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.

### 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

### FORECASTING TASKS

- **Target variables:** Average temperature and Accumulated precipitation
- **Lead times:** Weeks 3-4 ahead and Weeks 5-6 ahead
- **Geographical region:** U.S. 1x1° resolution, G = 462 gridpoints
- **Loss function:** RMSE, skill
- **Dataset:** Improved Subseasonal (Huang et al., 2019)

### MODELS

**Baselines:**
- **Climatology:** average temperature or precipitation for a specific day and month over 1981-2010
- **CFSv2:** operational U.S. physics-based model from NCEP
- **Persistence:** predict most recent value

**Our toolkit:**
- **AutoKNN:** included in (Huang et al., 2019)
- **InForesee:** included in (Zhou, 2019)
- **LocalBoosting:** included in (Prokhorenkova et al., 2018)
- **MultiLIR:** included in (Zhou et al., 2019)
- **NL-ENet:** introduced in (O clen, 2020)
- **Prophet:** included in (Taylor and Letham, 2018)
- **Salient 2:** included in (Schmitt, 2020)

**Our models:**
- **Climatology:** use adaptively selected window around target day for averaging
- **CFSv2+:** average over range of issuance date and lead times, adaptively debiasing using selected window
- **Persistence:** learn correlation between lagged measurements with NWP

### ENSEMBLING

**Uniform ensemble:**
- **Average over base models**
- **Typical solution in the weather community**

**Online ensemble:**
- Runs a follow-the-regularized-leader online learning method
- Results in a adaptive convex combination of base models

**Base models:**
- **Climatology+**, CFSv2+, Persistence++

### RESULTS

**Table 1:** Average percentage skill and percentage improvement over mean debiased CFSv2 RMSE across 2011-2020 in the contiguous U.S. The best performing model in each model group is bolded, and the best performing model overall is shown in green.

**Table 2:** Average percentage skill and percentage improvement over mean debiased CFSv2 RMSE across 2016-2020 in the contiguous U.S. The best performing model in each model group is bolded, and the best performing model overall is shown in green.

**Figure 1:** Per season and per year improvement over mean debiased CFSv2 RMSE across the contiguous U.S. and the years 2011-2020. Despite their simplicity, the toplist models (solid lines) consistently outperform debiased CFSv2 and the state-of-the-art learners (dotted lines).

**Figure 2:** Per season and per year average skill across the contiguous U.S. and the years 2011-2020. Despite their simplicity, the toplist models (solid lines) consistently outperform debiased CFSv2 and the state-of-the-art learners (dotted lines).

### COMPARING TO ECMWF

**Figure 3:** Percentage improvement over mean debiased CFSv2 RMSE in the contiguous U.S. over 2011-2020. White grid points indicate negative or 0% improvement.

**Figure 4:** Model bias in the contiguous U.S. over 2011-2020. White grid points indicate zero bias.

### WESTERN U.S. COMPETITION

**Table 3:** Percentage improvement over mean debiased CFSv2 RMSE over 26 contest dates (2019-2020) in the Western U.S. The best performing models within each class of models are shown in bold, while the best performing models overall are shown in green.

**Figure 5:** Temporal plot (left) and scatter plot (right) of yearly total precipitation and percentage improvement over mean debiased CFSv2 RMSE in the Western U.S. across 2011-2020.

### References