Learned Benchmarks for Subseasonal Forecasting

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Key Points:

• We benchmark a subseasonal forecasting toolkit of 3 simple learned models that enhance the skill of dynamical models and statistical baselines
• The toolkit is more skillful than the US and European operational dynamical models and 7 state-of-the-art machine and deep learning methods
• To facilitate future development, we release our dataset and Python code for the machine learning models and statistical baselines

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Abstract

We benchmark a subseasonal forecasting toolkit of simple learned models that outperform both operational practice and state-of-the-art machine learning and deep learning methods. These models, introduced by Mouatadid et al. (2022), include (a) Climatology++, an adaptive alternative to climatology that, for precipitation, is 9% more accurate and 250% more skillful than the United States operational Climate Forecasting System (CFSv2); (b) CFSv2++, a learned CFSv2 correction that improves temperature and precipitation accuracy by 7-8% and skill by 50-275%; and (c) Persistence++, an augmented persistence model that combines CFSv2 forecasts with lagged measurements to improve temperature and precipitation accuracy by 6-9% and skill by 40-130%. Across the contiguous U.S., the Climatology++, CFSv2++, and Persistence++ toolkit consistently outperforms standard meteorological baselines, state-of-the-art machine and deep learning methods, and the European Centre for Medium-Range Weather Forecasts ensemble.

1 Introduction

Water and fire managers rely on subseasonal forecasts 2-6 weeks in advance to allocate water, manage wildfires, and prepare for droughts and other weather extremes (Merryfield et al., 2020; White et al., 2017). However, skillful forecasts for the subseasonal regime are lacking due to the complex dependence on both local weather and global climate variables and the chaotic nature of weather. While short-term forecasting accuracy is largely sustained by physics-based dynamical models, these deterministic methods have limited subseasonal accuracy due to chaos (Lorenz, 1963). Indeed, subseasonal forecasting has long been considered a “predictability desert” due to its complex dependence on both local weather and global climate variables (Vitart et al., 2012). Nevertheless, the subseasonal capabilities of operational physics-based models have noticeably improved in the recent years (Vitart et al., 2017; Pegion et al., 2019; Lang et al., 2020), while the value of machine learning and deep learning methods in improving subseasonal forecasting has become clear (Li et al., 2016; Cohen et al., 2018; Hwang et al., 2019; Arcomano et al., 2020; He et al., 2021; Yamagami & Matsueda, 2020; Wang et al., 2021; Watson-Parris, 2021; Weyn et al., 2021; Srinivasan et al., 2021).

In this paper, we benchmark the subseasonal forecasting toolkit introduced by Mouatadid et al. (2022), which consists of simple, learned models that outperform both the operational United States Climate Forecasting System (CFSv2) and state-of-the-art machine learning and deep learning methods from the literature. These toolkit models augment traditional forecasting strategies with learned enhancements to improve both accuracy, as measured by spatial root mean squared error, and skill, as measured by uncentered anomaly correlation (see Section 2). The learned benchmarks include:

- **Climatology++**: an adaptive alternative to climatology that, for precipitation, is 9% more accurate and 250% more skillful than a 32-member debiased CFSv2 ensemble;
- **CFSv2++**: a learned correction for CFSv2 that improves debiased CFSv2 temperature and precipitation accuracy by 7-8% and skill by 50-275%; and
- **Persistence++**: an augmented persistence model that combines lagged measurements, CFSv2 ensemble forecasts, and climatology to improve debiased CFSv2 temperature and precipitation accuracy by 6-9% and skill by 40-130%.

In Section 5, we evaluate the toolkit models in the contiguous U.S. over the years 2011-2020 and demonstrate consistent improvement over standard meteorological baselines, state-of-the-art learning models, and the leading European Centre for Medium-Range Weather Forecasts (ECMWF) dynamical model. Moreover, combining the toolkit model forecasts with online ensembling (Flaspohler et al., 2021) leads to further gains in both accuracy and skill. Overall, we find the toolkit models lead to substantial improvements in subseasonal forecasting skill. To facilitate future benchmarking, we have shared our model code through the subseasonal_toolkit Python package and introduced our regularly updated Sub-
seasonalClimateUSA dataset for developing and evaluating subseasonal forecasters (see Section 3).

2 Forecasting Tasks

We consider two prediction targets: average temperature (°C) and accumulated precipitation (mm) over a two-week period, and two time horizons: 15-28 days ahead (weeks 3-4) and 29-42 days ahead (weeks 5-6). We forecast each variable at $G = 862$ grid points on a $1° \times 1°$ grid across the contiguous U.S., bounded by latitudes 25N to 50N and longitudes 125W to 67W.

These prediction targets and time horizons were the focus of the Subseasonal Forecast Rodeos I and II (Nowak et al., 2020), two yearlong real-time forecasting competitions sponsored by the U.S. Bureau of Reclamation (USBR) and the National Oceanic and Atmospheric Administration to advance the state of subseasonal climate prediction. The same targets are used by water managers to apportion water resources, control wildfires, and anticipate droughts and other extreme weather (Nowak et al., 2017; White et al., 2017).

We evaluate each forecast according to two metrics recommended by the USBR (Nowak et al., 2017, 2020): root mean squared error (RMSE) and skill (also known as uncentered anomaly correlation Wilks, 2011). For a two-week period starting on date $t$, let $y_t \in \mathbb{R}^G$ denote the vector of ground-truth measurements $y_{t,g}$ for each grid point $g$ and $\hat{y}_t \in \mathbb{R}^G$ denote a corresponding vector of forecasts. In addition, define climatology $c_t$ as the average ground-truth values for a given month and day over the years 1981-2010. Then the RMSE is given by

$$\text{RMSE}(\hat{y}_t, y_t) = \sqrt{\frac{1}{G} \sum_{g=1}^{G} (\hat{y}_{t,g} - y_{t,g})^2}$$

with a smaller value indicating a more accurate forecast, and skill is defined by

$$\text{skill}(\hat{y}_t, y_t) = \frac{(\hat{y}_t - c_t)^T (y_t - c_t)}{||y_t - c_t||^2} \in [-1, 1]$$

with a larger value indicating higher quality. For a collection of dates, we report average RMSE and average percentage skill, which is 100 times the average skill.

3 SubseasonalClimateUSA Dataset

To train and evaluate the models in this work we constructed a SubseasonalClimateUSA dataset housing a diverse collection of ground-truth measurements and model forecasts relevant to subseasonal timescales:

- **Temperature**: average of daily maximum and minimum temperature at 2 meters in °C (Fan & Van den Dool, 2008; NOAA/OAR/ESRL PSL, 2021a)
- **Precipitation**: daily precipitation in mm aggregated by summing over each two-week period (Xie et al., 2007; Chen et al., 2008; Xie et al., 2010; NOAA/OAR/ESRL PSL, 2021b,c)
- **CFSv2**: daily 32-member ensemble mean forecasts of temperature and precipitation from the coupled atmosphere-ocean-land dynamical model with 0.5-29.5 day lead times (Saha et al., 2014; Kirtman et al., 2017; SubX data, 2021)
- **Stratospheric geopotential height**: daily indicator of polar vortex variability; top three principal components of geopotential height at 10mb were extracted from global 1948-2010 loadings (Kalnay et al., 1996; NOAA/OAR/ESRL PSL, 2021e)
- **Madden-Julian Oscillation (MJO)**: daily measure of tropical convection known to impact subseasonal climate; phase and amplitude were extracted but not aggregated (Wheeler & Hendon, 2004; MJO data, 2021)
- **Multivariate ENSO index (MEI.v2)**: bimonthly scalar summary of the state of the El Niño–Southern Oscillation, an ocean-atmosphere coupled climate mode (Wolter & Timlin, 1993, 1998, 2011; NOAA/OAR/ESRL PSL, 2021d)
• **Pressure** and **relative humidity**: daily pressure and relative humidity near the surface (sigma level 0.995) (Kalnay et al., 1996; NOAA/OAR/ESRL PSL, 2021e)

• **Sea surface temperature** and **sea ice concentration**: top three principal components for each variable using global 1981-2010 loadings (Reynolds et al., 2007; NOAA/OAR/ESRL PSL, 2021f)

To facilitate data analysis in Python, the data is organized into Python Pandas Dataframes and Series (Wes McKinney, 2010; pandas development team, 2020) with spatial variables interpolated onto a 1° × 1° latitude-longitude grid and daily variables replaced with moving averages over two-week periods (unless otherwise specified above). The SubseasonalClimateUSA dataset can be viewed as a successor to the SubseasonalRodeo dataset of Hwang et al. (2018). While the SubseasonalRodeo dataset targeted the Western U.S. and offered a static data snapshot ending in 2018, the SubseasonalClimateUSA dataset provides features suitable for contiguous U.S. forecasting, is regularly updated, and is publicly accessible through the subseasonal_data Python package. For more details please see Appendix A.

4 Models

Our study will evaluate three classes of forecasting methods: the standard meteorological baselines of Section 4.1, the toolkit models introduced in (Mouatadid et al., 2022) (Section 4.2), and state-of-the-art machine learning and deep learning methods drawn from the literature (Section 4.3). We will also evaluate ensemble forecasts derived from these models using the techniques described in Section 4.4. An implementation of each model evaluated is available at https://github.com/microsoft/subseasonal_toolkit, and supplementary model details can be found in Appendix B.

4.1 Meteorological Baselines

We first consider three standard subseasonal forecasting baselines.

4.1.1 Climatology

Climatology is a standard measure of the expected temperature or precipitation at a location. For a given grid point and target date, it forecasts the average value of the target variable on the same day and month over 1981-2010 (Arguez et al., 2012).

4.1.2 Debiased CFSv2

The National Centers for Environmental Prediction (NCEP) Climate Forecasting System version 2 (CFSv2) is an operational dynamical model commonly used for subseasonal forecasting (Saha et al., 2014). Debiased CFSv2 is a corrected ensemble forecast used as a benchmark in the two Subseasonal Climate Forecast Rodeo competitions (Nowak et al., 2020; Hwang et al., 2019). First, a CFSv2 ensemble forecast is formed by averaging 32 forecasts for the target period based on 4 different model initializations produced at 8 different lead times. The ensemble is then debiased by adding the mean value of the target variable on the target month and day over the period 1999-2010 and subtracting the mean ensemble CFSv2 reforecast over the same period.

4.1.3 Persistence

The standard Persistence baseline (see, e.g., Mittermaier, 2008; Weyn et al., 2021) forecasts the most recently observed two-week target value.
4.2 Toolkit Models

We next evaluate the toolkit models introduced by Mouatadid et al. (2022), that enhance each of the baseline models by leveraging simple and effective statistical machine learning techniques. While these learning models are simple and computationally inexpensive, we will see in Section 5 that each enhancement improves over both operational practice and state-of-the-art learning techniques. All three models are described in detail in Mouatadid et al. (2022).

4.2.1 Climatology++

Climatology++ improves upon Climatology by predicting the historical mean or geographic median over all days in a window around the target day of year. The number of training years and the size of the observation window are determined adaptively.

4.2.2 CFSv2++

CFSv2++ is a learned correction for raw CFSv2 forecasts. After averaging CFSv2 forecasts over a range of issuance dates and lead times, CFSv2++ debiases the ensemble forecast 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. The range of ensembled lead times, the number of averaged issuance dates, and the size of the observation window employed are selected adaptively.

4.2.3 Persistence++

Persistence++ combines climatology, lagged temperature or precipitation measurements, and a CFSv2 ensemble forecast by fitting a least squares regression per grid point.

4.3 State-of-the-art Learning Methods

We also consider seven state-of-the-art learning methods.

4.3.1 AutoKNN

The AutoKNN model of Hwang et al. (2019) was part of a winning solution in the Subseasonal Climate Forecast Rodeo I (Nowak et al., 2020) and was shown to outperform deep fully connected neural networks (He et al., 2020). AutoKNN first identifies a set of historical dates most similar to the target date and then forecasts a weighted locally linear combination of the anomalies measured on similar dates and recent dates. Our implementation matches that of Hwang et al. but adapts the model to target our primary RMSE objective by (i) using mean (negative) RMSE as the similarity measure instead of mean skill, (ii) using raw measurement vectors $y_t$ instead of anomaly vectors $a_t$, and (iii) using equal datapoint weights in the final local linear regression.

4.3.2 Informer

The Informer is a transformer-based deep learning model for time series forecasting shown to have state-of-the-art performance on a number of short term weather forecasting tasks (Zhou et al., 2021). We retrain the Informer every four months to predict temperature from past temperature and precipitation from past precipitation independently at each grid point.
4.3.3 LocalBoosting

In recent subseasonal experiments of He et al. (2020), boosted decision tree models yielded the best performance. Our boosted decision tree model, based on CatBoost (Prokhorenkova et al., 2018), uses as features the value of 10 SubseasonalClimateUSA variables in a geographic region around the target grid point. This gives the algorithm enough flexibility to adapt the weights of the features to each particular grid point while still taking into account neighboring spatial information. The geographic region is determined by a bounding box of 2 degrees in each direction, and the 10 variables are chosen for each task via their predictive power on validation years.

4.3.4 MultiLLR

The MultiLLR model of Hwang et al. (2019) was also part of a winning solution in the Subseasonal Climate Forecast Rodeo I (Nowak et al., 2020) and has since been used to improve subseasonal precipitation prediction in China (Wang et al., 2021). For each target date, MultiLLR uses a customized backward stepwise procedure to select SubseasonalClimateUSA features relevant for prediction and local linear regression to combine those features into a forecast for each grid point. Our implementation matches that of Hwang et al. but adapts the model to target our primary RMSE objective by using mean (negative) RMSE instead of mean skill as the feature selection criterion. In addition, we replace their MEI features with corresponding MEI.v2 features and their monthly NWP forecast features with daily debiased CFSv2 forecasts; see Appendix B7 for more details.

4.3.5 N-BEATS

N-BEATS (Oreshkin et al., 2020) is a neural network time series forecaster that obtained state-of-the-art results on the Makridakis M3 (Makridakis & Hibon, 2000) and M4 (Makridakis et al., 2020) benchmarks for time-series forecasting. We retrain N-BEATS every two months to predict temperature from past temperature and precipitation from past precipitation independently at each grid point.

4.3.6 Prophet

The Prophet model of Taylor & Letham (2018) was one of the winning solutions in the Subseasonal Forecast Rodeo II (Nowak et al., 2020). Prophet is an additive regression model for time-series forecasting that predicts weekly and yearly seasonal trends on top of a piecewise linear or logistic growth curve. We trained the model to predict each grid point independently with yearly seasonality enabled (to capture predictable whether trends) and weekly seasonality disabled.

4.3.7 Salient 2.0

We developed the Salient 2.0 model based on Salient (Schmitt, 2019), a winning solution for the Subseasonal Forecast Rodeo I (Nowak et al., 2020). Salient consists of an ensemble of feed-forward fully-connected neural networks, trained on historical sea surface temperature (SST) data from 1990 to 2017 and an encoding of the day of the year. Salient’s training protocol follows a multi-task learning framework (Ruder, 2017). It starts by training 50 randomly generated fully connected neural networks, each of which provides a prediction for the average temperature and accumulated precipitation at 3, 4, 5, and 6 weeks ahead, at every grid cell. The forecasts are then obtained by combining the predictions for weeks 3 and 4 and for weeks 5 and 6. The final ensemble model forecasts correspond to the mean of the top 10 ensemble members with the lowest validation error.

For Salient 2.0 in this work, the input features were augmented with geopotential heights at different pressure levels (10, 100, 500 and 850 hPa) along with MEI and MJO indices. In
addition, instead of training the ensemble on the whole of the 1990-2017 data, a sequence of models was trained using data up until each of the years in our validation period of 2010-2020. These submodels with earlier training data cut-offs were then used to generate hindcasts that informed the model’s tuning decisions.

### 4.4 Ensembling Models

Ensemble forecasts that combine the predictions of multiple models have been shown to improve the performance of long-, mid-, and short-range operational forecasting (Du et al., 2018; Palmer, 2019; Hwang et al., 2019). Here, we evaluate two ensembling strategies: Uniform Toolkit, which forms an equal-weighted average of the toolkit model forecasts (Krishnamurti et al., 1999), and Online Toolkit, which uses the AdaHedgeD algorithm of Flaspohler et al. (2021) to choose weights adaptively to reflect relative model performance. See Appendices B11 and B12 for more details.

### 5 Experiments

We now turn to evaluating the models of Section 4 on the four subseasonal forecasting tasks of Section 2. We generate forecasts for each Wednesday in the years 2011-2020 and, for each reported evaluation period, we assess both mean RMSE relative to a baseline model and average percentage skill.

#### 5.1 Overall Performance

Table 1 summarizes model performance across the entire ten-year period 2011-2020. On each task, we find that the toolkit models provide both the best RMSE and the best skill performance. For example, on the two precipitation tasks, Climatology++ alone improves upon debiased CFSv2 RMSE by 9% and skill by 161-250%, outperforming each of the meteorological baselines and state-of-the-art learning methods. On the two temperature tasks, CFSv2++ and Persistence++ each outperform all meteorological baselines and state-of-the-art learning methods, with CFSv2++ improving debiased CFSv2 RMSE by 6-7% and skill by 30-53%. On every task, we observe further improvements in both RMSE and skill by ensembling the predictions of the three toolkit models.

Amongst the state-of-the-art learning methods, we find that Prophet performs the best for temperature weeks 5-6 and the two precipitation tasks, while MultiLLR performs the best for temperature weeks 3-4. Amongst the neural network methods (Informer, N-BEATS, and Salient 2.0), Salient 2.0 is the top performer with skill that rivals the other learning methods and precipitation RMSE that outpaces debiased CFSv2. In the more detailed analyses to follow, we omit Informer and N-BEATS due to space constraints and their relatively poor performance overall.

#### 5.2 Performance by Season and by Year

We observe the same trends when performance is disaggregated by season (Figure 1) or by year (Figure 1). For example, in every season, Climatology++ outperforms debiased CFSv2 and each state-of-the-art learner for the two precipitation tasks, while CFSv2++ and Persistence++ outperform debiased CFSv2 and each state-of-the-art learner each season for the two temperature tasks. Similarly and despite significant heterogeneity in all models’ performances from year to year, the toolkit models provide the best RMSE performance in 9 out of 10 years for temperature weeks 3-4 and in 10 out of 10 years for the two precipitation tasks. Indeed, Persistence++ alone dominates the temperature weeks 3-4 baselines and learners every year save 2019, and the more detailed RMSE summary of Appendix C2 shows that the Uniform and Online Toolkit ensembles dominate the precipitation baselines and learners every year. In Figure 1, we observe nearly identical improvement patterns for skill.
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.

| Group     | Model                  | % Improvement over Mean Deb. CFSv2 RMSE | Average % Skill |
|-----------|------------------------|----------------------------------------|-----------------|
|           |                        | TEMPERATURE | PRECIPITATION | TEMPERATURE | PRECIPITATION |
|           |                        | WEEKS 3-4 | WEEKS 5-6 | WEEKS 3-4 | WEEKS 5-6 | WEEKS 3-4 | WEEKS 5-6 |
| Baselines | Climatology            | 0.13      | 2.93    | 7.79    | 7.51    | -       | -       |
|           | Debias CFSv2           | -         | -       | -       | -       | 24.94   | 19.12   |
|           | Persistence             | -109.94   | -170.1  | -28.27  | -31.92  | 10.64   | 6.22    |
| Toolkit   | Climatology++          | 2.06      | 4.83    | 8.86    | 8.57    | 18.61   | 18.87   |
|           | CFSv2+                 | 5.94      | 7.09    | 8.37    | 8.06    | 32.38   | 29.19   |
|           | Persistence++          | 6.00      | 6.43    | 8.61    | 7.89    | 32.4    | 26.73   |
| Learning  | AutoKNN                | 0.93      | 3.22    | 7.73    | 7.33    | 12.43   | 8.56    |
|           | Informer               | -40.61    | -39.57  | -2.05   | -2.53   | 0.55    | 0.01    |
|           | LocalBoosting          | -0.76     | -0.29   | 7.36    | 6.89    | 14.44   | 12.69   |
|           | MultiLLR               | 2.45      | 2.21    | 7.12    | 6.65    | 24.5    | 16.68   |
|           | N-BEATS                | -46.71    | -52.05  | -19.19  | -21.32  | 9.21    | 4.16    |
|           | Prophet                | 1.13      | 3.78    | 8.42    | 8.12    | 20.21   | 19.78   |
|           | Salient 2.0            | -6.95     | -4.05   | 2.97    | 2.65    | 11.24   | 11.77   |
| Ensembles | Uniform Toolkit        | 6.47      | 7.55    | 9.47    | 9.05    | 33.58   | 30.56   |
|           | Online Toolkit         | 6.67      | 7.67    | 9.51    | 9.04    | 33.27   | 30.06   |

5.3 Spatial Performance

Figure 2 displays how the errors of the leading models are distributed across the contiguous U.S. Here we focus on the toolkit models, the best deep learning model (Salient 2.0), the best learning model (Prophet), and the best ensemble model (Online Toolkit) and provide RMSE improvement maps for the remaining models in Appendix C4. At each grid point location, darker green indicates stronger improvement over debiased CFSv2, and we simultaneously witness two noteworthy phenomena. First, the improvements of each model are heterogeneous across space with the strongest improvements often occurring in the Western U.S., in Florida, or in Maine. Second, despite this heterogeneity, the toolkit models tend to outperform the state-of-the-art learners consistently across space.
Figure 1: Per season and per year average skill and improvement over mean debiased CFSv2 RMSE across the contiguous U.S. and the years 2011-2020. Despite their simplicity, the toolkit models (solid lines) consistently outperform debiased CFSv2 and the state-of-the-art learners (dotted lines).
Figure 2: Percentage improvement over mean debiased CFSv2 RMSE in the contiguous U.S. over 2011-2020. White grid points indicate negative or 0% improvement.
5.4 ECMWF Comparison

To compare our toolkit models with the state-of-the-art ECMWF S2S dynamical model, we evaluate on the $1.5^\circ \times 1.5^\circ$ grid and 2016-2020 twice-weekly target date range available from ECMWF S2S data (2021); Vitart et al. (2012). We debias both the ECMWF control forecast and its 50-member ensemble forecast following the operational protocol described by Weyn et al. (2021); see Appendix B13 for more details. Table 2 summarizes model performance. Remarkably, for precipitation, Climatology ++ improves upon both the skill and the RMSE of ECMWF, despite making no use of dynamical model forecasts. Meanwhile, the Uniform Toolkit ensemble outperforms ECMWF in both metrics for all four tasks.

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.

| GROUP            | MODEL             | % IMPROVEMENT OVER MEAN DEBIASED CFSv2 RMSE | AVERAGE % SKILL |
|------------------|-------------------|---------------------------------------------|----------------|
| WEEKS 3-4        | TEMPERATURE       | PRECIPITATION                               | TEMPERATURE | PRECIPITATION |
| Baselines        | Climatology       | 1.56                                        | 3.92        | 8.7          | 7.56          | 22.64 | 15.71 | 2.84 | 1.68 |
|                  | Debiased CFSv2++  | -                                          | -           | -            | -             | 22.64 | 15.71 | 2.84 | 1.68 |
|                  | Persistence       | -105.57                                    | -169.22     | -28.05       | -33.43        | 9.12  | 2.27  | 8.11 | 6.21 |
| Toolkit          | Climatology++     | 3.88                                        | 6.44        | 9.79         | 8.61          | 22.09 | 23.2  | 15.34 | 15.06 |
|                  | CFSv2++           | 5.65                                        | 6.65        | 8.94         | 7.6           | 30.91 | 26.87 | 14.6 | 13.85 |
|                  | Persistence++     | 7.06                                        | 7.86        | 9.06         | 7.57          | 31.46 | 28.04 | 10.03 | 6.61 |
| ECMWF            | Debiased Control  | -29.05                                      | -33.25      | -30.81       | -31.84        | 18.52 | 13.71 | 0.82 | 3.17 |
|                  | Debiased Ensemble | 4.62                                        | 3.69        | 7.90         | 6.41          | 32.27 | 26.61 | 13.12 | 9.10 |
| Ensembles        | Uniform Toolkit   | 7.43                                        | 8.27        | 10.04        | 8.77          | 32.77 | 29.78 | 16.53 | 15.71 |
|                  | Online Toolkit    | 7.2                                        | 7.96        | 10.08        | 8.62          | 32.22 | 28.38 | 17.19 | 15.42 |

5.5 Western U.S. Competition Results

Finally, we evaluate our models on the exact geographic region and target dates of the recent Subseasonal Climate Forecast Rodeo II competition. Specifically, we produce forecasts for the Western U.S. region, delimited by latitudes 25N to 50N and longitudes 125W to 93W, at a $1^\circ \times 1^\circ$ resolution for a total of $G = 514$ grid points. Forecasts were issued every two weeks for a yearlong period with initial issuance date October 29, 2019 and final issuance date October 27, 2020, leading to a noisier evaluation with only 26 observations.

Table C5 in Appendix C6 compares the predictive accuracy of the models studied in this work with the accuracy of the contest baselines (debiased CFSv2, Climatology, and, for precipitation only, the Rodeo I Salient model of Schmitt (2019)) and the performance of the top competitors for each task. For temperature weeks 3-4, Persistence++ provides a 16.59% improvement over the mean debiased CFSv2 RMSE, outperforming the contest baselines, the state-of-the-art learning methods, and all but two of the competitors (the top three competitors improved by 17.12%, 16.67%, and 15.47%). For temperature weeks 5-6, CFSv2++ provides a 9.26% improvement over debiased CFSv2 and, despite its simplicity, outperforms the contest baselines, the state-of-the-art learning methods, and all of the competitors in the subseasonal forecasting competition (the top competitor improved by 8.47%). On this task, the Uniform and Online Toolkit ensembles also outperform all competitors.

On the precipitation tasks, the Salient baseline performed strongly and ultimately placed second and fourth respectively for the weeks 3-4 and weeks 5-6 tasks. Our Salient 2.0 model also performs remarkably well, outscoring all contestants and baselines with 12.65% improvement for weeks 3-4. For comparison, the top competitors for weeks 3-4 and weeks 5-6 improved by 11.54% and 8.63% respectively. Our Uniform Toolkit ensemble outperforms the remaining baselines and state-of-the-art learning methods but falls short of the exceptional Salient performance. In this setting, applying the adaptive online learning ensemble to the
union of the toolkit models and the state-of-the-art learners (denoted by Online Toolkit + Learning in Table C5) allows the user to exploit the irregular complementary benefits of the learning methods yielding 12.52% and 8.18% improvements in weeks 3-4 and weeks 5-6.

6 Conclusions

In this work, we benchmarked a toolkit of learning models for subseasonal forecasting that augment traditional forecasters with simple but effective learned enhancements. These simple, low-cost strategies are 10% more accurate and 329% more skillful than the U.S. operational CFSv2 and outperform both state-of-the-art machine and deep learning methods and the leading ECMWF dynamical model when applied to temperature and precipitation forecasting in the contiguous U.S. While we showcased these techniques with CFSv2 forecasts, the same procedures can be used to integrate and enhance any dynamical model forecast. Overall, the insights presented in this study enable substantial skill improvements for state-of-the-art dynamical forecasting models, thus helping advance extended range forecasting. We release both our model code and our routinely updated SubseasonalClimateUSA dataset to facilitate future subseasonal benchmarking.

Data Availability Statement

The SubseasonalClimateUSA dataset is available for download via the subseasonal_data Python package: https://github.com/microsoft/subseasonal_data. We acknowledge the agencies that support the SubX system, and we thank the climate modeling groups (Environment Canada, NASA, NOAA/NCEP, NRL and University of Miami) for producing and making available their model output. NOAA/MAPP, ONR, NASA, NOAA/NWS jointly provided coordinating support and led development of the SubX system. This work is based on S2S data. S2S is a joint initiative of the World Weather Research Programme (WWRP) and the World Climate Research Programme (WCRP). The original S2S database is hosted at ECMWF as an extension of the TIGGE database.

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References

Arcomano, T., Szunyogh, I., Pathak, J., Wikner, A., Hunt, B. R., & Ott, E. (2020). A machine learning-based global atmospheric forecast model. Geophysical Research Letters, 47(9), e2020GL087776.

Arguez, A., Durre, I., Applequist, S., Vose, R. S., Squires, M. F., Yin, X., … Owen, T. W. (2012). NOAA’s 1981–2010 US climate normals: an overview. Bulletin of the American Meteorological Society, 93(11), 1687–1697.

Chen, M., Shi, W., Xie, P., Silva, V. B., Kousky, V. E., Wayne Higgins, R., & Janowiak, J. E. (2008). Assessing objective techniques for gauge-based analyses of global daily precipitation. Journal of Geophysical Research: Atmospheres, 113(D4).

Cohen, J., Coumou, D., Hwang, J., Mackey, L., Orenstein, P., Totz, S., & Tziperman, E. (2018). S2S reboot: An argument for greater inclusion of machine learning in subseasonal to seasonal (S2S) forecasts. WIREs Climate Change, 10. doi: 10.1002/wcc.567.

Du, J., Berner, J., Buizza, R., Charron, M., Houtekamer, P. L., Hou, D., … others (2018). Ensemble methods for meteorological predictions. Office note (National Centers for Environmental Prediction (U.S.)).

ECMWF S2S data. (2021). Ecmwf S2S ecmf: Ecmwf ensemble. https://iridl.ldeo.columbia.edu/SOURCES/.ECMWF/.S2S/.ECMWF/.
Fan, Y., & Van den Dool, H. (2008). A global monthly land surface air temperature analysis for 1948–present. *Journal of Geophysical Research: Atmospheres, 113*(D1).

Flaspohler, G., Orabona, F., Cohen, J., Mouatadid, S., Oprescu, M., Orenstein, P., & Mackey, L. (2021). Online learning with optimism and delay. In *International conference on machine learning*.

He, S., Li, X., DelSole, T., Ravikumar, P., & Banerjee, A. (2020). Sub-seasonal climate forecasting via machine learning: Challenges, analysis, and advances. *arXiv preprint arXiv:2006.07972*.

He, S., Li, X., DelSole, T., Ravikumar, P., & Banerjee, A. (2021). Sub-seasonal climate forecasting via machine learning: Challenges, analysis, and advances. In *Proceedings of the aaii conference on artificial intelligence* (Vol. 35, pp. 169–177).

Hendrycks, D., & Gimpel, K. (2016). Gaussian error linear units (gelus). *arXiv preprint arXiv:1606.08415*.

Hwang, J., Orenstein, P., Cohen, J., & Mackey, L. (2018). The SubseasonalRodeo dataset. Harvard Dataverse. Retrieved from https://doi.org/10.7910/DVN/IHBANG (Harvard Dataverse).

Hwang, J., Orenstein, P., Cohen, J., Pfeiffer, K., & Mackey, L. (2019). Improving sub-seasonal forecasting in the western U.S. with machine learning. In *Proceedings of the 25th acm sigkdd international conference on knowledge discovery & data mining* (p. 2325–2335). New York, NY, USA: Association for Computing Machinery. Retrieved from https://doi.org/10.1145/3292500.3330674 doi: 10.1145/3292500.3330674

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., … others (1996). The ncep/near 40-year reanalysis project. *Bulletin of the American meteorological Society, 77*(3), 437–472.

Kirtman, B., Pegion, K., DelSole, T., Tippett, M., Robertson, A., Bell, M., … others (2017). The subseasonal experiment (subx). *IRI Data Library, 10, D8PG249H*.

Krishnamurti, T., Kistawal, C. M., LaRow, T. E., Bachiochi, D. R., Zhang, Z., Williford, C. E., … Surendran, S. (1999). Improved weather and seasonal climate forecasts from multimodel superensemble. *Science, 285*(5433), 1548–1550.

Lang, A. L., Pegion, K., & Barnes, E. A. (2020). Introduction to special collection: “bridging weather and climate: Subseasonal-to-seasonal (S2S) prediction”. *Journal of Geophysical Research: Atmospheres, 125*(4), e2019JD031833.

Lea, D., Mirouze, I., Martin, M., King, R., Hines, A., Walters, D., & Thurlow, M. (2015). Assessing a new coupled data assimilation system based on the met office coupled atmosphere–land–ocean–sea ice model. *Monthly Weather Review, 143*(11), 4678–4694.

Li, L., Schmitt, R. W., Ummenhofer, C. C., & Karnauskas, K. B. (2016). Implications of north atlantic sea surface salinity for summer precipitation over the us midwest: Mechanisms and predictive value. *Journal of Climate, 29*(9), 3143–3159.

Lorenz, E. (1963). Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences, 20*(2), 130–141.

Makridakis, S., & Hibon, M. (2000). The m3-competition: results, conclusions and implications. *International journal of forecasting, 16*(4), 451–476.

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The m4 competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting, 36*(1), 54–74.

Merryfield, W. J., Baehr, J., Butté, L., Becker, E. J., Butler, A. H., Coelho, C. A., … others (2020). Current and emerging developments in subseasonal to decadal prediction. *Bulletin of the American Meteorological Society, 101*(6), E869–E896.

Mittermaier, M. P. (2008). The potential impact of using persistence as a reference forecast on perceived forecast skill. *Weather and forecasting, 23*(5), 1022–1031.

MJO data. (2021). *Real-time multivariate Madden Julian Oscillation index*. https://iridl.ldeo.columbia.edu/dochelp/QA/Technical/citation.html.

Mouatadid, S., Orenstein, P., Flaspohler, G., Cohen, J., Oprescu, M., Fraenkel, E., &
Mackey, L. (2022). Adaptive bias correction for improved subseasonal forecasting. *arXiv preprint arXiv:2209.10666.*

NOAA/OAR/ESRL PSL. (2021a). *CPC global temperature data.* [ftp://ftp.cdc.noaa.gov/Datasets/cpc_global_temp/](ftp://ftp.cdc.noaa.gov/Datasets/cpc_global_temp/).

NOAA/OAR/ESRL PSL. (2021b). *CPC global unified precipitation data.* [ftp://ftp.cdc.noaa.gov/Datasets/cpc_global_precip/](ftp://ftp.cdc.noaa.gov/Datasets/cpc_global_precip/).

NOAA/OAR/ESRL PSL. (2021c). *CPC US unified precipitation data.* [ftp://ftp.cdc.noaa.gov/Datasets/cpc_us_precip/](ftp://ftp.cdc.noaa.gov/Datasets/cpc_us_precip/).

NOAA/OAR/ESRL PSL. (2021d). *Multivariate El Niño/Southern Oscillation (ENSO) index.* [https://psl.noaa.gov/enso/mei/data/meiv2.data](https://psl.noaa.gov/enso/mei/data/meiv2.data).

NOAA/OAR/ESRL PSL. (2021e). *NCEP reanalysis data.* Geopotential height: [ftp://ftp.cdc.noaa.gov/Datasets/ncep.reanalysis.dailyavgs/pressure/](ftp://ftp.cdc.noaa.gov/Datasets/ncep.reanalysis.dailyavgs/pressure/), Relative humidity: [ftp://ftp.cdc.noaa.gov/Datasets/ncep.reanalysis/surface/](ftp://ftp.cdc.noaa.gov/Datasets/ncep.reanalysis/surface/), Sea level pressure: [ftp://ftp.cdc.noaa.gov/Datasets/ncep.reanalysis/surface_gauss/](ftp://ftp.cdc.noaa.gov/Datasets/ncep.reanalysis/surface_gauss/).

NOAA/OAR/ESRL PSL. (2021f). *NOAA high resolution SST data.* [ftp://ftp.cdc.noaa.gov/Projects/Datasets/noaa.oisst.v2.highres/](ftp://ftp.cdc.noaa.gov/Projects/Datasets/noaa.oisst.v2.highres/).

Nowak, K., Ferguson, I. M., Beardsley, J., & Brekke, L. D. (2020). Enhancing western united states sub-seasonal forecasts: Forecast rodeo prize competition series. In *Agu fall meeting 2020.*

Nowak, K., Webb, R., Cifelli, R., & Brekke, L. (2017). Sub-seasonal climate forecast rodeo. In *2017 agu fall meeting, new orleans, la* (pp. 11–15).

Oreshkin, B. N., Carpov, D., Chapados, N., & Bengio, Y. (2020). N-BEATS: neural basis expansion analysis for interpretable time series forecasting. In *8th international conference on learning representations, ICLR 2020, addis ababa, ethiopia, april 26-30, 2020.* OpenReview.net. Retrieved from [https://openreview.net/forum?id=r1ecqn4YwB](https://openreview.net/forum?id=r1ecqn4YwB).

Palmer, T. (2019). The ecmwf ensemble prediction system: Looking back (more than) 25 years and projecting forward 25 years. *Quarterly Journal of the Royal Meteorological Society, 145,* 12–24.

Pandas development team, T. (2020, February). *pandas-dev/pandas: Pandas.* Zenodo. Retrieved from [https://doi.org/10.5281/zenodo.3509134](https://doi.org/10.5281/zenodo.3509134) doi: 10.5281/zenodo.3509134.

Pegion, K., Kirtman, B. P., Becker, E., Collins, D. C., LaJoie, E., Burgman, R., ... others (2019). The subseasonal experiment (subx): A multimodel subseasonal prediction experiment. *Bulletin of the American Meteorological Society, 100*(10), 2043–2060.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). Catboost: unbiased boosting with categorical features. In *Advances in neural information processing systems* (pp. 6638–6648).

Reynolds, R. W., Smith, T. M., Liu, C., Chelton, D. B., Casey, K. S., & Schlax, M. G. (2007). Daily high-resolution-blended analyses for sea surface temperature. *Journal of climate, 20*(22), 5473–5496.

Ruder, S. (2017). An overview of multi-task learning in deep neural networks. *arXiv preprint arXiv:1706.05098.*

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., ... others (2014). The ncep climate forecast system version 2. *Journal of climate, 27*(6), 2185–2208.

Schmitt, R. (2019). *Salient predictions: Validation summary.* [https://storage.googleapis.com/content.saliencypredictions.com/Salient%20Validation%20Summary.pdf](https://storage.googleapis.com/content.saliencypredictions.com/Salient%20Validation%20Summary.pdf). (Accessed: 2021-05-29)

Schmitt, R. (2021, Jul.). private communication.

Srinivasan, V., Khim, J., Banerjee, A., & Ravikumar, P. (2021). Subseasonal climate prediction in the western us using bayesian spatial models. In *Uncertainty in artificial intelligence* (Vol. 37).

SubX data. (2021). [http://iridl.ldeo.columbia.edu/SOURCES/.Models/](http://iridl.ldeo.columbia.edu/SOURCES/.Models/)
Taylor, S. J., & Letham, B. (2018). Forecasting at scale. *The American Statistician, 72*(1), 37–45.

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., … SciPy 1.0 Contributors (2020). SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods, 17*, 261–272. doi: 10.1038/s41592-019-0686-2

Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., … others (2017). The subseasonal to seasonal (S2S) prediction project database. *Bulletin of the American Meteorological Society, 98*(1), 163–173.

Vitart, F., Robertson, A. W., & Anderson, D. L. (2012). Subseasonal to seasonal prediction project: Bridging the gap between weather and climate. *Bulletin of the World Meteorological Organization, 61*(2), 23.

Wang, C., Jia, Z., Yin, Z., Liu, F., Lu, G., & Zheng, J. (2021). Improving the accuracy of subseasonal forecasting of China precipitation with a machine learning approach. *Front. Earth Sci, 9*, 659310.

Watson-Parris, D. (2021). Machine learning for weather and climate are worlds apart. *Philosophical Transactions of the Royal Society A, 379*(2194), 20200098.

Wes McKinney. (2010). Data Structures for Statistical Computing in Python. In Stefan van der Walt & Jarrod Millman (Eds.), *Proceedings of the 9th Python in Science Conference* (p. 56 - 61). doi: 10.25080/Majora-92bf1922-00a

Weyn, J. A., Durran, D. R., Caruana, R., & Cresswell-Clay, N. (2021). Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. *Journal of Advances in Modeling Earth Systems, 13*(7), e2021MS002502. doi: https://doi.org/10.1029/2021MS002502

Wheeler, M. C., & Hendon, H. H. (2004). An all-season real-time multivariate mjo index: Development of an index for monitoring and prediction. *Monthly weather review, 132*(8), 1917–1932.

White, C. J., Carlsen, H., Robertson, A. W., Klein, R. J., Lazo, J. K., Kumar, A., … Zebiak, S. E. (2017). Potential applications of subseasonal-to-seasonal (S2S) predictions. *Meteorological Applications, 24*(3), 315-325. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/met.1654 doi: 10.1002/met.1654

Wilks, D. S. (2011). *Statistical methods in the atmospheric sciences* (Vol. 100). Academic press.

Wolter, K., & Timlin, M. S. (1993). Monitoring enso in coads with a seasonally adjusted principal. In *Proc. of the 17th climate diagnostics workshop, norman, ok, noaa/nmc/cac, nssl, oklahoma clim. survey, cimms and the school of meteor., univ. of oklahoma*, 52 (Vol. 57).

Wolter, K., & Timlin, M. S. (1998). Measuring the strength of ENSO events: How does 1997/98 rank? *Weather, 53*(9), 315–324.

Wolter, K., & Timlin, M. S. (2011). El Niño/Southern Oscillation behaviour since 1871 as diagnosed in an extended multivariate ENSO index (MEI.ext). *International Journal of Climatology, 31*(7), 1074–1087.

Xie, P., Chen, M., & Shi, W. (2010). CPC unified gauge-based analysis of global daily precipitation. In *Preprints, 24th conf. on hydrology, atlanta, ga, amer. meteor. soc* (Vol. 2).

Xie, P., Chen, M., Yang, S., Yatagai, A., Hayasaka, T., Fukushima, Y., & Liu, C. (2007). A gauge-based analysis of daily precipitation over east asia. *Journal of Hydrometeorology, 8*(3), 607–626.

Yamagami, A., & Matsueda, M. (2020). Subseasonal forecast skill for weekly mean atmospheric variability over the northern hemisphere in winter and its relationship to midlatitude teleconnections. *Geophysical Research Letters, 47*(17), e2020GL088508.

Zhou, H., Zhang, S., Peng, J., Zhang, S., Li, J., Xiong, H., & Zhang, W. (2021). Informer: Beyond efficient transformer for long sequence time-series forecasting. In *The thirty-fifth AAAI conference on artificial intelligence, AAAI 2021* (p. online). AAAI Press.
Appendix A SubseasonalClimateUSA Supplementary Details

The subseasonal_data Python package provides a detailed description of the SubseasonalClimateUSA dataset contents, sources, and processing steps.

A1 Western U.S. Competition Data Details

Following Hwang et al. (2019), for the Western U.S. competition experiments of Section 5.5, the sea surface temperature and sea ice concentration variables were formed by identifying the top three principal components for each variable restricted to the Pacific basin region (20S to 65N, 150E to 90W) using loadings from 1981-2010.
Appendix B  Model Implementation Details

This section describes the implementation details for each learning model, including the training, hyperparameter tuning, and validation protocols. All models were implemented in Python 3.

B1 Climatology++ (Section 4.2.1)

Climatology++ was trained and tuned following the protocol described in Mouatadid et al. (2022). Figure B1 displays the selected window length (the span $s$) and number of years $Y$ for each target date in 2011-2020 when forecasting for the contiguous U.S. We see that the temperature models preferred fewer training years and larger windows around the target day in recent history but focused more exclusively on the target day of year (via a span of 0) in 2013-2016 and preferred more training years in 2011. Meanwhile, the precipitation models selected the largest available window (corresponding to higher bias but lower variance estimates) for nearly every target date.

![Climatology++ hyperparameters automatically selected for each target date in 2011-2020](image)

Figure B1: Climatology++ hyperparameters automatically selected for each target date in 2011-2020

B2 CFSv2++ (Section 4.2.2)

B20.1 Training  CFSv2 was trained and tuned following the protocol described in Mouatadid et al. (2022). Figure B2 displays the selected window length (the span $s$), lead time range, and issuance date count for each target date in 2011-2020 when forecasting for the contiguous U.S. In each task, we observe a significant amount of variability in the optimal span, lead, and date count selections, highlighting the value of adaptive ensembling and debiasing over the static ensembling and debiasing strategies employed by standard debiased CFSv2.

B3 Persistence++ (Section 4.2.3)

Persistence++ was trained and tuned following the protocol described in Mouatadid et al. (2022). Figures B3 to B6 display the learned Persistence++ regression weights for the final target date in 2020 for each of the four contiguous U.S. forecasting tasks. In each case, we observe significant spatial variation in the optimal weights used to combine lagged measurements, climatology, and CFSv2 ensemble forecasts.

B4 AutoKNN (Section 4.3.1)

B40.1 Training  The k-nearest neighbors (KNN) step of AutoKNN identifies a set of historical dates most similar to the target date and while the autoregression step forecasts a weighted locally linear combination of the anomalies measured on similar dates and recent dates. For a given target date $t^*$ and lead time $l^*$, the AutoKNN training set is restricted to
Figure B2: CFSv2++ hyperparameters automatically selected for each target date in 2011-2020

Figure B3: Spatial variation in Persistence++ learned regression weights when forecasting temperature in weeks 3-4 for the final target date, December 23, 2020.

data fully observable one day prior to the issuance date, that is, to dates \( t \leq t^* - l^* - L - 1 \) where \( L = 14 \) represents the forecast period length.

B4.0.2 Tuning All hyperparameters were set to the default values specified in Hwang et al. (2019).

B5 Informer (Section 4.3.2)

B5.0.1 Features For a given grid point and target date \( t^* \), the input features used to construct a forecast are the lagged target variable observations from dates \( t_{\text{last}}^*, t_{\text{last}} - 1, t_{\text{last}} - 2, \ldots, t_{\text{last}} - 95 \) for where \( t_{\text{last}} = t^* - l^* - L \) represents the last complete observation prior to \( t^* \) and \( L = 14 \) represents the forecast period length.
B50.2 Training  We divide the set of target dates in 2011–2020 into consecutive, non-overlapping four-month blocks and retrain the Informer model after every four-month block. For a given lead time $l^*$, grid point, and four-month block beginning with date $t^*$:

1. The training set is chosen to start at most 10,000 days before $t$ (or at the beginning of the training set, whichever is later) and then ends 301 days before $t$.
2. The validation set is chosen to start 300 days before $t$ and to end on the date prior to $t^* - l^* - L$.
3. We use early stopping with patience equal to three to determine when to stop the training: when we have three consecutive epochs $e + 1, e + 2, e + 3$ with validation loss no
lower than that of epoch \( e \), we terminate training and use the model at epoch \( e \) as the final trained model.

4. We use the trained model to generate forecasts for each target date in the four-month block.

B50.3 Tuning We use the default Informer architecture and hyperparameters for univariate time series forecasting: the model has 3 encoder layers, 2 decoder layers, and has an 8-headed attention with 7-dimensional keys and feed-forward layers with 1024 hidden units, and has GeLU activations Hendrycks & Gimpel (2016).

B6 LocalBoosting (Section 4.3.3)

B60.1 Training For a given target date \( t^\ast \) and lead time \( l^\ast \), the LocalBoosting training set \( T \) is restricted to data fully observable one day prior to the issuance date, that is, to dates \( t \leq t^\ast - l^\ast - L - 1 \) where \( L = 14 \) represents the forecast period length. LocalBoosting uses CatBoost Prokhorenkova et al. (2018) to regress, for each gridpoint and each date, the value of a set of lagged weather variables in a geographic region around the gridpoint.

B60.2 Tuning There are two hyperparameters to consider: (i) which lagged weather variables to use; and (ii) the number of neighborhood cells around a gridpoint to define the geographic region. Bounding boxes of with side length of 2 or 3 cells were considered. Larger sizes were computationally infeasible. In each case, the 10 or 20 most important features in the SubseasonalClimateUSA dataset were considered. Here, features were chosen by their performance over 2001-2010 in terms of RMSE.

For each target date, LocalBoosting is run with the hyperparameter configuration that achieved the smallest mean RMSE over the preceding 3 years. See Figure B7 for a visualization of the hyperparameters automatically selected for each target date in 2011-2020.

B7 MultiLLR (Section 4.3.4)

B70.1 Training For a given target date \( t^\ast \) and lead time \( l^\ast \), the MultiLLR training set is restricted to data fully observable one day prior to the issuance date, that is, to dates...
Figure B7: LocalBoosting hyperparameters automatically selected for each target date in 2011-2020.

\[ t \leq t^* - l^* - L - 1 \]

where \( L = 14 \) represents the forecast period length. The coarse-grained NWP input feature \( \text{nmme}_\text{wo}_\text{ccsm3}_\text{nasa} \) of Hwang et al. (2019) was replaced with the daily debiased CFSv2 forecast features

- \( \text{subx}_\text{cfsv2}_\text{tmp2m-14.5d_shift15} \) and \( \text{subx}_\text{cfsv2}_\text{tmp2m-0.5d_shift15} \) for predicting temperature at weeks 3-4,
- \( \text{subx}_\text{cfsv2}_\text{tmp2m-28.5d_shift29} \) and \( \text{subx}_\text{cfsv2}_\text{tmp2m-0.5d_shift29} \) for predicting temperature at weeks 5-6,
- \( \text{subx}_\text{cfsv2}_\text{precip-14.5d_shift15} \) and \( \text{subx}_\text{cfsv2}_\text{precip-0.5d_shift15} \) for predicting precipitation at weeks 3-4, and
- \( \text{subx}_\text{cfsv2}_\text{precip-28.5d_shift29} \) and \( \text{subx}_\text{cfsv2}_\text{precip-0.5d_shift29} \) for predicting precipitation at weeks 5-6.

**B70.2 Tuning** All hyperparameters were set to the default values specified in Hwang et al. (2019), save for the tolerance parameter which was set to 0.001 to accommodate the new RMSE selection criterion.

**B8 N-BEATS (Section 4.3.5)**

**B80.1 Features** For a given grid point and target date \( t^* \), the input features used to construct a forecast are the lagged target variable observations from dates \( t_{last}, t_{last} - 4, t_{last} - 8, \ldots, t_{last} - 48 \) for where \( t_{last} = t^* - l^* - L \) represents the last complete observation prior to \( t^* \) and \( L = 14 \) represents the forecast period length.

**B80.2 Training** We divide the set of target dates in 2011-2020 into consecutive, non-overlapping two-month blocks and retrain the N-BEATS model after every two-month block. For a given lead time \( l^* \), grid point, and two-month block beginning with date \( t^* \):

1. We train on all dates \( t \leq t^* - l^* - L \).
2. For the initial two-month block, we train for 30 epochs.
3. For subsequent two-month blocks, we initialize our model weights to the learned weights from the prior block and then fine-tune for 8 epochs.
4. We use the trained model to generate forecasts for each target date in the two-month block.

**B80.3 Tuning** We use the default N-BEATS architecture and hyperparameters for univariate time series forecasting Oreshkin et al. (2020). The N-BEATS model has two stacks, where each stack is used to understand different patterns. Each stack consists of three blocks,
which themselves are each comprised of six fully connected layers with ReLU activations. We used the Adam optimizer with learning rate 0.001 and a batch size of 512.

**B9 Prophet (Section 4.3.6)**

**B9.1 Training** Prophet takes as input a sequence of (univariate) time-series values and then predicts the next $k$ dates from those, arbitrarily far in the future.

First, we split the problem into a many univariate time-series prediction problems. When evaluating, we consider periods of 4 months (e.g. January 2010 - April 2010), train the model on all available historical temperatures (which may depend on the lead time) at that grid point, and make predictions for that four month period. We then run this for all relevant periods of four months.

**B9.2 Tuning** The prophet model is trained in the univariate mode with yearly seasonality on (to capture predictable weather trends), weekly seasonality off (as weekends are unlikely to be special).

**B10 Salient 2.0 (Section 4.3.7)**

Salient 2.0 relies on two sources of sea surface temperature training data. The first data source is the weekly sea surface temperature from NOAA Reynolds et al. (2007) and covers dates from 17 January 1990 to 02 February 2017. This dataset contains weekly data centered around Wednesdays and has a $1^\circ \times 1^\circ$ resolution. It was re-gridded to a $4^\circ \times 4^\circ$ using spline interpolation of order equal to 2, under the Python Scipy package (Virtanen et al., 2020).

For dates from February 2017 to present, a second source of sea surface temperature data from the MET Office (Lea et al., 2015) is used. This dataset has a daily temporal resolution and is averaged to obtain weekly data centered around Wednesdays. This data is initially downloaded in a $0.25^\circ \times 0.25^\circ$ spatial resolution and is re-gridded to a $4^\circ \times 4^\circ$. A linear interpolation is then used to fill in any missing values (under the Python Scipy package Virtanen et al. (2020)).

**B10.1 Training** Salient 2.0 is an ensemble of 50 feed-forward fully connected neural networks. All 50 neural networks are trained on a pre-determined combination of input features, including weekly sea surface temperature, MEI, as well as the phase and amplitude features of MJO. The combinations of input features considered are:

- `d2wk_cop_sst`: sea surface temperature,
- `d2wk_cop_sst_mei`: sea surface temperature and ENSO,
- `d2wk_cop_sst_mjo`: sea surface temperature and MJO,
- `d2wk_cop_sst_mei_mjo`: sea surface temperature, ENSO and MJO.

In total, four ensemble models, corresponding to the four input feature combinations above, each including 50 neural networks, are trained. Each ensemble model is trained in a rolling fashion, where the start year of the training dataset is 1990 and the ensemble is trained up until each year in the range [2006, 2019], where a model ending on a year $y$ is used to generate forecasts for target dates with year $y + 1$.

For each of the 50 neural networks within a given ensemble model, the input features can further be augmented using a time vector obtained by converting dates to a float representing the fraction of the year passed by that date. The addition of the time vector is decided by generating a random integer in the range [0, 1], with 1 corresponding to the addition of the time vector and 0 otherwise. Additionally, for each of the 50 neural networks, the input feature vector for an individual training example consists of a concatenation of the prior 10 weeks of data.
For each of the 50 neural networks within a given ensemble model, the output consists of a prediction for the average temperature and accumulated precipitation at 3, 4, 5 and 6 weeks ahead. The predictions for weeks 3 and 4 and the predictions for weeks 5 and 6 are combined separately, by averaging temperatures and summing precipitation. The top 10 neural networks with the lowest validation error are selected as the final ensemble members. The final predictions for each ensemble model correspond to the mean of the 10 selected ensemble members.

**B100.2 Tuning** Each of the 50 neural networks within a given ensemble model is trained using a batch size equal to 128 and a train ratio equal to 0.89. In addition, each neural network’s hyperparameters are randomly generated, with the number of epochs sampled in the range \[100, 500\], the number of layers in the range \[3, 7\], and the number of units per layer in the range \[100, 600\].

At test time, for each target date, Salient 2.0 is run using the ensemble model that achieved the smallest mean RMSE over the preceding 3 years. Figure B8 shows which ensemble models were used to generate predictions for which target dates.

![Figure B8: Salient 2.0 hyperparameters automatically selected for each target date in 2011-2020.](image)

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**B11 Uniform Ensemble (Section 4.4)**

We consider two Uniform Ensemble models, where the ensemble is produced using a set of models \(C\) as input:

1. **Uniform Toolkit**: \(C = \{ \text{Climatology++}, \text{CFSv2++}, \text{Persistence++} \} \)
2. **Uniform Toolkit + Learning**: \(C = \{ \text{Climatology++}, \text{CFSv2++}, \text{Persistence++}, \text{LocalBoosting}, \text{MultiLLR}, \text{AutoKNN}, \text{Prophet}, \text{Salient 2.0} \} \), the toolkit models plus all learning models save the very low performing Informer and N-BEATS models.

Uniform ensemble forecasts are produced as the uniform or unweighted average of input models. Letting \(X_{t,c}\) be the forecast made by model \(c \in C\) on target date \(t\), we produce the forecast:

\[
\hat{y}_t = \frac{1}{|C|} \sum_{c \in C} X_{t,c}.
\]

**B12 Online Ensemble (Section 4.4)**

We consider two Online Ensemble models, where the ensemble is produced using a set of models \(C\) as input:

1. **Online Toolkit**: \(C = \{ \text{Climatology++}, \text{CFSv2++}, \text{Persistence++} \} \)
2. **Online Toolkit + Learning**: \( C = \{ \text{Climatology}++, \text{CFSv2}++, \text{Persistence}++, \text{LocalBoosting}, \text{MultiLLR}, \text{AutoKNN}, \text{Prophet}, \text{Salient 2.0} \} \), the toolkit models plus all learning models save the very low performing Informer and N-BEATS models.

To learn a time-dependent adaptive ensemble weight \( w_t \), we employ the online learning method presented in Flaspohler et al. (2021). We applied the AdaHedgeD algorithm with the recommended recent_g optimism setting. The algorithm was run with a delay parameter of \( D = 2 \) for the 3-4 weeks horizon tasks and \( D = 3 \) for the 5-6 weeks horizon tasks. We ran the online learning algorithm over the full set of target dates \( T = 520 \), without performing the yearly resetting suggested in the original implementation. The learner optimized the RMSE loss over gridpoints in the region of interest, as described in the experimental details of Flaspohler et al. (2021).

Online ensemble forecasts are produced as the weighted average of input models, with weight \( w_t \) determined by the online learning algorithm. Letting \( X_{t,c} \) be the forecast made by model \( c \in C \) on target date \( t \) and \( w_t \) be the weights produced by AdaHedgeD, we produce the forecast:

\[
\hat{y}_t = \sum_{c \in C} w_{t,c} * X_{t,c}.
\]

**B13 Debiased ECMWF (Section 5.4)**

We implement the operational ECMWF bias correction protocol detailed in Weyn et al. (2021). For each target forecast date, we debias both our ECMWF control and ensemble forecasts using the last 20 years of reforecasts with dates within ±6 days from the target forecast date. The average of the 1 control and 10 ensemble reforecasts on the 1.5x1.5 degree grid are used for debiasing.
Appendix C Supplementary Results

C1 Percentage Improvement over Meteorological Baselines

To highlight the improvement of individual toolkit models over their traditional counterparts, Figures C1 and C2 show the percentage RMSE improvements of Climatology++, CFSv2++, and Persistence++ relative to their respective baselines Climatology, debiased CFSv2, and Persistence by season and by year.

For all four tasks, the toolkit models are consistently better across seasons and years. The result is particularly striking for Persistence++ and highlights the value of integrating lagged measurements, numerical weather prediction, and climatology. Figures C1 and C2 show the per season and per year improvement of each toolkit model over its corresponding baseline across the contiguous U.S. and the years 2011-2020. Note the learned toolkit benchmarks yield consistent improvements in mean RMSE.

![Figure C1: Per season improvement of each toolkit model over its corresponding baseline across the contiguous U.S. and the years 2011-2020. The learned toolkit benchmarks yield consistent improvements in mean RMSE.](image1)

![Figure C2: Per year improvement of each toolkit model over its corresponding baseline across the contiguous U.S. and the years 2011-2020. The learned toolkit benchmarks yield consistent improvements in mean RMSE.](image2)

C2 Yearly Percentage Improvement over Mean Debiased CFSv2 RMSE

Tables C1 and C2 present the yearly improvement of each model over debiased CFSv2, as measured by mean RMSE across the contiguous U.S. in the years 2011-2020.
Table C1: Percentage improvement over mean debiased CFSv2 RMSE when forecasting temperature in the contiguous 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.

| Group | Model | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Overall |
|-------|-------|------|------|------|------|------|------|------|------|------|------|--------|
| Baselines | Climatology | 0.09 | 0.89 | 0.00 | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Toolkit | Climatology++ | 0.68 | 0.68 | 0.70 | 0.72 | 0.74 | 0.76 | 0.78 | 0.80 | 0.82 | 0.84 | 0.86 |
| | CFSSv2++ | 9.35 | 8.71 | 7.36 | 6.28 | 5.89 | 5.94 | 5.98 | 5.98 | 5.98 | 5.98 | 5.98 |
| | Persistence++ | 7.06 | 7.06 | 7.06 | 7.06 | 7.06 | 7.06 | 7.06 | 7.06 | 7.06 | 7.06 | 7.06 |
| Learning | AutoKNN | 0.02 | 0.00 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| | LocalBoosting | -3.74 | -3.74 | -3.74 | -3.74 | -3.74 | -3.74 | -3.74 | -3.74 | -3.74 | -3.74 | -3.74 |
| | MultiLLR | 6.37 | 5.97 | 5.57 | 5.17 | 4.77 | 4.37 | 4.00 | 3.73 | 3.47 | 3.21 | 3.00 |
| | Prophet | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 |
| | Salient 2.0 | -7.40 | -7.40 | -7.40 | -7.40 | -7.40 | -7.40 | -7.40 | -7.40 | -7.40 | -7.40 | -7.40 |
| Ensembles | Uniform Toolkit | 6.23 | 6.23 | 6.23 | 6.23 | 6.23 | 6.23 | 6.23 | 6.23 | 6.23 | 6.23 | 6.23 |
| Online Toolkit | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 |

Table C2: Percentage improvement over mean debiased CFSv2 RMSE when forecasting precipitation in the contiguous 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.

| Group | Model | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Overall |
|-------|-------|------|------|------|------|------|------|------|------|------|------|--------|
| Baselines | Climatology | 5.37 | 5.37 | 5.37 | 5.37 | 5.37 | 5.37 | 5.37 | 5.37 | 5.37 | 5.37 | 5.37 |
| Toolkit | Climatology++ | 6.03 | 6.03 | 6.03 | 6.03 | 6.03 | 6.03 | 6.03 | 6.03 | 6.03 | 6.03 | 6.03 |
| | CFSSv2++ | 8.62 | 8.62 | 8.62 | 8.62 | 8.62 | 8.62 | 8.62 | 8.62 | 8.62 | 8.62 | 8.62 |
| | Persistence++ | 7.60 | 7.60 | 7.60 | 7.60 | 7.60 | 7.60 | 7.60 | 7.60 | 7.60 | 7.60 | 7.60 |
| Learning | AutoKNN | 6.33 | 6.33 | 6.33 | 6.33 | 6.33 | 6.33 | 6.33 | 6.33 | 6.33 | 6.33 | 6.33 |
| | LocalBoosting | 4.37 | 4.37 | 4.37 | 4.37 | 4.37 | 4.37 | 4.37 | 4.37 | 4.37 | 4.37 | 4.37 |
| | MultiLLR | 4.91 | 4.91 | 4.91 | 4.91 | 4.91 | 4.91 | 4.91 | 4.91 | 4.91 | 4.91 | 4.91 |
| | Prophet | 6.96 | 6.96 | 6.96 | 6.96 | 6.96 | 6.96 | 6.96 | 6.96 | 6.96 | 6.96 | 6.96 |
| | Salient 2.0 | 3.20 | 3.20 | 3.20 | 3.20 | 3.20 | 3.20 | 3.20 | 3.20 | 3.20 | 3.20 | 3.20 |
| Ensembles | Uniform Toolkit | 8.34 | 8.34 | 8.34 | 8.34 | 8.34 | 8.34 | 8.34 | 8.34 | 8.34 | 8.34 | 8.34 |
| Online Toolkit | 8.82 | 8.82 | 8.82 | 8.82 | 8.82 | 8.82 | 8.82 | 8.82 | 8.82 | 8.82 | 8.82 |

Temperature, weeks 3-4

Temperature, weeks 5-6
# C3 Yearly Average Skill

Tables C3 and C4 present the yearly average skill of each model across the contiguous U.S. in the years 2011-2020.

Table C3: Average percentage skill when forecasting temperature in the contiguous U.S. The best performing models within each group are shown in bold, while the best performing models overall are shown in green.

| Group       | Model         | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  | 2019  | 2020  | Overall |
|-------------|---------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|
| Baselines   | Deb. CFSv2    | 33.26 | 26.66 | 17.32 | 27.66 | 35.73 | 33.07 | 13.36 | 19.42 | 18.39 | 24.14 | 24.94   |
|             | Persistence   | 27.76 | −1.64 | −2.16 | 17.98 | 20.41 | 7.50  | 3.78  | −0.39 | 13.74 | 19.19 | 10.64   |
| Toolkit     | Climatology++ | 11.50 | 12.83 | 7.48  | 10.93 | 29.44 | 16.45 | 20.17 | 18.19 | 22.39 | 36.79 | 18.61   |
|             | CFSv2++       | 34.46 | 43.23 | 13.67 | 32.30 | 38.18 | 42.30 | 27.95 | 26.93 | 33.85 | 30.77 | 32.38   |
|             | Persistence++ | 41.21 | 47.39 | 12.48 | 27.99 | 37.44 | 41.03 | 24.48 | 32.64 | 18.51 | 40.53 | 32.40   |
| Learning    | AutoKNN       | 16.77 | 3.01  | 5.62  | 4.74  | 12.99 | 14.60 | 11.32 | 11.65 | 29.20 | 12.43 |         |
|             | LocalBoosting | 10.51 | 17.85 | 5.12  | 15.50 | 20.68 | 17.94 | 1.99  | 18.95 | 17.46 | 14.44 |         |
|             | MultiLLR      | 34.05 | 31.03 | 9.57  | 22.70 | 29.87 | 15.03 | 24.37 | 19.70 | 35.74 | 20.21 |         |
|             | Prophet       | 18.31 | 14.51 | 3.86  | 14.30 | 14.80 | 27.74 | 26.60 | 25.76 | 20.76 | 35.74 | 20.21   |
|             | Salient 2.0   | 6.29  | 2.31  | 0.01  | −5.73 | 15.13 | −4.32 | 23.01 | 28.83 | 14.54 | 32.73 | 11.24   |
| Ensembles   | Uniform Toolkit | 40.16 | 45.49 | 12.40 | 30.33 | 39.72 | 41.90 | 28.86 | 29.12 | 37.34 | 33.58 |         |
|             | Online Toolkit | 35.98 | 45.10 | 12.50 | 31.75 | 39.18 | 43.10 | 28.30 | 29.25 | 31.15 | 36.19 | 32.27   |

| Group       | Model         | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  | 2019  | 2020  | Overall |
|-------------|---------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|
| Baselines   | Deb. CFSv2    | 33.40 | 36.09 | 1.35  | 15.48 | 25.72 | 26.47 | 4.31  | 15.82 | 8.47  | 23.54 | 19.12   |
|             | Persistence   | 20.28 | −9.52 | 0.40  | 18.22 | 23.24 | −1.24 | −3.89 | −5.41 | 6.15  | 13.55 | 6.22    |
| Toolkit     | Climatology++ | 11.50 | 12.83 | 7.48  | 10.93 | 29.44 | 16.45 | 22.79 | 18.19 | 22.39 | 36.79 | 18.87   |
|             | CFSv2++       | 34.74 | 39.38 | 6.45  | 16.37 | 32.26 | 36.06 | 16.26 | 25.05 | 18.43 | 41.90 | 26.73   |
|             | Persistence++ | 31.11 | 38.71 | 8.61  | 34.55 | 40.15 | 43.80 | 15.03 | 24.37 | 19.70 | 35.38 | 29.19   |
| Learning    | AutoKNN       | 4.73  | −0.32 | 8.06  | 5.80  | 11.43 | 6.28  | 9.89  | 8.21  | 4.44  | 27.12 | 8.56    |
|             | LocalBoosting | 8.63  | 15.77 | 3.24  | 5.81  | 22.93 | 7.99  | 7.84  | 18.43 | 13.22 | 22.87 | 12.69   |
|             | MultiLLR      | 19.89 | 23.05 | 3.55  | 17.71 | 13.20 | 26.98 | 12.09 | 12.08 | 14.44 | 23.63 | 16.68   |
|             | Prophet       | 17.23 | 13.04 | 3.45  | 12.99 | 13.74 | 27.20 | 27.74 | 26.16 | 20.72 | 35.83 | 19.78   |
|             | Salient 2.0   | 7.13  | −1.75 | 8.14  | −5.24 | 13.94 | −9.70 | 23.99 | 30.29 | 16.04 | 35.36 | 11.77   |
| Ensembles   | Uniform Toolkit | 36.14 | 41.01 | 8.85  | 28.47 | 40.17 | 41.60 | 19.54 | 26.02 | 21.86 | 41.53 | 30.56   |
|             | Online Toolkit | 31.29 | 40.09 | 7.75  | 30.39 | 40.57 | 42.62 | 17.64 | 25.82 | 21.25 | 40.65 | 30.06   |
Table C4: Average percentage skill when forecasting precipitation in the contiguous U.S. The best performing models within each group are shown in bold, while the best performing models overall are shown in green.

| Group       | Model         | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Overall |
|-------------|---------------|------|------|------|------|------|------|------|------|------|------|---------|
| Precipitation, weeks 3-4 |
| Baselines   | Deb. CFSv2    | 15.26| 8.99 | 5.96 | 5.69 | 3.69 | 2.19 | 0.34 | 4.01 | 3.76 | 7.19 | 5.77    |
|             | Persistence   | 14.24| 9.61 | 5.96 | 6.46 | 7.20 | 1.30 | 13.46| 6.72 | 8.43 | 10.32| 8.31    |
| Toolkit     | Climatology++ | 12.24| 24.09| 13.40| 15.67| 7.97 | 17.88| 14.29| 13.39| 8.76 | 22.65| 15.04   |
|             | CFSv2++       | 24.58| 19.08| 17.44| 16.15| 8.74 | 12.95| 14.75| 13.42| 13.09| 23.05| 16.34   |
|             | Persistence++ | 21.98| 14.03| 16.63| 13.90| 9.38 | 8.12 | 5.10 | 13.33| 12.89| 17.48| 13.38   |
| Learning    | AutoKNN       | 13.86| 18.66| 10.13| 8.60 | 3.11 | 3.03 | 5.29 | -0.50| -3.27| 7.56 | 6.66    |
|             | LocalBoosting | 6.32 | 15.96| 15.73| 7.70 | 4.27 | 2.64 | 11.77| 13.79| 10.68| 19.46| 10.82   |
|             | MultiLLR      | 12.44| 4.87 | 14.72| 10.74| 5.47 | 5.75 | 8.49 | 7.83 | 8.28 | 16.16| 9.49    |
|             | Prophet       | 18.23| 12.42| 14.29| 15.85| 5.33 | 13.49| 11.31| 13.19| 10.77| 20.01| 13.51   |
|             | Salient 2.0   | 17.06| 20.38| 17.82| 11.24| 5.95 | 3.00 | 5.45 | 2.44 | 2.28 | 14.99| 10.11   |
| Ensembles   | Uniform Toolkit | 26.71| 23.16| 19.92| 19.79| 11.93| 15.79| 15.01| 16.49| 14.98| 25.16| 18.94   |
|             | Online Toolkit | 24.72| 23.37| 18.79| 20.07| 11.94| 18.14| 15.51| 16.27| 14.39| 25.02| 18.86   |

| Group       | Model         | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Overall |
|-------------|---------------|------|------|------|------|------|------|------|------|------|------|---------|
| Precipitation, weeks 5-6 |
| Baselines   | Deb. CFSv2    | 11.73| 10.98| 8.35 | 1.03 | -4.91| 0.98 | 2.77 | 4.24 | -1.30| 8.73 | 4.28    |
|             | Persistence   | 6.85 | 6.96 | 12.34| 4.32 | 3.83 | 1.87 | 10.90| 8.73 | 5.62 | 13.04| 7.41    |
| Toolkit     | Climatology++ | 12.28| 24.11| 13.33| 15.67| 7.97 | 17.88| 13.66| 13.39| 8.76 | 22.65| 14.99   |
|             | CFSv2++       | 23.11| 18.75| 22.87| 14.88| 8.51 | 13.17| 7.74 | 15.34| 13.40| 22.17| 16.09   |
|             | Persistence++ | 17.44| 9.98 | 16.90| 7.68 | 2.44 | 3.83 | 11.26| 7.60 | 16.26| 9.77 |         |
| Learning    | AutoKNN       | 12.33| 16.31| 11.16| 6.85 | 3.31 | 5.07 | 1.53 | -1.05| -4.58| 7.88 | 5.93    |
|             | LocalBoosting | 9.81 | 9.26 | 13.24| 4.53 | 5.31 | 6.70 | 10.25| 13.55| 10.31| 14.30| 9.72    |
|             | MultiLLR      | 12.42| 5.99 | 10.69| 7.46 | 0.63 | 1.97 | 10.03| 8.46 | 6.83 | 15.50| 7.97    |
|             | Prophet       | 17.92| 12.41| 14.74| 15.86| 5.44 | 13.54| 10.06| 13.08| 10.75| 19.94| 13.41   |
|             | Salient 2.0   | 17.06| 20.26| 17.73| 11.48| 5.91 | 2.77 | 5.10 | 2.06 | 2.10 | 14.86| 9.99    |
| Ensembles   | Uniform Toolkit | 25.31| 23.12| 23.43| 17.89| 9.36 | 16.42| 11.23| 16.80| 13.93| 25.24| 18.35   |
|             | Online Toolkit | 23.28| 23.38| 21.60| 18.11| 8.24 | 17.01| 12.47| 16.28| 12.86| 25.22| 17.91   |
C4 Spatial Improvement over Mean Debiased CFSv2 RMSE

Figure C3 presents the spatial improvement of each model over debiased CFSv2 when predicting U.S. temperature across 2011-2020. For both the weeks 3-4 and the weeks 5-6 lead times, the toolkit models uniformly improve over debiased CFSv2 and outperform both the baseline models and the state-of-the-art learning methods. The best overall performance at each lead time is obtained by the Online Toolkit ensemble.

Figure C3: Percentage improvement over mean debiased CFSv2 RMSE when forecasting temperature in the contiguous U.S. over 2011-2020. White grid points indicate negative or 0% improvement.

Figure C4 displays the spatial improvement of each model over debiased CFSv2 when forecasting U.S. precipitation across 2011-2020. For precipitation, all models exhibit larger gains over debiased CFSv2, and all models, including Climatology, achieve larger improvements in the Western U.S. than in the Eastern U.S.

Figure C4: Percentage improvement over mean debiased CFSv2 RMSE when forecasting precipitation in the contiguous U.S. over 2011-2020. White grid points indicate negative or 0% improvement.
C5 Spatial Bias Maps

This section explores the spatial bias (the mean forecast minus the mean observation at each grid point in the contiguous U.S.) of each model across 2011-2020. The temperature maps of Figure C5 indicate a cold bias for most models over the southern half of the U.S. and an additional warm bias for several models in the center north. This warm bias is particularly pronounced for Salient 2.0. In precipitation maps of Figure C6, all models Salient 2.0 and AutoKNN show wet biases in the western half of the U.S. and dry biases in the eastern half. AutoKNN exhibits a dry bias extending from the Eastern U.S. to include the Northern U.S. as well, while Salient 2.0 displays a strong dry bias across the entire contiguous U.S. that is especially pronounced in the eastern half.

The Prophet model is noticeably less biased than the other evaluated models; however, this bias reduction does not immediately translate into improved performance, as Prophet is outperformed by toolkit models with larger bias in all four tasks. This indicates that Prophet’s reduced bias comes at a cost of unnecessarily high variance relative to the dominating toolkit model forecasts.

Figure C5: Model bias when forecasting temperature in the contiguous U.S. over 2011-2020.

Figure C6: Model bias when forecasting precipitation in the contiguous U.S. over 2011-2020.
Table C5: 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.

| Group                  | Model         | Temp. weeks 3-4 | Temp. weeks 5-6 | Precip. weeks 3-4 | Precip. weeks 5-6 |
|------------------------|---------------|-----------------|-----------------|-------------------|-------------------|
| Contest baselines      | Salient       | –               | –               | 11.10             | 7.02              |
|                        | Climatology   | 10.22           | -0.76           | 5.82              | 2.25              |
| Contestants            |               |                 |                 |                   |                   |
| 1\textsuperscript{st}  |               | 17.12           | 8.47            | 11.54             | 8.63              |
| 2\textsuperscript{nd}  |               | 16.67           | 7.04            | 11.10             | 8.03              |
| 3\textsuperscript{rd}  |               | 15.47           | 6.90            | 10.62             | 7.94              |
| Learning               |               |                 |                 |                   |                   |
| AutoKNN                |               | 13.09           | 2.90            | 7.50              | 3.05              |
| LocalBoosting          |               | 12.85           | 4.09            | 7.25              | 3.71              |
| MultiLLR               |               | 9.54            | 1.12            | 8.95              | 4.58              |
| Prophet                |               | 15.68           | 6.86            | 6.88              | 3.40              |
| Salient 2.0            |               | 11.15           | 2.91            | 12.65             | 8.56              |
| Toolkit                |               |                 |                 |                   |                   |
| Climatology++          |               | 15.54           | 6.43            | 8.35              | 4.69              |
| CFSv2++                |               | 6.67            | 9.26            | 8.70              | 5.51              |
| Persistence++          |               | 16.59           | 8.27            | 8.20              | 4.51              |
| Ensembles              |               |                 |                 |                   |                   |
| Uniform Toolkit        |               | 14.96           | 9.58            | 9.31              | 5.89              |
| Uniform Toolkit + Learning |           | 15.89           | 8.79            | 10.43             | 6.79              |
| Online Toolkit         |               | 16.71           | 8.70            | 8.85              | 5.19              |
| Online Toolkit + Learning |           | 14.70           | 7.97            | 12.52             | 8.18              |

C6 Western U.S. Competition Results

C7 Salient 2.0 Dry Bias

We hypothesized that the exceptional Western U.S. contest performance of Salient 2.0 in Table C5 was due in part to the dry bias observed in Figure C6, as 2020 was an unusually dry year in the Western U.S. To explore this hypothesis, we focus on forecasting precipitation weeks 3-4 in the Western U.S. and display in Figure C7 (left) the percentage improvement of Salient 2.0 and CFSv2++ over debiased CFSv2 alongside the inverse total precipitation each year in 2011-2020. As anticipated, the steep decrease in cumulative precipitation for 2020 is accompanied by a steep increase in Salient 2.0 predictive accuracy. In addition, the rises and falls in total precipitation track the accuracy of Salient 2.0 well but appear largely unassociated with the performance curve of other accurate models like CFSv2++. The scatter plots and best-fit lines of Figure C7 (right) paint a similar picture. Salient 2.0 exhibits a distinctly negative correlation between percentage improvement and total precipitation in the Western U.S., while this relationship is absent for other accurate models like CFSv2++.

The developers of the Rodeo I Salient model attribute this dry bias to the log-normal distribution of precipitation, which leads to more frequent anomalously dry conditions than anomalously wet conditions and in turn encourages drier model forecasts Schmitt (2021). More recent versions of the Salient model mitigate this bias by training on seasonal anomalies in place of raw temperature and precipitation values Schmitt (2021).
Figure C7: 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.