ICML 2021 Workshop: Tackling Climate Change with Machine Learning

An Accurate and Scalable Subseasonal Forecasting Toolkit for the United States

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Introduction

California

Big Sur fire: hundreds of firefighters battle blaze raging in California

Willow fire is one of dozens burning across US west, including Arizona, Utah and New Mexico, amid dry conditions

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Tue 22 Jun 2021 12.52 EDT

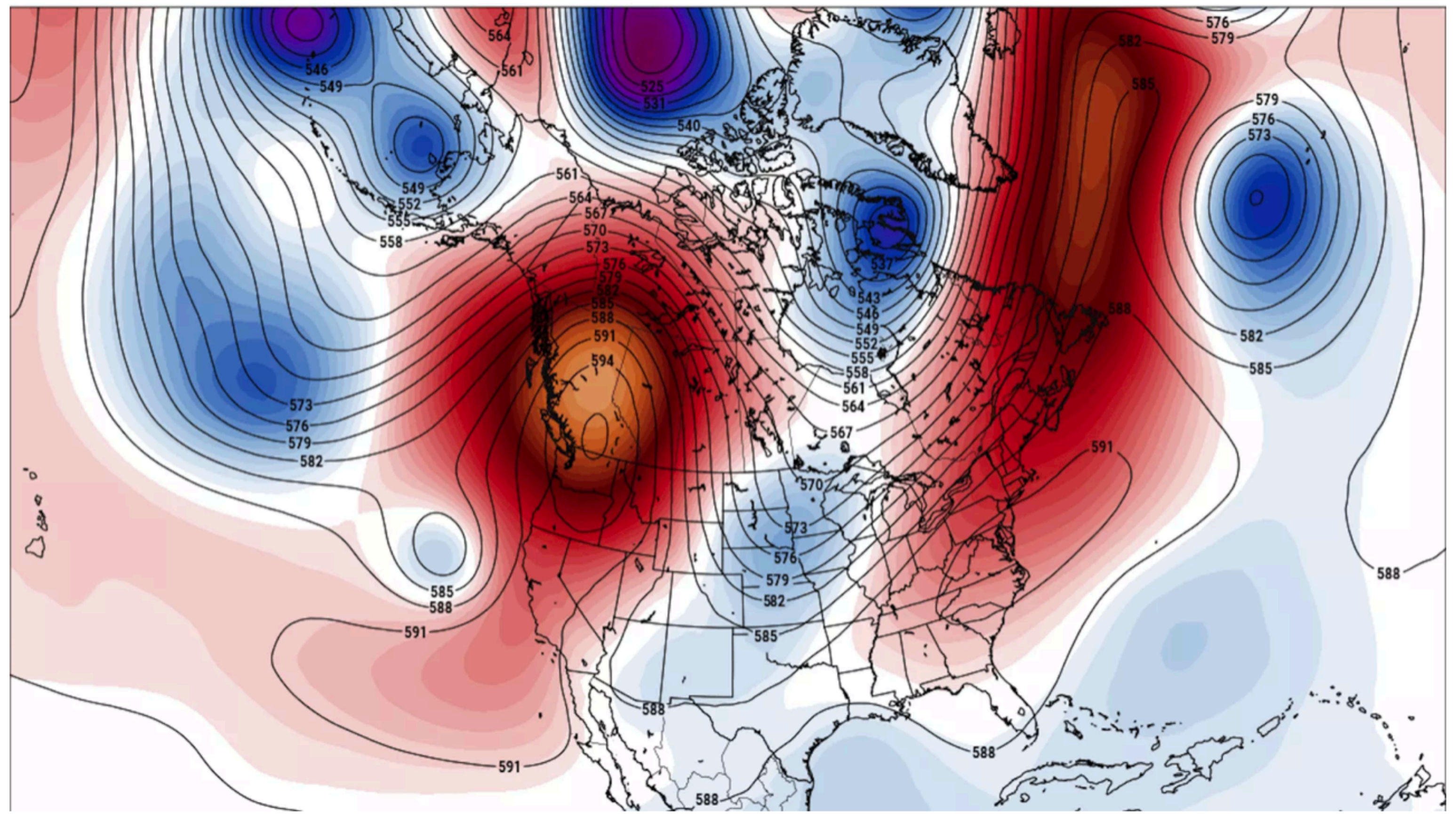
▲ Smoke rises from the Willow fire near Big Sur, California, on Sunday. Photograph: AP

Firefighters are battling to contain a wildfire that erupted near Big Sur last week, as the flames continue to engulf the dry California landscape and threaten historical sites, cabins and ranches.

https://www.theguardian.com/us-news/2021/jun/21/big-sur-wildfire-willow-fire

Pacific Northwest soon to be ground zero for record-shattering heat

Andrew Freedman



Computer model projection showing the unusually strong heat dome over the Pacific Northwest on Sunday. (PivotalWeather).

https://www.axios.com/pacific-northwest-heat-wave-all-time-records-17b55cac-7049-4583-86f0-4296093d5691.html

Introduction

- Subseasonal weather prediction (3-6 weeks ahead) is very important:
  - agriculture planning
  - allocation of water resources
  - preparing droughts and floods
  - managing wildfires

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

- We develop a toolkit of sub seasonal models that outperform operational weather models as well as state-of-the-art learning methods from the literature

Forecasting tasks

- Four tasks:
  - average temperature on weeks 3-4 ahead
  - average temperature on weeks 5-6 ahead
  - accumulated precipitation on weeks 3-4 ahead
  - accumulated precipitation on weeks 5-6 ahead
- Geographical Region: US, 1°x1° resolution, G=862 gridpoints
- Loss function: root mean squared error

$$\mathrm{rmse}_d = \sqrt{\frac{1}{G}\sum_{g=1}^{G}(\hat{y}_{d,g} - y_{d,g})^2}$$

Dataset

- Updated and improved `SubseasonalRodeo` dataset (Hwang et al., 2019)
- Variables included:
  - Temperature
  - Precipitation
  - Sea surface temperature
  - Sea ice concentration
  - Multivariate ENSO index
  - Madden-Julian oscillation
  - Relative humidity
  - Geopotential height
  - Numerical weather prediction (NWP) forecasts

Baseline Models

- **Climatology**
  - Standard baseline for subseasonal forecasting
  - Average temperature or precipitation for specific day and month over 1981-2010
- **CFSv2**
  - Operational US physics-based model from NCEP
  - Main NWP baseline
- **Persistence**
  - Predict most recent value

Learning Models

- **AutoKNN**, introduced in (Hwang et al, 2019)
- **Informer**, introduced in (Zhou, 2021)
- **LocalBoosting**, based on (Prokhorenkova et al, 2018)
- **MultiLLR**, introduced in (Hwang et al, 2019)
- **N-BEATS**, introduced in (Oreshkin, 2020)
- **Prophet**, introduced in (Taylor and Letham, 2018)
- **Salient 2.0**, based on (Schmitt, 2019)

Our Toolkit

- **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++**
  - Learned combination of lagged measurements with NWP

Ensembling

- **Uniform ensemble**
  - Averages over base models
  - Typical solution in the weather community
- **Online ensemble**, introduced in Flaspohler et al (2021)
  - Runs a follow-the-regularized-leader online learning method
  - Results in an adaptive convex combination of base models
- **Base Models**
  - Climatology++, CFSv2++, Persistence++, LocalBoosting, MultiLLR and Salient 2.0

Results

Toolkit improvements

- For all tasks, toolkit generally improves over baselines in the years 2011-2020

	Clim	Clim++	CFSv2	CFSv2++	Pers	Pers++
Temp. 3-4w	-0.29	**1.60**	-14.17	**5.49**	-110.83	**5.60**
Temp. 5-6w	1.97	**3.90**	-15.37	**6.16**	-172.76	**5.51**
Precip. 3-4w	7.96	**9.03**	-4.57	**8.53**	-28.03	**8.78**
Precip. 5-6w	7.79	**8.85**	-4.83	**8.34**	-31.51	**8.17**

Results

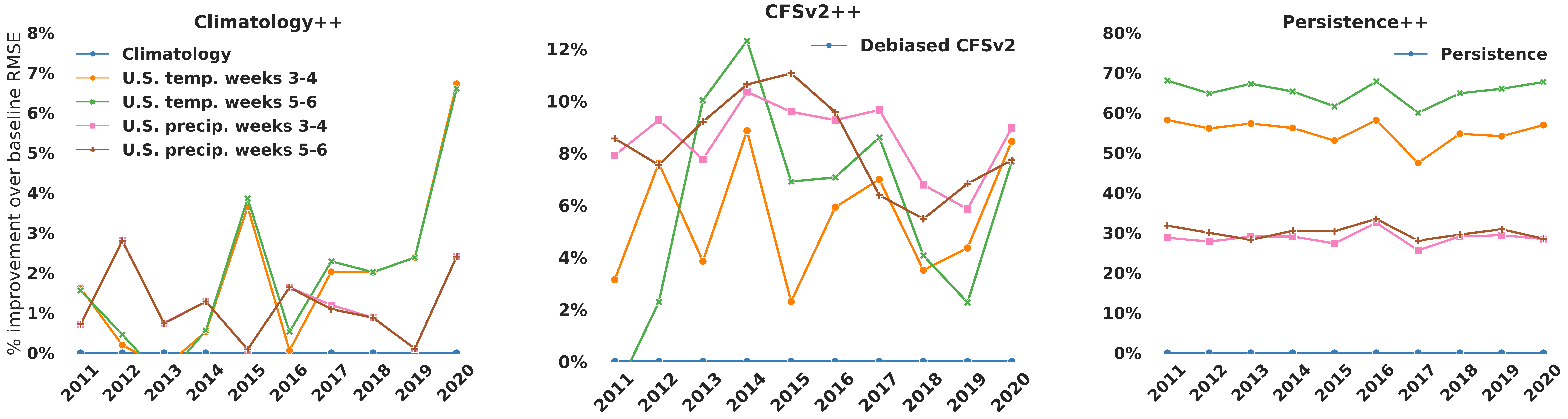
Toolkit improvements

- For all tasks, toolkit generally improves over learning methods in 2011-2020
- Ensembling provides further improvements

	Toolkit			Learning							Ensembles	
	Clim++	CFSv2++	Pers++	AKNN	LBoost	Inform.	MLLR	N-Beats	Prophet	Sal. 2.0	Uniform	Online
Temp. 3-4w	1.60	5.49	5.60	0.51	−1.18	−40.58	2.04	−47.33	0.71	−9.28	6.07	**6.23**
Temp. 5-6w	3.90	6.16	5.51	2.26	−1.28	−65.27	1.24	−53.55	2.83	−4.98	6.64	**6.79**
Precip. 3-4w	9.03	8.53	8.78	7.90	7.53	0.83	7.29	−18.97	8.59	3.17	9.63	**9.69**
Precip. 5-6w	8.85	8.34	8.17	7.62	7.17	0.49	6.94	−20.95	8.40	2.96	**9.33**	9.27

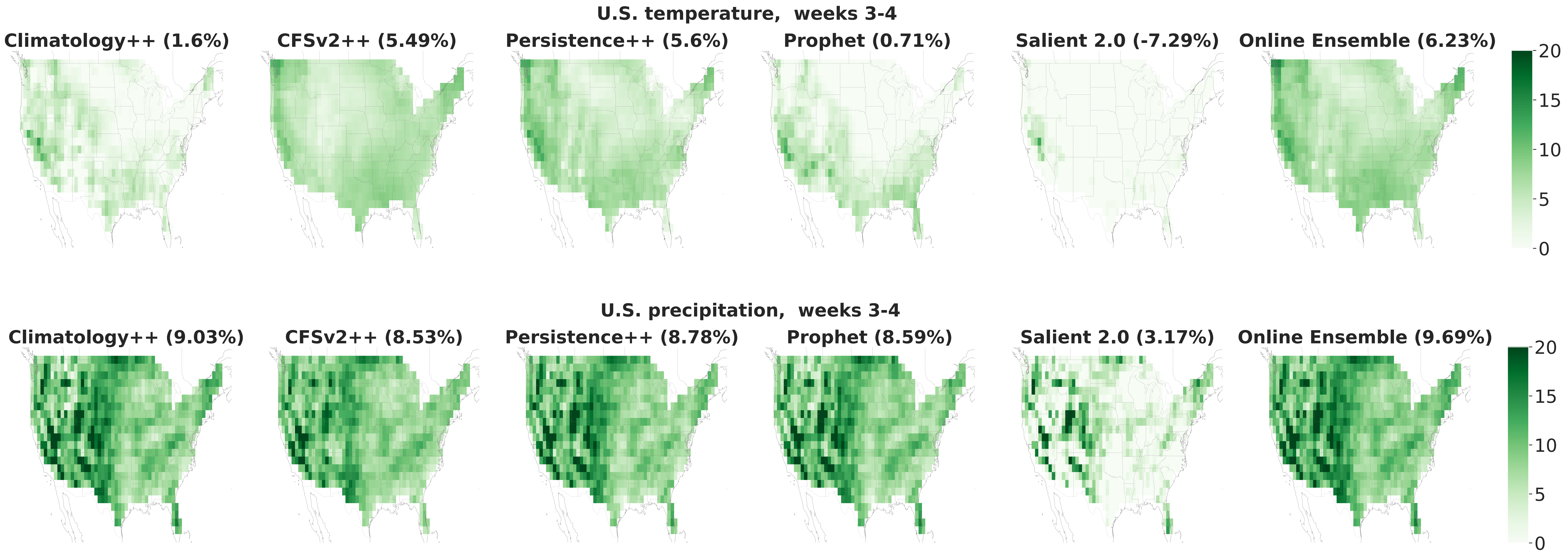
Results

Performance of models vary over time…



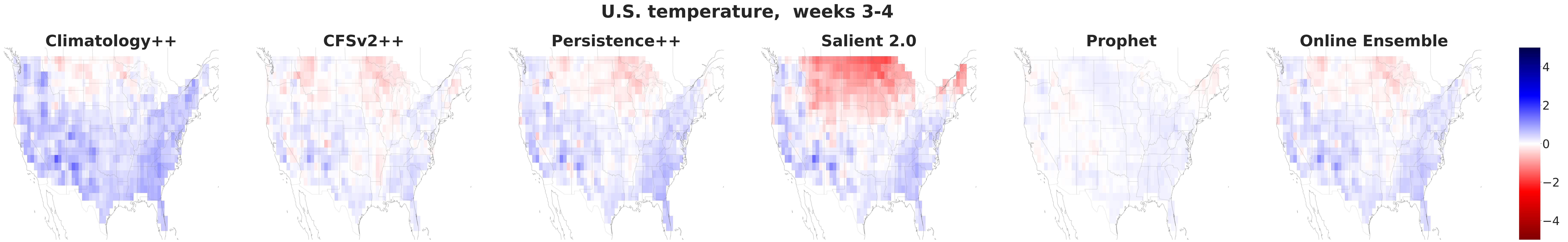
Results

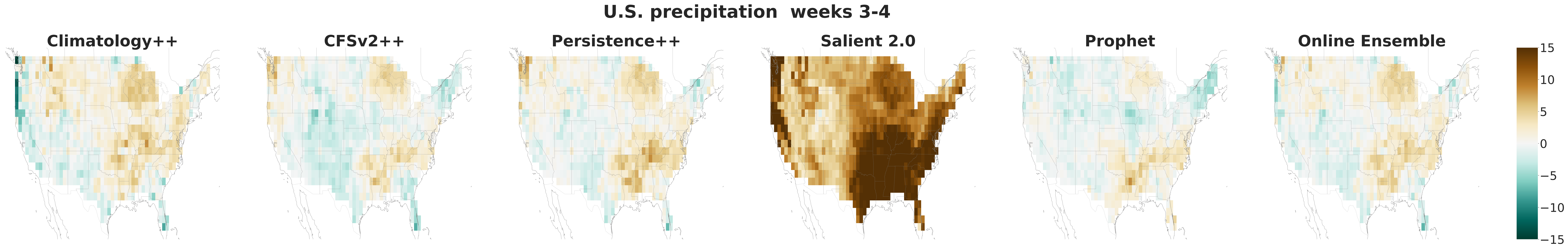
Performance of models vary over space



Results

Performance of models vary over space





Conclusion

- Subseasonal forecasting is a hard but fundamental problem
- Simple modifications of classical weather models yield sizable improvements
- The toolkit introduced has better performance than ML alternatives
- Toolkit models are not only accurate, but highly scalable
- Ensembling is very advantageous; great application of online learning
- Combining weather and ML models is a powerful strategy
- For more information: `https://www.microsoft.com/en-us/research/project/subseasonal-climate-forecasting/`