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# A Review of Bias-correction Methods in Meteorological Models

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## Abstract

Meteorological models are crucial tools for predicting weather and climate patterns. However, these models often exhibit biases due to imperfections in model physics, initial conditions, and parameterizations. Bias correction methods are employed to adjust model outputs, enhancing their accuracy and reliability. This review examines various bias-correction techniques used in meteorological modeling, evaluating their effectiveness, advantages, and limitations. We explore statistical methods, dynamical approaches, and machine learning techniques, providing a comprehensive overview of current practices and future directions in the field. The review aims to guide researchers and practitioners in selecting appropriate bias-correction methods for improving meteorological predictions.

**Keywords:** Bias correction • Meteorological models • Statistical methods

## Introduction

Meteorological models are indispensable tools for understanding and predicting weather and climate phenomena. These models simulate atmospheric processes using mathematical representations of physical laws. Despite their sophistication, all meteorological models contain biases—systematic deviations between model outputs and observed data. These biases can arise from various sources, including inaccuracies in model parameterizations, boundary conditions, and initial states. As a result, bias correction is a critical step in the process of weather and climate prediction. Bias correction aims to adjust the outputs of meteorological models to align more closely with observed data. This review provides an overview of the primary bias-correction methods, categorized into statistical methods, dynamical approaches, and machine learning techniques. We discuss the principles behind each method, their applications, and their strengths and weaknesses. By examining the current state of bias-correction methodologies, this review aims to offer insights into best practices and future research directions [1].

## Literature Review

Statistical bias-correction methods adjust model outputs based on statistical relationships between model predictions and observed data. These methods are widely used due to their simplicity and effectiveness. Linear scaling is one of the simplest bias-correction methods. It adjusts model outputs by applying a constant scaling factor. The scaling factor is derived from the ratio of observed to modeled means. This method is particularly effective for correcting biases in mean values but may not address biases in variability or higher-order statistics. Quantile Mapping (QM) is a more sophisticated statistical method. It corrects biases by matching the Cumulative Distribution Functions (CDFs) of model outputs and observed data. This approach can effectively correct biases in both the mean and variability of model outputs. QM involves transforming model outputs such that their quantiles align with the observed quantiles. Empirical Quantile Mapping (EQM) extends the concept of QM by using empirical distributions instead of parametric ones. EQM adjusts model outputs based on observed quantiles, offering a more flexible approach to bias correction. It is particularly useful when the model and observed data do not follow standard parametric distributions. Variance inflation adjusts the variability of model outputs to match observed variability. This method is often used in conjunction with other bias-correction techniques to ensure that both the mean and variability of model outputs are accurately represented. Variance inflation involves scaling the deviations of model outputs from their mean to match the observed standard deviation [2].

Distribution-based approaches correct biases by fitting statistical distributions to model outputs and observed data. These methods adjust the parameters of the fitted distributions to align model outputs with observed data. Examples include fitting normal or gamma distributions and adjusting their parameters to correct biases in mean, variance, and higher-order moments. Dynamical approaches to bias correction involve modifying the underlying model physics or parameterizations to reduce biases. These methods are more complex and computationally intensive than statistical methods but can offer more comprehensive solutions to bias issues. Model tuning involves adjusting model parameters to improve agreement with observed data [3]. This process can be iterative, with parameters being systematically varied and the model re-run until the biases are minimized. Model tuning requires a deep understanding of the model and its sensitivity to various parameters. Nudging, also known as data assimilation, integrates observed data into the model during its simulation. This approach corrects biases by continually adjusting the model state towards observed values. Nudging can be applied at various temporal and spatial scales, offering a dynamic correction mechanism. Regional downscaling involves using higher-resolution regional models to correct biases in coarser global models. The regional models are driven by the outputs of the global models but include finer-scale processes and higher-resolution data. This approach can reduce biases related to local-scale phenomena that global models may not capture accurately. Superparameterization embeds high-resolution cloud-resolving models within larger-scale climate models. This approach improves the representation of cloud processes, which are often a significant source of bias in meteorological models. Superparameterization can reduce biases in precipitation and cloud-related variables [4].

## Discussion

Machine Learning (ML) offers innovative and flexible approaches to bias correction. These techniques can capture complex, non-linear relationships between model outputs and observed data. Artificial Neural Networks (ANNs) are ML models that can learn non-linear mappings between inputs and outputs. ANNs can be trained to correct biases in meteorological model

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outputs by learning the relationship between model predictions and observed data. They are particularly effective for handling large datasets and capturing intricate patterns. Random Forests (RFs) are ensemble learning methods that combine multiple decision trees to improve prediction accuracy. RFs can be used for bias correction by training the ensemble on the differences between model outputs and observations. This approach can capture complex relationships and interactions between variables. Support Vector Machines (SVMs) are supervised learning algorithms that can be used for classification and regression tasks. In bias correction, SVMs can learn the mapping between model outputs and observed data, providing a robust method for reducing biases [5].

Deep Learning (DL) techniques, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), offer advanced capabilities for bias correction. DL models can capture spatial and temporal dependencies in meteorological data, making them suitable for correcting biases in complex, high-dimensional datasets. Hybrid methods combine traditional statistical approaches with ML techniques to leverage the strengths of both. For example, a hybrid method might use quantile mapping to correct biases in the mean and variance and an ANN to address non-linear relationships. These approaches can provide comprehensive and flexible bias correction solutions. The effectiveness of bias-correction methods varies depending on the specific application and the characteristics of the model and observed data [6]. Here, we present a few case studies that illustrate the application of different bias-correction methods in meteorological modeling.

**Case study 1: Temperature bias correction:** In a study focused on correcting temperature biases in a regional climate model, researchers applied quantile mapping to adjust the model outputs. The results showed significant improvements in the mean and variability of temperature predictions, demonstrating the effectiveness of quantile mapping for temperature bias correction.

**Case study 2: Precipitation bias correction:** A global climate model exhibited substantial biases in precipitation patterns. Researchers employed a hybrid approach, combining empirical quantile mapping with artificial neural networks. This method effectively reduced biases in both the intensity and frequency of precipitation events, highlighting the potential of hybrid methods for complex bias correction tasks.

**Case study 3: Wind speed bias correction:** Biases in wind speed predictions were addressed using a random forest model. The random forest was trained on the differences between observed and modeled wind speeds. The results indicated a significant reduction in biases, particularly in capturing extreme wind speed events.

**Case study 4: Seasonal forecasts:** Seasonal forecasts from a dynamical climate model were corrected using variance inflation. This approach improved the representation of seasonal variability, enhancing the reliability of seasonal climate predictions. Variance inflation proved effective in adjusting the model's variability to match observed seasonal patterns.

## Conclusion

While bias-correction methods have shown considerable success, several challenges remain. One key challenge is the transferability of bias-correction techniques across different models and regions. Methods that work well for one model or region may not perform as effectively for others. Another challenge is the computational cost associated with more complex dynamical and ML-based approaches Additionally, there is a need for systematic evaluations of bias-correction methods across diverse models and datasets to establish best practices and guidelines. Bias correction is a vital step in improving the accuracy and reliability of meteorological models. This review has highlighted various bias-correction methods, including statistical approaches, dynamical methods, and machine learning techniques. Each method has its strengths and limitations, and the choice of method depends on the specific application and characteristics of the model and data. By providing a comprehensive overview of bias-correction methods, this review aims to guide researchers and practitioners in selecting appropriate techniques for their needs. As meteorological modeling continues to evolve, ongoing research and innovation in bias correction will be essential for advancing our ability to predict weather and climate with greater accuracy.

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## Conflict of Interest

None.

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