Salient Predictions: White Paper

Seasonal weather forecasts worth their salt

Overview

Salient Predictions (SP) provides state-of-the-art long-range weather forecasts. Developed by scientists from the Massachusetts Institute of Technology and Woods Hole Oceanographic Institution, SP models utilize novel sources of climate predictability and deep learning techniques to outperform traditional methods for sub-seasonal to seasonal (S2S) forecasts of 3 weeks to 12 months lead.

The S2S Prediction Problem

Accurate S2S weather forecasts have the potential to provide large ROI for industries susceptible to weather risk. This includes many sectors that deal with the allocation of physical resources and assets on weekly to monthly timescales, including agriculture, energy, reinsurance, commodities, and supply chain management.

Despite high demand, the accuracy of existing S2S products lags far behind that of short-term weather forecasts. Historically, the top S2S models have been run by government agencies such as ECMWF and NOAA, and most commercial forecasting services are based on these models. They rely on the same methodology used for short-term forecasting: dynamical models which solve the physical equations of the atmosphere to project its current state into the future. Because the climate system is inherently chaotic, these model solutions diverge rapidly within two weeks. Hence, conventional S2S forecasts have large uncertainty and low skill in many regions.

SP Modeling Framework

Given the limitations of physical modeling for S2S forecasting, SP uses a different methodology with two key principles:

1. **Focus on elements of the climate system with inertia.** These are properties that change slowly and continue to affect weather into the future. The current state of the atmosphere actually has minimal impact on S2S predictability. Instead, ocean and land surface conditions provide the largest influences on seasonal weather patterns. The ocean in particular has 1000x the heat capacity of the atmosphere and holds 97% of Earth's water. With backgrounds in ocean science, SP researchers utilize unconventional ocean data sources to improve forecasts. One example is ocean salinity: salty signals appear when evaporation is strong over the ocean, indicating a supply of freshwater and latent heat to the atmosphere, and have been shown to improve rainfall predictions on land.
2. **Leverage cutting-edge machine learning tools.** Instead of physics-based models, SP uses a statistical framework built on machine learning. Historically, only a few simple climate indices (e.g. ENSO, IOD, AMO, QBO) have been used in statistical models to make S2S forecasts. New deep learning tools can efficiently comb through large datasets and identify complex climate system relationships, providing a breakthrough in predictability.

With this philosophy, SP has built a global-scale machine learning platform using deep neural networks which ingests a wide range of climate data. Because our models are statistical in nature, they aren't bogged down in the details of atmospheric physics, but have the scale and complexity to find predictability in all aspects of the climate system.

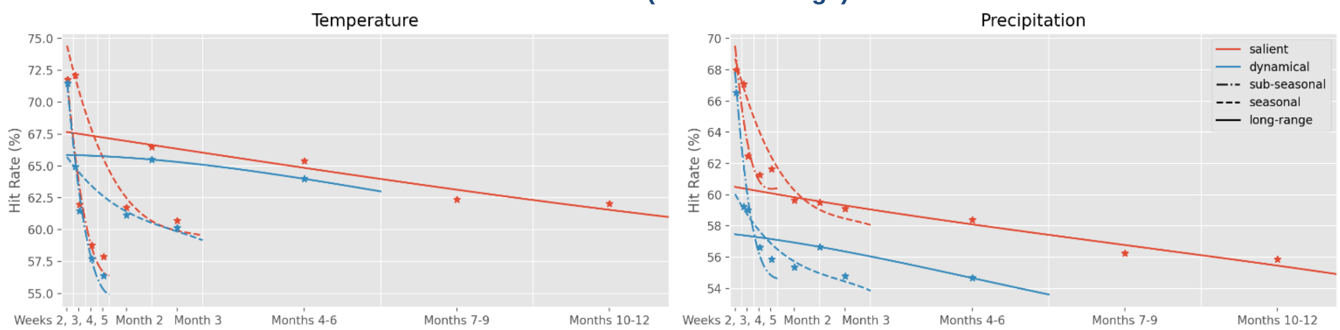
Working with Uncertainty

While our forecasts outperform traditional methods, we know that S2S weather predictions will never be exact; this is the well-known "butterfly effect" of chaotic systems. Therefore, we offer a fully transparent and thorough validation for the skill of our models broken down by location and season. This allows customers to understand how confident they should be in a particular forecast and make business decisions accordingly. For those who simply want to see the most likely scenario for next season's weather, that is our baseline forecast. For businesses who can make use of probabilistic information, we also offer a set of ensemble forecasts and comparison with dynamical models for detailed statistics on the range of possible outcomes.

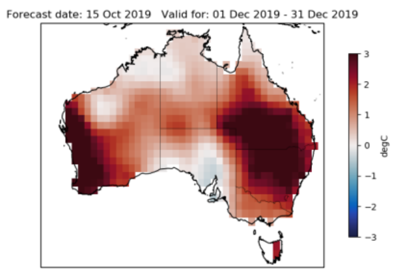
Proof of Skill

After preliminary model development, the SP team entered the US Bureau of Reclamation's S2S Forecast Rodeo in 2018 and took $250k in prizes for the most accurate rainfall forecasts across the US West, beating several professional forecasting companies. Our models have since been validated through a variety of customer use cases. Additionally, 30-year hindcast experiments (1990-2020) are available for analysis on our API. SP models beat top competitors, such as the ECMWF SEAS5 system across most S2S timescales, and have successfully anticipated many damaging weather patterns in recent years. Shown below is a summary of forecast accuracy across timescales, compared to state-of-the-art dynamical models from ECMWF and NOAA. Forecast hit rate is calculated from seasonal anomalies using the ERA5 dataset as the ground truth. SP models have the largest skill improvements for precipitation and at longer lead times.

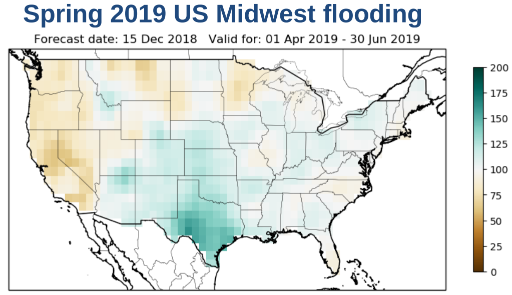
Skill Scores (Global Average)



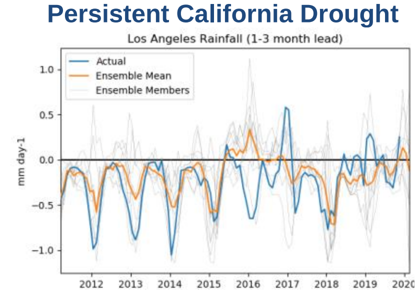
Dec. 2019 Australia heatwave



Spring 2019 US Midwest flooding



Persistent California Drought



Products Offered

SP provides temperature and precipitation forecasts at up to 1/4° (25km) spatial resolution updated weekly, with models optimized for three separate timescales to cover the inherent predictability windows of S2S weather:

- Sub-seasonal: weeks 1, 2, 3, 4, 5
- Seasonal: months 1, 2, 3
- Long-range: months 1-3, 4-6, 7-9, 10-12

Raw forecast data is available via gridded NetCDF format through an API, or can be viewed through a GUI web tool or weekly graphical summaries. SP models have global coverage, with the ability to design customized forecasts with optimized predictors and accuracy for smaller regions.

Models for additional weather variables are currently under development, including hydro, wind, solar, and demand forecasts for the energy sector, as well as soil moisture and humidity for agriculture use cases.

Team Members

President	Chief Scientist	Machine Learning	Engineering	Funding
				
Ray Schmitt	Sam Levang	Jesse Palma	Eric Schmitt	First Star VC