Adaptive Bias Correction for Improved Subseasonal Forecasting

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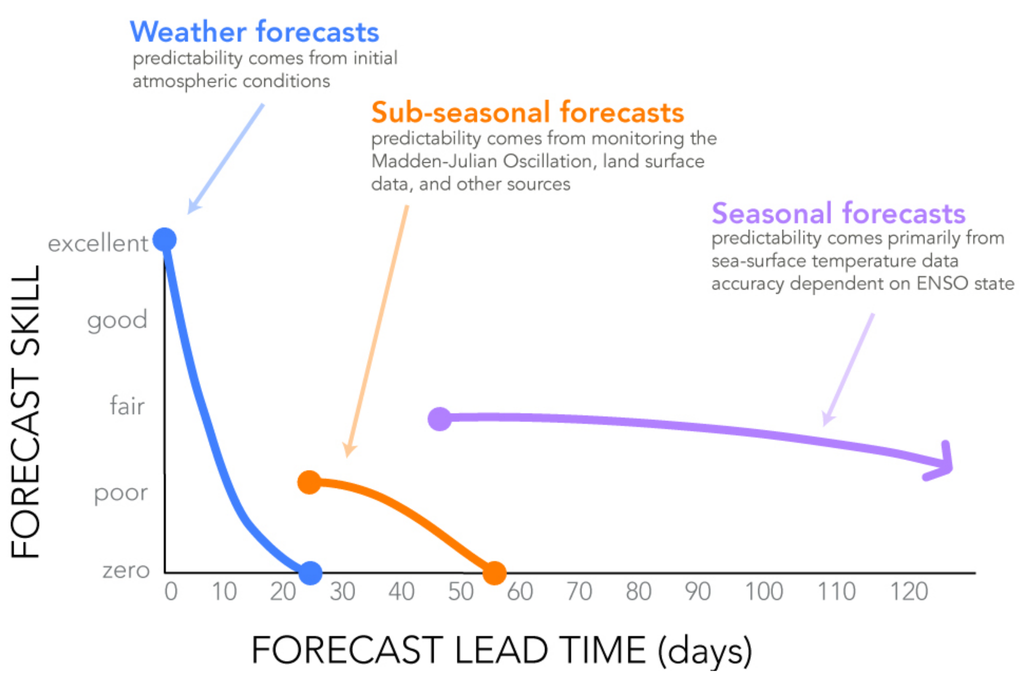
INTRODUCTION

Subseasonal weather prediction (3-6 weeks ahead) is a crucial pre-requisite for:

- Preparing droughts and floods
- Agriculture planning
- Allocation of water resources
- Managing wildfires

It is a challenging forecast horizon for both meteorological and ML models:



Source: https://iri.columbia.edu/news/qa-subseasonal-prediction-project/

FORECASTING TASKS

Objective:

We learn to adaptively correct the biases of dynamical models and introduce a hybrid dynamical-learning *adaptive bias correction* (ABC) framework to improve the skill of subseasonal temperature and precipitation forecasts.

Target variables:	Average temperature and Accumulated precipitation
Lead times:	Weeks 3-4 ahead and Weeks 5-6 ahead
Geographical region:	U.S., 1.5°x1.5° resolution
Loss function:	RMSE, Skill
Dataset:	Subseasonal Climate USA dataset (Subseasonal Data, 2021)

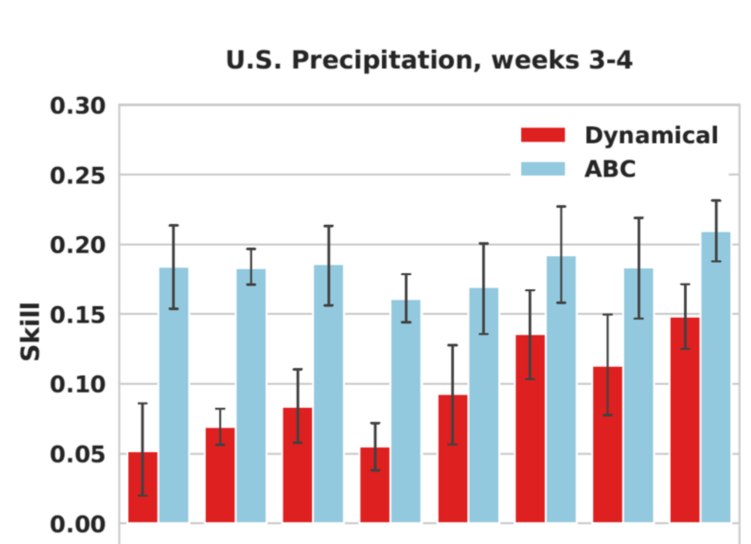
ADAPTIVE BIAS CORRECTION (ABC)

ABC is a uniformly-weighted ensemble of three machine learning models, Climatology++, Dynamical++, and Persistence++.

- **Climatology++:** is a locally constant prediction rule that minimizes historical forecasting error, specified by a user-supplied loss function, over all days in a window around the target day of year.
- **Dynamical++:** After averaging dynamical forecasts over a range of issuance dates and lead times, Dynamical++ debiases the ensemble forecast for each grid cell by adding the mean value of the target variable and subtracting the mean forecast over a learned window of observations around the target day of year.
- **Persistence++:** fits a least-squares regression per grid point to optimally combine lagged temperature or precipitation measurements, climatology, and a dynamical ensemble forecast.

RESULTS : MODEL SKILL – SUBX VS. ABC (2018 - 2021)

Figure 1: Average forecast skill for dynamical models (red) and their ABC-corrected counterparts (blue). Across the contiguous U.S. and the years 2018–2021.

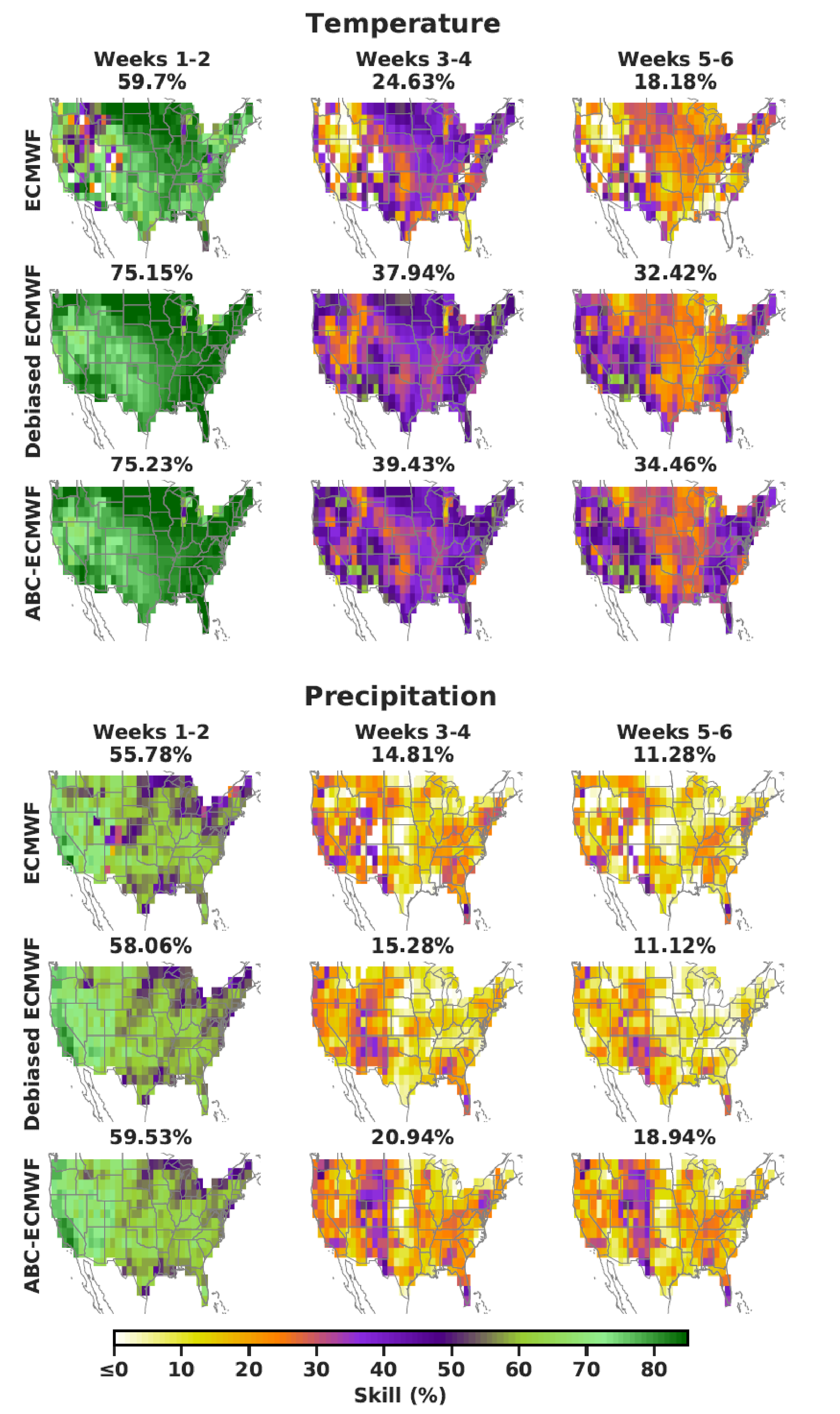


- **Takeaway:**

  ABC provides a pronounced improvement in skill for each SubX or ECMWF dynamical model input.

MODEL SKILL ON TEST DATA (2011 - 2020)

Figure 2: Spatial skill distribution of dynamical models and ABC corrections, across the contiguous U.S. and the years 2018–2021.



- **Takeaway:**

  Dynamical model skill drops precipitously at subseasonal timescales (weeks 3-4 and 5-6), but ABC attenuates the degradation, Taking the same raw model forecasts as input, ABC provides consistent improvements over operational debiasing protocols, improving the precipitation skill of debiased ECMWF by 70%. The average skill over all sites is displayed above each map.

IDENTIFYING STATISTICAL FORECASTS OF OPPORTUNITY

So far:

- The results presented assess overall model skill, averaged across all forecast dates.

However:

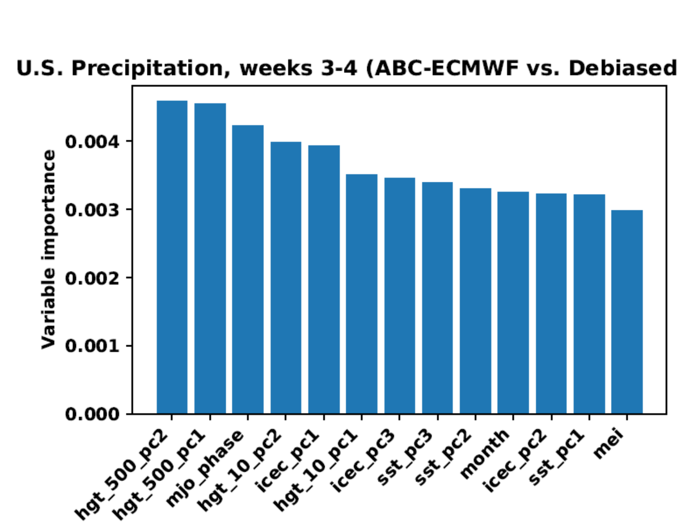
- There is a growing appreciation that subseasonal forecasts can also benefit from selective deployment during **"windows of opportunity"**, periods defined by observable climate conditions in which specific forecasters are likely to have higher skill (Mariotti, A. et al., 2020).

We propose:

- A practical **opportunistic ABC workflow** that uses a candidate set of explanatory variables to identify windows in which ABC is especially likely to improve upon a baseline model. The same workflow can be used to explain the skill improvements achieved by ABC in terms of the explanatory variables.

COHORT SHAPLEY FOR SUBSEASONAL FORECASTS

Figure 3: Global variable importance: overall importance of each explanatory variable in explaining the weeks 3-4 precipitation skill improvement of ABC-ECMWF over debiased ECMWF, as measured by Shapley effects.

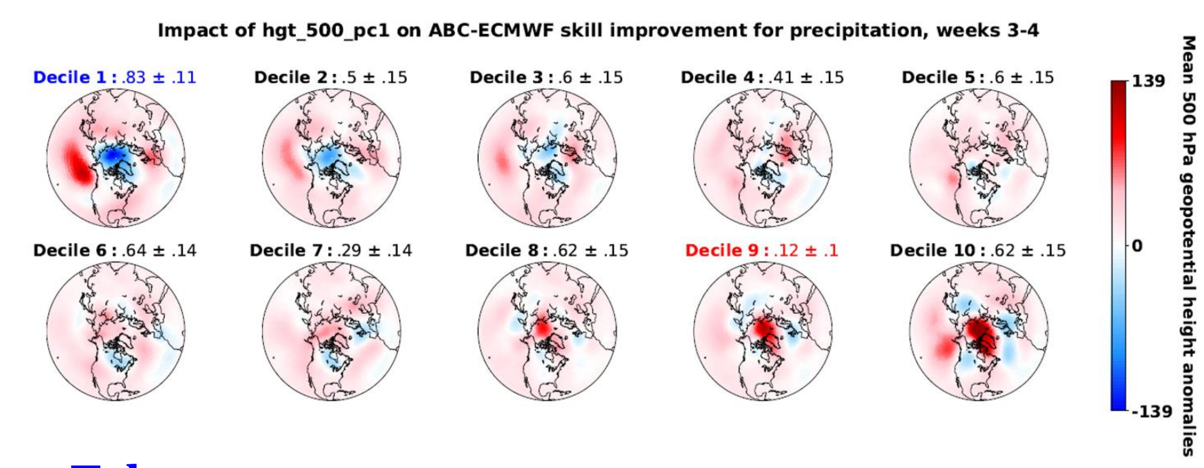


Most important predictors:

- Geopotential height
- MJO
- Ice concentration
- Sea surface temperature

MOST IMPORTANT PREDICTOR: HGT 500

Figure 4: Impact of hgt_500_pc1 on ABC-ECMWF skill improvement. Top: To summarize the impact of hgt_500_pc1 on ABC-ECMWF skill improvement for precipitation weeks 3-4, we divide our forecasts into 10 bins, determined by the deciles of hgt_500_pc1, and compute the probability of positive impact in each bin, as shown above each bin map. The highest probabilities of positive impact are shown in blue and the lowest probabilities of positive impact are shown in red.



- **Takeaway:**

  We find that hgt_500_pc1 is most likely to have a positive impact on skill improvement in decile 1, which features a positive Arctic Oscillation (AO) pattern, and least likely in decile 9, which features AO in the opposite phase.

OPPORTUNISTIC ABC

Next:

- We use the identified contexts to define windows of opportunity for operational deployment.

Opportunistic ABC:

- Since all explanatory variables are observable on the forecast issuance date, we can selectively apply ABC when multiple variables are likely to have a positive impact on skill and otherwise issue a default, standard forecast (e.g., debiased ECMWF). We call this selective forecasting model *opportunistic ABC*.

Question:

- How many high-impact variables should we require when defining these windows of opportunity?

OPPORTUNISTIC ABC WORKFLOW

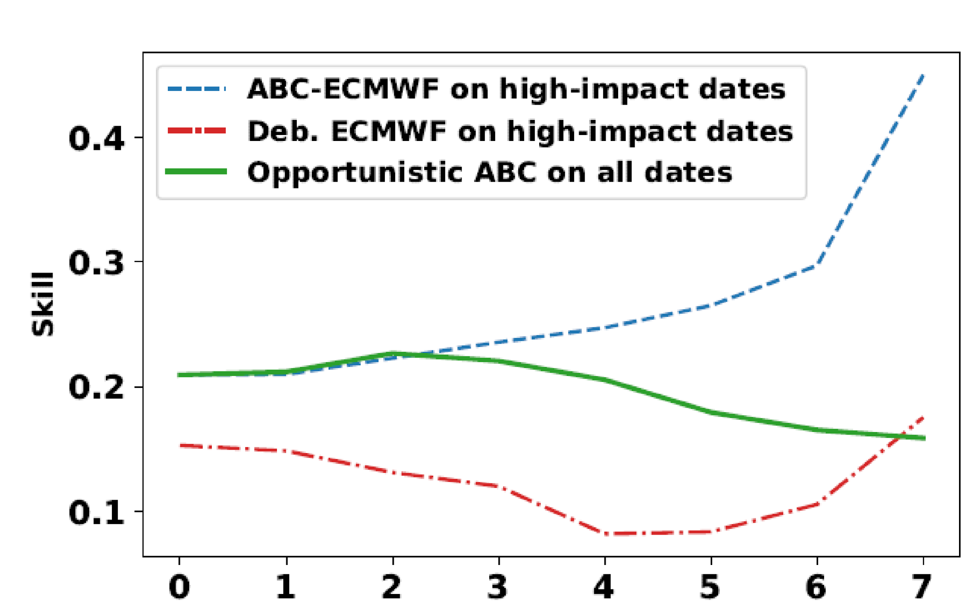
Question:

How many high-impact variables should we require when defining these windows of opportunity?

➔ Requiring a larger number of high-impact variables will tend to increase the skill gains of ABC but simultaneously reduce the number of dates on which ABC is deployed.

Figure 5: Defining windows of opportunity for opportunistic ABC forecasting. Here we focus on forecasting precipitation in weeks 3-4. Top: When more explanatory variables fall into high impact deciles or bins (e.g., the blue bins of Figures 4 and 5), the mean skill of ABC-ECMWF improves, but the percentage of forecasts using ABC declines. Bottom: The overall skill of opportunistic ABC is maximized when ABC-ECMWF is deployed for target dates with two or more high-impact variables and standard debiased ECMWF is deployed otherwise.

# High-impact variables	% Forecasts using ABC	High-impact skill (%) ABC	Debiased
0 or more	100.00	20.94	15.28
1 or more	95.93	20.99	14.84
2 or more	80.62	22.29	13.12
3 or more	58.61	23.56	12.00
4 or more	31.82	24.72	8.18
5 or more	14.59	26.51	8.35
6 or more	6.46	29.72	10.55
7 or more	2.15	45.00	17.53



- **Takeaway:**

  Opportunistic ABC skill is maximized when two or more high-impact variables are required. With this choice, ABC is used for approximately 81% of forecasts and debiased ECMWF is used for the remainder.

References

- Mariotti, A. et al. Windows of opportunity for skillful forecasts subseasonal to seasonal and beyond. Bulletin of the American Meteorological Society 101 (5), E608–E625 (2020) .
- Subseasonal Data. Subseasonal data Python package. https://github.com/Microsoft/subseasonal_data (2021).