Predictability of North Atlantic Sea Surface Temperature and Ocean Heat Content

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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.
  - Branstator et al., 2012 find that predictability of upper ocean heat content varies widely amongst CMIP5 models, particularly in the North Atlantic.
  - DelSole et al., 2013 identify common predictable components in CMIP5 models.

This work: calculate statistical measures of predictability timescales from ocean data products and CMIP5 models.

1. What portion of geographic variations in predictability timescales can be explained by variations in maximum climatological (e.g., wintertime) mixed layer depths?
2. How realistic are predictability timescales in CMIP5 models?

FOCUS OF THIS TALK: gridded observational products and ocean reanalysis

See NOAA “AMOC mechanisms and decadal predictability” webinar (Fall 2016) for discussion of CMIP5 models.

Predictability of SST and ocean heat content

1. SST: wintertime SST best reflects ocean memory.
   - In summer memory lost due to formation of seasonal thermocline.
   - Anomalies may reemerge when mixed layer deepens in winter (e.g., Namais and Born, 1970).
   - SSTw=average SST January—March
2. Ocean heat content: heat contained in the layer between the surface and the maximum climatological mixed layer depth (D).

$$H = \rho_o C_p \int_{-D}^{\eta} T \, dz$$

   - Layer of the ocean that interacts with the atmosphere seasonally.
   - H covaries with SST on interannual timescales (Buckley et al., 2014).
   - Meaningful heat budgets can be computed for this layer (Buckley et al., 2014, 2015).

Can geographic variations of predictability of SSTw and H be related to variations in D, i.e., higher predictability where D is deeper?

Simple statistical measures of predictability

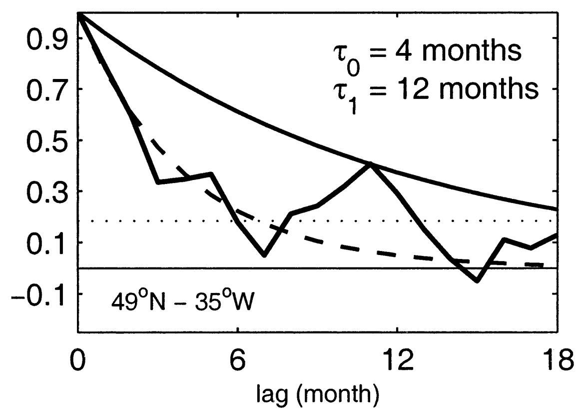
1) e-folding timescale: $\rho_\tau = e^{-|\tau|/\tau_d}.$

2) Decorrelation time: (DelSole, 2001) $T_1 = \frac{1}{2}\int_{-\infty}^{\infty} \rho_\tau d\tau.$

3) Decorrelation time: (DelSole, 2001) $T_2 = \int_{-\infty}^{\infty} \rho_\tau^2 d\tau.$

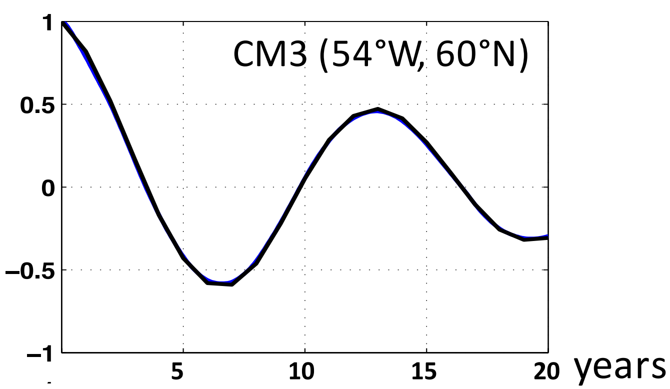
ρ_τ is the autocorrelation function (ACF)

- $T_1=T_2=\tau_d$ for exponential decay.
- In other cases, the three measures may differ.



(De Coetlogon and Frankignoul, 2003)

Reemergence: T_1, $T_2 > \tau_d$



Periodic behavior: $T_2 > T_1$, τ_d

Estimating T_1 and T_2

Average SST over January—March → SSTw

Integrate temperature over D → heat content (H)

IF HAVE LONG TIMESERIES (e.g., CMIP5 models)

- Calculate sample autocorrelation function (ρ_τ) at each gridpoint.
- Sum ρ_τ and ρ_τ^2 from lag 0 to lag τ_* to get T_1 and T_2, respectively.
  $\tau_d \ll \tau_* \ll t_l$ (t_l is length of time series)

IF HAVE SHORT TIMESERIES (e.g., observationally-based products)

- The sample autocorrelation function will be noisy.
- Instead fit an autoregressive (AR) model at each gridpoint and use AR parameters to calculate theoretical autocorrelation function (ρ_τ^*)
- Integrate ρ_τ^* and $(\rho_\tau^*)^2$ to find T_1 and T_2, respectively.

Estimating T_1 and T_2

TODAY: Focus is on estimating T_1 and T_2 in three data-based products

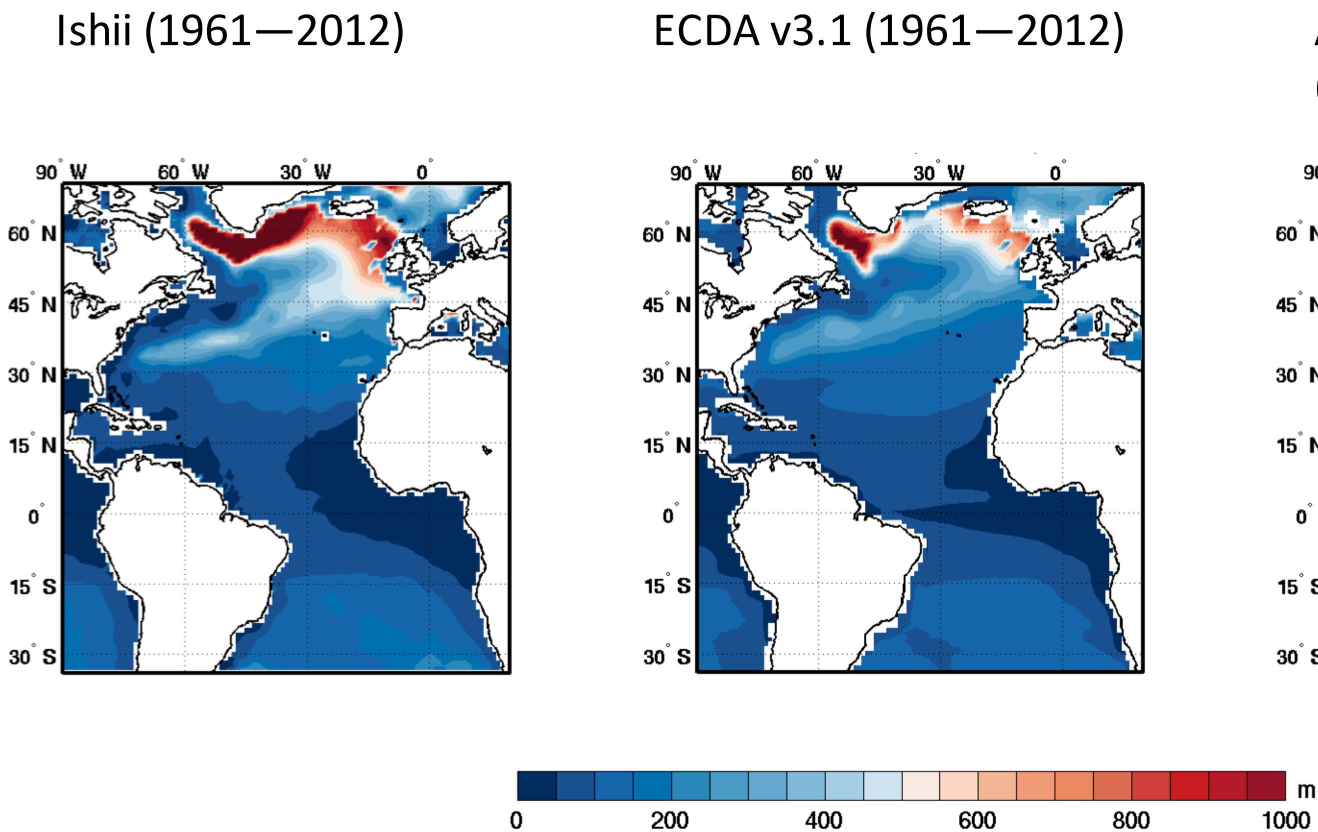
- SSTw: ERSST, v3b (1854—present)
- H: Ishii, gridded observational product (1945—2012)
- H: GFDL Ensemble Coupled Data Assimilation (ECDA v3.1, 1961—2012)

DETAILS:

- Restrict all to common period, 1961—2012.
- Use yearly averages of H

  (results are similar for wintertime averages).
- Detrend prior to computing AR fits.
- Tried AR order 1—3 and found little sensitivity to AR order particularly for AR order greater than 2.
- Present results for AR2.

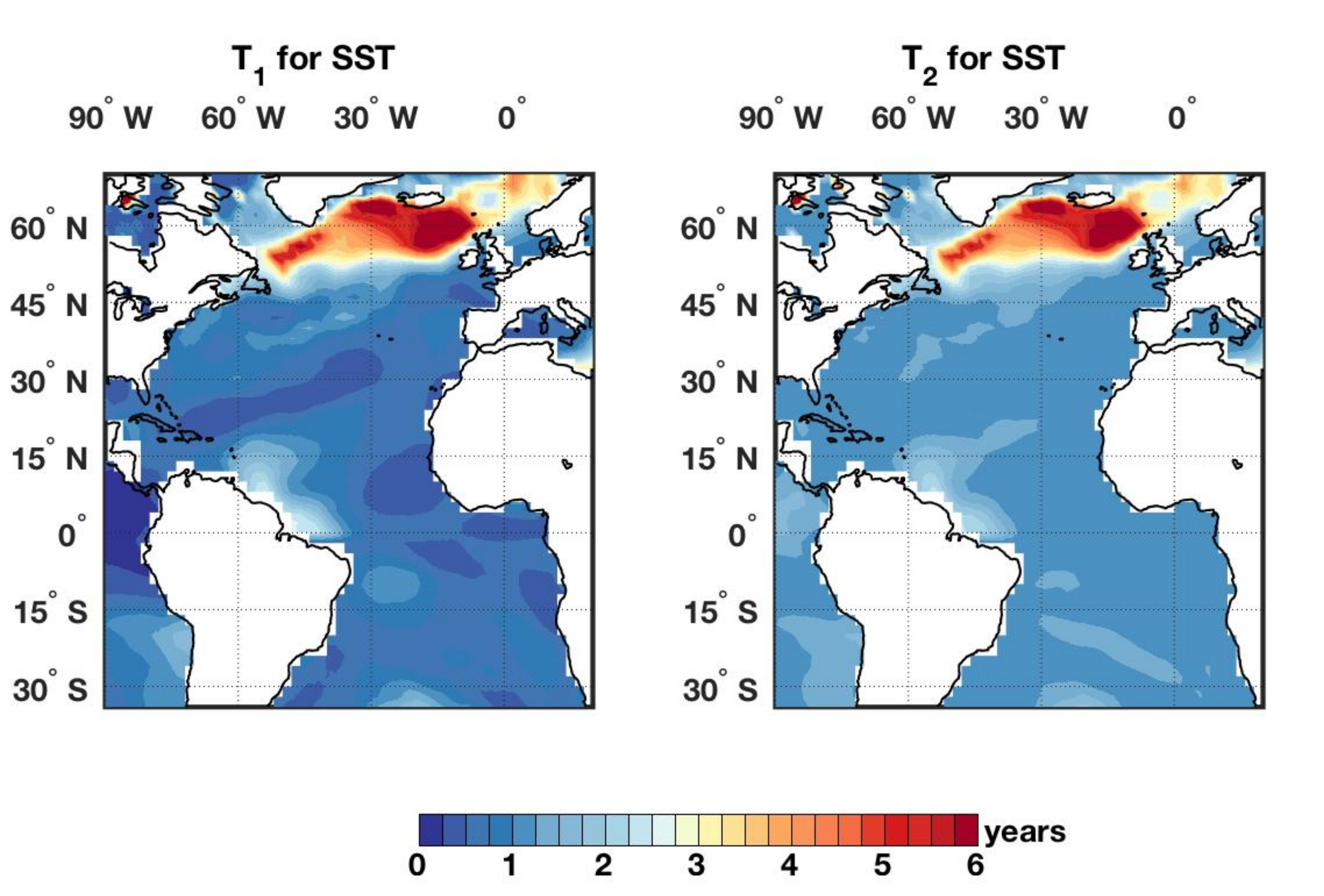
Maximum Climatological Mixed Layer Depth (D)



Holte and Talley (Holte et al., 2017)

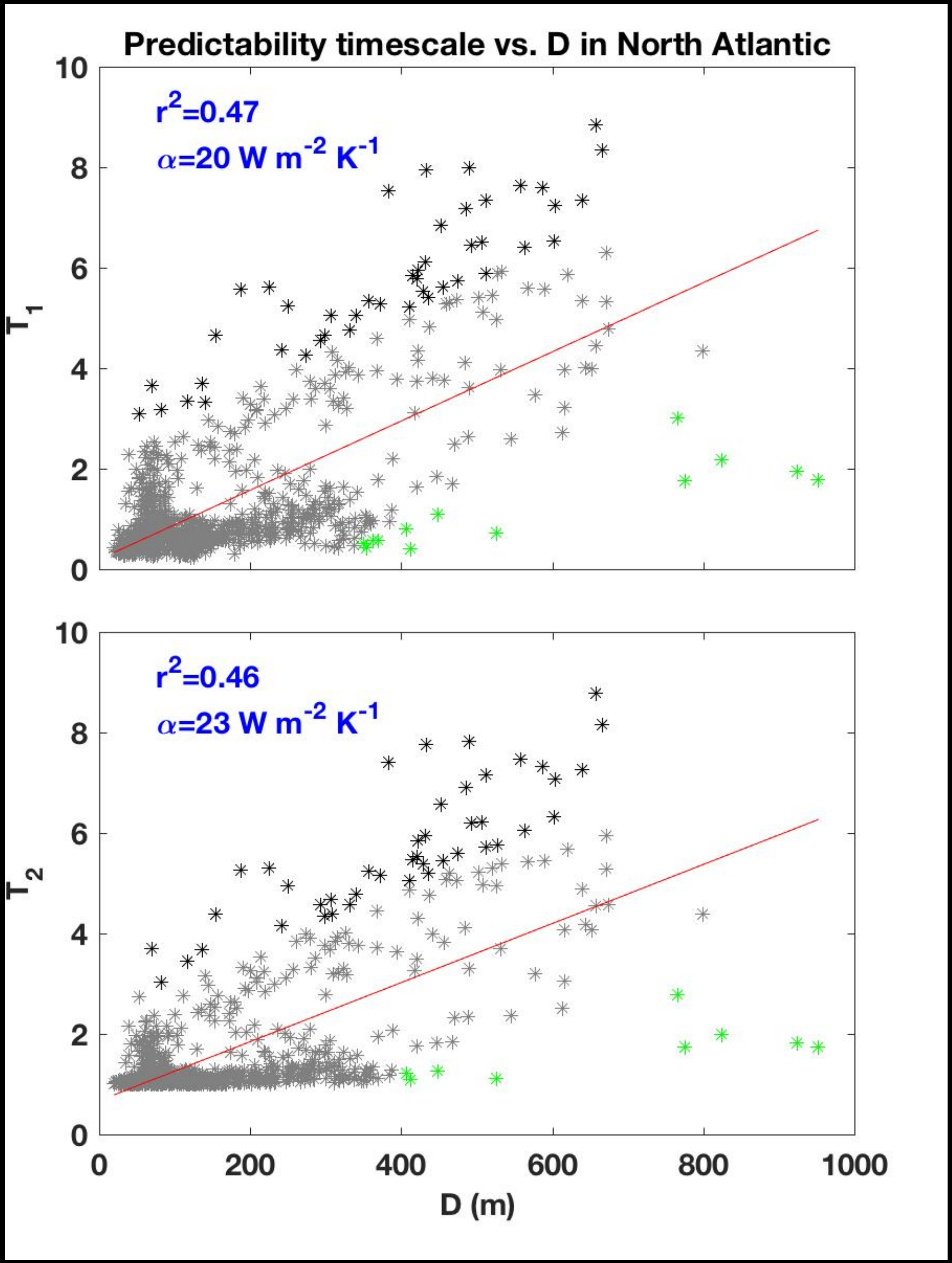
- Ishii: fixed density criterion of 0.125 kg m^{-3} applied to gridded monthly data
- ECDA: fixed density criterion criterion 0.03 kg m^{-3} applied to model profiles
- Argo MLD: variable density criterion of 0.2°C density equivalent applied to profiles (equivalent to 0.03 kg m^{-3} for reference T=8°C and S=35).

Predictability of wintertime SST in ERSST



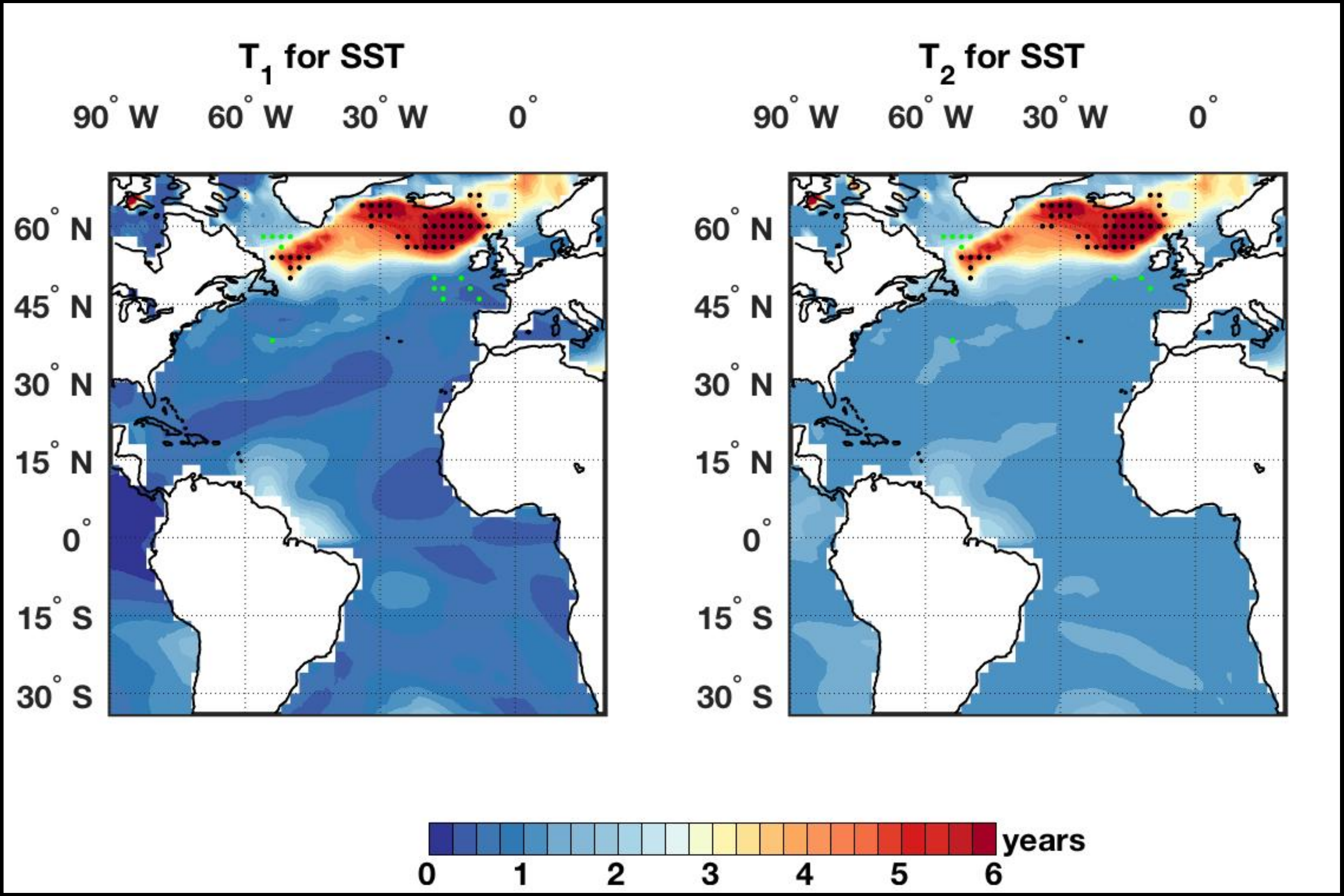
- Longest predictability timescales are in the subpolar gyre.
- T_1 and T_2 are very similar (periodic variability not playing a role).
- For all points in North Atlantic correlation between T_1, T_2 is 0.99.

Predictability as a function of D in the North Atlantic



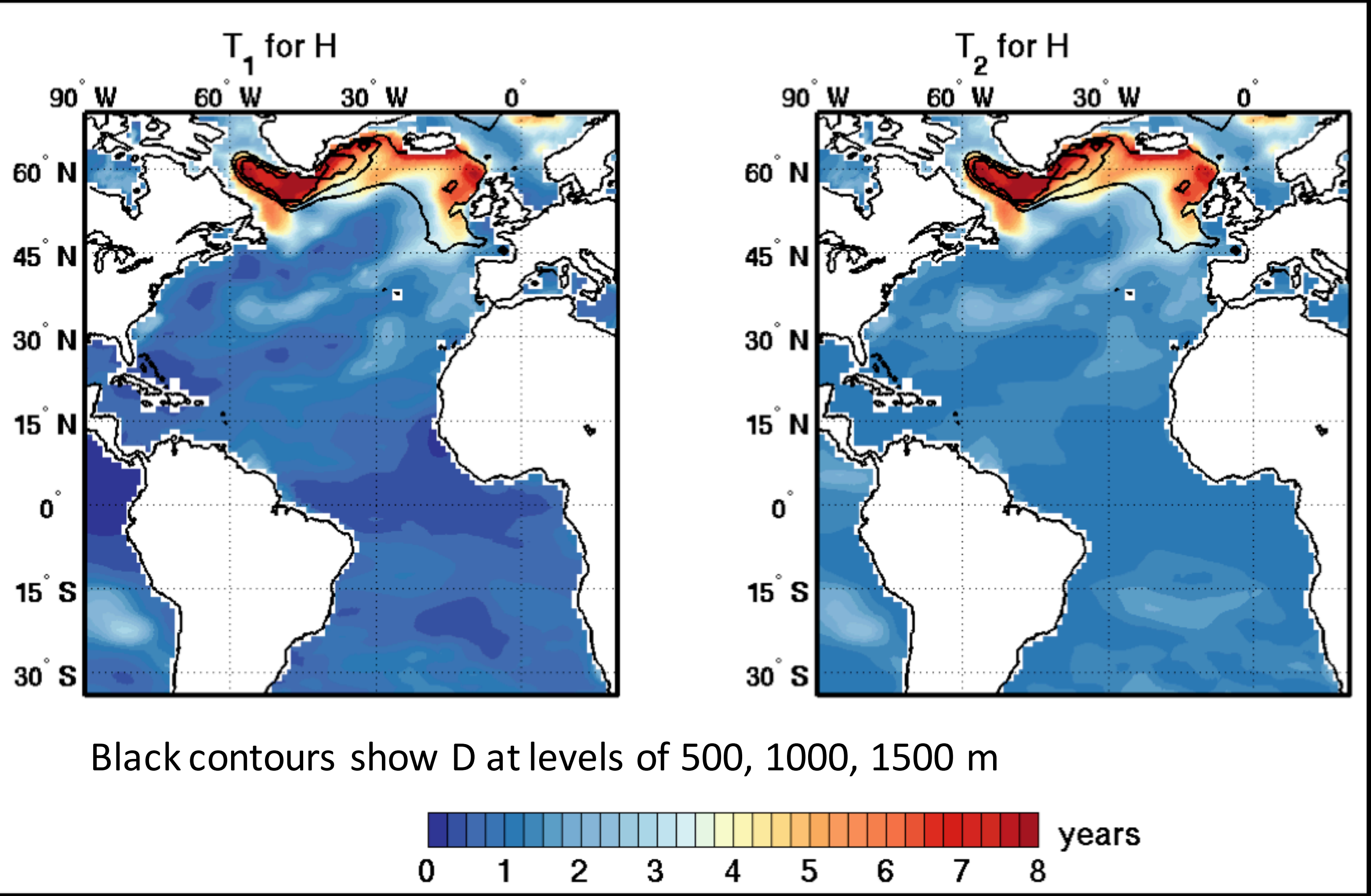
- D is from Holte and Talley MLD climatology.
- ~45% of spatial variance of predictability timescales explained by variations in D.
- Slope of fit suggests a damping parameter ~20 W m^{-2} K^{-1} in accord with estimates in literature (e.g., Frankignoul, 1981).
- More outliers with higher-than-expected predictability (black points) than lower-than-expected predictability (green points).

Outliers: predictability timescale not explained by D



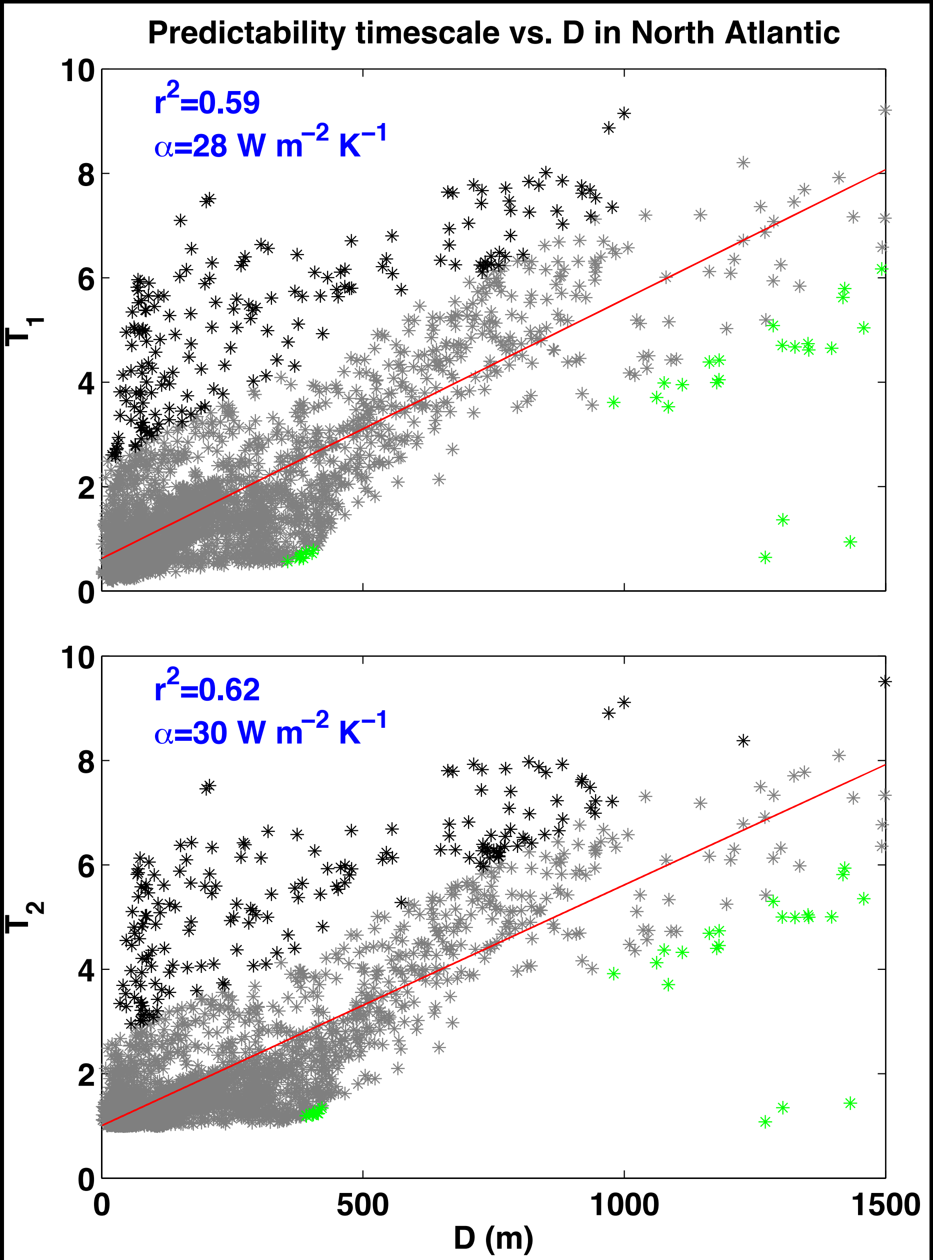
- Most outliers are in the subpolar gyre.
- Most outliers have higher-than-expected predictability.
- Large region higher-than-expected predictability south of Iceland
- Labrador Sea has lower-than-expected predictability.

Predictability of H in Ishii



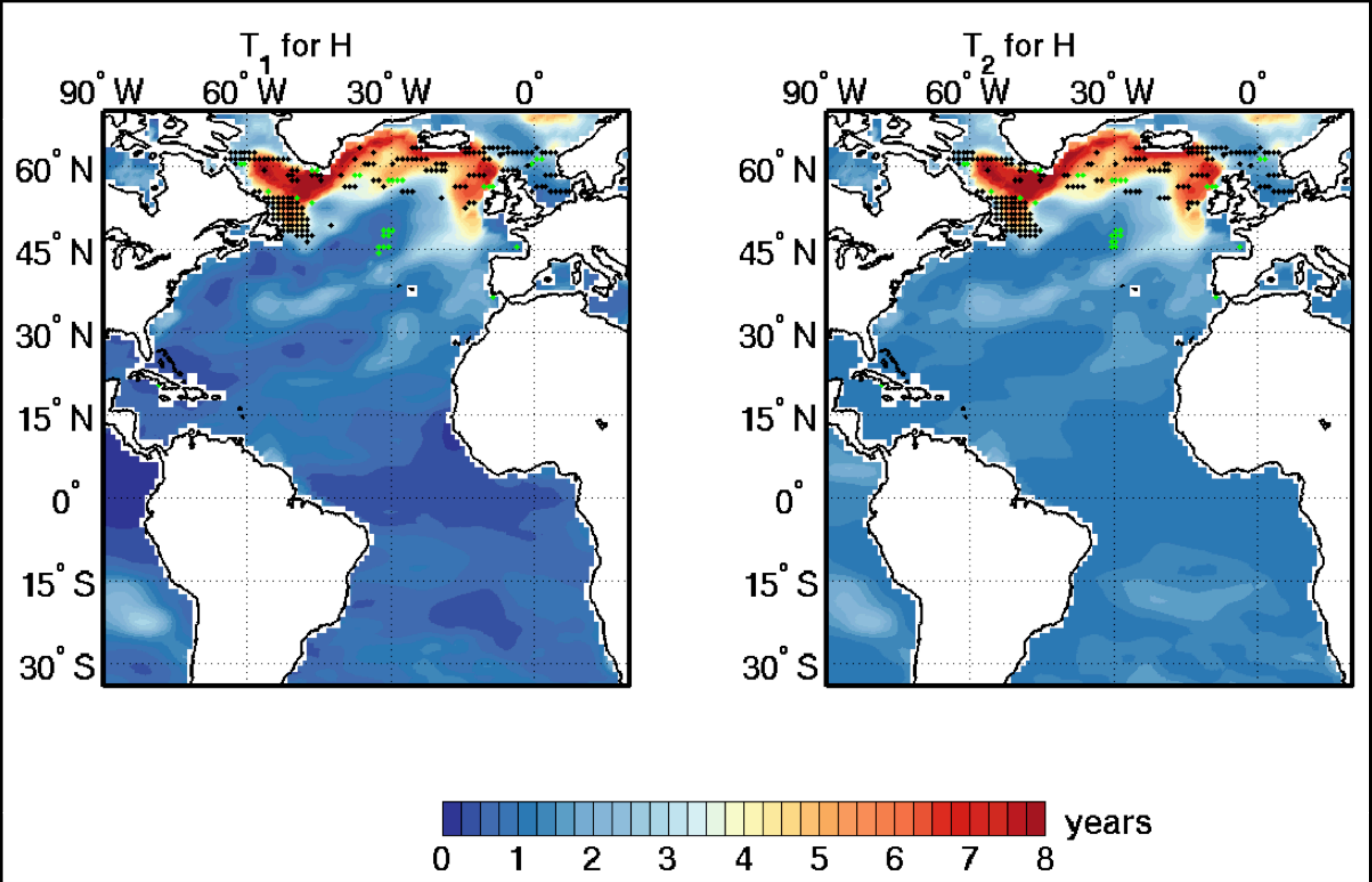
- Longest predictability timescales are in the subpolar gyre.
- T_1 and T_2 are very similar (periodic variability not playing a role).
- For all points in North Atlantic correlation between T_1, T_2 is 0.98.
- Predictability timescales are longer for H than for SSTw, particularly in Labrador Sea.

Ishii: Predictability as a function of D in the North Atlantic



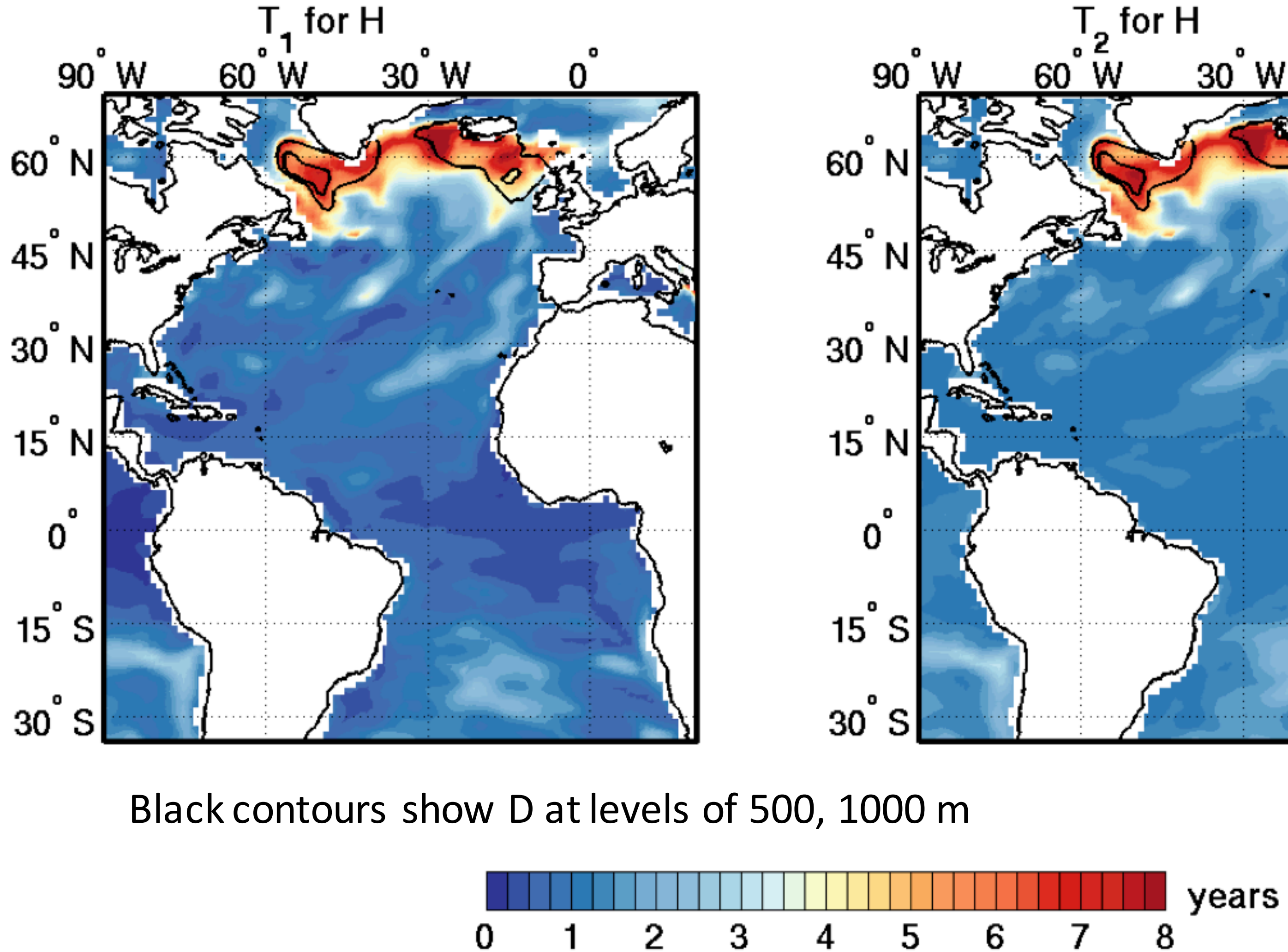
- ~60% of spatial variance of predictability timescales explained by variations in D.
- Slope of fit suggests a damping parameter ~30 W m^{-2} K^{-1} in accord with estimates in literature (e.g., Frankignoul, 1981).
- More outliers with higher-than-expected predictability (black points) than lower-than-expected predictability (green points).

Outliers: predictability timescale not explained by D



- Most outliers are in the subpolar gyre.
- Most outliers have higher-than-expected predictability.
- Large region higher-than-expected predictability just south of very deep D.

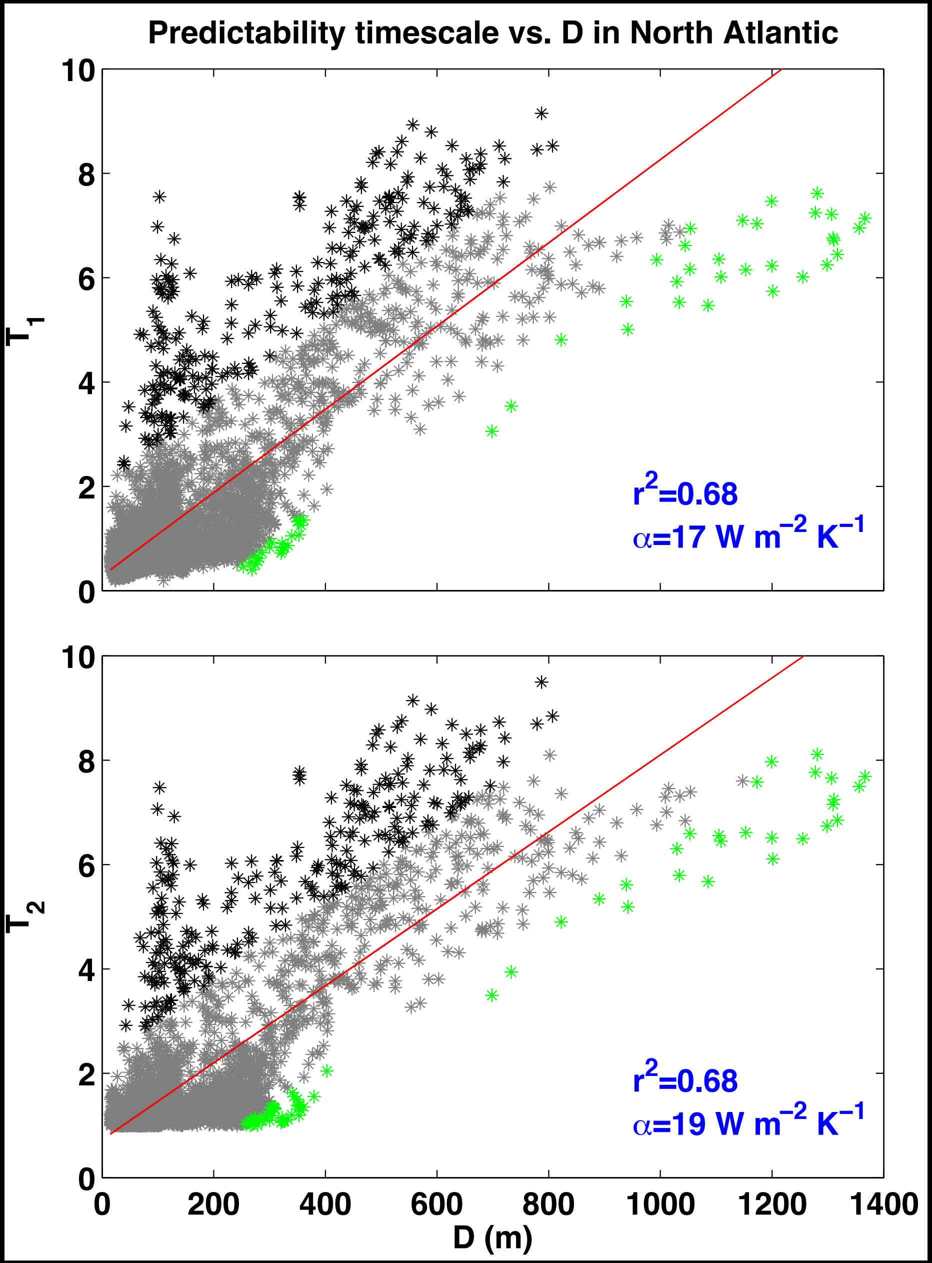
Predictability of H in ECDA v3.1



Black contours show D at levels of 500, 1000 m

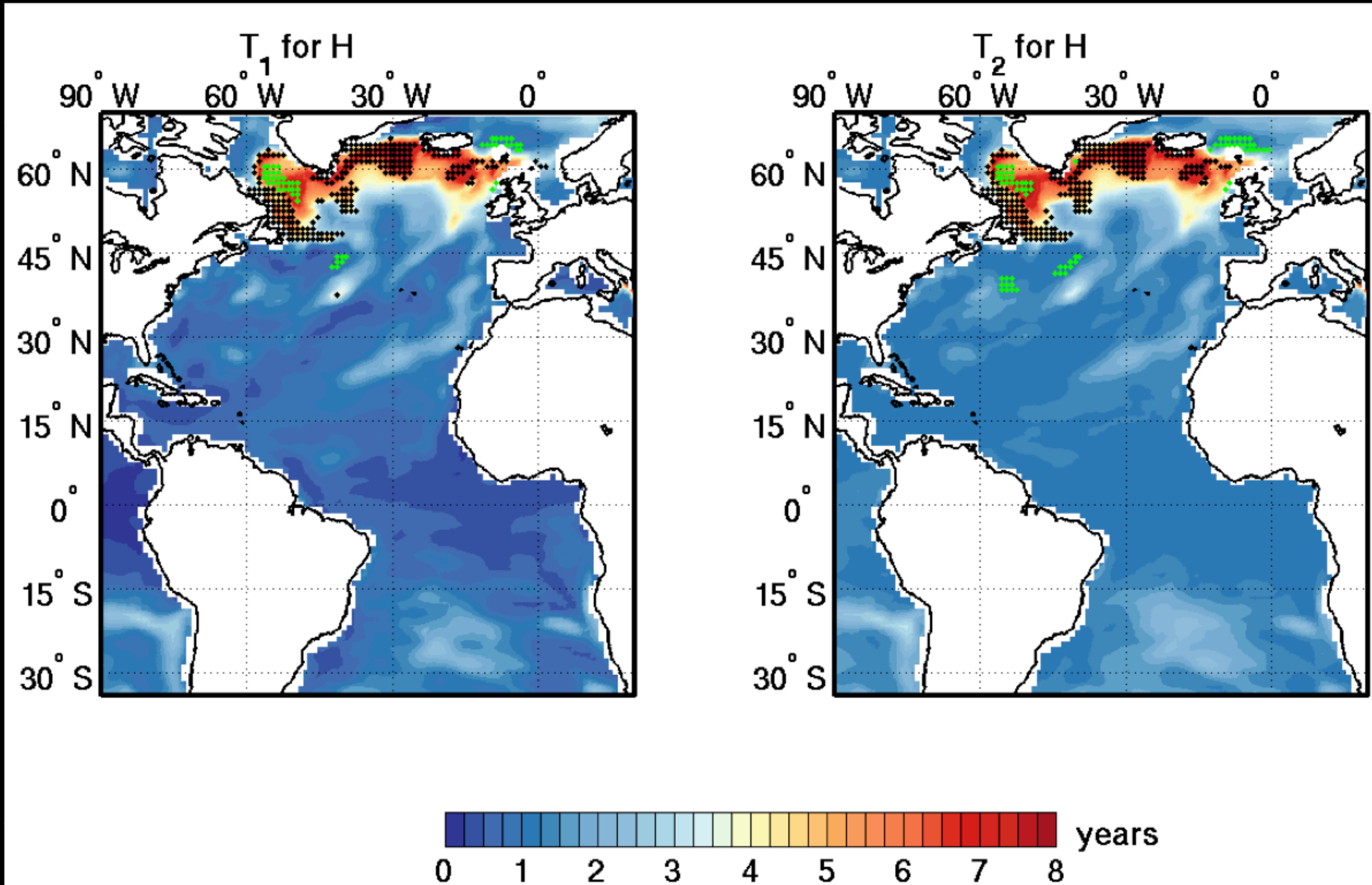
- Longest predictability timescales are in the subpolar gyre.
- T_1 and T_2 are very similar (periodic variability not playing a role).
- For all points in North Atlantic correlation between T_1 and T_2 is 0.98.

ECDA: Predictability as a function of D in the North Atlantic



- ~70% of spatial variance of predictability timescales explained by variations in D.
- Slope of fit suggests a damping parameter ~20 W m^{-2} K^{-1} in accord with estimates in literature (e.g., Frankignoul, 1981).
- More outliers with higher-than-expected predictability (black points) than lower-than-expected. predictability (green points).

Outliers: predictability timescale not explained by D



- Most outliers are in the subpolar gyre.
- Most outliers have higher-than-expected predictability.
- In regions with large gradients in D, predictability doesn't follow local D.

Conclusions

- Introduced diagnostics for ocean predictability:
  - SSTw: wintertime SST
  - H: heat content in the layer between the surface and the maximum climatological mixed layer depth.
- Used gridded observational products (e.g. ERSST, Ishii) and ocean reanalyses (e.g. ECDA) to estimate 2 statistical measures of predictability of SSTw and H: T_1 and T_2.
- Predictability timescales are longest in the subpolar gyre.
- $T_1 \approx T_2$, suggesting periodic variability does not play a role, at least on the timescales that can be resolved by our data-products (1961—2012).
- Predictability timescales are longer for H than for SSTw, suggesting that depth averaging is an effective lowpass filter.
- Predictability timescales are related to the wintertime mixed layer depth, D.
  - SSTw: ~45% of spatial variations in T_1, T_2 can be explained by variations in D.
  - H: ~60-70% of spatial variations in T_1, T_2 can be explained by variations in D.

Future Work

- Apply to other gridded observational products and ocean reanalysis.
- Work to better understand regions of higher-than-expected predictability, where H does not follow D.
- Compare to CMIP5 models to access their realism.
- Compare predictability timescales to results from a theoretical model without ocean dynamics (Liafang Li).
- Do predictability timescales scale with D in the extratropical North Pacific?