A Guideline for Calibrating IMERG-Late Precipitation Estimates Using U-Net and CMPA in China

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Abstract: Accurate precipitation estimation is crucial for hydrological and meteorological applications. IMERG-Late, a widely used global satellite-based precipitation product, exhibits biases in China due to complex topography and climate variability. This study proposes a U-Net-based deep learning framework for calibrating IMERG-Late precipitation estimates using CMPA as the ground truth. The model effectively learns spatial and temporal patterns to reduce systematic errors and improve precipitation consistency. Comparative experiments demonstrate that U-Net outperforms traditional interpolation, statistical correction, and other deep learning methods in enhancing precipitation accuracy. While the approach significantly improves satellite-based precipitation estimates, challenges such as computational costs and generalization in extreme weather events remain. Future work will explore hybrid deep learning-physical model approaches and Transformer-based architectures to further enhance precipitation calibration.

Keywords: Precipitation Calibration, IMERG-Late, CMPA, U-Net, Deep Learning, Satellite-based Precipitation, Climate Modeling

1. Introduction

1.1. Background and Importance

Precipitation is a fundamental component of the global hydrological cycle, essential for agriculture, water resource management, and disaster prevention [1], [2], [3], [4], [5]. Remote sensing techniques have significantly advanced precipitation monitoring due to their broad spatial coverage and high temporal resolution [6], [7], [8]. However, satellite-based precipitation products often exhibit biases due to sensor limitations and complex atmospheric conditions [9], [10], [11].

The Integrated Multi-satellite Retrievals for GPM (IMERG-Late) provides hourly, high-resolution global precipitation estimates using microwave, infrared, and radar data [6], [7], [12]. Although widely utilized for short-term precipitation forecasting and hydrological studies, IMERG-Late exhibits substantial uncertainties in China, particularly over mountainous and coastal regions [9], [10], [13], [14].

In contrast, the China Meteorological Administration Precipitation Analysis (CMPA) integrates ground-based rain gauge observations with satellite data to provide more accurate regional precipitation estimates

[15], [16], [17], [18]. Leveraging CMPA as ground truth for calibrating IMERG-Late could enhance precipitation accuracy over China.

1.2. Research Problem

IMERG-Late precipitation estimates are prone to errors in regions with complex topography (e.g., the Tibetan Plateau and southwestern China) and extreme weather conditions (e.g., typhoons and heavy rainfall) [13], [19], [20], [21], [22]. Traditional calibration methods include:

- **Interpolation techniques**, such as kriging and inverse distance weighting, which compensate for spatial inconsistencies but fail to model nonlinear precipitation patterns [19].
- **Physical models**, such as numerical weather prediction (NWP), which incorporate atmospheric dynamics but require extensive computational resources [20].
- **Statistical downscaling methods**, including Bayesian approaches and regression models, which correct biases but struggle with highly variable precipitation patterns [21].

Deep learning has recently demonstrated superior performance in remote sensing and meteorological applications [23], [24], [25], [26], [27]. U-Net, with its encoder-decoder architecture, effectively captures spatial structures and fine details, making it a promising tool for precipitation data correction. However, its application to IMERG-Late calibration remains underexplored.

This study investigates:

- Can U-Net effectively improve IMERG-Late precipitation accuracy in China?
- How does deep learning perform under complex topographic and extreme weather conditions?
- What are the advantages and limitations of U-Net compared to traditional calibration methods?

1.3. Contributions of This Study

This study proposes a U-Net-based calibration framework for IMERG-Late using CMPA as ground truth. The key contributions are:

- Developing a deep learning-based calibration approach to enhance IMERG-Late precipitation estimates in China.
- Comparing U-Net against interpolation, statistical downscaling, and physical models.
- Evaluating model performance across different climatic regions, including temperate monsoon (North China), subtropical monsoon (South China), and mountainous terrains (Southwest China).

The experimental results demonstrate the potential of U-Net in reducing IMERG-Late biases, improving its usability for regional precipitation analysis.

2. Related Work

2.1. IMERG-Late and CMPA Datasets

IMERG-Late (Integrated Multi-satellite Retrievals for GPM - Late Run) is a globally available satellite-based precipitation product that integrates multiple sources, including microwave, infrared, and radar data, to provide high spatial and temporal resolution precipitation estimates [1]. It has been widely used in global hydrological and meteorological studies, including flood prediction, drought monitoring, and climate change research. However, IMERG-Late exhibits significant biases in China due to complex topography, varying climatic conditions, and limited validation with ground-based observations [9], [10]. Studies have shown that IMERG-Late tends to underestimate heavy precipitation events and overestimate light precipitation, particularly in mountainous and coastal regions [13].

CMPA (China Meteorological Administration Precipitation Analysis) is a high-resolution precipitation dataset specifically developed for China. It integrates ground-based gauge observations with satellite data, offering improved accuracy compared to satellite-only estimates [15]. CMPA provides a finer spatial resolution and better temporal consistency, making it a reliable reference for regional precipitation analysis [16], [17]. Previous research has demonstrated that CMPA data aligns closely with ground-based observations and significantly outperforms satellite-derived precipitation products in capturing extreme weather events [18].

Leveraging CMPA as a ground truth dataset for calibrating IMERG-Late can enhance precipitation estimation accuracy, making IMERG-Late more suitable for regional studies in China. Several studies have successfully used CMPA to adjust and validate global precipitation datasets [28], [29], demonstrating the potential for integrating CMPA with deep learning models for enhanced calibration.

2.2. Precipitation Data Calibration Methods

Several approaches have been developed to calibrate satellite-based precipitation estimates, including:

- **Traditional Methods**: Techniques such as interpolation (e.g., kriging, inverse distance weighting) [19] and Bayesian statistical models have been used for precipitation bias correction. While effective in some cases, these methods often struggle with capturing nonlinear relationships in precipitation patterns [21]. Furthermore, interpolation techniques assume spatial continuity, which is not always valid for highly variable precipitation fields, leading to errors in regions with complex terrain.
- **Physical Models**: Numerical weather prediction (NWP) models incorporate atmospheric dynamics and physical processes to improve precipitation forecasts [20]. These models utilize sophisticated atmospheric physics to simulate precipitation processes; however, their accuracy depends on initial conditions, computational resources, and parameterization schemes. While NWP models provide high accuracy for short-term forecasting, they often require extensive post-processing to reduce systematic biases [30].
- **Machine Learning Methods**: Recent advances in machine learning have introduced models such as convolutional neural networks (CNNs) [24], recurrent neural networks (RNNs) [25], and Transformer-based approaches for precipitation bias correction [23]. These models can learn complex spatiotemporal relationships in precipitation data, outperforming traditional methods in many scenarios. CNNs excel in capturing spatial dependencies, while RNNs and Transformers are more suited for temporal sequence modeling. Hybrid models combining CNNs with RNNs have been explored for precipitation estimation, demonstrating improved performance in dynamic precipitation systems [31].

Despite the success of machine learning models, challenges remain in training data availability, model interpretability, and generalization across different climatic regions. Ensuring robustness in extreme precipitation conditions and minimizing overfitting to specific geographic areas are active areas of research [32].

2.3. U-Net in Remote Sensing and Precipitation Data Processing

U-Net, originally developed for biomedical image segmentation [26], has been successfully adapted for various remote sensing applications, including land cover classification, cloud detection, and precipitation estimation [27]. The model's encoder-decoder architecture enables efficient feature extraction and spatial resolution preservation, making it well-suited for precipitation data calibration.

Recent studies have demonstrated the effectiveness of U-Net in downscaling coarse-resolution precipitation data, enhancing the spatial details of satellite-derived precipitation estimates [33]. Compared to conventional interpolation methods, U-Net can better capture precipitation gradients and localized extreme events. Additionally, attention-based mechanisms integrated into U-Net have shown further improvements in bias correction by selectively focusing on key precipitation regions [34].

While U-Net has demonstrated promising results in remote sensing, its application to IMERG-Late calibration remains an open research area. Challenges include optimizing the model for precipitation data, handling regional climatic variations, and ensuring generalizability across different precipitation regimes. Further exploration of its strengths and limitations in precipitation bias correction is necessary for improving satellite-based precipitation products [35].

3. Methodology

3.1. Data Preprocessing

To ensure the effective calibration of IMERG-Late precipitation estimates using CMPA as ground truth, several preprocessing steps are required:

- **Dataset Selection and Alignment**: IMERG-Late is used as the input dataset, while CMPA serves as the target reference. The two datasets are temporally and spatially aligned by matching timestamps and regridding IMERG-Late to the resolution of CMPA using bilinear interpolation.
- **Baseline Processing**: Traditional methods such as interpolation (kriging, inverse distance weighting) and statistical downscaling techniques (quantile mapping, Bayesian calibration) are employed as baseline comparisons.
- **Data Normalization**: Precipitation values are normalized to stabilize training, typically using min-max scaling or standardization.
- **Data Augmentation**: Techniques such as random cropping, flipping, and rotation are applied to enhance the model's robustness.
- **Outlier Detection**: Extreme precipitation values are identified and handled using statistical thresholding methods to mitigate anomalies in training data.

3.2. U-Net Model Architecture

U-Net is selected due to its efficient encoder-decoder structure, which preserves spatial features while enabling effective learning of precipitation patterns. The architecture consists of:

- **Encoder**: A series of convolutional layers with ReLU activation and max-pooling operations to extract multi-scale precipitation features.
- **Bottleneck**: A set of fully connected layers that capture high-level spatial information and relationships between precipitation patterns.
- **Decoder**: A series of upsampling and convolutional layers with skip connections that restore spatial resolution while maintaining essential feature representations.
- **Output Layer**: A single convolutional layer with a linear activation function to generate the calibrated precipitation estimates.

3.3. Loss Function Selection

To optimize model performance, different loss functions are evaluated:

- **Mean Squared Error (MSE)**: Measures the average squared difference between predicted and true precipitation values.
- **Mean Absolute Error (MAE)**: Captures the absolute difference between predictions and observations, providing robustness against extreme values.
- **Structural Similarity Index (SSIM)**: Evaluates the similarity between predicted and observed precipitation fields, focusing on structural consistency.

3.4. Training Strategy

- **Data Splitting**: The dataset is divided into training (70%), validation (15%), and testing (15%) subsets to evaluate generalization performance.
- **Optimization Strategy**: The Adam optimizer is employed with an initial learning rate of 10^{-3}, progressively reduced using a learning rate decay strategy.
- **Regularization Techniques**: L2 regularization and dropout layers are incorporated to prevent overfitting. Data augmentation further improves robustness.

3.5. Model Optimization

To enhance U-Net's effectiveness in precipitation calibration, the following enhancements are applied:

- **Skip Connections**: Preserve fine-scale spatial features by linking encoder layers with corresponding decoder layers.

- **Attention Mechanism**: Integrates attention modules (e.g., self-attention or spatial attention) to enhance feature selection in critical precipitation regions.
- **Multi-Scale Feature Extraction**: Additional convolutional layers at different resolutions to improve the model's ability to capture both large-scale and localized precipitation patterns.

4. Experiments and Results

4.1. Experimental Setup

The experiments are conducted using a high-performance computing environment with the following specifications:

- **Hardware**: NVIDIA A100 GPU with 40GB memory.
- **Software**: Python-based deep learning frameworks, including TensorFlow 2.8 and PyTorch 1.11.
- **Training Parameters**: Batch size of 32, learning rate set to 10^{-3} with exponential decay, and a total of 100 epochs.
- **Evaluation Metrics**: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Structural Similarity Index (SSIM) are used to assess model performance.

4.2. Baseline Comparisons

To evaluate the effectiveness of the U-Net-based calibration method, we compare it against several baseline approaches:

- **Traditional Interpolation Methods**: Kriging and inverse distance weighting (IDW) are used to adjust IMERG-Late precipitation estimates.
- **Statistical Calibration Methods**: Bayesian correction and quantile mapping are implemented for systematic bias reduction.
- **Machine Learning Models**: CNN-based and Transformer-based precipitation correction models are trained for comparison.

Results indicate that U-Net significantly outperforms traditional interpolation and statistical methods, achieving lower RMSE and higher SSIM values. Compared to other deep learning models, U-Net demonstrates superior generalization due to its effective spatial feature preservation.

4.3. Regional Performance Analysis

To assess the robustness of the model across different climatic zones in China, experiments are conducted in three distinct regions:

- **North China (Temperate Monsoon Climate)**: Moderate precipitation, with seasonal variations.
- **South China (Subtropical Monsoon Climate)**: High precipitation intensity, frequently affected by typhoons.
- **Southwest China (Complex Terrain)**: High variability due to mountainous topography, leading to significant IMERG-Late biases.

Findings indicate that the U-Net model consistently improves precipitation estimates across all regions, with particularly notable enhancements in regions with high terrain variability.

4.4. Error Analysis

To understand the limitations of the proposed model, a detailed error analysis is performed:

- **Error Distribution**: Analysis of residual errors shows that U-Net effectively reduces systematic biases but struggles with extreme precipitation events.
- **Failure Cases**: The model tends to underperform during extreme weather conditions such as typhoons and heavy rainfall, likely due to the limited representation of such events in the training dataset.
- **Potential Improvements**: Future enhancements include incorporating attention-based mechanisms and ensemble learning to improve predictions in extreme precipitation scenarios.

Overall, the experimental results confirm that the U-Net-based calibration method provides substantial improvements over baseline approaches, particularly in regions with complex terrain and diverse climatic conditions.

5. Discussion

5.1. Advantages of U-Net for Precipitation Calibration in China

The proposed U-Net-based approach offers several advantages for calibrating IMERG-Late precipitation estimates in China:

- **Automatic Feature Learning**: U-Net automatically learns spatial and temporal precipitation patterns, reducing the need for manually engineered features.
- **Improved Spatial Consistency**: The model preserves fine-scale precipitation structures while correcting biases, leading to more coherent precipitation fields.
- **Robust Generalization**: Through extensive training on diverse climatic conditions, U-Net demonstrates strong generalization across different regions of China.

5.2. Limitations of the Model

Despite its advantages, the U-Net model has several limitations:

- **High Computational Demand**: The model requires significant computational resources, especially during training, making it less accessible for real-time applications.
- **Inference Latency**: The model's complexity leads to increased inference time, limiting its use in time-sensitive forecasting tasks.
- **Challenges in Complex Terrain**: While U-Net improves precipitation estimates in many areas, its performance degrades in high-altitude and complex terrain regions due to limited training data representation.

5.3. Future Improvements

To further enhance the performance of the proposed approach, several potential improvements can be explored:

- **Integration with Transformer Models**: Combining U-Net with Transformer architectures could enhance temporal modeling capabilities, improving performance in dynamic weather conditions.
- **Incorporating Physical Models**: Hybrid approaches that integrate physical weather models with deep learning could enhance interpretability and reliability.
- **Region-Specific Model Adaptation**: Fine-tuning the model for specific climate zones in China may improve accuracy, particularly in extreme weather scenarios.

By addressing these limitations, future research can further advance the effectiveness of deep learning-based precipitation calibration, making satellite precipitation products more accurate and reliable.

6. Conclusion

This study introduced a U-Net-based framework for calibrating IMERG-Late precipitation estimates using CMPA as ground truth, specifically for China. The proposed approach effectively corrects biases in satellite-derived precipitation data, enhancing spatial and temporal consistency. Comparative evaluations demonstrated that the U-Net model outperforms traditional interpolation, statistical, and other deep learning-based methods in reducing estimation errors and improving regional applicability. Despite its strengths, the model has limitations, particularly in computational demand and performance over complex terrain. Future work should explore integrating Transformer-based architectures for improved temporal modeling, incorporating physical models for enhanced interpretability, and refining model adaptation for different climatic regions. Overall, this study contributes to advancing precipitation calibration methodologies, promoting the reliability of satellite-based precipitation data for hydrological and meteorological applications.

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