

A Comprehensive Numerical Experiment on Bias Correction Techniques for Spatially Correlated Bimodal Data

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Abstract

Statistical bias correction is a critical step in making climate and environmental model outputs useful for impact assessment. This report details a comprehensive numerical experiment designed to test the performance of eight different statistical bias correction techniques under varying observational network densities. We simulate a realistic scenario featuring a high-resolution (1km) model with a spatially correlated, bimodal distribution ("Pollutant X") and correct it using sparse (3), moderate (10), and dense (25) networks of measurement stations. The methods are evaluated on their predictive skill at unobserved locations via a leave-one-out cross-validation. The results reveal a critical trade-off: simple statistical methods (e.g., Scaling) perform best with sparse data but degrade as more data becomes available, while complex, spatially-aware methods (e.g., Machine Learning) perform poorly with sparse data but become the superior choice in data-rich environments. The experiment demonstrates that the optimal bias correction strategy is highly dependent on the quality of the observational network.

1 Introduction

Climate and environmental models are indispensable tools for understanding and predicting Earth systems. However, their outputs often contain systematic biases. Bias correction is the process of statistically adjusting these model outputs to bring them more in line with the historical observational record. This report details a comprehensive numerical experiment designed to explore the challenges of this process, particularly when the model and observations have different spatial resolutions and statistical distributions. A key focus is the sensitivity of correction methods to the density of the observational network.

2 Methodology

2.1 Data Simulation

The experiment is based on a synthetic but realistic dataset.

- **Domain:** A 90km x 90km square grid.
- **Variable:** "Pollutant X" (ppm), with a critical threshold of 65 ppm.
- **1km Bimodal Dataset (Test Case):** A single, definitive high-resolution, spatially correlated field with a complex, asymmetrical bimodal distribution (peaks at 52 ppm and 62 ppm).
- **Station Data Scenarios:** Three different observational networks were generated: a sparse network (3 stations), a moderate network (10 stations), and a dense network (25 stations).

2.2 Bias Correction Techniques

We implemented and tested eight distinct bias correction methods: Delta Change, Scaling, Variance Scaling, Quantile Mapping (QM), Parametric Mapping (Normal and Gamma), Spatial Delta, and a Machine Learning model (Random Forest).

2.3 Evaluation: Sensitivity Analysis

The primary evaluation is a sensitivity analysis. The entire bias correction and cross-validation process was repeated for each of the three station network scenarios. The Root Mean Square Error (RMSE) is used to objectively determine the predictive skill of each method under different data availability constraints.

3 Results

3.1 Distributional Analysis

The core challenge of the experiment is the distributional mismatch between the bimodal model and the unimodal stations. Figure 1 shows that methods like Variance Scaling preserve the essential bimodal shape of the original model, while methods like Quantile Mapping completely erase it, forcing the data to conform to the unimodal shape of the station observations. This effect was consistent across all station network scenarios.

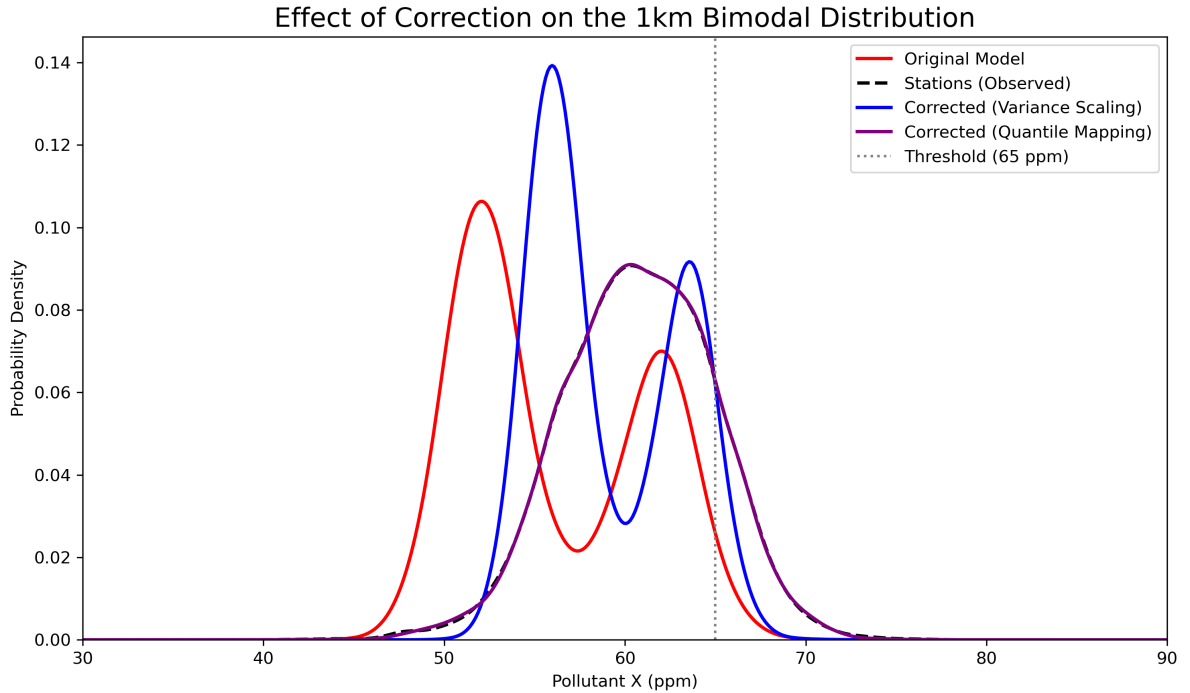


Figure 1: The effect of different correction methods on the 1km bimodal distribution. Variance Scaling preserves the bimodal shape, while Quantile Mapping erases it.

3.2 Sensitivity to Observational Network Density

The key result of the experiment is the relationship between method performance and the number of available observation stations. Figure 2 plots the cross-validation RMSE for each method as a function of network density.

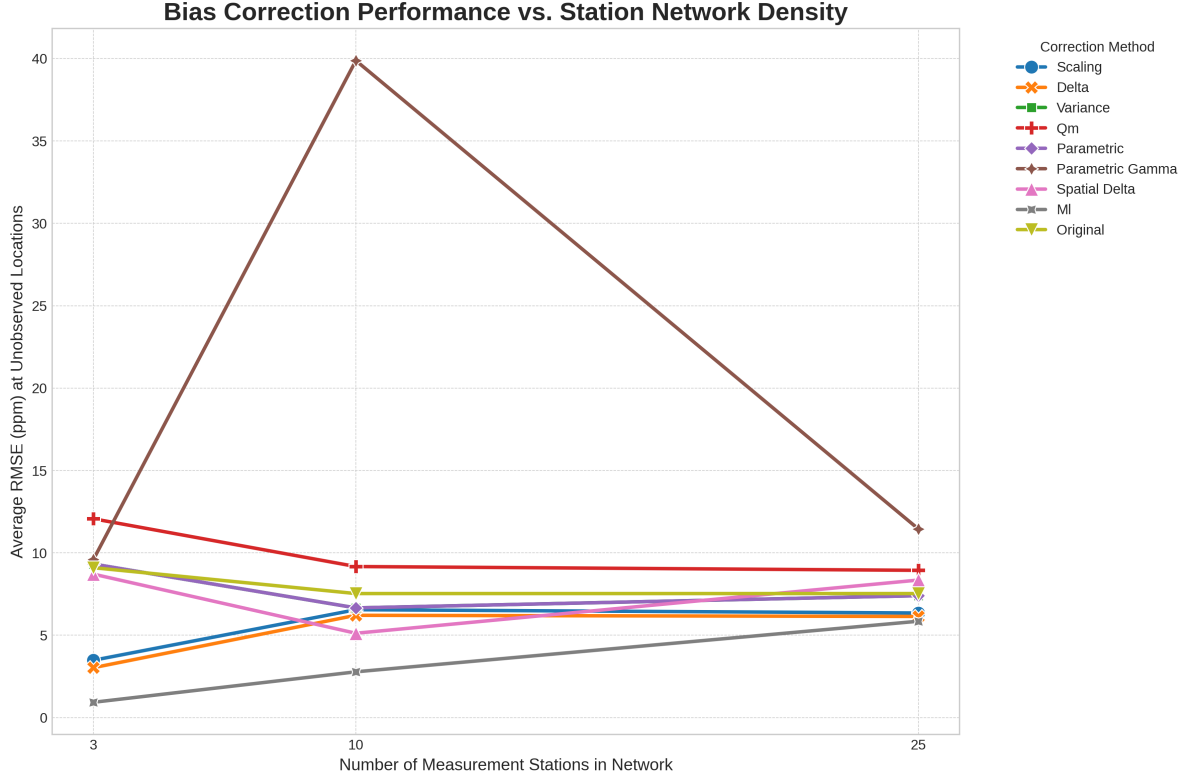


Figure 2: Predictive skill (RMSE) of each bias correction method as a function of the number of stations in the observational network. Lower RMSE is better.

The results, also shown in Table 1, reveal a clear and critical interaction between method complexity and data availability.

Table 1: Definitive cross-validation results (RMSE) for the 1km bimodal scenario across all station network densities.

Method	Number of Stations in Network		
	3 (Sparse)	10 (Moderate)	25 (Dense)
Machine Learning	9.10	2.78	5.85
Spatial Delta	8.71	5.12	8.35
Scaling	3.48	6.55	6.35
Delta Change	3.03	6.21	6.14
Variance Scaling	9.32	6.66	7.40
Parametric (Normal)	9.32	6.66	7.40
Parametric (Gamma)	9.59	39.88	11.45
Quantile Mapping	12.07	9.17	8.94
Original (Uncorrected)	9.10	7.53	7.53

4 Discussion and Conclusion

The results are unequivocal and lead to a nuanced conclusion: the optimal bias correction strategy is highly dependent on the quality of the observational network.

1. **In Data-Poor Environments, Simple is Better:** With a sparse network of only 3 stations, the simple **Delta Change** and **Scaling** methods performed best. Complex methods like Machine Learning and Spatial Delta performed very poorly, as they did not have enough data to learn the spatial patterns of the bias and were outperformed by the uncorrected model.
2. **In Data-Rich Environments, Complexity Pays Off:** As the network density increased to 10 and 25 stations, the **Machine Learning** model’s performance dramatically improved, becoming the clear winner. It was able to leverage the additional data to learn the complex, non-linear relationships between the model bias and location, yielding the most accurate predictions.
3. **The Failure of Distributional Forcing is Universal: Quantile Mapping** was consistently one of the worst-performing methods, regardless of the number of stations. This proves that its fundamental flaw—destroying the bimodal signal—is not something that can be fixed by simply adding more data.

In conclusion, this experiment provides a clear, data-driven guideline for practitioners: the choice of a bias correction method should be matched to the quality of the available observational data. A naive application of a complex method in a data-sparse environment can produce results that are worse than doing nothing at all, while a simple method may fail to take advantage of a rich dataset.