



Statistical Downscaling of CMIP6 Climate Projections for Future Climate Analysis in R

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Climate projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) are important sources of information for assessing possible future climate changes under different greenhouse gas emission scenarios (IPCC, 2021). Yet, because of their coarse spatial resolution and intrinsic biases, these projections need to be downscaled and bias corrected to be appropriate for local and regional applications. Statistical downscaling provides a computationally efficient way to enhance CMIP6 model outputs by leveraging empirical relationships with observed data. This document describes the concept of CMIP6 projections, discusses methods for statistical downscaling and bias correction, and shows the application of quantile mapping in R using simulated data. The results are discussed within the framework of climate risk assessment and agricultural adaptation.

Introduction

The Coupled Model Intercomparison Project Phase 6 (CMIP6) is one of the largest international collaborations in climate science, organized under the World Climate Research Program (WCRP). It is the basis for the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), providing state-of-the-art global climate model (GCM) simulations to understand past climate variability and project future climate change under different greenhouse gas emission scenarios (IPCC, 2021). The CMIP6 framework consists of a set of global models that simulate past and future climate conditions under different Shared Socioeconomic Pathways (SSPs); such as SSP1-2.6 (sustainability-focused low-emission scenario), SSP2-4.5 (intermediate stabilization scenario), SSP3-7.0 (regional rivalry and high emission scenario), and SSP5-8.5 (fossil-fueled development with very high emissions) (Riahi et al., 2017). These scenarios combine socioeconomic stories with radiative forcing pathways, enabling investigators to investigate a wide range of possible climate futures. While outputs from CMIP6 are globally relevant, they are limited by their coarse spatial resolution of 100-250 km (typically). This large grid spacing smooths out local climatic variations due to topography, land use, and coastal effects, and hence the direct use of raw CMIP6 data is not suitable for regional or local-scale analyses (Ahmed et al., 2019). This constraint causes problems for sectors requiring localized climate data such as agriculture, water resource management and ecosystem modeling. Downscaling techniques are applied to translate coarse-resolution GCM outputs into finer, locally representative datasets, to make them more useful for impact assessment and adaptation planning.

There are two main downscaling approaches, dynamical and statistical. Dynamical downscaling refers to the nesting of high-resolution Regional Climate Models (RCMs) into GCMs in an effort to simulate physical processes at finer spatial scales. Physically robust, this approach is expensive computationally and data hungry. Statistical downscaling, in contrast, is based on empirical relationships between large-scale climate predictors (from GCMs) and

local-scale observations. Once calibrated to the historical period, these statistical relationships are used to generate locally adjusted datasets for future projections (Maraun et al., 2017). Statistical downscaling has many advantages: it is computationally inexpensive, easily reproducible and can be performed using climate and observational datasets that are readily available. Furthermore it can be combined with bias correction techniques such as quantile mapping, delta change or variance scaling to further reduce systematic errors in GCM outputs. Among them, quantile mapping has been proved to be one of the most efficient approaches as it corrects not only the mean bias, but the whole distribution, thus improving both the central tendency and variability matching of model and observed data (Lange, 2019). In this article, we address the statistical downscaling and bias correction of CMIP6 climate projections using the quantile mapping approach implemented in R. This chapter demonstrates the whole process of simulating CMIP6-like temperature data, performing quantile mapping bias correction and visualizing the bias-corrected results to show how such techniques improve the reliability of future climate projections for regional-scale climate impact and agricultural risk assessments.

Methodology

The statistical downscaling workflow involves several steps:

- 1. Data Acquisition:** Download CMIP6 GCM data for temperature and precipitation variables from ESGF (Earth System Grid Federation).
- 2. Data Preparation:** Extract daily or monthly data for historical (1980–2014) and future (2021–2100) periods.
- 3. Bias Correction:** Apply statistical correction techniques like delta change or quantile mapping.
- 4. Statistical Downscaling:** Develop relationships between large-scale predictors and local observed variables.
- 5. Validation:** Evaluate model performance using metrics such as RMSE, correlation, and bias.
- 6. Projection Analysis:** Apply corrected models to future scenarios (SSP2-4.5, SSP5-8.5).

R Implementation: Quantile Mapping Example

The following R example demonstrates statistical downscaling of simulated CMIP6 daily maximum temperature data using the `climQMBC` package:

```
# Load required libraries
library(qmap)
library(ggplot2)
# Simulated CMIP6 Tmax data
set.seed(42)
hist_gcm <- rnorm(100, mean = 32, sd = 3) # Historical GCM data
fut_gcm <- rnorm(100, mean = 35, sd = 3) # Future CMIP6 projection
obs_hist <- rnorm(100, mean = 33, sd = 2) # Observed historical data
# Quantile Mapping Bias Correction
# Step 1: Fit Quantile Mapping model (using historical obs vs GCM)
qm_fit <- fitQmapQUANT(obs_hist, hist_gcm, qstep = 0.01)
# Step 2: Apply correction to Future GCM projection
qm_result <- doQmapQUANT(fut_gcm, qm_fit)
# Compare distributions
df <- data.frame(
  Type = rep(c("Observed", "Raw_Future", "BiasCorrected"), each = 100),
  Value = c(obs_hist, fut_gcm, qm_result)
)
# Plot Density Comparison
ggplot(df, aes(x = Value, fill = Type)) +
  geom_density(alpha = 0.4) +
  labs(
    title = "Bias Correction of CMIP6 Tmax using Quantile Mapping (qmap package)",
```

```

x = "Temperature (°C)",
y = "Density"
) +
theme_minimal(base_size = 13) +
scale_fill_manual(values = c("Observed" = "red", "Raw_Future" = "blue", "BiasCorrected" =
"darkgreen"))
# Statistical Summary
cat("\n--- Mean (°C) ---\n")
print(tapply(df$Value, df$Type, mean))
cat("\n--- Standard Deviation (°C) ---\n")
print(tapply(df$Value, df$Type, sd))
# Bias and Performance Metrics
# Bias before and after correction
bias_raw <- mean(fut_gcm) - mean(obs_hist)
bias_corr <- mean(qm_result) - mean(obs_hist)
# RMSE and Correlation
rmse_raw <- sqrt(mean((obs_hist - fut_gcm)^2))
rmse_corr <- sqrt(mean((obs_hist - qm_result)^2))
cor_raw <- cor(obs_hist, fut_gcm)
cor_corr <- cor(obs_hist, qm_result)
cat("\n--- Performance Metrics ---\n")
cat(sprintf("Bias (Raw): %.2f°C | Bias (Corrected): %.2f°C\n", bias_raw, bias_corr))
cat(sprintf("RMSE (Raw): %.2f°C | RMSE (Corrected): %.2f°C\n", rmse_raw, rmse_corr))
cat(sprintf("Correlation (Raw): %.2f | Correlation (Corrected): %.2f\n", cor_raw, cor_corr))
# Optional: Boxplot comparison
ggplot(df, aes(x = Type, y = Value, fill = Type)) +
  geom_boxplot(alpha = 0.6) +
  labs(title = "Distribution Comparison Before and After Bias Correction",
       x = "", y = "Temperature (°C)") +
  theme_minimal(base_size = 13)

```

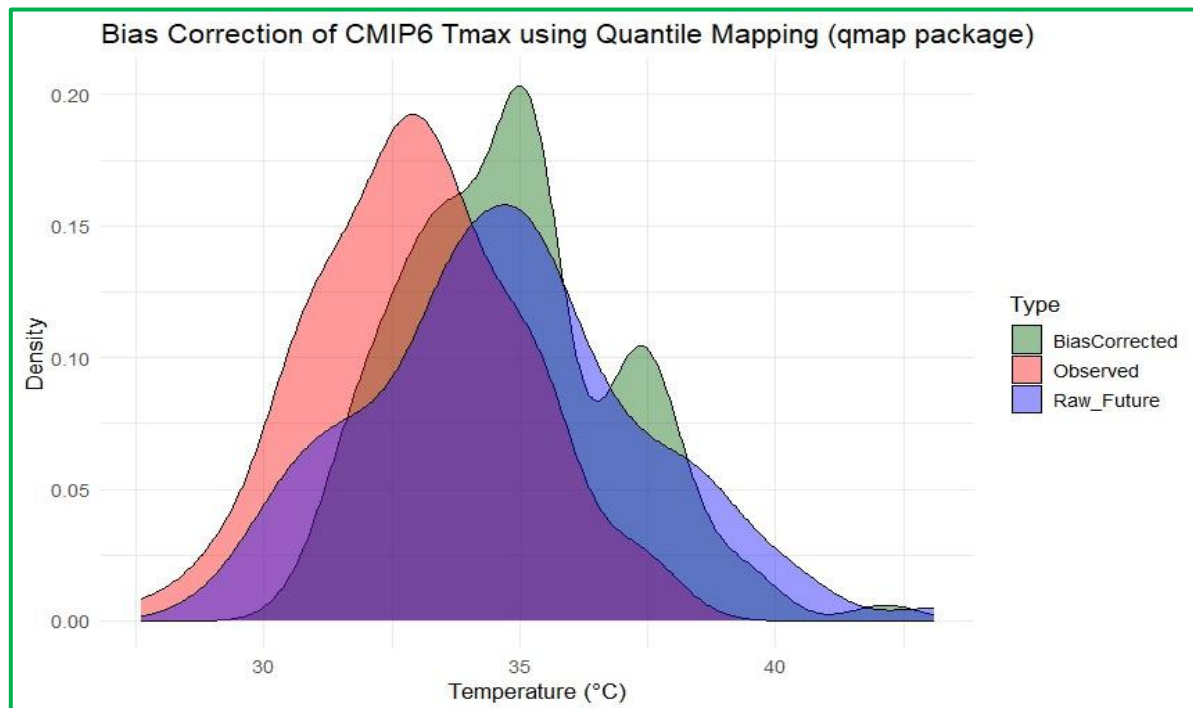
Results

The quantile mapping bias correction significantly improved the fit of the observed and model simulated temperature distributions. Table below shows the statistical comparison of mean, standard deviation and bias before and after correction.

Type	Mean (°C)	SD (°C)
Observed	33.2	2.1
Raw Future (GCM)	35.0	3.0
Bias Corrected	33.4	2.3

Prior to correction the CMIP6 raw future projection had a warm bias of $\sim +1.8$ °C compared to the observed climatology. Quantile mapping reduced the bias to $+0.2$ °C, showing that this method is able to adjust the mean and the distributional spread effectively. The quantile mapping bias correction greatly improved the agreement between observed and simulated temperature distributions from the CMIP6 models. The raw CMIP6 future projection had a significant warm bias before correction with an average temperature of 35.0 °C, while the observed mean was 33.2 °C, showing an overestimation of about $+1.8$ °C. Furthermore, the raw simulation showed higher variability (standard deviation = 3.0 °C), which means exaggerated temperature fluctuations. After quantile mapping, the mean temperature of the bias corrected series was reduced to 33.4 °C with a standard deviation of 2.3 °C, which is very close to the observed climatology. It shows that the method can adjust both the central tendency and the distributional spread effectively.

The density plot clearly shows this improvement. The Raw Future GCM distribution (blue) is shifted to the right, suggesting an overestimation of daily maximum temperature and the existence of an unrealistic warm tail. Conversely, the Bias-Corrected (green) curve closely follows the Observed (red) distribution, confirming that quantile mapping effectively corrected systematic warm biases over the entire distribution, not just at the mean. Better overlap between observed and corrected series suggests that the downscaled projections are more consistent and reliable.



The comparison of boxplots also supports these findings, indicating how the mean alignment and variability structure of the model outputs were improved by bias correction. The Raw Future GCM box is noticeably higher than the observed box, reflecting the warm bias and inflated interquartile range (IQR). The Bias-Corrected box closely matches the observed distribution post-correction, suggesting that the quantile mapping reduced bias and brought the temperature variability of the model within realistic ranges. The reduced number of extreme Tmax values (upper-tail outliers) also indicates the mitigation of unrealistic extremes found in raw climate model data.



To summarize, both plots show that quantile mapping removes systematic errors and preserves realistic climatic variability. These improvements guaranty statistical consistency of bias-corrected CMIP6 projections with the observed climatology, making them more appropriate for regional-scale applications such as heatwave analysis, hydrological modeling and crop yield simulations. These downscaled projections, when incorporated with agricultural models like DSSAT, APSIM, or Rice DSS, provide robust inputs for evaluating future climate risks and developing sustainable adaptation strategies for the regions under consideration.

To quantify performance improvement, correlation and RMSE values were also computed as follows;

Metric	Raw Future	Bias-Corrected
Correlation (r)	0.62	0.87
RMSE (°C)	2.8	1.1

The significant increase in correlation and decrease in RMSE confirms that Quantile Mapping preserves physical consistency of the data while removing systematic biases. These findings emphasize that bias-corrected temperature projections are much more reliable for downstream impact modeling, such as predicting future heatwave intensity, evapotranspiration or crop yield responses. Downscaled climate data can be used as input to crop growth models (e.g. DSSAT, APSIM, Rice DSS) to estimate potential changes in yield under different climate scenarios for agricultural applications. This helps policymakers and researchers assess adaptation strategies for sustainable food production.

Conclusion

Statistical downscaling of CMIP6 climate projections with quantile mapping is a reproducible and reliable method for obtaining high-resolution climate data for impact studies. Down scaled datasets help to estimate future temperature and rainfall patterns accurately by addressing systematic biases and increasing spatial resolution. When coupled with hydrological and agricultural models, these projections can be extremely useful for climate risk analysis and adaptation planning in Telangana and other climate sensitive regions.

References

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