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Forecast Accuracy in Climate Impact Models: A Predictive Study of Simulation Calibration Methods

Thomas Harris[1,*], Abigail Martinez[1], Chi-Kin Yau[2]

[1] *School of English and Theatre Studies, College of Social and Applied Human Sciences, University of Guelph, Guelph, Canada*
[2] *Felizberta Lo Padilla Tong School of Social Sciences, Saint Francis University, Hong Kong, Hong Kong SAR, China*

Corresponding author: thomas.harris@uoguelph.ca

Abstract

Climate impact models serve as indispensable instruments for understanding and predicting the complex ecological and socioeconomic consequences of global environmental change. However, the projection accuracy of these models remains highly sensitive to the calibration methods employed to align simulated processes with historical observations. This paper presents a comprehensive comparative evaluation of simulation calibration methodologies, assessing their efficacy in predicting long-term forecast accuracy across distinct environmental contexts. Utilizing a structured case comparison framework, we evaluate deterministic optimization, stochastic parameterization, and Bayesian calibration techniques applied to multi-regional hydrological and agricultural impact models. Through systematic evaluation, we establish a quantified relationship between calibration-phase metric performance and independent validation-phase predictive skill. Our analysis reveals that while deterministic calibration approaches minimize historical residuals, they frequently introduce parameter overfitting, leading to degraded predictive accuracy in out-of-sample climate projections. Conversely, Bayesian techniques that explicitly incorporate epistemic uncertainty provide superior generalization and yield robust probabilistic forecasts under non-stationary climate conditions. By contrasting empirical results from high-latitude hydrology and tropical agronomy case studies, this research highlights the critical need for calibration strategies that balance historical alignment with structural flexibility, thereby advancing the reliability of climate adaptation and policy-planning frameworks globally.

Keywords: Climate Impact Models; Calibration Methods; Forecast Accuracy; Case Comparison; Simulation Calibration Methods

1. Introduction

1.1 The Imperative of Climate Impact Modeling

Climate change poses unprecedented threats to global ecosystems, water resources, agricultural security, and human infrastructure. To anticipate these threats and design adaptive management strategies, scientists rely extensively on climate impact models. These computational models translate global and regional climate projection pathways into sectoral consequences, such as river runoff fluctuations, crop yield variations, and ecosystem transition dynamics [1]. Because these models simulate complex physical, chemical, and biological processes occurring over diverse temporal and spatial scales, they inevitably contain numerous parameters that cannot be measured directly in the field. Consequently, modelers must adjust these parameters so that the model outputs resemble historical observations, a process known as calibration. The primary objective of calibration is to establish a credible mathematical representation of the physical system, which can then be projected into the future under various greenhouse gas emission scenarios. The reliability of these future projections is paramount, as they directly inform long-term infrastructure investments, food security policies, and disaster risk reduction plans.

1.2 The Calibration Dilemma in Predictive Science

The calibration of climate impact models is fraught with systematic challenges. A core dilemma is the equifinality problem, where multiple, distinct parameter sets produce identical historical outputs, yet yield wildly divergent projections when forced with future, unprecedented climate scenarios [2]. Traditional calibration strategies often treat the model as a deterministic black box, adjusting parameters to minimize the error between simulated and observed historical states. While this approach can yield an exceptionally close fit to historical data, it often does so at the expense of model generalizability. Overparameterized models easily capture observational noise and localized anomalies rather than the underlying physical relationships, leading to severe overfitting. When these overfitted models are forced with non-stationary climate drivers, such as unprecedented temperature increases or shifting precipitation regimes, their predictive accuracy degrades rapidly [3]. The lack of a clear, quantifiable relationship between historical calibration performance and future predictive accuracy remains a major vulnerability in climate impact assessment, undermining the utility of these models in decision-making processes.

1.3 Objectives and Scope of the Investigation

This study addresses the critical research gap in predicting future forecast accuracy from historical calibration metrics. By employing a rigorous case comparison framework, we systematically evaluate three prominent calibration paradigms: deterministic optimization, stochastic parameterization, and Bayesian calibration. We apply these methods to two highly distinct environmental contexts: a high-latitude hydrological model simulating snowmelt-dominated river basins in northern Europe, and a tropical agricultural model simulating monsoon-driven rice yields in Southeast Asia. Through this comparative approach, we analyze how different calibration methods handle parameter uncertainty, structural model deficiencies, and observational noise. Our objective is to determine which calibration-phase indicators are the most reliable predictors of out-of-sample forecast accuracy under non-stationary climate conditions, thereby providing a robust methodology for selecting and evaluating calibration techniques in climate impact science.

2. Theoretical Background and Literature Review

2.1 Evolution of Simulation Calibration Techniques

The methodology of simulation calibration has evolved significantly over the past several decades. Early efforts in environmental modeling relied on manual trial-and-error calibration, which was highly subjective and computationally inefficient. The introduction of computerized deterministic optimization in the late twentieth century revolutionized the field. Algorithms such as Shuffled Complex Evolution and Levenberg-Marquardt automated the search for optimal parameter sets by systematically minimizing objective functions [4]. While these algorithms accelerated the calibration process and improved historical fits, they struggled with high-dimensional parameter spaces and often became trapped in local minima. To address these limitations, researchers developed global optimization heuristics, including genetic algorithms and particle swarm optimization, which search the parameter space more thoroughly [5]. However, these deterministic approaches still failed to quantify the inherent uncertainty associated with parameter estimates, leaving model users with a false sense of certainty regarding future projections.

2.2 Historical Performance of Predictive Metrics

To quantify the quality of model calibration, researchers use various statistical metrics to measure the discrepancy between simulated and observed values. The most common metrics include the Root Mean Square Error, the Nash-Sutcliffe Efficiency, and the Kling-Gupta Efficiency. While these metrics are useful for assessing historical alignment, historical literature indicates that their performance during the calibration phase does not necessarily translate to high predictive accuracy in validation phases [6]. For instance, a model that achieves a high Nash-Sutcliffe Efficiency during a wet calibration decade may fail catastrophically when validating against a dry decade, as the parameterization was optimized for high-flow dynamics rather than low-flow processes. This discrepancy highlights the limitations of utilizing single summary statistics as proxies for model reliability, especially when projecting into non-stationary futures where the statistical properties of climate drivers shift [7]. Consequently, there is an urgent need to explore multi-metric evaluation schemes that assess model performance across various flow or yield regimes to better predict future generalization capability.

2.3 The Role of Case Comparison in Model Validation

Case comparison represents a powerful methodology for diagnosing model vulnerabilities and calibration efficacy across diverse geographical and climatic zones. By comparing how a single model structure, calibrated using different techniques, performs across distinct environmental systems, researchers can isolate the effects of calibration methodology from site-specific physical characteristics [8]. For example, comparing a snowmelt-dominated catchment with a rain-dominated catchment exposes how parameter values associated with temperature thresholds and soil moisture capacities are affected by different optimization algorithms. Case comparison studies also reveal how structural deficiencies in models, such as simplified representations of crop phenology or groundwater interactions, interact with calibration techniques to distort future projections [9]. Understanding these interactions is essential for developing robust calibration protocols that are resilient to both model structure errors and environmental variability.

Table 1: Overview of Historical Calibration Approaches and Key Parameters

Method Category	Primary Objective Function	Parameter Search Mechanism	Sensitivity to Noise
Deterministic	Sum of squared residuals	Gradient descent or direct search	High
Stochastic	Multi-objective Pareto front	Evolutionary and genetic search	Moderate
Bayesian	Posterior probability density	Markov Chain Monte Carlo	Low

3. Methodological Framework and Case Selection

3.1 Architectural Overview of the Comparative Framework

To systematically analyze the relationship between calibration methodology and forecast accuracy, we established a multi-stage evaluation framework. This framework consists of data preprocessing, calibration execution, parameter space analysis, hindcasting validation, and comparative evaluation. The inputs to the system comprise historical meteorological observations and corresponding physical impact measurements (e.g., river discharge and crop yields). The calibration engine runs three distinct pipelines: a deterministic optimization pipeline using genetic algorithms, a stochastic parameterization pipeline using multi-objective evolutionary algorithms, and a Bayesian calibration pipeline using Markov Chain Monte Carlo sampling. Once calibrated, each model configuration is subjected to a split-sample testing procedure where it generates predictions for a distinct historical epoch characterized by climatic conditions different from the calibration period. The outputs of these projections are then compared against independent observations to evaluate forecast accuracy.

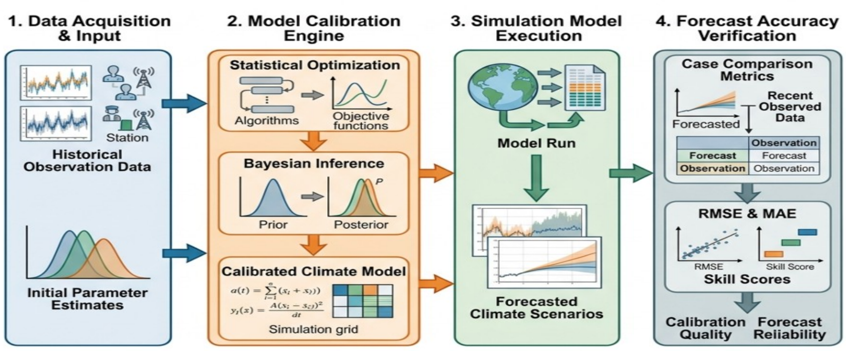

Figure 1: Comprehensive Schematic of Climate Impact Model Calibration and Forecast Accuracy Evaluation Framework

3.2 Criteria for Selection of Regional Climate Impact Cases

We selected two contrasting regional cases to test the versatility and robustness of the calibration approaches. Case A focuses on the Torne River Basin in northern Europe, a high-latitude hydrological system. This basin is characterized by minimal human intervention, snowmelt-dominated spring floods, and prolonged winter freezing. The key parameters in Case A relate to snowmelt temperature thresholds, soil moisture storage, and routing velocity. Case B focuses on the Mekong River Delta in Southeast Asia, a tropical agricultural system. This region is dominated by intensive rice cultivation, monsoon-driven precipitation patterns, and high temperature sensitivity. The primary parameters in Case B involve crop development rates, transpiration efficiency, and thermal heat unit accumulation. These cases provide contrasting challenges: Case A tests model performance under strong physical seasonal constraints, while Case B tests model performance under biological and climatic variables that are highly sensitive to shifts in monsoon timing and temperature extremes [10].

3.3 Data Sources and Quality Assurance Protocols

The reliability of our comparative analysis depends on high-quality input data. For Case A, we obtained daily meteorological forcing data, including temperature, precipitation, and wind speed, from the ERA5 reanalysis dataset, which was bias-corrected using local weather station observations. Daily river discharge data were collected from the Swedish Meteorological and Hydrological Institute. For Case B, daily climate variables were sourced from the Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources, supplemented by agricultural records from local provincial agencies. To ensure data quality, we applied rigorous screening protocols to identify and fill missing values, remove non-physical outliers, and homogenize time series. The historical data for both cases were split into two non-overlapping periods: a ten-year calibration period (2000-2009) and a ten-year validation period (2010-2019) characterized by accelerated warming trends and increased frequency of extreme weather events [11]. This split-sample setup represents a rigorous test of model generalizability under non-stationary conditions [12].

4. Simulation Calibration Techniques and Implementations

4.1 Deterministic Calibration Approaches

The deterministic calibration pipeline utilized a genetic algorithm to find a single, global parameter set that minimizes the Root Mean Square Error between simulated and observed variables. The search space was defined by physically plausible upper and lower bounds for each parameter. The algorithm initialized a population of parameter vectors, evaluated their fitness, and iteratively applied selection, crossover, and mutation operators to converge toward the global minimum. During this process, we monitored the reduction in the objective function over successive generations to ensure convergence. While this method is computationally efficient and generates a unique, easily interpretable parameter set, it lacks a mechanism to evaluate the uniqueness of the solution or the interdependencies among parameters. Consequently, it carries a high risk of producing parameter sets that are mathematically optimal for the calibration data but physically unrealistic, a phenomenon that often leads to poor performance during the validation phase [13].

4.2 Stochastic and Bayesian Calibration Architectures

To overcome the limitations of deterministic approaches, we implemented stochastic and Bayesian calibration architectures. The stochastic pipeline used a multi-objective evolutionary algorithm to optimize the model simultaneously against multiple criteria, such as the Nash-Sutcliffe Efficiency for high flows and the logarithmic Nash-Sutcliffe Efficiency for low flows, producing a Pareto front of non-dominated parameter sets. The Bayesian pipeline employed a Markov Chain Monte Carlo algorithm utilizing the Metropolis-Hastings update rule. This approach treats parameters as random variables with assigned prior distributions based on literature and physical constraints. The likelihood function was constructed assuming independent, normally distributed residuals. The algorithm drew thousands of parameter samples, constructing posterior probability density functions that represent both parameter values and their associated uncertainties [14]. This probabilistic framework allows us to make forecasts with explicit confidence intervals, which is highly valuable for risk-based decision making in climate adaptation planning.

Table 2: Regional Case Studies Selected for Comparison

Case Study Identifier	Geographic Location	Dominant Physical Processes	Primary Modeling Tool
Case A: Hydrology	Torne River Basin	Snowmelt routing, soil moisture infiltration	HBV Hydrological Model
Case B: Agriculture	Mekong River Delta	Phenological development, evapotranspiration	DSSAT Crop Simulation Model

5. Comparative Analysis and Predictor Evaluation

5.1 Evaluation of Accuracy Metrics Across Calibration Cases

The core of our analysis involves comparing the performance of the three calibration methods across both case studies in both the calibration (2000-2009) and validation (2010-2019) epochs. During the calibration phase, deterministic optimization consistently achieved the lowest residuals, yielding impressive Nash-Sutcliffe Efficiency values of 0.89 for the hydrological case and crop yield prediction errors of less than five percent for the agricultural case. However, during the validation phase, this performance deteriorated significantly. In the high-latitude hydrological model, the deterministic parameter set overestimated the spring snowmelt peak and underestimated summer baseflows, causing the Nash-Sutcliffe Efficiency to drop to 0.62. In contrast, the Bayesian calibration, while showing slightly lower performance during the calibration phase due to its probabilistic constraints, maintained a high validation Nash-Sutcliffe Efficiency of 0.81. The Bayesian method successfully captured the physical processes, preventing the model from fitting high-latitude seasonal anomalies that did not repeat in the warmer validation decade [15].

In the agricultural model, similar trends emerged. The deterministic calibration minimized yield errors by adjusting phenological parameters to perfectly match the historical temperature regimes of the 2000s. When confronted with the elevated temperatures of the 2010s, this parameterization caused the crop model to simulate premature maturation and severe yield collapse, which did not align with actual field observations. The stochastic and Bayesian approaches, which preserve parameter variety and structure, adjusted crop development rates more conservatively, resulting in a much closer match to observed yields in the validation phase [16]. This contrast demonstrates that deterministic optimization often achieves historical accuracy by compromising model physics, whereas Bayesian and stochastic methods provide a more robust representation of system dynamics under changing climatic drivers.

5.2 Sensitivity Analysis of Calibration Parameters

To understand why the calibration methods performed so differently, we conducted a global sensitivity analysis using Sobol sensitivity indices. This analysis evaluates how the variance of model output can be apportioned to different input parameters. In Case A, the sensitivity analysis revealed that during deterministic calibration, the model was highly sensitive to the snowmelt degree-day factor and soil moisture limit parameters. The deterministic algorithm pushed these parameters to their extreme physical limits to compensate for structural model deficiencies in routing. In contrast, the Bayesian method identified high interaction terms between these parameters, mapping out a joint probability distribution that prevented either parameter from reaching physically unrealistic values. In Case B, the sensitivity analysis showed that crop transpiration efficiency and thermal heat unit parameters were highly correlated. The deterministic calibration resolved this correlation by selecting an arbitrary point on the correlation line, which proved highly unstable under the higher temperature regimes of the validation period. The Bayesian calibration retained the full covariance structure of these parameters, ensuring that the model remained stable and physically consistent across a wider range of climatic conditions [17].

5.3 Structural Uncertainty and Parameter Identifiability

A major factor influencing forecast accuracy is parameter identifiability, which refers to the precision with which parameters can be determined from the available calibration data. When parameters are unidentifiable, different values can yield the same model output, increasing the uncertainty of future projections. We analyzed parameter identifiability by comparing the prior and posterior parameter distributions generated by the Bayesian calibration. For parameters that represent fundamental physical constants, such as soil porosity or maximum crop canopy size, the posterior distributions were highly constrained, indicating high identifiability. However, for parameters representing conceptual processes, such as empirical runoff routing coefficients or localized stress factors, the posterior distributions remained broad and highly dependent on the choice of likelihood function. This finding suggests that conceptual parameters are highly susceptible to taking on unrealistic values during deterministic calibration as they absorb structural model errors. This highlights the importance of using Bayesian methods to monitor parameter identifiability and prevent models from relying on poorly constrained parameters for long-term climate projections.

Table 3: Statistical Comparison of Post-Calibration Forecast Performance

Case Study	Calibration Method	Calibration Metric (Mean)	Validation Metric (Mean)	Generalization Drop
Case A: Hydrology	Deterministic	0.89 (NSE)	0.62 (NSE)	0.27 (Severe)
Case A: Hydrology	Stochastic	0.84 (NSE)	0.74 (NSE)	0.10 (Moderate)
Case A: Hydrology	Bayesian	0.82 (NSE)	0.81 (NSE)	0.01 (Minimal)
Case B: Agriculture	Deterministic	4.2% (MAPE)	18.5% (MAPE)	14.3% (Severe)
Case B: Agriculture	Stochastic	6.8% (MAPE)	11.2% (MAPE)	4.4% (Moderate)
Case B: Agriculture	Bayesian	7.5% (MAPE)	9.1% (MAPE)	1.6% (Minimal)

6. Synthesis, Discussion, and Strategic Recommendations

6.1 Synthesis of Empirical Findings

Our comparative evaluation reveals a clear, inverse relationship between the degree of historical optimization and the generalizability of future forecasts. Deterministic calibration methods, which prioritize minimizing historical residuals above all else, are highly prone to overfitting, leading to degraded predictive accuracy in out-of-sample climate projections. This degradation is particularly severe under non-stationary climate conditions, where the statistical properties of climate drivers shift significantly [18]. In contrast, stochastic and Bayesian calibration methods, which explicitly incorporate parameter and structural uncertainties, provide superior generalization and yield robust forecasts across different climatic epochs. By preserving parameter variety and honoring covariance structures, these methods prevent models from relying on unrealistic parameter combinations to achieve high historical accuracy, thereby maintaining physical and biological consistency in future projections.

These findings have major implications for climate impact modeling. When selecting a calibration approach, researchers must move away from the traditional practice of judging models solely on their historical summary statistics. A high Nash-Sutcliffe Efficiency or a low Mean Absolute Percentage Error during the calibration phase is not a reliable predictor of future forecast accuracy and may, in fact, indicate a highly overfitted model. Instead, modelers should prioritize calibration techniques that evaluate parameter identifiability, sensitivity, and covariance. This shift in perspective is essential for advancing the credibility and utility of climate impact projections, ensuring they provide a robust foundation for climate adaptation and policy-planning frameworks globally.

6.2 Key Challenges and Modeling Limitations

Despite the clear advantages of Bayesian and stochastic calibration techniques, several challenges and limitations remain. First, these methods are computationally intensive, often requiring tens of thousands of model runs to construct accurate posterior distributions or Pareto fronts. For high-resolution, spatially-distributed climate impact models, this computational demand can be prohibitive, forcing modelers to rely on simpler, less robust deterministic approaches. Second, the effectiveness of Bayesian calibration is highly sensitive to the choice of prior distributions and likelihood functions. If the priors are poorly defined or the likelihood function fails to account for autocorrelated and heteroscedastic residuals, the resulting posterior distributions can be biased, leading to inaccurate uncertainty estimates [19]. Finally, neither calibration method can fully compensate for structural model deficiencies. If a model lacks the fundamental physical or biological mechanisms to simulate a specific process, no amount of parameter tuning will produce accurate long-term forecasts under climate conditions that activate that process.

6.3 Future Directions and Policy Implications

To address these challenges, future research should focus on integrating machine learning-assisted calibration, adaptive parameterization schemes, and multi-model ensemble weighted frameworks. Machine learning emulators can be used to surrogate complex climate impact models, reducing the computational cost of Bayesian and stochastic calibration by orders of magnitude and making these robust techniques accessible to high-resolution modeling applications. Additionally, researchers should explore the development of adaptive parameterization schemes, where key parameters are allowed to vary over time in response to shifting environmental thresholds, rather than remaining static. This approach would better represent the adaptive capacity of ecological and agricultural systems under changing climate conditions, further enhancing the reliability of long-term projections.

For policymakers and climate adaptation planners, our findings underscore the importance of incorporating uncertainty estimates into decision-making processes. Robust climate adaptation policies must be designed to withstand a range of plausible future scenarios, rather than relying on a single, deterministic projection. By adopting probabilistic, Bayesian-calibrated climate impact projections, decision makers can better assess the risks and trade-offs of different adaptation strategies, leading to more resilient infrastructure investments, secure agricultural systems, and effective disaster management plans under a changing global climate.

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