Analysis of DPLE Predictive Skill Across ENSO Regimes via ACC Score

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1. Introduction

ENSO is one of the largest modes of variability in the climate system. It has profound impacts on temperature and precipitation around the world. Because of these large impacts on global climate, ENSO is often cited as a source of climate predictability. While we know that ENSO as a whole is a source of predictability, we wanted to understand how the two modes of ENSO vary in their contribution to predictability on sub-decadal time scales.

Much like the Lorenz 63 model, our climate system is chaotic. This means that it is extremely sensitive to initial conditions. Not only does the accuracy of the initial conditions impact predictability, but the location of the initial conditions relative to the two attractor spaces impacts predictability. ENSO is a mode of climate variability that has two modes, and these modes can be compared to the attractor spaces in the Lorenz model. Much like this model, we hypothesize that initial conditions located near one of the attractor spaces offer superior predictability in comparison to initial conditions located in between attractor spaces. We further want to examine if one of these attractor spaces offers more predictability when compared to the other. This leads us to our research question:

How do ENSO regimes impact sea surface temperature and precipitation predictability on sub-decadal time scales?

2. Datasets

In this project we used a variety of datasets including the DPLE-CESM1-LE dataset, Met Office data, GCPC data, and NOAA ENSO data. The DPLE - CESM1-LE dataset provides forecasts from CESM1 initialized every year in November. This dataset contains 62 40-member ensembles, initialized every year in November from 1954-2015, and propagated forward for 122 months. Initial conditions were obtained from reanalysis-forced simulations of CESM. The Met Office Data is an observational dataset containing ocean temperature and salinity profiles collected from 1900 to present. From this dataset, sea surface temperatures (SST) were obtained in order to compare it to the DPLE dataset containing SST. The GCPC (Global Precipitation Climatology Project) is a dataset in which a variety of observational data from 1979 to present have been merged to estimate global monthly rainfall on a 2.5° grid. Some of the sources of observations included in this dataset include rain gauge stations, satellites and soundings. One noted limitation is that satellite data is used to estimate precipitation in regions over the ocean, which can result in a low bias during periods of low precipitation. Lastly, Niño 3.4 monthly temperature anomaly data was obtained from NOAA to select years of strong or neutral ENSO phases.

3. Methods

The first step of our analysis was to use NOAA Niño 3.4 anomaly data to select El Niño years and La Niña years by averaging the temperature anomaly in the Niño 3.4 region over December, January and February. Three months are typically used to generate the Niño index, and DJF was selected due to the fact that ENSO typically peaks during this time period. The selected years are as follows:

El Niño years = [1982, 1986, 1991, 1997, 2009]

Neutral years = [1980, 1981, 1985, 1989, 1990, 1992, 1993, 2001, 2003]

La Niña years = [1984, 1988, 1998, 1999, 2007, 2010]

These years were restricted by the availability of observational datasets. The upper limit is 2011 due to the 12 year forecast length, resulting in data needed through January of 2023. The lower limit was also determined by the availability of observations, with the GCPC dataset beginning in 1979. For a plot of annual Niño indices and selected years see the appendix.

Once these years were identified, we then proceeded to calculate the anomaly correlation coefficient (ACC) as a metric of predictive skill between the DPLE forecasts and the observational datasets. We computed the ACC by first detrending the datasets with respect to time, computing climatology, and then subtracting these values from the detrended data. This generated detrended anomaly data for our respective variables. The next step in analysis involved regridding the DPLE data to match the coarser spatial resolution of the observational datasets. We then calculated the correlation coefficient of these anomalies over 1-5, 3-7 and 5-9 years out from the DPLE initialization year and produced maps that show the spatial relationship of the ACC score over these three ranges of years. The final step in our computational process is to average these maps over the El Niño, La Niña and neutral year categories so that we may draw conclusions about the predictability of different ENSO regimes. Additionally, further analysis of precipitation was conducted. For the methods and results of this analysis see the appendix.

4. Results

4.1 Precipitaion

We don't expect to have very high skill in predicting precipitation on decadal timescales because of a number of factors. These factors include the variety of processes that are involved in modeling precipitation that all introduce error growth, in addition to threshold based nature of these processes, and the lack of spatial resolution needed to accurately model subgrid scale processes. However, despite these factors that limit the predictability of precipitation on decadal timescales,one region that demonstrates significant predictive skill is the Equatorial Pacific. The increased predictive skill over this region makes sense as this is the region most directly affected by ENSO. The nature of ENSO is variability of sea surface temperatures in this region. Additionally, rates of deep convection are tightly associated with SST. These spatial and physical relationships may explain why this region offers more predictive skill than anywhere else.

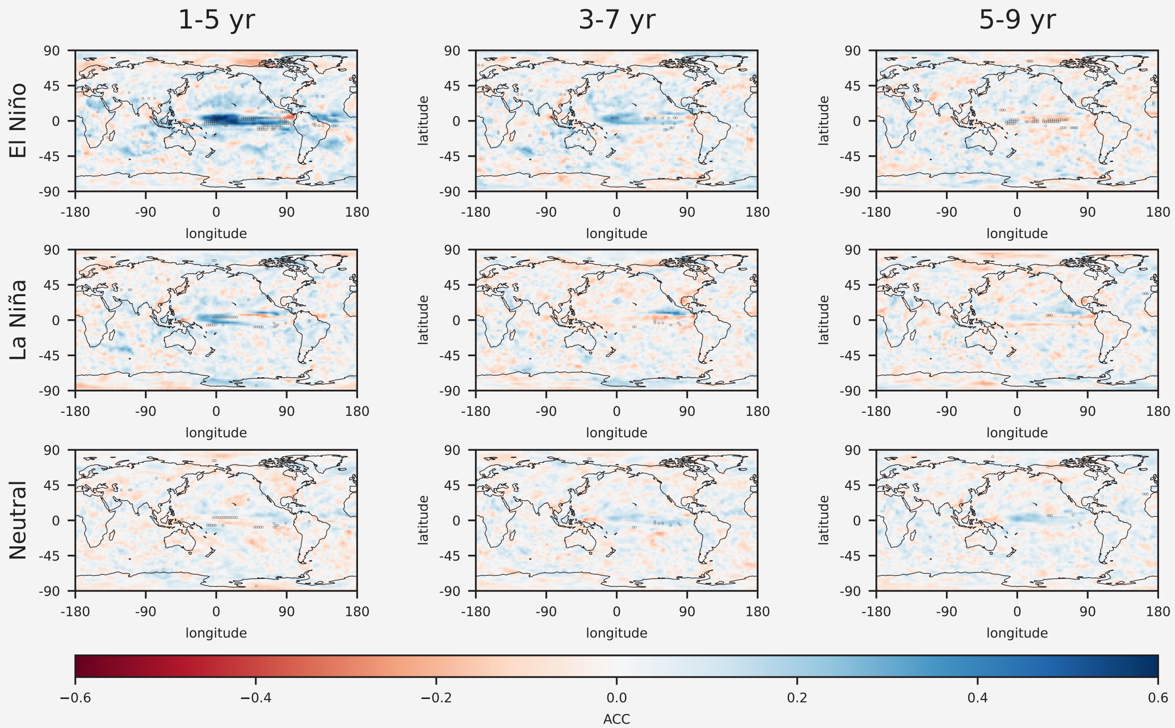

Figure 1. ACC score calculated for DPLE precipitation and GCPC precipitation data. Rows are separated into El Niño, La Niña and Neutral initialization years. Columns are separated by range in years following the initialization year over which ACC was calculated.

For precipitation, forecasts initialized in both La Niña and El Niño offered superior predictive skill when compared to forecasts initialized in neutral years. Forecasts initialized during strong El Niño and La Niña years both demonstrated similar trends in relationship to forecast length. As the length of the forecast increased, their predictive skill gradually tapered off. In contrast, forecasts initialized in neutral years had a consistent level of low predictive skill across all of the 3 ranges of years.

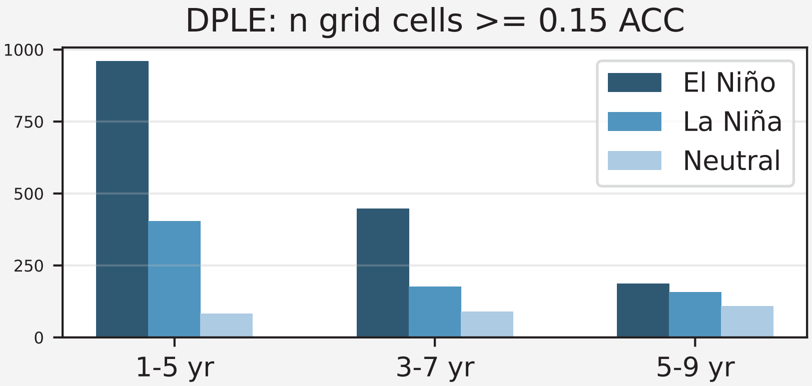

Figure 2. Bar plot showing the number of grid cells who had an ACC score calculated for DPLE precipitation and GCPC precipitation data above 0.15. Initialization ENSO regime is indicated by the color of the bars (shown in legend). Year ranges indicate the time period after the initialization year of the DPLE forecast.

4.2 Sea Surface Temperature (SST)

The plots below show the results for the anomaly correlation coefficient (ACC) calculated and plotted spatially in order to see where in the world the ACC of SST is the greatest. These results will allow us to determine where the CESM1-DPLE model has the highest predictive skill. A notable result is specifically in the neutral years in which the ENSO 3.4 area specifically has a dramatic decrease in the ACC as the forecast length increases. This result also occurs in the ENSO regimes, but on a much smaller scale than the magnitude in the neutral years.

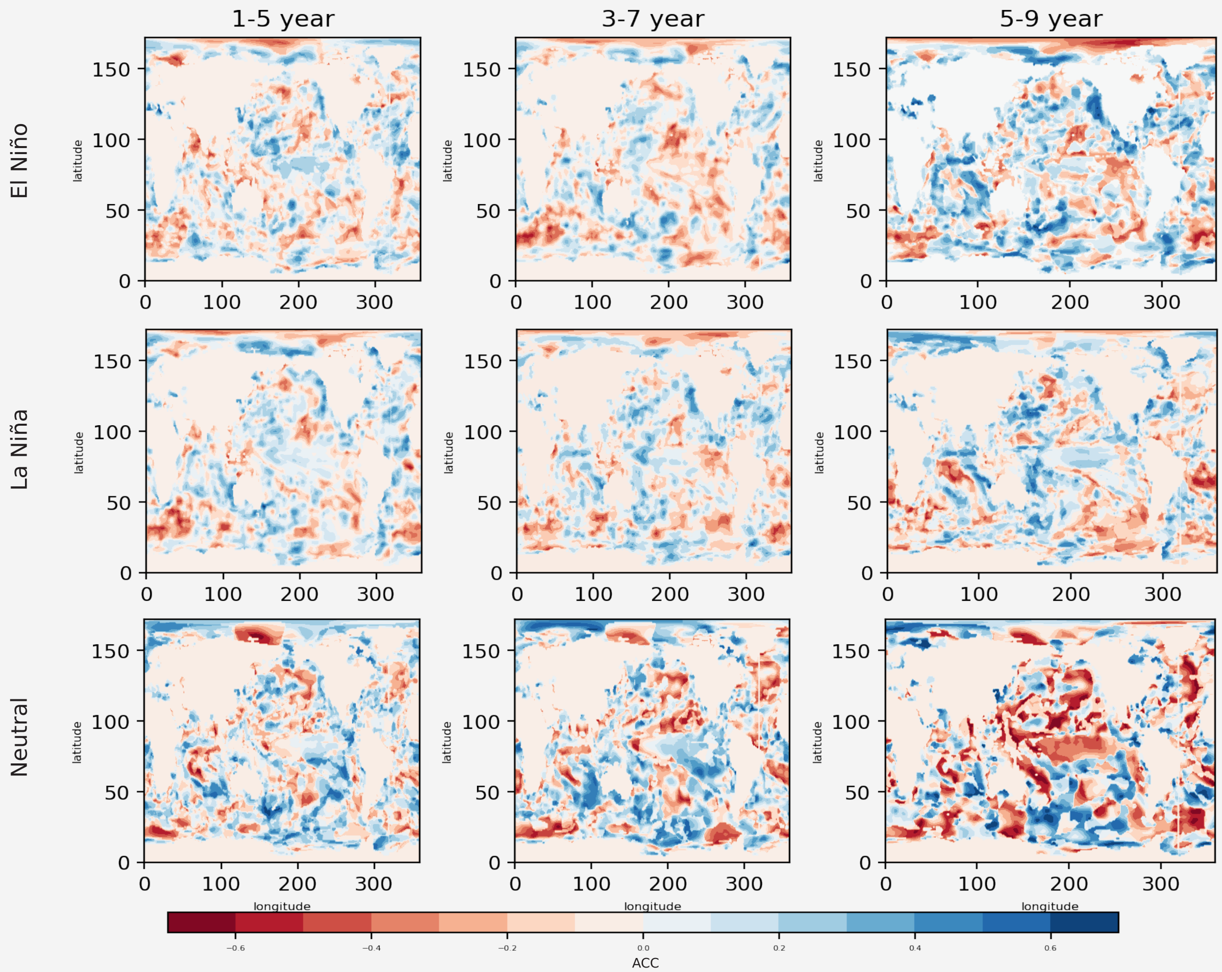

Figure 3. ACC score calculated for DPLE SST and Met Office SST data. Rows are separated into El Niño, La Niña and Neutral initialization years. Columns are separated by range in years following the initialization year over which ACC was calculated.

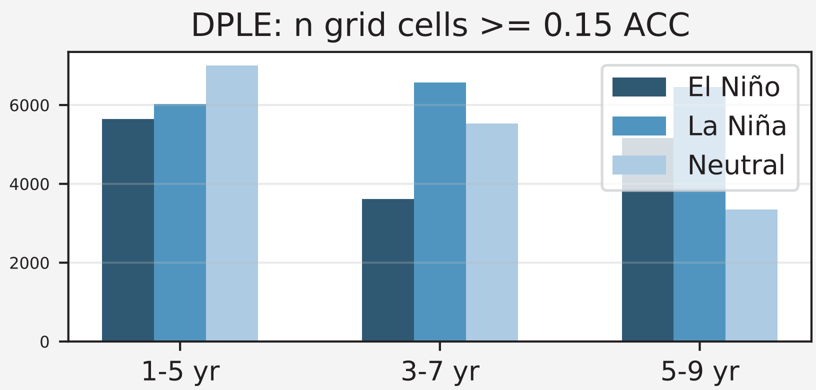

Figure 4. Bar plot showing the number of grid cells who had an ACC score calculated for DPLE SST and Met Office SST data above 0.15. Initialization ENSO regime is indicated by the color of the bars (shown in legend). Year ranges indicate the time period after the initialization year of the DPLE forecast.

For SST, the neutral years offered the greatest predictive skill in the first forecast of years 1-5 while La Niña predictive skill dominated the other forecast year ranges. These results differ from what we would normally expect since La Niña proved to have a higher predictive skill than El Niño in the later years. Between these two regimes, it was not predicted for La Niña to have a greater predictive skill than El Niño.

5. Discussion

For SST, the forecasts initialized for the neutral years, specifically for the 1-5 year forecast period, offered a much higher predictive skill than the ENSO regimes. However, with the increase in the forecast length comes a decrease in predictive skill with the neutral years, but La Niña increases in predictive skill when the forecast length is increased to the 3-7 year range. Once the forecast is propagated forward to the 5-9 year range, the predictive skill in the La Niña regime decreases. With the El Niño regime, the predictive skill is essentially the opposite of the La Niña regime where the predictive skill decreases going into the 3-7 year forecast but then increases going into the 5-9 year forecast period. Overall, the El Niño predictive skill was either almost the same as the La Niña predictive skill or smaller, which was unexpected. It is possible that this could be attributed to a cold temperature bias that is possible in the CESM1-DPLE model. In previous work, it has been found that there is a possible cold tongue bias within the model as concluded by X. Wu et al. Though this is not proven, it can answer how the predictive skill of La Niña is greater than the predictive skill of El Niño.

Results from the analysis of DPLE's precipitation predictive skill indicated that the hypothesis that initial conditions located within one ENSO regime offer more predictability than initial conditions located between regimes is correct. Additionally, initial conditions located within the El Niño regime offer more precipitation predictability than those located within the La Niña regime. However, it is still unclear where this source of predictability originates.

The difference between the predictive skill of SST and the predictive skill of precipitation was to be expected, given that the predictive skill of SST was greater overall than the predictive skill of precipitation. We expected this to be true as it is more difficult to predict precipitation overall since there are several different ways that precipitation can be affected by outside forcings. Another contributing factor to the observed discrepancy in predictive skill between precipitation and SST is the spatial and temporal scale of the dynamics that drive changes over time. Processes that affect SST include large scale wind patterns and large scale ocean circulation, in addition to many smaller scale processes as well. However, both of these types of large scale dynamics operate on longer timescales and are more accurately modeled at the resolution provided by the DPLE model. In contrast, precipitation is predominantly affected by a multitude of subgrid scale processes, in addition to being influenced by the same large-scale dynamics as SST. However, the main contrast is that the physical mechanisms that facilitate precipitation, such as convection, happen on much shorter timescales, influencing their difficulty to predict.

Further research exploring the observed gaps of predictive skill between strong ENSO phases and neutral years is required to understand the origin of their respective increases or decreases in predictive skill. One example of further research in the area is to conduct the same analysis technique using historic CESM-LE runs. This would highlight the benefit associated with initializations in the respective ENSO regimes or neutral years. Another area that requires further exploration is to quantify the upper limit of predictability for SST and precipitation. This could be analyzed through the analysis of CESM-LE's skill in predicting itself. Additionally, conducting this same type of analysis on the DPLE dataset would help quantify the upper limit of predictability with respect to initialization years that coincide with strong ENSO regimes.

6. Summary

ENSO has a variety of impacts on climate around the globe due to its large variability, but can also contain a high level of predictive skill depending on what variable you are attempting to forecast. We particularly look at the two modes of variability of ENSO, El Niño and La Niña, comparing the predictive skill as well as analyzing exactly how these two modes affect the global climate. The goal of this project was to quantify the impacts of the ENSO regimes on predictive skill on precipitation and sea surface temperature on sub-decadal time scales. This was achieved by first gathering the years in which the ENSO regimes had higher peaks (above a certain threshold). With these years acting as initialization years, the anomaly correlation coefficient (ACC) was calculated between observational data (datasets differ between variables) and the DPLE model. The ACC was calculated between those two datasets and then forecasted for 1-5 years, 3-7 years, and 5-9 years, then plotted spatially in order to visualize the difference in ACC across the globe.

The results have shown us very different things between SST and precipitation, overall there is a higher predictive skill with SST compared to precipitation. With precipitation, the predictive skill for the different ENSO regimes and the neutral years were as expected with El Niño having the highest predictive skill compared to La Niña and the neutral years. Along with that result, it was also expected that the predictive skill decreased as the forecast length increased within the range of years that the ACC was calculated for. However, with SST, what we expected from the ACC calculations was not what the results showed us. For the first forecast of 1-5 years, the neutral years have the highest predictive skill while, as the forecast length increases, the La Niña regime has the highest predictive skill. While some of the results were as expected and some were not, we are still able to show the impact ENSO has on the global climate from the two variables tested. Further analysis is required in order to show the origin of the observed differences in DPLE predictive skill across the ENSO regimes, as well as the origin for the higher predictive skill of La Niña when it comes to sea surface temperature.

7. Appendix

7.1 ENSO Year Selection

The first step of our analysis was to use NOAA Niño 3.4 anomaly data to select El Niño years and La Niña years by averaging the temperature anomaly in the Niño 3.4 region over December, January and February. Three months are typically used to generate the Niño index, and DJF was selected due to the fact that ENSO typically peaks during this time period. The selected years are as follows:

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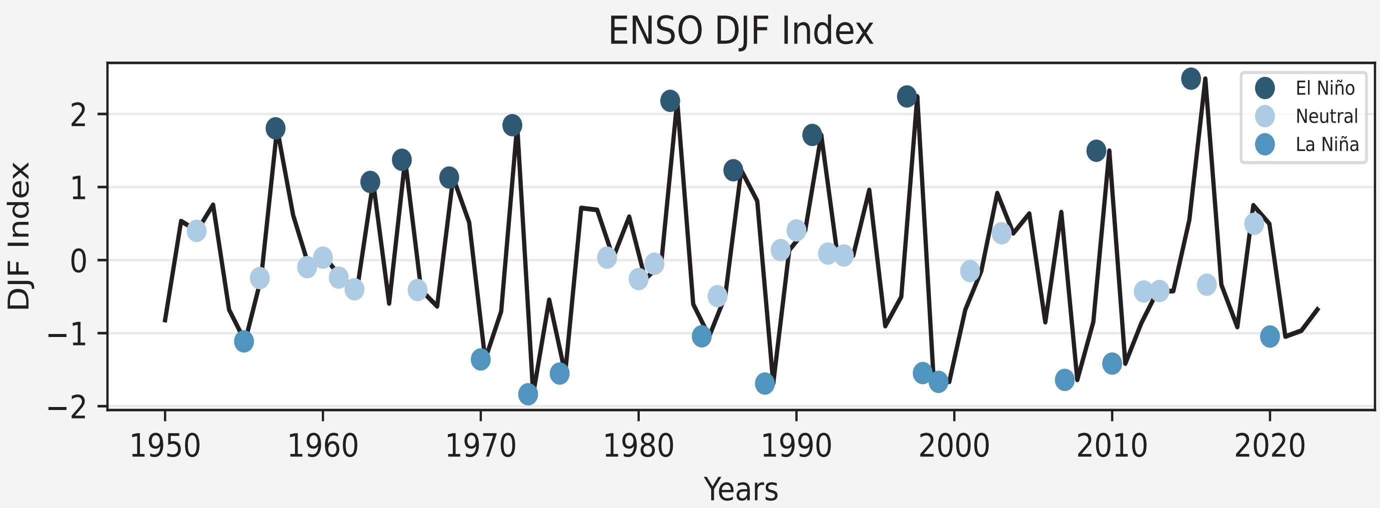

Figure 5. This graph shows the DJF index for each year. Circles indicate years that were selected for their respective ENSO regime. El Niño and La Niña were selected using 1.0 and -1.0 index values, respectively. Neutral years were selected using the index range -0.5 to 0.5.

7.2 Persistence Methods

Similar methods to the analysis applied to the DPLE to observations ACC core generation were employed. The primary distinction is the use of the first month of data, December of the initialization year, as the data for the following 122 simulation months. Climatology was calculated from the original DPLE dataset and subtracted from the persistent values to general anomalies. This data was then regridded to match the spatial resolution of observations, and correlated over the same 1-5, 3-7 and 5-9 year ranges after initialization.

7.3 Persistent Results

The results of persistence indicated that the DPLE dataset does a remarkably great job of predicting precipitation. By contrast, the persistence model had very low skill scores, with the maximum skill score ranging across all three year ranges was less than 0.2, with around 10 grid cells demonstrating significant ACC scores. Additionally, very few of these significant ACC scores coincided with regions of positive ACC values.

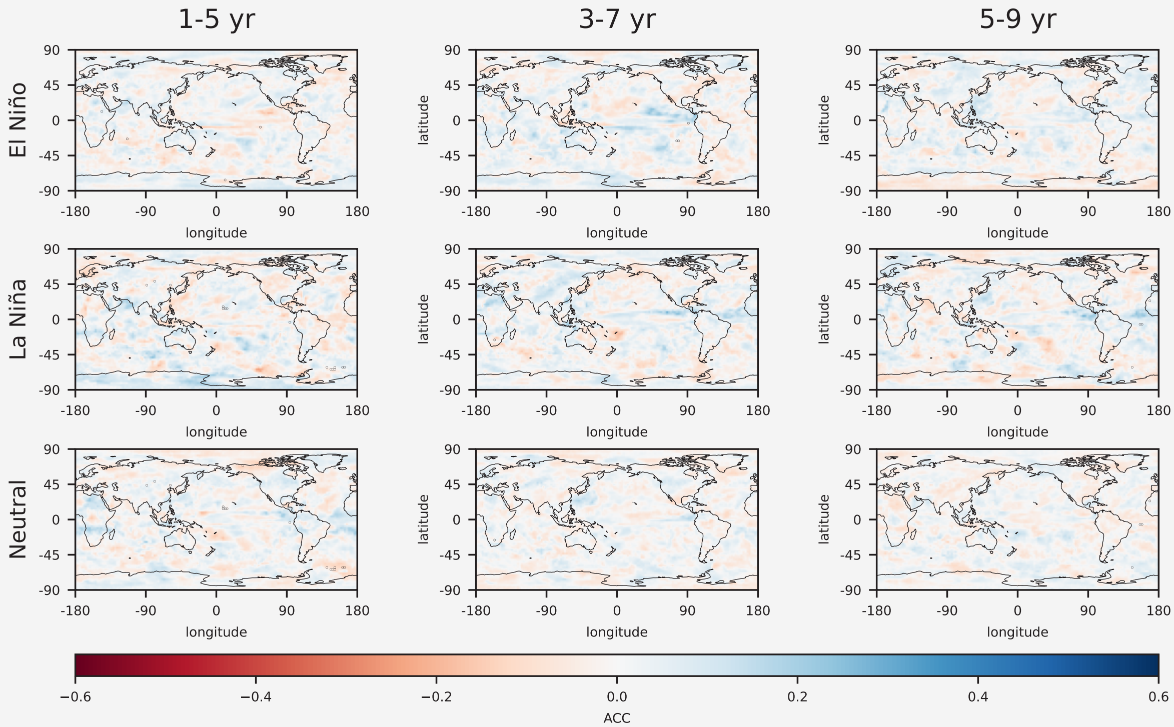

Figure 6. ACC score calculated for Persistence and GCPC precipitation data. Rows are separated into El Niño, La Niña and Neutral initialization years. Columns are separated by range in years following the initialization year over which ACC was calculated.

8. Citations

Wu, X., Y. M. Okumura, P. N. DiNezio, S. G. Yeager, and C. Deser, 2022: The Equatorial Pacific Cold Tongue Bias in CESM1 and Its Influence on ENSO Forecasts. J. Climate, 35, 3261–3277, https://doi.org/10.1175/JCLI-D-21-0470.1.

Yeager, S. G., and Coauthors, 2018: Predicting Near-Term Changes in the Earth System: A Large Ensemble of Initialized Decadal Prediction Simulations Using the Community Earth System Model. Bull. Amer. Meteor. Soc., 99, 1867–1886, https://doi.org/10.1175/BAMS-D-17-0098.1.

Good, S. A., Martin, M. J., and Rayner, N. A. (2013), EN4: Quality controlled ocean temperature and salinity profiles and monthly objective analyses with uncertainty estimates, J. Geophys. Res. Oceans, 118, 6704–6716, doi:10.1002/2013JC009067.

Dataset Information:

DPLE: https://www.cesm.ucar.edu/community-projects/dple

NOAA: https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/detrend.nino34.ascii.txt

Met Office Data: https://www.metoffice.gov.uk/hadobs/en4/#:~:text=The%20EN4%20dataset%20consists%20of,profile%20data%20with%20uncertainty%20estimates.

GCPC dataset: https://climatedataguide.ucar.edu/climate-data/gpcp-monthly-global-precipitation-climatology-project