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ATMOSPHERIC & OCEANIC SCIENCE

Local atmosphere–ocean predictability: dynamical origins, lead times, and seasonality

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Local Atmosphere–Ocean Predictability: Dynamical Origins, Lead Times, and Seasonality

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- Want to determine where and for how long ocean improves prediction of the atmosphere, and vice-versa. First such global analysis.
- This can allow us to target regions where prediction could be improved.
- The predictability has physical origins, so it can help interpret physical interactions.

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- SSTs an important source of climate predictability, especially in tropics due to lack of baroclinic instability.
- In extratropics, effect of SSTs is much harder to measure due to low signal-to-noise ratio. Usually studied with GCMs.

Methods

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- *The method is local.*

Granger causality

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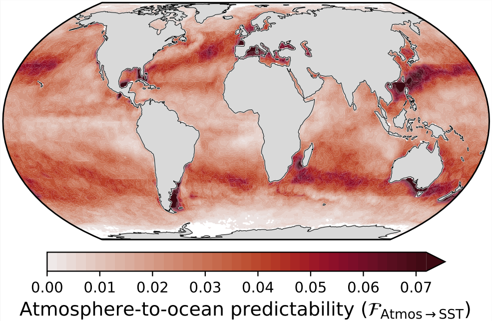
- In other words, is there a significant improvement in the prediction of the future of the ocean by observing the atmosphere (and vice-versa)?

Results

Atmosphere-to-ocean predictability



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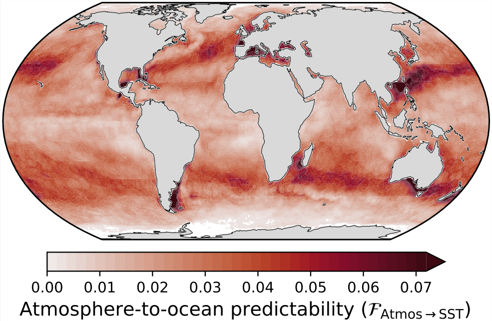

- Atmosphere-to-ocean predictability is significant almost everywhere, strongest in midlatitudes.

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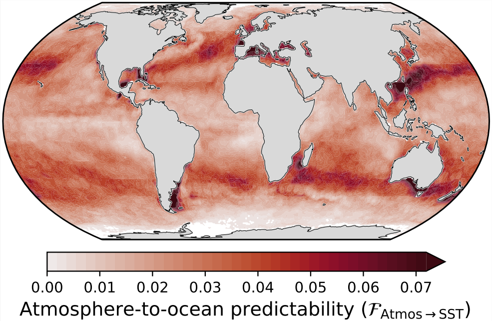
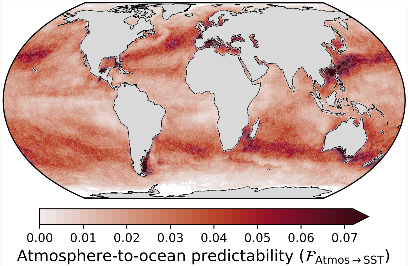
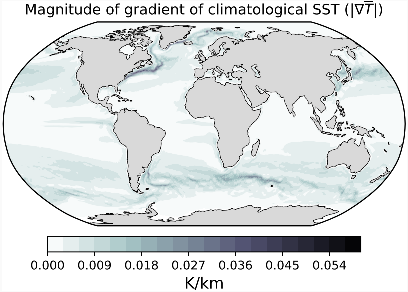


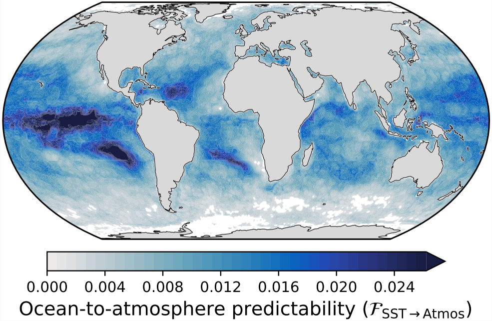
- Atmosphere-to-ocean predictability is significant almost everywhere, strongest in midlatitudes.
- Large in regions of large climatological SST gradients, where temperature advection due to Ekman currents is strongest.

Atmosphere-to-ocean predictability





Ocean-to-atmosphere predictability



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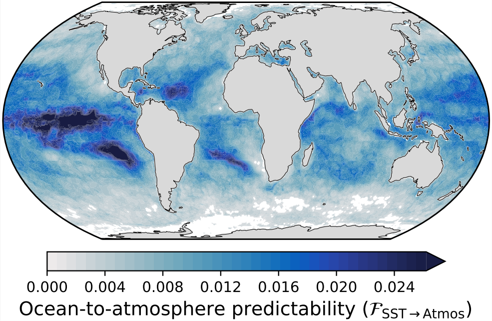

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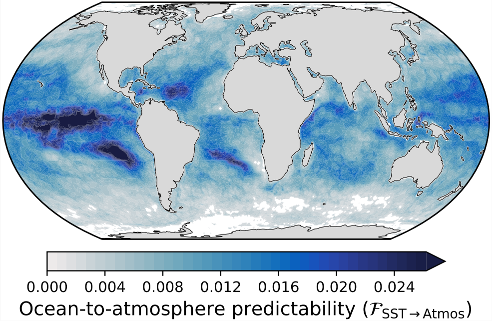

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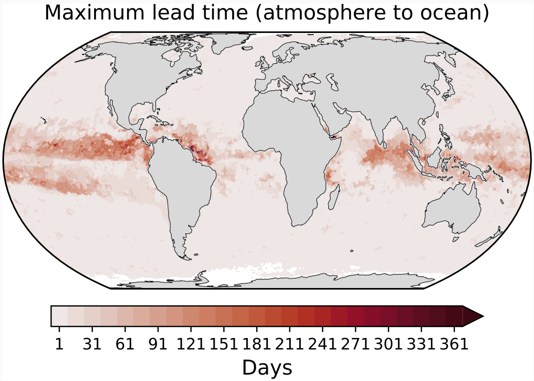
- The significance of the effect in the extratropics is notable and difficult to obtain with GCM studies.

Atmosphere-to-ocean lead times



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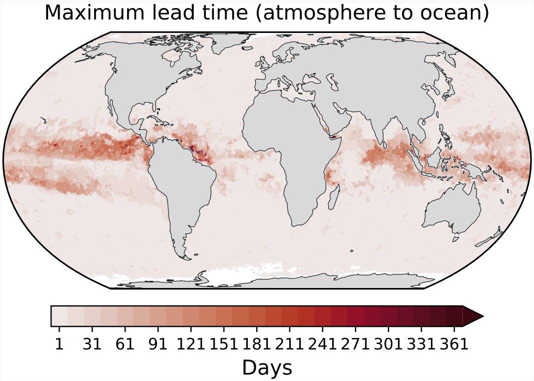

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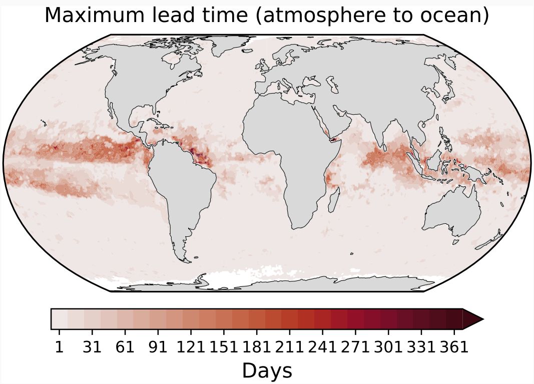
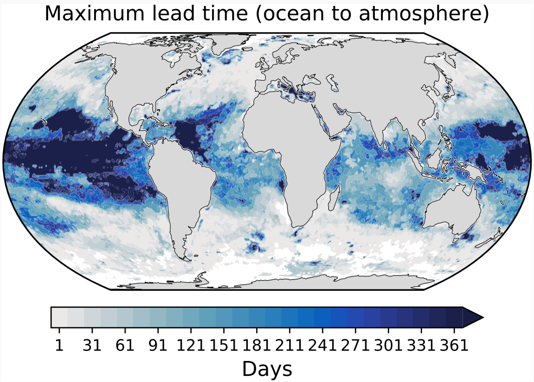


- The atmosphere-to-ocean predictability is short-lived in the extratropics, generally fewer than 10 days.
- In the tropical Indian and Pacific Oceans there is longer predictability, several months.

Ocean-to-atmosphere lead times



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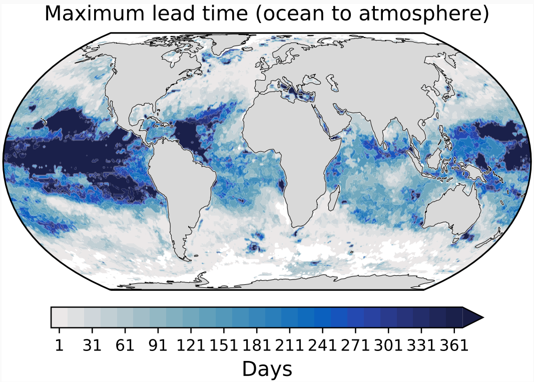
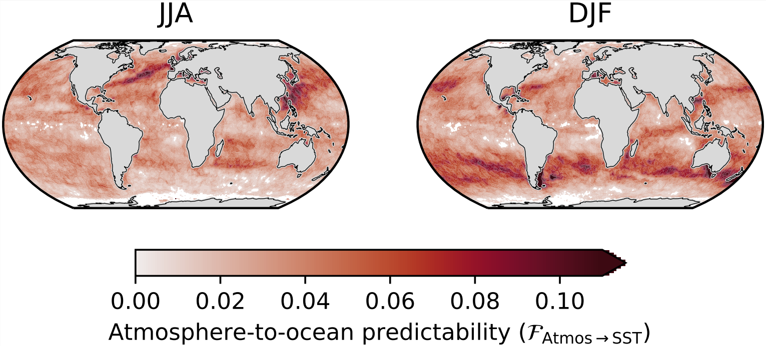


- The ocean-to-atmosphere predictability is long-lived in the tropics (over a year over much of the tropical Pacific), consistent with previous work showing that the tropical atmosphere is highly predictable from SST.

Seasonality



- Atmosphere-to-ocean predictability stronger in the summer hemisphere.

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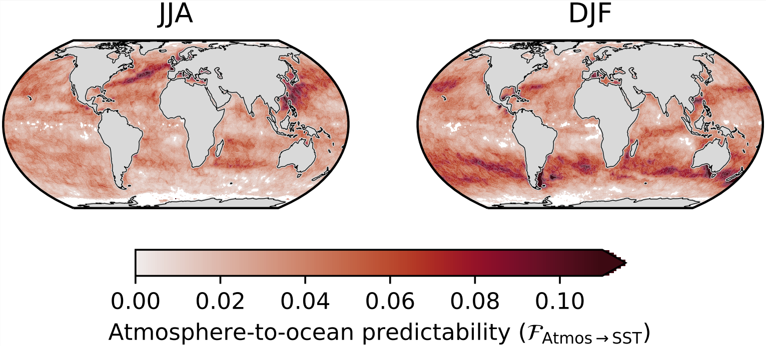
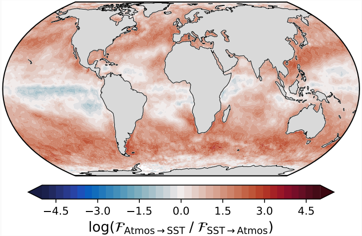
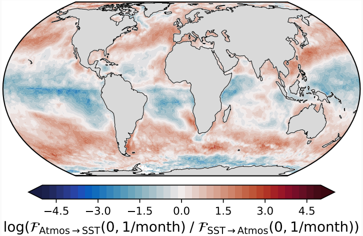


- Atmosphere-to-ocean predictability stronger in the summer hemisphere.
- Due to the higher persistence of SST in the winter (deeper mixed layer), there is more “room to improve” by including the atmosphere in the summer.

Local driver



(a) Daily resolution



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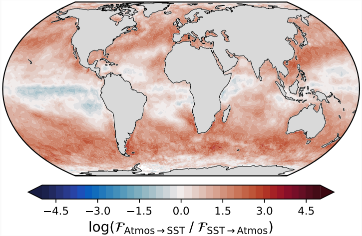
Local driver



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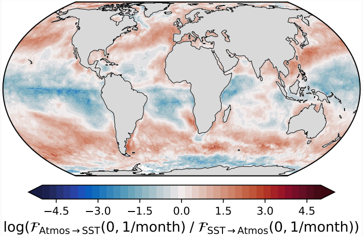

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- At daily resolution, the atmosphere is the local driver except for a narrow band of latitudes around the Equator.
- At lower frequencies, ocean-driven regions expand.

Conclusions

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- We find a strong and long-lived influence of the ocean on the atmosphere in the tropics, weaker and short-lived in the extratropics.
- Could have applications for subseasonal-to-seasonal predictability and coupled data assimilation.

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Extra slides

Granger causality

- To test whether X (the "cause") improves prediction of Y (the "effect"), we first model the two time-series each as a p-order vector autoregressive (VAR) stochastic process:

$$\mathsf{U}_t = \begin{pmatrix} \mathsf{X}_t \\ \mathsf{Y}_t \end{pmatrix} = \sum_{i=1}^{p} \begin{pmatrix} A_{xx} & A_{xy} \\ A_{yx} & A_{yy} \end{pmatrix}_i \begin{pmatrix} \mathsf{X}_{t-i} \\ \mathsf{Y}_{t-i} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\epsilon}_{x,t} \\ \boldsymbol{\epsilon}_{y,t} \end{pmatrix}. \tag{1}$$

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- Granger causality is based on the principle that "X causes Y" if *X assists in predicting the future of Y beyond the degree to which Y already predicts its own future.*
- To test whether including X improves our ability to predict the future of Y, we perform a separate reduced regression on Y where X is excluded:

$$\mathsf{Y}_t = \sum_{i=1}^{p} A'_{yy,i} \mathsf{Y}_{t-i} + \boldsymbol{\epsilon}'_{y,t}. \tag{2}$$

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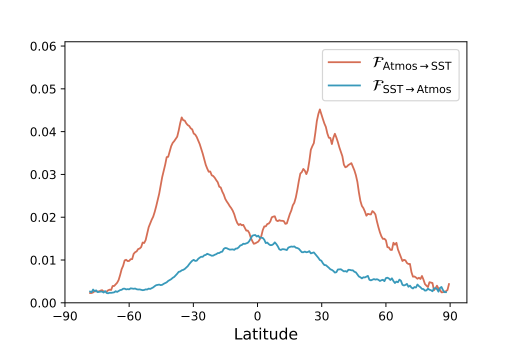
- A trade-off between goodness of fit (log-likelihood $\log\hat{L}$) and complexity of model (degrees of freedom k)

Results



$\mathcal{F}_{\mathrm{Atmos}\rightarrow\mathrm{SST}}$
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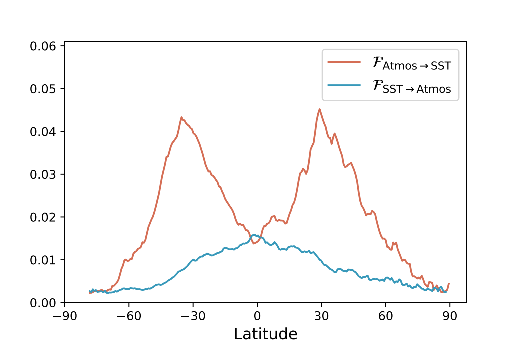
0.06
0.05
0.04
0.03
0.02
0.01
0.00
−90
−60
−30
0
30
60
90
Latitude

Results



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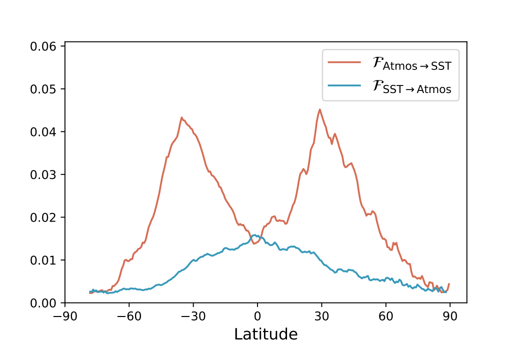
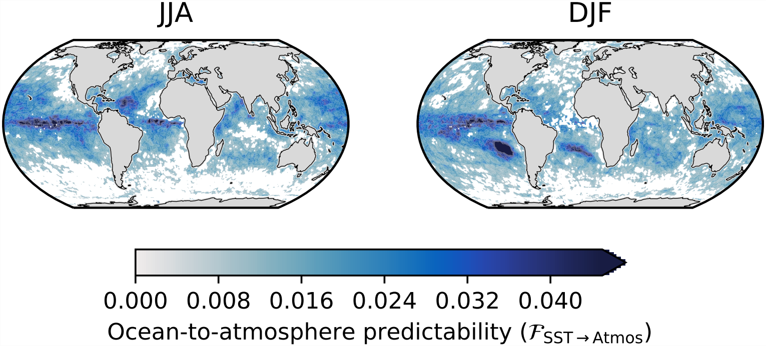
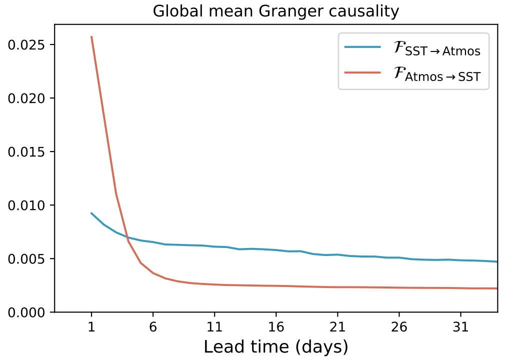


- The atmosphere-to-ocean predictability dominates in the extratropics, consistent with the classic view of atmospheric forcing inducing SST anomalies
- The ocean-to-atmosphere predictability is stronger in the tropics, consistent with convection driving atmospheric flow in the tropics.

Seasonality

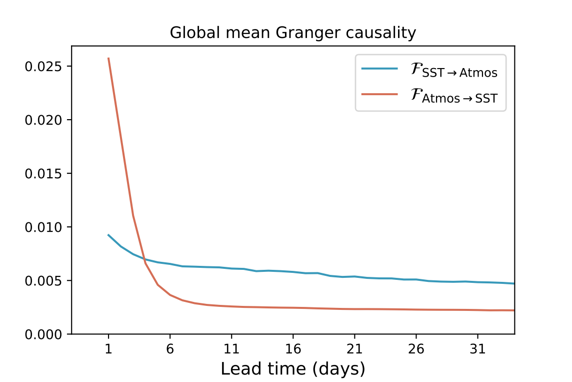


Lead times



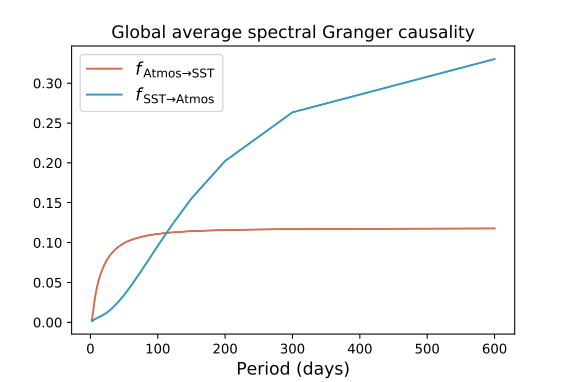
Global mean Granger causality
$\mathcal{F}_{\mathrm{SST}\rightarrow\mathrm{Atmos}}$
$\mathcal{F}_{\mathrm{Atmos}\rightarrow\mathrm{SST}}$
0.025
0.020
0.015
0.010
0.005
0.000
1
6
11
16
21
26
31
Lead time (days)

Lead times



- The atmosphere-to-ocean predictability starts off larger, but quickly decays. Ocean-to-atmosphere predictability takes much longer to decay.

Spectral decomposition



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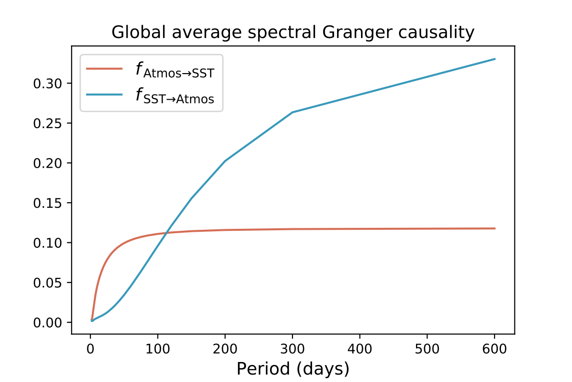

- Both the atmosphere-to-ocean and ocean-to-atmosphere predictability are strongest at low frequencies, but the ocean-to-atmosphere predictability much more so.

Applications

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- Variable localization is the problem of determining when to “strongly couple” variables in coupled atmosphere–ocean DA. In some cases, this may degrade the analysis due to spurious correlations.
- The background error correlation (Yoshida and Kalnay 2018) has been used as a way to determine whether to strongly couple. The Granger causality could be tested as an alternate method.