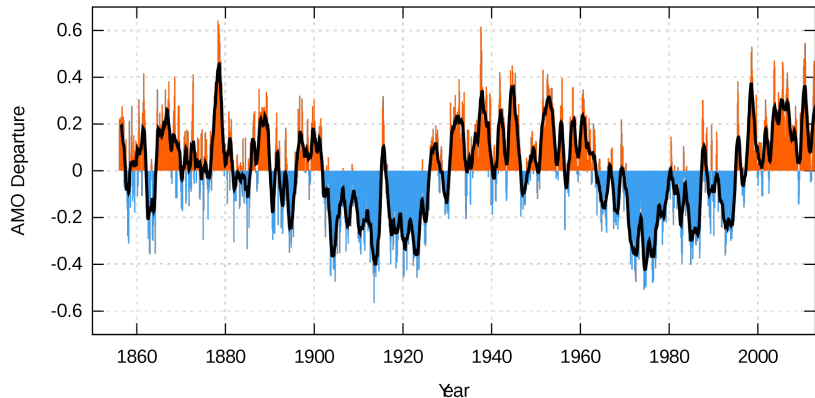


The North Atlantic Multidecadal Oscillation (AMO)

Students: Daniel Tapia-Reyes, Cecilia Florenza-Lamberti, Vanessa Tosello, and Zoé Remita

Advisor: Sally Close

Monthly values for the AMO index, 1856 -2013



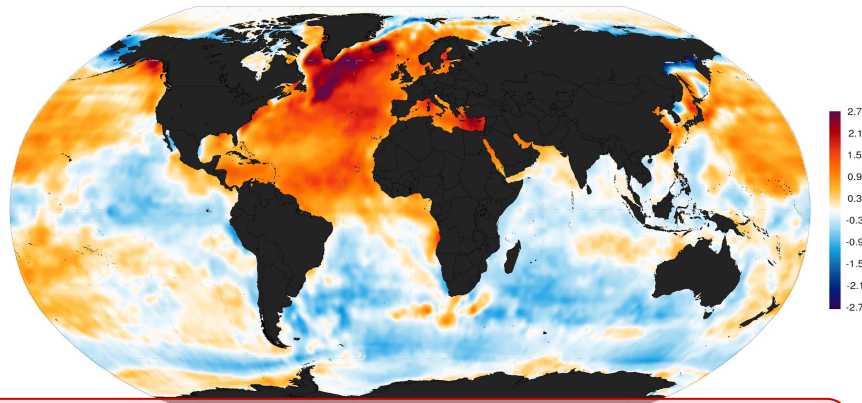
The **cold/warm phases** may last for **20-40 years**.

It has wide **impacts** on the **climate** of the **Northern Hemisphere**: hurricane activity, precipitation patterns, global temperature trends

The AMO is:

- a **low-frequency climate cycle**,
- characterized by variations in sea surface temperature (SST) over the North Atlantic Ocean.

Atlantic Multidecadal Oscillation



Objective: calculate the Atlantic Multidecadal Oscillation index in future climate projections

Coupled Model Intercomparison Project (CMIP6)

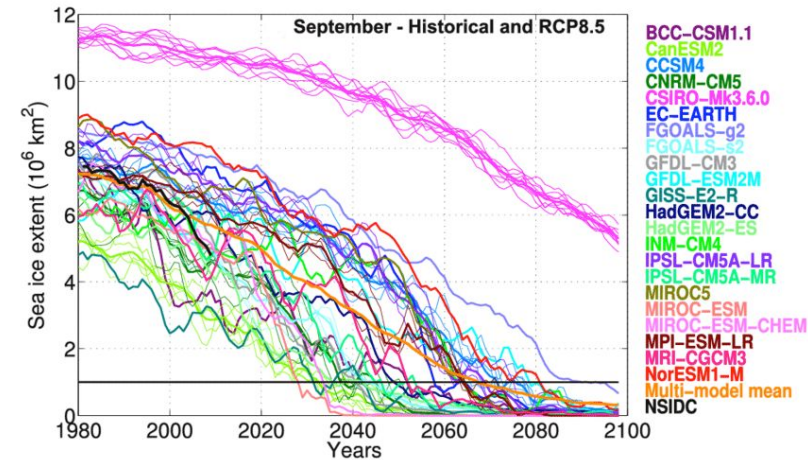
Collaborative framework involving research centers worldwide for producing climate model simulations.

Includes a variety of **Shared Socioeconomic Pathways (SSP)**:

- Climate scenarios imagining different futures based on global development and greenhouse gas emissions.

Uses an **ensemble approach**:

- Multiple simulations produced for each scenario
- Same model configuration, but different initial conditions



Data

Available in Google Cloud

- data ~ 150 YEARS OF DATA
- > 100 models
- > 40 research centers
- > 1000 variables

CMIP6 catalogue: <https://storage.googleapis.com/cmip6/cmip6-zarr-consolidated-stores.csv>

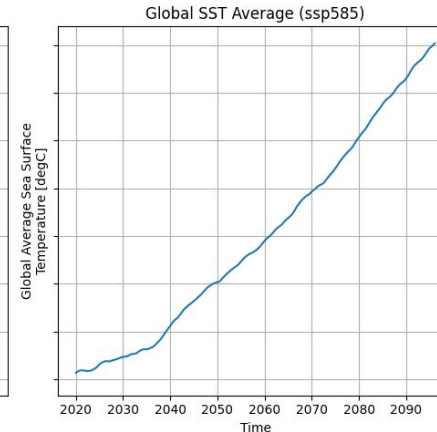
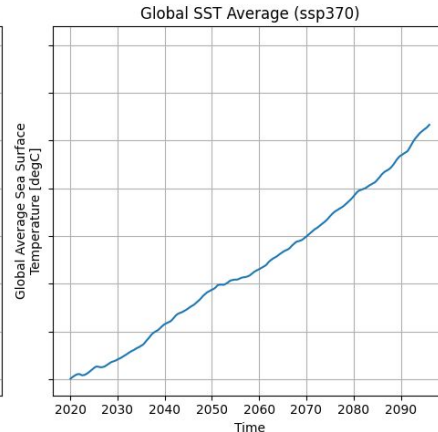
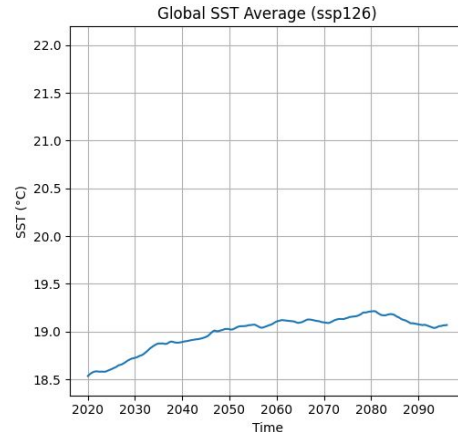
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320 rows x 13 columns

Accessing Zarr Datasets with Xarray

Data

- **Model** (*source_id*): IPSL-CM6A-LR (Institut Pierre-Simon Laplace)
- **Member** (*member_id*): only one
- **Scenarios** (*experiment_id*): SSP1-2.6, SSP3-7.0, SSP5-8.5
- **Variables:**
 - *tos*: Sea surface temperature [°C] (monthly time step)
 - *tosga*: Global Sea Surface Temperature [°C] (monthly time step)
 - *areacello*: Grid-Cell Area for Ocean Variables [m²]



Calculate the North Atlantic SST Average

$$A = \frac{\sum sst(x, y) \cdot areacello(x, y)}{total\ area}$$

- SST: **tos** variable, which provides SST at each point (x, y) on the grid
- **areacello**: area of each grid cell. Weighting the SST values by the cell area ensures the calculation is accurate and unbiased
- Divide by the **total area** of the region to compute the average

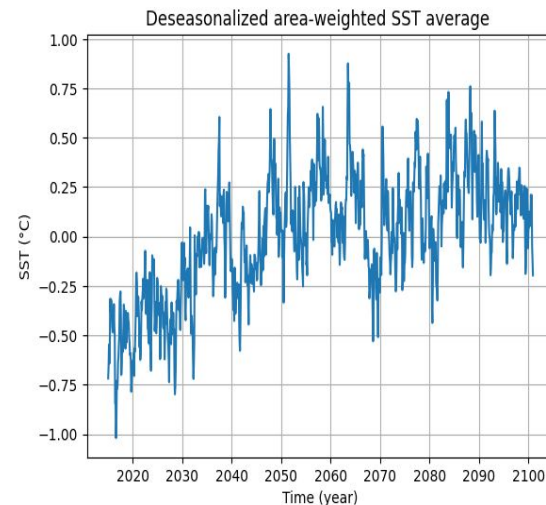
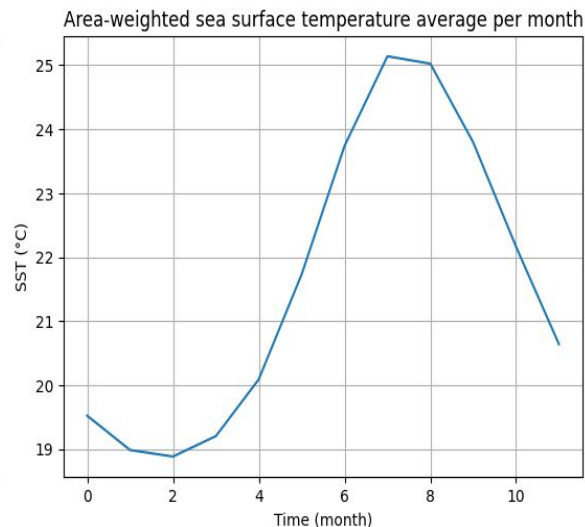
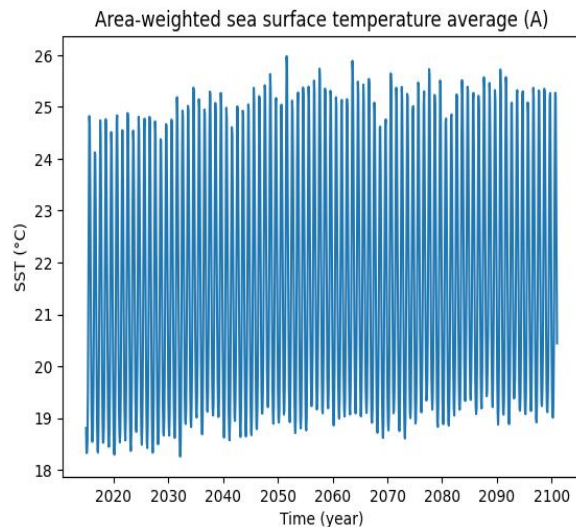


Components of North Atlantic SST Variability

$$A = \underbrace{\text{AMO}}_{\text{North Atlantic Multidecadal Oscillation}} + \underbrace{\text{climate change}}_{\text{long-term trend of increasing global temperatures}} + \underbrace{\text{seasonal cycle}}_{\text{regular annual pattern of SST variation}} + \underbrace{\text{random variability}}_{\text{unpredictable fluctuations}}$$

Remove the seasonal cycle

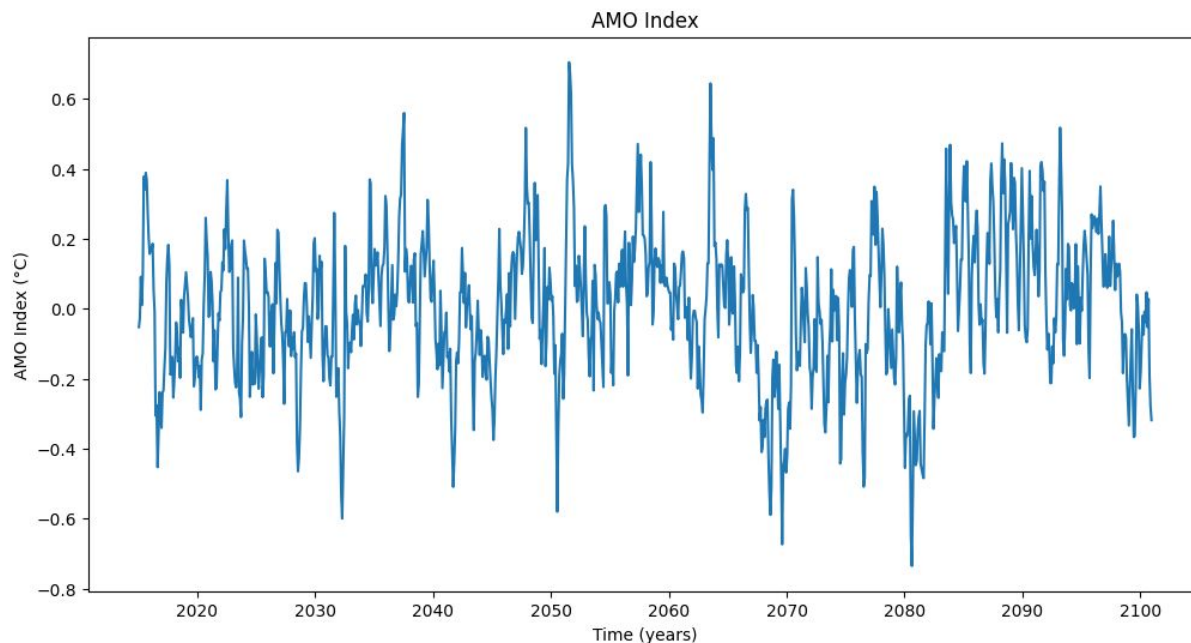
```
monthly_mean = A.groupby('time.month').mean(dim='time')
```



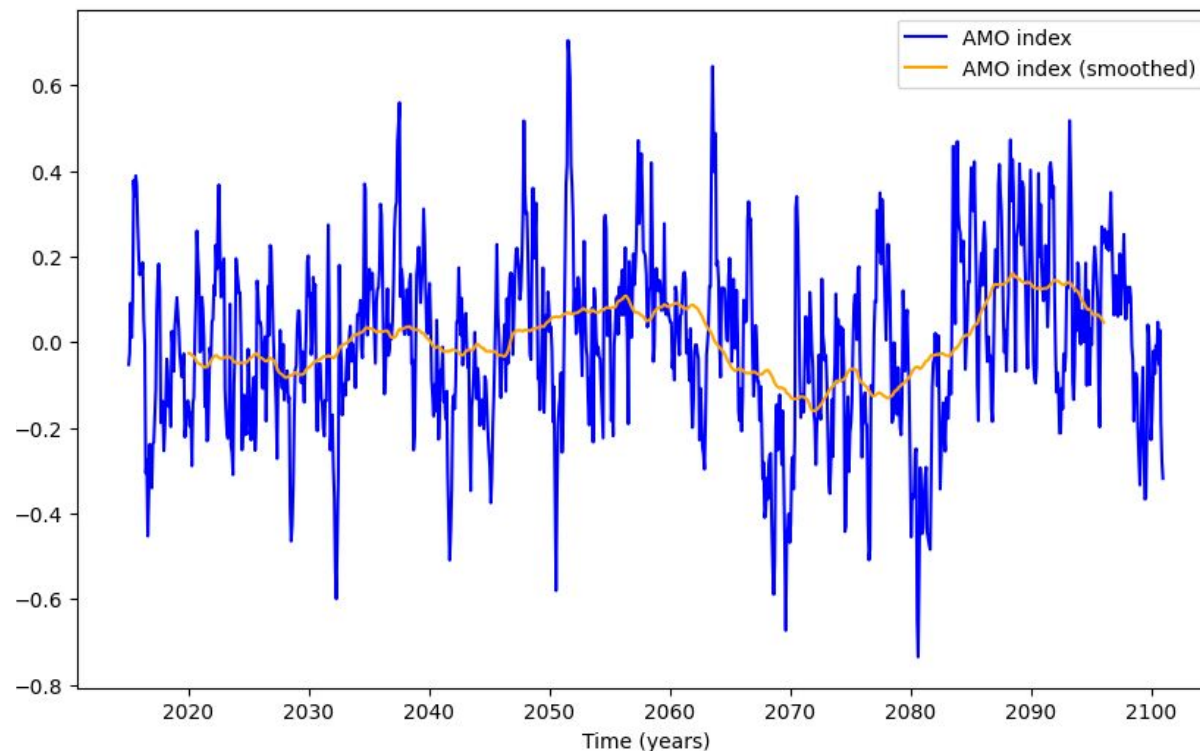
$A - \text{monthly_mean} = \text{AMO} + \text{climate change} + \text{random variability}$

Remove the global warming signal

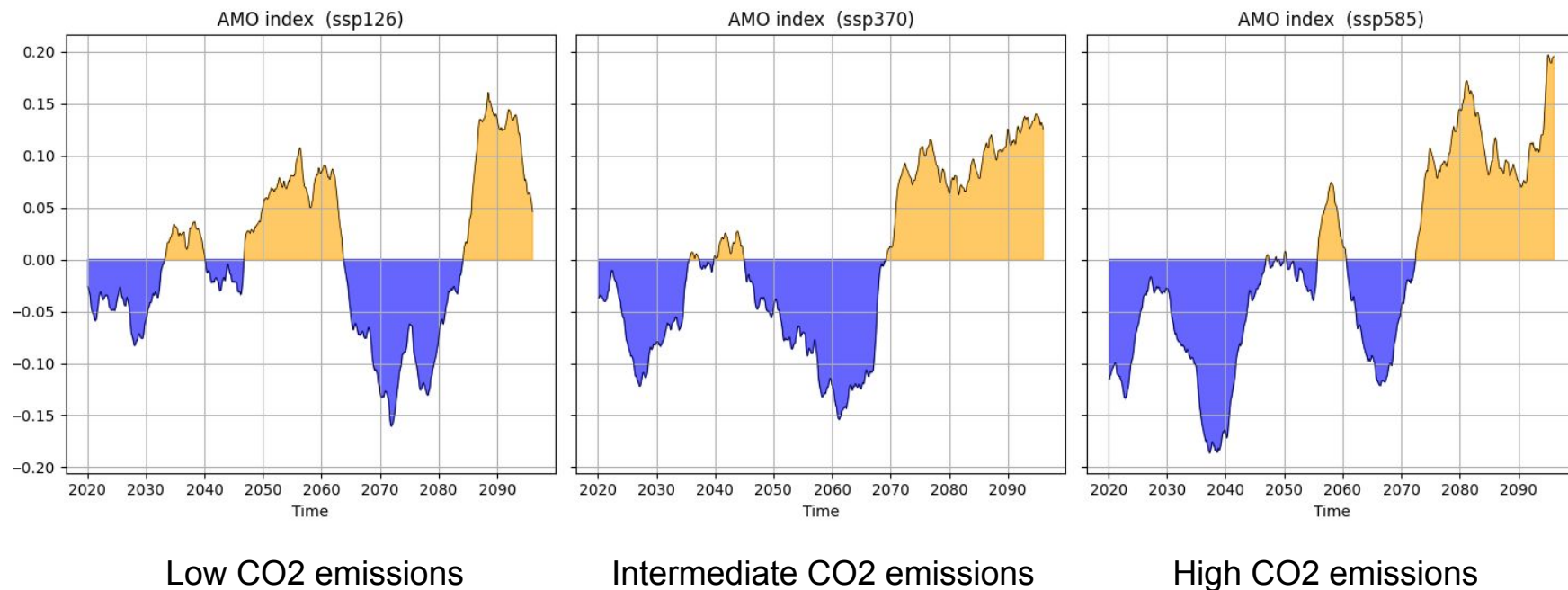
$$A' = A - \text{tosga} = \text{AMO} + \text{random variable}$$



AMO index: apply a 10-years low pass filter

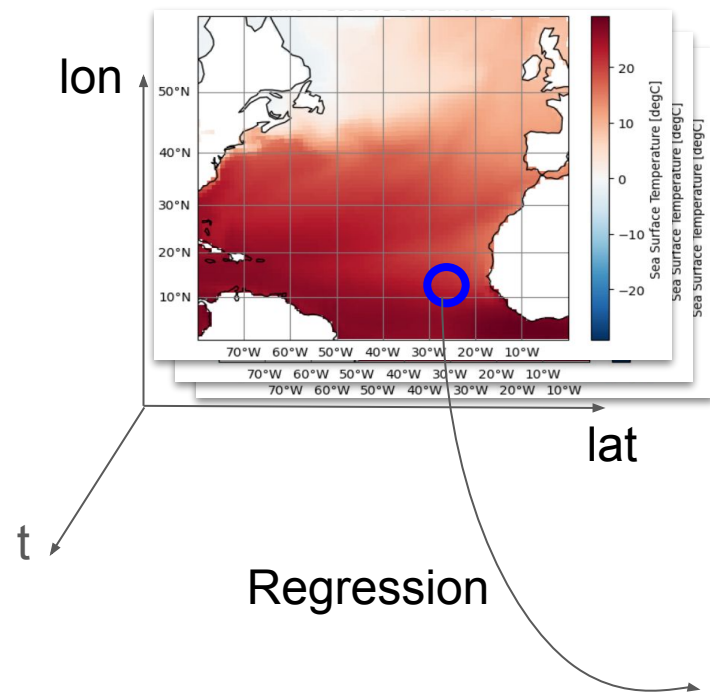


AMO index



AMO pattern

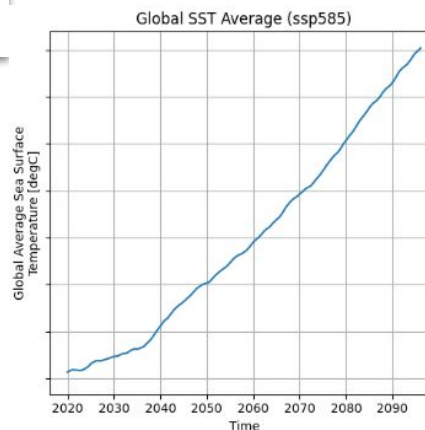
Linear Regression with Global SSTA



In order to remove the signature of the global SSTA change at each point. We fit the North Atlantic SSTA to global SSTA for each grid point to calculate the regression coefficients.

With the coefficients, we estimate SSTA using:

$$SSTA_{\text{estimated}}(t, \text{lat}, \text{lon}) = \beta_1(\text{lat}, \text{lon}) \cdot SSTA_{\text{global}}(t) + \beta_0(\text{lat}, \text{lon})$$



We subtract this estimate from the original SSTA.

$$SSTA_{\text{residual}} = SSTA_{\text{local}} - SSTA_{\text{estimated}}$$

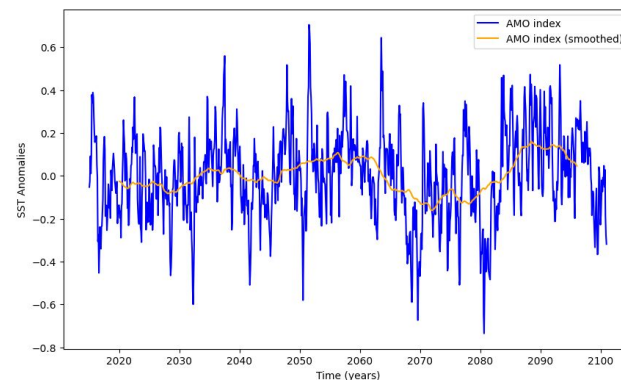
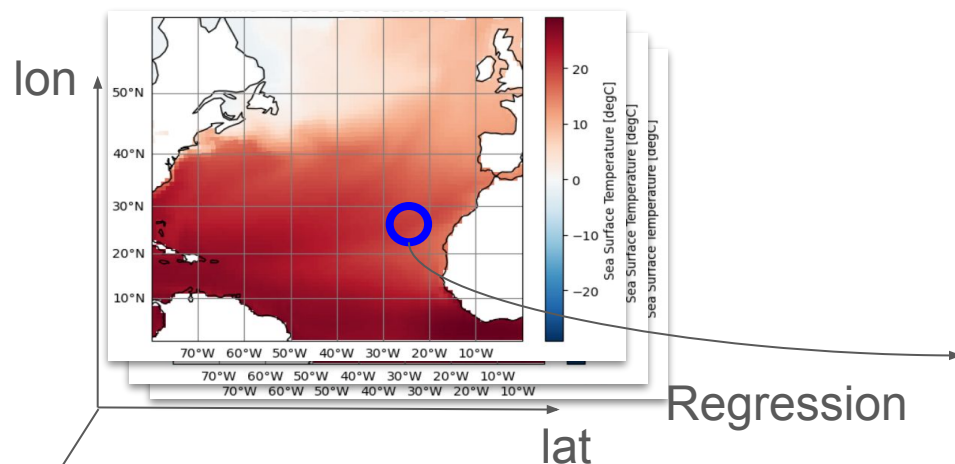
This leaves us with an SSTA anomaly relative to the global SSTA change at each point.

AMO pattern

Linear Regression with Global SSTA

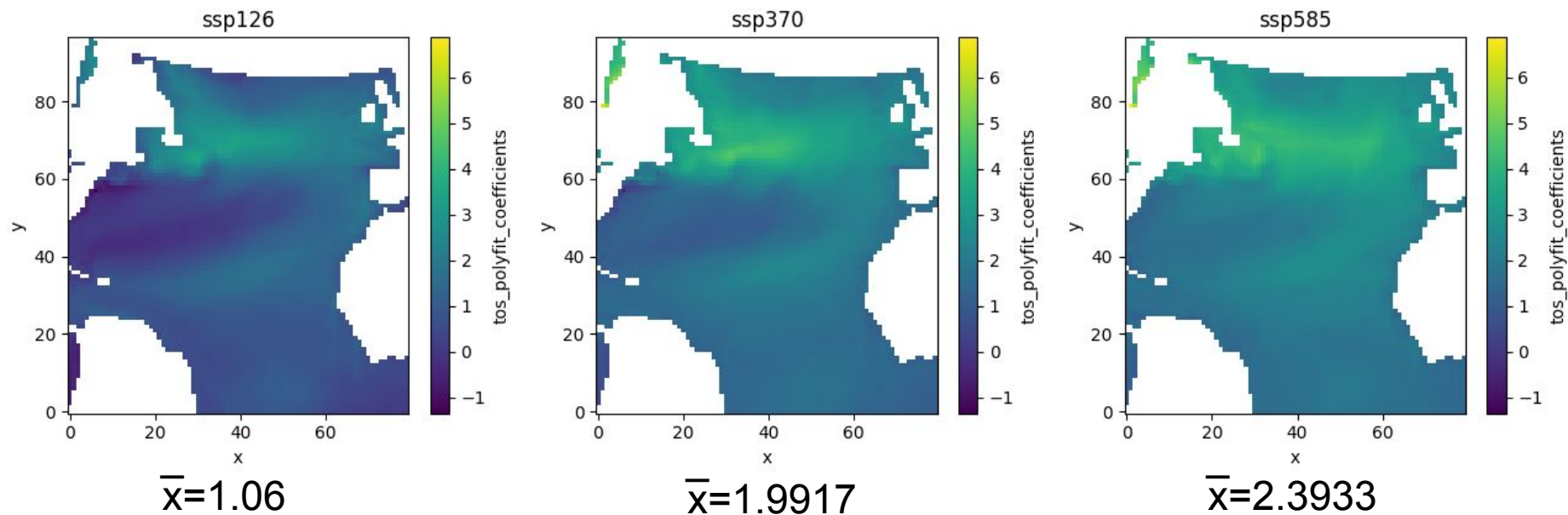
To obtain the AMO pattern, we fit the residual SSTA to the AMO index for each grid point, to obtain their coefficients.

$$SSTA_{\text{residual}}(t, \text{lat}, \text{lon}) = \alpha_1(\text{lat}, \text{lon}) \cdot \text{AMO}_{\text{index}}(t) + \alpha_0(\text{lat}, \text{lon})$$



Results: AMO pattern

A spatial map of coefficients degree = 1 showing how each point in the North Atlantic responds to the AMO index.



Perspectives

Link with the North Atlantic Oscillation (NAO):

- Use PCA (principal component analysis) on sea level pressure in winter
- Calculate NAO for different models and investigate potential covariability with the AMO

Find Common Features Across Models:

- Group models into categories of similar behavior using methods such as:
 - **Classification:** Identify scenarios based on time series characteristics
 - **Clustering:** Detect common patterns in AMO spatial variability or indices

Predict the AMO:

- Predict the last third of the AMO time series using earlier parts
- Forecast model behavior under one forcing scenario based on results from another scenario