus reduced data leakage and maintained seasonal variability, to better model generalization [Singh et al., 2021].

During the training of the proposed model, regularization techniques and dropout layers were applied to mitigate overfitting. Model performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (3)$$

$$MSE = \sum_{i=1}^n (x_i - \hat{x}_i)^2 \quad (4)$$

Where  $y_i$  means the real values and  $x_i$  means the forecasted values.

### Experimental Design

This paper compares three deep learning systems to model a complicated space-temporal interaction of climate data.

#### Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are deep learning networks that employ convolutional operations to automatically learn hierarchical spatial features on input data.

The CNN architecture (Sequential 1) is aimed at extracting localized spatial correlations in meteorological images. It has three convolutional layers with the ReLU activation, and the max-pooling layers to reduce the dimension. The network has a Conv2D layer (32 filters, 64 \* 64 input), a layer with 64 and one layer with 128 filters. The features are flattened and subjected to dense layers (128 and 4096 neurons) to do the final prediction. This model consists of 4.81 million parameters to be trained.

#### Convolutional Long Short-Term Memory (Conv-LSTM)

The Conv-LSTM architecture (Sequential 2) was used to deal with time-related dependencies. This architecture adds LSTM units to CNN features to enable the model to acquire image sequence relationships [12]. It has two ConvLSTM2D (64 and 128 filters) layers that are configured to produce spatiotemporal features together. The design helps the model to retain long term weather trends. The model contains 68.67 million parameters, which offer greater ability to model complex spatiotemporal models.

#### DWT-ConvLSTM Hybrid Model

The hybrid DWT-ConvLSTM network (Sequential 3) is a combination of frequency-domain and spatiotemporal learners. To isolate sudden and slow atmospheric variations, first the Discrete Wavelet Transform (DWT) is used to break a meteorological time series into high and low-frequency parts. The disaggregated sequences are processed using TimeDistributed convolutional layers, followed by an LSTM layer comprising 128 units. The prediction is obtained as a final thick layer. This architecture has a good balance between learning capacity and computational cost with a number of parameters of about 2.71 million.

#### Model Hyperparameters (All Models)

All models used Adam optimizer (learning rate=0.001), Mean Squared Error (MSE) loss, batch size=32, and trained for 100 epochs with early stopping (patience=15). Dropout (0.3) prevented overfitting.

#### CNN Architecture (Sequential 1)

Three Conv2D layers (32→64→128 filters, 3×3 kernel, ReLU), MaxPooling2D (2×2), Flatten, Dense (128→4096 neurons). Total parameters: 4.81M.

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 64, 64, 32)	608
max_pooling2d_2 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_4 (Conv2D)	(None, 32, 32, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_5 (Conv2D)	(None, 16, 16, 128)	73,856
flatten_1 (Flatten)	(None, 32768)	0
dense_3 (Dense)	(None, 128)	4,194,432
dense_4 (Dense)	(None, 4096)	528,384

Total params: 4,815,776 (18.37 MB)  
 Trainable params: 4,815,776 (18.37 MB)  
 Non-trainable params: 0 (0.00 B)

Figure 2(a): CNN model (sequential\_1) with convolutional and dense layers

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
conv_lstm2d (ConvLSTM2D)	(None, 10, 64, 64, 64)	152,320
conv_lstm2d_1 (ConvLSTM2D)	(None, 64, 64, 128)	885,248
flatten_2 (Flatten)	(None, 524288)	0
dense_6 (Dense)	(None, 128)	67,108,992
dense_7 (Dense)	(None, 4096)	528,384

Total params: 68,674,944 (261.97 MB)  
 Trainable params: 68,674,944 (261.97 MB)  
 Non-trainable params: 0 (0.00 B)

Figure 2(b): Conv-LSTM model (sequential\_2) with ConvLSTM2D layers

Model: "functional\_11"

Layer (type)	Output Shape	Param #
input_layer_12 (InputLayer)	(None, 12, 32, 32, 2)	0
time_distributed_68 (TimeDistributed)	(None, 12, 32, 32, 32)	608
time_distributed_69 (TimeDistributed)	(None, 12, 16, 16, 32)	0
time_distributed_70 (TimeDistributed)	(None, 12, 16, 16, 64)	18,496
time_distributed_71 (TimeDistributed)	(None, 12, 8, 8, 64)	0
time_distributed_72 (TimeDistributed)	(None, 12, 4096)	0
lstm_21 (LSTM)	(None, 128)	2,163,200
dense_14 (Dense)	(None, 4096)	528,384
reshape_11 (Reshape)	(None, 64, 64, 1)	0

Total params: 2,710,688 (10.34 MB)  
 Trainable params: 2,710,688 (10.34 MB)  
 Non-trainable params: 0 (0.00 B)

Figure 2(c): DWT-ConvLSTM model (sequential\_3) integrating frequency and spatiotemporal learning

### Conv-LSTM Architecture (Sequential 2)

Two ConvLSTM2D layers (64→128 filters, return\_sequences=True). Total parameters: 68.67M.

### DWT-ConvLSTM Hybrid (Sequential 3)

Discrete Wavelet Transform (db4 wavelet, 3 decomposition levels) → TimeDistributed Conv2D → LSTM (128 units) → Dense output. Total parameters: 2.71M.

## Result And Analysis

Table I summarizes model performance on the test set. The

Table 1: Model Performance Comparison

Model	MAE	RMSE
CNN	0.0471	0.0747
Conv-LSTM	0.0421	0.0723
DWT-ConvLSTM	0.037	0.057

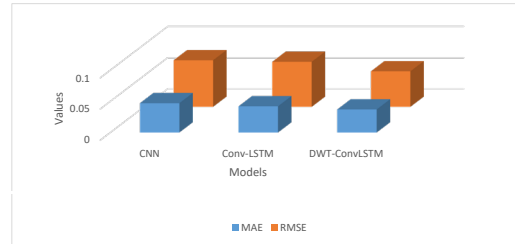


Figure 3: Graphical representation of MAE and RMSE values

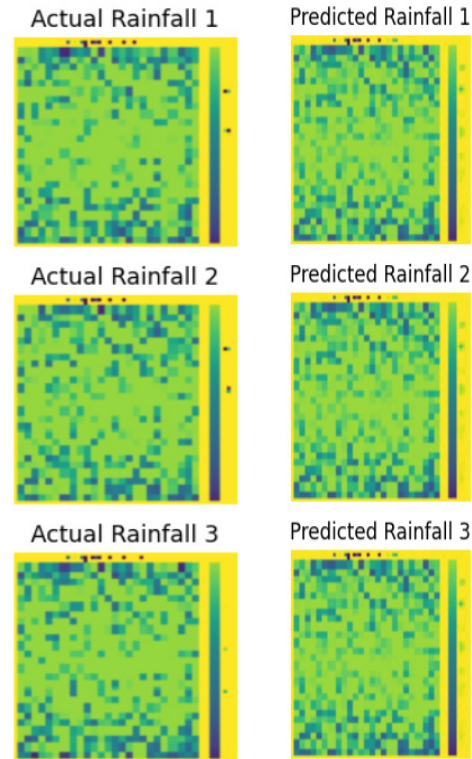
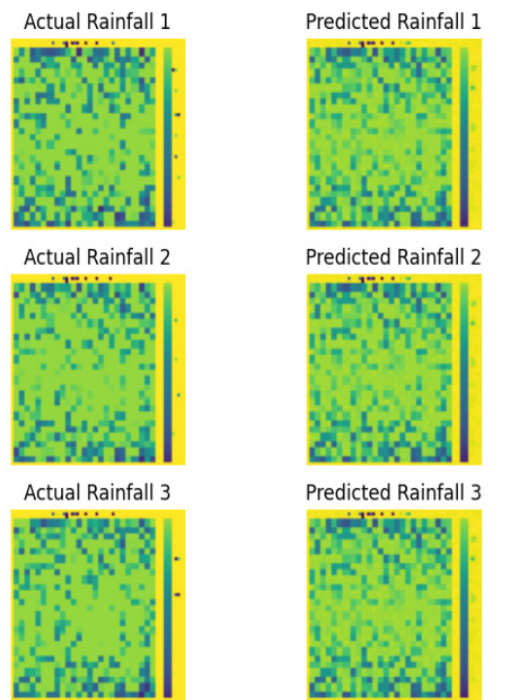


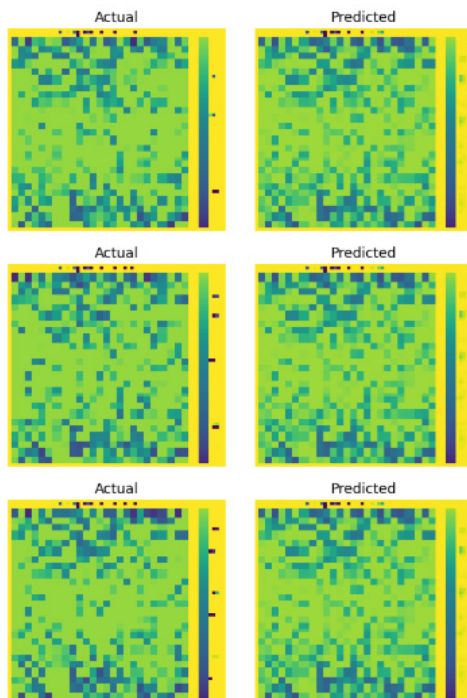
Figure 4: Actual Vs. Predicted Rainfall using Conv-LSTM Model

DWT-ConvLSTM hybrid achieved the lowest errors (MAE: 0.0370, RMSE: 0.0570), outperforming Conv-LSTM by 12% and CNN by 21%. This demonstrates the value of frequency decomposition for capturing multi-scale climate patterns.

Visual analysis (Fig 4-6) confirms DWT-ConvLSTM preserves fine-scale rainfall patterns and spatial coherence better than baselines, crucial for localized agricultural planning.



**Figure 5:** Actual Vs. Predicted Rainfall using CNN Model



**Figure 6:** Actual Vs. Predicted Rainfall using DWT-ConvLSTM Model

## Conclusion

This study demonstrates the superior performance of the DWT-ConvLSTM hybrid model for regional rainfall prediction in Gujarat, achieving MAE 0.0370 and RMSE 0.0570 using ERA5 data. The 12% improvement over Conv-

LSTM highlights frequency-domain preprocessing's role in modeling complex spatiotemporal climate patterns.

While computationally intensive, the hybrid approach offers significant potential for precision agriculture and water management. Future work will optimize efficiency for resource-constrained deployment and extend the dataset to capture multi-decadal climate cycles.

## Author Contributions

All authors agreed to submit and publish this manuscript.

## Disclosure Statement

No potential conflict of interest was reported by the author(s).

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## Data Availability Statement

The ERA5 data are publicly available and can be accessed through Google Earth Engine (<https://earthengine.google.com/>) after free registration. The original ERA5 dataset is distributed via the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu>).

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