Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Next Generation of IPCC SSP Climate Change Scenarios for Colombia in High Spatial Resolution Using CMIP6 Models Under WMO Prediction Standards

José Franklyn Ruiz-Murcia[1]
Universidad Nacional de Colombia
jfruizm @unal.edu.co

Ángel G. Muñoz[2]
Columbia University International Research Institute for Climate and Society
agmunoz @iri.columbia.edu

Xavier Corredor-Llano[3]
University of Northern British Columbia
llano @unbc.ca

Jeimmy Yanely Melo-Franco[4]
Universidad Ean
jmelo @universidadean.edu.co

Fecha de recepción: 25 de agosto de 2023
Fecha de aprobación: 8 de noviembre de 2023

Cómo citar este artículo: Ruiz-Murcia, J.F.; Muñoz, Á.; Corredor-Llano, X.; Melo-Franco, J.Y. (2023). Next Generation of IPCC SSP Climate Change Scenarios for Colombia in High Spatial Resolution Using CMIP6 Models Under WMO Prediction Standards. *Revista Ontare, 11*, (páginas). DOI:

Abstract

In august 2021, the Intergovernmental Panel on Climate Change (IPCC) released new findings on the next generation of climate change scenarios, known as Shared Socioeconomic Pathways (SSPs). These scenarios illustrate projected changes in temperature and precipitation throughout the 21st century under four climate change models, based on approximately 33 low-resolution simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6). The primary objective of these findings is to enable statistical downscaling, generating high-resolution climate projections at the national level. This process adheres to the prediction standards established by the World Meteorological Organization (WMO), which recommend using multiple models calibrated for spatial patterns and delivering forecasts in a flexible format, such as probability density functions. The next generation of climate change scenarios predicts a mean temperature increase of 1.1 °C to 2.0 °C under the SSP1-2.6 scenario and 3.5 °C to 6.2 °C under the SSP5-8.5 scenario by the end of the

1 Físico, Especialista y Magíster en Ciencias-Meteorología. Universidad Nacional de Colombia. Docente Auxiliar Cátedra Facultad de Ciencias – Departamento de Geociencias - Postgrado de Meteorología. Universidad Nacional de Colombia. ORCID: https://orcid.org/0000-0002-1925-3329
2 B.Sc. in Physics. Universidad del Zulia. PhD. Earth and Environmental Sciences. Columbia University. ORCID: https://orcid.org/0000-0002-2212-6654
3 Ingeniero de Sistemas. Universidad Nacional de Colombia. PhD Student Natural Resources and Enviromnental Studies. University of Northern British Columbia. ORCID: https://orcid.org/0000-0001-7593-6477
4 Ingeniera de Sistemas y Especialista Gerencia Informática. Universidad Ean. Magíster en Ciencias-Meteorología. Universidad Nacional de Colombia. ORCID: https://orcid.org/0000-0001-6700-6827

21st century, relative to the 1981-2010 reference climatology. The most significant temperature increases are expected in the southern Caribbean, the central and southern Andes, and extensive areas of the Orinoco and Amazon regions. Regardless of the scenario, annual precipitation volumes are not projected to change significantly compared to the current climate. However, according to Lang's climate classification, these shifts suggest that the Caribbean and parts of the Andean region may transition from semi-arid to arid conditions, while sections of the Amazon could shift from super-humid to humid climates.

Keywords: Climate change; scenarios; climatology; IPCC; CMIP6; NextGen.

****

Nueva generación de escenarios de cambio climático SSP del IPCC para Colombia en alta resolución espacial utilizando modelos CMIP6 bajo los estándares de predicción de la OMM

Resumen
En agosto de 2021, el Panel Intergubernamental sobre Cambio Climático (IPCC) presentó nuevos resultados sobre la próxima generación de escenarios de cambio climático, denominado: "Trayectorias Socioeconómicas Compartidas". Estos escenarios expresan los cambios de temperatura y precipitación bajo 4 escenarios de cambio climático durante el resto del siglo XXI, utilizando alrededor de 33 modelos de baja resolución que forman parte del Couple Model Intercomparison Project Phase 6 (CMIP6). El objetivo de utilizar estos resultados fue realizar un *downscaling* estadístico para obtener escenarios de alta resolución espacial a nivel nacional a lo largo del siglo XXI. Para ello, se utilizaron los estándares de predicción desarrollados por la Organización Meteorológica Mundial (OMM, 2020), que sugieren el uso de varios modelos, utilizando solo aquellos que están calibrados por patrones espaciales, y entregando predicciones en un formato flexible (función de densidad de probabilidad). La próxima generación de escenarios de cambio climático sugiere que la temperatura media aumentará entre 1,1 °C y 2,0 °C en un escenario SSP1-2,6, y entre 3,5 °C y 6,2 °C en un escenario SSP5-8,5 para finales del siglo XXI. con respecto a la climatología de referencia 1981-2010. Los mayores incrementos se encuentran en la región Caribe Sur, Andina Central y Sur, y en gran parte de la Orinoquía y Amazonía. Independientemente del escenario, los volúmenes anuales de precipitación no cambiarán demasiado con respecto al clima actual. Con esos cambios en la temperatura media y la precipitación, la clasificación climática de Lang estima que el Caribe y partes de la región Andina dejarán de ser zonas semiáridas y migrarán hacia condiciones áridas, mientras que áreas de la Amazonía migrarán de superhúmedo a climas húmedos.

Palabras clave: cambio climático, escenarios, climatología, IPCC, CMIP6, *NextGen*.

****

1. Introduction

On august 9, 2021, Working Group I of the Intergovernmental Panel on Climate Change (IPCC) released its scientific contribution to the Sixth Assessment Report (AR6), titled Climate Change 2021: The Physical Science Basis. In its summary for policymakers, the group introduced five new illustrative emissions scenarios to assess the climate's response to a broader range of greenhouse gas (GHG) emissions, land use changes, and air pollution trajectories compared to those considered in the Fifth Assessment Report (AR5). As an improvement over the previous report, these projections also incorporate variations in solar activity and background forcing from volcanic activity. The results for the 21st century are presented across three time frames: short-term (2021-2040), medium-term (2041-2060), and long-term (2081-2100), relative to the 1850-1900 baseline (IPCC, 2021).

The Shared Socioeconomic Pathways (SSP) scenarios, which begin in 2015, outline different potential trajectories for GHG emissions. These include high and very high emission scenarios (SSP3-7.0 and SSP5-8.5), where CO_2 emissions nearly double current levels by 2100 and 2050, respectively. Intermediate scenarios (SSP2-4.5) depict CO_2 emissions stabilizing around present levels until mid-century. Additionally, low and very low emission scenarios project CO_2 levels decreasing to zero around or after 2050, followed by varying degrees of net negative CO_2 emissions (SSP1-1.9 and SSP1-2.6). Emission variations across these scenarios depend on socioeconomic factors, climate change mitigation measures, aerosols, ozone precursors (excluding methane), and air pollution control policies (IPCC, 2021). These scenarios are based on distinct socioeconomic narratives (O'Neill *et al*., 2016).

SSP1: the sustainable and "green" pathway. This scenario envisions a world where global commons are preserved, and natural limits are respected. The focus shifts from economic growth to human well-being, prioritizing sustainability and environmental conservation. Efforts aim to reduce income inequality both within and between countries. Consumption patterns emphasize minimizing material resource and energy use.

SSP2: the "middle path". This scenario projects current global development trends into the future. Economic disparities persist, with some countries growing while others lag.

International cooperation remains limited, with few new agreements beyond existing ones. Population growth is moderate, stabilizing in the second half of the century. Environmental degradation continues at a steady pace due to a lack of significant mitigation efforts.

SSP3: regional rivalry. This scenario depicts a world dominated by nationalism and regional conflicts, where global challenges are deprioritized. Policies focus on national and regional security, limiting international cooperation. Investment in education and technology declines, widening global disparities. Inequality intensifies, and some regions experience severe environmental degradation due to a lack of sustainability initiatives.

SSP4: inequality. This scenario describes a growing divide between developed nations engaged in global cooperation and underdeveloped regions facing economic stagnation and limited educational opportunities. The gap between these groups continues to widen. While some regions implement effective local environmental policies, others fail to do so, resulting in uneven sustainability progress.

SSP5: fossil fuel-powered development. This scenario envisions a highly integrated global market driving technological innovation and economic expansion. However, development relies heavily on intensified fossil fuel consumption, particularly coal, and energy-intensive lifestyles. While economic growth is strong and local environmental issues like air pollution are managed effectively, dependence on fossil fuels raises concerns about long-term sustainability and broader environmental impacts.

To develop these scenarios, the report assessed the results from climate models participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) of the World Climate Research Program. These models incorporate new and enhanced representations of physical, chemical, and biological processes, offering higher resolution than those used in previous IPCC assessment reports. This advancement has improved the simulation of large-scale climate indicators, climate change, and other aspects of the climate system. Despite these improvements, some discrepancies with observed data remain, particularly in regional precipitation patterns. The ensemble of historical CMIP6 simulations evaluated in this report (AR6) shows a temperature difference within 0.2 °C of observed values for most of the historical period, with observed warming falling within the very likely range of the CMIP6 ensemble. Nevertheless, some CMIP6 models predict warming that is either above or below the observed warming, even within this very likely range.

According to the findings of AR6 Working Group I, it is very likely that the global surface temperature averaged over 2081-2100 will be between 1.0 °C and 1.8 °C higher compared to 1850-1900 under the very low GHG emissions scenario (SSP1-1.9); between 2.1 °C and 3.5 °C under the intermediate GHG emissions scenario (SSP2-4.5); and between 3.3 °C and 5.7 °C under the very high GHG emissions scenario (SSP5-8.5). The last time global surface temperatures were 2.5 °C or above those of 1850-1900 was over 3 million years ago (with medium confidence) (IPCC, 2021). The AR6 report also indicates that El Niño/Southern Oscillation-related precipitation variability will likely intensify in the latter half of the 21st century under the SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios.

The goal of working with climate change scenarios is not to predict the exact future but to explore a wide range of potential climate behaviors and understand the associated uncertainties. This approach helps guide robust decision-making by anticipating possible future events and allows for developing practical actions today. Doing so facilitates introducing necessary social, environmental, economic, and political changes to avoid undesirable future outcomes (Ideam *et al*., 2015).

Climate change scenarios are a starting point for formulating adaptation and mitigation plans in various socioeconomic and environmental sectors. These scenarios also present development opportunities: for example, if precipitation decreases due to climate change, the water resource for electricity supply may be affected, making cleaner energies such as solar and wind power a viable alternative to complement that need. In agriculture, crops resistant to drought and high temperatures would be essential to ensure food supply. Risk management offices could focus human and logistical efforts on preventing damage from avalanches and floods in the face of potentially heavy rainfall, thereby protecting human lives and material goods. The migration of vectors that transmit diseases to humans due to climate change adaptation is another research challenge for public health.

Colombia has presented climate change scenarios in its three previous national communications (Bedoya *et al*., 2010; Ideam, 2015; Ideam *et al*., 2001). This updating activity occurs whenever the IPCC, through its modeling groups, presents low-resolution scenarios that need to be refined to the national scale with high spatial resolution results. This is due to the international scientific community's improved understanding of the interaction between the climate system (atmosphere, lithosphere, hydrosphere, and cryosphere) and atmospheric chemistry resulting from CO_2 emissions and other greenhouse gases. The lithosphere is important, primarily when land-use changes occur (deforestation).

At the national level, it is important to reference previous studies that have generated climate change scenarios for temperature and precipitation throughout the 21st century in Colombia. Notable works include those by Molina *et al*. (2003), Pabón (2003, 2008, 2012), World Bank *et al.* (2007), Ruiz (2007, 2010) and Oglesby & Rowe (2017). These studies utilized CO_2 doubling scenarios and/or global model outputs from the IPCC's AR4 (SRES emission scenarios) and AR5 (RCP scenarios) as input data. They employed various downscaling techniques and methodologies to produce detailed results nationally. While these studies generally agree on the projected increase in temperature for the remainder of the 21st century, they exhibit differences in precipitation patterns, both in magnitude and spatial distribution, relative to the reference climate used.

For the Third National Communication on Climate Change, Colombia presented projections of rainfall and temperature changes for the 21st century compared to the 1976-2005 reference climatology. These projections were based on radiative forcing scenarios from the Representative Concentration Pathways (RCPs) and utilized outputs from global models of the CMIP5 project. Statistical downscaling was applied using the Reliability Ensemble Averaging (REA) method, as described by Giorgi & Mearns (2002). The analysis indicated that under the most pessimistic scenario (i.e., higher radiative forcing), Colombia's temperature is expected to increase by 3.5 °C to 4.0 °C by the end of the century. Precipitation is projected to decrease by 10% to 40% in the Caribbean and Amazon regions, while rainfall in the central Andean region is expected to increase by 10% to 30%. In the Orinoco region and other parts of the country, no significant changes are anticipated compared to the current climate, with variations projected to remain within ±10% (Ideam *et al*., 2015).

In Colombia, Arias *et al*. (2021) conducted a verification of CMIP6 global circulation model ensembles (GCMs) against observations from various sources, including data from the Institute of Hydrology, Meteorology, and Environmental Studies (Ideam), satellite-derived data, and different reanalyses. Their study found that the latest generation of models (CMIP6) demonstrated improved performance compared to the previous generation (CMIP5), although some biases persist. Part of these biases was attributed to challenges in representing topographic effects in simulations with a grid size of approximately 50 km or larger. Additionally, biases may arise from using cumulus convection parameterizations, which are necessary for simulations with grid sizes greater than 10 km but are not explicitly resolved by general circulation models. As a result, the study identified the most significant temperature biases over the Colombian Andes.

The remainder of this paper details the data from CMIP6 models and observational sources, describes the statistical downscaling methodology used to derive high-resolution climate change scenarios, and presents the results of applying this technique.

Regarding the statistical downscaling methodology, the WMO (2020) notes a broad array of statistical methods with varying levels of complexity, among which linear regression models are the most commonly used. Simple linear regression models use a single predictor variable, while multiple linear regression models incorporate several predictors. To address challenges such as multicollinearity (where predictors are not entirely independent) and multiplicity (where an excessive number of predictors is present), dimensionality reduction is often applied. This is typically achieved by calculating the empirical orthogonal functions (EOFs) of the predictor variables. When a regression model employs EOFs as predictors, it is referred to as principal component regression (PCR).

In multi-location models, predictands may exhibit intercorrelation, leading to inconsistencies in predictions generated through principal component regression (PCR) due to sampling errors in model coefficient estimation. In such cases, canonical correlation analysis (CCA) models can be used to mitigate these issues. CCA maximizes the correlation between linear combinations of the predictors' empirical orthogonal functions (EOFs) and the selected predictors. For this reason, CCA was employed as the multivariate analysis methodology to generate the climate scenarios, using data from CMIP6 dynamic models as predictors and the Enhancing National Climate Services initiative (ENACTS) gridded data as the predictands.

The World Meteorological Organization [WMO] (2020) highlights several advantages of empirical methods, including their low computational resource requirements, ease of operational implementation, consistency with observational data (often incorporating bias correction for mean values), and ability to provide predictions in both deterministic values and probabilities. For the new scenarios, it is noteworthy that each model's deterministic output was used, with uncertainty expressed by indicating the 5th and 95th percentile values calculated from the model ensemble, following the approach employed by the IPCC in its global and regional analyses. The WMO (2020) emphasized that while the ensemble mean may be presented as a single deterministic value, it remains part of a probabilistic ensemble prediction system. The ensemble mean, representing an average of multiple forecast realizations, does not correspond to a single forecast outcome but rather reflects the mean of several possible outcomes. It serves as a straightforward indicator of the magnitude of forecast anomalies.

However, empirical methods have some limitations. Most of these methods assume stationarity in the climate system, meaning they may not effectively capture trends and other variations over time. Additionally, they may struggle to reproduce the observed variance of the predictors and, due to their reliance on linear relationships, may have difficulty representing nonlinear interactions within the climate system (WMO, 2020).

Although empirical methods typically use observed fields, such as sea surface temperatures or atmospheric circulation variables, as predictors (Alfaro, 2007; Amador & Alfaro, 2009; Díaz & Villegas, 2015), they can also incorporate outputs from dynamic models. For example, dynamically predicted precipitation fields can be used as predictors, with observed precipitation as the predictand. This hybrid approach can also help correct model biases (WMO, 2020). A similar method was applied for mean temperature predictions.

The results presented correspond to the annual mean temperature and precipitation for the periods defined by the IPCC (2021-2040, 2041-2060, and 2081-2100). These results differ in that changes in mean temperature and total annual precipitation are compared to the 1981-2010 reference climate, following the methodology used in the IPCC interactive atlas. The focus on an annual scale aimed to apply Lang's climate classification of Ideam (2005; 2015) and provide a synthesized view of how climate classes across the national territory might evolve throughout the 21st century. This approach follows the methodology used by Bedoya *et al*. (2010) for Colombia's Second National Communication on Climate Change. To achieve the annual scale, it was necessary to generate the seasonal cycle for the entire century, defined as the climate variability signal corresponding to monthly climate fluctuations (Ideam, 2005; 2015).

2. Data and methodology

According to the WMO (2020), making predictions requires two variables: the predictor and the predictand. The predictor is the independent variable, which explains the prediction, whereas the predictand is the dependent variable.

In this context, the predictor is represented by the mean temperature and precipitation outputs from the CMIP6 low-resolution global model ensemble. Meanwhile, the predictand consists of high-resolution gridded data for these meteorological variables, provided by the ENACTS project of the International Research Institute for Climate and Society (IRI). It is important to note that the high-resolution mean temperature predictand is derived from the low-resolution mean temperature data of the CMIP6 global models. The same approach was applied to precipitation data.

Regarding the predictor data, these were obtained from the Copernicus program database at the following URL: https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip6. The historical period available from this data source spans 1850-2014. However, for the

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

climate analyses in this study, the selected historical period was 1981-2014, as high-resolution predictand data are available from 1981-2016, as described below.

Fifty-one climate models are available for the period 1850-2014. However, only 36 models ran the SSP1-2.6 scenario, 34 ran the SSP2-4.5 scenario, 30 ran the SSP3-7.0 scenario, and 38 ran the SSP5-8.5 scenario. The spatial resolutions of these models range from 0.4° to 2°. Although daily data are available, this study used data aggregated into monthly averages for the period 1981-2100.

The predictand consists of mean temperature and precipitation data at the monthly level for the period 1981-2014, obtained from the following source: https://iridl.ldeo.columbia.edu/SOURCES/.Colombia/.ENACTS/.ENACTS_v1/.ALL.

These data, available at a daily level for the Colombian continental territory from 1981-2016, were produced by Ideam-IRI using methodologies outlined by Tufa *et al*. (2022) within the ENACTS project (Enhancing National Climate Services initiative), as described by Thomson & Mason (2018). According to Ideam (2021), the data underwent quality control using the Climate Data Tool (CDT). This process involved addressing spatial and temporal gaps in the historical climate record by integrating observations from meteorological stations with satellite estimates, reanalysis data, and adjustments for orography, resulting in gridded data with a spatial resolution of 0.1° (approximately 11.1 km × 11.1 km).

Regarding the methodological aspects, an initial analysis of current climate trends for mean temperature and precipitation was conducted, along with an assessment of their statistical significance using the p-value statistic for the annual series from 1981-2010. The NextGen methodology, adopted by the Colombian meteorological service (Ideam) for generating climate change scenarios, was applied for seasonal predictions, as outlined by the WMO (2020). Therefore, this methodology will be referred to as NextGen in the following sections.

The implementation of the NextGen methodology to generate the next generation of climate change scenarios for Colombia was conducted in two phases. The first phase involved a retrospective analysis for the period 1981-2014, with the following objectives: (1) to identify

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

the optimal model configuration within the canonical correlation analysis (CCA), (2) to select the models for inclusion in the ensemble after calibration by spatial patterns, and (3) to assess the predictive skill of the models chosen for the final ensemble. Once these steps were completed, the second phase involved executing predictions for 2015-2100 through cross-validation. This was done for each of the four climate change scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) using the selected models, based on the configuration determined in the first phase, to run the CCA model with the support of the Climate Predictability Tool (CPT).

To understand calibration by spatial patterns, it is helpful to first grasp the concept of canonical correlation analysis (CCA). CCA identifies spatial patterns between two fields with shared temporal variability by maximizing their correlation coefficient. This coefficient measures the degree of linear association between the fields, indicating how changes in one field (predictor) directly influence changes in the other (predictand). Typically, these fields are represented by the principal components of the original datasets, reducing the spatial dimensions by focusing on modes that capture most of the variance and minimizing the risk of including noise in the analysis (Wilks, 2006). Similar to principal component analysis, CCA produces representative series known as canonical components, spatial patterns referred to as canonical maps, and a scalar representing the degree of association between the predictor and predictand fields, called canonical correlation (Muñoz, 2009).

Additionally, it is important to note that, during the first phase, calculation domains were defined for both the predictor and the predictand. The analysis area for the predictor encompassed latitudes from 10 °S to 20 °N and longitudes from 90 °W to 60 °W. For the predictand, the analysis area covered latitudes from 5 °S to 15 °N and longitudes from 80 °W to 65 °W.

In the retrospective analysis, the Climate Predictability Tool (CPT) divided the 34-year series (1981-2014) into two 17-year periods; the first 17 years served as the control period, and the remaining 17 years were used as the test period for prediction. The Canonical Correlation Analysis (CCA) model was initially configured with five modes for the predictor and the

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

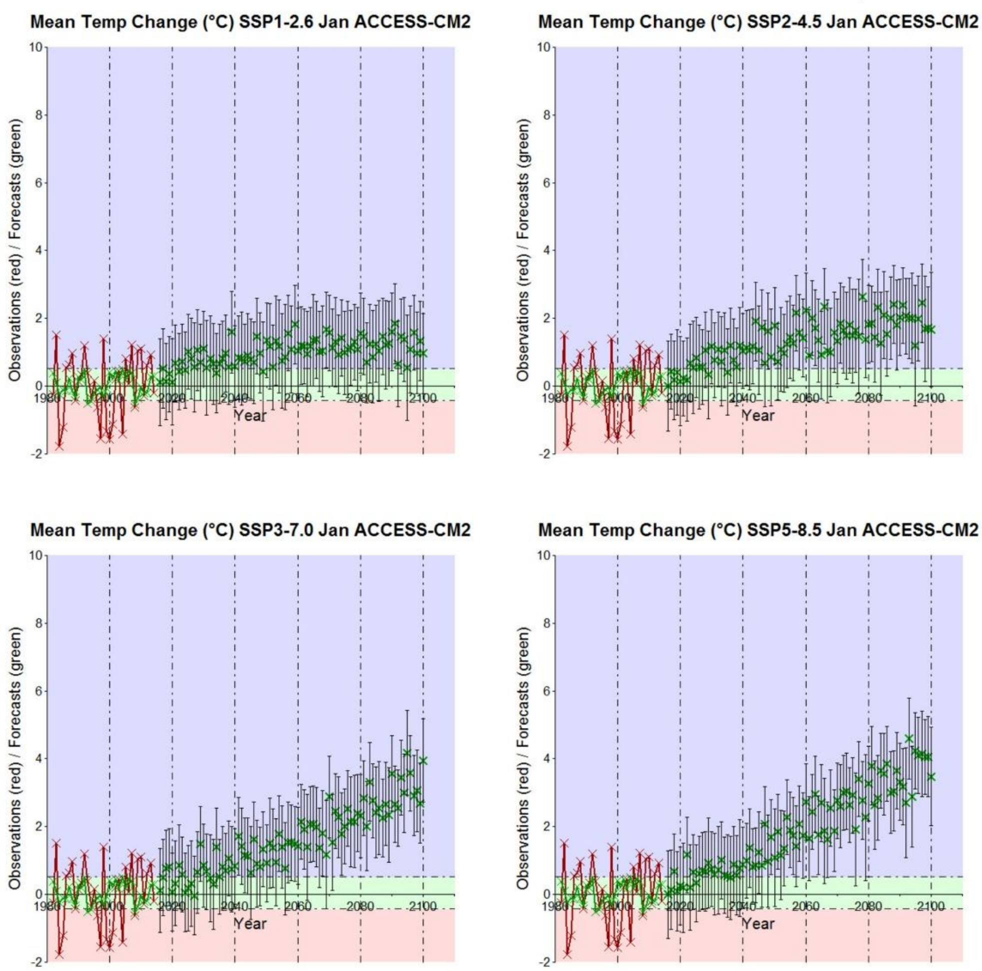
predictand. The CPT tool was instructed to treat temperature data as following an empirical distribution and precipitation data as following a gamma distribution.

With this initial configuration, the scree plot was examined. For temperature, the first five modes captured approximately 80% of the observed variance for both the predictor and the predictand. However, for precipitation, the plot suggested using seven modes for the predictor and ten modes for the predictand (ENACTS data). The CCA was then rerun with these configurations to assess spatial pattern similarity, focusing on the first three modes observed in the canonical load maps for both the predictor and the predictand. Models that exhibited similar spatial patterns in at least the first two modes were selected for the ensemble. Their predictive skill was evaluated using four statistical metrics: Pearson's correlation, bias, root mean square error (RMSE), and percentage of hits. This evaluation aimed to assess the degree of association between the CMIP6 models and observations, determine whether these models overestimate or underestimate meteorological variables, and gauge their effectiveness in high-resolution predictions for the country.

In the second phase (the prediction phase), and only for the models that enter the final ensemble (those that presented similar spatial patterns between predictor and predictand in the first phase), it is important to keep in mind that the CCA in the CPT tool was configured as follows: the training period between predictor and predictand covers the 34 years of present climate from 1981 to 2014, and the prediction period was set from 2015 to 2100 for the four climate change scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The modes for the predictor and predictand in the CCA were those identified in the diagnosis (first phase). The reference period for the calculations of the change in mean temperature (°C) and change in total precipitation (%) was set relative to 1981-2010, which is one of the reference periods used by the IPCC in its atlas (Gutiérrez *et al*., 2021). The treatment of the data remained consistent (empirical distribution for temperature and gamma distribution for precipitation). After performing the cross-validation, the predictions for 2015-2100 were obtained for the four climate change scenarios, similar to those shown in figure 1. In the case of precipitation prediction, the CPT was configured with zero adjustments to ensure positive values in the prediction.

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Figure 1. Climate change scenarios of mean temperature for January over a point in the center of the Andean region, using one of the CMIP6 models that are part of the NextGen ensemble



Note. This analysis was also conducted for precipitation across the 9616 grid points of the ENACTS observations.

Source. Own elaboration (created with CPT Tool).

It is important to note that this analysis was performed for each of the 12 months of the year to derive the seasonal cycle for the periods 2021-2040, 2041-2060, and 2081-2100. These monthly results were then used to calculate annual values. These annual calculations enabled the application of Lang's climate classification, as described by Ideam (2005) and Ideam

(2015). This classification divides the total annual precipitation by the mean annual temperature for a reference period, categorizing the climate as follows: desert (0 to 20), arid (20.1 to 40), semi-arid (40.1 to 60), semi-humid (60.1 to 100), humid (100.1 to 160), and super-humid (greater than 160.1).

A presentation standard used by the IPCC to communicate its results is based on model ensembles. This approach provides the average expected values throughout the 21st century and utilizes the range of low-resolution models to convey uncertainty. Following the IPCC methodology, the 5th, 10th, 25th, 75th, 90th, and 95th percentiles were calculated from the models included in the national ensemble. These models were selected in phase 1 of the CCA if they exhibited similar spatial patterns to current climate observations (1981-2014). This method allows for understanding the mean value (50th percentile) and the range of possible values for meteorological variables over the three analyzed periods (2021-2040, 2041-2060 and 2081-2100).

This work differs from other studies in its methodological approach. In most studies, model selection has relied more on statistical correlations between observed data and data from global models in the present climate, without accounting for corrections in mean values, data variability, and the representation of spatial patterns. A canonical correlation analysis was performed after calculating the Empirical Orthogonal Functions (EOF) or Principal Component Regression (PCR) for both model data and observations. This dimensionality reduction provided by the EOF translates into finding climatically homogeneous regions for both data sources. In this case, the best statistic for model selection is the canonical correlation, which ranges from -1 to 1; values close to 1 indicate that the spatial patterns (or homogeneous regions) are similar between the observed data and the models. Therefore, models that met the above criteria were included in the ensemble of selected models. The ensemble itself is the average of the selected models.

It is important to note again that this process was carried out for each model and each month of the year. Only those models that exhibited similar spatial patterns to the observations (ENACTS) were included in the final ensemble. This was done to generate the monthly values

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

and annual cycles of precipitation and mean air temperature for climate change scenarios for the remainder of the 21st century.

Although this methodology is the most recommended by the WMO for climate prediction when high computational resources are not available for dynamic downscaling, future research should consider other methodologies, such as those outlined below (Hernanz *et al*., 2023).

Raw:

- Raw: no downscaling (nearest grid point).
- Raw-bil: no downscaling (bilinear interpolation).

Model output statistics:

- QM: empirical quantile mapping (Themeßl et al., 2011).
- DQM: detrended quantile mapping (Cannon et al., 2015). Quantile adjustment over detrended series.
- QDM: quantile delta mapping (Cannon et al., 2015). Delta change over quantiles.
- PSDM: (Parametric) scaled distribution mapping (Switanek et al., 2017).

Analogs/weather typing:

- ANA-SYN: analog based on synoptic analogy. 1NN: nearest analog, kNN: k-nearest analogs, rand: random analog from probability density function (Hernanz et al., 2022).
- ANA-LOC: same as ANA-SYN but using synoptic+local analogy (Amblar Francés et al., 2017; Hernanz et al., 2022; Petisco de Lara, 2008a).
- ANA-VAR: same as ANA-SYN but using the spatial pattern of the target variable itself.

Linear:

- MLR: multiple linear regression (Amblar Francés et al., 2017; Hernanz et al., 2022). Based on SDSM (Wilby et al., 2002).

- MLR-ANA: multiple linear regression based on analogs (Amblar-Francés et al., 2017; Hernanz et al., 2022; Petisco de Lara, 2008b).
- MLR-WT: multiple linear regression based on weather types. Similar to ANA-MLR but using precalibrated relationships for each weather type.
- GLM: generalized linear model. Logistic + MLR (LIN), or over transformed data (EXP for exponential and CUB for cubic regression) (Amblar Francés et al., 2017; Hernanz et al., 2022). Based on SDSM (Wilby et al., 2002).

Machine learning:

- SVM: support vector machine. Non-linear machine learning classification/regression.
- LS-SVM: least square support vector machine. Non-linear machine learning classification/regression.
- RF: random forest. Non-linear machine learning classification/regression. This method is combined with an MLR to extrapolate values out of the observed range (configurable).
- XGB: extreme gradient boost. Non-linear machine learning classification/regression. This method is combined with an MLR to extrapolate values out of the observed range (configurable).
- ANN: artificial neural networks. Non-linear machine learning classification/regression (García-Valero, 2021).
- CNN: Convolutional Neural Networks. Non-linear machine learning classification/regression (Hernanz et al., 2022).

Weather generators:

- WG-PDF: downscaling parameters of the distributions instead of downscaling daily data (Benestad, 2021; Erlandsen et al., 2020) .
- WG-NMM: non-homogeneous markov model. Non-parametric weather generator based on a first-order two-state (wet/dry) Markov chain. Both the transition probabilities and the empirical distributions used for the intensity are conditioned on the precipitation given by the reanalysis/models (Richardson, 1981).

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

3. Discussion and results

3.1. Model ensemble results

As mentioned throughout the text, only those models that, in the present climate, showed similar spatial patterns (as determined by canonical correlation analysis) to the dataset provided by observations from 1981-2010 were included in the final model ensemble.

For example, table 1 shows that 11 models were used to generate air temperature projections for January, while nine models were used for April. This indicates that the same model does not necessarily represent the spatial pattern well for all months of the year; similarly, some models do not correctly capture this pattern. Of the approximately 33 models considered, 25 participated in the final ensemble, but not necessarily with well-represented patterns for all months. The exception is the INM-CM5-0 model, which performed well for all months of the year.

In the case of precipitation, September was the month for which the models had the best representation of spatial patterns compared to the observations (ENACTS), as 26 models were included in the final ensemble. For precipitation, it was also observed that more models were included in the final ensemble for april (18 models). However, in general, most models did not adequately represent the spatial patterns for all 12 months of the year. Perhaps the best model in this regard was CanESMS-CanOE, which showed that 9 out of the 12 months were well represented in spatial patterns according to the canonical correlation analysis.

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Table 1. Model ensemble results for temperature and precipitation

TEMPERATURE													
CMIP6 Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	TOTAL
ACCESS-CM2	1	1				1	1	1	1	1	1	1	9
AWI-CM-1-1-MR	1				1	1	1			1	1	1	7
BCC-CSM2-MR		1	1	1		1	1	1	1	1	1	1	10
CAMS-CSM1-0		1	1					1	1			1	5
CanESM5-CanOE		1		1	1	1	1	1	1	1	1	1	10
CESM2							1		1	1		1	4
CMCC-CM2-SR5			1						1		1		3
CNRM-CM6-1-HR	1	1	1		1	1	1	1	1	1	1	1	11
CNRM-ESM2-1													0
FGOALS-F3-L	1	1	1	1							1		5
FGOALS-G3													0
GFDL-ESM4	1	1	1	1	1	1	1		1		1	1	10
IITM-ESM													0
INM-CM4-8	1		1	1	1	1	1	1	1	1	1	1	11
INM-CM5-0	1	1	1	1	1	1	1	1	1	1	1	1	12
IPSL-CM6A-LR									1	1	1	1	4
KACE-1-0-G	1				1	1			1				4
MCM-UA-1-0							1				1		2
MIROC6	1			1									2
MIROC-ES2L	1												1
MPI-ESM1-2-LR		1	1			1			1		1		5
MRI-ESM2-0													0
NorESM2-MM		1	1	1				1	1	1	1	1	8
TaiESM1				1	1	1	1		1	1		1	7
UKESM1-0-LL	1	1	1		1		1	1	1	1	1	1	10
TOTAL	11	11	11	9	9	11	12	9	16	12	15	14	140

PRECIPITATION													
CMIP6 Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	TOTAL
ACCESS-CM2							1		1			1	3
AWI-CM-1-1-MR	1	1	1	1				1			1	1	7
BCC-CSM2-MR	1			1		1		1			1	1	6
CAMS-CSM1-0		1	1	1					1				4
CanESM5-CanOE	1		1		1	1	1	1	1	1		1	9
CESM2	1		1		1			1	1	1	1		7
CMCC-CM2-SR5						1					1	1	3
CNRM-CM6-1-HR	1		1	1	1	1		1	1	1			8
CNRM-ESM2-1				1		1	1			1	1		5
EC-Earth3-VEG-LR	1			1		1	1		1		1	1	7
FGOALS-F3-L	1			1		1	1					1	5
FGOALS-G3	1			1			1	1		1	1	1	7
GFDL-ESM4	1		1		1		1		1			1	6
IITM-ESM		1	1	1		1					1	1	6
INM-CM4-8		1	1	1		1	1		1				6
INM-CM5-0		1	1	1					1	1	1		6
IPSL-CM6A-LR	1			1	1	1	1				1	1	7
KACE-1-0-G	1		1			1					1	1	5
MCM-UA-1-0		1			1				1				3
MIROC6	1			1		1					1	1	5
MIROC-ES2L				1		1		1			1		4
MPI-ESM1-2-LR		1		1			1					1	4
MRI-ESM2-0				1		1					1	1	4
NorESM2-MM'				1	1		1				1	1	5
TaiESM1					1	1			1				3
UKESM1-0-LL	1			1					1	1	1	1	6
TOTAL	13	7	10	18	8	15	11	7	12	7	16	17	141

Source. Own elaboration.

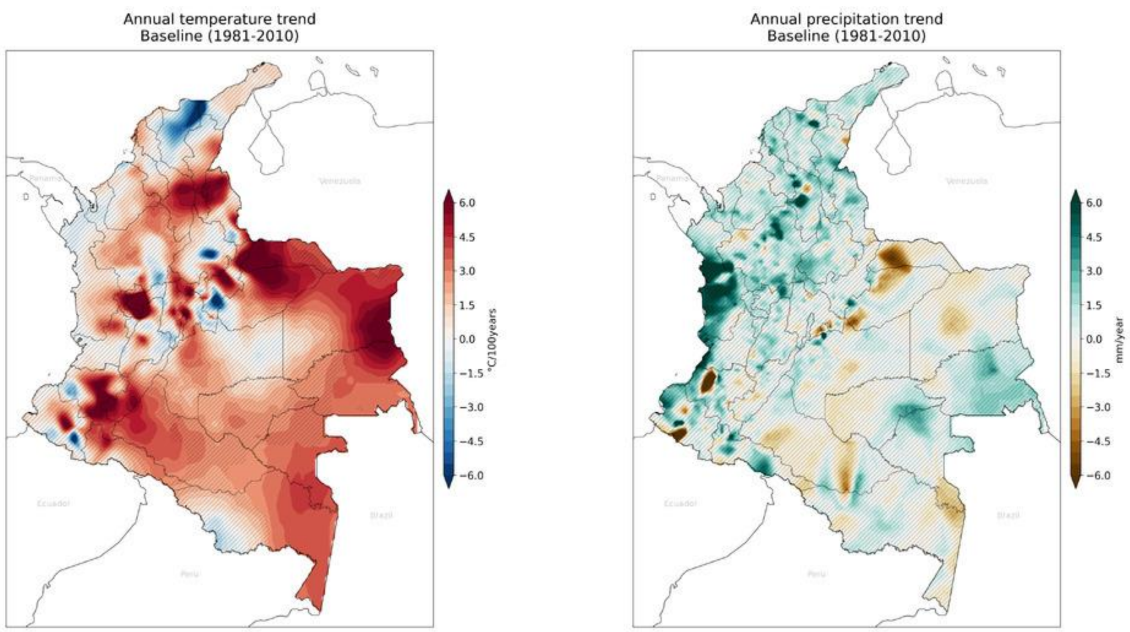
3.2. Present climate trend analysis (1981-2010)

The trend analysis, which involved fitting a straight line using the least squares method to the data, indicates that mean temperatures are rising across much of Colombia. Notable exceptions include the Sierra Nevada de Santa Marta (Snow-Covered Mountain Range of Saint Martha), parts of Santander, southeastern Antioquia, and eastern Caldas, as well as central Chocó in the Pacific region, and Casanare, Arauca, Vichada, and western Meta in the Orinoco region. Most of the Amazon region also exhibits warming trends. Temperature increases in these areas range from 1 °C to over 6 °C per 100 years, with the southern Caribbean, central and southern Andean regions, and much of the eastern part of the country experiencing increases greater than 3.5 °C/100 years. These trends are statistically significant, with 95% confidence, as illustrated in figura 2. Additionally, the data series reveals a statistically significant cooling trend in the eastern part of the Sierra Nevada de Santa Marta, with rates of change between -2 °C and -6 °C/100 years.

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Regarding precipitation, the data indicate that this variable is increasing at a rate of 1 mm to values equal to or exceeding 6 mm per year in large areas of the Caribbean, Andean, and Pacific regions, as well as in the eastern Amazon. Conversely, rainfall volumes are decreasing in western Arauca and specific locations in Vichada, Meta, and Caquetá. However, these decreasing trends are not statistically significant for the country as a whole (p-value > 0.05).

Figure 2. Temperature and precipitation trends in the present climate (1981-2010)



Note. The diagonal line represents a threshold indicating that trends not exceeding this line are not statistically significant.

Source. Own elaboration.

3.3. Predictive skill of CMIP6 models in present climate (1981-2014)

Pearson correlation: after performing the t-student test on the correlation results, it was found that for 34 data points (the number of years analyzed for each month), values equal to or greater than 0.26 indicate a statistically significant correlation, suggesting that two sets of variables are related to each other. Thus, when this occurs, it can be stated that the CMIP6 model data are associated (or in phase) with the observations (ENACTS) for both meteorological variables. For precipitation, this association is generally observed across

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

most of the country, with correlation values close to 0.3. In contrast, correlation values exceed 0.6 for mean temperature, particularly in relatively flat areas such as the Caribbean, Orinoco, and Amazon regions throughout the year.

Bias and RMSE: the bias analysis indicates that the set of models used for the NextGen ensemble tends to underestimate mean temperature. The Root Mean Square Error (RMSE) shows that this underestimation ranges from 0.2 °C to 0.8 °C across most of the country and throughout the year, except in january over the northeastern Orinoco, where it ranges from 1.2 °C to 1.4 °C. For precipitation, the bias analysis indicates an overall underestimation of rainfall in most of the country. However, in the Orinoco region during february, june, july, august, and september, the models tend to overestimate monthly precipitation values compared to the observations. The RMSE reveals that underestimates of rainfall can vary from a few millimeters in the Caribbean dry season to up to 250 mm in the Pacific region, which is humid year-round. For the overestimated months in the Orinoco region, february shows increases of 15 to 20 mm, while june, july, august, and september show increases ranging from 40 to 120 mm.

Hit score: the validation of the present climate reveals that for mean temperature predictions, accuracy ranges from 40% to 60% in the Caribbean, Andean, and southern Pacific regions. In contrast, accuracy improves to between 55% and over 80% in the northern and central Pacific regions, the Orinoco, and Amazon regions. For precipitation, accuracy generally ranges between 45% and 50% across most of the country and for all 12 months of the year.

3.4. Multimodel NextGen ensemble for the 4 SSP scenarios

As indicated in the methodology, this ensemble is called NextGen because it includes only those CMIP6 models that demonstrated similar spatial patterns with the observations when comparing the canonical load maps of the predictor and the predictand for the present climate. This approach aims to ensure that the selected models more accurately capture the dynamics over the Colombian national territory and better represent the spatial distribution of mean temperature and precipitation fields for the remainder of the 21st century.

Before presenting the changes in mean temperature (anomalies) and changes (%) in annual total precipitation at the national level concerning the reference climatology (1981-2010), table 2 outlines the results provided by the IPCC regional atlas for north-western and northern South America on the continental territory. Specifically, Colombia's Caribbean, Pacific, and Andean regions fall within the first region mentioned, while the Orinoco and Amazon regions are part of the second. The results are presented on an annual basis.

In particular, the IPCC atlas indicates that the average air temperature is projected to increase from 1.0 °C (2021-2040) to 1.5 °C (2081-2100) for the SSP1-2.6 scenario, from 1.0 °C (2021-2040) to 2.6 °C (2081-2100) for the SSP2-4.5 scenario, from 1.0 °C (2021-2040) to 3.9 °C (2081-2100) for the SSP3-7.0 scenario, and from 1.2 °C (2021-2040) to 5.0 °C (2081-2100) for the SSP5-8.5 scenario.

Changes in precipitation are projected to range from -3.5% to 4.0% (2021-2040) and from -5.1% to 5.5% (2081-2100) for the SSP1-2.6 scenario, from -3.4% to 4.1% (2021-2040) and from -7.1% to 7.0% (2081-2100) for the SSP2-4.5 scenario, from -5.2% to 4.0% (2021-2040) and from -14.3% to 4.0% (2081-2100) for the SSP3-7.0 scenario, and from -5.6% to 4.2% (2021-2040) and from -15.5% to 9.0% (2081-2100) for the SSP5-8.5 scenario.

The NextGen ensemble suggests that mean temperature in Colombia will increase from 1.0 °C (2021-2040) to 1.4 °C (2081-2100) for the SSP1-2.6 scenario, from 1.1 °C (2021-2040) to 2.9 °C (2081-2100) for the SSP2-4.5 scenario, from 1.0 °C (2021-2040) to 3.4 °C (2081-2100) for the SSP3-7.0 scenario, and from 1.2 °C (2021-2040) to 4.6 °C (2081-2100) for the SSP5-8.5 scenario, as shown in table 3. The spatial distribution of these temperature changes for the three periods proposed by the IPCC is presented in figure 3.

However, the range of variation for mean temperature in Colombia would be between 0.8 °C and 1.3 °C (2021-2040) to 1.1 °C and 2.0 °C (2081-2100) for the SSP1-2.6 scenario, between 0.8 °C and 1.4 °C (2021-2040) to 2.3 °C and 3.8 °C (2081-2100) for the SSP2-4.5 scenario, between 0.8 °C and 1.3 °C (2021-2040) to 2.5 °C and 4.6 °C (2081-2100) for the SSP3-7.0 scenario, and between 0.9 °C and 1.5 °C (2021-2040) to 3.5 °C and 6.2 °C (2081-2100) for the SSP5-8.5 scenario.

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

The change (%) in total annual precipitation in Colombia concerning the current climate (1981-2010) will range between -0.5% (2021-2040) and -0.4% (2081-2100) for the SSP1-2.6 scenario, between -0.5% (2021-2040) and -1.1% (2081-2100) for the SSP2-4.5 scenario, between -0.4% (2021-2040) and -1.7% (2081-2100) for the SSP3-7.0 scenario, and between -0.4% and -2.9% (2081-2100) for the SSP5-8.5 scenario, as shown in table 3. These projections indicate slight decreases in total annual precipitation, consistent with findings by Arias *et al*. (2021). The spatial distribution for the three periods proposed by the IPCC is shown in figure 4. The greatest changes compared to the present climate are observed in the Caribbean and Andean regions for 2081-2100 under the SSP3-7.0 and SSP5-8.5 scenarios, where decreases relative to the 1981-2010 reference climatology are evident.

Table 2. Change in annual mean temperature (°C) and change in total annual precipitation (%) estimated by the ensemble of approximately 33 CMIP6 models for the IPCC north-western and northern regions of South America

North-Western South America, Northern South America (Land) Ensemble IPCC-CMIP6							
Change (°C) Mean Temperature	**p05**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**
Period: 2021-2040 Scenario: SSP1-2.6	0,6	0,7	0,8	1,0	1,1	1,5	1,6
Period: 2021-2040 Scenario: SSP2-4.5	0,7	0,7	0,9	1,0	1,1	1,4	1,7
Period: 2021-2040 Scenario: SSP3-7.0	0,7	0,7	0,8	1,0	1,1	1,4	1,7
Period: 2021-2040 Scenario: SSP5-8.5	0,7	0,8	1,0	1,2	1,4	1,8	1,9
Period: 2041-2060 Scenario: SSP1-2.6	0,8	0,9	1,0	1,4	1,6	2,1	2,2
Period: 2041-2060 Scenario: SSP2-4.5	1,0	1,2	1,4	1,7	1,8	2,4	2,8
Period: 2041-2060 Scenario: SSP3-7.0	1,3	1,4	1,5	1,9	2,0	2,4	2,9
Period: 2041-2060 Scenario: SSP5-8.5	1,4	1,7	1,9	2,3	2,4	3,3	3,6
Period: 2081-2100 Scenario: SSP1-2.6	0,7	0,8	1,1	1,5	1,8	2,2	2,4
Period: 2081-2100 Scenario: SSP2-4.5	1,6	1,7	2,0	2,6	3,0	3,5	4,2
Period: 2081-2100 Scenario: SSP3-7.0	2,4	2,5	3,2	3,9	4,4	4,9	5,9
Period: 2081-2100 Scenario: SSP5-8.5	3,0	3,2	3,9	5,0	5,7	7,3	7,7
Change (%) Annual Total Precipitation	**p05**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**
Period: 2021-2040 Scenario: SSP1-2.6	-3,5	-1,4	-0,1	0,6	1,8	3,5	4,0
Period: 2021-2040 Scenario: SSP2-4.5	-3,4	-2,9	-1,9	0,1	1,9	2,9	4,1
Period: 2021-2040 Scenario: SSP3-7.0	-5,2	-4,2	-3,2	-0,6	1,4	3,3	4,0
Period: 2021-2040 Scenario: SSP5-8.5	-5,6	-4,7	-3,4	-1,0	1,0	2,3	4,2
Period: 2041-2060 Scenario: SSP1-2.6	-6,0	-5,0	-0,8	0,6	2,9	5,0	6,1
Period: 2041-2060 Scenario: SSP2-4.5	-6,3	-5,3	-1,6	-0,4	1,4	2,4	4,4
Period: 2041-2060 Scenario: SSP3-7.0	-7,4	-6,1	-4,3	-2,0	-0,2	1,8	2,7
Period: 2041-2060 Scenario: SSP5-8.5	-6,9	-6,5	-5,8	-2,0	1,1	3,2	3,7
Period: 2081-2100 Scenario: SSP1-2.6	-5,1	-4,0	-1,4	0,4	2,3	4,0	5,5
Period: 2081-2100 Scenario: SSP2-4.5	-7,0	-6,5	-3,1	0,0	2,9	5,5	7,0
Period: 2081-2100 Scenario: SSP3-7.0	-14,3	-14,0	-11,0	-4,4	-0,1	3,8	4,0
Period: 2081-2100 Scenario: SSP5-8.5	-15,5	-14,5	-12,2	-4,1	1,9	4,0	9,0

Source. Own elaboration (created from advance IPCC regional atlas).

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Table 3. Change in annual mean temperature (°C) and change in total annual precipitation (%) estimated by the NextGen ensemble for Colombia (only land)

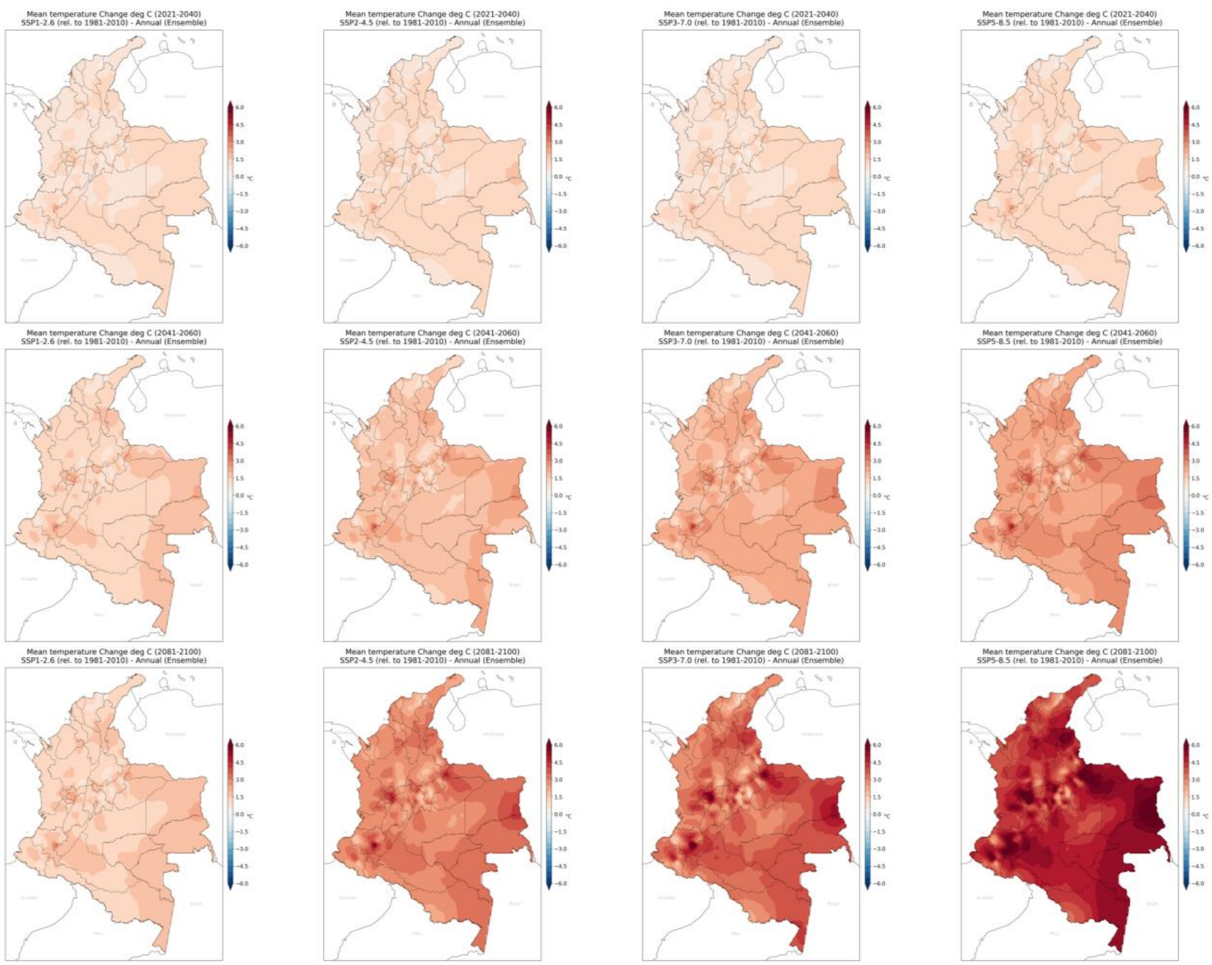
COLOMBIA							
Change (°C) Mean Temperature	**p05**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**
Period: 2021-2040 Scenario: SSP1-2.6	0,8	0,8	0,9	1,0	1,1	1,2	1,3
Period: 2021-2040 Scenario: SSP2-4.5	0,8	0,9	1,0	1,1	1,2	1,3	1,4
Period: 2021-2040 Scenario: SSP3-7.0	0,8	0,8	0,9	1,0	1,1	1,3	1,3
Period: 2021-2040 Scenario: SSP5-8.5	0,9	1,0	1,0	1,2	1,3	1,4	1,5
Period: 2041-2060 Scenario: SSP1-2.6	1,0	1,1	1,2	1,4	1,5	1,7	1,9
Period: 2041-2060 Scenario: SSP2-4.5	1,4	1,5	1,6	1,7	1,9	2,1	2,3
Period: 2041-2060 Scenario: SSP3-7.0	1,7	1,8	1,9	2,1	2,3	2,5	2,7
Period: 2041-2060 Scenario: SSP5-8.5	2,0	2,1	2,2	2,4	2,7	2,9	3,1
Period: 2061-2080 Scenario: SSP1-2.6	1,1	1,2	1,3	1,4	1,6	1,8	2,0
Period: 2061-2080 Scenario: SSP2-4.5	1,9	2,0	2,1	2,3	2,5	2,8	3,0
Period: 2061-2080 Scenario: SSP3-7.0	2,1	2,2	2,5	2,7	3,0	3,3	3,6
Period: 2061-2080 Scenario: SSP5-8.5	2,7	2,9	3,1	3,5	3,8	4,2	4,6
Period: 2081-2100 Scenario: SSP1-2.6	1,1	1,2	1,3	1,4	1,6	1,9	2,0
Period: 2081-2100 Scenario: SSP2-4.5	2,3	2,5	2,7	2,9	3,2	3,5	3,8
Period: 2081-2100 Scenario: SSP3-7.0	2,5	2,7	3,0	3,4	3,8	4,2	4,6
Period: 2081-2100 Scenario: SSP5-8.5	3,5	3,7	4,1	4,6	5,1	5,6	6,2
Change (%) Annual Total Precipitation	**p05**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**
Period: 2021-2040 Scenario: SSP1-2.6	-6,5	-5,2	-2,8	-0,5	1,8	4,1	5,3
Period: 2021-2040 Scenario: SSP2-4.5	-6,0	-4,8	-2,7	-0,5	1,7	3,7	4,8
Period: 2021-2040 Scenario: SSP3-7.0	-5,9	-4,8	-2,7	-0,4	1,9	4,0	5,1
Period: 2021-2040 Scenario: SSP5-8.5	-7,2	-5,8	-3,1	-0,4	1,9	4,1	5,4
Period: 2041-2060 Scenario: SSP1-2.6	-7,0	-5,7	-3,3	-0,5	2,1	4,7	6,2
Period: 2041-2060 Scenario: SSP2-4.5	-7,5	-6,0	-3,3	-0,4	1,9	3,7	4,8
Period: 2041-2060 Scenario: SSP3-7.0	-8,9	-7,2	-4,2	-1,2	1,5	4,1	5,5
Period: 2041-2060 Scenario: SSP5-8.5	-9,3	-7,5	-4,3	-1,1	1,5	4,2	5,8
Period: 2061-2080 Scenario: SSP1-2.6	-6,7	-5,4	-3,2	-0,8	1,8	4,2	5,8
Period: 2061-2080 Scenario: SSP2-4.5	-8,1	-6,7	-4,2	-1,2	1,8	4,8	6,5
Period: 2061-2080 Scenario: SSP3-7.0	-10,3	-8,4	-5,0	-1,5	2,1	5,2	7,1
Period: 2061-2080 Scenario: SSP5-8.5	-13,0	-10,2	-5,9	-1,9	1,8	5,8	8,5
Period: 2081-2100 Scenario: SSP1-2.6	-6,6	-5,1	-2,8	-0,4	1,7	4,0	5,4
Period: 2081-2100 Scenario: SSP2-4.5	-9,3	-7,7	-4,5	-1,1	2,1	5,1	6,9
Period: 2081-2100 Scenario: SSP3-7.0	-13,0	-10,4	-5,8	-1,7	2,4	6,0	8,5
Period: 2081-2100 Scenario: SSP5-8.5	-17,4	-14,1	-8,2	-2,9	2,3	7,7	11,1

Source. Own elaboration.

Este artículo es un *online first* (versión definitiva del contenido del artículo, con diagramación provisional y asignación de DOI). Aún no cuenta con páginas definitivas, pero es citable utilizando su código DOI.

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

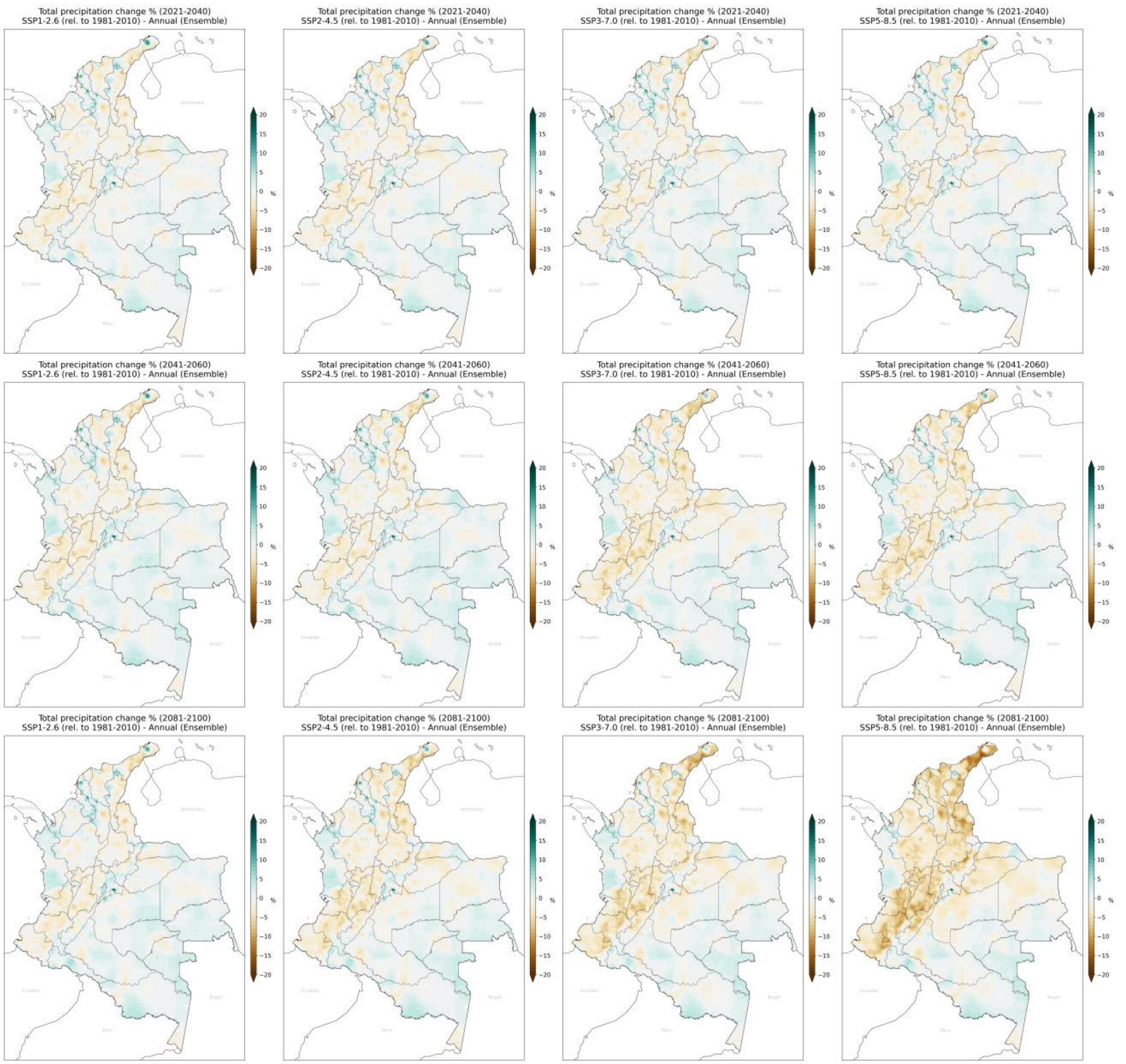
Figure 3. Estimated mean temperature change (°C) for scenarios SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 (from left to right) for the periods 2021-2040 (top), 2041-2060 (middle), and 2081-2100 (bottom)



Source. Own elaboration.

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Figure 4. Total precipitation change (%) estimated for SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios (from left to right) for the periods 2021-2040 (top), 2041-2060 (middle), and 2081-2100 (bottom)



Source. Own elaboration.

The change (%) in total annual precipitation in Colombia compared to the current climate (1981-2010) is projected to range from -6.5% to 5.3% for the period 2021-2040 and from -6.6% to 5.4% for the period 2081-2100 under the SSP1-2.6 scenario. For the SSP2-4.5

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

scenario, the range is from -6.0% to 4.8% (2021-2040) and from -9.3% to 6.9% (2081-2100). Under the SSP3-7.0 scenario, it is expected to vary between -5.9% and 5.1% (2021-2040) and between -13.0% and 8.5% (2081-2100). For the SSP5-8.5 scenario, the changes are projected to range from -7.2% to 5.4% (2021-2040) and from -17.4% to 11.1% (2081-2100). The spatial patterns of precipitation change across Colombia are consistent with findings from Pabón (2008) and Ruiz (2010).

3.5. Lang's climate classification for the 4 SSP scenarios

The statistical downscaling of Colombia's next generation of IPCC climate change scenarios indicates that total annual precipitation is expected to remain relatively stable throughout the 21st century compared to the 1981-2010 reference climatology, regardless of the scenario. In contrast, mean temperature is projected to rise at varying rates depending on the scenario. The lowest increases are anticipated under the SSP1-2.6 scenario, while the highest increases are projected under the SSP5-8.5 scenario. Intermediate increases are expected for the SSP2-4.5 and SSP3-7.0 scenarios. Thus, the rise in temperature emerges as the primary variable driving climate changes in Colombia for the remainder of the 21st century.

As a result, the aridity index exhibits more pronounced changes towards the end of the 21st century, particularly under scenarios with higher greenhouse gas (GHG) and CO_2 emissions. Notably, the trend analysis of mean temperature for the 1981-2010 period (Section 3.1), where the data are statistically significant, shows trends comparable to the temperature increases projected by the SSP3-7.0 and SSP5-8.5 scenarios.

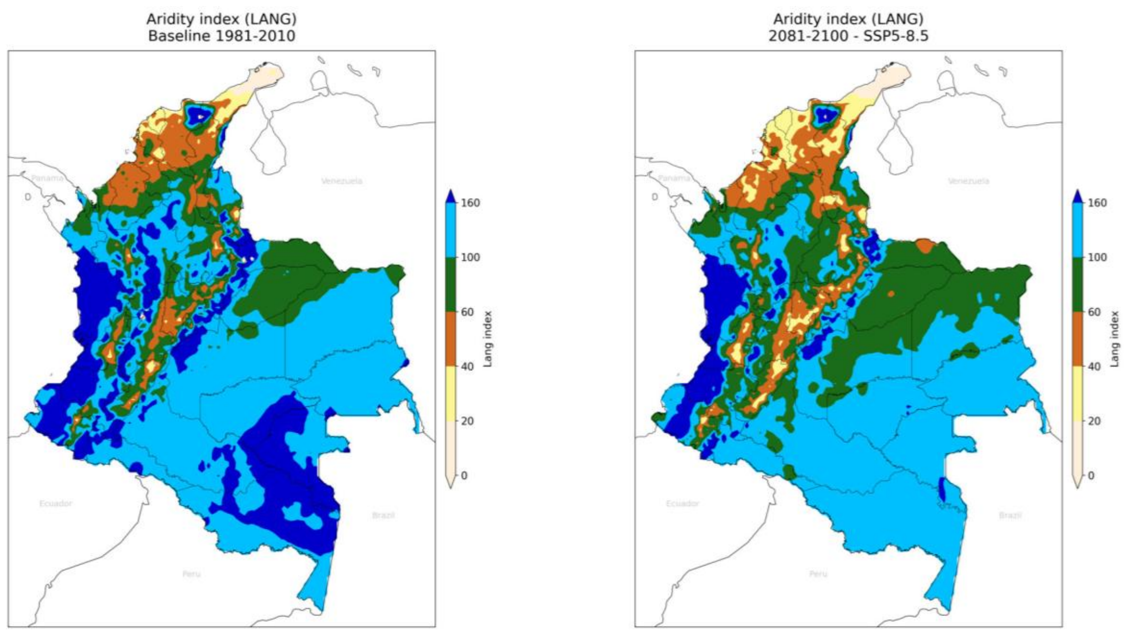
Under such scenarios, it is projected that Atlántico, central Córdoba, northern Magdalena, and Cesar in the Caribbean region will shift from semi-arid to arid climates. Similarly, the southern parts of Norte de Santander, the Altiplano Cundiboyacense, eastern Tolima, eastern Valle, and much of Huila in the Andean region are expected to experience a transition from humid to semi-humid climates. In the Orinoco region, north-central Vichada and many parts of Meta will shift from humid to semi-humid climates. Additionally, eastern Caquetá, Guaviare, western Vaupés, and much of north-central Amazonas in the Colombian Amazon

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

will move from super-humid to humid climates. These changes are illustrated in Fig. 5 for the SSP5-8.5 scenario towards the end of the 21st century (2081-2100). Most of the Pacific region is expected to remain essentially unchanged from the 1981-2010 reference climatology and will continue to experience super-humid conditions.

As previously noted, Lang's climate classification calculation relies on the estimated seasonal cycle. Therefore, the precipitation and mean temperature changes for the SSP5-8.5 scenario at the end of the 21st century are illustrated in figure 6.

Figure 5. On the left: lang climate classification for the reference climate (1981-2010). On the right: lang climate classification for 2081-2100 under the SSP5-8.5 scenario.

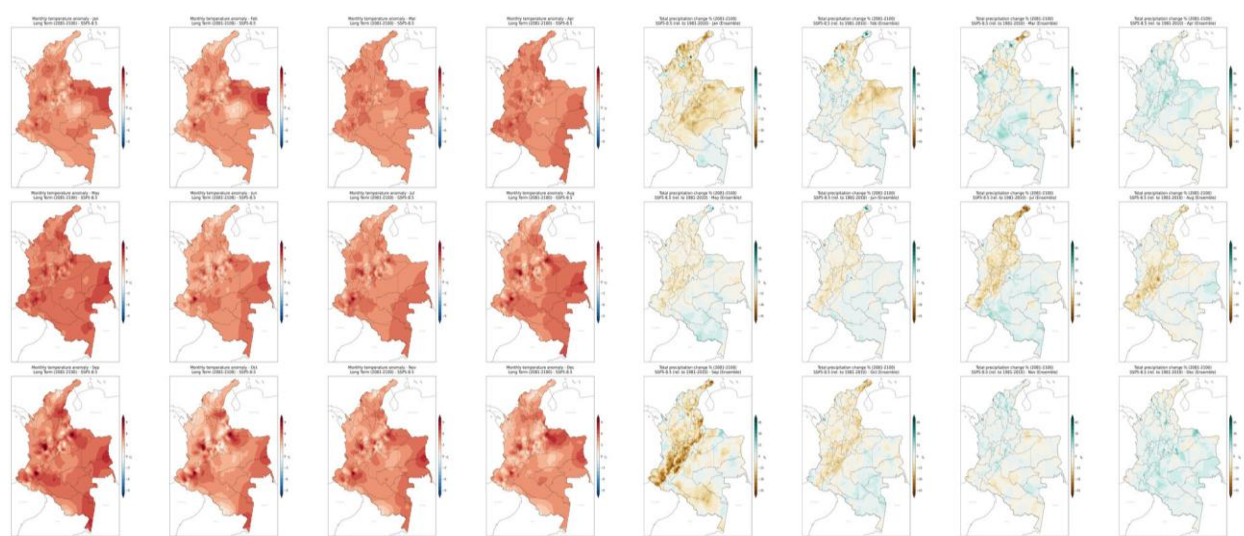


Note. Classification categories include: desert (0 to 20), arid (20.1 to 40), semi-arid (40.1 to 60), semi-humid (60.1 to 100), humid (100.1 to 160), and super-humid (greater than 160.1)

Source. Own elaboration.

Revista Ontare- Volumen 11 - enero a diciembre de 2023
ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Figure 6. On the left: Change in monthly mean temperature (°C) for the SSP5-8.5 scenario during 2081-2100. On the right: Change in monthly total precipitation (%) for the SSP5-8.5 scenario during 2081-2100



Source. Own elaboration.

There is a consensus that mean temperature will rise throughout the year. However, precipitation is expected to decrease, especially in the beginning and middle of the year, compared to the 1981-2010 reference climatology. Notably, for february, april, october, and november, the SSP5-8.5 scenario generally forecasts increases in precipitation compared to the reference period, particularly in the Andean and Caribbean regions. These findings align with the results reported by Ruiz (2010, 2017), who performed dynamic downscaling with the PRECIS model using SRES emission scenarios from the IPCC Fourth Assessment Report (AR4) and with the CCSM4-WRF model using RCP8.5 scenarios from the IPCC Fifth Assessment Report (AR5), respectively.

4. Conclusions

Regarding climate change evidence, mean temperature rises at a spatially varied rate between 1.0 °C and 6.0 °C per 100 years. However, in some areas of the northern Caribbean and specific sites in the central Andean region, the temperature is decreasing between 2.0 °C and 6.0 °C per 100 years.

These values are statistically significant in parts of the southern Caribbean, southern Andean region, and a large portion of the Colombian Orinoco and Amazon regions, where the rates of change exceed 3.5 °C per 100 years.

For precipitation, the data indicate increases ranging from 1 to 6 mm per year in the Caribbean, Pacific, northern Andean, and northeastern Amazon regions. In the rest of the country, no significant trends are observed. However, these changes are not statistically significant, as there is less than 95% confidence that these variations are occurring (p-value > 0.05).

The review of spatial patterns identified that the IPCC models used in the ensemble varied both by month and by meteorological variable. Specifically, depending on the month, 11 and 16 models were employed for mean temperature, while 7 and 17 models were used for precipitation.

The validation of the 1981-2014 climate series, using the first 17 years as a control period and the remaining 17 years as a test period, revealed that mean temperature correlations between observations and IPCC models averaged higher than 0.6 across most of the country. For precipitation, the Pearson correlations ranged between 0.3 and 0.5 for all 12 months. These correlation values are statistically significant for a dataset of 34 years.

In evaluating predictive skill, the bias analysis revealed that, generally, the CMIP6 models tend to underestimate mean temperature. The RMSE indicates that this underestimation ranges from 0.2 °C to 0.8 °C throughout the year in most parts of the country. For precipitation, the models show errors ranging from 1 mm to 5 mm during the rainy season in the Caribbean region and exceeding 250 mm per month in the Pacific region of Colombia, which remains humid year-round.

The hit score for mean temperature ranged from 40% to 60% in the Caribbean, Andean, and Pacific regions and exceeded 55%, reaching over 80% in the Orinoco and Amazon regions. For precipitation, the hit score ranged between 45% and 50%. Consequently, there is greater confidence in the model outputs for temperature scenarios than precipitation scenarios, aligning with the findings of the latest IPCC report. This highlights the need to investigate higher-frequency signals, such as interannual or intraseasonal variability, to understand precipitation behavior better.

Regarding the change in mean temperature (°C) in Colombia, the NextGen ensemble of models estimates an average increase from 1.0 °C between 2021 and 2040 to 1.4 °C by 2081 and 2100 under the SSP1-2.6 scenario. In contrast, for the SSP5-8.5 scenario, the increase is projected to range from 1.2°C (2021-2040) to 4.5 °C (2081-2100) relative to the 1981-2010 reference climatology.

Similarly, the range of change in mean temperature (°C) estimated by the NextGen ensemble varies from 0.8 °C (2021-2040) to 2.0 °C (2081-2100) under the SSP1-2.6 scenario. For the SSP5-8.5 scenario, the range is between 0.9 °C (2021-2040) and 6.2 °C (2081-2100), based on the 5th and 95th percentiles of the calibrated models.

Consistent with the IPCC global model ensemble, the statistical downscaling does not predict significant changes in annual total precipitation values over the 21st century compared to the 1981-2010 reference climate. The percentage changes in annual precipitation range from -0.4% for the SSP1-2.6 scenario during 2021-2040 to -2.9% for the SSP5-8.5 scenario by 2081-2100.

By the end of the 21st century (2081-2100), the 5th and 95th percentiles of the NextGen ensemble of models estimate changes in total annual precipitation ranging from -6.5% to +5.3% under the SSP1-2.6 scenario. In contrast, under the SSP5-8.5 scenario, the range of changes is between -17.4% and +11.1%.

Under the SSP5-8.5 scenario, Lang's climate classification indicates that the most significant changes will occur in the Caribbean region. Most of this area will shift from semi-arid to arid climates, except for Guajira, which will retain its current arid climate. Similarly, the Magdalena Valley of Huila and Tolima and the Altiplano Cundiboyacense in the Andean region will also experience this shift from semi-arid to arid.

In the Orinoco region, the climate will transition from humid to semi-humid, except in Casanare and Arauca, where it is currently semi-humid. In the Amazon, southeastern Guaviare, western Vaupés, and Amazonas are expected to shift from super-humid to humid climates. At the same time, the rest of the region will maintain its current humid condition.

The Pacific region is projected to remain super-humid throughout the 21st century.

Acknowledgment. *ÁGM was partially supported by the Grant RYC2021-034691-I, funded by MCIN/AEI/10.13039/501100011033 and the European Union NextGenerationEU/PRTR.*

5. References

Alfaro, E.J. (2007). Uso del análisis de correlación canónica para la predicción de la precipitación pluvial en Centroamérica. *Ingeniería y Competitividad*, *9*(2), 33-48. https://doi.org/10.25100/iyc.v9i2.2486

Amador, J.A. y Alfaro, E.J. (2009). Métodos de reducción de escala: aplicaciones al tiempo, clima, variabilidad climática y cambio climático. *Revista Iberoamericana de Economía Ecológica, 11,* 39-52. https://redibec.org/ojs/index.php/revibec/article/view/260

Amblar Francés, P., Casado Calle, M. J., Pastor Saavedra, M. A., Ramos Calzado, P. y Rodríguez Camino, E. (2017). *Guía de escenarios regionalizados de cambio climático sobre España a partir de los resultados del IPCC-AR5.* https://www.aemet.es/documentos/es/conocermas/recursos_en_linea/publicaciones_y_estudios/publicaciones/Guia_escenarios_AR5/Guia_escenarios_AR5.pdf

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Arias, P., Ortega G., Villegas, L.D. & Martínez, J.A. (2021). Colombian climatology in CMIP5/CMIP6models: Persistent biases and improvements. *Revista Facultad de Ingeniería,* (100), 75-96. https://doi.org/10.17533/udea.redin.20210525

Bedoya, M., Cabrera, M., Carrillo, H., Contreras, C., Cuervo, P., Duarte, M., Gómez, C., Jaramillo, O., Lamprea, S., León, G., Lozano, R., Moreno, G., Osorio, S., Pava, J., Piñeres, A., Ruiz, J. F. y Tobón, E. (2010). *2.ª Comunicación Nacional ante la Convención Marco de las Naciones Unidas sobre Cambio Climático: República de Colombia. Capítulo 4. Vulnerabilidad*.

Benestad, R. E. (2021). *A Norwegian approach to downscaling*. Geoscientific Model Development Discussion. https://doi.org/10.5194/gmd-2021-176

Cannon, A. J., Sobie, S. R. & Murdock, T. Q. (2015). Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate, 28*(17), 6938-6959, https://doi.org/10.1175/JCLI-D-14-00754.1

Díaz, D. y Villegas, N. (2015). Correlación canónica entre índices macroclimáticos y variables meteorológicas de superficie en Colombia. *Revista U.D.C.A Actualidad & Divulgación Científica 18*(2), 543-552. https://doi.org/10.31910/rudca.v18.n2.2015.185

Erlandsen, H. B., Parding, K.M., Benestad, R., Mezghani, A. & Pontoppidan, M. (2020). A hybrid downscaling approach for future temperature and precipitation change. *Journal of Applied Meteorology and Climatology, 59*(11), 1793-1807. https://doi.org/10.1175/JAMC-D-20-0013.1

García-Valero, J. A. (2021). *Redes neuronales artificiales: aplicación a la regionalización de la precipitación y temperaturas diarias. Nota técnica 34 de AEMET*. Agencia Estatal de Metereología. https://dx.doi.org/10.31978/666-20-028-5

Giorgi, F. & Mearns, L. (2002). Calculation of average, uncertainty range, and reliability of regional climate changes from AOGCM simulations via the ''Reliability Ensemble Averaging'' (REA) method. *Journal of Climate*, *15*(10), 1141-1158 https://doi.org/10.1175/1520-0442(2002)015<1141:COAURA>2.0.CO;2

Gutiérrez, J. M., Jones, R. G., Narisma, G. T., Alves, L. M., Amjad, M., Gorodetskaya, I. V., Grose, M., Klutse, N.A., Krakovska, S., Li, J., Martínez-Castro, D., Mearns, L., Mernild, O. H., Ngo-Duc, T. van den Hurk, B. & Yoon, J. H. (2021). *Atlas. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.*

Hernanz, A., García-Valero, J. A., Domínguez, M., Ramos-Calzado, P., Pastor-Saavedra, M. A. & Rodríguez-Camino, E. (2022). Evaluation of statistical downscaling methods for climate change projections over Spain: present conditions with perfect predictors. *International Journal of Climatology, 42*(2), 762-776. https://doi.org/10.1002/joc.7271

Hernanz, A., Correa, C., García-Valero, J. A., Domínguez, M., Rodríguez-Guisado, E. & Rodríguez-Camino, E. (2023). PyClim-SDM: service for generation of statistical downscaled climate change projections supporting national adaptation strategies. *Climate Services*, *32*, 100408. https://doi.org/10.1016/j.cliser.2023.100408

Ideam, PNUD, MADS. (2001). *Primera comunicación nacional ante la convención marco de las Naciones Unidas sobre el cambio climático*. https://www.car.gov.co/uploads/files/5ade495093144.pdf

Ideam. (2005). *Atlas climatológico de Colombia. Parte II: distribución espacio-temporal de las variables del clima.*

Ideam. (2015). *Atlas climatológico de Colombia*. *Volumen 1*.

Ideam, PNUD, MADS, DNP, Cancillería. (2015). *Nuevos escenarios de cambio climático para Colombia 2011-2100. Herramientas científicas para la toma de decisiones -enfoque nacional- regional: tercera comunicación nacional de cambio climático*. https://www.undp.org/es/colombia/publicaciones/tercera-comunicacion-nacional-de-cambio-climatico-enfoque-nacional-departamental

Ideam. (2021). *Proyecto DL & ENACTS Colombia*. *Informe n.° 1*. Ideam-IRI. Subdirección de Meteorología.

IPCC. (2021). *Climate change 2021: the physical science basis. Working Group I Contribution to the IPCC Sixth Assessment Report*. https://www.ipcc.ch/report/ar6/wg1/about/how-to-cite-this-report

Molina, A., Bernal, N., Vega, E., Collantes, J. y Pabón., J. (2003). Cambios en la temperatura del aire en Colombia bajo un escenario de duplicación de dióxido de carbono. *Meteorología Colombiana*, (7), 21-35.

Muñoz, C. (2009). *Variabilidad interanual de la precipitación invernal en Chile central no asociada al ciclo El Niño-Oscilación del Sur*. [Tesis para optar al título profesional de Geofísico]. Universidad de Concepción. https://www.dgeo.udec.cl/wp-content/uploads/2012/09/munoz-cristian_tesis.pdf

Oglesby, R. & Rowe, C. (2017). *Strengthening institutional capacity to improve the assessment of impacts of climate change in Latin America and the Caribbean*. http://rccdp.unl.edu/reports/TechReport_5.pdf

O'Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J. F., Lowe, J., Meehl, G. A., Moss, R., Riahi, K. & Sanderson, B. M. (2016). The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geoscientific Model Development, 9*(9), 3461-3482, https://doi.org/10.5194/gmd-9-3461-2016

Pabón, J. D. (2003). El cambio climático global y su manifestación en Colombia. *Cuadernos de Geografía*: *Revista Colombiana de Geografía*, *12*(1-2), 111-119. https://revistas.unal.edu.co/index.php/rcg/article/view/10277

Pabón, J. D. (2008). *Escenarios de cambio climático para las 24 regiones de Colombia*. *Informe presentado en el marco del proyecto Integrated National Adaptation Pilot (INAP)*. Conservación Internacional. Departamento de Geografía. Universidad Nacional de Colombia.

Pabón, J. D. (2012). Cambio climático en Colombia: tendencias en la segunda mitad del siglo XX y escenarios posibles para el siglo XXI. *Revista Académica Colombiana de Ciencias, 36*(139), 261-278. http://www.scielo.org.co/pdf/racefn/v36n139/v36n139a10.pdf

Petisco de Lara, S. E. (2008a). *Método de regionalización de precipitación basado en análogos. Explicación y validación. AEMET nota técnica 3A, área de evaluación y modelización del cambio climático*. AEMET.

Petisco de Lara, S. E. (2008b). *Método de regionalización de temperatura basado en análogos. Explicación y validación. AEMET nota técnica 3B, área de evaluación y modelización del cambio climático.* AEMET.

Richardson, C. W. (1981). Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water Resources Research, 17*(1), 182-190, https://doi.org/10.1029/WR017i001p00182

Ruiz, J. F. (2007). *Escenarios de cambio climático, algunos modelos y resultados de lluvia para Colombia bajo el escenario A1B*. http://bit.ly/44fSxUI

Ruiz, J. F. (2010). *Cambio climático en temperatura, precipitación y humedad relativa para Colombia usando modelos de alta resolución (panorama 2011-2100). Nota Técnica de IDEAM. N.° IDEAM-METEO/005-2010*. https://www.scirp.org/reference/referencespapers?referenceid=1787880

Switanek, M. B., Troch, P. A., Castro, C. L., Leuprecht, A., Chang, H. I., Mukherjee, R. & Demaria, E.M. (2017). Scaled distribution mapping: A bias correction method that preserves raw climate model projected changes. *Hydrology and Earth System Sciences*, *21*(6), 2649-2666. https://doi.org/10.5194/hess-21-2649-2017

Themeßl, M. J., Gobiet, A. & Leuprecht, A. (2011). Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. *International Journal of Climatology*, *31*(10), 1530-1544. https://doi.org/10.1002/joc.2168

Thomson, M. & Mason, S. (2018). *Climate informatiom for public health action*. Routledge. https://www.routledge.com/Climate-Information-for-Public-Health-Action/Thomson-Mason/p/book/9781138069640

Tufa, D., Faniriantsoa, R., Cousin, R., Khomyakov, I., Vadillo, A., Hansen, J. & Grossi, A. (2022). ENACTS: Advancing climate services across Africa*. Frontiers in Climate*, *3*(787683). https://doi.org/10.3389/fclim.2021.787683

Wilby, R., Dawson, C. & Barrow, E. M. (2002). SDSM-a decision support tool for the assessment of regional climate change impacts. *Environmental Modelling & Software, 17*, 145-157. https://doi.org/10.1016/S1364-8152(01)00060-3

ISSN: 2382-3399 (Impreso)
ISSN: 2745-2220 (En línea)

Wilks, D. S. (2006). *Statistical methods in the atmospheric sciences* (2nd ed.). Elsevier.

World Meteorological Organization [WMO]. (2020). *Guidance on operational practices for objective seasonal forecasting*. https://library.wmo.int/idurl/4/57090

World Bank, Japan Agency for Marine-Earth Science and Technology, INE, Ideam, Senamhi & Inamhi. (2007). *Visualizing future climate in Latin America: results from the application of the earth simulator.* https://www.senamhi.gob.pe/pdf/estudios/PublicacionesDMA/2007/SDWP_Future_Climate.pdf