ITM Web of Conferences **85**, 01002 (2026) https://doi.org/10.1051/itmconf/20268501002
ISSF 2026

A Generative Model for Rainfall Prediction based on Variational Autoencoder (VAE) Using Time-Series Weather parameters

Dr. S. Prakasam[1], S. Hariharan[2] and Dr. P. Shanmugapriya[3]

[1] Associate Professor, Department of Computer Science and Applications, Sri Chandrasekharendra Saraswathi Viswa Mahavidyalaya, Kanchipuram, Tamil Nadu, 631561 – India, Email: sp@kanchiuniv.ac.in

[2] Research Scholar, Department of Computer Science and Applications, Sri Chandrasekharendra Saraswathi Viswa Mahavidyalaya, Kanchipuram, Tamil Nadu, 631561 – India, Email: haranlog@gmail.com
.
[3] Associate Professor, Department of Computer Science and Engineering, Sri Chandrasekharendra Saraswathi Viswa Mahavidyalaya, Kanchipuram, Tamil Nadu, 631561 – India, Email: pshanmugapriya@kanchiuniv.ac.in

Abstract- Rainfall prediction has always been elusive and challenging due to the stochastic nature of the atmospheric processes involved in the rainfall occurrence, especially under extreme weather conditions. Traditionally, various deterministic and statistical methods have been used for rainfall prediction; however, they have failed to capture the uncertainty involved in the process. In this paper, a novel generative probabilistic rainfall prediction framework based on Variational Auto Encoders (VAE) is proposed. The method encapsulates weather information in a compact dimension mapped to a latent space that governs rainfall generation. The Encoder learns to transform the daily weather parameters into a probabilistic cloud in a low-dimensional latent space characterized by mean and variance, capturing both the prominent atmospheric configuration and its uncertainty. The Decoder samples the clusters that emerge in the latent space due to recurring atmospheric situations and outputs the probability of rainfall occurrence for a given day's weather parameters. The experimental analysis on weather data shows that the VAE-based approach improves the probabilistic accuracy and uncertainty calibration in comparison to deterministic methods. The proposed generative framework provides an interpretable latent representation of atmospheric states for reliable rainfall prediction.

1. Introduction

Reliable Rainfall prediction plays a vital role in sustainable agricultural practices and the volume of their produce, as it goes hand-in-hand with a nation's development. Rainfall forecasting also helps with better water resource management and disaster mitigation in case of extreme weather events. It provides leeway for better crop planning and climate risk assessment. The rainfall is impacted by non-linear interactions among atmospheric variables such as moisture availability, instability and circulation. These complex interactions give rise to uncertainty and variability in reliable rainfall prediction. Traditional approaches rely on numerical weather prediction models or statistical methods, while classical models like regression assume linearity in the weather data.

Recent Deep learning models operate at a deterministic level, which fails to incorporate uncertainty in the prediction. As Rainfall prediction is inherently probabilistic, the Variational Auto Encoder (VAE) offers a probabilistic model to represent the weather parameters in the latent space, which enables quantifying uncertainty and generative capability [1]. The VAE-based rainfall prediction model maps the daily weather parameters into a reduced-dimensional latent space of atmospheric states and decodes the states into probabilistic rainfall predictions [7]. The model is boosted by its ability to learn and organize the weather parameters into latent axes that align with the coherent patterns of the recurring atmospheric situations [3]. We report both deterministic and probabilistic evaluations to examine how latent space sampling and loss design affect calibration and extreme event detection using metrics such as Prediction Interval Coverage Probability (PICP) and Continuous Ranked Probability Score (CRPS) [12]. Our contribution is a light-weight VAE-based probabilistic rainfall predictor that targets calibrated outputs and demonstrates how latent space sampling improves extreme event representation. The study provides interpretable latent axis for atmospheric states useful for decision support in agriculture and risk management.

1.1 Problem Statement

The objective of the study is to build a probabilistic, generative and data-driven framework that can learn hidden atmospheric configurations with the ability to model uncertainty and variability inherent in the rainfall generation process and, in turn utilize the atmospheric states learnt during the training phase to decode the probability of rainfall occurrence.

1.2 Scope

The scope of the study is to develop and evaluate a generative rainfall model using a Variational Autoencoder (VAE)-based framework for probabilistic rainfall prediction using observed meteorological data. The scope extends to agriculture, where the farmers can make well-informed decisions and be better prepared for crop management as well as disaster management and weather risk management for mitigating the losses.

1.3. Variational Autoencoders (VAE)

A VAE contains an encoder that infers a probabilistic latent atmospheric state from the weather parameters and a decoder that generates the rainfall outcomes from sampled latent space. VAE architecture consists of the following:

1. Encoder:
   The encoder maps the weather parameters to a probabilistic latent space by learning the non-linear combination of input parameters.
2. Probabilistic Latent Space:
   The latent space represents the hidden atmospheric states in a reduced dimension that govern the rainfall.
3. Sampling Mechanism:
   A set of data points is sampled for identifying a plausible atmospheric state within the range of the latent cloud that corresponds to the mean $\mu(x)$ and variance $\sigma(x)$ of the input x.
4. Decoder:
   The Decoder represents the generative network that maps the sampled latent variables into rainfall outputs by learning a non-linear relationship between hidden states and rainfall.
5. Prior Distribution:
   It defines a reference distribution for the latent space, usually: $P(Z) = N(0,I)$
6. Loss Function:
   The VAE is trained using a composite loss consisting of
   a. Reconstruction Loss:
   Measures how well the decoder reproduces observed rainfall.
      - Mean-Squared Error
      - Negative Log-Likelihood

   b. KL Divergent Loss:
   Measures how close the learned the learned latent distribution is to the prior as given in equation-1.

$$KL(Q(Z|X) \,||\, P(Z) \qquad (1)$$

These components together enable Variational Autoencoders to infer a probabilistic latent representation, a latent space governed by a prior distribution, and a reparametrized sampling mechanism, a decoder that generates output from latent samples and a composite loss function that jointly enforces latent regularization.

2. Literature Survey

Research on rainfall prediction using VAE model is an exciting research area, as uncertainty and variance which are inherent to rainfall is being incorporated in the model. Here are some relevant research articles and papers:

Oliveira et al. (2024) demonstrate that VAE can synthesize spatial weather fields to produce extreme weather patterns and also show sampling strategies that expose extremes. However, the model tends to produce overly smooth structures and lacks spatial realism at a fine scale [1]. Cai et al. (2024), combine VAE latent representation with sequence modelling (GRU) to capture temporal dynamics exhibiting improved probabilistic skills. It lacks limited spatial coherence across stations [2]. Jahangir et al. use a Conditional VAE formulation to condition generation on covariates, showing CVAE is competitive with statistical and deep-learning baselines. But spatially explicit precipitation fields are not focused in the study [3]. Sun. et.al. (2023), demonstrate practical ensemble forecasting using VAE, showing how latent-based ensembles improve uncertainty quantification [4]. Wang et. al. (2024) uses Diffusion based models that show superior fidelity for precipitation fields, but are computationally expensive and less efficient at representing global atmospheric uncertainty [5]. Harris et al. (2022). benchmarks VAE-GAN against other generative approaches and examine extreme intensities and spatial statistics, focusing on downscaling and spatial realism but may underproduce most intense local peaks [6]. Szwarcman, D et. al. (2024), propose loss-quantization strategies that help VAE synthesize extreme weather fields better, but may require database balancing and careful hyperparameter tuning [7]. Yin. j. et al. (2024) integrates physics informed constraints into deep generative models for precipitation nowcasting, but results in increased model complexity and requires careful formulation [8]. Neil et.al. (2023) provide unsupervised feature learning for rainfall forecasting includes interpretability discussion, but lacks extensive probabilistic evaluation [9]. Transformer-Based Time Series Forecasting for Renewable Energy and Weather Data have been extensively studied which discusses the application of transformer models for time series forecasting, including weather data relevant to renewable energy forecasting [10].

3. Proposed Rainfall Prediction Model Using Variational Autoencoders (VAE)

The proposed rainfall prediction framework uses a Variational Autoencoder (VAE) model to learn the latent atmospheric states that are hidden in meteorological variables by mapping them to a latent space that compactly represents the input weather parameters, and generates the probabilistic rainfall that incorporates uncertainty and variation into the model [1].

Let (X_t) denote the vector of observed weather parameters at time-t such as Temperature, Humidity, Pressure, Wind speed, Wind direction and rainfall. Let Y_t represent the corresponding rainfall. The objective of the framework is to learn a probabilistic model that infers the conditional distribution $(P(Y|X_t)$ rather than a deterministic rainfall value that includes uncertainty and multiple plausible rainfall outcomes

3.1 Encoder

The Encoder maps a high-dimensional weather input (Xt) to a low-dimensional latent space representing the compact atmospheric state. The objective of the encoder is to infer the probabilistic latent atmospheric state. Each day's weather data is mapped to a latent cloud whose probabilistic space is represented as two vectors [2]:

$\mu(X_t)$ – Mean of latent distribution, which represents the most likely atmospheric state corresponding to observed weather.

$\sigma(X_t)$ – Standard deviation of the latent distribution representing the uncertainty associated with the atmospheric state.

The distribution over the latent distribution (Z_t) is modelled as in equation -2.

$$Q(Z_t \mid Xt) = N\left(\mu(X_t), \sigma(X_t)^2 \right) \quad (2)$$

3.2 Latent Space Representation and Sampling

The latent space represents a hidden atmospheric state that governs the rainfall generation. Each point in the latent space corresponds to an atmospheric configuration where nearby points represent similar rainfall-producing conditions and sparse regions correspond to rare or extreme events. Plausible atmospheric states are sampled from the latent distribution within the latent cloud, ensuring the samples are consistent with the input weather [3].

Multiple samples from the latent cloud help draw multiple rainfall scenarios and model uncertainty explicitly. Stochastic sampling is done as per the operation given in equation-3.

$$Z = \mu(X_t) + \sigma(X_t) \cdot \varepsilon \,,\ \varepsilon \sim \mathbb{N}(0,1) \quad (3)$$

3.3 Decoder

The decoder provides generative rainfall modelling that maps the sampled latent atmospheric states to output rainfall. The decoder learns nonlinear relationships between the hidden state and rainfall. For a latent sample Z_t, the decoder estimates the conditional rainfall distribution as given in equation-4.

$$P(Y_t \mid Z_t) \quad (4)$$

Depending on the different latent samples, the decoder generates multiple rainfall realizations, enabling the capture of rainfall uncertainty and variability.

The rainfall is modelled using a Gaussian likelihood as given in equation-5.

$$P(Y_t \mid Z_t) = \text{Normal}\left(\mu_Y(Z_t) + \sigma_Y(Z_t)^2 \right) \quad (5)$$

Where, $\mu_Y Z_t)$ is the predicted mean rainfall

$\sigma_Y(Z_t)^2$ is the predictive rainfall variance

The decoder learns a nonlinear mapping from latent atmospheric states to rainfall outcomes.

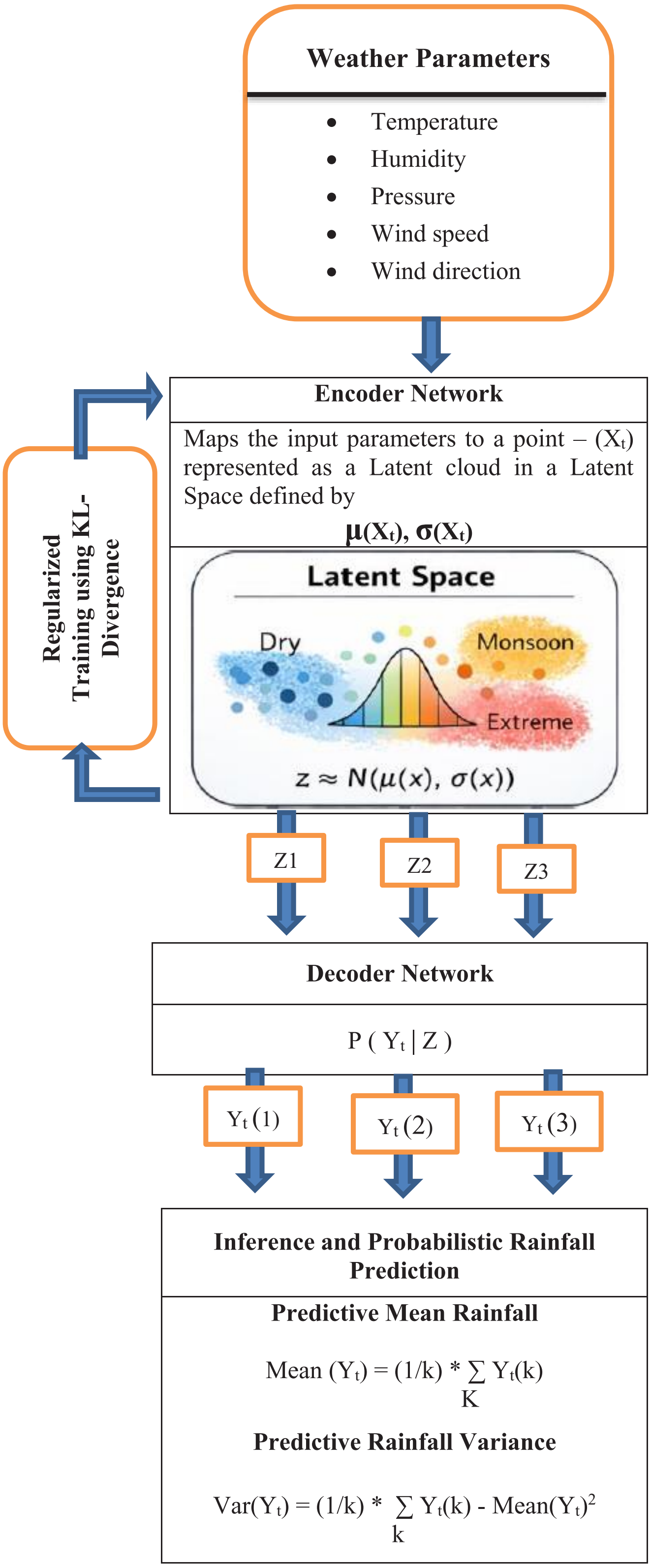

Fig. 1. Architecture of the VAE-based Rainfall prediction

Fig. 1 illustrates the architecture diagram of the VAE-based Rainfall prediction model, illustrating how the Encoder and Decoder help latent representation of the weather parameters that generate inference and probabilistic rainfall prediction.

3.4 Training Objective

The VAE is trained using a loss function that is based on KL_Divergence method.

The loss function is defined by equation-6.

$$\text{Loss} = \text{Reconstruction Loss} + \beta * \text{KL\_Divergence} \quad (6)$$

Where:

$$\text{Reconstruction\_Loss} = (Z_t \mid X_t) \,.\, \log P(Y_t \mid Z_t)$$

$$\text{KL\_Divergence} = \text{KL}\left(q\,(Z_t \mid X_t) \,\|\, P(Z_t) \right)$$

For Gaussian latent variables, the KL Divergence is computed as given in equation-7.

$$\text{KL} = 0.5 * \sum_{i=1}^{d} \sigma_i^2 + \mu_i^2 - 1 - \log(\sigma_i^2) \quad (7)$$

The hyperparameter β controls the strength of latent space regularization.

3.5 Inference and Probabilistic Rainfall Prediction

During Inference for a new input X_t,

- The encoder outputs $\mu(X_t)$ and $\sigma(X_t)$
- K latent samples are drawn: $Z_t(1), Z_t(2), Z_t(3), \ldots, Z_t(k)$
- Each latent sample is decoded into rainfall: $Y_t(1), Y_t(2), Y_t(3), \ldots, Y_t(K)$

The predictive mean rainfall is computed as given in equation-8.

$$\text{Mean}(Y_t) = (1/k) * \sum_{K} Y_t(k) \quad (8)$$

The predictive variance is computed as given in equation-9.

$$\text{Var}(Y_t) = (1/k) * \sum_{k} Y_t(k) - \text{Mean}(Y_t)^2 \quad (9)$$

4. Algorithm: Rainfall Prediction using Variational Autoencoder (VAE)

Inputs:

- Daily Weather Parameters
  X_t = [Temperature, Humidity, Wind Speed, Wind Direction, Cloud Cover, Pressure]
- Observed Rainfall - Y_t

Outputs:

- Predicted Rainfall
- Rainfall Uncertainty
- Probability of Rainfall

A. TRAINING PHASE:

Step-1: **Data Collection and Preparation:**

a. Collect daily weather parameters and corresponding rainfall data
b. Normalize weather parameters and rainfall values
c. Split the data into training and testing sets.

Step-2: **Encoder Forward Pass:**

For each training sample (Xt, Y_t)

a. Pass X_t to the Encoder, which maps X_t to a latent cloud in the latent space representing an atmospheric configuration.
b. Each mapped latent cloud is represented by

$\mu(X_t)$ – Mean of latent atmospheric state

$\sigma(X_t)$ – Standard deviation or Uncertainty

Step-3: **Latent Sampling:**

a. Generate random noise:

$$\varepsilon \sim \text{Normal}(0,1)$$

b. Sample latent atmospheric state

$$Z_t = \mu(X_t) + \sigma(X_t) * \varepsilon$$

Step-4: **Decoder Forward Pass:**

a. Pass sampled latent vector Z_t to the decoder.
b. The Decoder predicts rainfall-Y_t conditioned on the latent vector Z_t : $P(Y_t \mid Z_t)$

Step-5: **Computer Loss:**

a. Reconstruction Loss:
   Measures the difference between Y_t and $Y^{\wedge}_t$
b. Measure the difference between latent distribution and standard normal prior.
c. total Loss = Reconstruction Loss + β * KL_Divergence

Step-6: **Parameter Update:**

a. Backpropagate total loss
b. Update Encoder and Decoder weights
c. Repeat steps 2-3 until convergence

B. INFERENCE PHASE:

Step-7: **Encode New Weather Input:**

a. Input a day's weather parameter $X_{\_NEW}$ for which rainfall is to be predicted.

b. The Encoder maps this set of parameters to the Latent space in a latent cloud defined by:

- $\mu_{\text{-new}}$: Mean of latent cloud representing input X.
- $\sigma_{\text{-new}}$: Standard deviation or variance within the range of latent cloud for input X.

Step-8: **Sample Multiple Atmospheric States**:

For i = 1 to K

a. Randomly Sample $\varepsilon_i \sim$ Normal (0,1)

b. Compute latent state:

$$Z_i = \mu_{\text{-new}} + \sigma_{\text{-new}} * \varepsilon_i$$

Step-9: **Generate rainfall scenarios:**

For each latent state Z_k

a. Pass Zk through Decoder

b. Obtain rainfall prediction for the input $X_{\text{-new}}$

This step results in K-Plausible rainfall predictions.

Step-10: **Aggregate Prediction:**

a. Compute Mean Rainfall
Mean_Rainfall = Average (Y1, Y2, Y3, . ., YK)

b. Rainfall Uncertainty:
Variance_Rainfall = Variance (Y1, Y2, Y3, . ., YK)

C: OUTPUT PHASE:

- Expected Rainfall for the given input $X_{\text{-new}}$ is outputted.
- The associated uncertainty for the expected rainfall is output.
- The risk of extreme rainfall events is also output.

5. Experimental Analysis

The effectiveness and efficiency of the proposed rainfall prediction algorithm are evaluated in terms of prediction accuracy, uncertainty estimation, and the probability of rainfall occurrence.

5.1 Dataset Description and Experimental Setup

Daily weather observations, including parameters such as Temperature, Humidity, Wind speed, Wind direction, Pressure, and Cloud cover, were collected from 2015 to 2023 from the IMD website across 20 cities in the state of Tamil Nadu. The data were normalized to have a zero mean and unit variance. Data were split into 70% Training and 30% Testing sets.

Three models were evaluated for comparison:

1. Deterministic Neural Network (DNN)
2. VAE without Sampling (Mean-only)
3. Proposed VAE with Latent sampling

5.2 Evaluation Metrics

The following metrics were used for evaluating the performance of the models:

- Deterministic Metrics:
  a. Mean Absolute Error (MAE)
  b. Root Mean Square Error (RMSE)
- Probabilistic metrics:
  a. Prediction Interval Coverage Probability (PICP)
  b. Predictive Variance
  c. Continuous Ranked Probability Score (CRPS)
- Rainfall Occurrence Metric:
  a. Probability of Detection (POD)
  b. False Alarm Ratio (FAR)

5.3 Rainfall Prediction Accuracy

Table 1. Rainfall prediction accuracy of the models using MEA and RMSE

MODEL	MAE (mm)	RMSE (mm)
DNN	7.68	9.54
VAE without Sampling	5.54	9.35
Proposed VAE with Latent sampling	5.10	8.23

Table 1, signifies that the accuracy of rainfall estimation can be improved by preventing over-smoothing and capturing multiple plausible outcomes, which validates the superiority of the proposed algorithm. Figure 2 shows that the proposed model has a reduced error rate compared to the other models.

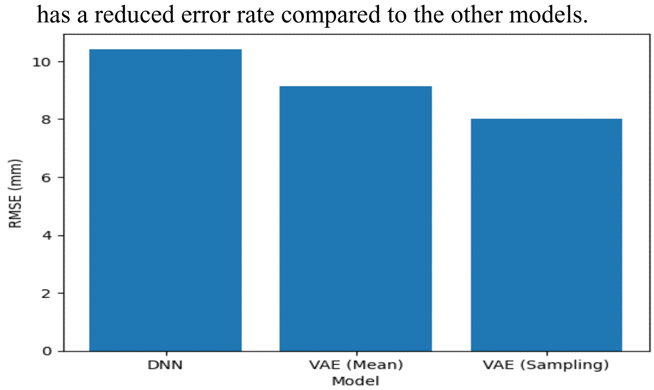

Fig. 2. RMSE Comparison across models

5.4 Uncertainty Quantification Performance

Table 2. Uncertainty Quantification Performance of the models using PICP and Mean Predictive Variance

MODEL	PICP (%)	Mean Predictive Variance	CRPS (mm)
VAE without Sampling	68.4	5.8	6.12
Proposed VAE with Latent sampling	92.3	12.2	4.87

Table 2, shows how the proposed algorithm is better at correctly capturing the uncertainty with latent cloud sampling (μ, σ), which validates the credentials of the proposed algorithm. Figure-3 shows that the observed rainfall and the predicted rainfall are aligned with respect to the lower bound and higher bound for rainfall occurrence. CRPS confirms that the entire predictive distribution is better aligned with observed rainfall [11] [12].

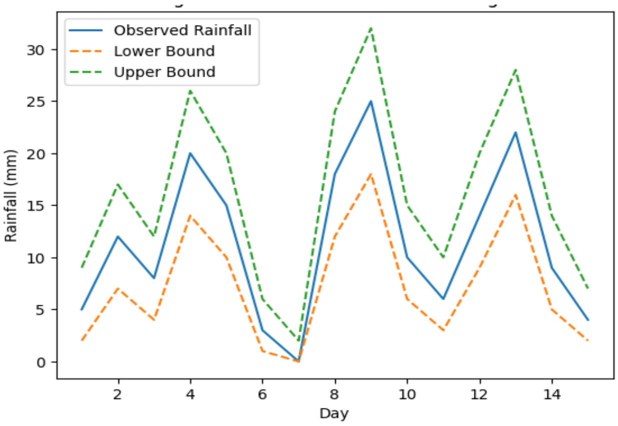

Fig. 3. Prediction Interval Coverage

5.5 Rainfall Occurrence and Extreme Event Detection:

Table 3. Rainfall occurrence and Extreme Event Detection using POD and FAR

MODEL	POD	FAR
DNN	0.54	0.46
VAE without Sampling	0.67	0.35
Proposed VAE with Latent sampling	0.79	0.26

Table 3, illustrates that the sampling of multiple atmospheric states in the proposed model proves vital to the reduction of the false alarms in the model as compared to the other models discussed. Figure-4 proves that under the proposed model, the observed rainfall matches the predicted rainfall.

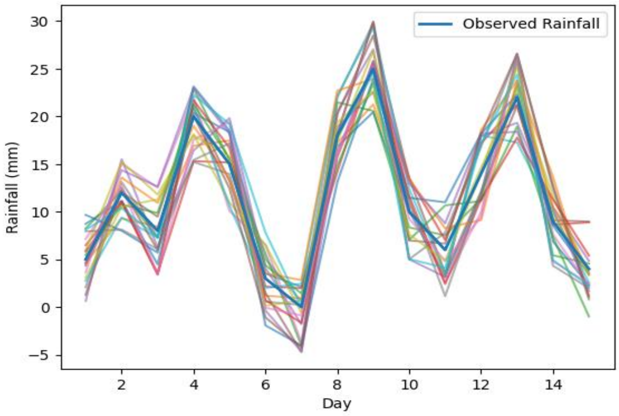

Fig. 4. Observed Rainfall Vs Predicted Rainfall

5.6 Comparison with existing studies

The observed improvement in probabilistic score (PICP = 92.3 %) and reduction in false alarms (FAR = 0.26) are consistent with recent studies involving generative approaches for rainfall prediction. For example, Oliveira et al. (2021) focus on spatial synthesis with VAE rather than rather than station level probabilistic prediction. Compared to diffusion-based generative models (Wang et al. 2024) that achieve high spatial fidelity at increased computation cost, the proposed VAE-based framework provides an efficient alternative for station-level forecasting, which also maintains strong uncertainty calibration. The achieved PICP of 92.3 % indicates good interval coverage with balanced calibration and sharpness. The proposed model achieves the lowest CRPS value, indicating superior probabilistic skill, demonstrating improved predictive accuracy and uncertainty calibration simultaneously [11][12].
The improvement in RMSE (8.23 mm) compared to DNN and mean-only VAE variants suggests that stochastic sampling prevents over-smoothing and captures multiple plausible rainfall realizations. The increase in predictive variance (12.2) relative to the mean-only VAE indicates an improved uncertainty-aware model. The corresponding increase in PICP and reduction in FAR confirm that the latent cloud sampling enhances both accuracy and reliability.

6. Conclusion

This study presents a probabilistic framework for rainfall prediction based on the Variational Autoencoder (VAE), which incorporates atmospheric uncertainty and variance through a low-dimensional latent representation. The model is successful in unearthing hidden atmospheric states that are conducive to rainfall generation and helps generate multiple plausible rainfall scenarios for a given climatological condition. The VAE framework, with its ability to naturally provide uncertainty estimates, makes it more suitable for the highly probabilistic rainfall prediction task. Experimental analysis proves the fact that latent space sampling significantly improves rainfall prediction accuracy and uncertainty compared to deterministic Neural Networks and Mean only-VAE variants. Experimental evaluation across 20 stations in Tamil Nadu demonstrated that latent sampling significantly improves predictive accuracy (RMSE = 8.23 mm), interval coverage (PICP = 92.3%) and extreme event detection (POD = 0.79; FAR = 0.26) compared to deterministic and mean-only VAE baselines. The model effectively represents rainfall variability and uncertainty. The results of the study amply demonstrate that the VAE model successfully learns compact and interpretable representations of atmospheric variability in relation to rainfall. Compared with the recent generative approaches in rainfall prediction, the proposed model offers a computationally efficient and interpretable solution for station-level rainfall forecasting. The study provides insights into recurring atmospheric regimes unearthed by the model's latent representation. The study demonstrates how VAE-based probabilistic modelling provides a robust and interpretable framework for rainfall prediction, making it uncertainty-aware and consistent rainfall forecasting.

References

[1] Oliveira, D. A. B., Guevara Diaz, J. L., Zadrozny, B., & Watson, C. D. (2021). *Controlling weather field synthesis using variational autoencoders* (ICML Climate Change AI Workshop).

[2] Cai, W., Lan, F., Huang, X., Hao, J., Xia, W., Tang, R., Feng, P., & Li, H. (2024). *Generative probabilistic prediction of precipitation-induced landslide deformation with variational autoencoder and gated recurrent unit.* Frontiers in Earth Science, 12, 1394129.

[3] Jahangir, M. S., & Quilty, J. (2024). *Generative deep learning for probabilistic streamflow forecasting: Conditional variational auto-encoder. Journal of Hydrology, 629*, Article 130498

[4] Sun, X., Zhang, H., Wang, J., Shi, C., Hua, D., & Li, J. (2022). *Ensemble streamflow forecasting based on variational mode decomposition and long short-term memory. Scientific Reports, 12*(1), 518.

[5] Wang, X., He, Z., & Peng, X. (2024). *Artificial-intelligence-generated content with diffusion models: A literature review. Mathematics, 12*(7), 977.

[6] Harris, L., McRae, A. T. T., Chantry, M., et al. (2022). *A generative deep learning approach to stochastic downscaling of precipitation forecasts. Journal of Advances in Modeling Earth Systems, 14*(??), e2022MS003120.

[7] Szwarcman, D et.al.. (2024). *Title of paper: Loss-quantization strategies that improve variational autoencoder synthesis of extreme weather fields. Proceedings.*

[8] Yin, J., Meo, C., Roy, A., Bou Cher, Z., Wang, Y., Imhoff, R., Uijlenhoet, R., & Dauwels, J. (2024). *Precipitation nowcasting using physics informed discriminator generative models. arXiv*

[9] Neil et al. (2023) — Unsupervised feature learning for rainfall forecasting, Temporal Forecasting of Rainfall", Journal of Hydroinformatics

[10] Wani, O. A., & colleagues. (2024). *Predicting rainfall using machine learning, deep learning, and time series methodologies. Scientific Reports, 14*, Article 77687

[11] W. Hu, H. Zhang, X. Li, and Y. Chen, "Deep learning–based probabilistic precipitation forecasting with uncertainty quantification evaluated using CRPS," *Monthly Weather Review*, vol. 151, no. 8, pp. 2345–2362, 2023.

[12] L. Main, K. Browning, R. Thompson, and P. Clark, "Skilful probabilistic medium-range precipitation forecasting and evaluation using CRPS and reliability diagnostics," *Meteorological Applications*, vol. 31, no. 2, 2024.