Predictability timescales for Atlantic SST in CMIP6 models and observations

Martha W. Buckley (GMU)

Collaborators:

Tim DelSole (GMU)

Laurie Trenary (GMU)

Laure Zanna (NYU)

Predictability of North Atlantic SST and ocean heat content

- North Atlantic is a region of high predictability of sea surface temperatures and ocean heat content, as seen by:
  - initialized predictions (e.g., Smith et al., 2007; Keenlyside et al. 2008; Yeager et al., 2012)
  - statistical estimates of predictability (e.g., Branstator et al., 2012; Branstator and Teng, 2012; DelSole et al., 2013)
- Degree of predictability varies substantially between models.

  e.g., Branstator et al., 2012 find that predictability of upper ocean heat content varies amongst CMIP5 models, particularly in the North Atlantic.

Our approach

Estimate statistical measures of predictability of SST and upper ocean heat content (UOHC) from gridded observations and CMIP6 models.

1. Predictability of SST and UOHC in gridded observations (Buckley et al., 2019*, J. Climate*).
2. Predictability of SST and UOHC in preindustrial control runs of CMIP6 models (Buckley et al., to be submitted to *J. Climate*).
3. Predictability of SST and UOHC in historical Large Ensembles (future).

This talk: predictability of SST in preindustrial control runs of CMIP6 models. For context, we will compare results qualitatively to those from observations.

Can geographic variations of SST predictability be related to variations in mixed layer depths (MLD), i.e., higher predictability where MLD deeper?

SST: Models and Gridded Observations

CMIP6 Model	# years
GFDM-ESM4**	500
MRI-ESM2-0	701
NCAR CESM2**	801
NCAR CESM2-FV2	500
NCAR CESM2-WACCM-FV2	500
MPI-ESM1-2-HR**	500
MPI-ESM1-2-LR	1000
MPI-ESM1-2-HAM	780
BCC-CSM2-MR	600
MOHC-HadGEM3**	500
MOHC-UKESM1-0-LL	1100
CAS-FGOALS-g3	500
ACCESS-CM2	500
ACCESS-ESM1-5	900
CAMS-CSM1-0	500
CanESM5	1000
CanESM5-CanOE	501

Dataset	Period
ERSSTv5	1854-2020
HadISST	1870-2020

- Diagnostic: wintertime SST: $\overline{SST}^{w}$
- Higher predictability expected to be associated with wintertime SST due to deeper winter mixed layer depths.
- CMIP6 models: Preindustrial control simulations with > 500 years output.
- Observations: analyze the period 1945-present
- For both models and observations, removed a quadratic from time series of SST prior to analysis.

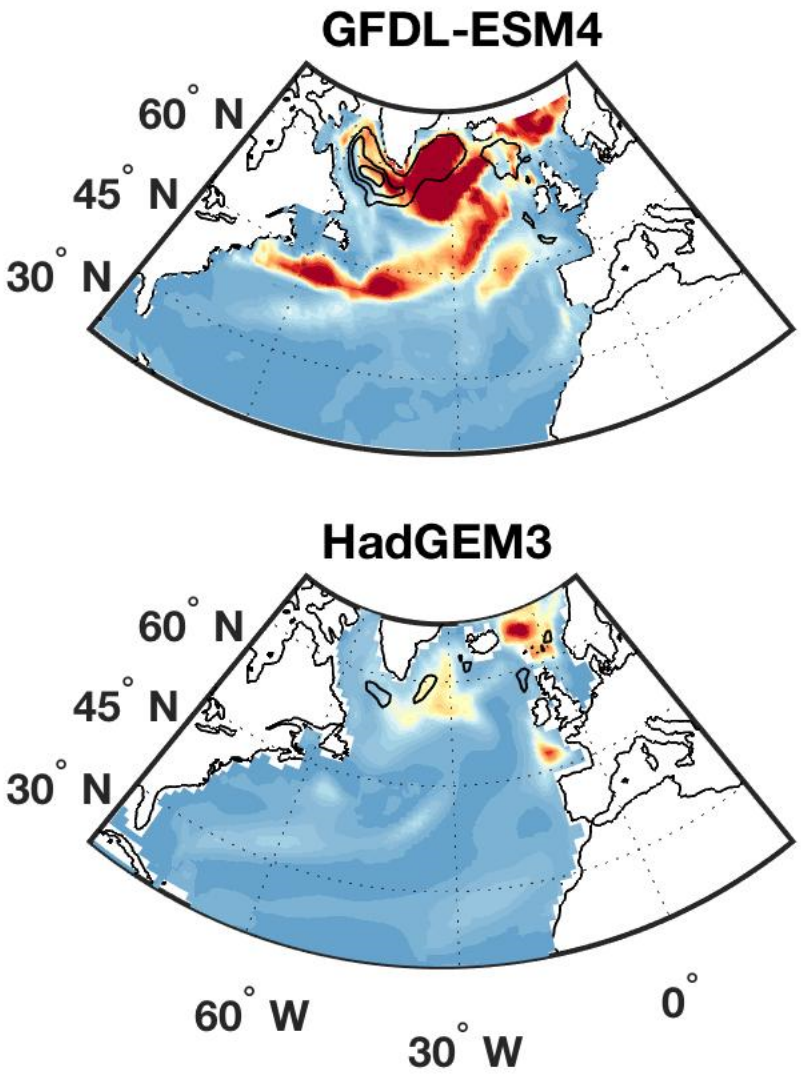
Simple statistical measure of predictability

Decorrelation timescale (DelSole, 2001)

$$T_2 = \sum_{k=-\infty}^{+\infty} \rho_k^2$$

- A lower bound on predictability based on the local autocorrelation function ρ_k.
- Can estimate predictability in presence of oscillatory variations.
- In order to calculate the autocorrelation function:
  - Fit an autoregressive (AR) model to SST at each gridpoint.
  - AR order chosen by the corrected Akake Information Criterion (DelSole and Tippett, 2021)
  - Use AR parameters to calculate theoretical autocorrelation function $\tilde{\rho}_k$.
  - Replace ρ_k with $\tilde{\rho}_k$ in the equation for T_2.

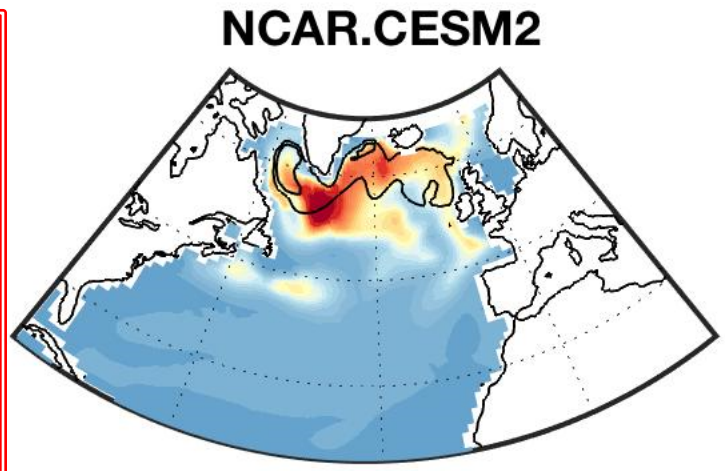
Decorrelation timescales for wintertime SST

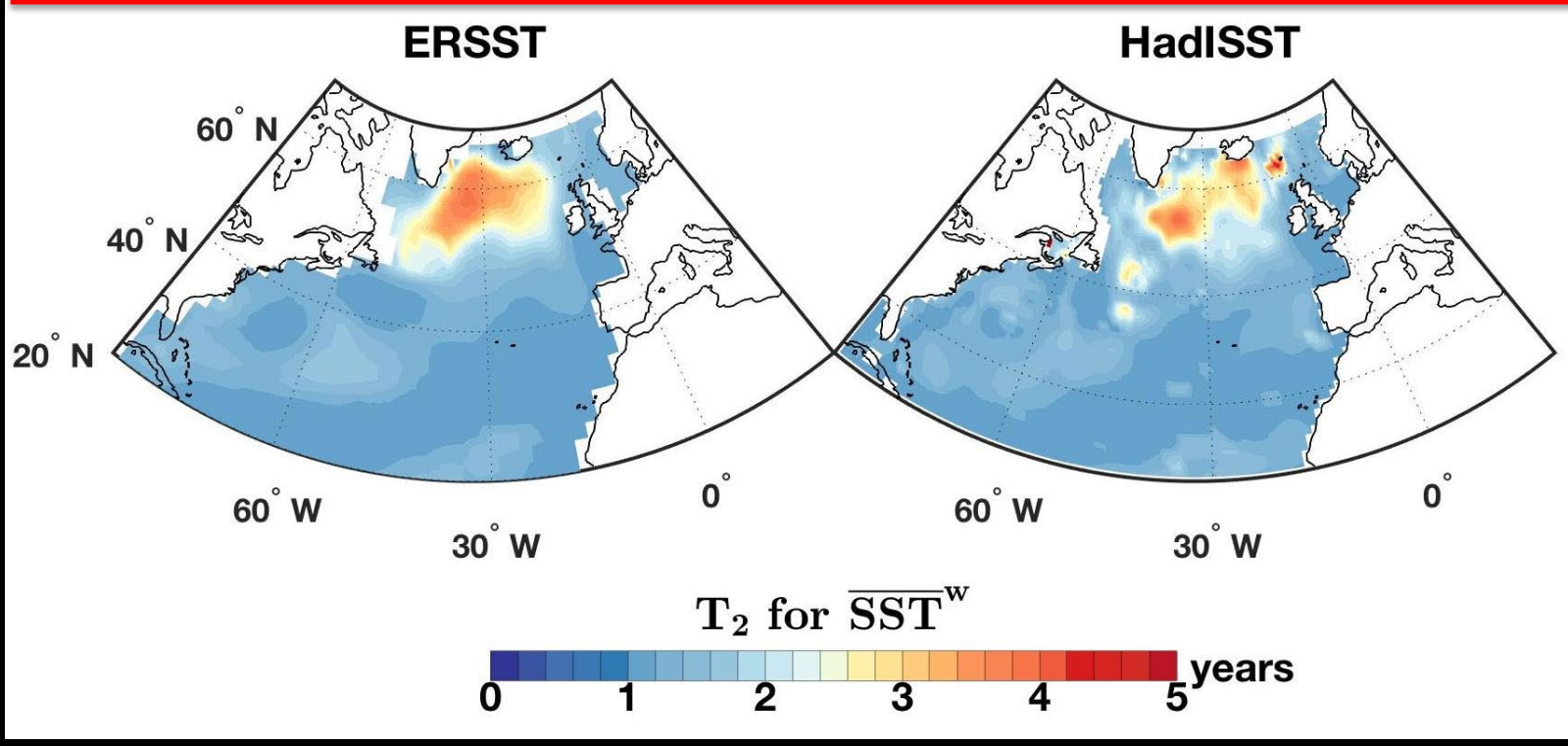


- T_2 longest in subpolar North Atlantic
- D = wintertime climatological MLD
- Area southeast of Greenland is region with large T_2.
- Labrador Sea is region with small T_2 due to large interannual variations in MLDs.
- Magnitude of T_2 differs among models.

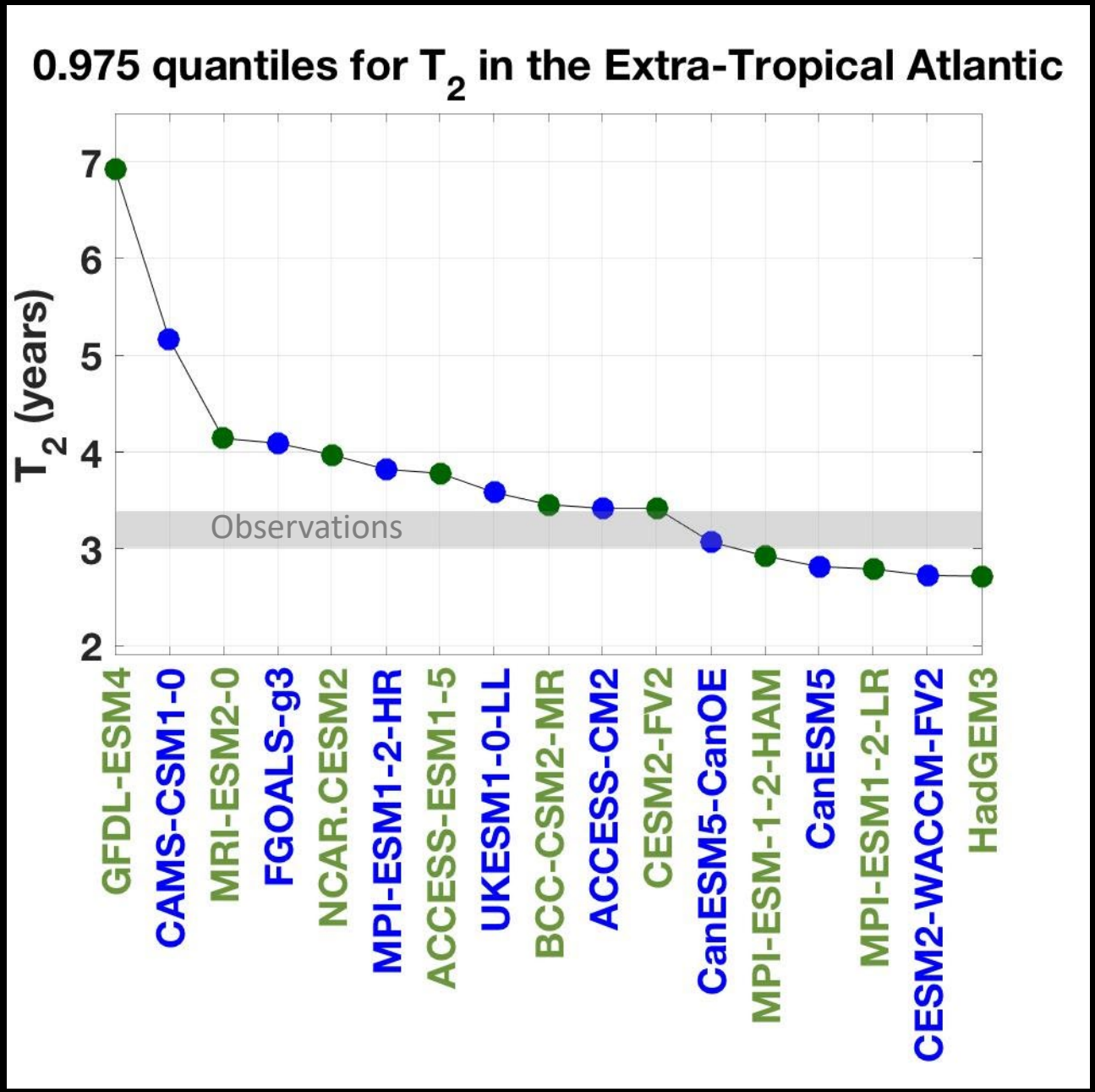
Decorrelation timescales in models and observations

- T_2 longest in subpolar North Atlantic.
- Area south of Greenland is region of high T_2.
- Labrador Sea is region of low T_2.





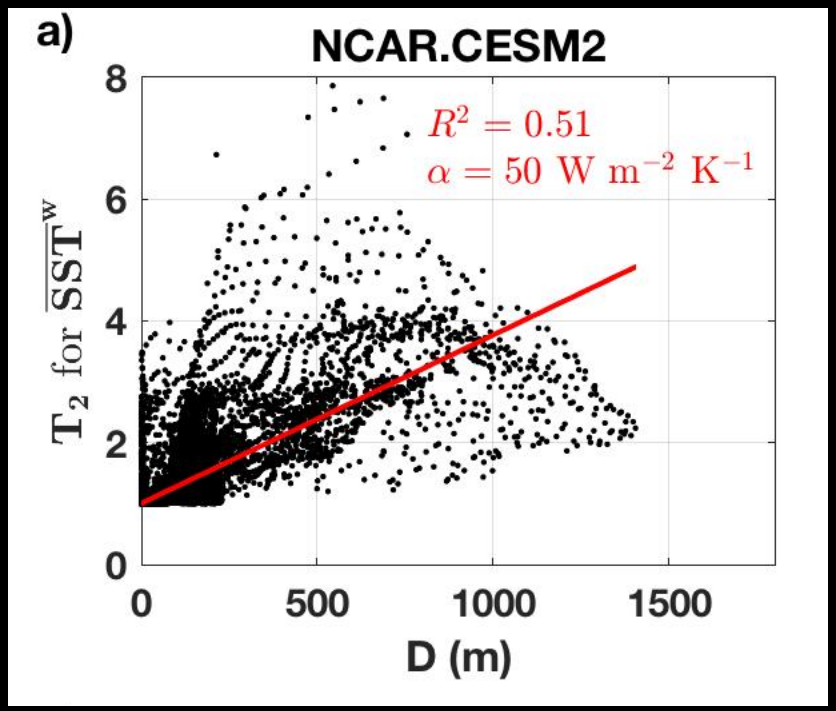
Magnitude of T_2 varies substantially between models.

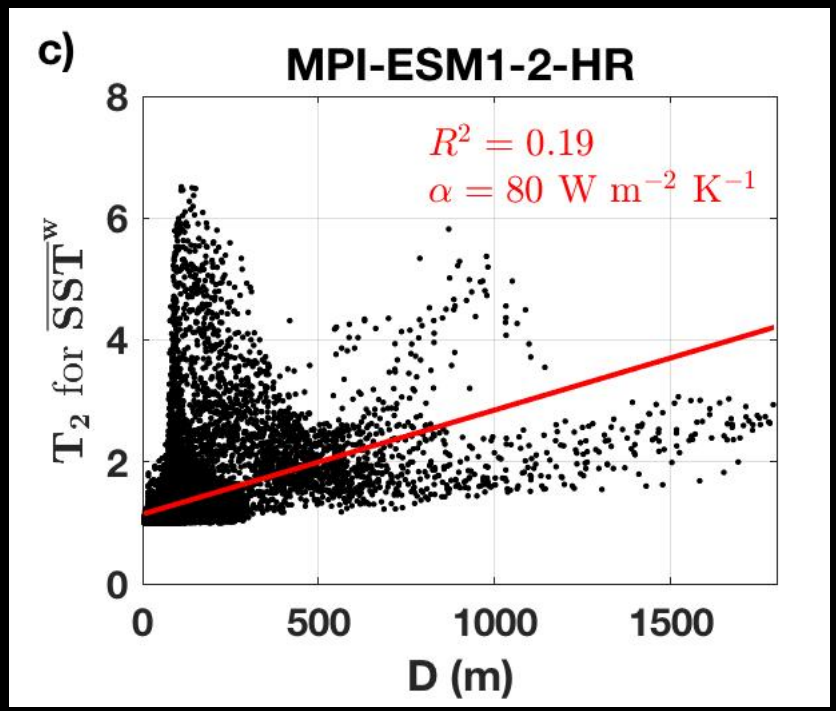


Can MLD variations explain variations in T_2?

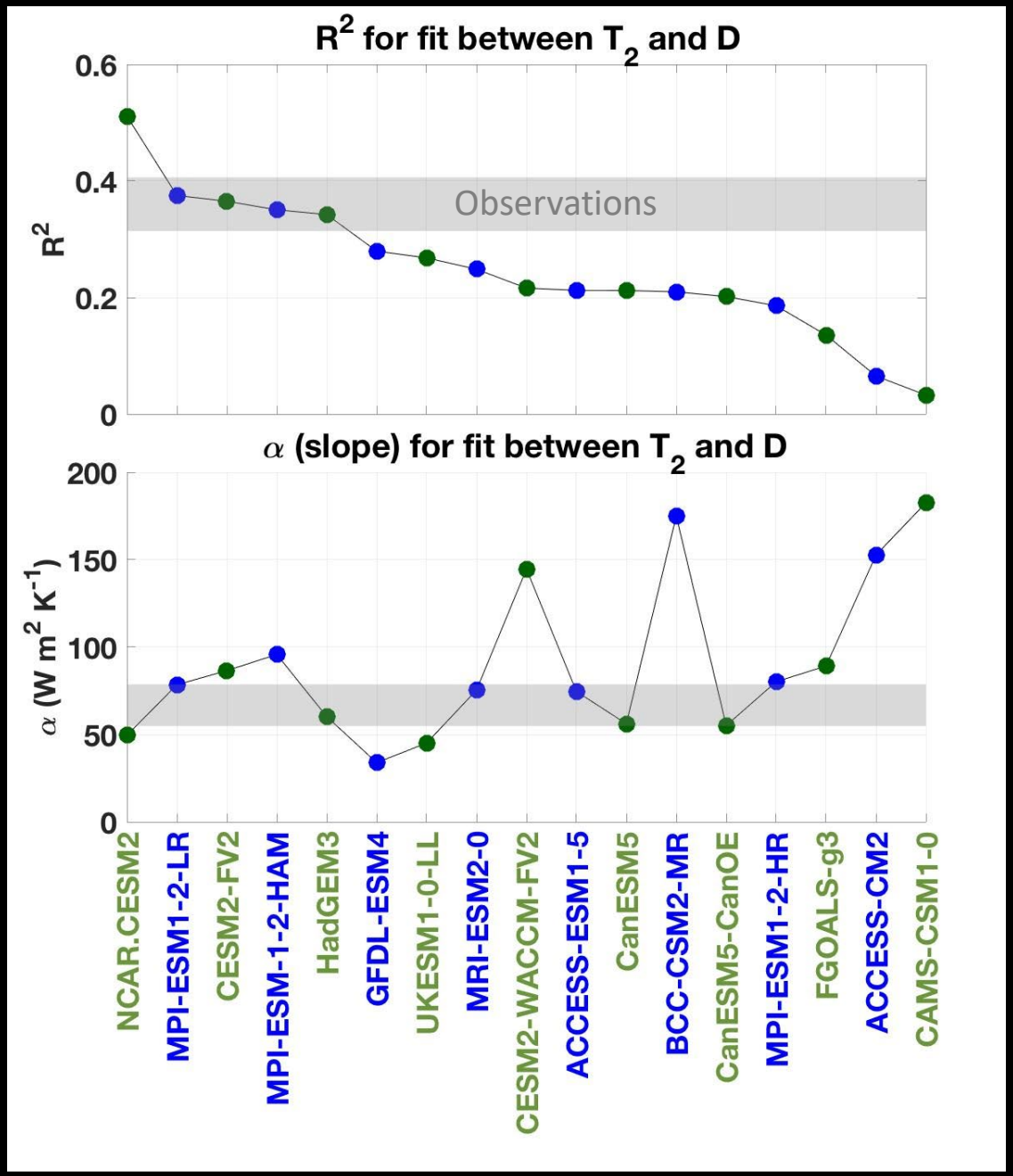
For each model calculate linear fit between T_2 and the climatological wintertime MLD, D, for all points in North Atlantic.

- R^2 : fraction spatial variations in T_2 explained by spatial variations in D
- α: inverse slope of linear fit, expressed in units of the damping parameter (canonical value of $\alpha = 20$ W m^{-2} K^{-1}, Frankignoul et al., 1998)



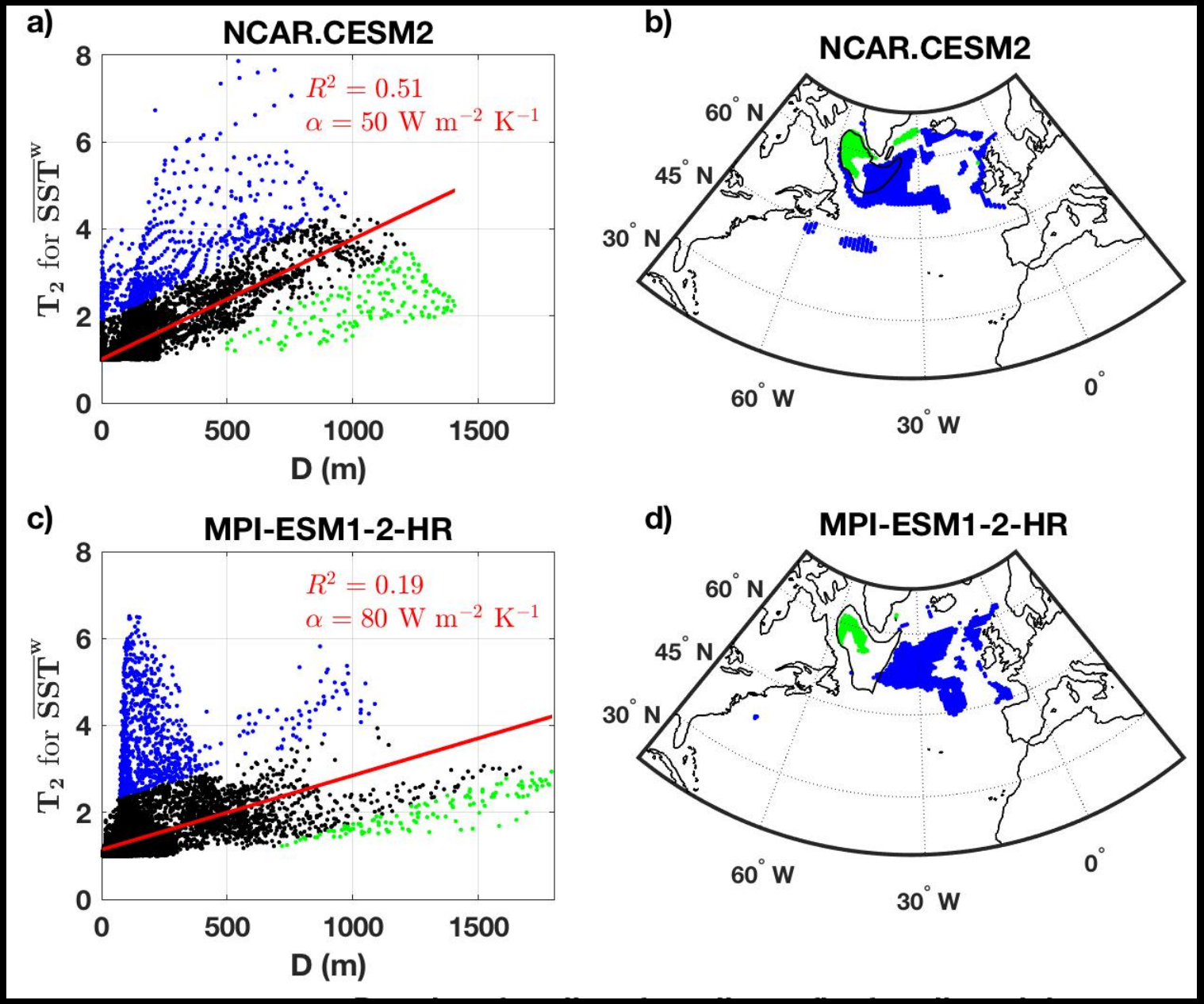


Can MLD variations explain variations in T_2?

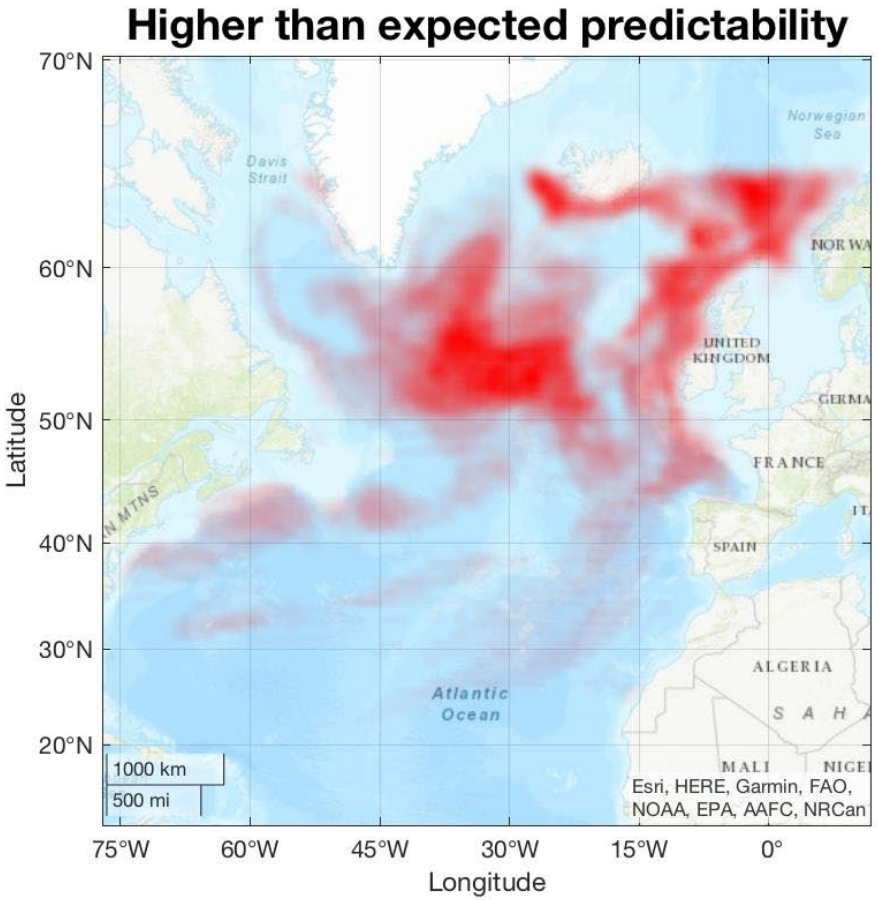


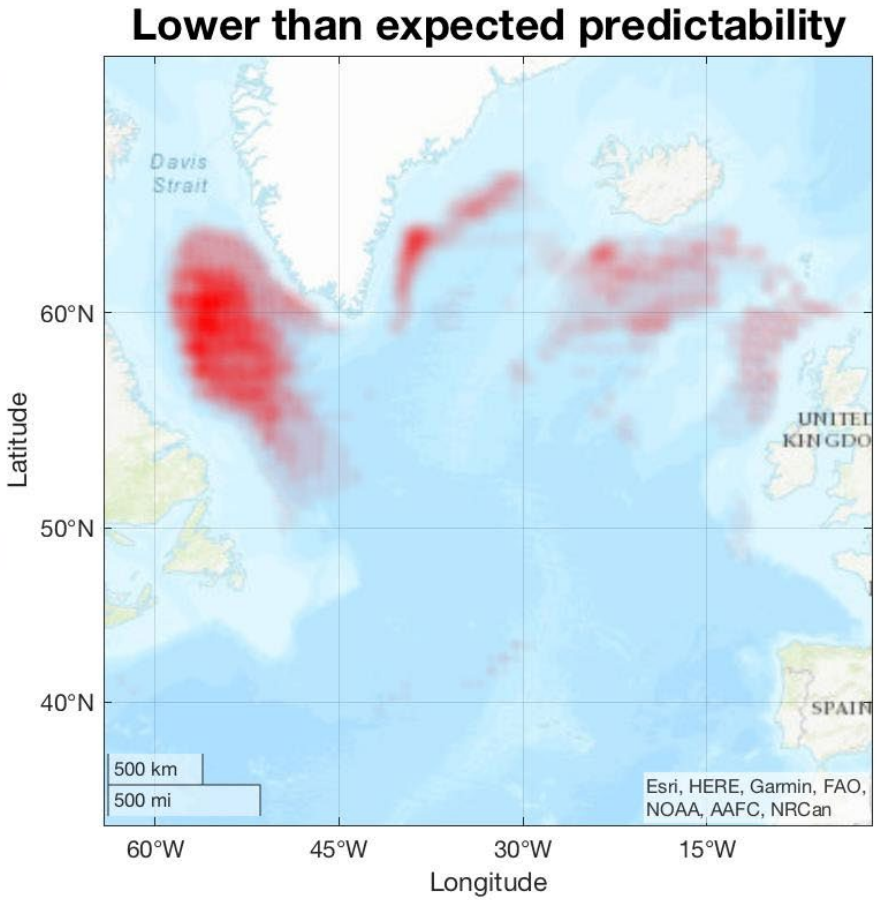
- Model diversity in R^2, range from 50%- 0%.
- R^2 in models generally smaller than in observations.
- α in models varies substantially and is generally consistent with or larger than observations.
- α is affected by model biases in MLDs.

Where does T_2 not follow the MLD?



Outliers from the fit between T_2 and D





- Higher than expected T_2 in region southeast of Greenland.

- Lower than expected T_2 in Labrador Sea
  - Large interannual variations in MLD disrupt predictability.

Conclusions

- Estimated decorrelation timescales for wintertime SST using gridded observations & CMIP6 models.
- Magnitude of decorrelation times scales are largest in the subpolar North Atlantic (97.5% quantile is 3 years in observations, 2.75-7 years in models).
- Spatial variations in decorrelation timescales have a modest linear relationship with spatial variations in wintertime climatological MLDs (R^2=0.4 in observations, R^2 ranges from 0.5 to 0 in models.)
- Labrador Sea is a region of low predictability in models and observations
  - interannual MLD variations disrupt predictability.
- Region southeast of Greenland appears as a region of high predictability in both models and observations, despite relatively shallow MLDs in this region.
  - This region has been argued to be impacted by variations in the Atlantic Meridional Overturning Circulation (e.g., Keil et al., 2020).
  - Strong air-sea heat fluxes and reemergence have also been implicated in SST variations in this region (e.g., Duchez et al., 2016).
- Next step: analyze large ensembles of historical simulations to determine model-data consistency/inconsistency.