Rainfall Amount Prediction with Climate Data and Geospatial Data

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Presentation Overview

- Introduction to the project
- Approaches & Methodology
- Hyperparameter Tuning
- Single Best Model
- Ensemble Cross-Validation Model
- Comparison and Analysis
- Limitations and Areas for Improvement
- Conclusion

Introduction

3 Key Components for Prediction

- Climate reanalysis data:
- Digital Elevation Model (DEM):
- Temporal Information:

Rainfall Prediction Models

Single Best Model: An optimized single LAND model with the best hyperparameters

Ensemble Cross-Validation Model: A robust ensemble of multiple models trained with k-fold cross-validation

Approaches and Methodology

Data Resources

Climate Reanalysis Data: We used 16 atmospheric variables from climate reanalysis datasets
Such as air temperature difference for each levels, geospatial heights, humidities, moistures, etc.

Digital Elevation Model (DEM) Data: Topographical information at two scaled formats:

Local DEM: 3×3 patches with 4 km per cell (12km total coverage)

Regional DEM: 3×3 patches with 20 km per cell (60km total coverage)

Temporal Information: One-hot encoded months to observe seasonality

Neural Network Architecture

Climate Branch: 16 variables, dense layer with batch normalization

Local DEM Branch: flatten 3x3 local DEM patch, dense layer with batch normalization

Regional DEM Branch: flatten 3x3 regional DEM patch, dense layer with batch normalization

Month Branch: One-hot encoded month, dense layer with batch normalization

Hyperparameter Tuning

Tunable Parameters

Network Architecture: #nuerons, #units of each branch, Activation function

Regularization: Dropout rate, learning rate for L2 regularization,

Optimization Parameters: Weights decay for AdamW, Learning rate schedule parameters

Tuning Process

The hyperparameter tuning process was configured with the following settings:

Algorithm: Bayesian Optimization with Hyperband early stopping

Number of Trials: 100

Epochs per Trial: Up to 50 with early stopping

Objective: Minimize validation loss (MSE)

Early Stopping: Patience of 15 epochs

Optimal Hyperparameters

na: 512

nb: 384

dropout_rate: 0.1

l2_reg: 1e-06

learning_rate: 0.01

weight_decay: 1e-07

local_dem_units: 64

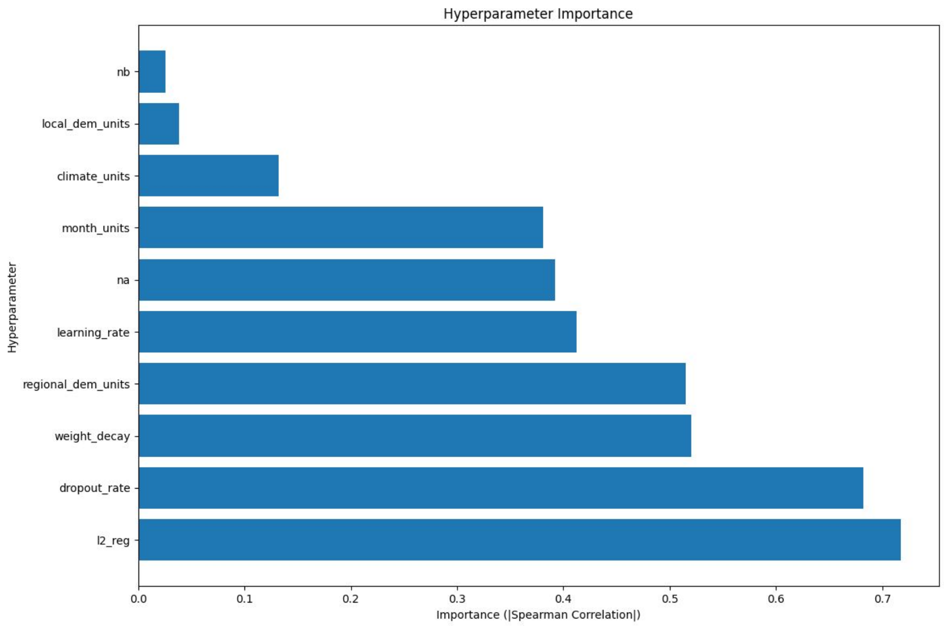
regional_dem_units: 32

month_units: 16

climate_units: 384

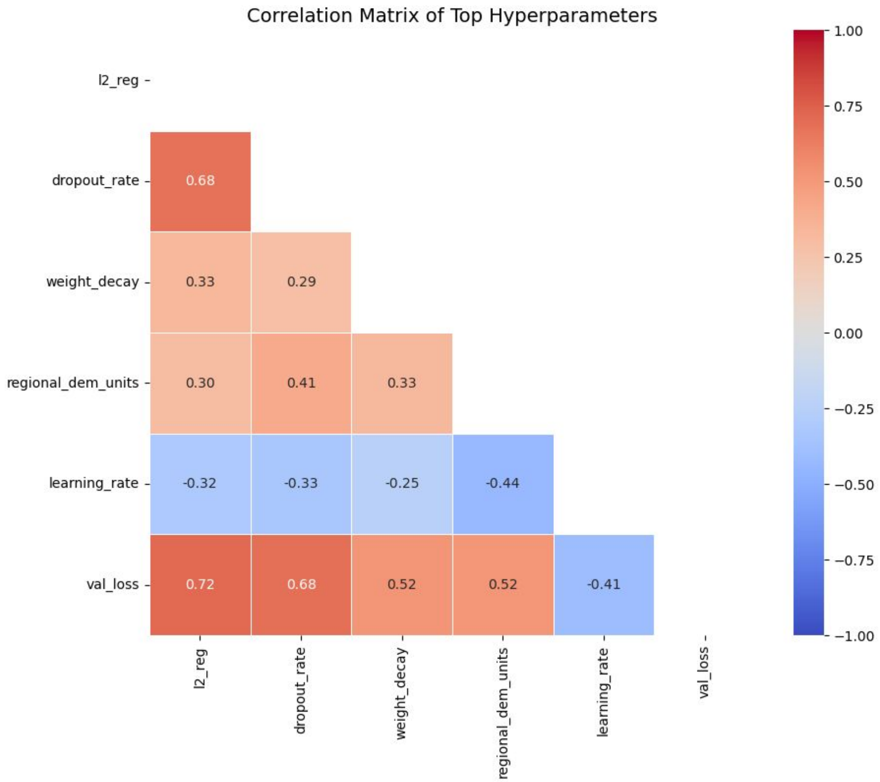
use_residual: False

activation: relu



Top 5 Most Important Predictors

1. **L2 regulation**
2. **Dropout Rate**
3. **Weight Decay**
4. **Regional DEM Units**
5. **Learning Rate**



Single Best Model

Single Best Model Implementation

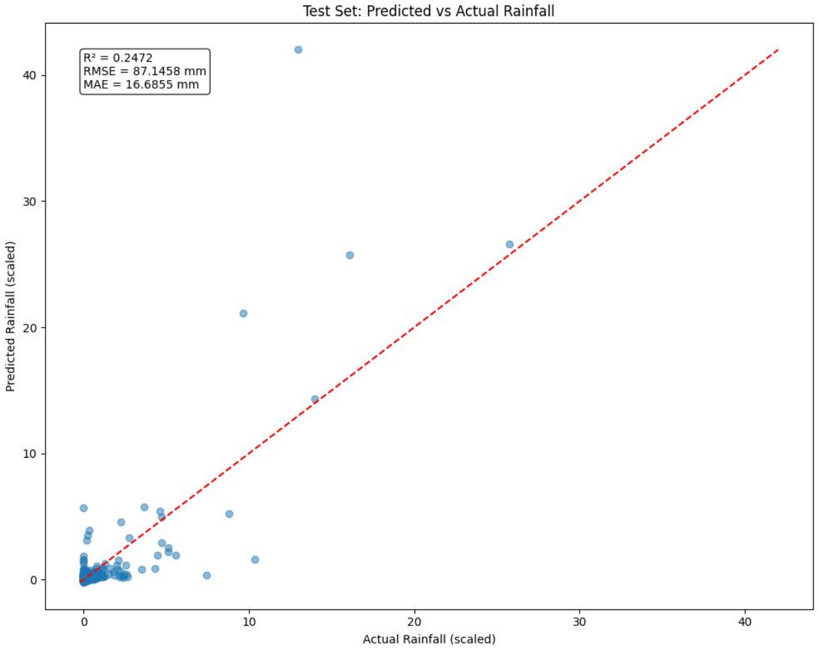
Optimal batches
- Climate branch: 384 units
- Local DEM branch: 64 units
- Regional DEM branch: 32 units
- Month encoding branch: 16 units

Dense Layers
- First layer: 512 units with ReLU activation
- **Second layer:** 384 units with ReLU activation

Regularization
- Dropout (rate = 0.1)
- L2 regularization (1e-06)
- Batch normalization after each dense layer

Single Best Model Result

Validation	Test
R^2: 0.7212	R^2: 0.2472
RMSE: 49.13 mm	RMSE: 87.15 mm
MAE: 13.24 mm	MAE: 16.69 mm



Single Best Model Limitations

Higher Variance

Overfitting Risk

Initialization Sensitivity

Limited Generalization

Ensemble Cross-Validation Model

Ensemble Cross-Validation Model Implementation

Structure of the ensemble model:
- 5 cross-validation folds:
- 5 models per fold:
- 25 total models:

Training Process:

Splitting Data: 80% for training data and 20% for validation data

Ensemble Aggregation: Average of 25 models in total

Test Evaluation:

Ensemble Cross-Validation Model Result

Avg. across 5 folds	**Best fold (Fold 5)**	**held-out test set**
R^2: 0.6253	R^2: 0.7012	R^2: 0.7955
RMSE: 63.3445 mm	RMSE: 58.9465 mm	RMSE: 45.4200 mm
MAE: 14.4308 mm	MAE: 13.8226 mm	MAE: 13.2535 mm

Ensemble Cross-Validation Model Advantages

Advantages of Ensemble Model over the Single Model

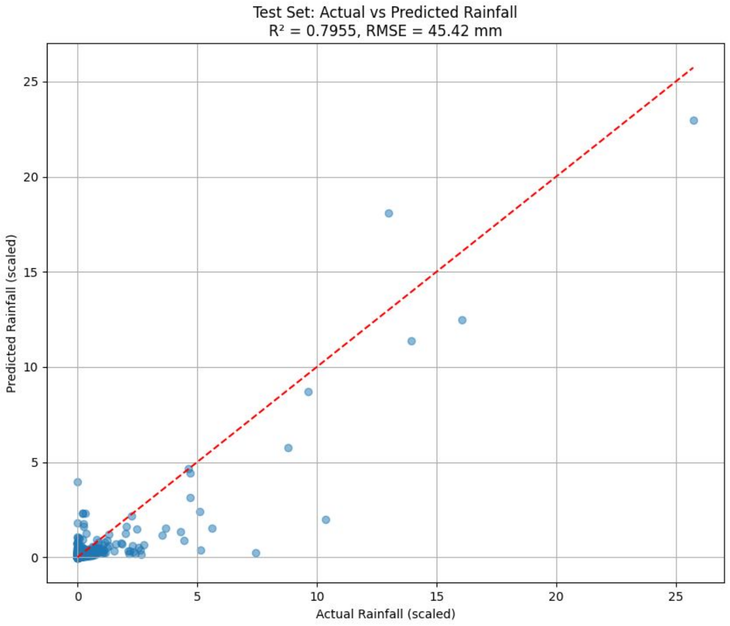
Reduced Variance

Improved Generalization

Robustness to Initialization

Uncertainty Quantification

Overfitting Prevention



6.1 Performance Comparison

The table below summarizes the performance metrics for both the ensemble cross-validation model and the single best model:

Model	Validation R^2	Test R^2	Test RMSE (mm)	Test MAE (mm)
Ensemble CV Model	0.6253 (avg)	0.7955	45.42	13.25
Single Best Model	0.7212	0.2472	87.15	16.69

This comparison reveals several important insights:

1. Generalization Gap: The single model shows a significant drop in performance from validation to test set (R^2 drop of 0.474), while the ensemble model actually performs better on the test set than on validation (R^2 improvement of 0.1702).
2. Superior Test Performance: The ensemble model's test R^2 (0.7955) is substantially higher than the single model's (0.2472), representing a 221% improvement in explained variance.
3. Error Reduction: The ensemble approach reduces RMSE by 48% (from 87.15 mm to 45.42 mm) and MAE by 20% (from 16.69 mm to 13.25 mm) compared to the single model.

Summary & Conclusion

- We developed a rainfall prediction model using the LAND (Location-Agnostic Neural Downscaling) method with deep learning.
- Two models were compared:
    - Single Best Model showed strong validation performance but overfitted and had weak test results.
    - Ensemble Cross-Validation Model achieved exceptional performance with a test R^2 of 0.7955, explaining nearly 80% of rainfall variation.
- The ensemble approach reduced overfitting, improved generalization, and produced more reliable prediction results.
- This study shows that deep learning combined with ensemble strategies can significantly improve rainfall prediction performance(R^2 score).