

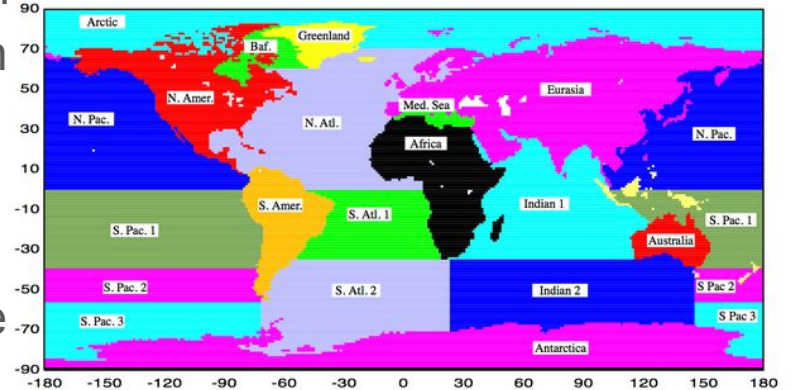
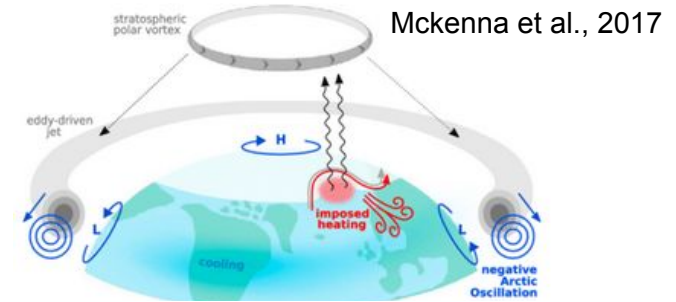


A New Approach to Exploring Arctic-Extra Arctic Linkages Using ML

Balu Nadiga, LANL and Ben Kravitz, Indiana Univ.
HiLAT-RASM

Arctic Atmosphere and Global Near-Surface Temperature

- **Using JRA55** (1958 to 1979 6 hourly data with 60 day moving average)
- **Examine teleconnections** between
- Horizontally averaged ($>72^{\circ}\text{N}$) geopotential height (37 levels) and specific humidity (27 hPa)
- And 850mb temperature averaged over distinct geographic regions
- **Using ML-based predictive models**
- e.g., L'Heureux et al. 2017 find strong predictability related ENSO-AO relation in the North American Multimodel Ensemble



We consider three ML-based prediction systems

Notionally partition Arctic warming into local and remote components

$$G = A + E \text{ (Global = Arctic + Extra-Arctic)}$$

1. Global evolution: $\frac{dG}{dt} = F(G)$ (global autonomous)

2. Arctic-only evolution: $\frac{dA}{dt} = f(A)$ (local autonomous)

3. Arctic evolution with specified Extra-Arctic forcing:

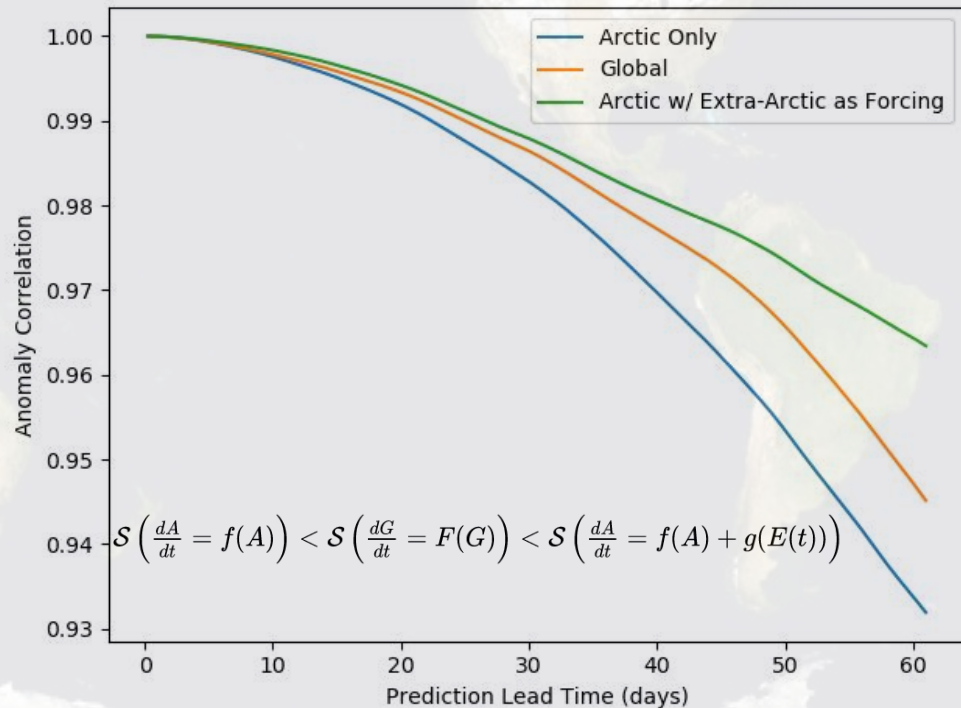
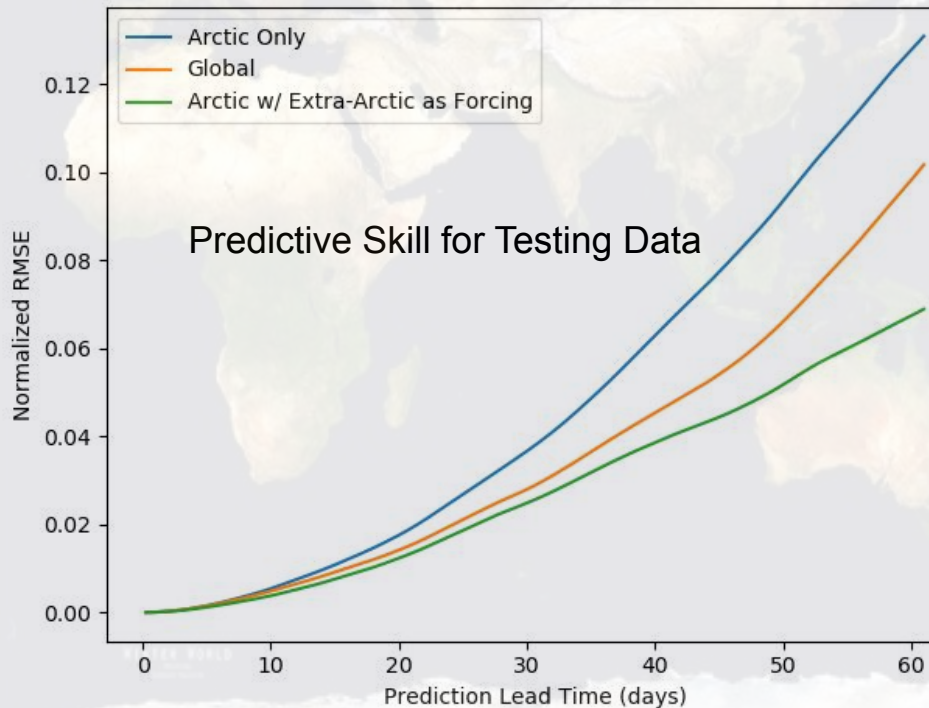
$$\frac{dA}{dt} = f(A) + g(E(t)) \text{ (local non-autonomous)}$$

Arctic Warming: Local vs. Remote Drivers

- If Arctic warming is dominated by local processes and feedbacks Arctic-local system $\frac{dA}{dt} = f(A)$ would be most skillful
- If remote processes and feedbacks were important as well:
skill(local) < skill(global) < skill(local w/ specified external forcing)

$$\mathcal{S} \left(\frac{dA}{dt} = f(A) \right) < \mathcal{S} \left(\frac{dG}{dt} = F(G) \right) < \mathcal{S} \left(\frac{dA}{dt} = f(A) + g(E(t)) \right)$$

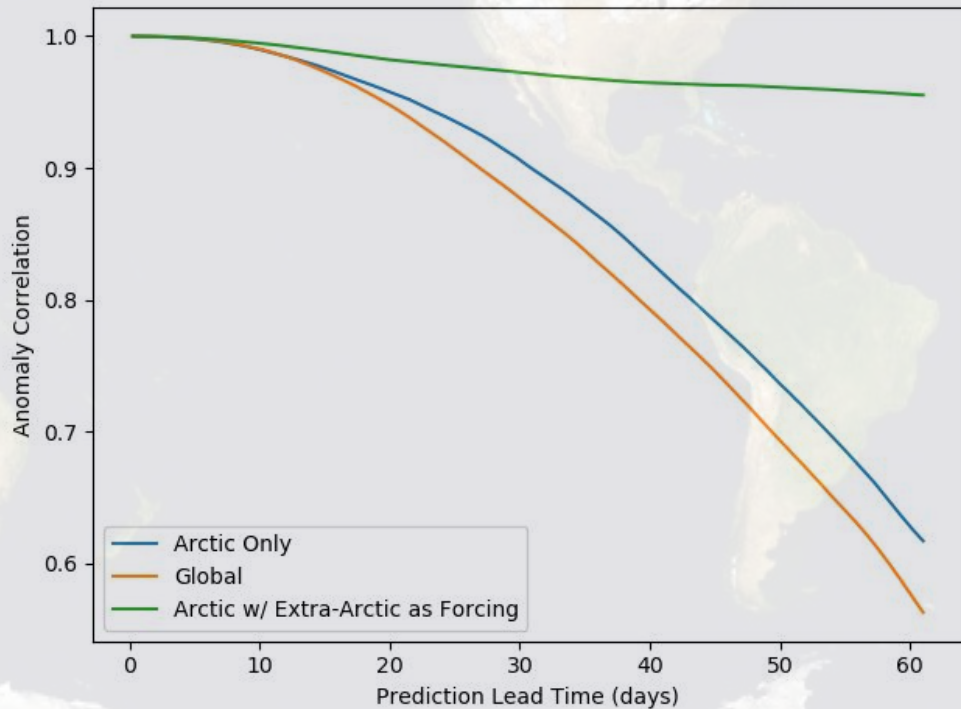
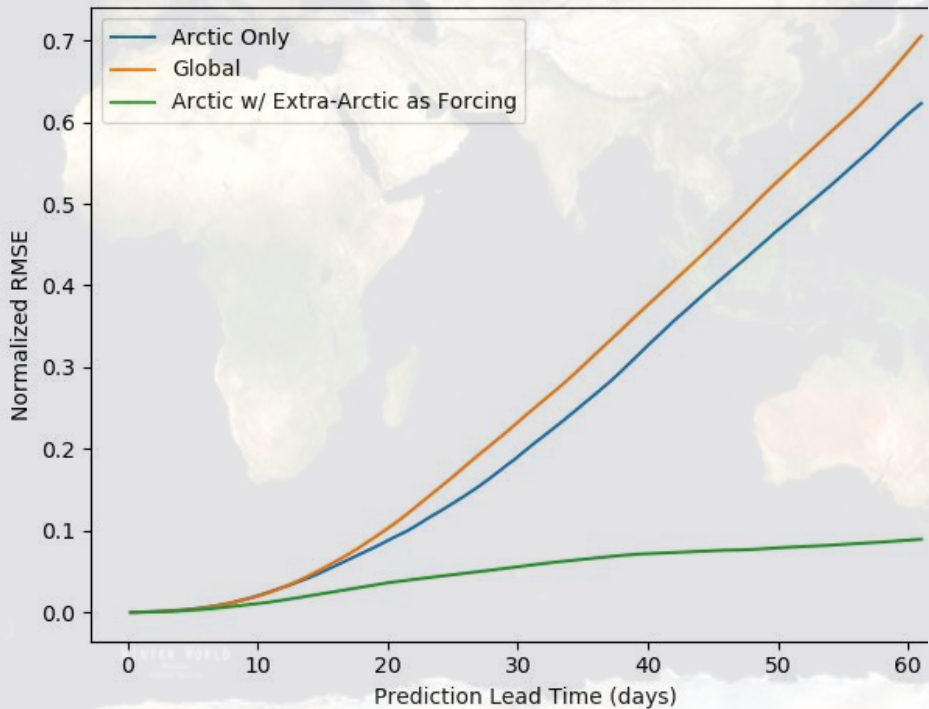
With ML-models, both skill measures (RMSE and ACC) show a role for remote forcing of Arctic warming



$$\mathcal{S}\left(\frac{dA}{dt} = f(A)\right) < \mathcal{S}\left(\frac{dG}{dt} = F(G)\right) < \mathcal{S}\left(\frac{dA}{dt} = f(A) + g(E(t))\right)$$

Long Training Period (12 years)
Validation and testing periods: 4 years each

Typical ML is data hungry: we are pursuing ML techniques for performance with limited data



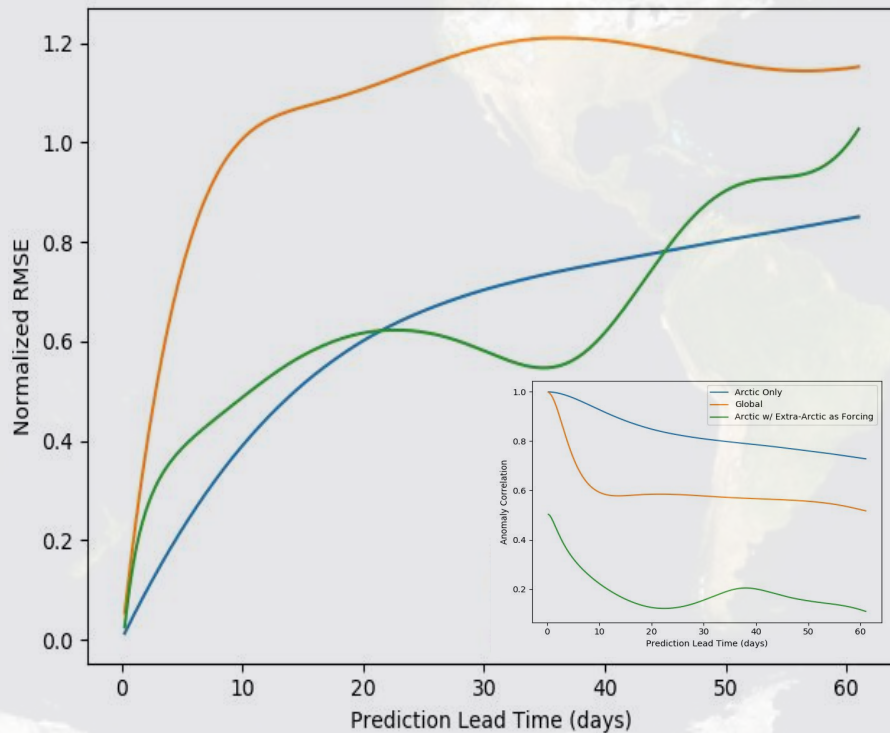
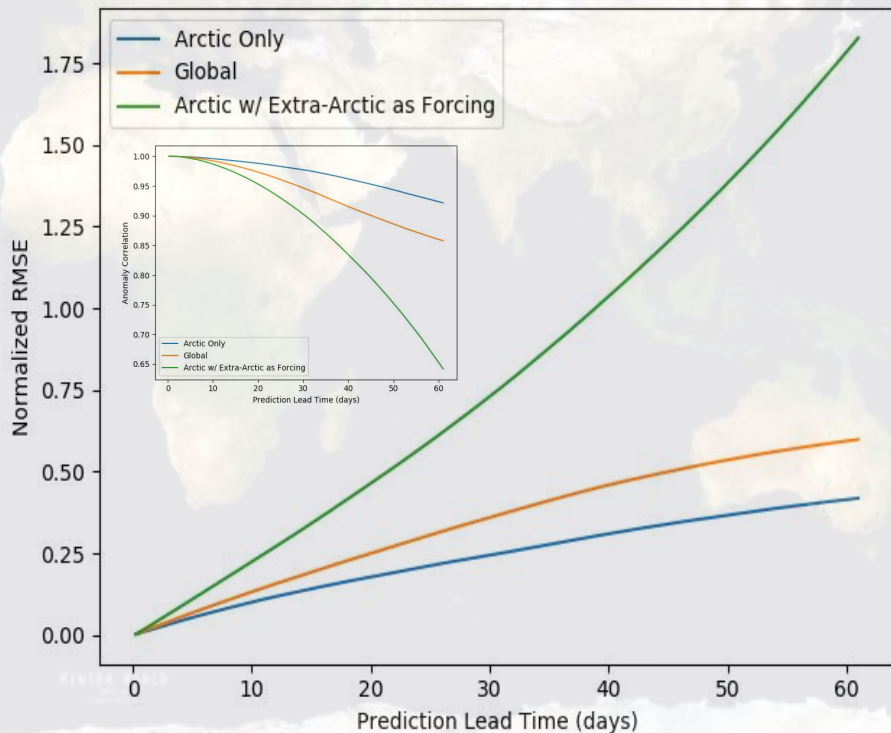
Very short training Period (1 or 2 years)
Validation and testing periods: 2 months each

Summary and Conclusions

- We are developing and applying new ML based techniques to investigate the issue of local vs. remote drivers of Arctic warming in the context of a small effort under the HiLAT-RASM project
- A limited preliminary study suggests a significant role for remote drivers
- Results from linear methods are confounding and need to be verified/debugged (didn't discuss in talk)
- This area is fertile for collaborations across the various RGMA projects/groups. Looking forward to them! Contact me at balu@lanl.gov

Comparison to State of the Art: LIM, FDT, CRF, DMD, Koopman Op.

Left: long (12 year) training; Right: short (1 year) training (caveat: in figure on right, frequent blow-ups have been eliminated)



LIM results argue for the dominance of local processes and feedbacks in determining Arctic warming (buggy?)

(LIM: Linear Inverse Modeling; FDT: Fluctuation Dissipation Theorem; CRF: Climate Response Function; DMD: Dynamic Mode Decomposition)