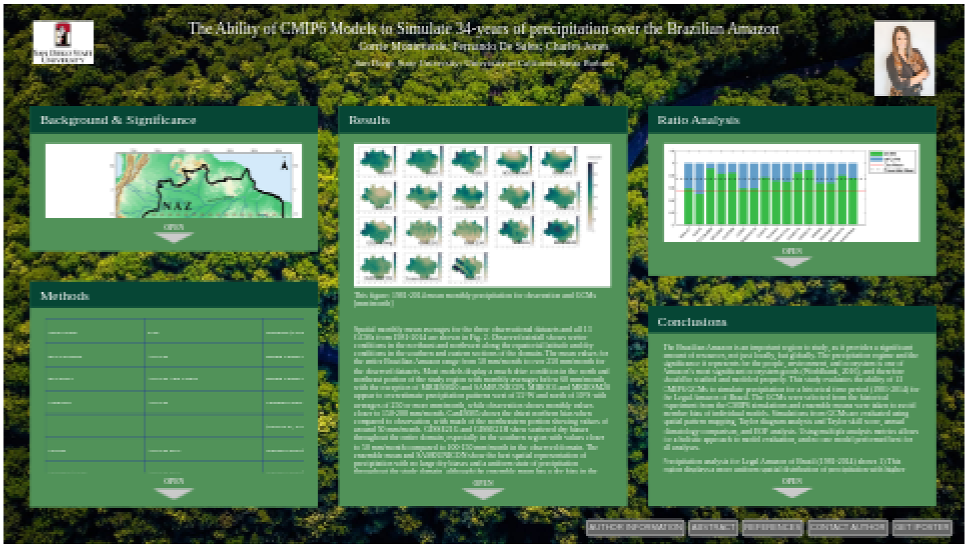
The Ability of CMIP6 Models to Simulate 34-years of precipitation over the Brazilian Amazon



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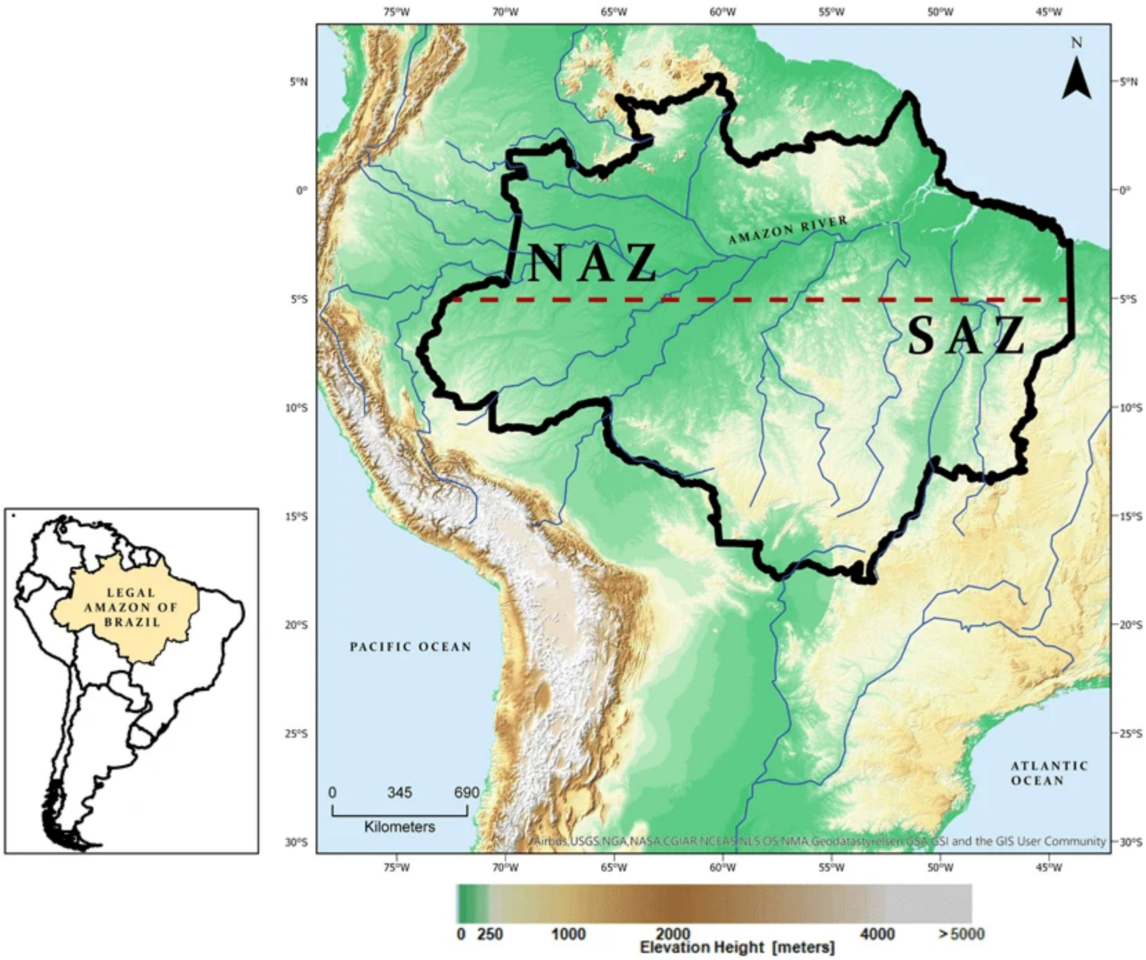
PRESENTED AT:

BACKGROUND & SIGNIFICANCE



This figure: Brazilian Amazon study area with red dotted line indicating a split domain for further analysis. Northern Brazilian Amazon (NAZ) and Southern Brazilian Amazon (SAZ)

The Amazon rainforest provides a ***wealth of ecosystem goods and services*** (Foley et al., 2007), including regulation of climate and water feedbacks (Lima et al., 2014), agricultural and timber goods, hotspot for biodiversity (Dale et al., 1994; Hopkins, 2007), watershed services (Wu et al., 2017), regulation of rainfall regimes (Martinelli et al., 1996), and climate change regulation by acting as a carbon sink (Chambers et al., 2001).

Brazilian Amazon is a region where the precipitation regime is important to study and simulate properly as ***moisture and rainfall play a large role in maintaining proper climate regulations***.

METHODS & RESULTS

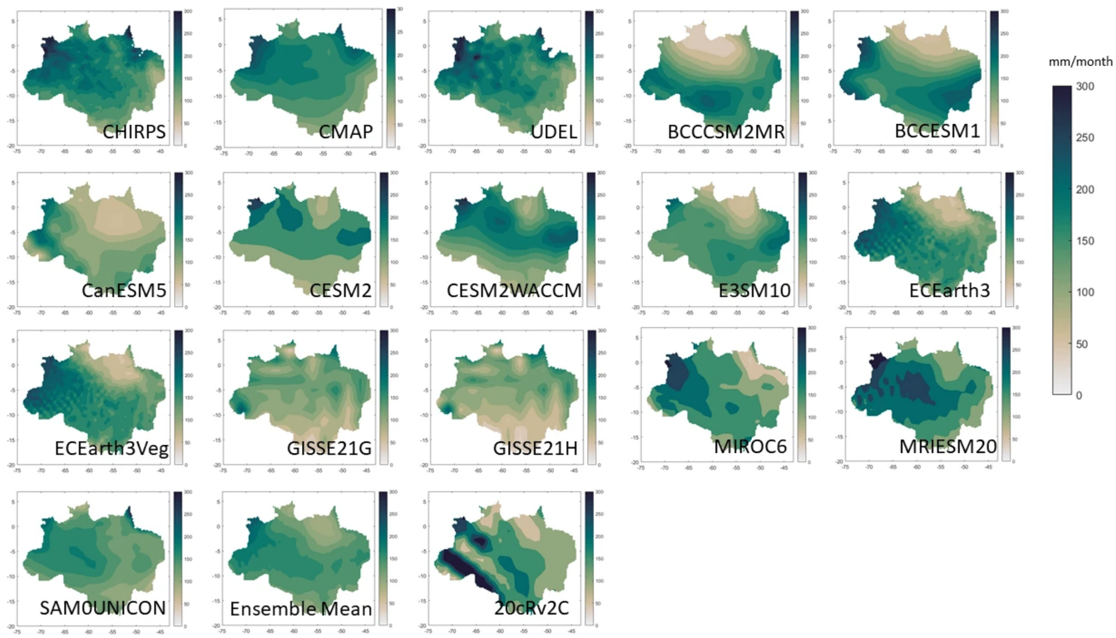


Fig. 1: 1981-2014 mean monthly precipitation for observation and GCMs [mm/month]

(Fig. 1) Spatial monthly mean averages for the three observational datasets and all 13 GCMs from 1981-2014. Most models display a much ***drier condition in the north and northeast*** portion of the study region with monthly averages below 60 mm/month. The ensemble mean and SAM0UNICON show the best spatial representation of precipitation with no large dry biases and a uniform state of precipitation throughout the study domain, although the ensemble mean has a dry bias in the north due to most models underestimating precipitation here.

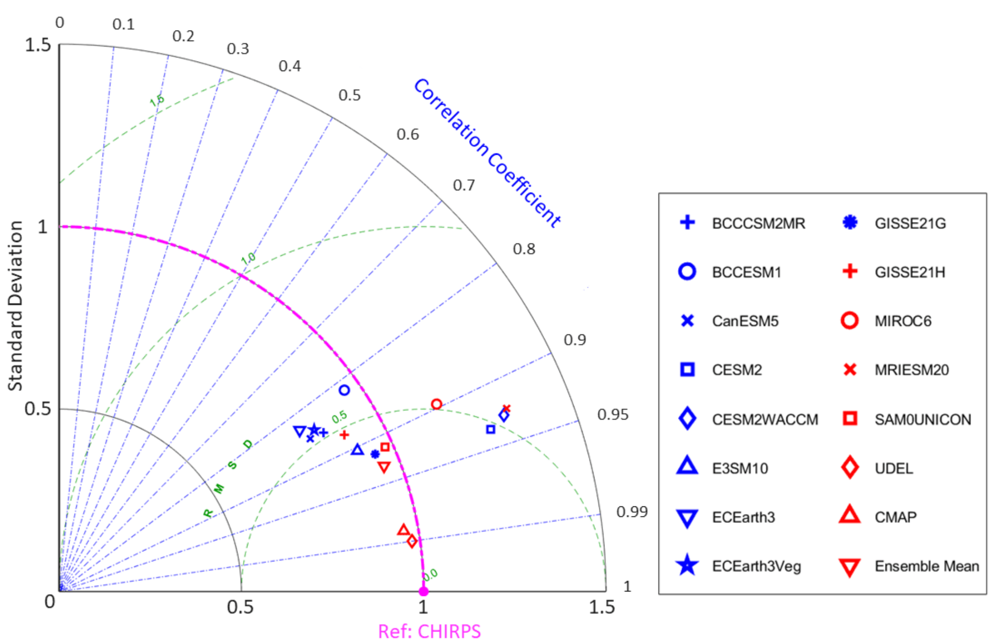


Fig. 2: Taylor diagram of daily precipitation for the Brazilian Amazon from 1981-2014 [mm day-1]. CHIRPS is the reference dataset and symbols indicate models, observation, and ensemble mean. Results have been normalized to CHIRPS standard deviation

(Fig. 2): Taylor diagram provides information on the normalized standard deviation and centered root mean square, along with the correlation coefficient of the spatially averaged time for all models and observational datasets for the entire Brazilian Amazon. ***The ensemble mean performed best for the entire Brazilian Amazon.***

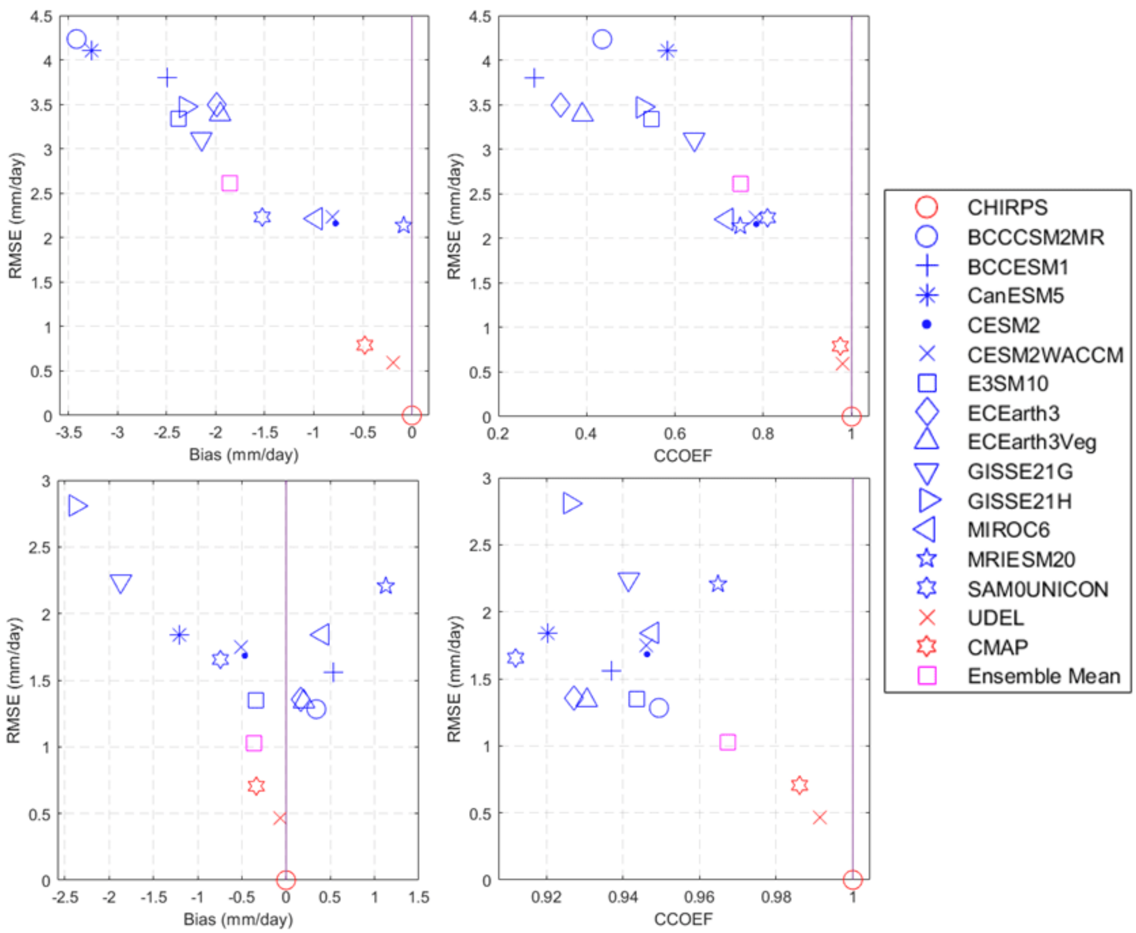


Fig. 3: RMSE versus bias (left) and RMSE versus correlation coefficient (right) for 1981-2014 [mm day-1] for Northern Amazon (top panels) and Southern Amazon (bottom panels)

(Fig. 3): RMSE-bias and RMSE-correlation coefficient diagrams further illustrate the relationship between these performance metrics for the models. Overall, the ***top models include CESM2, CESM2WACCM, MIROC6, SAM0UNICON, BCCCSM2MR, E3SM10, BCCESM1, ECEarth3, ECEarth3veg, and the Ensemble Mean***. Although BCCCSM2MR, E3SM10, BCCESM1, ECEarth3, and ECEarth3Veg did not perform as well for NAZ.

METHODS:

Table 1:____

Model NameTypeInstitution (Location) and reference

BCCCSM2MRAOGCMBeijing Climate Center (China) (Wu et al., 2019)

BCCESM1AOGCM AER CHEMBeijing Climate Center (China) (Wu et al., 2019)

CanESM5AOGCMCanadian Center for Climate Modeling and Analysis (Canada)

(Swart et al., 2019)

CESM2AOGCM BGCNational Center for Atmospheric Research (NCAR) (United States) (Gettelman et al., 2019)

CESM2WACCMAOGCM BGCNational Center for Atmospheric Research (NCAR) (United States) (Gettelman et al., 2019)

E3SM10AOGCM AERLawrence Livermore National Laboratory (LLNL) (United States)

(Golaz et al., 2019)

ECEarth3AOGCMEC-Earth Consortium (Europe) (Doblas-Reyes et al., (2018)

ECEarth3VegAOGCMEC-Earth Consortium (Europe) (Doblas-Reyes et al., (2018)

GISSE21GAOGCMGoddard Institute for Space Studies (NASA-GISS) (United States)

(Kelley et al., 2020)

GISSE21HAOGCMGoddard Institute for Space Studies (NASA-GISS) (United States)

(Kelley et al., 2020)

MIROC6AOGCM AERJapan Agency for Marine-Earth Science and Technology (JAMSTEC) (Japan) (Tatebe et al., 2019)

MRIESM20AOGCM AER CHEMMeteorological Research Institute (Japan) (Yukimoto et al., 2019)

SAM0UNICONAOGCM AER BGCSeoul National University (South Korea) (Park et al., 2019)

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(Table 1): This study uses a subset of ***13 CMIP6 models*** to evaluate the representation of the historical Brazilian Amazon precipitation regime for 1981-2014. Model types include atmosphere-ocean general circulation models (AOGCM) with additional model components, such as aerosols (AER), chemistry (CHEM), and biogeochemistry (BGC). Table 1 presents the 13 models, their type, and corresponding institution, location and reference.

To evaluate the ability of CMIP6 models to simulate the historical precipitation regime for the Brazilian Amazon, results were compared to observations for the period 1981-2014. We selected this period because it incorporates recent updates in Global Telecommunications System and recent satellite-derived improvements in data collection. To evaluate annual cycles, we used the statistical metrics: ***root mean square error (RMSE), bias, and the spatial and temporal Pearson relation coefficient***. Both the monthly averages and anomalies of precipitation were evaluated. A ***taylor diagram*** (Taylor, 2001a) was produced for the entire Brazilian Amazon, to give an overall idea of model performance for the region.

In addition to the model performance comparison, we performed ***EOF analysis*** to characterize the precipitation intraseasonal variability of the 13 CMIP6 models. To quantify the EOF eigenvector sampling error, we used the method described in (North et al., 1982). Finally, the ***Taylor Skill Score*** (Xia et al., 2015 and Taylor, 2001), was used to give an overview of model performance (Eqn.3). Where S is the skill score, R is the correlation between the simulated and reference datasets, R_0 is the theoretical maximum correlation (assumed to be 1) and σ is the standard deviation of the simulated dataset.

$$S=4(1+R)/[\sigma+(1/\sigma)]^2 (1+R_0)$$

EOF ANALYSIS

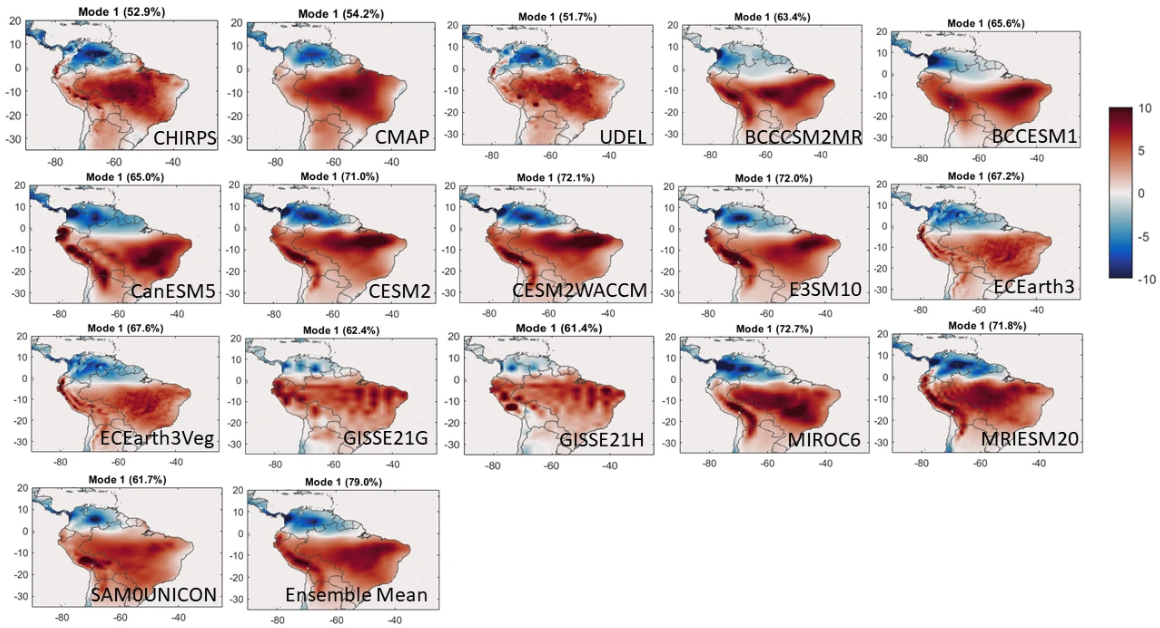


Fig. 1: EOF eigenvector one for each dataset (1981-2014) with long-term mean removed

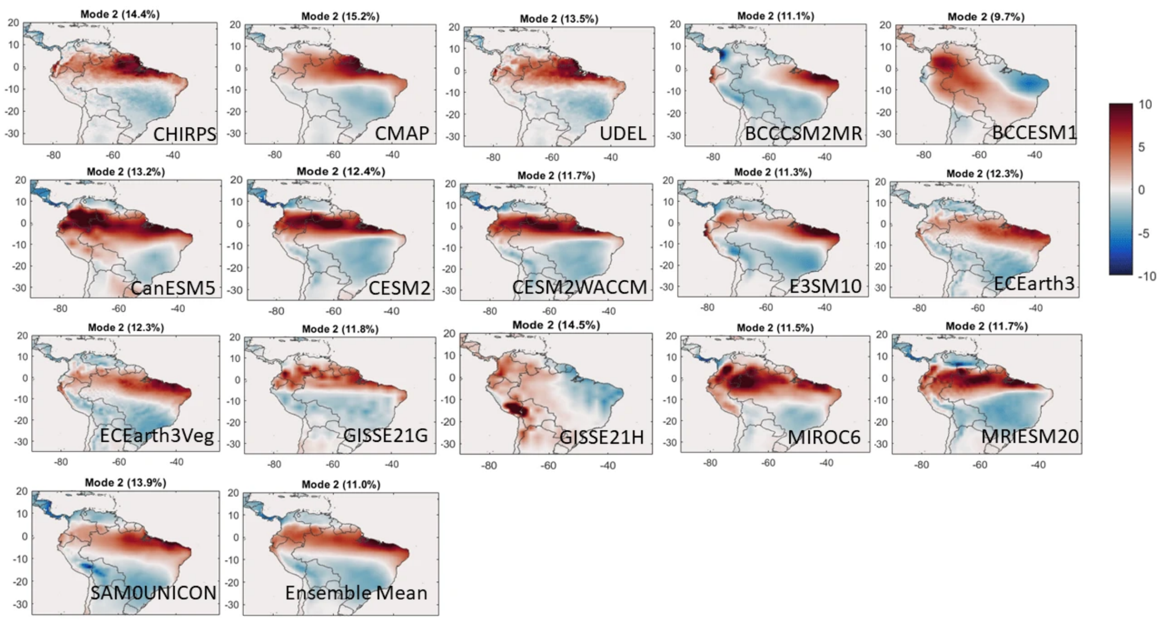


Fig. 2: EOF eigenvector two for each dataset (1981-2014) with long-term mean removed

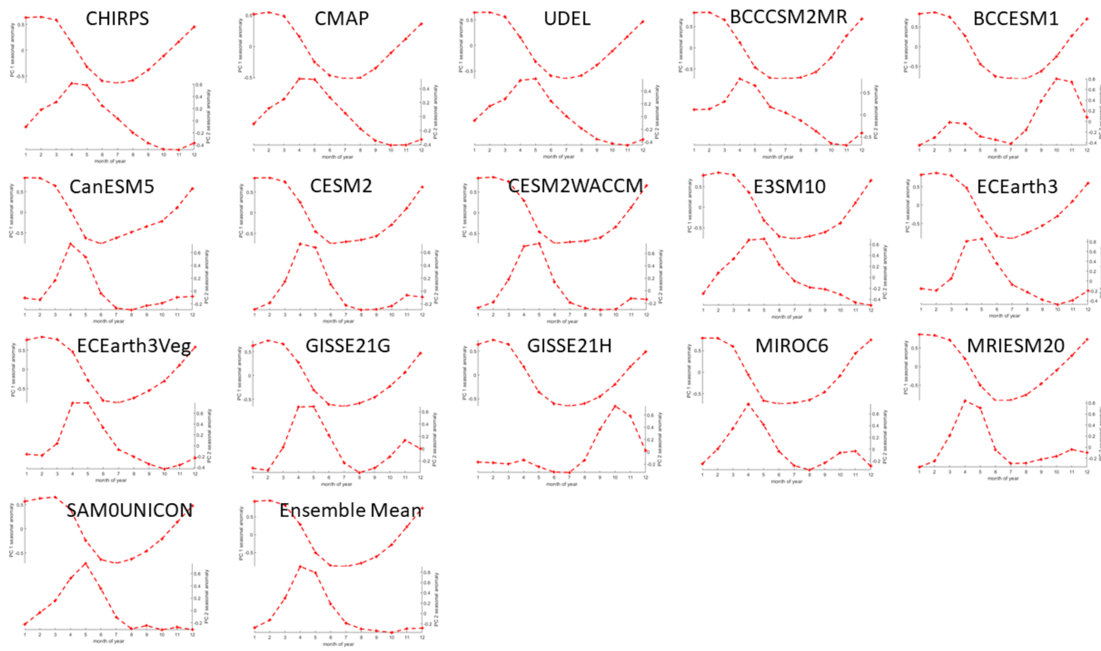
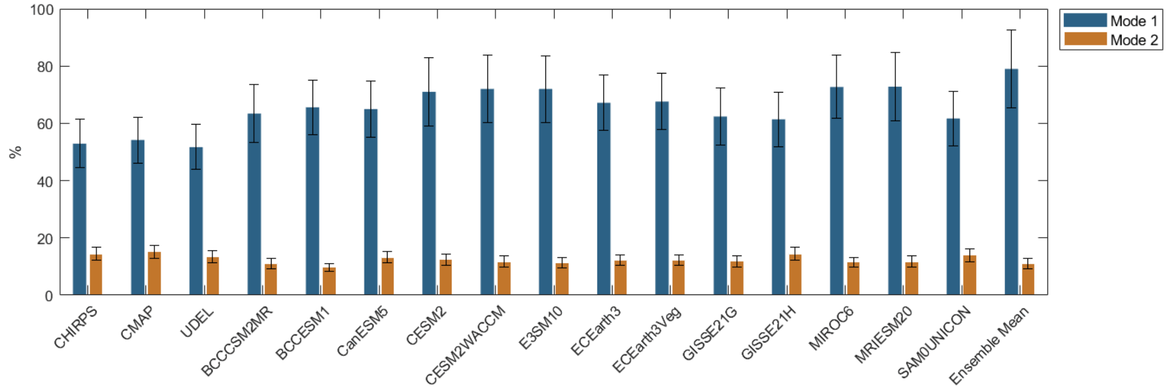


Fig. 3: Principal component (PC) Time Series of first two modes for each dataset

Only the two first modes of EOF analysis are described in this section as together they explain over 67% of the precipitation variability (Fig. 7 and 8)

The first EOF (Fig. 1) ***explains approximately*** 52.9% within observational datasets and around ***68% for CMIP6 models and follows a temporal pattern similar to the annual cycle of precipitation***, with a dry season around JJA and a wet season mainly in the months of DJF. There is a dipole nature to this eigenvector around the equator for the 0 value eigenvector and represents how these two regions of South America differ in terms of the temporal evolution of the SAMS.

The second EOF (Fig. 2) ***explains approximately*** 14.4% within observational datasets and around ***12% for CMIP6 models and most likely follows the pattern of a transition between the SAMS and the North American Monsoon System (NAMS)*** (Arias and Fu, 2010). The PC time series (Fig. 3) shows a ***delay in the onset of the wet season for this eigenvector with observation showing its onset around April and May*** and models showing a similar pattern, with the exception of BCCESM1 and GISSE11H. This delay signals the time evolution of SAMS across the vast land area of Brazil. Models seem to capture the tripole nature of the transitional SAMS, excluding BCCSM2MR, BCCESM1, and GISSE21H. Models are more accurate in placing the correct explanation (%) for this mode. CESM2, CESM2WAACCM, GISSE21G, MIROC6, MRIESM20, SAM0UNICON, and the ensemble mean to appear to have captured the second eigenvector most accurately.



This figure: Explained variance of eigenvalue with sampling error bars

Overall, models were able to capture the seasonal cycle and dipole nature of SAMS, although the variance explained by models were much higher than observation; up to +26% for the ensemble mean (Fig. 10). Average observation eigenvector 1 explained 52.9% while the eigenvector 2 explained 9.3% of the variability. Models had a combined eigenvector 1 explanation of 67.2% (14.3% higher than observation) and 12.1% explanation for eigenvector 2 (2.8% higher than observation). ***Models had a more difficult time simulating the temporal progression of the second mode of variability***. Although some models, like CESM2, CESM2WAACCM, GISSE21G, MIROC6, MRIESM20, SAM0UNICON, and the ensemble mean, were able to simulate the mapped eigenvector well.

RATIO ANALYSIS

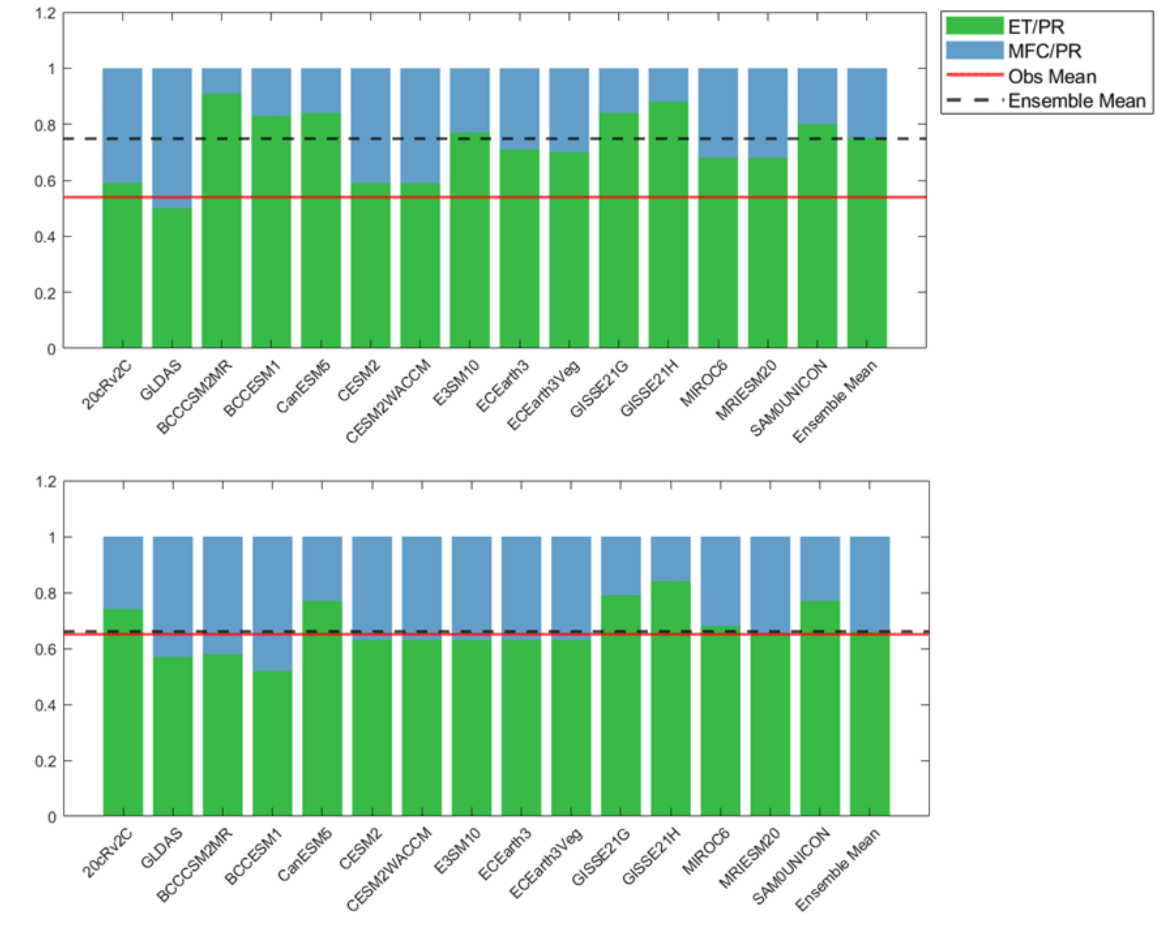


Fig. 1: 1981-2014 ET/PR (green) and MFC/PR (blue) ratio analysis [mm day-1] with observation mean (red line) and ensemble mean (black dashed line) ET/PR analysis for NAZ (top panel) and SAZ (bottom panel) for GLDAS and 20cRv2C reanalyses and GCMs

(Fig. 1): To explore GCM performances, we use ET/PR and MFC/PR ratio analysis to ***investigate how CMIP6 models partition the source of rainfall moisture*** between the surface source (evapotranspiration) and atmospheric source (moisture flux convergence) for both northern and southern subdomains. Observations show that NAZ ET/PR ratio is lower than SAZ by an average of 0.11 and therefore there were greater amounts of MFC compared to ET values when compared to SAZ. SAZ showed greater values of ET when compared to NAZ MFC ratio analysis for observations. Models show a higher average mean by 0.21 for NAZ and 0.01 for SAZ. Models were better at capturing SAZ partition of precipitation sources between ET and MFC for 1981-2014.

Despite generally higher values of simulated ET, the ***models might not be producing enough moisture from convergence flux to simulate PR accurately***, resulting in low PR when compared to CHIRPS, CMAP, and UDEL. This is not the only research that has found that models tend to underestimate PR, as other studies have shown that CMIP models tend to underestimate precipitation in this region (Gulizia and Camilloni, 2015). More work needs to be completed to analyze the physical mechanisms and schemes within each model which produce the biases in precipitation, ET, and MFC which is beyond the scope of this paper. Understanding the underlying physics of each GCM is an important component of model evaluation, which individual modeling teams can contribute towards.

CONCLUSIONS

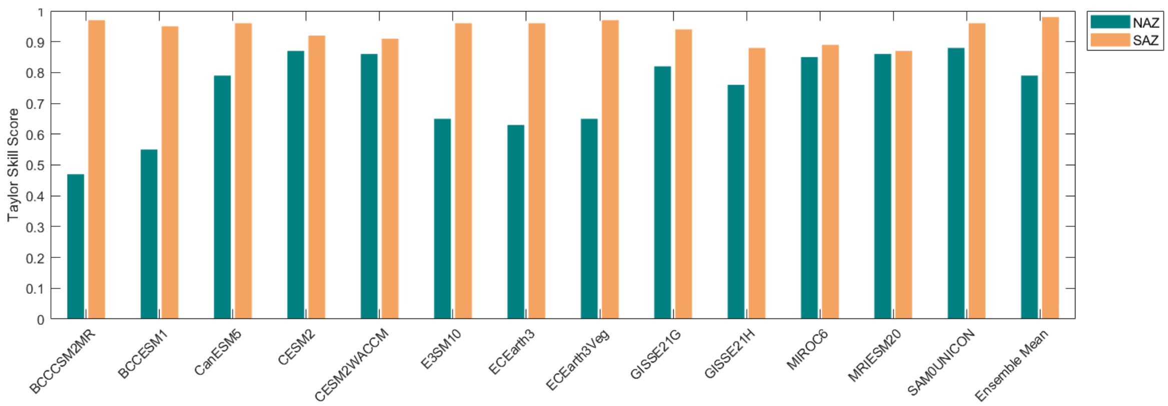


Fig. 1: Taylor skill score for NAZ (green) and SAZ (orange) for all GCMs compared to CHIRPS observational precipitation for 1981-2014

(Fig. 1): To evaluate overall model effectiveness, the taylor skill score was calculated for all GCMs and the ensemble mean for both subdomains. Overall, ***models performed best in SAZ when compared to NAZ***. Model ensembles can be constructed based on the highest performing GCMs for this region.

The Brazilian Amazon is an important region to study, as it provides a significant amount of resources, not just locally, but globally. The ***precipitation regime*** and the significance it represents for the people, environment, and ecosystem is ***one of Amazon's most significant ecosystem goods*** (Worldbank, 2016), and therefore should be studied and modeled properly.

<u>Precipitation analysis for Legal Amazon of Brazil (1981-2014) shows:</u>

1) This region displays a more uniform spatial distribution of precipitation with higher rainfall in the north-northwest and drier conditions in the south. Models tend to underestimate northern values or overestimate the central to northwest averages.

2) SAZ has a much more defined dry season (JJA) and wet season (DJF) and models are able to simulate this well. NAZ dry season tends to occur in ASO and the wet season occurs in MAM, and models are not able to capture the climatology as well. Models tend to produce too much rainfall at the start of the wet season and tend to either over-or underestimate the dry season (although the ensemble mean captures the anomalies for SAZ very well). The ensemble mean for NAZ is able to simulate the wet season decline.

3) EOF analysis of GCMs was able to capture the dominant mode of variability, which is largely the annual cycle or SAMS. Some models tend to overestimate precipitation over the Andes and place too high of explanation (%) on the first eigenvector by up to 26% for the ensemble mean. The second mode showed a triple difference and displays a transition from the SAMS to the NAMS, as there is a delay in the onset of the principal component time series when compared to the first.

4) When all evaluation metrics are taken into account the models that perform best are CESM2, MIROC6, MRIESM20, SAM0UNICON, and the ensemble mean.

AUTHOR INFORMATION

I study climate and atmospheric processes, focusing specifically on regional climate modeling, applied climatology, and climate change impacts. I utilize climate models and statistical software to conduct my research. As a climate scientist, I am invested in local and regional success at adapting to a changing environment. I am interested in changes in precipitation and temperature regimes and linking these with processes or conditions that impact farmers, growers, businesses, and communities. I would like to utilize climatology studies to inform both policy and climate product end-users.

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ABSTRACT

The Brazilian Amazon provides important hydrological cycle functions, including precipitation regimes that bring water to the people and environment and are critical to moisture recycling and transport, and represents an important variable for climate models to simulate accurately. This paper evaluates the performance of 13 Coupled Model Intercomparison Project phase 6 (CMIP6) models. This is done by discussing results from spatial pattern mapping, Taylor diagram analysis and Taylor skill score, annual climatology comparison, and Empirical Orthogonal Function (EOF) analysis. Precipitation analysis shows 1) This region displays a more uniform spatial distribution of precipitation with higher rainfall in the north-northwest and drier conditions in the south. Models tend to underestimate northern values or overestimate the central to northwest averages. 2) Southern Amazon has a more defined dry season (June, July, and August) and wet season (December, January, and February) and models are able to simulate this well. Northern Amazon dry season tends to occur in August, September, and October and the wet season occurs in March, April, and May, and models are not able to capture the climatology as well. Models tend to produce too much rainfall at the start of the wet season and tend to either over- or under-estimate the dry season, although ensemble means typically display the overall pattern more precisely. 3) EOF analysis of models are able to capture the dominant mode of variability, which was the annual cycle or SAMS. 4) When all evaluation metrics are taken into account the models that perform best are CESM2, MIROC6, MRIESM20, SAM0UNICON, and the ensemble mean. This paper supports research in determining the most up to date CMIP6 model performance of precipitation regime for 1981-2014 for the Brazilian Amazon. Results will aid in understanding future projections of precipitation for the selected subset of global climate models and allow scientists to construct reliable model ensembles, as precipitation plays a role in many sectors of the economy, including the ecosystem, agriculture, energy, and water security.

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