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

 ⟹ 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

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

\[
\frac{dx}{dt} = (Lx) + (\xi)
\]

• LIM forecast signal

• LIM noise forcing (forecast uncertainty)

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

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

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

**Graph:**

- **NAO hindcast skill (1997-2016)**
  - **Correlation**
  - **Week**
  - **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

2m temperature forecasts

Questions:

1. What dynamical climate modes caused the CAO?

2. What dynamical modes were *predictable* at subseasonal forecast leads?

- 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)
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)
What dynamical processes caused the CAO?

Eigendecomposition of $\frac{dx}{dt} = \mathbf{L} \mathbf{x}$ yields eigenmodes with 3 important characteristics:

1. Period/frequency of oscillation
2. E-folding decay time
3. Relative amplitude in each LIM state vector ($\mathbf{L}$)

Example: LIM MJO eigenmode

- Period (frequency) of oscillation = 52 days (0.02 days$^{-1}$)
- E-folding decay time = 21 days
- ERA-Interim 250 hPa geopotential heights (contours)
- GPCP precipitation (filled contours)

(Hendersen et al. J.Clim. 2017)

MJO phase 3

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:

- 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

- Internal variability
  - Large subspace of modes
  - Largely unpredictable on S2S timescales

- MJO

(References: 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)