# Identifying Drivers of Subseasonal-to-Seasonal Sea Level Predictability Using Uncertainty-Permitting Machine Learning

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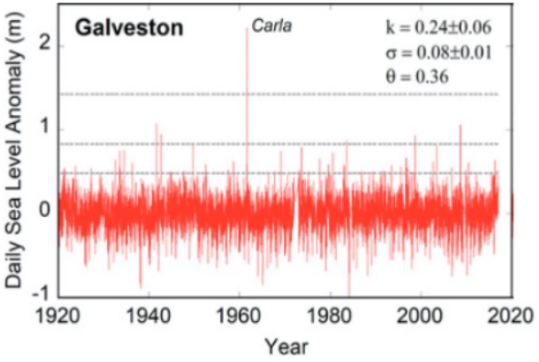
# Timescales for sea level: a challenge for subseasonal-to-seasonal (S2S) prediction

**Hourly to daily**

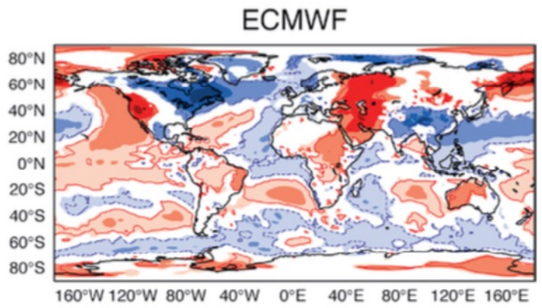
**Subseasonal to seasonal**
(~2wk-3mo)

**Seasonal to interannual**
(~3-24 mo)

**Multidecadal to centennial**

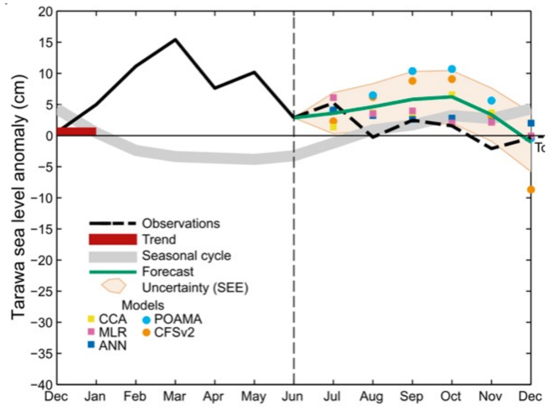



Yin et al 2020

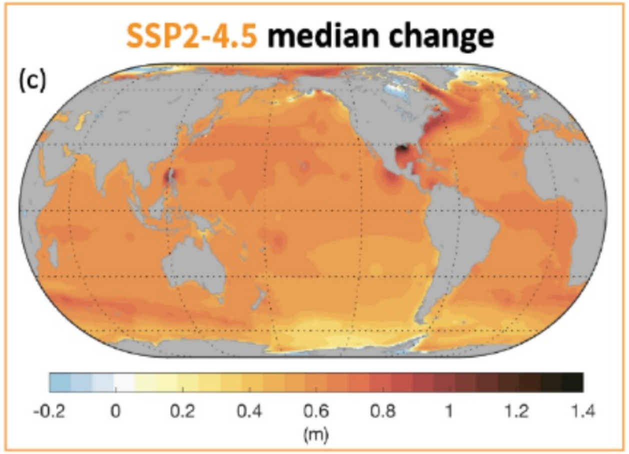



ECMWF 12-18 day ensemble mean forecast of SSTs

Vitart et al 2017




Widlansky et al 2017




IPCC 2022

Deterministic forecasts of point estimates

Probabilistic predictions conditioned on current state

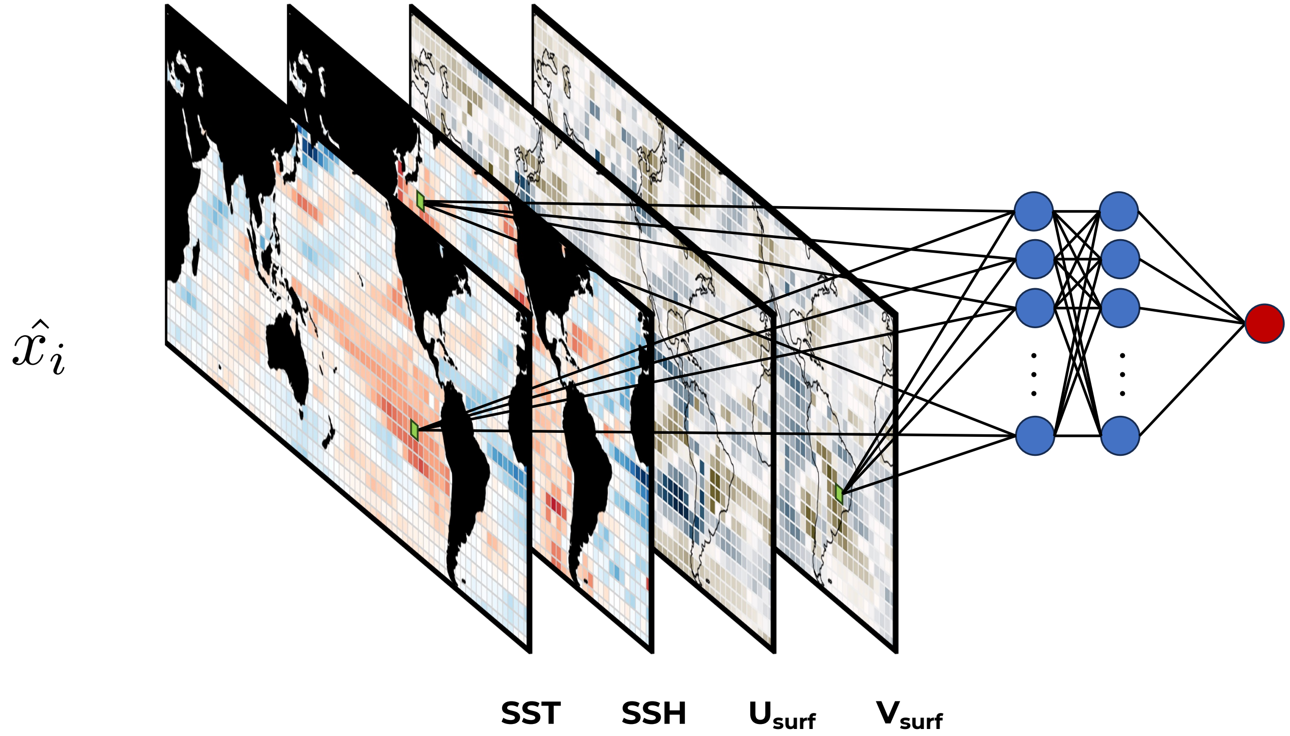
Estimates of changes in statistical states

# Quantifying uncertainty using maximum-likelihood loss function

Use fully-connected artificial neural networks to

1. forecast dynamic sea level at a given location and time horizon τ, and
2. quantify the uncertainty associated with the prediction.

CESM Large Ensemble inputs




**Part 1: predict point-estimate for sea level at time τ**

$\hat{\mu}_i$

$$\mathcal{L}_{\text{MSE}}(\boldsymbol{y}, \hat{\boldsymbol{\mu}}) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{\mu}_i)^2$$

**Part 2: quantify prediction uncertainty**

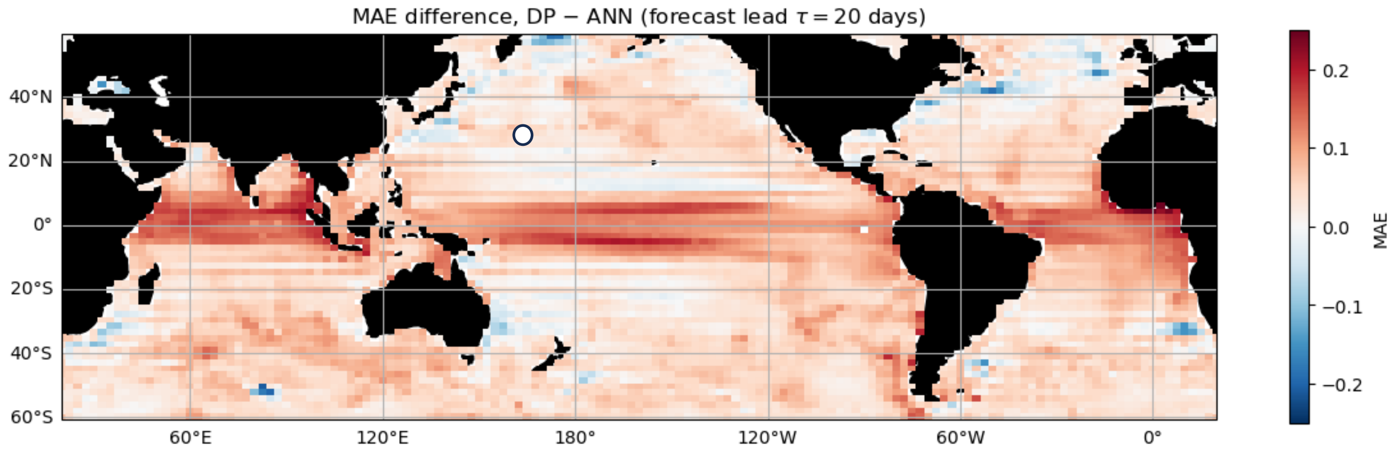
$\log \hat{\sigma}_i^2$

$$\mathcal{L}_{\text{NLL}}(\boldsymbol{y}|\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\sigma}}^2) = -\log p(\boldsymbol{y}|\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\sigma}})$$

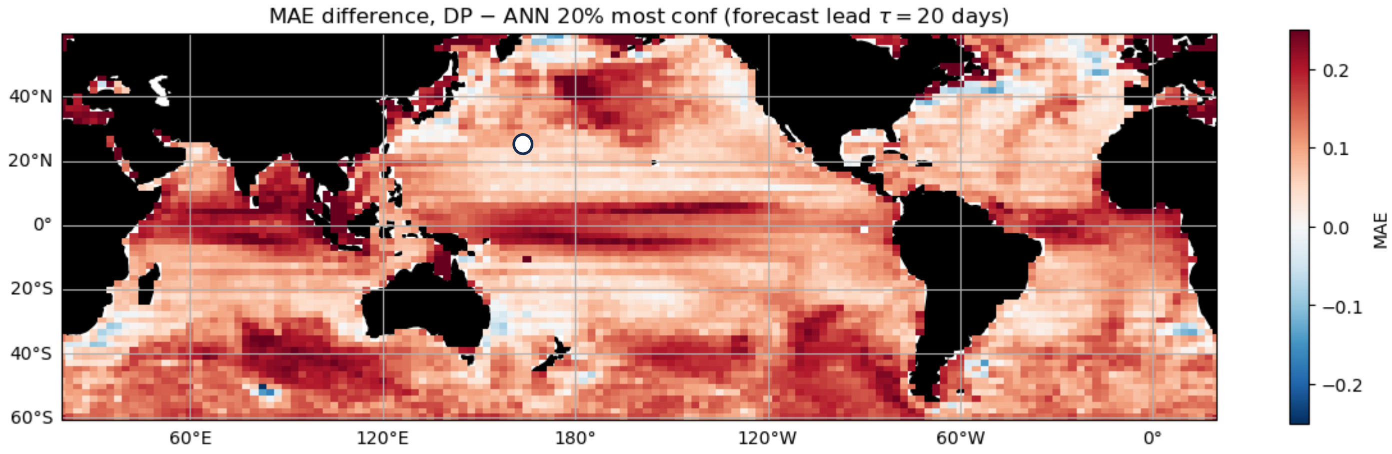
$$p(\boldsymbol{y}|\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\sigma}}) = \prod_{i=1}^{n}\frac{1}{\hat{\sigma}_i\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{y_i - \hat{\mu}_i}{\hat{\sigma}_i}\right)^2\right]$$

# Uncertainty-permitting forecasts

- Most regions exhibit nonlinear, nonlocal sources of predictability

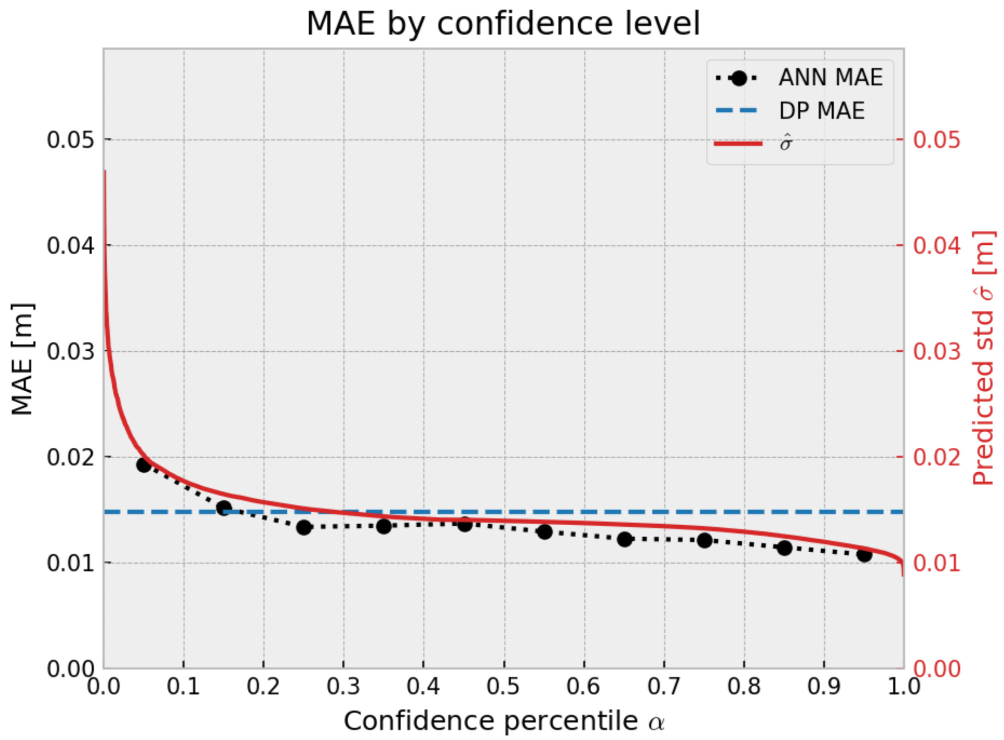



- Initial conditions can often be leveraged to make better predictions (forecasts of opportunity)

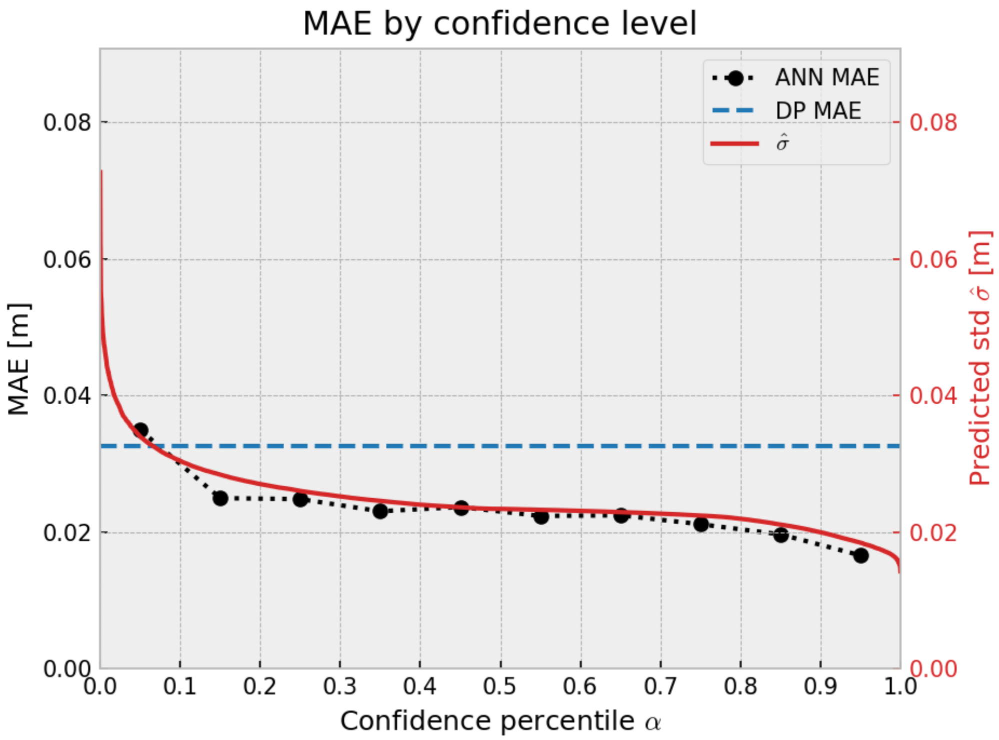


# Emergence of forecasts of opportunity

Forecasts of τ=20 days




Forecasts of τ=120 days




Nonlinear, nonlocal sources of predictability emerge on S2S timescales

Initial conditions favorable to forecasts of opportunity emerge on S2S timescales

# Drivers of predictability

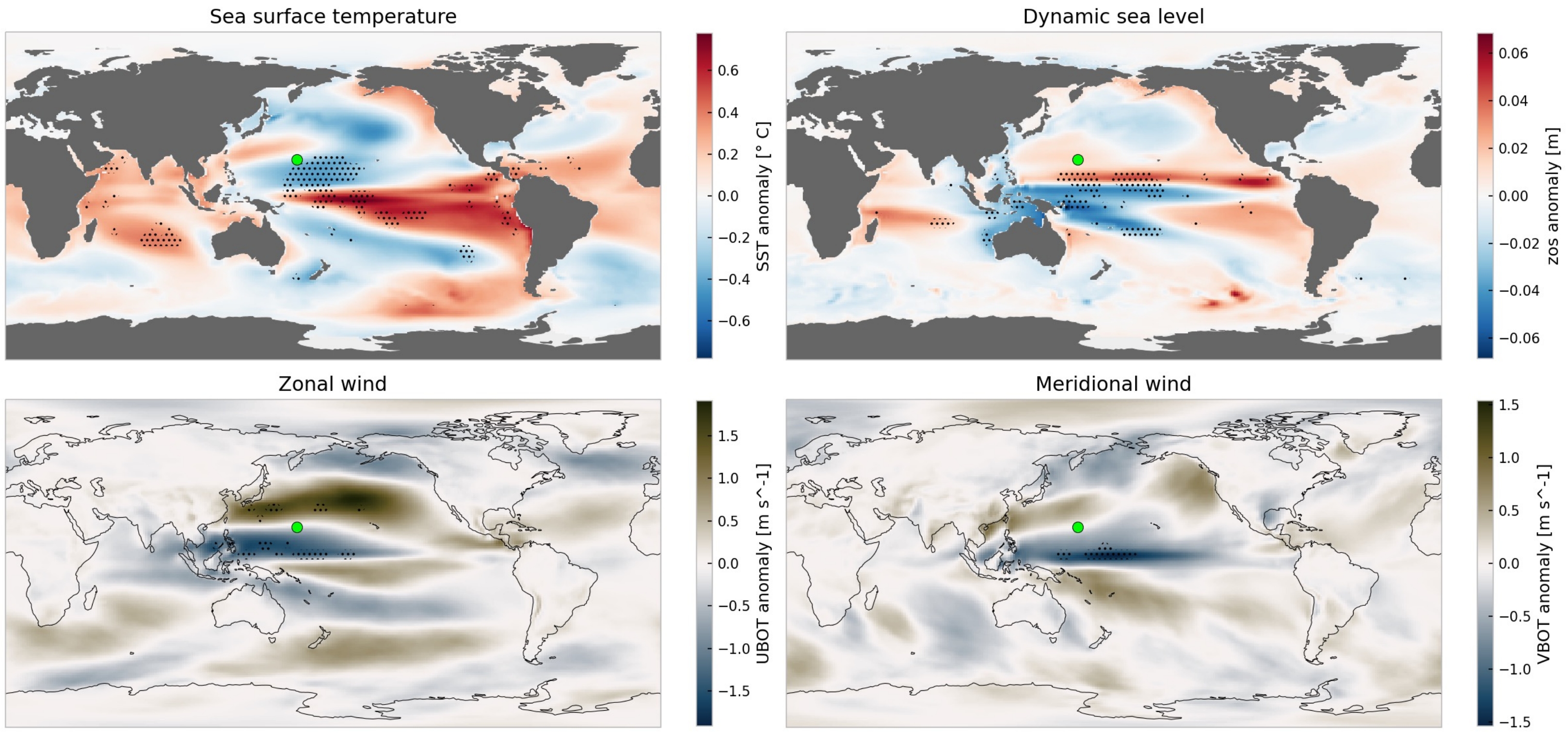
Inputs times gradients

$$\Delta f \approx \sum_{i=1}^{D} \underbrace{\frac{\partial f}{\partial x_i} \Delta x_i}$$

$$R_{i,j} = \frac{\partial f}{\partial x_i}(x_{ij} - x_i^*)$$

i : feature index
j : sample index

**Composites from most confident predictions, forecasts of τ=20 days**




Local persistence drives predictability on time horizons of 20 days

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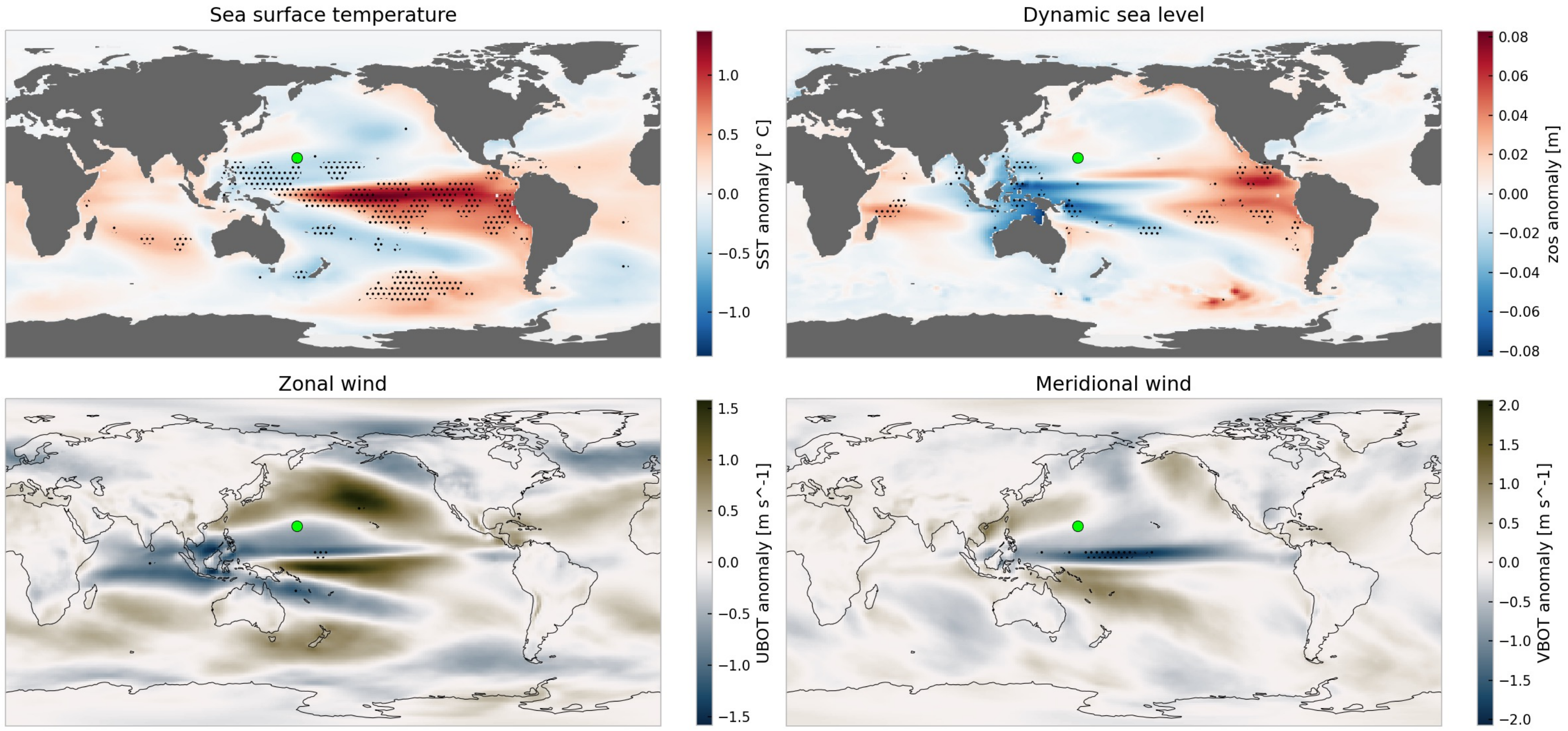
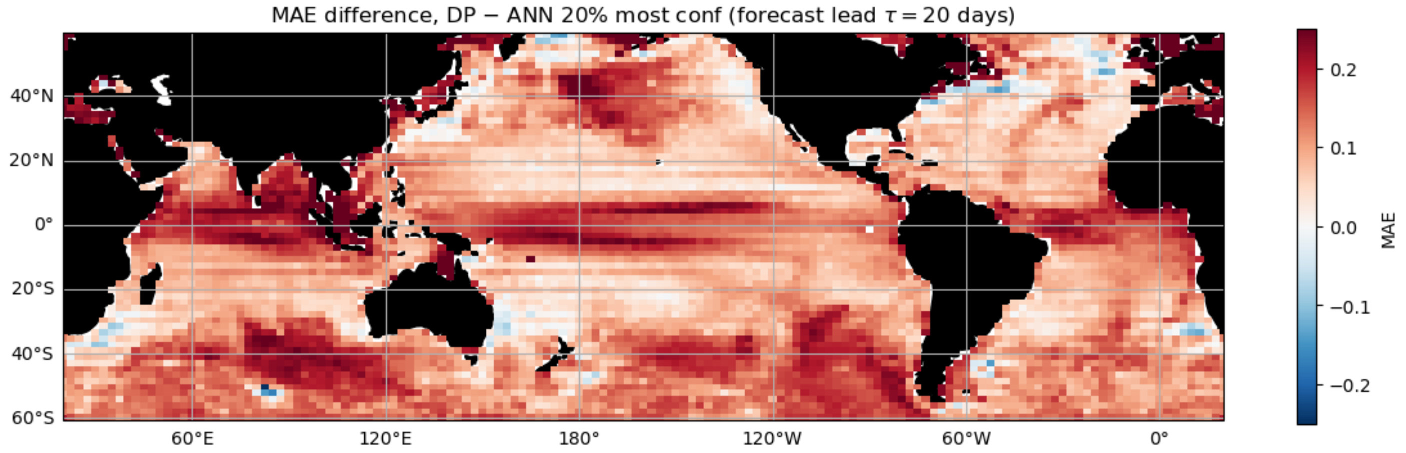


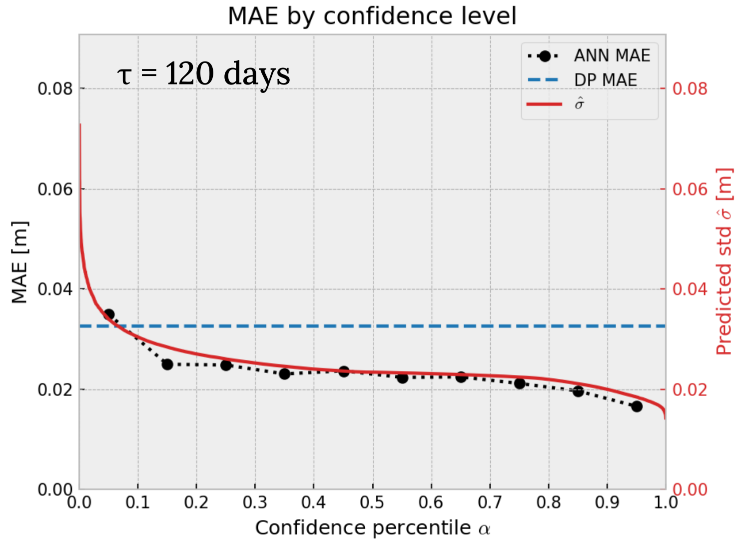

Equatorial SSTs are a dominant source of sea level predictability at τ=120 days

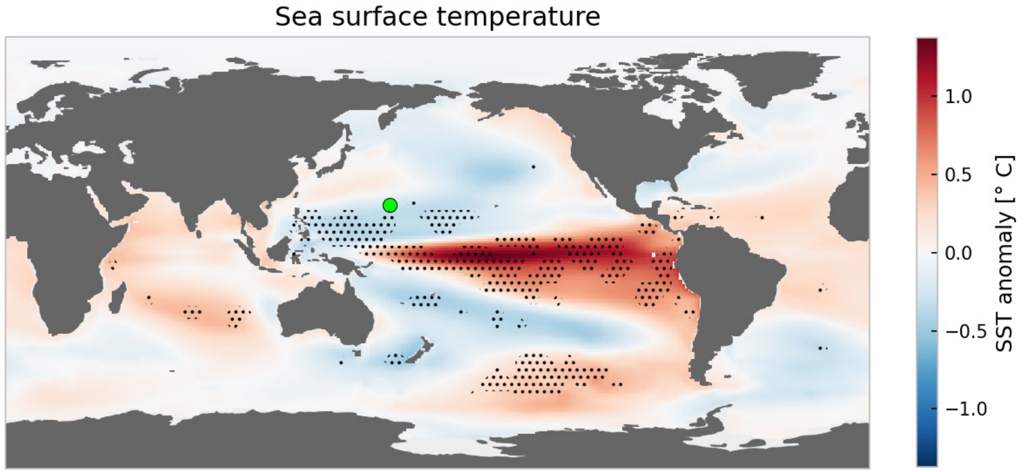
# Summary




Quantified uncertainty in sea level forecasts using neural networks

Showed emergence of predictability and forecasts of opportunity on S2S timescales




Identified sources of sea level predictability using network's gradients

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