A DATASET OF HIGH-RESOLUTION CLIMATE CHANGE PROJECTIONS OVER SOUTH AMERICA WITH BIAS CORRECTION

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ABSTRACT

Accurate and detailed datasets are crucial for assessing climate change impacts. Regional climate models provide high-resolution simulations and are key tools but often exhibit systematic biases. Therefore, this paper presents a dataset derived from bias-corrected Eta regional model simulations and projections driven by four global CMIP5 models. The correction applied to daily precipitation, potential evapotranspiration, actual evapotranspiration, and 2-m air temperature, was conducted on a 0.2° x 0.2° grid over South America. The dataset covers two periods: 1976-2005 (baseline) and 2006-2099 (future) under RCP4.5 and RCP8.5 scenarios. Empirical quantile mapping was used to adjust the Eta model outputs to better match observational data. This method modified the accumulated probability curves of the Eta model outputs to align with observational curves for both baseline and future climates. Two observational datasets were used for correction and evaluation. The new dataset shows that bias correction significantly reduced the errors in the Eta simulations, especially for the frequent values of precipitation, potential evapotranspiration, and 2-m temperature, and also corrected the annual cycle and frequency distribution of these variables, approaching the observations. The pattern of extreme precipitation indices from the bias-corrected Eta dataset also reduced error. Bias correction was applied to future projections. The comparison against the raw Eta dataset showed that the trends of changes were preserved, but in general, the peaks of the changes were smoothed. As in the raw Eta dataset, the RCP8.5 scenario showed a higher change rate than RCP4.5. This work also revealed the large uncertainty of the observational dataset; some of the remaining errors after the bias correction were mostly due to differences between the two correction and evaluation observational datasets. The described dataset is freely available from the CNPq LattesData repository at the following link: https://doi.org/10.57810/lattesdata/WAVGSL.

Keywords: Regional climate model; Eta model; Empirical quantile mapping; Cumulative distribution frequency.

RESUMO

UM CONJUNTO DE DADOS DE PROJEÇÕES DE MUDANÇAS CLIMÁTICAS DE ALTA RESOLUÇÃO PARA A AMÉRICA DO SUL COM CORREÇÃO DE VIÉS. Conjuntos de dados precisos e detalhados são cruciais para avaliar os impactos das mudanças climáticas. Modelos climáticos regionais fornecem simulações de alta resolução e são ferramentas essenciais, mas frequentemente exibem vieses sistemáticos. Assim, este artigo apresenta um conjunto de dados derivado de simulações e projeções do modelo regional Eta com viés corrigido, aninhado a quatro modelos globais do CMIP5. A correção foi aplicada à precipitação diária, evapotranspiração potencial, evapotranspiração real e temperatura do ar de 2 m em ponto de grade regular de 0,2° x 0,2° sobre a América do Sul. O conjunto de dados abrange dois períodos: 1976-2005 (período de referência) e 2006-2099 (período do clima futuro) sob os cenários RCP4.5 e RCP8.5. O método utilizado para redução de viés consiste no mapeamento quantil empírico, que compara as curvas de probabilidade acumulada entre as variáveis observadas e as simuladas pelo modelo climático, tanto para o clima presente quanto para as projeções do clima futuro. O método pressupõe que os erros sistemáticos são reduzidos pelo deslocamento das curvas de distribuição das simulações para o mesmo nível de frequência das observações. Foram empregados dois conjuntos de dados observacionais distintos: um para a etapa de correção e outro para a etapa de avaliação. O conjunto de dados corrigido revela uma redução substancial dos erros nas simulações do modelo Eta, particularmente para os valores mais frequentes de precipitação, evapotranspiração potencial e temperatura a 2 m. A correção melhorou a representação do ciclo anual e a distribuição de frequência dessas variáveis, aproximando-os das observações. A correção de viés contribuiu também para redução dos erros na representação dos índices de extremos de precipitação. A correção de viés foi aplicada às projeções futuras. A comparação com o conjunto de dados Eta bruto (sem correção) mostrou que as tendências das mudanças foram preservadas, mas, em geral, os picos das mudanças foram suavizados. Assim como no conjunto de dados Eta bruto, o cenário RCP8.5 mostrou uma taxa de mudança maior do que o RCP4.5. Este trabalho também revelou uma grande incerteza do conjunto de dados observacionais; alguns dos erros restantes após a correção de viés foram principalmente devido a diferenças entre os dois conjuntos de dados observacionais de correção e avaliação. O conjunto de dados descrito está disponível gratuitamente no repositório LattesData do CNPq no seguinte link: https://doi.org/10.57810/lattesdata/WAVGSL.

Palavras-chave: Modelo climático regional; Modelo Eta; Mapeamento quantil empírico; Distribuição de frequência acumulada.

RESUMEN

UN CONJUNTO DE DATOS DE PROYECCIONES DE CAMBIOS CLIMÁTICOS DE ALTA RESOLUCIÓN PARA AMÉRICA DEL SUR CON CORRECCIÓN DE SESGO. Los conjuntos de datos precisos y detallados son cruciales para evaluar los impactos del cambio climático. Los modelos climáticos regionales proporcionan simulaciones de alta resolución y son herramientas esenciales, pero a menudo presentan sesgos sistemáticos. En este contexto, el artículo presenta un conjunto de datos derivado de simulaciones y proyecciones del modelo regional Eta con sesgo corregido, acoplado a cuatro modelos globales del CMIP5. La corrección se aplicó a la precipitación diaria, la evapotranspiración potencial, la evapotranspiración real y la temperatura del aire a 2 m en una rejilla regular de 0,2° x 0,2° sobre América del Sur. El conjunto de datos cubre dos períodos: 1976-2005 (período de referencia) y 2006-2099 (período del clima futuro) bajo los escenarios RCP4.5 y RCP8.5. El método utilizado para la reducción de sesgo consiste en el mapeo cuantílico empírico, que compara las curvas de probabilidad acumulada entre las variables observadas y las simuladas por el modelo climático, tanto para el clima presente como para las proyecciones del clima futuro. El método asume que los errores sistemáticos se reducen al ajustar las curvas de distribución de las simulaciones para coincidir con el mismo nivel de frecuencia de las observaciones. Se emplearon dos conjuntos de datos observacionales distintos: uno para la etapa de corrección y otro para la etapa de evaluación. El conjunto de datos corregido revela una reducción sustancial de los errores en las simulaciones del modelo Eta, particularmente para los valores más frecuentes de precipitación, evapotranspiración potencial y temperatura a 2 m. La corrección mejoró la representación del ciclo anual y la distribución de frecuencia de estas variables, acercándolas a las observaciones. La corrección de sesgo también contribuyó a la reducción de errores en la representación de los índices de extremos de precipitación. La corrección de sesgo se aplicó a las proyecciones futuras. La comparación con el conjunto de datos bruto de Eta (sin corrección) mostró que las tendencias de cambio se preservaron, pero en general, los picos de cambio se suavizaron. Al igual que en el conjunto de datos bruto de Eta, el escenario RCP8.5 mostró una tasa de cambio mayor que el RCP4.5. Este trabajo también reveló una gran incertidumbre en el conjunto de datos observacionales; algunos de los errores restantes después de la corrección de sesgo se debieron principalmente a diferencias entre los dos conjuntos de datos observacionales utilizados para la corrección y la evaluación. El conjunto de datos descrito está disponible gratuitamente en el repositorio LattesData del CNPq en el siguiente enlace: https://doi.org/10.57810/lattesdata/WAVGSL.

Palabras clave: Modelo climático regional; Modelo Eta; Mapeo empírico de cuantiles; Distribución de frecuencia acumulada.

1 INTRODUCTION

Identifying the impacts of climate change has required the development of a series of datasets. Global climate models are widely used in studies of the impacts of climate change (IPCC 2007, 2013, 2021). Although global models currently present more refined spatial resolutions and higher quality simulations (FLATO et al. 2013, GUO et al. 2020), they still have a coarse spatial resolution in relation to regional models, limiting the adequate representation of the surface and mesoscale processes (NAVARRO-RACINES et al. 2020). Applying generated by global climate models at local and regional scales often requires dynamical downscaling using regional climate models. This approach is essential for studies in agriculture and water resource management (WILBY et al. 2009, ADAM et al. 2011). LYRA et al. (2018) showed that climate simulations for Southeast Brazil, using the Eta regional model with high spatial resolution, improved the representation of the frequency and intensity of extreme precipitation and temperature events.

Although dynamical downscaling of simulations provides more detailed representations of climate patterns, systematic errors inherent in global and regional models persist and may be amplified in regional modeling (WU & LYNCH 2000, SATO et al. 2007, XU & YANG 2012, XU et al. 2021). These discrepancies, especially in representing precipitation and extreme events (IPCC 2021), are due to model simplifications and parameterizations (MCGRATTAN & TOMAN 2011, LAFFERTY & SRIVER 2023). Driving hydrological or agricultural impact models from those climate model outputs may cause error propagation through modeling cascades. Several bias correction methodologies have been developed and applied to global and regional climate model outputs to reduce these error propagations (THEMEßL et al. 2011, BÁRDOSSY & PEGRAM 2013, KRINNER et al. 2020, GUO et al. 2020, XU et al. 2021, QIAN & CHANG 2021, JOSE & DWARAKISH 2022, TRAN-ANH et al. 2023). These techniques, which are generally based on comparisons with observations and use statistical methods (MARAUN 2016), aim to reduce systematic errors and calibrate climate simulations, making them more consistent with observed conditions. Consequently, the bias-corrected climate model outputs become more suitable for impact studies and for developing adaptation measures in various sectors, such as agriculture, energy, and health.

Bias correction methodologies differ according to statistical complexity, ranging from simpler scaling methods, such as linear scaling (LENDERINK et al. 2007), variance scaling (TERINK et al. 2010, TEUTSCHBEIN & SEIBERT 2012) or Local Intensity Scaling (SCHMIDLI et al. 2006), to more sophisticated methods of mapping probability distributions (normal distribution mapping (PIANI et al. 2010, GUDMUNDSSON et al. 2012, QIAN & CHANG

2021), empirical quantile mapping (BÁRDOSSY & PEGRAM 2011, THEMEßL et al. 2011, QIAN & CHANG 2021), quantile mapping with linear transformation function (PIANI et al. 2010, QIAN & CHANG 2021), and delta quantile mapping (CANNON et al. 2015, QIAN & CHANG 2021).

Empirical quantile mapping (EQM) is a non-parametric bias correction method (THEMEßL et al. 2011, FANG et al. 2015, VELASQUEZ et al. 2020), which consists of adjusting the variance of the model distribution to better match the variance of the observation distribution by using a transfer function of distribution based on empirical quantiles that are linearly interpolated (THEMEßL et al. 2012, FANG et al. 2015, MARAUN 2016). This technique has been applied to historical and future climate series for different emission scenarios produced by several global and regional models, mainly for precipitation, as it generally produces satisfactory results compared to other methods such as linear scaling and local intensity scaling (*e.g.*, THEMEßL et al. 2011, 2012; VELASQUEZ et al. 2020; MENDEZ et al. 2020). Furthermore, THEMEßL et al. (2011) found that the EQM performed best at high quantiles, which makes it suitable for extreme events.

BALLARIN et al. (2023) used the delta quantile mapping to correct biases in time series of precipitation, maximum and minimum temperatures, net solar radiation, wind speed, and relative humidity output by the set of 19 CMIP6 (Coupled Model Intercomparison Project 6) global models over entire Brazil for the historical (1980-2013) and future (2015-2100) periods and under two emission scenarios (SSP2-4.5 and SSP5-8.5). The results showed an adequate performance in removing bias in the historical series, while the future series had the simulated trends preserved. DE OLIVEIRA et al. (2015) evaluated the effectiveness of several bias correction methods in simulations of the regional Eta model, nested in different members of the global HadCM3 model, for Southern Brazil from 1976 to 1990. The methods compared included the delta change approach, the direct method, and quantile mapping, applied to climate variables such as precipitation. The results showed that, although there were significant differences between the methods – especially for precipitation, with discrepancies of up to 20% – none of them stood out as superior in all the analyzed criteria. BILLERBECK et al. (2021) also tested different methodologies of bias correction for precipitation simulated by the Eta model nested into four global models (CHOU et al. 2014a) over the Piracicaba basin in Southeast Brazil from 1961 to 2005. All methods were efficient in bias removal compared to uncorrected outputs; however, less complex methods, such as linear scaling, performed better than methods using quantile mapping. Nevertheless, the correction methods were applied to monthly values in these previous works. TSCHÖKE et al. (2017) tested two distribution functions to correct the bias of the Eta Model precipitation climate simulations in a small catchment in Southeast Brazil. They found that the Gamma distribution adjustment provided more efficient correction than the Power transformation technique. An adaptive filter technique based on the Recursive Least Squares algorithm was applied to reduce the Eta model's bias in climate forecasts at the upper and mid-level of the troposphere.

Although the scientific literature´s results regarding the effectiveness of bias correction techniques vary, the consensus is that these methodologies are essential for applying climate model data in impact studies. In Brazil, simulations of the regional Eta model from the National Institute for Space Research (INPE) have been widely used, especially for Brazil's National Communications to the United Nations Framework Convention on Climate Change (MCTI 2010, 2016, 2021).

This article aims to describe the bias-corrected dataset for the daily outputs of the Eta model, covering both the historical period and future climate projections. The quality of the new dataset is assessed through comparisons with observed data for the historical period. In addition, climate trends in the corrected and uncorrected outputs are compared for future climate periods. The climate variables corrected include precipitation, potential and actual evapotranspiration, and 2-m temperature. Although the corrected dataset was produced for a large area covering South America and adjacent regions, the present analysis focuses on the Brazilian region.

This article is organized as follows: Section 2 describes the Eta model dataset, the observational datasets used for correction and validation, and the bias correction methodology; Section 3 shows the validation for the historical period and the statistical features reproduced of the future projections after the bias correction procedure; and Section 4 concludes on the constructed dataset.

2 DATA AND METHODOLOGY

In this section, the climate model is initially described. Then, the dataset used for correction and validation is described, and lastly, the bias correction methodology is detailed.

2.1 Eta model dataset

The Eta model is a complex numerical model representing the physical and dynamic processes of the atmosphere. This is the category of models called regional or limited area models, which, therefore, require global models to provide information about the atmosphere in the lateral contours. A feature of the model that gives it its name is the use of the vertical coordinate eta (η), considered more suitable for simulations in regions with complex topography, such as the Andes Mountains. A better representation of the topography is achieved through the etas coordinate, which represents the topography in discrete steps. The approximately horizontal surfaces of the eta coordinate contribute to reducing errors in calculations of horizontal derivatives, such as those related to the force of the horizontal pressure gradient (MESINGER 1984).

The Eta model has been developed at INPE since 1996 (MESINGER et al. 2012, GOMES et al. 2023) and has been widely used in several applications, including short- and medium-term weather forecasts (SIQUEIRA et al. 2016, CALADO et al. 2018, SAULO et al. 2000, SELUCHI et al. 2003), extended and seasonal forecasts (CHOU et al. 2005, 2018, 2020b; PILOTTO et al. 2012) and climate change studies (PESQUERO et al. 2010; CHOU et al. 2012, 2014a, b, 2020a, b; IMBACH et al. 2018).

In recent years, the Eta model has undergone significant updates to improve its ability to simulate various atmospheric and climate phenomena (MESINGER et al. 2012, MESINGER et al. 2016). These improvements include the implementation of new physical parameterizations, such as more advanced convection schemes and more realistic representations of topography, resulting in a better representation of processes such as cloud formation, precipitation, and interactions between the atmosphere and the surface. In addition, the model has been optimized to run on high-performance computing platforms, allowing simulations with greater spatial and temporal resolution.

One of the main innovations was developing a unified version of the Eta model (GOMES et al. 2023), in which a single configuration treats all time scales (short, medium, and long term). This unification simplifies the model's use and facilitates the comparison of results across different time scales. Furthermore, the Eta model has been continuously developed to meet the demands of different scientific communities and end users.

Precipitation, potential and actual evapotranspiration, and 2-m temperature are the output of the Eta Model from dynamically downscaling four global climate models (CHOU et al. 2014a, b): BESM (Brazilian Earth System Model; NOBRE et al. 2013), CanESM2 (Canadian Earth System Model Second Generation; ARORA et al. 2011), HadGEM2-ES (Hadley Center Global Environmental Model; COLLINS et al. 2011), and MIROC5 (Model for Interdisciplinary Research, version 5; WATANABE et al. 2010). The Global Climate models produced experiments following the CMIP5 (Coupled Model Intercomparison Project Phase 5) protocol to support the IPCC (Intergovernmental Panel on Climate Change) Fifth Assessment Report (AR5) (IPCC 2013). For the future, climate projections considered two greenhouse gas concentration scenarios (Representative Concentration Pathways, RCP): RCP4.5 and RCP8.5. The RCP4.5 is intermediate between the most optimistic and the most pessimistic AR5 scenarios. This RCP is directed towards a future with a relatively optimistic reduction in emissions, with equivalent CO_2 concentrations of 600 ppm, showing stabilization after the end of the 21st century (BJØRNÆS 2013). The RCP8.5 scenario is the most pessimistic of the AR5 scenarios, where a future without public policy changes to reduce emissions is assumed, contributing to the increase in CO_2 emissions at the end of the century by three times more than current levels (BJØRNÆS 2013). Hereafter, the four-member Eta downscaling ensemble simulations of the baseline period will be referred to as Eta simulations and the four-member ensemble Eta downscaling projections of the future climate as Eta RCP4.5 or Eta RCP8.5 projections.

It is essential to highlight that, despite the availability of CMIP6 and its SSP (Shared Socioeconomic Pathways) scenarios, the Eta-CMIP5 projections remain an important reference for impact studies in South America. The concomitant use of both sets will allow a more robust analysis of future climate uncertainties and an assessment of the evolution of climate projections over time.

The Eta Model outputs the downscaling at a regular grid of 0.2 x 0.2 degrees latitude x longitude at 3-hour intervals for surface variables and 6-hour intervals for three-dimensional variables, covering South America, a part of Central America, and the Caribbean. The bias-corrected dataset was produced at the daily scale, maintaining the same spatial coverage (Figure S1 in the supplementary material) and horizontal resolution as the raw Eta model outputs. This dataset spans from 1976 to 2005, regarded as the historical period or baseline, and from 2006 to 2099, regarded as the future period.

2.2 Observational datasets

Two groups of observational datasets are used in this study. One group is intended to apply bias correction, while the other is intended to validate the correction. Using two distinct groups of observational datasets ensures that the validation step is independent of the correction step. Both datasets were selected considering the availability of daily observation, time series with at least thirty years, and a horizontal resolution closer to or higher than that of the Eta model outputs. Bias corrections were applied to precipitation, potential and actual evapotranspiration, and 2-m air temperature. The potential evapotranspiration output from the Eta model is estimated from the reference evapotranspiration, based on the Penman-Monteith method developed by the Food and Agriculture Organization of the United Nations (FAO) (ALLEN et al. 1998), from now on referred to as PM-FAO56.

The observational datasets used as a reference for model bias correction are comprised of the MSWEP for precipitation, the ERA5-Land for evapotranspiration (actual and potential), and a combination of the BR-DWGD (Brazilian Daily Weather Gridded Data), which covers only the Brazilian territory, and the ERA5 for the rest of model domain for the 2-m temperature. The datasets BR-DWGD for precipitation and potential evapotranspiration, GLEAM for actual evapotranspiration, and SAMeT for 2 m temperature were used to validate the bias-corrected outputs. All datasets were resampled to the same grid and resolution of the Eta model outputs using the native bilinear interpolation function of the GrADS (Grid Analysis and Display System) software. All datasets provide 30 years of data for approximately similar periods, providing robustness and reliability to the analyses, except for the one used for temperature validation (i.e., SAMeT). Table 1 summarizes the datasets used in this work, with additional descriptions presented below.

MSWEP (Multi-Source Weighted-Ensemble Precipitation; BECK et al. 2017) is a global precipitation dataset of approximately 10 km horizontal resolution, spanning from 1979 to the present day with a temporal frequency of 3 hours, daily and monthly, specifically built for hydrological modeling. MSWEP was produced from the combination of rainfall stations, satellite precipitation estimates, and atmospheric reanalysis. Due to its good performance compared to other satellite products and *in situ* data (SUN et al. 2018, MOREIRA et al. 2019), MSWEP has been recommended for use in studies and applications that require high-resolution precipitation data (SATGÉ et al. 2020, CONDOM et al. 2020, BRÊDA et al. 2022), and is therefore chosen to correct the outputs of the Eta model.

The ERA5-Land reanalysis (MUNOZ-SABATER et al. 2021) is a comprehensive dataset that provides surface variables simulated by the offline CHTESSEL land surface model, which

TABLE 1 – Corrected climate variables, data sources used for correction and validation, and availability period.

Climate variable	*Observational datasets for bias correction*	*Period*	*Observational datasets for validation*	*Period*
Precipitation	MSWEP (BECK et al. 2017)	1980-2009	BR-DWGD (XAVIER et al. 2022)	1976-2005
Actual Evapotranspiration	ERA5-Land (MUÑOZ-SABATER et al. 2021)	1981-2010	GLEAM (MIRALLES et al. 2011)	1980-2009
Potential Evapotranspiration	ERA5-Land (SINGER et al. 2021)	1981-2010	BR-DWGD (XAVIER et al. 2022)	1976-2005
2-m air temperature	BR-DWGD + ERA5 (XAVIER et al. 2022, HERSBACH et al. 2019)	1981-2010	SAMeT (ROZANTE et al. 2021)	2000-2005

stands for Carbon Hydrology-Tiled ECMWF (European Centre for Medium-Range Weather Forecasts) Scheme for Surface Exchanges over the Land surface model. The CHTESSEL model is forced by ERA5 reanalysis (HERSBACH et al. 2019) to produce the ERA5-Land dataset. The ERA5-Land dataset, with 9-km spatial resolution and hourly frequency, provides a detailed representation of the Earth's surface, including elevation correction for near-surface temperature. Due to their high spatial resolution and excellent performance, "ERA" reanalysis has been used to remove biases in atmospheric models (JOHNSON et al. 2019, LORENZ et al. 2021). For this reason, ERA5-Land was chosen as a reference to correct the evapotranspiration outputs of the Eta model. Actual evapotranspiration, provided directly by ERA5-Land, is based on the Penman-Monteith method. Potential evapotranspiration was estimated using the PM-FAO56 method, applied to the ERA5-Land variables, as supplied by SINGER et al. (2021).

The BR-DWGD, often referred to as the XAVIER et al. (2022) dataset, has a grid resolution of 0.1° x 0.1° over the Brazilian territory and covers 60 years, from 1961 to 2020. This dataset was used as a reference to perform the temperature correction. Produced from the interpolation of in situ observational data from the National Water and Sanitation Agency (ANA) and the National Institute of Meteorology (INMET), BR-DWGD offers a detailed representation of the Brazilian climate and is widely applied in hydrometeorological and impacts in Brazil (BALLARIN et al. 2023). To complete the coverage of South America, since the BR-DWGD dataset only covers the Brazilian territory, ERA5 reanalysis data were used (HERSBACH et al. 2019). The choice of ERA5 is justified by its superiority in representing the annual 2-meter temperature cycle in the region, compared to other sets such as the CRU (Climatic Research Unit; NEW et al. 1999). The combination of BR-DWGD with ERA5 allowed the construction of a homogeneous and high-quality dataset for South America.

Thus, as mentioned, the corrected Eta model outputs were validated using the BR-DWGD datasets for precipitation and potential evapotranspiration, GLEAM for actual evapotranspiration, and SAMeT for 2-m temperature. Potential evapotranspiration from the BR-DWGD dataset is estimated from a reference crop based on the PM-FAO56 method (XAVIER et al. 2016, XAVIER et al. 2022). In the GLEAM (Global Land Evaporation Amsterdam Model) dataset, evapotranspiration processes are based on the Priestley-Taylor equation, which divides the terrestrial components of evapotranspiration into canopy transpiration, soil and open water evaporation, interception loss, and sublimation (MIRALLES et al. 2011, MARTENS et al. 2017). Each grid box comprises four land cover fractions: bare soil, sparse vegetation, dense vegetation, and open water. The evapotranspiration rate is calculated individually for each type of cover and then added to obtain the grid box value. The Priestley-Taylor equation is used to estimate potential evapotranspiration, which is then adjusted for actual evapotranspiration, considering the type of soil cover and an evaporative stress factor derived from root zone soil moisture and water content of plants. The GLEAM used in this study (v3.3a) has 0.25° of resolution and is composed of daily information from 1980 to the present. SAMeT (South American Mapping of Temperature) is a set of high-resolution daily temperature data (0.05° x 0.05°) covering South America from 2000 to the present day (ROZANTE et al. 2021). The dataset combines information from meteorological stations and satellite products. Additionally, SAMeT incorporates temperature adjustments based on elevation and lapse rate.

2.3 Bias correction method

2.3.1 Applied to the baseline period

In this work, the Empirical Quantile Mapping (EQM) method (BÁRDOSSY & PEGRAM 2011) was selected to correct the bias in the Eta model outputs. EQM is a distribution transformation method that stands out for its effectiveness and broad applicability. Quantile Mapping (QM) methods have the advantage of correcting not only the mean and standard deviation but also higher-order distributional moments, such as skewness and kurtosis (GUDMUNDSSON et al. 2012), which is crucial for the representation of extreme events. Furthermore, EQM does not require assumptions about the data distribution, making it suitable for a wide range of climate variables. Among the QM methods, EQM was selected because of its wide application and good performance in several studies (THEMEßL et al. 2011, CHEN et al. 2013, IVANOV & KOTLARSKI 2017, MENDEZ et al. 2020, YERSAW & CHANE 2024) and ability to preserve the statistical characteristics of the data. In addition, the approach used to correct the future climate, as presented in the following subsection, tends to preserve the trends of the raw projections (BÁRDOSSY & PEGRAM 2011), which is essential for climate change analysis. Although EQM is an effective tool, it is important to note that its performance may vary depending on the characteristics of the data and the specific application (ZHAO et al. 2017). Other QM methods, such as quantile delta mapping (CANNON et al. 2015), scaled distribution mapping (SWITANEK et al. 2017), multivariate quantile delta mapping (CANNON 2018), piecewise-quantile mapping (ZHANG et al. 2022), among others, also have their advantages and may be more appropriate in certain situations. However, EQM was selected for this study due to its flexibility, ease of application, and ability to preserve climate trends, having been successfully applied to the outputs of the regional Eta model in previous studies (MOHOR et al. 2015; MARTINS et al. 2018, 2019, 2023; PAIVA et al. 2024).

EQM is based on constructing empirical cumulative distribution functions (CDFs), which are daily values of observations and model data sets. CDFs are estimated at regularly spaced quantile levels, ranging from 0 to 1. Linear interpolation is applied to obtain the corresponding values for quantile levels that were not directly observed. CDFs are constructed for each grid point and each month of the year. The method assumes that systematic errors are reduced by shifting the distribution curves of the simulations to the same frequency level as the observations. The correction of the simulated variable for the grid point x and day t can be expressed as follows:

$$Z_D(x,t) = F_O^{-1}(F_R(Z_R(x,t),x),x) \qquad (1)$$

Where Z_D is the corrected variable, Z_R is the variable from the model output in the baseline period, and F_O and F_R are the CDFs from observations and model outputs of the baseline period, respectively. The transformation guarantees that if the observation and model output have equal periods, the CDFs from both datasets, i.e., CDF of the observation (F_O) and the CDF of the bias-adjusted model output (F_D), will be equal:

$$F_D(z,x) = F_O(z,x) \qquad (2)$$

2.3.2 Applied to the future period

This work employed the Double Empirical Quantile Mapping (DEQM) approach (BÁRDOSSY & PEGRAM 2011) to correct the climate model outputs in the future part of the dataset. The method assumes that future climate projections have systematic and therefore persistent errors. This approach recognizes the potential for changes in the responses of climate variables from the current climate toward the future climate, implicitly incorporating them into the correction process of the projections. The bias correction process in the DEQM approach is divided into three steps. The first step is to match the future value with the corresponding value of the baseline CDFs. In the second step, the corresponding value's quantile-quantile transform (QQ) is obtained from the horizontal shift at the same quantile level from the baseline CDF to the observational CDF. Finally, in the third step, the same QQ transform is applied to the future value to obtain the final bias-corrected value of the projections. Therefore, the mathematical relationship for applying the correction of the future projections for the grid point x and day t is given by equation (3), illustrated in figure 1.

$$Z_{DF}(x,t) = F_O^{-1}(F_R(Z_{RF}(x,t),x),x) \qquad (3)$$

Where Z_{DF} is the bias-corrected value of a variable in the future climate projections, Z_{RF} is the original value in the future climate projections, and F_O and F_R are, respectively, the CDFs of the observations and simulations of the baseline period.

2.4 Assessment of precipitation extremes

To gain a more comprehensive understanding of the precipitation extremes reproduced by the Eta ensemble in Brazil, six precipitation extreme indices defined by the ETCDDI (Expert Team on Climate Change Detection and Indices; KARL et al. 1999, PETERSON et al. 2001) were estimated to provide information on the extreme precipitation events' frequency, intensity, and duration. The indices are the number of consecutive dry and consecutive wet days (CDD and CWD, respectively); the total annual precipitation on very rainy and extremely rainy days (R95p and R99p, the 95th percentile and the 99th percentile of the daily precipitation distribution); and maximum 1-day and maximum 5-day precipitation (RX1day and RX5day).

These indices were calculated from the Eta model, raw and bias-corrected datasets, and

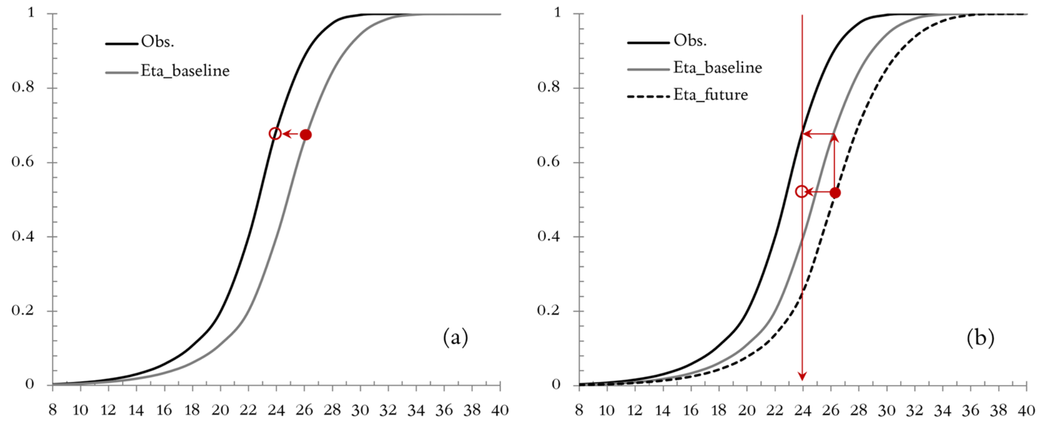

FIGURE 1 – A sketch of the quantile-quantile transform applied to the baseline climate (a) and the double quantile-quantile transform applied to the future climate (b), both based on Bárdossy and Pegram (2011). The CDF curves are fitted to the same level as the observational frequency in the baseline climate transform. In the double transform for future climate, a future frequency distribution function is related to the observational CDF through the corresponding CDF of the Eta model obtained from the baseline period. The Eta future point (closed red circle) is paired with the same value in the Eta baseline CDF. The point is shifted at the same quantile level toward the observational CDF and back to the same quantile level in the future value. The result is the point on the open circle, preserving the probability of the shifted value.

the BR-DWGD observational dataset used for validation. An additional precipitation dataset, the NEX-GDDP dataset (NASA Earth Exchange Global Daily Downscaled Climate Projections; THRASHER et al. 2012), was included for comparison. The NEX-GDDP ensemble is derived from the statistical downscaling of CMIP5 (Coupled Model Intercomparison Project version 5) global model simulations. The horizontal resolution is 0.25° x 0.25°.

AVILA-DIAZ et al. (2020) analysis showed that the climate indices from the NEX-GDDP ensemble performed better than the raw Eta ensemble. The extreme precipitation indices from NEX-GDDP were included in the analyses by taking the average of the four best models, according to AVILA-DIAZ et al. (2020): the CNRM-CM5, CCSM4, MRI-CGCM3, and CESM1-BGC. The same period of the Eta dataset was considered, 1976-2005.

3 RESULTS AND DISCUSSION

3.1 Evaluation of the baseline period dataset

The Eta simulations before the bias correction are referred to as the raw dataset; in contrast, the Eta ensemble simulations with bias correction are referred to as the bias-corrected dataset. The bias correction was applied to each member of the ensemble. The evaluation was based on the ensemble mean of the Eta simulations driven by the four CMIP5 global climate models for the historical, or baseline, period between 1976 and 2005. The averages are further taken for the model grid points over the Brazilian territory. Despite the technique being applied over the entire continental domain, as shown in figure S1, the evaluation is shown over the Brazilian territory.

3.1.1 Annual mean

Figure 2 shows the annual mean of precipitation, actual and potential evapotranspiration, and 2-m temperature for the baseline period. The bias correction applied to precipitation more adequately adjusts its spatial pattern throughout Brazil, mainly in the central and eastern Amazon, where without the correction, the simulated precipitation ranged from 30% to 60% less than observed precipitation records. This adjustment is significant since Amazon rain is essential in maintaining atmospheric moisture in the region that is transported to the south and southeast of the South American continent (*e.g.*, MARTINEZ & DOMINGUEZ 2014). A significant reduction in precipitation errors in some coastal regions stands out, such as in the northernmost part of the Amazon, the coastal areas in Southeast Brazil, and South Brazil. This improvement is produced by the more refined spatial resolution of the observational database to correct precipitation. The Percentage

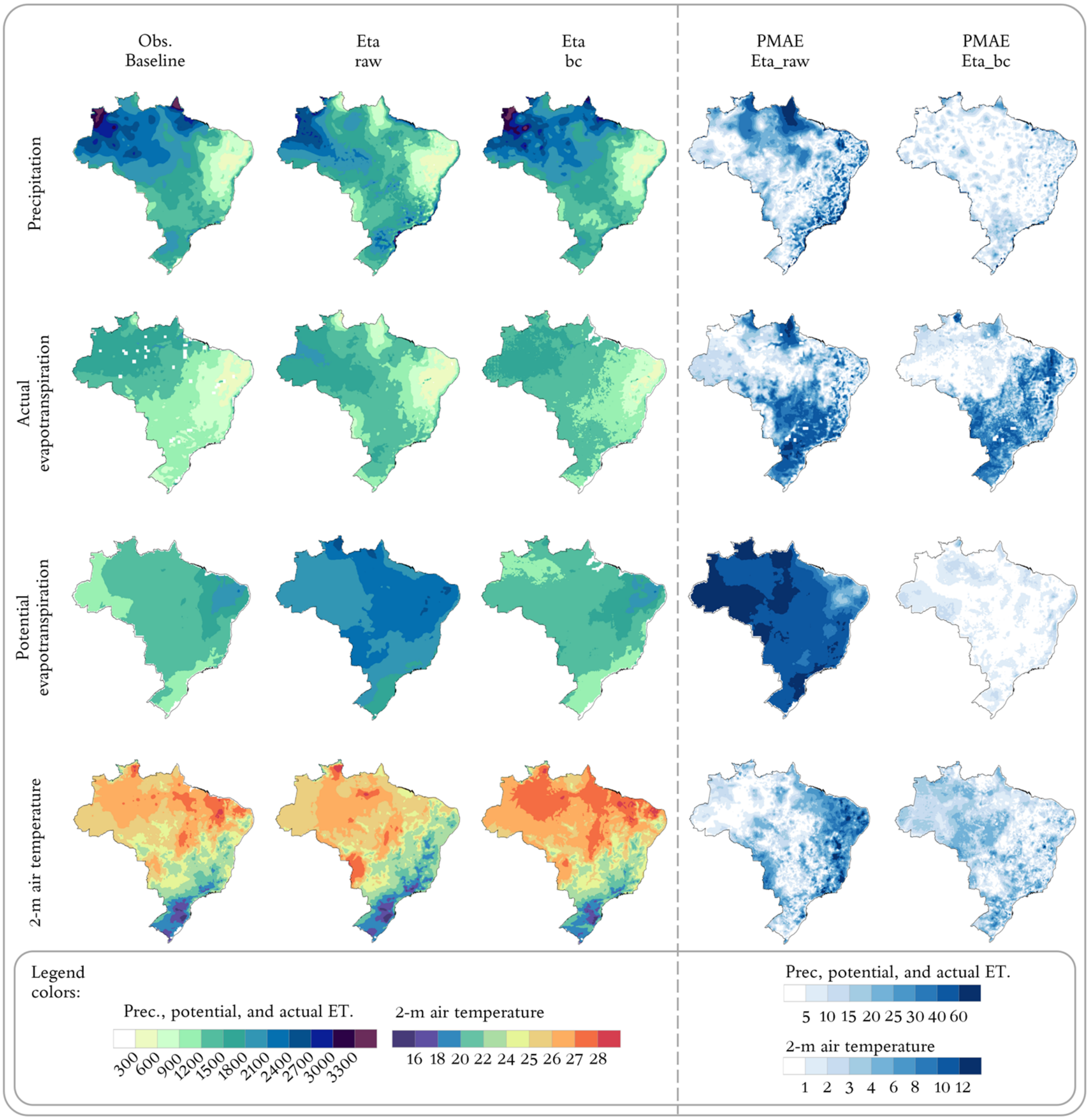

FIGURE 2 – Annual total precipitation (from the top, first row), actual evapotranspiration (second row), potential evaporation (third row) in mm/year, and annual mean 2-m temperature (fourth row) (°C). From the left, the observations (first column), Eta simulations (second column), and Eta simulations after bias correction (third column). The two rightmost columns are the Percentage Mean Absolute Error (PMAE) of the Eta simulations (fourth column) and the Eta simulations after bias correction (fifth column).

Mean Absolute Errors (PMAE) of the precipitation simulations confirm that applying bias correction to the Eta simulations dataset improves precipitation patterns by reducing errors throughout Brazil.

After applying bias correction, the pattern of real evapotranspiration simulated by the Eta model generally agreed with the GLEAM dataset, especially in Brazil's North, Southeast, and Central-West regions. The PMAE was significantly reduced in these areas. However, a small increase in PMAE was noted in the Northeast of Brazil after bias correction. This result can be explained by the differences between the real evapotranspiration estimates between the GLEAM dataset and the ERA5-land reanalysis, used as a reference for bias correction. After bias correction using the EQM method, the climatological pattern of the corrected dataset presents the same pattern as the reference set used for correction, as shown in figure S2 (supplementary material). The differences between the GLEAM and ERA5-Land datasets can be attributed in part to the different methods used for estimating actual evapotranspiration (Priestley-Taylor vs. Penman-Monteith), as well as the different spatial resolutions adopted (25 km vs. 9 km).

Uncertainties in the estimates of actual evapotranspiration from different global datasets, which result in significant variations in the values obtained, have also been pointed out in other studies (SÖRENSSON & RUSCICA 2018, ELNASHAR et al. 2021, RUHOFF et al. 2022). In South America, RUHOFF et al. (2022) compared eight global products and noticed more uncertainties among those datasets derived from remote sensing, such as the GLEAM dataset. The reduction of the actual evapotranspiration PMAE would be more robust if the SGAE dataset (Synthesis of Global Actual Evapotranspiration; ELNASHAR et al. 2021) were used for validation (Figure S2). SGAE is a product constructed from twelve global actual evapotranspiration datasets, so it carries a relatively lower uncertainty. However, the SGAE dataset is only available on a monthly mean basis; therefore, it did not fulfill the requirement for this study.

Unlike actual evapotranspiration, applying bias correction to potential evapotranspiration resulted in a substantial reduction of approximately 40% across the entire Brazilian territory, as indicated by the PMAE. The original error in the raw dataset was due to excessive potential evapotranspiration. This reduction in error is especially relevant in tropical regions such as the Amazon, where potential evapotranspiration should be lower than precipitation and closer to actual evapotranspiration (ZHANG et al. 2001). The relationship between these water balance components is improved after the application of bias correction, thus demonstrating the importance of adjusting the outputs of numerical models. The accurate representation of the climatic characteristics of precipitation in South America, especially in the Amazon, is a recurring challenge for regional and global climate models. As demonstrated by Eta model simulations, the underestimation of precipitation in the tropical region is a common pattern (YIN et al. 2013, GULIZIA & CAMILLONI 2014, ALMAZROUI et al. 2021, ORTEGA et al. 2021, DIAS & REBOITA 2021, OLMO et al. 2022, BRESCIANI et al. 2023). The combination of dynamic and statistical downscaling is promising in generating more accurate model-derived datasets and reducing errors in the water balance components. This improvement has significant implications for projecting extreme events such as droughts and floods, which can contribute to more efficient water resource planning, especially in regions with high water vulnerability. However, it is important to emphasize that bias correction is a complementary statistical tool and that continuous improvement of climate models is essential for a more physically based reproduction of the climate system. This is particularly crucial in complex regions such as the Amazon, where the interaction between atmosphere, vegetation, and soil plays a fundamental role in the hydrological cycle.

The raw dataset of the Eta simulations reproduces the annual mean 2-m temperature pattern in Brazil, with warmer air towards the Equator, cooler air towards the extratropic, and the topographic features revealed by the cooler air. However, in most of Brazil, the raw dataset has a cold bias, which was reduced by about 10%, especially in the eastern part, such as Northeast Brazil.

3.1.2 Annual cycle

The raw dataset of the Eta simulations shows a small amplitude in the precipitation annual cycle. The bias correction technique increases the precipitation amount during the rainy season, from November until April, and reduces the precipitation overestimated during the dry season, from June until August (Figure 3a). The bias-corrected precipitation annual cycle overlays the MSWEP and the BR-DWGD observed precipitation cycles.

The raw dataset of the Eta simulations of the actual evapotranspiration shows overestimates (Figure 3b). The technique corrects the annual cycle by reducing the overestimates from July until September. It may appear that the technique has failed to remove the bias from October to March, as the raw Eta simulation of actual evapotranspiration more closely matches the observational cycle; however, this reveals the uncertainty of the observational datasets of actual evapotranspiration. The annual cycle of actual evapotranspiration from the ERA5-land dataset, used for correction, disagrees with the cycle of the GLEAM dataset, used for validation. Despite the uncertainties, the amplitude of the annual cycle of the bias-corrected actual evapotranspiration has improved over the raw actual evapotranspiration.

Unlike the actual evapotranspiration, the raw Eta simulations of potential evapotranspiration practically show constant overestimates in all months of the year (Figure 3c). This discrepancy can be attributed, in part, to the systematic errors

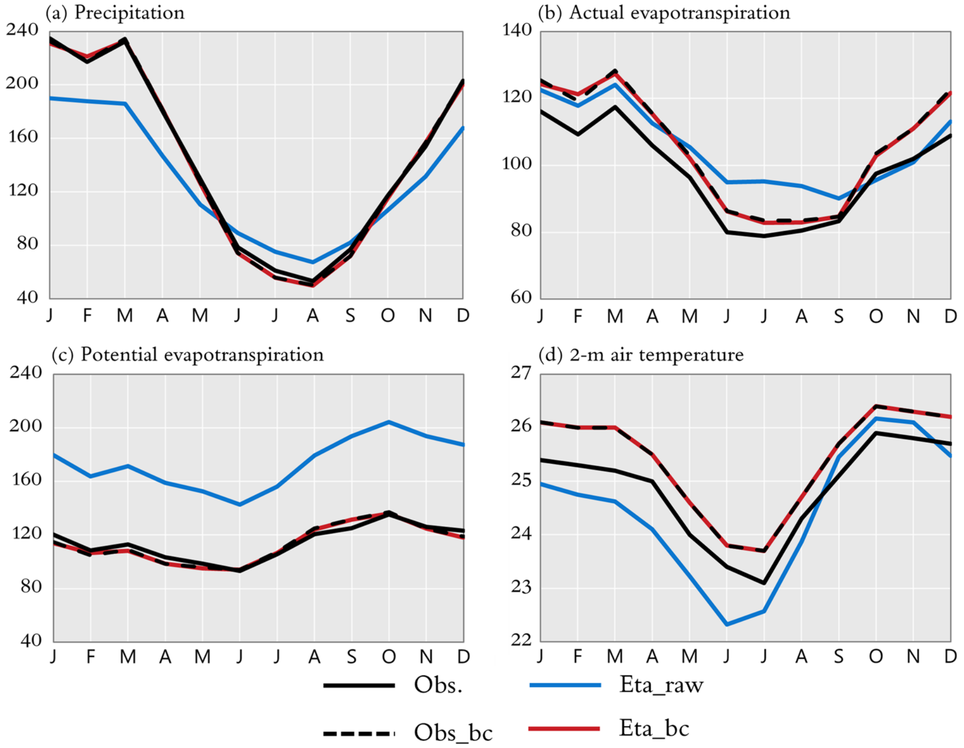

FIGURE 3 – Annual cycle of (a) Precipitation (mm/month), (b) Actual Evapotranspiration (mm/month), (c) Potential evapotranspiration (mm/month), and (d) 2-m temperature (°C). Black curves refer to the monthly mean of the observations for validation (Table 1), solid blue lines refer to the Eta ensemble mean simulations, and solid red lines refer to the simulations after bias correction. The observations used for bias correction of the Eta ensemble are also presented (dashed black curves). Mean values are taken over the Brazilian territory.

of the variables input to the Penman-Monteith-FAO56 method, such as solar radiation, which is overestimated by the Eta model, as demonstrated by CAMPOS et al. (2018). However, after applying the bias correction, the annual cycle of potential evapotranspiration simulated by Eta shows a better agreement with the annual cycle observed in the GLEAM dataset, indicating that the correction effectively reduced systematic discrepancies.

The raw Eta simulations of 2-m temperature show a larger annual cycle amplitude than the SAMeT observational dataset. The bias-corrected Eta simulation of 2-m temperature shows an annual cycle closer to the SAMeT dataset, particularly between April and August. However, it tends to overestimate the temperature in the other months, characteristics passed by the observational set used to correct the model (dashed black curve). The two observational 2-m temperature datasets, BR-DWGD and SAMeT, exhibit discrepancies throughout the year.

Additionally, one aspect to be considered in the analyses of annual cycles is that the approach used by the EQM method to apply the correction for the present climate, by ensuring the preservation of the observational mean values (Equation 2), leads, at the climatological scale, to the loss of variability between the different members of the Eta ensemble. This loss of variability results in almost identical annual climatological cycles of the corrected models, which can lead to an overestimation of the confidence in the analyses, as evidenced in figure S3 of the supplementary material.

3.1.3 Frequency distribution and extreme indices

The frequency distributions of the daily precipitation, actual and potential evapotranspiration, and 2-m temperature in Brazil are shown in figure 4. The frequency is on the main y-axis, while the PMAE is on the secondary y-axis. To highlight the extreme values of the distributions, both the main and secondary axes were plotted on a logarithmic scale. The frequency distributions of the two observational datasets enable comparisons against the bias-corrected Eta distributions and show the

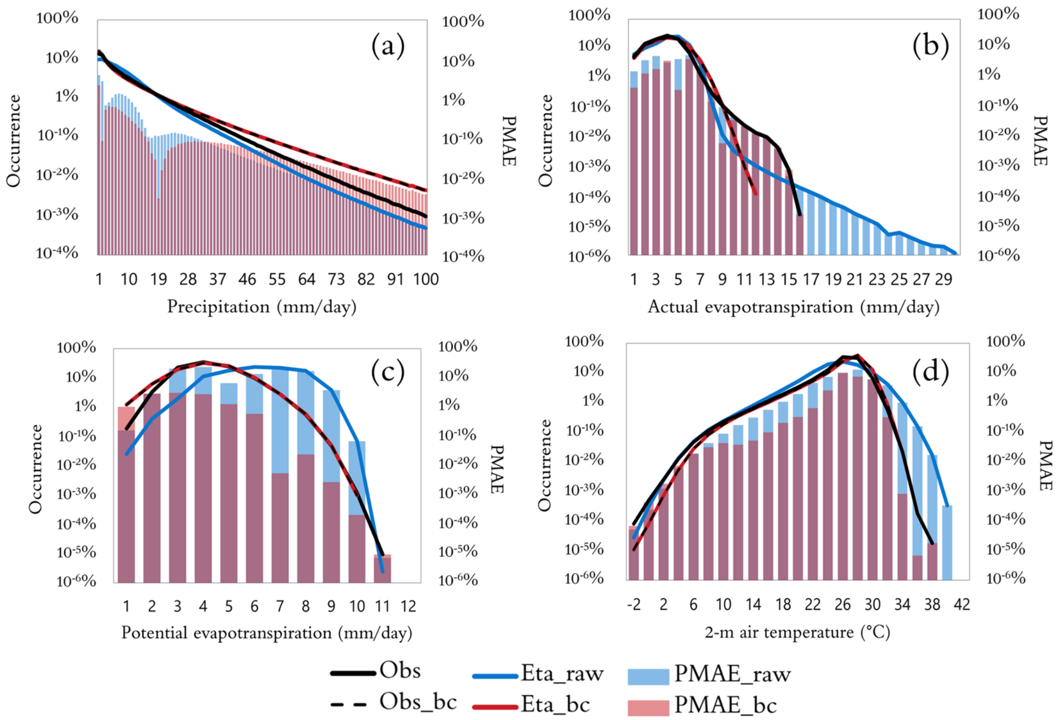

FIGURE 4 – Frequency distribution of daily values (%) of precipitation (mm/day) (a), actual evapotranspiration (mm/day) (b), potential evapotranspiration (mm/day) (c), and 2-m temperature (°C) extracted from Eta model simulations over Brazil, before (Eta_raw, blue bars) and after bias correction (Eta_bc, red curve). The observational dataset used for bias correction of the Eta ensemble (Obs_bc, black dashed curve) is shown underlying the Eta_bc curves. The secondary axis of the ordinates (the right axis) shows each variable's mean absolute percentage error (PMAE). The primary and secondary axes of the ordinates are on a logarithmic scale

observational dataset's uncertainty in a frequency distribution.

The bias-corrected distributions showed significant changes in the frequency of daily precipitation (Figure 4a), evapotranspiration (Figure 4b, c), and air temperature (Figure 4d) in Brazil, providing a better fit to the observed curve. This improvement is seen in reducing PMAE bars in the bias-corrected Eta dataset for all the analyzed variables. The frequency distribution of potential evapotranspiration, previously more frequent in higher values (6-8 mm/day), approached the observed distribution after correction, with the most frequent values occurring between 3 and 4 mm/day. Air temperature also showed a substantial adjustment, with the most frequent values varying from 24-26°C to 26-28°C, better aligned with the observations. The actual evapotranspiration agreed with observations for the most frequent values but overestimated extreme events, with values above 17 mm/day. The correction contributed to a better representation of these extreme events. Despite the gains of the correction, it is important to highlight that there are still observational uncertainties, especially the extremes of the distributions (maximum values), not only for real evapotranspiration but also for the other analyzed variables.

It should be noted that the bias correction applied to precipitation caused an increase in the frequency of daily precipitation above 33 mm. This more frequent heavy precipitation is a feature inherited from the MSWEP observational dataset used for correction. It is known that remote sensing-based or merged rainfall observational products (remote sensing + in situ data and atmospheric reanalysis), such as MSWEP, tend to diverge from in situ-only datasets at finer temporal scales (BAEZ-VILLANUEVA et al. 2021, SAPUCCI et al. 2022, GEBRECHORKOS et al. 2023, ZHANG et al. 2023). Furthermore, the divergence can also be attributed to the observational uncertainty of the datasets used for validation, such as the BR-DWGD, which is composed exclusively of in situ measurements. Given the vast territorial extension of Brazil and the low density of monitoring stations across the country (SALIO et al. 2015, XAVIER et al. 2021), especially given the relatively small spatial scale of the most intense rainfall events, it is probable that the most intense events may be missed by in situ measurements of a low-density observational network or smoothed by the interpolation method used to construct the gridded dataset. Despite the differences found, the choice for the MSWEP dataset for bias correction in this work is supported by its generally relatively superior performance compared to other rainfall products such as CHIRPS, TRMM, and CMORPH (BAEZ-VILLANUEVA et al. 2018, MOREIRA et al. 2019, BETTOLI et al. 2021, SAPUCCI et al. 2022).

Figure 5 presents six extreme precipitation indices to assess the Eta model's ability to represent

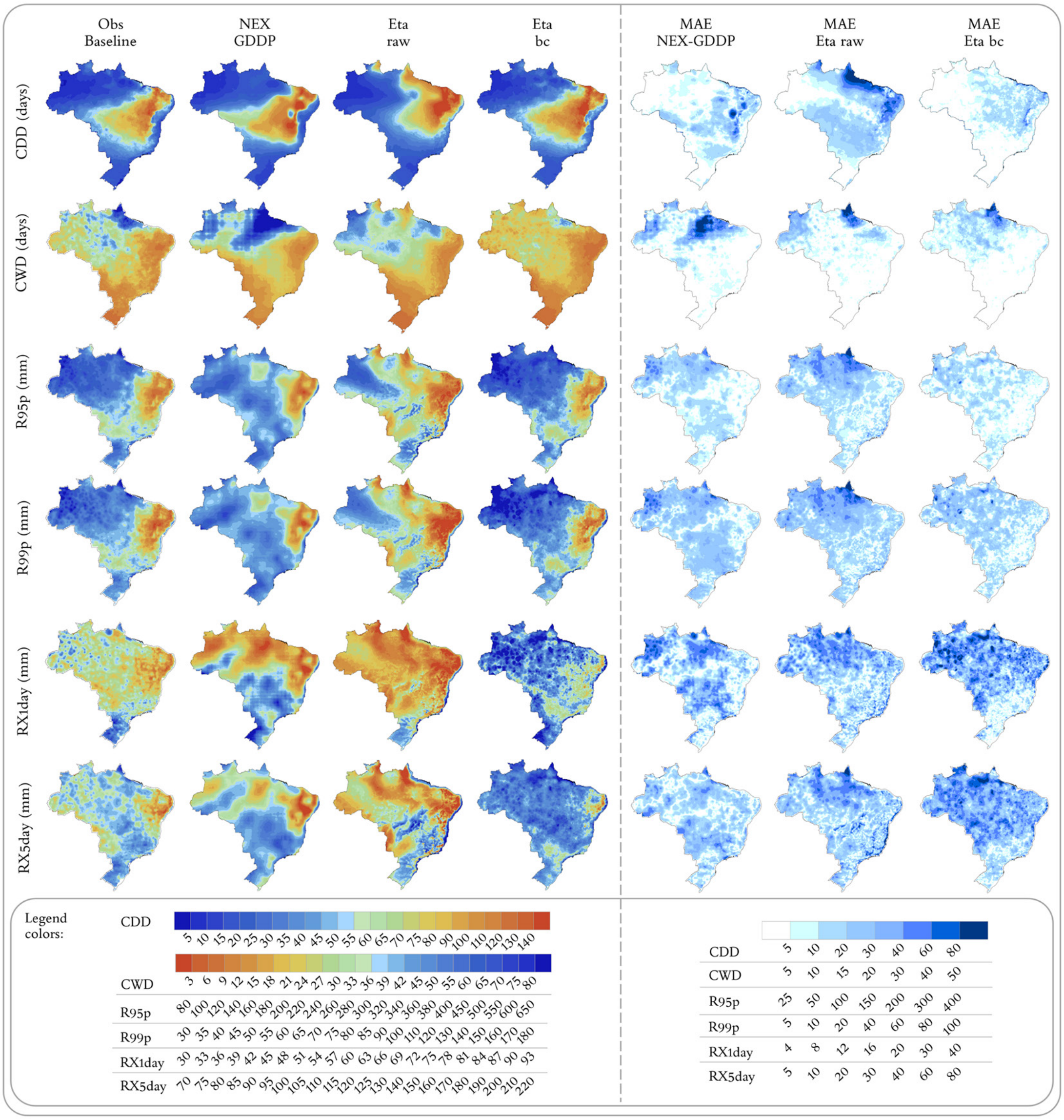

FIGURE 5 – Indices of the annual precipitation extremes averaged over the period 1976-2005, from left to right: the observational BR-DWGD dataset (first column), simulated by the NEX-GDDP datasets (NASA Earth Exchange Global Daily Downscaled Projections; second column) and simulated by the Eta model raw dataset (third column) and Eta simulations bias corrected dataset (fourth column). The three columns on the rightmost are the mean absolute error (MAE) of the NEX-GDDP dataset, Eta raw dataset, and bias-corrected dataset. The extreme indices are the consecutive dry days (CDD; days; first line), consecutive wet days (CWD; days; second line), the 95th percentile of daily precipitation or very wet day precipitation (R95p; mm; third line), the 99th percentile of daily precipitation or extremely wet day precipitation (R99p; mm; fourth line), maximum 1-day precipitation (RX1day; mm; fifth line) and maximum 5-day precipitation (RX5day; mm; sixth line).

extreme precipitation events in Brazil after bias correction. This figure includes not only the raw and bias-corrected datasets from the model and the BR-DWGD observational data but also the extreme precipitation indices averaged from four models from the NEX-GDDP ensemble, which have shown excellent performance for Brazil (AVILA-DIAZ et al. 2020).

The bias correction applied to the Eta simulations produced substantial added value in the annual indices of the duration of consecutive dry days (CDD) and total precipitation of very wet and extremely wet days (R95p and R99p), showing a spatial pattern similar to the observations and a significant reduction in the mean absolute error (MAE). As for the duration of consecutive wet days (CWD) index, although there are some pattern discrepancies, the bias-corrected Eta dataset has smaller errors than the raw Eta dataset, particularly in some areas of North Brazil. As for the maximum precipitation indices in one day (RX1day) and five consecutive days (RX5day), the bias correction did not significantly improve over the raw data. However, the lack of added value can be attributed to large differences in the observations to sample these extremes in the datasets used for correction (MSWEP) and validation (BR-DWGD). After correction, the values of the climate indices in the Eta ensemble tend to be close to or equal to those in the MSWEP ensemble (Figure S4 in the supplementary material).

Comparison between the raw Eta and NEX-GDDP datasets shows that performance varies significantly depending on the climate extreme index analyzed. The errors in the CDD of the raw Eta dataset are larger than those in the NEX-GDDP dataset, on the other hand, the errors in the CWD are smaller in the raw Eta dataset. For R95p, R99p, RX1day, and RX5day, the errors in the raw Eta and NEX-GDDP datasets are comparable in magnitude. The choice of the most appropriate ensemble depends on the specific application and the study area. However, it is essential to consider that, as shown previously, errors also result from the uncertainty of the observational dataset. Therefore, selecting a single ensemble as the "best" for all situations should be done cautiously, as it may not capture the uncertainties. In this sense, it is important not to neglect the different datasets available for Brazil, given that high-resolution simulations for the country are limited.

The comparison between the raw and bias-corrected Eta simulations and the NEX-GDDP dataset in reproducing the precipitation extremes in Brazil is shown in table 2. The mean error and the pattern correlation show that the bias-corrected Eta dataset significantly improved the extreme indices CDD, CWD, R95p, and R99p over the raw Eta and showed superior performance compared to the NEX-

TABLE 2 – Mean values, mean absolute errors, and pattern correlations of annual extreme precipitation indices over Brazil of the NEX-GDDP datasets, Eta raw simulations dataset, and Eta bias-corrected simulations concerning the BR-GWGD dataset for 1976-2005. The best-performing metrics are highlighted in bold. The extreme indices are the consecutive dry days (CDD; days), consecutive wet days (CWD; days), the 95th percentile of daily precipitation or very wet day precipitation (R95p; mm), the 99th percentile of daily precipitation or extremely wet day precipitation (R99p; mm), the maximum 1-day precipitation (RX1day; mm), and the maximum 5-day precipitation (RX5day; mm).

Index	*Evaluation Metric*	*BR-DWGD*	*NEX-GDDP*	*raw Eta*	*bc Eta*
	Mean value	42.5	45.8	47.9	48.7
CDD	MAE	---	9.3	18.9	**6.9**
	Pattern correlation	---	0.9	0.7	**1.0**
	Mean value	25.8	33.1	26.9	19.4
CWD	MAE	---	9.6	6.8	**6.6**
	Pattern correlation	---	**0.8**	0.6	**0.8**
	Mean value	335.7	336.8	275.3	389.2
R95p	MAE	---	62.1	91.4	**44.4**
	Pattern correlation	---	0.7	0.7	**0.9**
	Mean value	102.6	101.0	77.5	116.9
R99p	MAE	---	23.7	27.5	**17.0**
	Pattern correlation	---	0.5	0.7	**0.9**
	Mean value	56.8	55.5	44.8	73.4
RX1day	MAE	---	**12.7**	13.4	16.8
	Pattern correlation	---	0.3	**0.6**	0.5
	Mean value	126.5	128.3	110.9	157.4
RX5day	MAE	---	**17.3**	23.9	32.6
	Pattern correlation	---	**0.5**	**0.5**	**0.5**

GDDP dataset. On the other hand, for the remaining two indices, RX1day and RX5day, the NEX-GDDP dataset has smaller errors; however, their pattern correlations are equally low or even lower when compared with the Eta datasets.

3.2 Assessment of the bias-corrected future period dataset

After applying the bias correction technique to climate projections, a question arose: will the corrections alter the sign of the change in the projected climate? Figure 6 shows the changes in annual precipitation, actual evapotranspiration, potential evapotranspiration, and 2-m temperature between the two climate periods 2041-2070 and 1976-2005 under the two scenarios RCP4.5 and RCP8.5.

After the bias correction in both RCP scenarios, the reduction in annual precipitation in most parts of the country has weakened. The area of

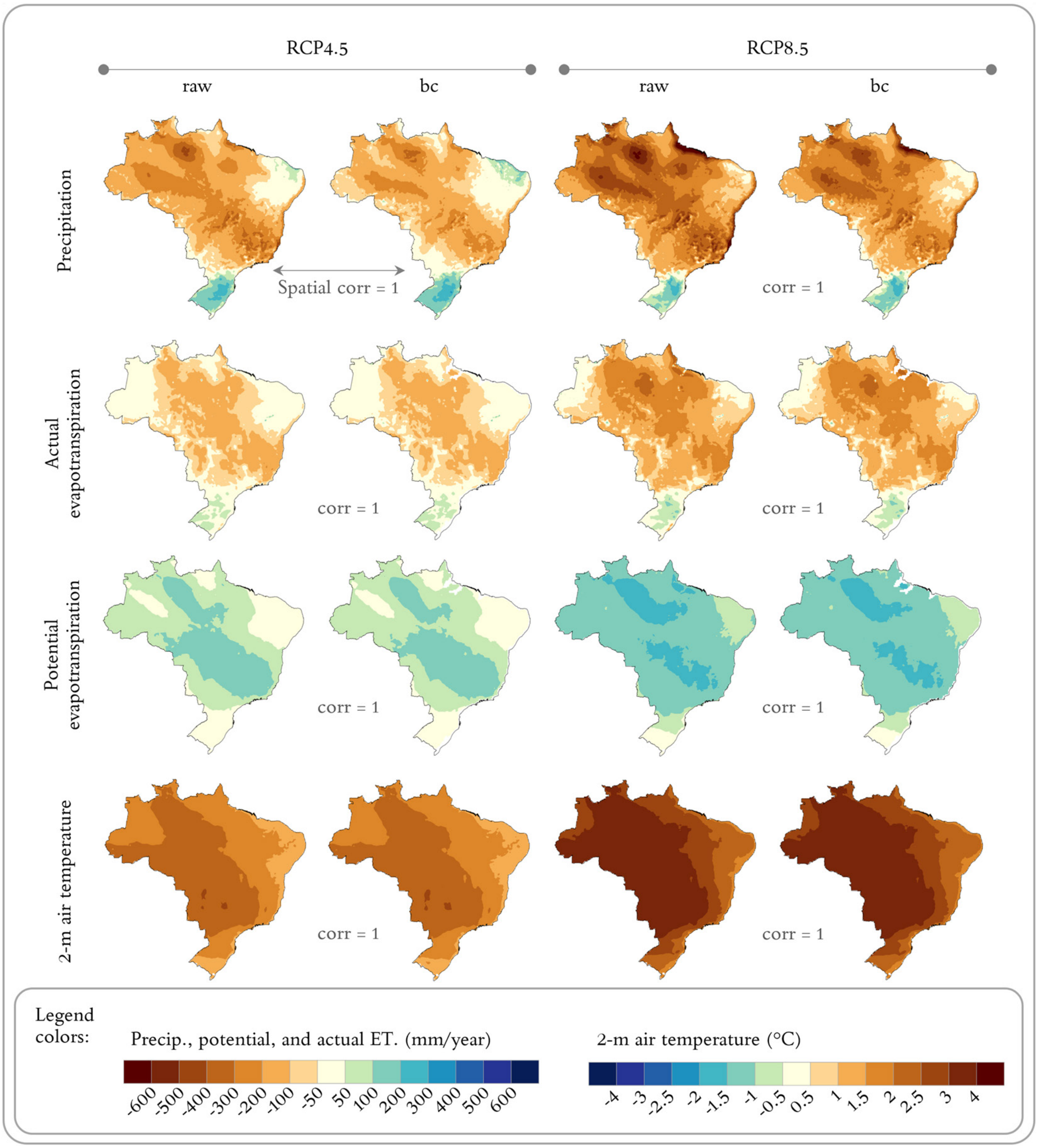

FIGURE 6 – Changes in annual precipitation (mm), actual evapotranspiration (mm), potential evapotranspiration (mm), and 2-m temperature (°C) between the future 2041-2070 and the historical 1976-2005 for the bias-corrected (bc) and uncorrected dataset (raw), average over the downscaling of the four global climate models. The pattern correlation (corr) between the raw and bc changes equals 1 in all variables and scenarios.

precipitation reduction in the raw dataset also shrank slightly in the bias-corrected dataset, leaving some areas of practically no change between the climate periods. In the northern part of Northeast Brazil, a small area of increase in precipitation has expanded in the bias-corrected dataset. In South Brazil, an area of increase in precipitation has no clear change from the raw to the bias-corrected dataset in both RCP scenarios.

Under RCP4.5, the areas of reduction in the annual actual evapotranspiration in most parts of the country show a weaker reduction. Similarly, the areas of increase in actual evapotranspiration in South Brazil also show a weaker reduction under RCP4.5. However, under RCP8.5, one can hardly notice any change after applying the bias correction. For potential evapotranspiration, the patterns of changes show no clear modification after applying the bias correction under both RCP scenarios. The spatial pattern of changes in temperature remains practically unchanged, as warming is expected everywhere in Brazil. The pattern correlation between the changes in the raw and the bias-corrected datasets is 1 for all four variables and RCP scenarios.

Another question that may arise after the bias correction of climate projections is whether the corrections alter the rate of the changes imposed by the RCP scenario trajectories. Figure 7 shows the time series of the mean annual 2-m temperature in

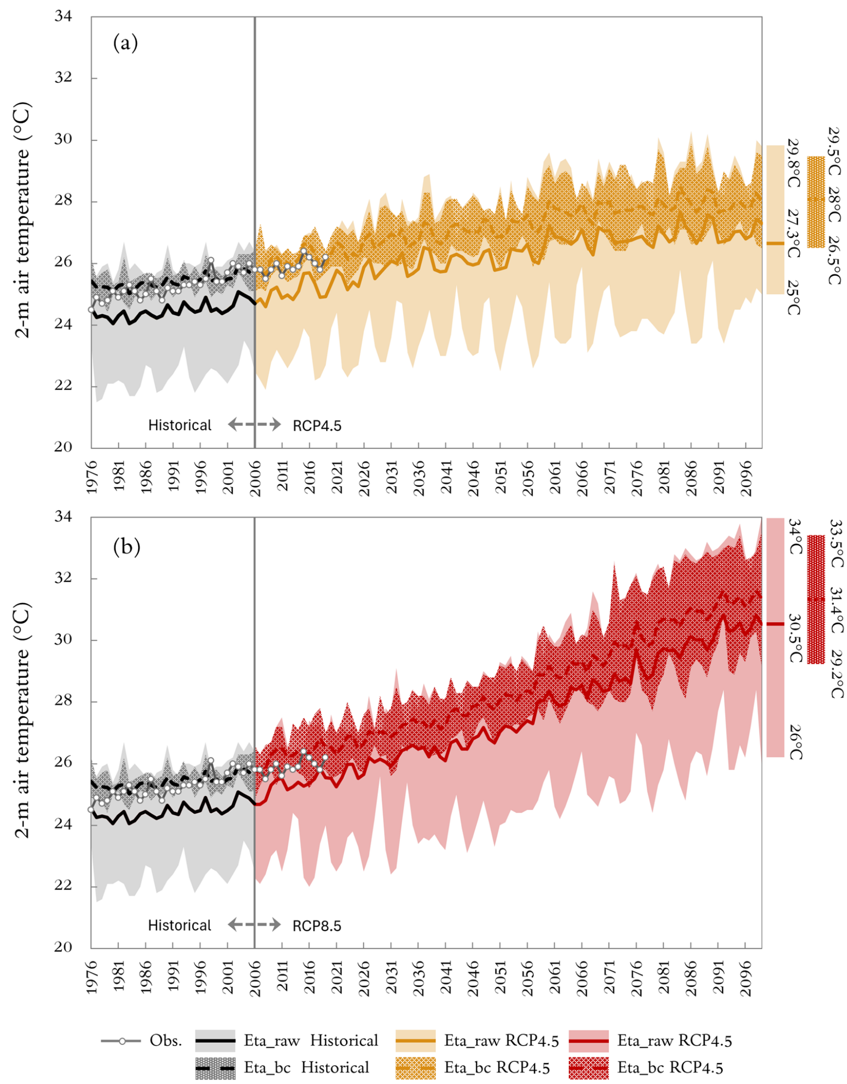

FIGURE 7 – Time series of the mean annual 2-m temperature (°C) in Brazil, obtained from simulations (gray line) and projections (RCPs scenarios) of the Eta model dataset, raw and bias-corrected, together with the annual mean values and the trend of observed values.

Brazil for the historical and future periods under RCP4.5 and RCP8.5. In the historical period, the raw dataset clearly shows a cold bias, which is substantially reduced after the bias correction is applied. After the correction, the model simulations more accurately reflected the observed historical trend. The reduction in the dispersion in the simulated values, evidenced by the gray-hatched plume, confirms the decrease in uncertainty in the simulations. This reinforces the quality of the model fit and suggests greater reliability in the projections of future scenarios. For the future period, a higher rate of warming is demonstrated in the scenarios projected with bias removal, reaching an annual mean value at the end of the 21st century of 28°C in the RCP4.5 scenario and 31.4°C in the RCP8.5 scenario. Furthermore, it is interesting to note that after 2005, in the future period, observations closely follow the corrected temperature trend of the RCP4.5 scenario.

4 CONCLUSIONS

The downscaling Eta simulations and projections driven by four CMIP5 global climate models contain errors like general numerical models. Impact models, such as crop and hydrological models, may use the Eta simulations and projections to drive their runs, which may have errors amplified in their outputs. Since the impact models are generally calibrated using observational datasets, bias-corrected climate model outputs to drive the impact models may result in smaller errors from the latter models. This work aimed to describe the bias-corrected dataset constructed from the Eta model ensemble simulations and projections that is, historical and future periods, driven by four CMIP5 global climate models. The future assumed two scenarios of greenhouse gas concentrations, RCP4.5 and RCP8.5.

The empirical quantile mapping technique reduced the errors in the precipitation pattern, potential evapotranspiration, and 2-m temperature simulations. The reduction of the errors in the actual evapotranspiration simulations was mainly limited to the eastern part of Brazil. The overall cold temperature bias was substantially removed.

The annual cycle of these variables showed substantial improvement after the bias correction. The too-small amplitude of the precipitation cycle and the too-large amplitude of the 2-m temperature cycle were corrected, and the bias-corrected cycle of these variables closely followed the observations. The apparently less efficient bias correction of actual evapotranspiration highlights the large uncertainty in the observational datasets containing this variable.

The frequency distribution of daily precipitation, potential and actual evapotranspiration, and 2-m temperature showed that the bias-corrected Eta dataset was significantly improved over the raw Eta, especially in reproducing the most frequent daily values. However, for precipitation, the bias-corrected dataset overestimated the frequency of the intense precipitation rates, inheriting the characteristics of the dataset used for the correction. This overestimation showed observational uncertainty, especially for daily rates above 33 mm/day. This uncertainty was also present in the bias correction of extreme precipitation indices RX1day and RX5day. Clearly, the bias correction produced significant gains in the CDD, CWD, R95p, and R99p indices over the raw Eta datasets.

The bias corrections were also applied to the projections of the future climate. For future datasets, the changes in the frequency distribution between the future and present climate are considered in the bias correction. The bias correction applied to the future projection datasets showed that the signs of the changes in the raw Eta simulations were mostly kept; however, the magnitude of the changes was generally reduced. The rate of changes in the RCP8.5 is generally larger than in the RCP4.5 scenarios. After the bias correction application, the rate of the changes of the climate variables was kept in the projections.

The described dataset is freely available from the CNPq LattesData repository at https://doi.org/10.57810/lattesdata/WAVGSL (TAVARES et al. 2023).

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