Machine learning for climate prediction and attribution: Use and best practices

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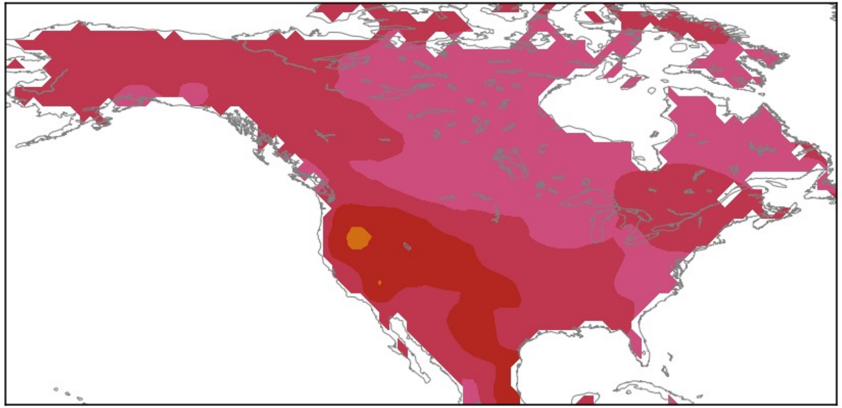
Fundamental problem in subseasonal-to-seasonal forecasting

- Forecast models have, on average, low skill for leads beyond 3 weeks

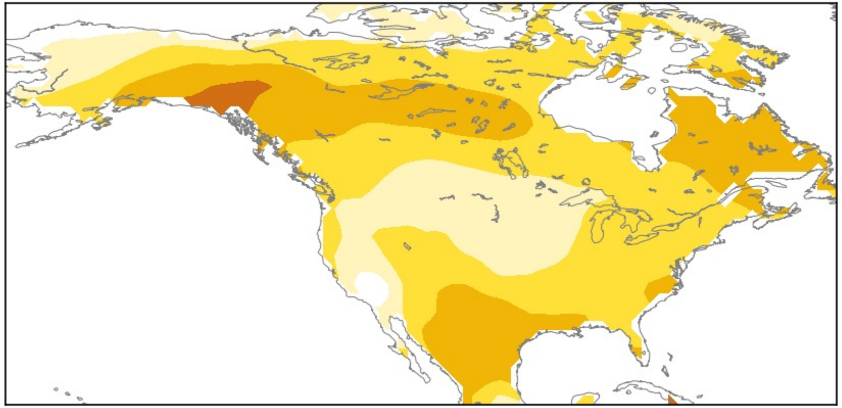
ECMWF IFS – 2m temperature skill (DJF 1999-2010)

Forecast Week 2

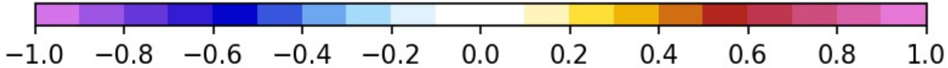


anomaly correlation > 0.5-0.7

Forecast Week 4



anomaly correlation < 0.2-0.3



What information/tools do forecasters use?

- Ensembles of models
- Methods for identifying ‘forecasts of opportunity’
- Knowledge of dynamical processes contributing to signals

$\Longrightarrow$ Consistency across tools builds forecast confidence

How can machine learning meet these needs?

- Ensembles of models

  ⟹ ML model must have comparable skill

- Methods for identifying 'forecasts of opportunity'

  ⟹ ML model must identify forecasts of opportunity ***at time of forecast***

- What dynamical processes are contributing to forecasts?

  ⟹ Ideally relate forecasts of opportunity to known climate modes

ML examples that meet these criteria to various degrees:

- Linear inverse models *(detailed here, Albers and Newman 2020, 2021)*
- Explainable neural networks *(Mayer/Barnes 2021, van Straaten et al. 2022)*
- ML from GCM output *(Ding et al. 2018, Ham et al. 2019, Shin et al. 2020, Gibson et al. 2021)*
- Signal-to-noise ensemble forecast models *(Charlton-Perez et al. 2021)*

What is a LIM and how does it identify forecasts of opportunity?

Empirical model constructed from observed lag-covariances statistics

$\Longrightarrow$ Here, predicted variables in LIM state vector ($\boldsymbol{x}$) include: tropospheric and stratospheric mass and circulation, tropical SSTs and heating, 2m temperature (all taken from JRA-55 reanalysis)

LIM forecast signal

$$\frac{dx}{dt} = Lx + \xi$$

LIM noise forcing
(forecast uncertainty)

'*Expected skill*' of a perfect model infinite-member ensemble mean forecast

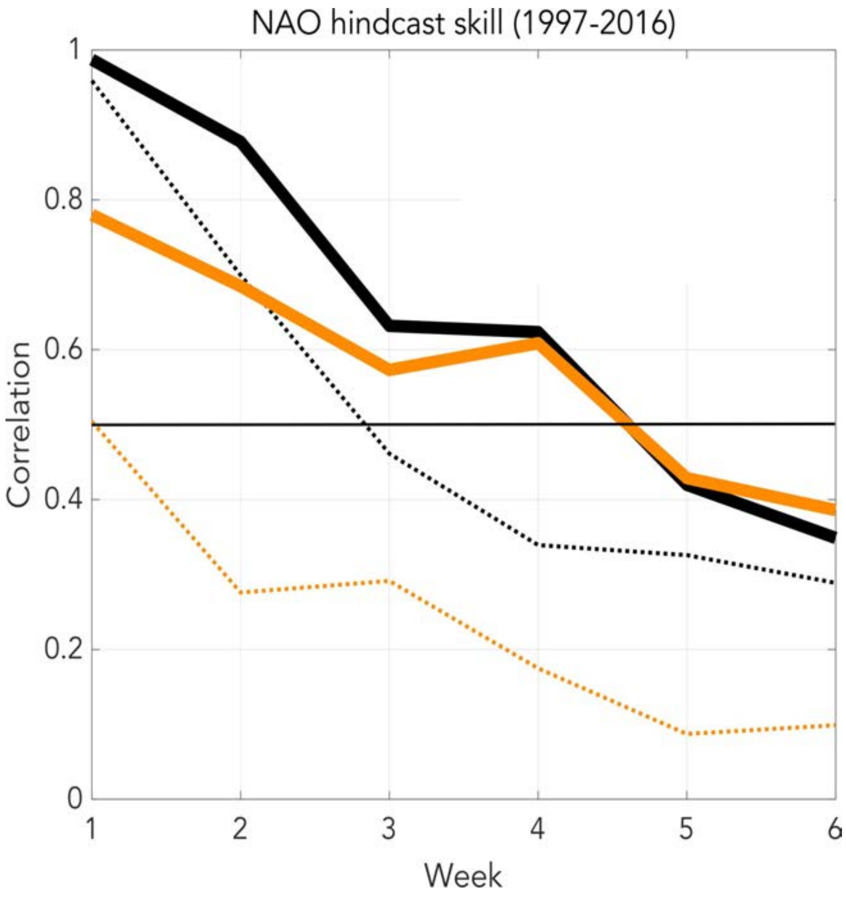
$$\rho_\infty(t;\tau) = \frac{S^2(t;\tau)}{\Big(\big[S^2(t;\tau)+1\big]S^2(t;\tau)\Big)^{1/2}}$$

- $S^2 \longrightarrow$ forecast signal-to-noise ratio (based on the LIM in our case)
- $t \longrightarrow$ forecast initial time
- $\tau \longrightarrow$ forecast lead

- Calculated at time of forecast (it is a *forecast of forecast skill*)
- Forecast lead dependent

(Sardeshmukh et al. 2000, Albers and Newman 2019, 2021)

High skill forecasts identified using LIM's signal-to-noise ratio



- LIM identifies skillful forecasts for itself *AND* in other numerical forecast models

LIM high expected skill

LIM low expected skill

IFS high expected skill

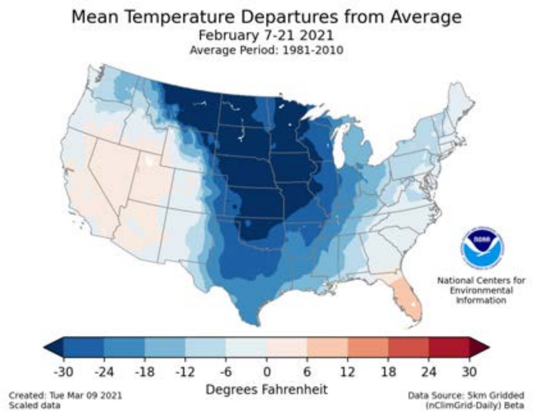
IFS low expected skill

High skill → top 15% of forecasts
Low skill → remaining 85%

(Albers and Newman 2021)

February 2021 extreme cold air outbreak

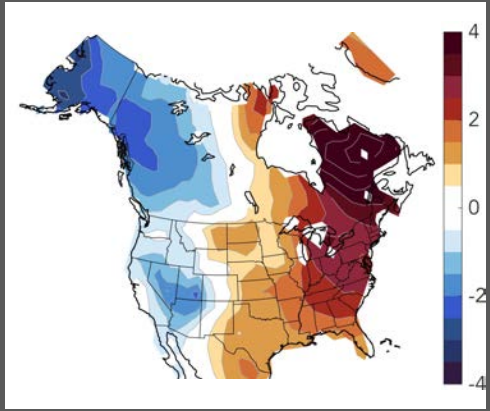
Verification



- Central United States 30° F below normal Feb. 7-21
- Shreveport, LA breaks record low by 19° F (low of 1° F)
- Widespread power and water outages
- More than 100 deaths and $200-300 billion in damages

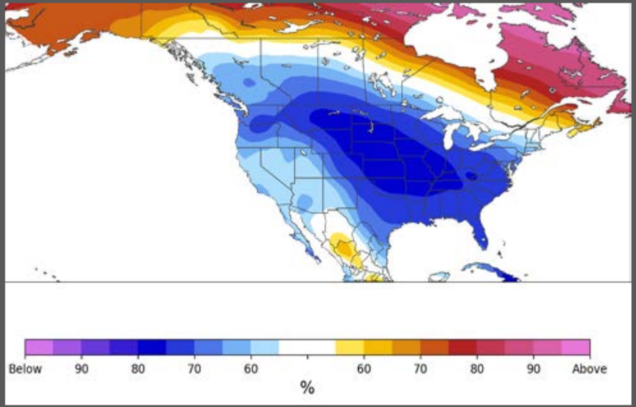
(sources: NOAA NWS and NCEI, AP, CBS)

2m temperature forecasts



ECMWF IFS Week 3/4 forecast

- Forecast initialized – Jan. 21
- Verification period – Feb. 5-18



NOAA CPC/PSL LIM probabilistic Week 4 forecast

- Forecast initialized – Jan. 19
- Verification period – Feb. 10-16

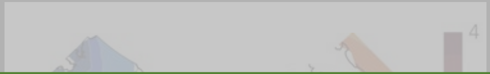
February 2021 extreme cold air outbreak

Verification

- Shreveport, LA breaks record low by 19° F (low of 1° F)
- Widespread power and water outages
- More than 100 deaths and $200-300 billion in damages

(sources: NOAA NWS and NCEI, AP, CBS)

2m temperature forecasts



- Forecast initialized – Jan. 21
- Verification period – Feb. 5-18

- Forecast initialized – Jan. 19
- Verification period – Feb. 10-16

Questions:

1. What dynamical climate modes caused the CAO?
2. What dynamical modes were *predictable* at subseasonal forecast leads?

Building a 'dynamical filter' for dynamical process attribution

LIM-based 'nonnormal' filter:

$$\frac{dx}{dt} = Lx + \xi$$

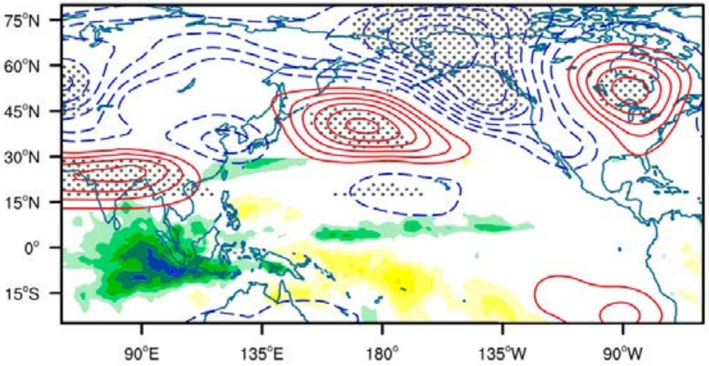
Eigendecomposition of L yields eigenmodes with 3 important characteristics:

1. Period/frequency of oscillation
2. e-folding decay time
3. Relative amplitude in each LIM state vector (x) variable

(e.g., Penland and Matrasova 2006, Albers and Newman 2021)

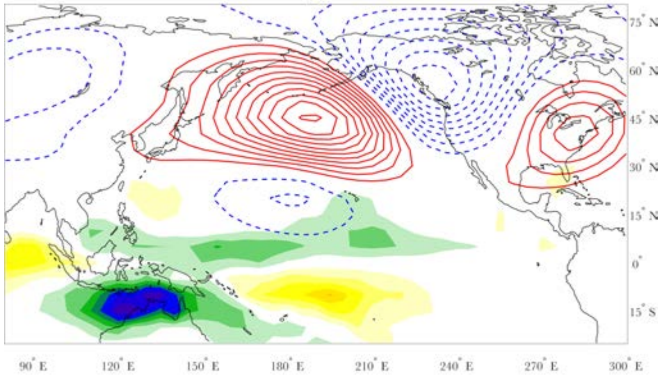
Example: LIM MJO eigenmode

MJO phase 3



- ERA-Interim 250 hPa geopotential heights (contours)
- GPCP precipitation (filled contours)

(Henderson et al. J. Clim. 2017)



LIM-based MJO eigenmode:

- 500 hPa geopotential heights (contours)
- tropical heating (filled contours)
- e-folding time = 21 days
- oscillation period = 52 days

Dynamical processes from LIM filter:

Total anomaly

Internal variability

- Large subspace of modes
- Largely unpredictable on S2S timescales

MJO

Tropical SST subspace

- Teleconnections through upper troposphere-lower stratosphere
- Captures ENSO diversity
- Captures 'ENSO-stratosphere' teleconnection pathway

Stratospheric NAM

- Captures downward SSW influence
- No SST component

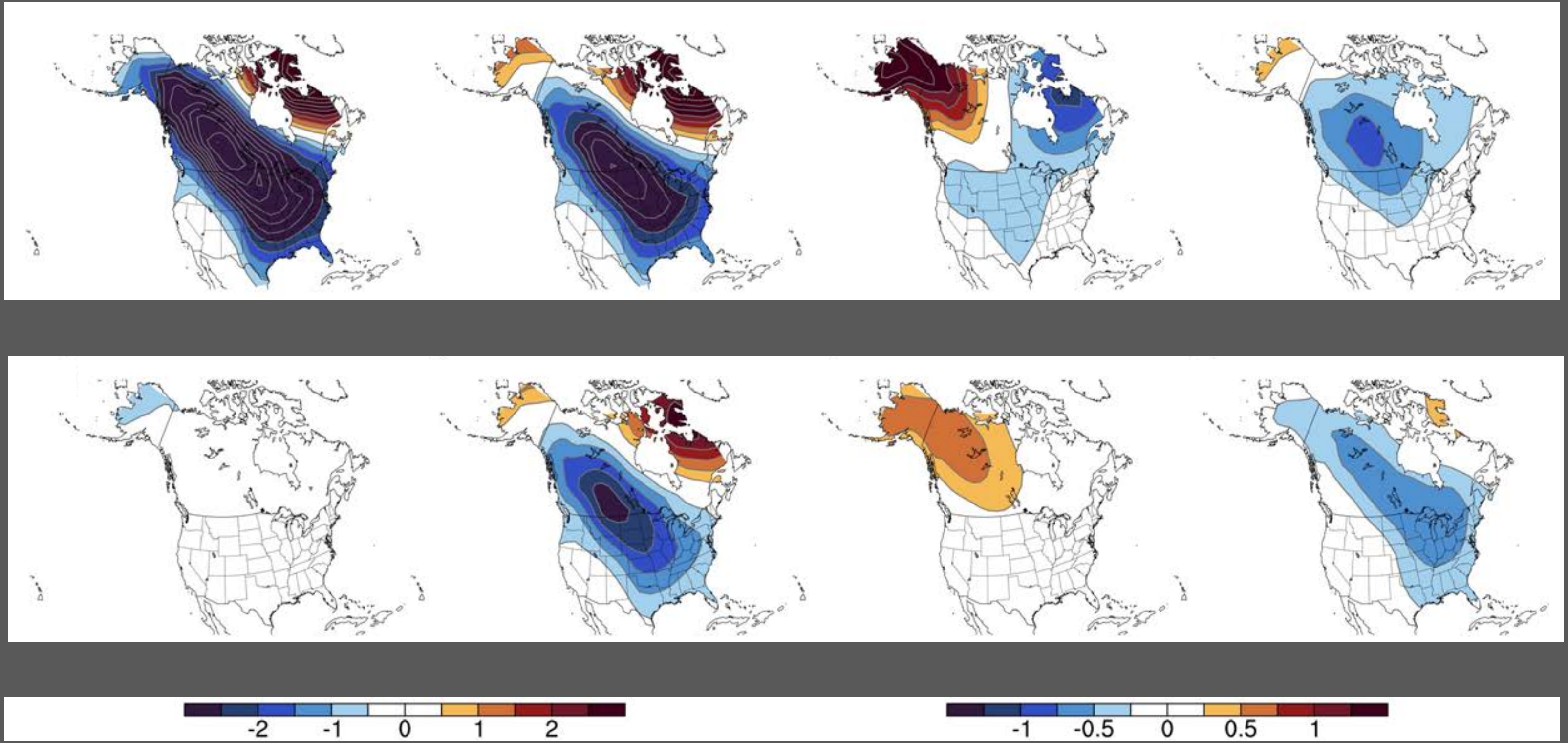
(<u>References:</u> SST-stratosphere-SSW modes → Albers and Newman 2021 – MJO-ENSO → Henderson et al. 2020)

2m temperature   Forecast initialized – Jan. 24   Forecast verified – Feb. 8 - 21

Total anomaly = Internal variability + Tropical SSTs (La Niña) + MJO + Stratospheric NAM (SSW)

Verifications

LIM forecasts



Conclusions:

- Machine learning models can contribute to S2S forecasting by:
  - Forecasts skillful enough to contribute to forecast ensemble
  - Help identify 'forecasts of opportunity'
  - Identify dynamical processes contributing to forecasts
- ML capabilities are actively being developed, promising approaches include:
  - Linear inverse models
  - 'Explainable' neural networks
  - ML from GCM output (e.g., convolutional neural network and model analog approaches)