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Advancements and challenges in bias correction quantile mapping for climate projections: A comprehensive review

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Bias correction quantile mapping (BCQM) has become a pivotal tool in climate science, particularly for refining the outputs of Global Climate Models (GCMs) and Regional Climate Models (RCMs) at local scales. While GCM outputs are invaluable for understanding climate change, their coarse resolution introduces uncertainties requiring downscaling techniques like BCQM. This review paper explores the advancements, practical applications, and limitations of BCQM methods, emphasizing their critical role in improving climate projections. BCQM operates by mapping observed data distributions to model outputs, thereby correcting biases and enhancing model accuracy. Recent developments have led to significant improvements, such as the successful application of multivariate BCQM in capturing complex climate interactions and hybrid empirical BCQM techniques that improve performance in extreme climate conditions. These methods have been effectively implemented in diverse regions, leading to more accurate temperature and precipitation projections, which support critical sectors like agriculture, water resource management, and disaster preparedness. Furthermore, BCQM has been instrumental in refining seasonal forecasts and long-term climate projections, providing valuable insights for policymakers and stakeholders. Despite these advancements, BCQM still faces challenges, such as the inability to correct for inherited GCM errors, poor representation of wet/dry spell occurrences, and limitations in extreme event correction. The review highlights the need for further research to address these challenges, particularly in the context of extreme climate events and non-stationarity biases. The paper calls for more robust BCQM methods that can handle the increasing complexity and volume of climate data, offering reliable projections for future climate scenarios. By refining BCQM techniques and incorporating additional climate factors, researchers can improve the accuracy and dependability of climate projections, ultimately aiding in better decision-making and risk assessment in the face of climate change.

Keywords: *Bias Correction Quantile Mapping (BCQM); climate projections; downscaling; Global Climate Models (GCMs); extreme events.*

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1. Introduction

Global Climate Models (GCMs) and Regional Climate Models (RCMs) are essential tools in climate science, providing critical data for understanding and predicting climate change. However, the coarse spatial resolution and inherent structural limitations of these models often introduce biases that can compromise the accuracy of climate projections. These biases require the use of downscaling techniques such as Bias Correction Quantile Mapping (BCQM), which adjusts model outputs to align more closely with observed historical records, thereby improving the accuracy of local-scale climate projections. BCQM has become increasingly important as climate scientists and policymakers seek more reliable projections to support decision-making. The technique works by mapping observed data

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distributions onto model outputs, correcting systematic biases in variables such as temperature, precipitation, and wind speed. This correction is particularly crucial for extreme events, which are often poorly represented in coarse-resolution models but have significant implications for climate risk assessment and management [1]. Despite its widespread use and growing advancements, BCQM is not without its challenges. A critical limitation is its inability to correct for inherited errors from GCMs, which may propagate uncertainties into the downscaled projections. Additionally, BCQM struggles with non-stationarity biases, where relationships between climate variables change over time due to evolving climate conditions potentially reducing the reliability of future projections. Moreover, the technique often encounters difficulties in accurately representing wet/dry spell occurrences and capturing the full range of climate extremes, which can significantly impact applications in water resource management, agriculture, and disaster preparedness. This review paper explores the advancements, performance, and limitations of BCQM methods, with a particular focus on their application in climate projections. It examines recent innovations, such as the integration of skewed probability distributions and additional climate factors, and discusses ongoing challenges, particularly in predicting extreme climate events and addressing non-stationarity issues. By providing a comprehensive overview of BCQM, this paper aims to highlight areas where further research is needed to enhance the reliability of climate projections and support better decision-making in the face of climate change [2].

2. Overview of quantile mapping (QM) and its applications

Quantile Mapping (QM) is a widely employed statistical technique used to correct biases in climate model outputs. The technique works by adjusting the distribution of model-simulated data to match observed data distributions, thereby mitigating systematic biases and improving the accuracy of climate projections. QM is particularly effective for correcting biases in climate variables such as temperature, precipitation, and wind speed, which are crucial for accurate climate modelling. QM methods have been extensively applied in downscaling GCM and RCM outputs to finer spatial resolutions, making them more relevant for local-scale studies. For instance, QM has been used to correct precipitation data, leading to more accurate flood risk assessments and better water resource management [3]. However, the existing QM methods have limitations, particularly in handling extreme weather events. These events, which often reside in the tails of the distribution, are frequently misrepresented in model outputs, leading to inaccuracies in projections. These events are crucial for understanding the full range of potential impacts of climate change, but their representation in models is often inadequate. In particular, the existing QM methods, typically assume a symmetric distribution of climate variables, which may not accurately capture the skewness inherent in extreme events. This can result in significant errors in projections, particularly in regions prone to extreme weather such as heavy rainfall, droughts, or heatwaves. Extreme data points or outliers in a data series can be treated by fitting extreme value distributions (EVD) in the BCQM. These outliers may be due to measurement errors, data collection issues, or extreme events. In BCQM, identifying and understanding outliers is crucial for ensuring the integrity and reliability of data. When properly implemented, BCQM can correct bias and improve the accuracy of model predictions [4]. The transfer function of BCQM is given as [5],

$$x_{\mathrm{corr}} = \mathrm{CDF}(x_o) - 1[\mathrm{CDF}(x_m)], \tag{1}$$

where x_{corr} is the corrected meteorological/hydrological variable between the observed and historical or estimated model output gridded GCM, x_o is the observation, and x_m is the historical/estimated model output gridded GCM. The cumulative distribution functions of the statistical distributions are shown in Equation (1). Figure 1 illustrates an example of extreme temperature modeling for annual maximum temperature using the generalized extreme value (GEV) distribution within the BCQM framework. The figure presents a probability plot comparing the modeled and observed values, where the closer the data points are to the straight line, the better the model fits the observed data. This visual representation highlights the effectiveness of GEV in capturing extreme temperature behavior, which is critical for applications such as climate risk assessment and infrastructure planning. The selection of an appropriate statistical distribution, such as Weibull or gamma distributions, is crucial in BCQM to ensure accurate representation of the underlying statistical characteristics of climate variables. To address non-stationarity in climate data, BCQM incorporates covariates such as linear trends and seasonal components, which help account for changing climate patterns over time [6]. Figure 2 provides further insights by showcasing boxplots and density plots of extreme temperature series. These visualizations compare historical GCM outputs with observations before and after bias correction using BCQM with the GEV distribution. The figure demonstrates how BCQM effectively reduces bias and enhances the alignment between the GCM projections and observed data, offering more reliable inputs for climate impact studies. The improved distributional fit after correction underscores BCQM's role in refining climate projections for better decision-making in sectors such as agriculture, energy planning, and disaster management. The log-likelihood functions for nonstationary GEV distribution in the BCQM are as follows:

Model 1: $\mu(t) = \mu_0 + \mu_1 t$, σ, and α are constants:

$$\ln L = -n \ln \sigma \sum_{i=1}^{n} \left[\left(\frac{1}{\alpha} - 1\right) \ln \left(1 - \frac{\alpha(x_i - (\mu_0 + \mu_1 t_i))}{\sigma}\right) - \left(\frac{\alpha(x_i - (\mu_0 + \mu_1 t_i))}{\sigma}\right)^{\frac{1}{\alpha}} \right]; \tag{2}$$

Model 2: $\sigma(t) = \exp(\sigma_0 + \sigma_1 t)$, μ and σ are constants:

$$\ln L = -n \ln \sigma + \sum_{i=1}^{n} \Bigg[\left(\frac{1}{\alpha} - 1\right) \ln \left(1 - \alpha(x_i - \mu)/\exp(\sigma_0 + \sigma_1 t_i)\right) - \left(\alpha(x_i - \mu)/\exp(\sigma_0 + \sigma_1 t_i)\right)^{\frac{1}{\alpha}} \Bigg]; \tag{3}$$

Model 3: $\mu(t) = \mu_0 + \mu_1 t$, $\sigma(t) = \exp(\sigma_0 + \sigma_1 t)$, α is a constant:

$$\ln L = -n \ln \sigma + \sum_{i=1}^{n} \Bigg[\left(\frac{1}{\alpha} - 1\right) \ln(1 - \alpha(x_i - (\mu_0 + \mu_1 t_i))/\exp(\sigma_0 + \sigma_1 t_i)) - \left(\alpha(x_i - (\mu_0 + \mu_1 t_i))/\exp(\sigma_0 + \sigma_1 t_i)\right)^{\frac{1}{\alpha}} \Bigg], \tag{4}$$

where $\mu(t) = \mu_0 + \mu_1 t$, and $\sigma(t) = \exp(\sigma_0 + \sigma_1 t)$.

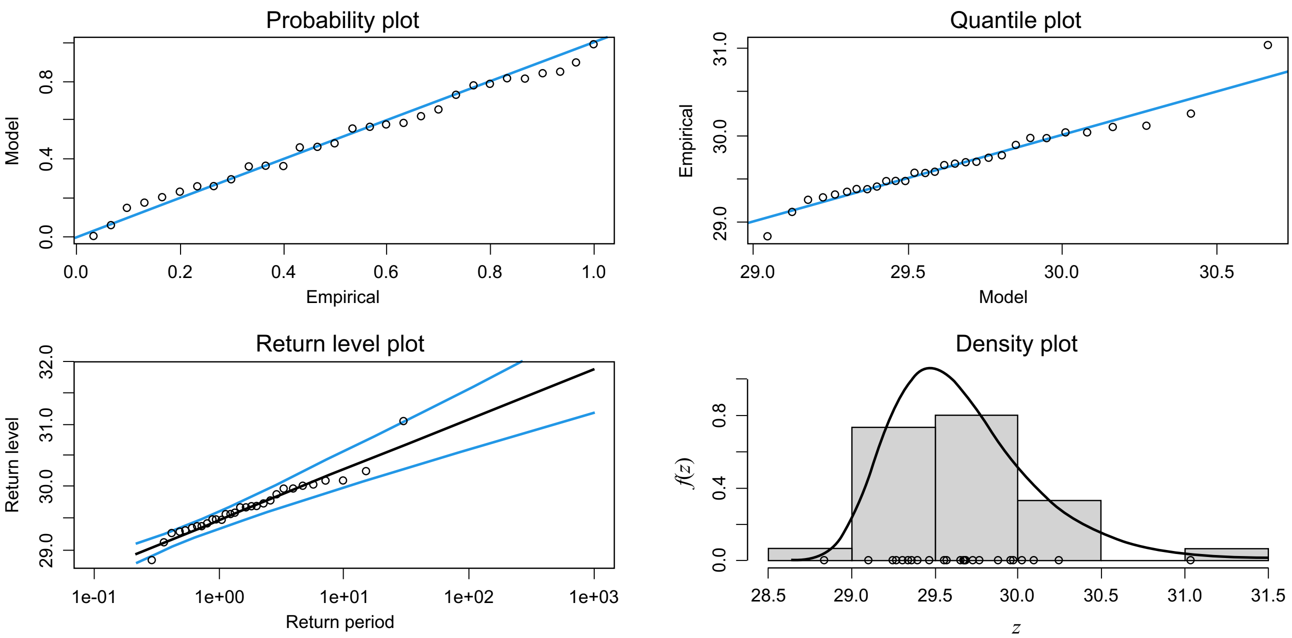

Fig. 1. Example of extreme modelling for annual maximum temperature using generalized extreme distribution.

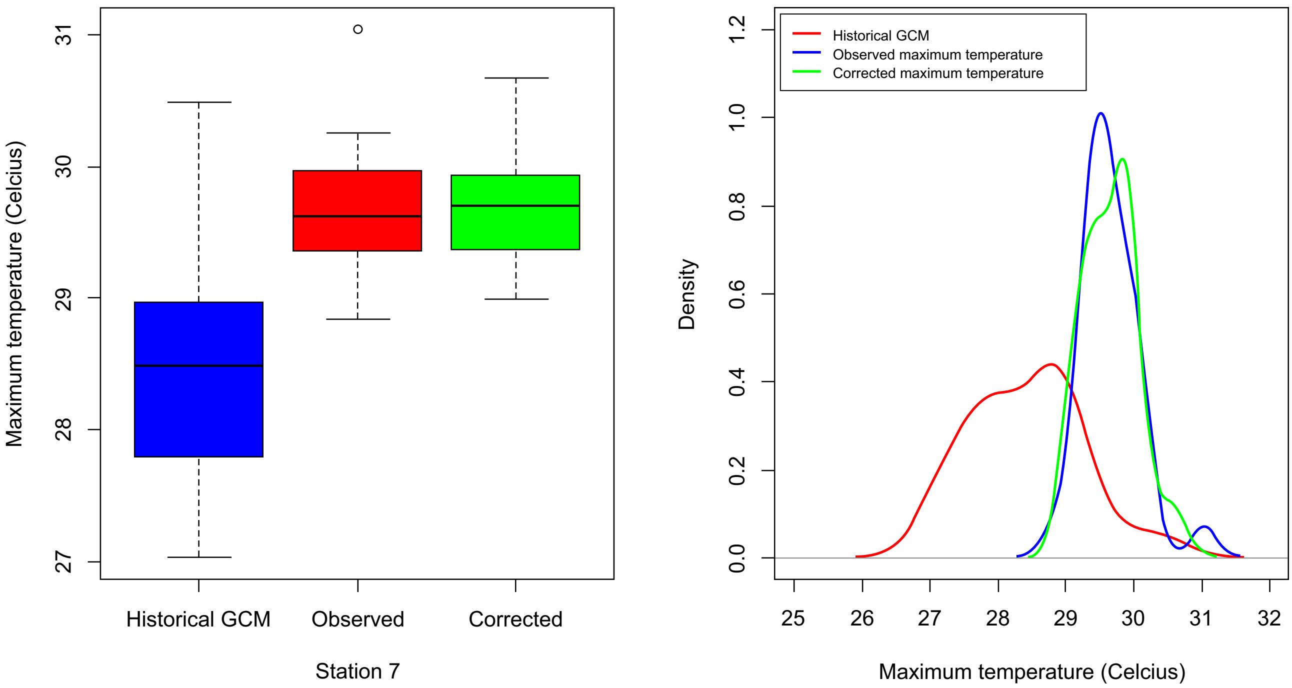

Fig. 2. Example of boxplots and density curve of historical GCM, observations, and corrected BCQM annual maximum temperatures values.

BCQM has been widely applied to address biases in raw data from GCM or RCM combinations [7]. Recently, multivariate BCQM was developed to address the physical inconsistency in univariate climatology BCQM because univariate BCQM tends to ignore the interdependence of variables. It incorporates multiple climatic factors into BCQM and coherently corrects biases in many climate variables to represent the climate system more accurately. However, implementing multivariate BCQM presents significant challenges, particularly in terms of computational demands and data requirements. On the one hand, substantial computing power is required to process the vast amounts of data involved in bias correction for multiple climate variables. The complexity of multivariate relationships necessitates iterative computations and high-dimensional statistical modelling, which increases both processing time and memory requirements. As climate datasets grow in size and resolution, the demand for high-performance computing (HPC) infrastructure becomes a critical limitation, especially for research institutions with limited access to such resources.

On the other hand, data availability and quality remain major concerns in the implementation of multivariate BCQM. High-quality, long-term observational datasets with consistent temporal and spatial coverage across multiple climate variables are essential for accurate bias correction. However, observational data are often incomplete or inconsistent across different climate variables, introducing uncertainties in the correction process. Additionally, differences in spatial resolution and observation periods between model simulations and real-world data further complicate the calibration and validation of BCQM methods. Ensuring data homogeneity across various sources and filling observational gaps are ongoing challenges that must be addressed to improve the reliability of bias correction results. Moreover, the integration of bias correction quantile delta mapping and multivariate copula BCQM techniques has been tested for bias correction of RCM-simulated precipitation [8–10]. While these approaches improve the representation of climate extremes, they further increase computational complexity due to the need for sophisticated statistical modelling and parameter estimation. A hybrid empirical BCQM (EBCQM) with a linear function, in which the majority of model data are corrected using EBCQM and the extreme tails are corrected using a linear transfer function, has also been established and found to enhance model skill, particularly at the extreme tails. This approach results in a better representation of climatological indices than what is achievable using conventional empirical BCQM [11]. However, the hybrid nature of these methods demands additional computational resources and careful tuning of parameters to balance bias correction performance with computational efficiency. In summary, while multivariate BCQM and hybrid methods offer significant advancements in climate bias correction, their practical application is hindered by the extensive computational power required and the challenges associated with acquiring and processing high-quality climate data. Addressing these challenges requires the development of more efficient algorithms, improved observational data collection efforts, and enhanced access to computational resources to support large-scale climate data analysis. Table 1 presents a comparative analysis of different BCQM approaches, evaluating their performance in terms of bias reduction, computational efficiency, and applicability across various climate variables.

Table 1. Performance comparison of different BCQM methods across key parameters.

BCQM Method	Bias Reduction	Computational Demand	Data Requirements
Univariate BCQM	Moderate	Low	Moderate
Multivariate BCQM	High	High	High
Hybrid Empirical BCQM	High	Moderate	Moderate
Quantile Delta Mapping	Moderate	Moderate	High

3. Advances in bias correction techniques

To address the limitations, recent advancements in BCQM have focused on incorporating skewed probability distributions and additional climate factors. These enhancements aim to improve the accuracy of climate projections by better representing the distribution of extreme events and accounting for a broader range of climatic conditions. A significant advancement in BCQM is the integration of skewed probability distributions, such as the GEV distribution. The existing BCQM methods often rely on symmetric distributions, which may not adequately capture the skewness inherent in many climate variables, particularly those related to extreme events. By incorporating skewed distributions, BCQM can more accurately model the heavy tails associated with extreme events, providing a more precise correction of biases in the model outputs. The application of skewed distributions in BCQM has been shown to improve the representation of extreme precipitation and temperature events, which are often characterized by significant skewness. For instance, in regions prone to heavy rainfall, the use of a GEV distribution within BCQM has enhanced the accuracy of extreme precipitation predictions, which is crucial for reliable flood risk assessments and water resource management [12]. In this study, particular attention is given to the performance of two-shape parameter probability distributions, namely the Generalized Lindley (GLD), Burr XII (BUR), and Kappa (KAP) distributions. These models provide greater flexibility compared to conventional probability distributions, which is crucial for accurately capturing the complex variability inherent in precipitation data. The study aims to determine whether these distributions can improve the BCQM process and yield a better fit than the conventional models.

Results from the study indicate that the KAP distribution outperforms both the GLD and BUR models, particularly in its ability to replicate the statistical characteristics of observed precipitation data and correct for extreme precipitation events. While the GLD distribution shows a performance on par with conventional models, the BUR distribution performs less effectively. Notably, the KAP distribution's ability to maintain spatial dependence among weather stations further highlights its potential for applications in flood modelling and other climate-related analyses. The study's findings are supported by a case study conducted in South Korea, utilizing simulation outputs from the Hadley Centre Global Environmental Model and observational data from a network of weather stations. The results demonstrate that the KAP distribution provides the best fit for both observed and simulated precipitation data, making it a suitable candidate for bias correction in similar contexts. Another significant advancement in BCQM is the integration of additional climate factors beyond the traditional focus on temperature and precipitation. Climate variables such as humidity, wind speed, and atmospheric pressure play crucial roles in influencing regional climate patterns and the occurrence of extreme events [13]. By including these factors in the BCQM process, the model can correct biases across a broader range of climatic conditions, leading to more accurate and robust climate projections. For instance, integrating wind speed and humidity into BCQM has improved the correction of temperature-related biases, especially in coastal regions where these factors significantly impact local climate conditions. Moreover, incorporating large-scale atmospheric phenomena such as the Madden–Julian oscillation (MJO) into BCQM has further refined the model's outputs, particularly in regions where these phenomena are key drivers of climate variability [14]. Several case studies demonstrate the effectiveness of these enhancements in BCQM. In the Indian subcontinent, the integration of skewed distributions within BCQM has led to more accurate predictions of extreme precipitation, improving flood risk assessments and informing better disaster preparedness strategies. In Southeast Asia, incorporating MJO phases into BCQM has enhanced the model's ability to predict extreme rainfall events, leading to more reliable climate projections and better agricultural planning [15].

4. Challenges and future directions

Despite the significant advancements in BCQM, several challenges remain to be addressed to fully realize the potential of these techniques. These challenges primarily revolve around computational complexity, data availability and quality, and non-stationarity in climate variables, all of which pose significant obstacles to the widespread and effective application of BCQM. Addressing these issues requires the development of innovative solutions, such as efficient algorithms, improved data infrastructures, and the integration of advanced technologies like machine learning.

4.1. Computational challenges

The integration of skewed distributions and additional climate factors into BCQM enhances its ability to capture extreme climate events, but it also increases computational complexity. The processing of large datasets with high spatial and temporal resolutions requires sophisticated algorithms and substantial computational resources, leading to longer processing times and potential feasibility issues, especially in resource-limited settings. To overcome these challenges, future research should focus on developing more efficient algorithms that optimize computation without compromising accuracy. This includes exploring machine learning-driven optimization techniques that can streamline bias correction processes by identifying patterns and automating corrections. Furthermore, leveraging HPC resources and cloud-based platforms can help handle the increasing demands of enhanced BCQM models, making them more accessible to a broader research community [16].

4.2. Data availability and quality

The success of enhanced BCQM methods is highly dependent on the availability and quality of observational data, which are crucial for calibrating and validating bias correction models. However, many regions, particularly developing countries and remote areas, face significant data gaps and inconsistencies that hinder the accuracy of BCQM applications. Poor spatial and temporal coverage of climate variables limits the effectiveness of bias correction, resulting in uncertainties in climate projections. Addressing these limitations requires concerted efforts to improve data collection and accessibility. Investment in new observation networks, enhancement of existing data infrastructures, and the development of advanced data assimilation techniques can help bridge data gaps. Additionally, using machine learning algorithms to impute missing data and improve data quality can enhance the reliability of climate projections [3]. Strengthening collaboration between governmental and private entities for data-sharing initiatives can further support these efforts.

4.3. Non-stationarity in climate variables

One of the most pressing challenges in climate modeling is the non-stationarity of climate variables, particularly concerning extreme events. Non-stationarity refers to the changing statistical properties of climate variables over time, which complicates the application of traditional statistical techniques like BCQM. The inherent variability in climate trends, such as shifts in precipitation patterns and temperature extremes, requires dynamic approaches to bias correction. Future research should focus on developing adaptive BCQM models that incorporate time-evolving statistical parameters and account for long-term trends and seasonal variations. The integration of artificial intelligence (AI) and machine learning techniques, which excel in identifying patterns within complex datasets, can significantly enhance the adaptability of BCQM to non-stationary environments. Developing hybrid models that combine statistical and AI-based approaches could further improve BCQM's performance under changing climate conditions.

4.4. Future research directions and international collaboration

Moving forward, addressing these challenges will require a multifaceted approach that combines technological advancements with strategic policy initiatives. Encouraging interdisciplinary research that brings together climate scientists, data scientists, and policymakers will be key to developing practical BCQM solutions. Additionally, international collaborations and technology transfer play a critical role in addressing global disparities in BCQM application. Many developing regions lack the technical capacity and infrastructure to implement advanced BCQM techniques, creating disparities in climate risk assessment and adaptation planning. Collaborative initiatives between developed and developing countries, knowledge-sharing programs, and capacity development efforts can help bridge this gap. For instance, technology transfer agreements can facilitate access to cutting-edge computational tools and methodologies, while partnerships with international climate organizations can support data-sharing frameworks that enhance global climate resilience.

In conclusion, while BCQM has demonstrated significant potential in improving climate model accuracy, addressing the challenges of computational complexity, data availability, and non-stationarity is critical to its broader application. Through continued advancements in algorithm development, data infrastructure improvements, and global collaboration, BCQM can become an even more robust tool for climate risk management and decision-making.

5. Conclusion

The integration of skewed probability distributions and additional climate factors into BCQM represents a significant advancement in climate modelling, improving the model's ability to accurately capture and represent extreme climate events. These enhancements allow BCQM to better reflect the complexities of climate data, particularly in the context of extreme weather events, leading to more accurate predictions and more informed decision-making. However, challenges related to computational complexity, data availability, and non-stationarity must be addressed to fully realize the potential of these advancements. By continuing to refine BCQM techniques and incorporating comprehensive climate data, researchers can enhance the model's performance and provide more reliable climate projections, ultimately aiding in better decision-making in the face of climate change.

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Досягнення та проблеми квантильного відображення з корекцією зміщення для кліматичних прогнозів: комплексний огляд

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Корекція зміщення квантильним відображенням (BCQM) стала ключовим інструментом у кліматології, особливо для уточнення результатів глобальних кліматичних моделей (GCM) та регіональних кліматичних моделей (RCM) на локальних масштабах. Хоча результати GCM є неоціненними для розуміння зміни клімату, їхня груба роздільна здатність створює невизначеності, що вимагають застосування методів зменшення масштабу, таких як BCQM. Ця оглядова стаття досліджує досягнення, практичні застосування та обмеження методів BCQM, підкреслюючи їхню вирішальну роль у покращенні кліматичних прогнозів. BCQM працює шляхом відображення розподілів спостережуваних даних на результати моделей, тим самим коригуючи зміщення та підвищуючи точність моделей. Недавні розробки призвели до значних покращень, таких як успішне застосування багатофакторного BCQM для врахування складних кліматичних взаємодій та гібридних емпіричних методів BCQM, що покращують ефективність в екстремальних кліматичних умовах. Ці методи були ефективно впроваджені в різних регіонах, що призвело до більш точних прогнозів температури та опадів, які підтримують такі критично важливі сектори, як сільське господарство, управління водними ресурсами та готовність до стихійних лих. Крім того, BCQM відіграє важливу роль в уточненні сезонних прогнозів та довгострокових кліматичних проекцій, надаючи цінну інформацію для політиків та зацікавлених сторін. Попри ці досягнення, BCQM все ще стикається з викликами, такими як нездатність коригувати успадковані помилки GCM, недостатнє відображення сухих/вологих періодів та обмеження в корекції екстремальних подій. Огляд підкреслює необхідність подальших досліджень для вирішення цих проблем, зокрема в контексті екстремальних кліматичних явищ та проблем їх нестаціонарності. Стаття закликає до розробки більш надійних методів BCQM, які зможуть обробляти зростаючу складність та обсяг кліматичних даних, пропонуючи надійні прогнози для майбутніх кліматичних сценаріїв. Удосконалюючи методи BCQM та включаючи додаткові кліматичні фактори, дослідники можуть підвищити точність та надійність кліматичних прогнозів, що зрештою сприятиме кращому ухваленню рішень та оцінці ризиків в умовах зміни клімату.

Ключові слова: *квантильне відображення з корекцією зміщення (BCQM); кліматичні прогнози; даунскалінг; глобальні кліматичні моделі (GCM); екстремальні події.*