v. 4, n. 5, 2024

Journal of Agricultural Sciences Research

DEVELOPMENT OF AN ASSEMBLED MODEL FOR THE PROJECTION OF CLIMATE CHANGE IN THE ENDORHEIC BASIN OF THE BOLIVIAN ALTIPLANO: EVALUATION AND VALIDATION OF HISTORICAL TEMPERATURE SIMULATIONS OF CMIP6 MODELS

Chapi Siñani Neftalí
Doctorate in Agricultural Sciences, Faculty of Agronomy, ``Universidad Mayor de San Andrés`` (UMSA)

Paola Alejandra Padilla Medina
National Fund for Comprehensive Development (FONADIN), Ministry of Rural Development and Lands (MDRyT)

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Abstract: The study evaluated and validated the historical temperature simulations of the CMIP6 models for the Endorheic Basin of the Bolivian Altiplano, using data and products from the Bolivian climate grid called GMET. Global and regional climate models were evaluated, and statistical bias correction techniques were applied to improve the quality of the simulations. The five best performing regional models were selected to generate temperature projections up to 2100, and the REA method was used to assemble (combine) the predictions from different individual models to improve accuracy and reduce uncertainty. Scenerys SSP2-4.5 and SSP5-8.5 were selected to carry out climate change projections in the basin. The results showed that the seven models evaluated have a good capacity to simulate the temperature in the basin, although there are significant differences in their individual performance. The GFDL, CNRM, MIROC, NorESM and HadGEM models perform best in simulating the historical temperature of the basin. The REA ensemble model shows a significant increase in minimum, mean, and maximum temperatures through 2100 under Scenerys SSP 245 and 585, with steeper projections for the high-emissions Scenery (SSP 585). However, there are limitations and differences in the models used, making it necessary to continue research and monitoring to understand and address climate changes in the basin.
Keywords: CMIP6; RCM; SSP; temperature; REA

INTRODUCTION

The Endorheic Basin of the Bolivian Altiplano is a region highly vulnerable to climate change, due to its high sensitivity to changes in temperature and precipitation. It is characterized by being an arid and semi-arid region, with a high sensitivity to seasonal climate variations (Cruz Fuentes, 2011). In this context, it is essential to have reliable future temperature projections for decision-making in adaptation to climate change (UNDP, 1990, Drenkhan et al., 2023). To better understand the impacts of climate change in the region, it is crucial to evaluate the ability of climate models to simulate historical climate and project future conditions.

Global Coupled Climate Models (GCM) are mathematical tools that represent the physical, chemical and biological processes that regulate the Earth's climate. These models are used to understand the past, present and future behavior of the climate. However, GCMs have limitations in representing small-scale processes, which can affect their ability to simulate climate in complex and specific regions (Flato & Marotzke, 2013). To address this limitation, Regional Climate Models (RCMs) were developed, which were designed to simulate climate at more specific spatial scales.

The Coupled Model Intercomparison Project Phase 6 (CMIP6) represents a significant advance in global climate modeling, with a new generation of GCMs offering greater resolution and complexity compared to previous versions. The regional database of the NEX-GDDP project presents climate change RCMs that have been generated from the results of the CMIP6 GCMs, using statistical and dynamic scaling techniques (NASA, 2024).

The validation of reliable climate change projections for the Endorheic Basin of the Bolivian Altiplano is a complex challenge due to the lack of robust evaluations of these CMIP6 RCMs. Additionally, the region's complex topography and variety of physical processes, including the interaction between atmospheric systems and the paucity of reliable observational data, limit the ability of models to simulate historical climate and project future conditions accurately (IWRM-TDPS, 2021).

To overcome the limitations of the CMIP6 regional climate models in the Endorheic Basin of the Bolivian Altiplano, a comprehensive approach is proposed that combines the strengths of multiple models by creating an ensemble model. This integrated approach will allow for more reliable climate projections and address uncertainties associated with the complexity of the region and the scarcity of reliable observational data.

Therefore, the present study aims to evaluate and validate the historical temperature simulations of the CMIP6 models for the Endorheic Basin of the Bolivian Altiplano. Based on this assessment, an ensemble model will be generated that combines projections from multiple models to obtain a more robust prediction of future climate change in the basin.

MATERIALS AND METHODS

LOCATION

The Altiplano hydrographic region has a surface area of 207,523 km², made up of the level 2 Hydrographic Units (HU) pfafstetter 01 and 02. This region is made up of the territories of Peru, Chile and Bolivia. Bolivia contributes territorially with 146,504 km², which represents 71% of this hydrographic region (Figure 1). It is a vast elongated depression, with an average width of 200 km. for a total length of around 1,000 km, wedged between the reliefs of the Eastern and Western mountain ranges of the Andes (Quintanilla et al., 1989).

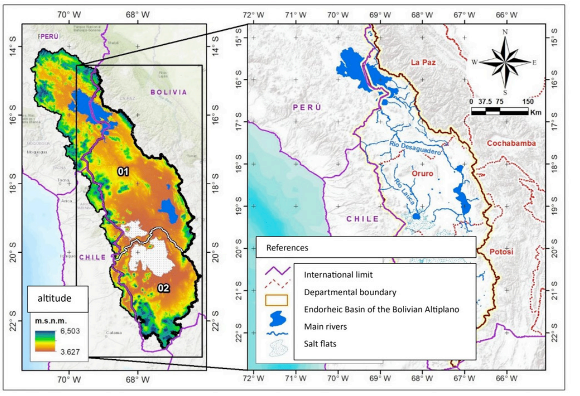


Figure 1 Location map of the Endorheic Basin of the Bolivian Altiplano.

The territorial limit of Bolivia for this hydrographic region will be called the Endorheic Basin of the Bolivian Altiplano in this article, and it is a closed system whose accumulation points are mostly lakes and salt flats of the continental plain formed by the Andes mountain range (MMAyA 2024). The two most representative bodies of water in this region are Lake Titicaca and Lake Poopó.

Precipitation decreases from the upper basin to the lower basin, that is, from the North to the South, with a Medium rainfall of 710 mm, for the Lake Titicaca basin; of 390 mm for the Lake Poopó basin of 240 mm., for the Salar de Uyuni basin, on the contrary, the rainfall regime is uniform, with a well-marked rainy season from December to March (Quintanilla et al., 1989, IWRM-TDPS, 2021). Evapotranspiration, on the other hand, is strongly conditioned by temperature, along with others such as solar radiation, relative humidity and wind speed (Vacher et al., 1995).

METHODOLOGY

Given that temperature is a key factor in the climate of the basin and it significantly affects the processes of evaporation and evapotranspiration, it is essential to study its variation and tendency to increase under different climate change models and scenarios. In order to understand and predict the potential impact that increasing temperatures could have on the region.

To evaluate this process, Regional Climate Change Models (RCM) were used, which provide more detailed information on climate patterns in a specific region. These models consider different Climate Change Sceneries that are based on a set of future trajectories of CO2 emissions. Greenhouse Effect (GHG) and other climate factors to simulate future climate. To date, these Scenerys correspond to the 6th Report of the Intergovernmental Panel on Climate Change (IPCC) corresponding to CMIP6 called Shared Socioeconomic Trajectories (SSP), which are divided into 5 future trajectories to 2100:

- SSP1-1.9 (SSP119): Low GHG emissions / Temperature increase ≈ 1.5 °C.
- SSP1-2.6 (SSP126): Moderate GHG emissions / Temperature increase ≈ 2 °C.
- SSP2-4.5 (SSP245): High GHG emissions / Temperature increase ≈ 3 °C.
- SSP3-7.0 (SSP370): Very high GHG emissions / Temperature increase ≈ 4 °C.
- SSP5-8.5 (SSP585): Extremely high GHG emissions / Temperature increase ≈ 5 °C or more.

From these future trajectories, SSP2-4.5 (SSP245) and SSP5-8.5 (SSP585) were selected as an intermediate and pessimistic Scenery, where SSP2-4.5 represents an "intermediate development" Scenery with moderate levels of mitigation, and SSP5 -8.5 represents a "high emissions" scenario due to economic growth based primarily on fossil fuels.

On the other hand, in order to carry out an analysis of the climate change projections and understand their evolution over time, the projections until the year 2100 were divided into three different time horizons. Firstly, the baseline was established, which covers the period 1980 – 2014, due to the availability of historical data from the climate change models that were used in this article. Subsequently, three future horizons of analysis were defined: i) Near horizon, which includes the years 2015 - 2045; ii) Middle horizon, which covers 2046 - 2075; iii) Long horizon, covering from 2076 - 2100.

SELECTION AND EVALUATION OF RCM MODELS

To evaluate the suitability of various RCM downscaling models in the basin, models were selected from the regional database of the NEX-GDDP project [1] (Coordinated Downscaling Experiment - Detection and Attribution of Greenhouse Gases and Aerosols). This database has a spatial resolution ≈ 25 km, and contains 21 models from research centers worldwide. However, not all of these models adjust to the specific climatic characteristics of the region. For this reason, 7 models have been selected that are widely used in different studies in South America (Cleofé-Valverde & Marengo, 2010, Chan Chou et al., 2014, De Souza Custodio, 2017, MMAyA, 2017, GIRH-TDPS, 2021, Avila-Diaz et al., 2022, Leidinice da Silva et al., 2023) (Table 1).

NUMBER	MODEL CMIP6	INSTITUTE
1	ACCESS-ESM	Commonwealth Scientific and Industrial Research Organization (CSIRO), **Australia**
2	CNRM-ESM	``*Centre National de Recherches Météorologiques*`` (CNRM), **France**
3	GFDL	Geophysical Fluid Dynamics Laboratory (GFDL), **United Kingdom**
4	HadGEM	Met Office Hadley Centre, **United Kingdom**
5	MIROC	Center for Climate System Research (CCSR), **Japan**
6	MPI	Max Planck Institute of Meteorology, Germany
7	NorESM	Norwegian Meteorological Institute (MET Norway), **Norway**

Table 1 RCMs CMIP 6 models used for evaluation.

1. https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6

These models were evaluated to see if they are coupled to the climatic characteristics related to the maximum, average and minimum temperatures of the basin. To do this, comparisons were carried out between simulations from the models and historical data obtained from the climate grid: GMET[2] (Gridded Meteorological Ensemble Tool) coming from the Ministry of Environment and Water (MMAyA 2024), to evaluate the capacity of the models to represent the spatial and temporal variability of temperatures in the basin.

The historical data from the 7 RCM models selected from CMIP6 cover the period from 1950 - 2014. These models consider both natural and anthropogenic forcings to simulate the climate of the past. Simulating these forcings in RCM models allows us to better understand the causes of climate change and project its future evolution (Eyring et al., 2016, Velásquez Fernández, 2021). This way, the historical period 1980 – 2014 (34 years) was extracted from the GMET climate grid that considers a period 1980 – 2020 (40 years), to subsequently evaluate them with the historical RCMs.

The performance evaluation of each model was carried out through cross-validation, through the use of comparative statistical tests integrated into a Taylor diagram, which graphically summarizes how a set of models coincide or are close to the observations, through of three metrics such as Pearson Correlation (COR), Root Mean Square Error (RMSE) and Standard Deviation Standard Deviation (STD DEV). These metrics allow us to quantify the degree of correspondence between the behavior of the different models and the observed damage (Taylor, 2001).

Likewise, in order to have a more precise and detailed evaluation of the performance of the models, an analysis was carried out at a quarterly level, which was based on the following seasonal divisions: DEF: December - January - February, corresponding to the season Of summer; JJA: June - July - August, representing winter; MAM: March - April - May, belonging to autumn; THEY ARE: September - October - November, representing spring; This is in order to obtain a deeper and more specific understanding of the performance of the models at each station before their final selection for assembly.

BIAS CORRECTION AND ASSEMBLY OF SELECTED MODELS

The selected RCM models are not suitable for direct use in an ensemble, as they present significant systematic biases when compared to observations. For this reason, it is necessary to carry out a bias correction process. Statistical bias correction methods aim to correct the systematic error that exists between observations and climate simulations, thus improving the precision and reliability of the data (Velázquez-Zapata et al., 2017).

The method used for this study is Linear Scaling (LS), which is a bias correction technique widely used in the scientific community to fit climate simulations to observations (Maraun & Widmann, 2015). This method is based on the application of a linear transformation to the simulated data, with the aim of eliminating systematic differences between them and the observations.

The equations used for the LS correction are described below:

$$T_{history}^{LS} = T_{history\_month} + (T_{observed\_month}^{\mu month} - T_{history\_month}^{\mu month})$$

$$T_{future}^{LS} = T_{future\_month} + (T_{observed\_month}^{\mu month} - T_{history\_month}^{\mu month})$$

Where:

T^{LS} *and* P^{LS} = Bias - corrected temperature and precipitation.

2. GMET was implemented by the Ministry of Environment and Water of Bolivia (MMAyA) within the framework of the National Water Balance, developed by the National Center for Atmospheric Research of the United States (NCAR) and Stockholm Environmental Institute (S.E.I.).

month = Monthly time step (1, 2, 3, ... 12).

history = RCM historical simulated data to be corrected.

future = RCM future simulated data to be corrected.

observed = Observed data (GMET or weather station).

Of the models selected and subsequently corrected using LS, these were assembled through the REA (Regional Ensemble Averaging) method. This technique allows simulations from multiple RCM models to be combined in order to improve the accuracy of regional climate projections. The weighted ensemble method was proposed and developed by Giorgi & Mearns (2002), and assigns greater relevance to RCMs that present lower error and bias compared to the variables observed at a specific grid point, thus optimizing the quality and reliability of climate projections (Hidalgo & Lyra, 2014, GIRH-TDPS, 2021).

The preparation of estimates of climate change and its associated range of uncertainty is based on a simple approximation. This takes into consideration, the temperature (T), which is calculated as the Medium of the set of all climate model simulations. This way, different models were assembled for the minimum, average and maximum temperatures, using the following equations:

$$\overline{\Delta T} = \frac{1}{N}\Sigma_{i=1,N}\Delta T_i \qquad \widetilde{\Delta T} = \tilde{A}(\Delta T) = \frac{\Sigma_i R_i \Delta T_i}{\Sigma_i R_i}$$

Where:

$\overline{\Delta T}$ = Medium assembly

ΔT_i = Simulated model change

N = Total number of models

$\widetilde{\Delta T}$ = Medium Change

$\tilde{A}$ = Medium Denotes; OER

R_i = Model reliability factor

The reliability factor is given by:

$$R_i = \left[(R_{B,i})^m * (R_{D,i})^n\right]^{1/(m*n)} = \left[\left[\frac{\varepsilon_T}{abs(B_{T,i})}\right]^m * \left[\frac{\varepsilon_T}{abs(D_{T,i})}\right]^n\right]^{1/(m*n)}$$

Where:

$R_{B,i}$ = Model reliability factor regarding bias ($B_{T,i}$).

$B_{T,i}$ = Model bias (> bias < model reliability).

Sesgo = Difference between simulated and observed mean temperature.

ε_T = Difference between Maximum and Minimum values of Temperature Moving Mediums.

$R_{D,i}$ = Factor that measures the reliability of the model in terms of distance ($R_{D,i}$).

$R_{D,i}$ = Distance change calculated by a given model and the change of the Medium REA (> distance < model reliability).

It is important to note that a large bias for a model does not necessarily imply a corresponding large distance, and vice versa. In other words, the models that are furthest from the Medium of the ensemble for future climate are not automatically the ones that perform the worst in reproducing present climate conditions. The parameters *m* and *n* allow each criterion to be weighted. In this case, they are assigned the same weight (*m* = *n* = *1*). The values of *RB* and *RD* are also set to 1 when B and D are less than ε, a parameter that represents the natural variability in the Medium of Minimum temperature, mean and maximum. For more details check out Giorgi & Mearns (2002).

RESULTS AND DISCUSSION

GMET HISTORICAL TEMPERATURE (1980 – 2020)

The spatial distribution of temperature in GMET is derived from 102 stations with maximum and minimum temperature data for the period 1980 – 2020. These data were used in a spatial interpolation process described by Newman et al. (2015), which is based on a local regression that establishes a direct relationship between temperature and surface elevation. The relationship between the grid data and the data observed at the stations was greater than 0.8, indicating a high degree of correlation (MMAyA, 2024).

Based on the GMET information, it is assumed to be observed information as it is derived from meteorological stations and has a high correlation, which is why it was extracted for the limit of the Endorheic Basin of the Bolivian Altiplano for the historical period 1980 – 2014. with the purpose of comparing with respect to the historical temporality available in the different RCM. Figure 2 shows the multi-annual monthly data for the different months of the year distributed spatially within the basin for the minimum, average and maximum temperatures.

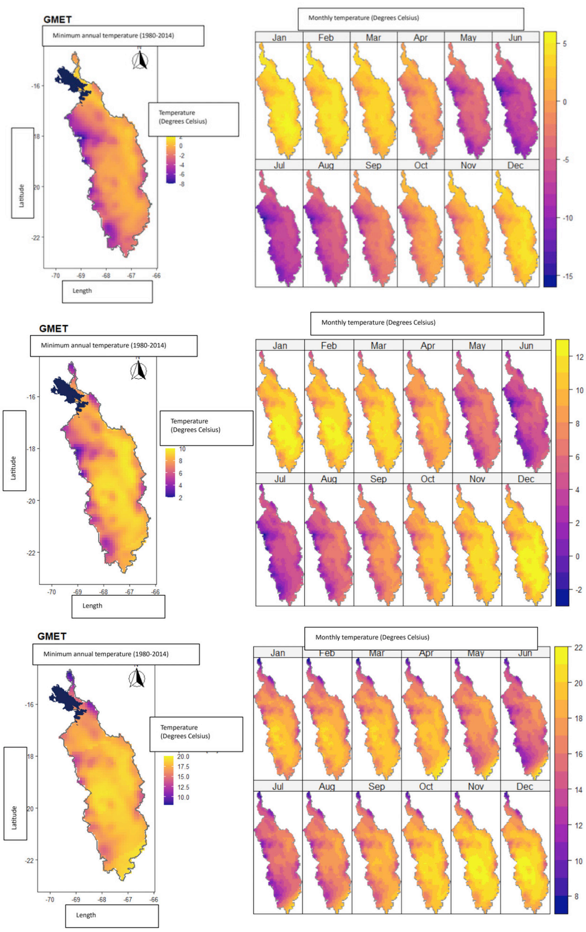


Figure 2 Multi-year monthly GMET temperature distribution historical period 1980 – 2020, for Minimum, average and maximum temperature.

The annual temperatures in the basin based on the GMET grid (1980 – 2020) present notable variability, where the annual Mediums for the entire basin indicate a Minimum temperature of -1.5 °C, an average of 7.9 °C and a maximum of 17.2°C. However, these values do not necessarily reflect the diversity of temperatures found in the basin because they are subject to significant altitudinal variation.

High areas experience considerably lower temperatures, with minimum temperatures reaching -8°C, maximum temperatures of 8.3°C and an average of -1.5°C. In contrast, the low areas have a warmer climate, with minimum temperatures around 1.4 °C, maximum temperatures reaching 19.5 °C and an average of 17.2 °C. Likewise, both areas register the highest temperatures during the summer season (December - January - February).

However, Andrade et al., (2018), based on information from meteorological stations, mentions that the maximum annual temperature in the Altiplano varies between 12 and 16.5 °C, reaching peaks in May and November, being more pronounced in spring than in summer. The lowest values are recorded in July and January, and its annual cycle resembles a bimodal distribution due to the high frequency of clouds in summer.

As for the annual Minimum temperature, it is around -1.5°C, dropping to -7°C in elevated areas. The highest minimums occur in summer, around 0 and 1.5°C, and the lowest in winter, between -6 and -4.5°C. The annual cycle of the Minimum temperature is monomodal, although it presents differences between summer and winter, especially in stations near Lake Titicaca compared to stations further south.

VALIDATION OF REGIONAL CLIMATE MODELS: NEX-GDDP

The validation of the NEX-GDDP models allowed us to evaluate the capacity of each of the eight models to represent historical climatic conditions based on their monthly and annual distribution with respect to GMET (Figure 3 and 4), obtaining valuable information for the selection of the most suitable models for later assembly.

The results obtained indicated that, in general terms, the eight models evaluated showed a good capacity to simulate temperature, although significant differences were observed in terms of their individual performance (Figure 5).

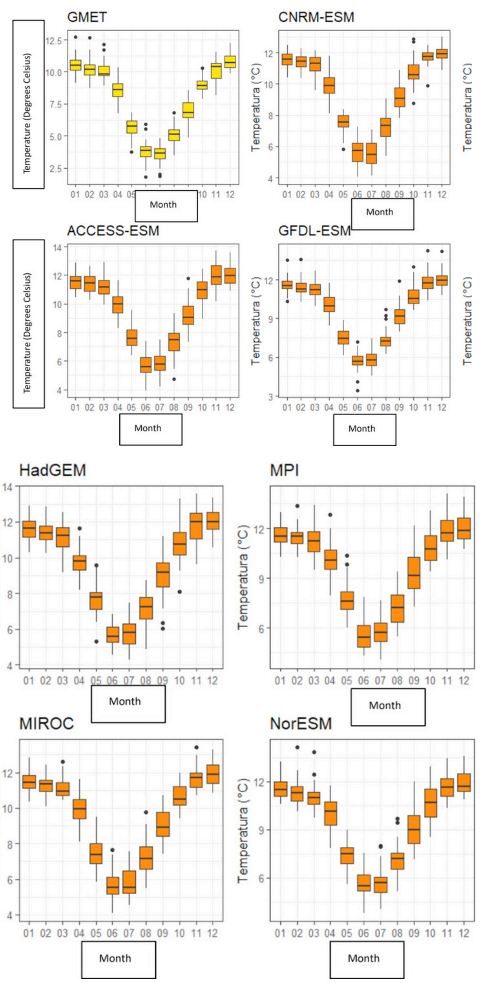
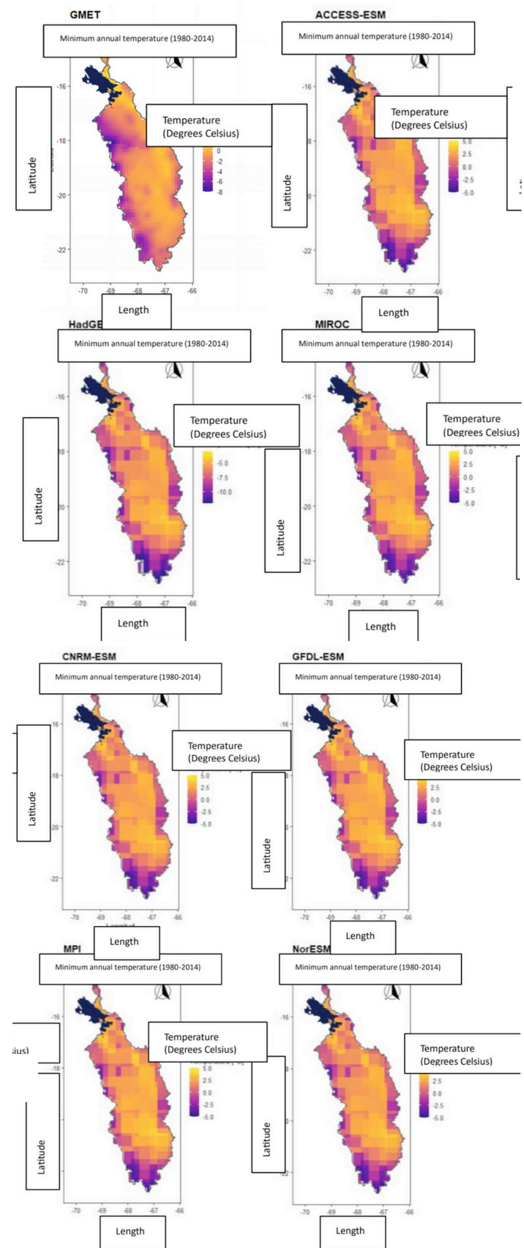
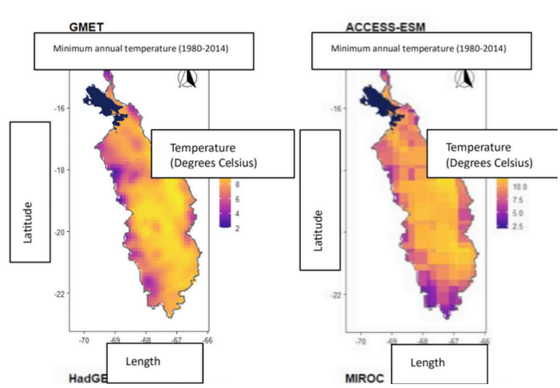


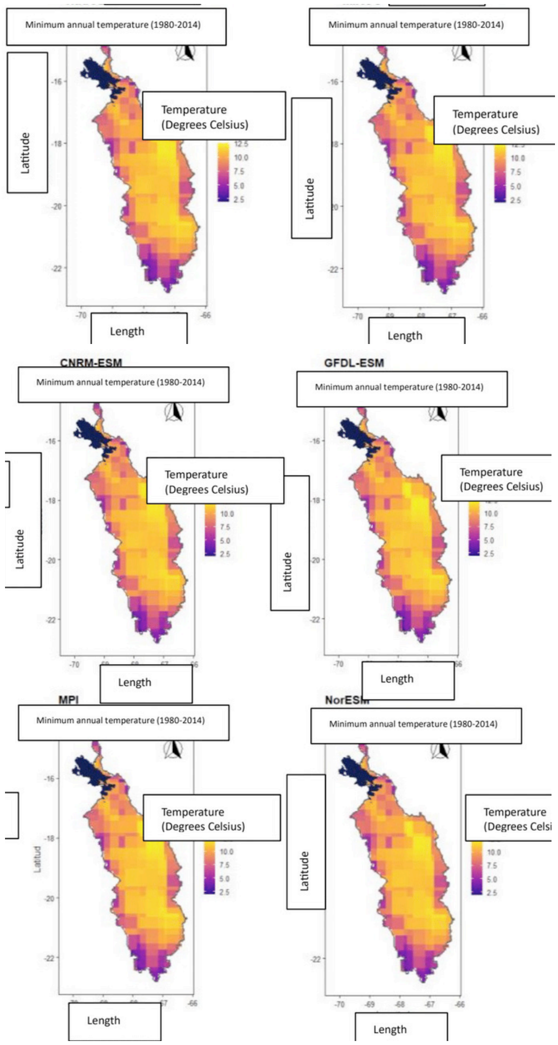
Figure 3 GMET monthly average temperature and RCMs for the historical period: 1980 – 2014.

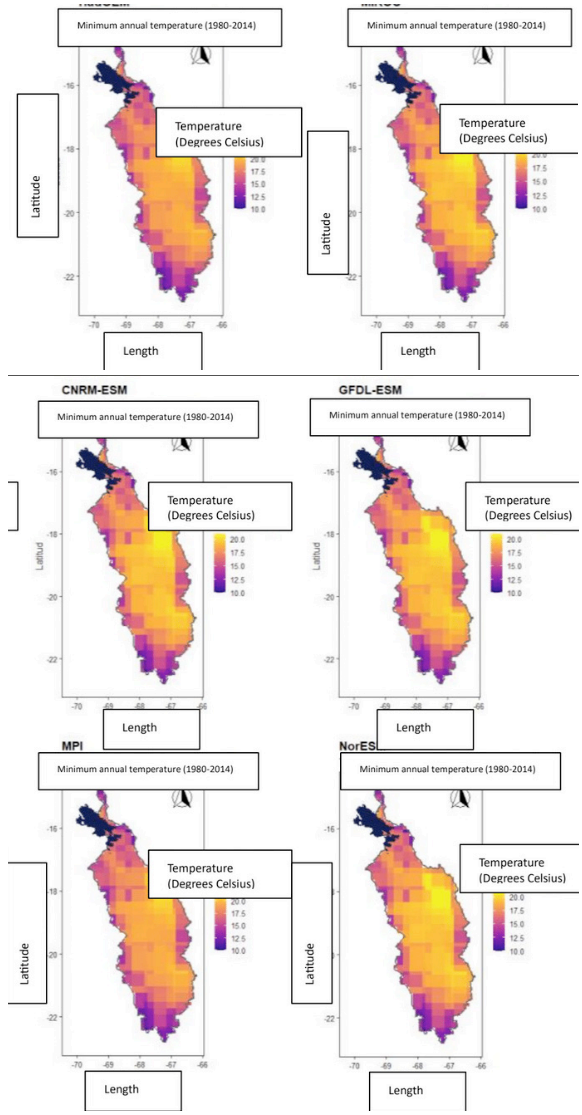
Minimum temperature



Temperature average







Maximum temperature

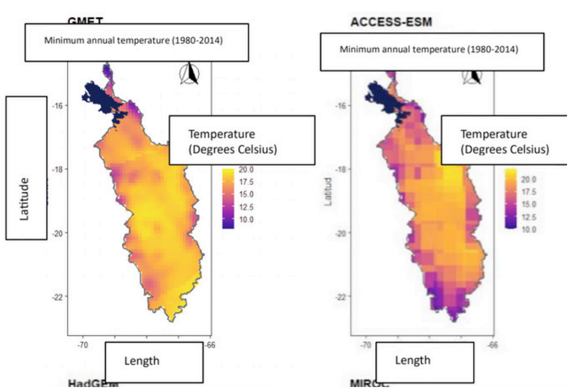
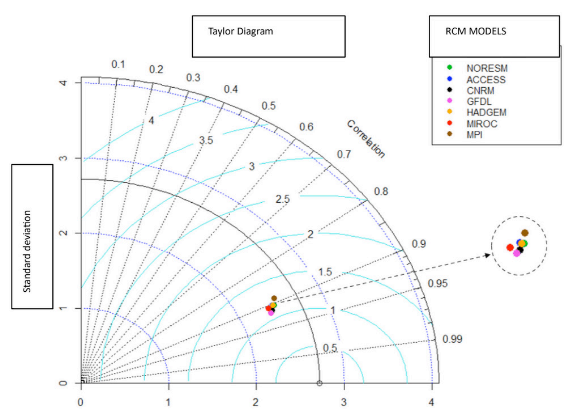


Figure 4 Annual distribution of GMET temperature and RCMs historical period 1980 – 2014.

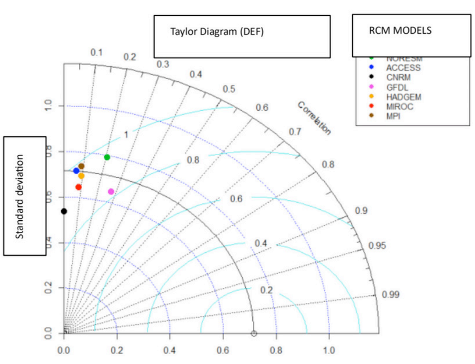


MODEL	RMSE	COLOR	DESV_STD
ACCESS-ESM	2.1	0.9	2.42
CNRM-ESM	1.96	0.91	2.39
GFDL	2.03	0.92	2.36
HadGEM	2.02	0.9	2.42
MIROC	1.98	0.91	2.36
NORESM	1.99	0.9	2.43
MPI			

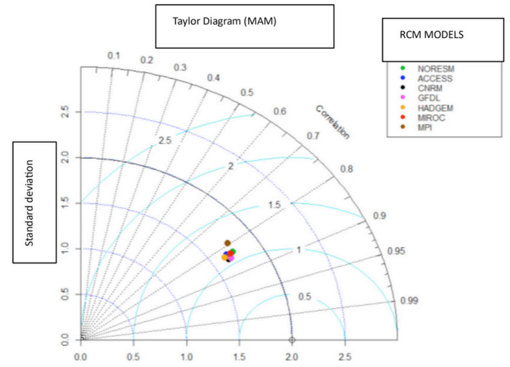
Figure 5 Taylor diagram of the performance of 7 RCM models to simulate the monthly average temperature in relation to the historical period 1980 – 2014.

The Taylor diagram shows that GFDL is the model that best fits the observations in terms of correlation, but has the largest mean square error. The CNRM-ESM and MIROC models have good performance in terms of correlation and RMSE compared to the rest of the models.

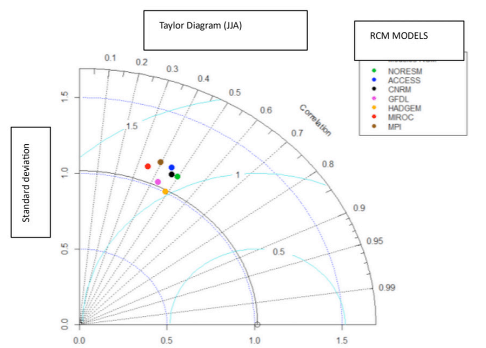
Regarding the evaluation of the performance of the different models at the seasonal level, a greater dispersion of models is observed in the DEF (December-January-February), JJA (June-July-August) and SON (September-October-November) stations.), while a greater concentration of models is seen in the MAM station (March-April-May) (Figure 6).



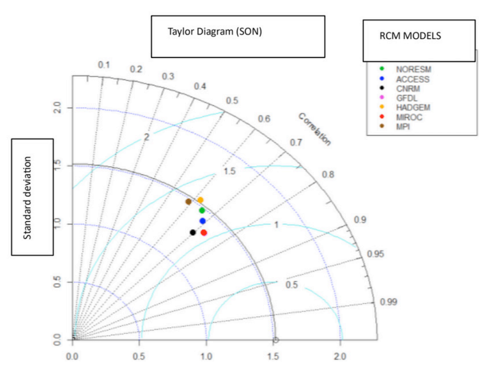
MODEL	RMSE	COLOR	DESV_STD
ACCESS-ESM	1.54	0.07	0.72
CNRM-ESM	1.42	0	0.54
GFDL	1.41	0.27	0.65
HadGEM	1.51	0.09	0.7
MIROC	1.41	0.08	0.65
NORESM	1.47	0.21	0.79
MPI	1.55	0.09	0.74



MODEL	RMSE	COLOR	DESV_STD
ACCESS-ESM	1.92	0.83	1.67
CNRM-ESM	1.82	0.84	1.66
GFDL	1.9	0.85	1.69
HadGEM	1.85	0.83	1.64
MIROC	1.83	0.83	1.71
NORESM	1.85	0.83	1.74
MPI	2.07	0.79	1.75



MODEL	RMSE	COLOR	DESV_STD
ACCESS-ESM	2.45	0.45	1.17
CNRM-ESM	2.31	0.47	1.13
GFDL	2.45	0.43	1.05
HadGEM	2.31	0.48	1.01
MIROC	2.45	0.35	1.12
NORESM	2.33	0.5	1.13
MPI	2.38	0.4	1.18



MODEL	RMSE	COLOR	DESV_STD
ACCESS-ESM	2.34	0.69	1.42
CNRM-ESM	2.16	0.7	1.3
GFDL	2.2	0.73	1.36
HadGEM	2.3	0.62	1.55
MIROC	2.07	0.73	1.35
NORESM	2.2	0.66	1.48
MPI	2.42	0.59	1.48

Figure 6 Taylor diagrams of performance of RCM models with respect to seasonal periods of mean temperature at the seasonal level: DEF - MAM - JJA - SON.

The performance of climate models in simulating the historical temperature of the basin varies depending on the season of the year, being ordered with respect to their existing correlation with the observed GMET data, such as DEF, JJA, SON and MAM.

In summer (DEF), neither model presents adequate performance. The models that come closest, although with low correlation with the observations, are GFDL, NorESM and MIROC, with relatively low RMSE and standard deviation values. In winter/dry (JJA), the performance of the models improves, but correlation values of 0.5 are not exceeded. The best models are NorESM, HadGEM and CNRM-ESM, with lower RMSE values than the rest. In spring (SON), the correlation increases, with values close to 0.73 for the GFDL, NorESM and CNRM-ESM models. These models also present the lowest RMSE and standard deviation values. In autumn (MAM), the correlations are greater than 0.83 for the CNRM-ESM, NorESM and MIROC models, which also have the lowest RMSE values.

After making a comparison of the performance of the models at the monthly level and aggregated at the seasonal level, it has been determined that the best models to consider for the assembly are: GFDL, CNRM, MIROC, NorESM and HadGEM. Therefore, MIROC and ACCESS-ESM models will be discarded for subsequent REA analysis.

PROJECTIONS OF TEMPERATURE CHANGES UNDER SCENERYS SSP 245 AND 585

After selecting the five climate models with the best performance, they were adjusted using the Linear Scaling technique. This tool, widely used in various fields of research, allows climate simulations to be adjusted to real observations (Madrigal-Barrera et al., 2017). The Linear Scaling process consisted of applying a linear relationship between the variables simulated by the models and the corresponding observations. This allowed adjusting both the variability and the trend of the temperature simulations to the presented GMET distribution patterns.

This way, after adjusting the five selected climate models, they were assembled using the REA method, which allows combining the strengths of different models to obtain a consolidated model with greater precision in temperature projection. REA is based on weighting the simulations of each of the five models according to their individual performance (RME, COR, DEV STD). This way, greater weight is given to the most reliable models, allowing for a more accurate climate projection.

The assembly of the 5 models also allows us to reduce the uncertainty associated with temperature projections. This is because the assembled model takes into account the variability between the simulations of the different models, resulting in a more robust and reliable projection.

The results obtained demonstrate that the assembly of the five selected models, using the REA method, provides a significant improvement in the accuracy of temperature projections compared to the individual models. Figure 7 illustrates the temperature projections for the year 2100 from the assembled model, along with the confidence interval (represented in lilac shading for SSP

585 and orange for SSP 245), which expands as the time horizons advance.

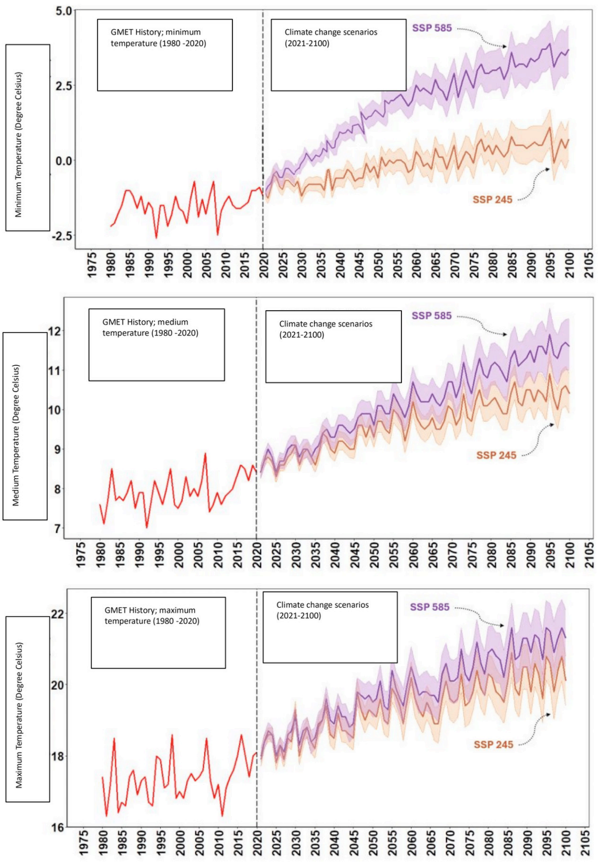


Figure 7 GMET historical time series and future projection according to REA SSP 245 and 585 assembly for minimum, average and maximum temperature.

The climate projections for the basin until the year 2100, under Scenerys SSP 245 and 585, indicate a significant increase in minimum, average and maximum temperatures in the three time horizons evaluated 2015 - 2045, 2046 - 2075 and 2076 - 2100. Without However, differences are observed in the trends of these increases (deltas), especially in the minimum temperatures, where different trends in increase are projected for both Sceneries, compared to the average and maximum temperatures.

This way, the projections of minimum temperature in the basin for Scenery SSP 245 show a gradual increase in the three time horizons evaluated, with a Medium increase of 0.7°C for the period 2015 - 2045, 1.5°C for the period 2046 - 2075 and 2.04°C for the period 2076 - 2100. For Scenery SSP 585, the projected Medium increases are significantly higher, with values of 2.57°C for the period 2015 - 2045, 3.76°C for the period 2046 - 2075 and 4.83°C for the period 2076 - 2100. It is important to highlight that the increase values vary depending on the Scenery considered, with ranges of variability expressed as Minimums, Medium and Maximums values presented in Table 1 and Figure 8.

The average temperature projections for Scenery SSP 245, similar to the previous one, show a gradual increase in the three time horizons evaluated, with a Medium increase of 0.96°C for the period 2015 - 2045, 1.5°C for the period 2046 - 2075 and 2.04°C for the period 2076 - 2100. For the Scenery SSP 585, the projected Medium increases are significantly higher, with values of 2.57°C for the period 2015 - 2045, 3.76°C for the period 2046 - 2075 and 4.83°C for the period 2076 - 2100 (Table 2 and Figure 9).

Regarding the maximum temperature projections for the Scenery SSP 245, there is a gradual increase in the three time horizons evaluated, with a Medium increase of 0.96°C for the period 2015 - 2045, 1.5°C for the period 2046 - 2075 and 2.04 °C for the period 2076 - 2100. For the Scenery SSP 585, the projected Medium increases are significantly higher, with values of 2.57°C for the period 2015 - 2045, 3.76°C for the period 2046 - 2075 and 4.83°C for the period 2015 - 2045. the period 2076 - 2100 (Table 3 and Figure 10).

Based on the results obtained, the existence of a future trend of a more marked increase in the minimum temperature compared to the average and maximum temperatures in the basin is suggested, which could have significant impacts on the natural and human systems of the region. Studies carried out

Journal of Agricultural Sciences Research ISSN 2764-0973 DOI https://doi.org/10.22533/at.ed.973452403049

by Thibeault & Garcia (2010), Valdivia et al. (2012) agree that the Bolivian Altiplano is experiencing accelerated warming, with a greater impact on minimum temperatures, as in the present study. Maximum temperatures also increase, but to a lesser extent.

Valdivia et al., (2012) have projected an increase in the average annual temperature throughout the Altiplano of 1.5°C, with the possibility that by the year 2099 it will exceed 4°C or be between 4 and 5°C (Thibeault & Garcia, 2010). The study carried out in the Titicaca-Desaguadero-Lago Poopó-Salar de Coipasa (TDPS) water system within the framework of the GIRH-TDPS project (2021) also shows a general increase in maximum and minimum temperatures throughout the system for a time horizon 2036 – 2065. However, the reported increases in maximum temperature are greater than those of the minimum, with annual changes of 3.1°C to 3.6°C and 1.3 to 2.5°C, respectively. These changes are consistent and progressive, indicating a high probability that temperatures will continue to increase in the region by mid-century, especially under a high greenhouse gas emission scenario.

On the other hand, it must be taken into account that the differences in the values reported in the aforementioned studies can be attributed mainly to the climate change models used. In the GIRH-TDPS (2021) study, CMIP5 models such as RCP (ACCESS1-0, HadGEM2-ES, GFDL-CM3, MPI-ESM-LR and CCSM4) were used, while in the study by Thibeault & Garcia (2010), CMIP3 models (A1B, A2, A1) were used, and in the present study CMIP 6 models were used, such as the SSP, which are relatively new and there are no specific studies for the basin. Therefore, it is important to consider the limitations and differences in the models used when comparing the results of different ones.

CONCLUSIONS

The results obtained indicate a constant and progressive warming trend in the studied basin. It is important to highlight that the trend of increase in the minimum temperature is more marked than that of the average and maximum temperatures, which suggests the need to implement mitigation and adaptation measures to climate change in order to take immediate and effective actions to address climate change and protect the water and ecological resources of the basin.

The seven regional climate models evaluated demonstrate a good capacity to simulate the temperature in the basin, however, there are significant differences in their individual performance. The GFDL, CNRM, MIROC, NorESM and HadGEM models are the ones that present the best performance in simulating historical and seasonal temperature, being the most accurate in the representation of thermal variations.

The REA ensemble model projects a significant increase in minimum, average and maximum temperatures until the year 2100 under the SSP 245 and 585 scenarios. The increase values vary between 2.04 and 4.83 for minimum temperatures, between 2.47 and 3.45 for average temperatures, and between 2.91 and 3.76 for maximum temperatures. It is important to note that the projections are more pronounced under the high emissions scenario (SSP 585), where the differences in the increase values become more accentuated as time progresses.

The projections in this study are based on regional climate models, which implies some uncertainty due to limitations and differences in the models used. Therefore, it is important to continue research and constant monitoring to improve understanding and response capacity to climate changes in the Endorheic Basin of the Bolivian Altiplano.

Scenery	Near horizon			Middle horizon			Distant horizon		
	Minimum	Medium	Maximum	Minimum	Medium	Maximum	Minimum	Medium	Maximum
SSP 245	0.57	0.7	0.87	1.32	1.5	1.73	1.71	2.04	2.31
SSP 585	2.25	2.57	2.91	3.03	3.76	4.25	4.01	4.83	5.41

Table 1 Minimum temperature variation with respect to the Near, Middle and Far horizon in relation to the historical period 1980 – 2014.

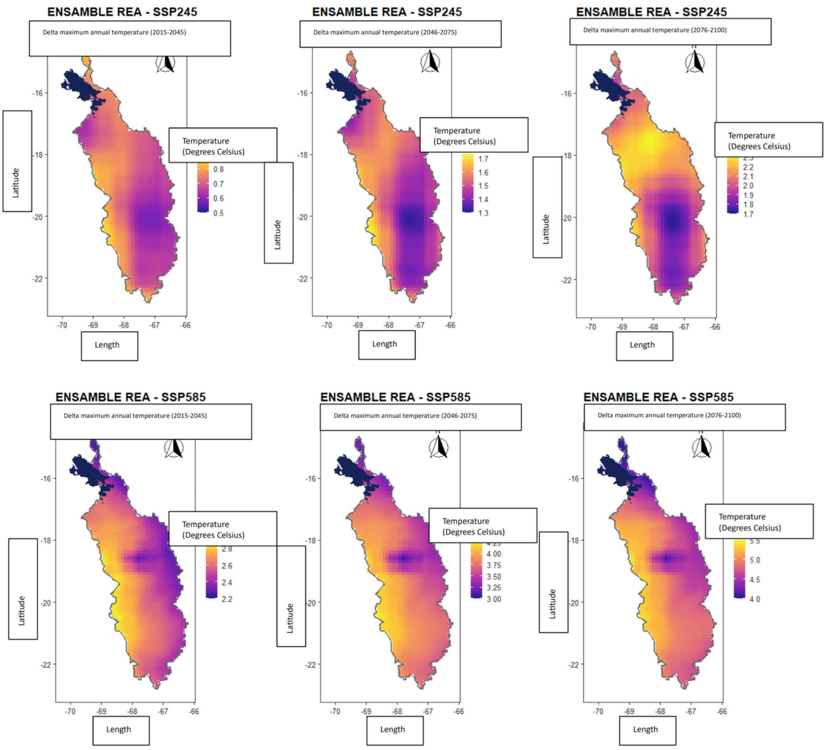
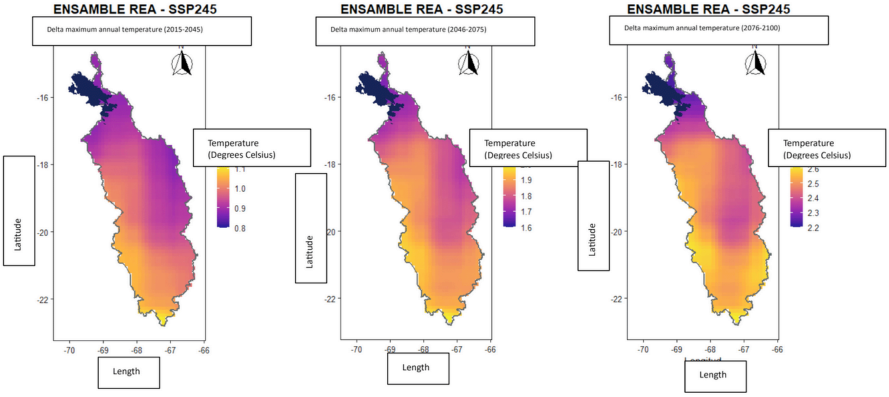


Figure 8. Projection of minimum temperature variations in °C according to the REA assembly for the Scenerys SSP 245 and 585 and time horizons to 2100.

Scenery	Near horizon			Middle horizon			Distant horizon		
	Minimum	Medium	Maximum	Minimum	Medium	Maximum	Minimum	Medium	Maximum
SSP 245	0.87	0.96	1.12	1.68	1.84	2.0	2.23	2.47	2.63
SSP 585	0.95	1.12	1.26	2.01	2.38	2.57	2.90	3.45	3.71

Table 2 Average temperature variation with respect to the Near, Middle and Far horizon in relation to the historical period 1980 – 2014.



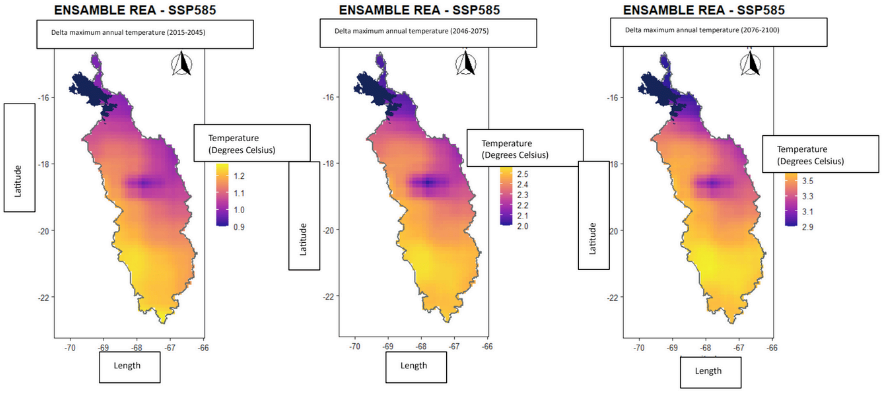


Figure 9. Projection of average temperature variations in °C according to the REA assembly for the Scenerys SSP 245 and 585 and time horizons to 2100.

Scenery	Near horizon			Middle horizon			Distant horizon		
	Minimum	Medium	Maximum	Minimum	Medium	Maximum	Minimum	Medium	Maximum
SSP 245	0.94	1.21	1.40	1.84	2.18	2.41	2.44	2.91	3.25
SSP 585	1.03	1.34	1.51	2.19	2.66	2.89	3.11	3.76	4.11

Table 3. Maximum temperature variation with respect to the Near, Middle and Far horizon in relation to the historical period 1980 – 2014.

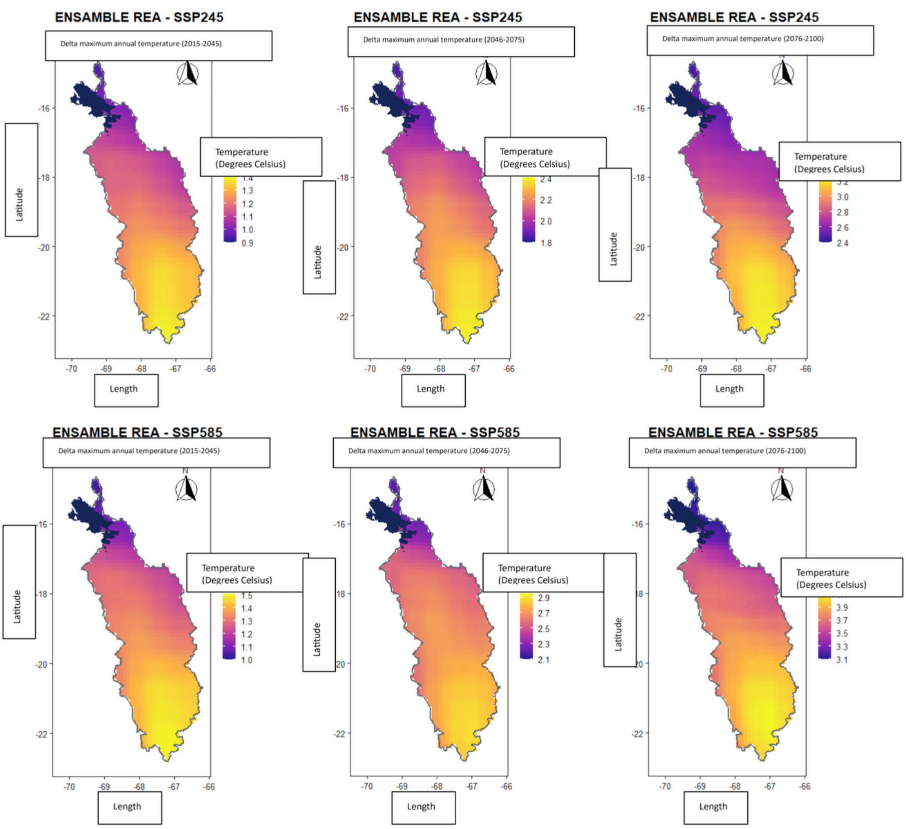


Figure 10. Projection of maximum temperature variations in °C according to the REA assembly for the SSP 245 and 585 scenarios and time horizons to 2100.

REFERENCES

Agua, M. d. (2017). *Balance Hìdrico Superficial de Bolivia: 1980 - 2016.* La Paz, Bolivia. Obtenido de https://datos.siarh.gob.bo/biblioteca/406

Andrade, M., Moreno, I., Calle, J., Ticona, L., Blacutt, L., Lavado-Casimiro, W.,.. Brönnimann, S. (2018). *Atlas - Clima y eventos extremos del Altiplano Central perú-boliviano/ Climate and extreme events from the Central Altiplano of Peru and Bolivia.* La Paz: Geographica Bernensia. doi:https://doi.org/DOI: 10.4480/GB2018.N01

Avila-Diaz, A., Rodrigues Torres, R., Felipe Zuluaga, C., L. Cerón, W., Oliveira, L., Benezoli, V.,.. Medeiros, F. (2022). Current and Future Climate Extremes Over Latin America and Caribbean: Assessing Earth System Models from High Resolution Model Intercomparison Project (HighResMIP). *Earth Systems and Environment*, pp 99-130. doi:https://link.springer.com/article/10.1007/s41748-022-00337-7

Chan Chou, S., Lyra, A., Mourão, C., Pereira Dereczynski, C., L. Pilotto, I., Jorge, G.,.. Chagas, D. (2014). Evaluation of the Eta Simulations Nested in Three Global Climate Models. *American Journal of Climate Change (Scientific Research Publishing)*, pp 438-454. doi:https://www.doi.org/10.4236/AJCC.2014.35039

Cleofé Valverde, M., & A. Marengo, J. (2010). Changes in the atmospheric circulation pattern over South America in future climate scenarios derived from the IPCC AR4 model climate simulations. *Revista Brasileira De Meteorologia (Sociedade Brasileira de Meteorologia)*, pp 125-145. doi:https://www.doi.org/10.1590/S0102-77862010000100011

Cruz Fuentes, D. (2011). *Persepciones Sociales sobre el Agua y Cambio Climático en Bolivia.* Cochabamba, Bolivia: Grupo de Trabajo Cambio Climático y Justicia – GTCCJ. Obtenido de https://gaiapacha.org/wp-content/uploads/2020/07/03-revista_agua_cambio_climatico.pdf

De Souza Custodio, M., Da Rocha, P., Ambrizzi, T., Luigi Vidale, P., & Demory, M.-E. (2017). Impact of increased horizontal resolution in coupled and atmosphere-only models of the HadGEM1 family upon the climate patterns of South America. *Climate Dynamics (Springer)*, pp 3341-3364. doi:https://link.springer.com/article/10.1007/s00382-016-3271-8

Drenkhan, F., Huggel, C., Hoyos, N., & Scott, C. (2023). Hydrology, water resources availability and management in the Andes under climate change and human impacts. *Journal of Hydrology: Regional Studies*, 5. Obtenido de https://www.researchgate.net/publication/373473842_Hydrology_water_resources_availability_and_management_in_the_Andes_under_climate_change_and_human_impacts

Eyring, V., Bony, S., Meehl, G., Senior, C., Stevens, B., Stouffer, R., & Taylor, K. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 1937–1958. doi:https://doi.org/10.5194/gmd-9-1937-2016

Flato, G., & Marotzke, J. (2013). *Evaluation of climate models. In Climate Change 2013: The Physical Science Basis.* Cambridge University Press. NY. USA: Evaluation of Climate Models CAP 9. En Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Obtenido de https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_Chapter09_FINAL.pdf

Giorgi, F., & Mearns, L. (2002). Calculation of climate change indices and their use to assess climate change impacts. In Climate change impacts and adaptation. *Springer Netherlands*, 183 - 204. Obtenido de https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2003GL017130

GIRH-TDPS. (2021). *Scenerys Climáticos en el Sistema Hídrico del Lago Titicaca, Río Desaguadero, Lago Poopo y Salar de Coipasa.* Puno: Proyecto GIRH-TDPS. Obtenido de https://girh-tdps.com/biblioteca/Informe_Scenerys_climaticos_Sistema_TDPS_SENAMHI_MMAyA_PNUD.pdf

Hidalgo, H., & Lyra, A. (2014). Regional climate change projections for South America using the RegCM4 model. Climate Dynamics. *Journal SAGEPUB*, 255-273. Obtenido de https://journals.sagepub.com/doi/abs/10.1177/10760296221082992

Leidinice da Silva, M., Prestrelo de Oliveira, C., Moisés Santos, C., & João, M. (2023). Dynamic downscaling of climate simulations and projected changes in tropical South America using RegCM4.7. *International Journal of Climatology*, 12. doi:https://doi.org/10.1002/joc.8035

Madrigal Barrera, J. J., Flores Fernández, G. C., Solera Solera, A., & Andreu, Á. J. (2017). Corrección del sesgo en los estadísticos de las series de precipitación de cambio climático, en la cuenca del río Angulo. *Revista - Universidad Politécnica de Valencia*, 8. Obtenido de https://www.researchgate.net/profile/Jaime-Madrigal-3/publication/317400970_Correccion_del_sesgo_en_los_estadisticos_de_las_series_de_precipitacion_de_cambio_climatico_en_la_cuenca_del_rio_Angulo/links/593917c8aca272bcd1a685ad/Correccion-del-sesgo-en-los-

Maraun, D., & Widmann, M. (2015). Bias correction of climate change simulations – a critical review. *Wiley Interdisciplinary Reviews: Climate Change, 6(6)*, 617 – 633. doi:https://doi.org/10.1002/wcc.382

Ministerio de Medio Ambiente y Agua. (2024). *Balance Hídrico de Bolivia: 1980 – 2020.* La Paz, Bolivia.

NASA Center for Climate Simulation. (30 de 01 de 2024). *NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6)*. Obtenido de https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6

PNUD. (1990). *Tras las huellas del cambio climático en Bolivia: estado del arte del conocimiento sobre adaptación al cambio climático, agua y seguridad alimentaria.* La Paz, Bolivia: ABBASE Ltda. Obtenido de https://www.undp.org/sites/g/files/zskgke326/files/migration/bo/Tras-las-huellas-del-Cambio-Climatico-en-Bolivia.pdf

Quintanilla, J., Calliconde, M., Guyot, J., Alain Roche, M., Noriega, L., Calle, H., & Cortés, J. (1989). Cargas en suspensión, salinidades y transportes de materia sobre el Altiplano Boliviano. *Revista de Ingenieria Sanitaria*, 54-59. Obtenido de https://horizon.documentation.ird.fr/exl-doc/pleins_textes/pleins_textes_7/b_fdi_59-60/010026669.pdf

Taylor, P. (2001). On the interpretation and use of Taylor diagrams. *Journal of Climate*, 14(23), 4853-4863.

Thibeault, J., & Garcia, A. (2010). Changing climate in the Bolivian Altiplano: CMIP3 projections for temperature and precipitation extremes. *Geophysical Research Atmosferes*, 12. Obtenido de https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2009JD012718

Vacher, J., Imaña, E., & Canqui, E. (1995). Las caracteristicas radiativas y la evapotranspiración potencial en el Altiplano Boliviano. (F. y. Facultad de Ciencias Agrícolas Pecuarias, Ed.) *Revista de Agricultura*, 4-11. Obtenido de https://horizon.documentation.ird.fr/exl-doc/pleins_textes/pleins_textes_6/b_fdi_35-36/41823.pdf

Valdivia, C., Anji, S., & Jiménez, E. (2012). *Cambo Climático y Adaptación en el Altiplano de Bolivia.* La Paz. Obtenido de https://dpp2012.wordpress.com/wp-content/uploads/2012/07/cambio-climatico-y-adaptaciin-2012-07-cc-sanrem-cides.pdf

Velásquez Fernández, S. (2021). *Evaluación de la capacidad de los modelos CMIP6 para simular la Evapotranspiración y Precipitación en el Norte de Sudamerica.* Medellin, Colombia: Universidad de Antioquia, Facultad de Ingenieria, Escuela Ambiental. Obtenido de https://bibliotecadigital.udea.edu.co/bitstream/10495/20034/3/VelasquezSusana_2021_EvaluacionCapacidadModelos.pdf

Velázquez-Zapata, J., Magali, T., & Dávila-Ortiz, R. (2017). Evaluación del impacto del cambio climático en los indicadores hidrológicos de una cuenca del centro de México con base en un ensamble de modelos climáticos y en el modelo hidrológico SWAT. *Ingeniería Investigación y Tecnología*, 341 - 351.