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Bias Adjustment of Satellite Products through Statistical and ML models

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Hybrid Downscaling of Precipitation Estimates

Concept

Satellite precipitation products (SPPs) are increasingly utilized for their higher spatio-temporal resolution; however, they often exhibit biases compared to ground observations, which hinders accurate local impact assessments. To address this, various statistical bias adjustment methods have been developed, ranging from simplistic linear scaling to more sophisticated quantile and Cumulative Distribution Function transferring (CDFt) techniques. However, many of these methods assume stationarity in relationships, leading to inaccuracies in regions with significant climate variability. Some alternative approaches, instead, like Equidistant CDF Matching (ECDFM) and Quantile Delta Mapping (QDM), aim to capture non-stationarity in precipitation data.

Additionally, to deal with zero-inflated datasets, methods range from simple methods, such as positive correction and threshold adaptation, to more complex techniques including left tail censoring, singularity stochastic removal, and zero-truncated hurdle modeling.

In the field of atmospheric sciences, phenomena such as climate variables and precipitation often exhibit teleconnections, where changes in one region can influence conditions in distant areas. Additionally, climate variability often demonstrates scale-invariance and long-term memory, indicating that past states of the system influence future states. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, offer promising avenues for capturing spatio-temporal spatial dependencies.

Scientific approach

Systematic biases in satellite products, termed Sensor-Specific biases, stem from data processing, retrieval algorithms, calibration procedures, and geolocation uncertainties. To address these challenges, our methodology employs a two-step approach.

Firstly, we implement statistical bias adjustment to correct systematic biases, including Quantile Mapping (QM), QDM, CDFt and ECDFM. To handle the issue related to zero inflation in input data, preprocessing is applied on data using 4 techniques such as, positive correction, left tail censoring, singularity stochastic removal and zero-truncated hurdle modelling. Additionally, location-wise multiplicative trend preserving method is applied in order to capture the climate change fluctuations.

Followed by the primary phase, we utilize a Convolutional 2D-LSTM network. The convolutional layers of the network enable it to extract spatial features from the input data, allowing it to understand the spatial patterns of precipitation estimates. This is crucial for capturing localized variations and ensuring accurate bias correction across different geographical regions. Moreover, the LSTM layers in the network facilitate the modeling of temporal dependencies by capturing the sequential nature of precipitation data over time. By integrating both convolutional and LSTM layers, the Convolutional 2D-LSTM network can effectively learn complex relationships between spatial and temporal dimensions of the data, thereby enhancing the accuracy of bias correction

Research objectives

1. Create gridded observational rainfall data from the integration of multisource ground measurements.
2. Evaluation of different distribution-based method of bias correction over the study region, focusing on three aspects of a precipitation event, including intensity, frequency and climate change trend preservation.
3. Evaluation of the impacts of parametric/nonparametric methods, the choice of distribution and zero handling techniques on the accuracy of data
4. Improving the SPPs using a combination of land/atmospheric predictors through ML models, including CNN-LSTM and Unet.
5. Downscaled satellite precipitation estimates at a spatial resolution of 0.01° geographical degree, applicable in regional hydrological models